COMPUTATIONAL MODELING OF COGNITIVE PROCESSES FOR CONTINUOUS IN-HOME ASSESSMENT OF COGNITIVE PERFORMANCE

By

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CERTIFICATE OF APPROVAL

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To my wife May and my daughters Emmy and Mika

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Table of Abbreviations

ADL	Activities of Daily Living
DST	Digit-Symbol Test
LHS	Left-Hand Side
MD	Mouse Dynamics
MMSE	Mini Mental State Exam
OLS	Ordinary Least Squares
PIR	Passive Infrared
RFID	Radio Frequency Identification
RHS	Right-Hand Side
RV	Random Variable
SH	Scavenger Hunt
TMT	Trail-Making Test
TMT-A	Trail-Making Test Part A
TMT-B	Trail-Making Test Part B

Table of Symbols

$E\{X\}$, $\langle X \rangle$	Mean Value of X
$M\{X\}$	Median Value of X
$\sigma\{X\}$	Standard Deviation of X
$IQR\{X\}$	Inter-Quartile Range of X
D	Total Movement Distance
N	Number of Errors on TMT
S	Test Score
P	Probability of Making an Error on Each Move of TMT
T	Movement Time
W	Target Width
a, b	Motor Parameters of Fitts' Law
p	Probability of Making an Error on Each Move of SH
v	Walking Speed
v_{cut}	Cut Speed
Δ	Net Movement Distance
α, β	Recall Time Transformation Parameters
γ	Dual-Tasking Transformation Parameter
χ, ξ	Motor Complexity

κ	Search Complexity
ρ	$10^{\nu_{cut}/\nu_0}$
τ_R	Characteristic Recall Time
τ_S	Characteristic Search Time
τ_{Sw}	Characteristic Set-Switching Time

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Abstract

Computational Modeling of Cognitive Processes for Continuous In-Home Assessment of Cognitive Performance

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A rapidly growing proportion of older adults in the populations of the US, EU, and Japan, combined with an increasing prevalence of conditions associated with aging, and further exacerbated by behavioral issues, comprise significant challenges to healthcare delivery. The development of cost-effective, proactive, and preventive approaches, focused on quality-of-life is therefore of utmost societal importance. Replacing institution-centered (clinic-centered) reactive approaches with user-centered sensor and computer-aided care is emerging as a potential solution that would allow early detection and intervention through continuous monitoring and assessment. In contrast to well controlled, in-clinic measurements, however, the context of the user-centered behavioral observations is typically unknown, and the quantities measured by the sensors are usually remote from the quantities of interest. These aspects pose significant challenges for the

development of robust algorithms. The only way to mitigate these impediments is the development of computational models that relate the observable quantities to meaningful behavioral metrics. The focus of this thesis is the development of several algorithmic techniques based on computational models of behaviors. These serve as examples of approaches that would enable inference of the patient state from unobtrusive, but continuous monitoring of everyday, real-life behaviors. I examine three techniques for performing in-home monitoring of cognitive performance. The first technique monitors an older adult's walking speed unobtrusively in the home using motion sensors placed on the ceiling or wall. The second technique monitors the older adult's cognitive performance by observing how the older adult plays a specially designed computer game. The third technique monitors the older adult's cognitive performance by observing how the older adult uses a computer in the course of everyday, real-life computer usage. In the case of the first technique, the walking speed serves as immediately behavioral metric, while in the cases of the second and third techniques, we define the behavioral metrics as the parameters of computational models of the behavior of playing the game or using the computer, respectively. The model-based inferences in the second and third techniques characterize the older adults' ability to utilize the component cognitive functions in order to carry out the task of playing the game or using the computer. The computational models that are used in the second and third techniques provide descriptions of how the behaviors are carried out physically, and the associated behavioral metrics characterize the older adults' physical performance of specific aspects of the behavior being measured. In this thesis, I demonstrate that the unobtrusive performance measurements combined with the computational model can provide estimates of cognitive functionality similar to that obtained in the controlled environment of a clinical assessment using standard neuropsychological tests – the walking speed, and the Trail-Making Test. In addition, I argue that the observations of older adults playing the computer game and going about everyday, real-life computer usage support a computational model of the Trail-Making Test in which set-switching is performed as a dual-task with movement during Trail-Making Test Part B.

Introduction

Chapter 1 – Background and Introduction

1.1 Overview

Larger portions of the populations of the European Union, Japan, and the United States are living to older ages. The associated costs of providing healthcare to a larger older population pose significant challenges to the economies of these regions. The costs of the treatment of a medical issue can be reduced by detecting and treating the issue earlier. Thus, cost-effective methods of early detection of medical issues can reduce the costs of providing healthcare to the growing older population.

The present, institution-centered (clinic-centered), model of providing healthcare through regular, clinical visits to a trained clinician has a number of shortcomings as a cost-effective means of providing early detection disease. These shortcomings relate to the necessary infrequency of clinic visits for economic and practical reasons. Alternative, user-centered, models of overall lifestyle health management by the ubiquitous and continuous application of technology to healthcare provide a potentially cost-effective method of constant healthcare monitoring.

The performance of technologies applied to the ubiquitous and continuous monitoring of subject performance for the purpose of early detection of disease can be enhanced greatly by the use of computational models of the behaviors that the technologies are being measuring. These computational models allow the clinician to make better measurements using the available, cost-effective technologies, and relate the ubiquitous and continuous measurements to standard clinical measurements.

In this thesis, I demonstrate that the unobtrusive performance measurements combined with the computational model can provide estimates of cognitive functionality similar to that obtained in the controlled environment of a clinical assessment using standard neuropsychological tests – the walking speed, and the Trail-Making Test. In addition, I argue that the observations of older adults playing the computer game and going about everyday, real-life computer usage support a computational model of the Trail-Making Test in which set-switching is performed as a dual-task with movement during Trail-Making Test Part B.

1.2 Background

1.2.1 Economics of Healthcare for an Aging Population

The populations of the European Union, Japan, and the United States are becoming older with a larger proportion of the population of advanced age. [1, 2] In the United States, the population of American aged 65 years or older will double in the next 25 years to about 72 million. [3] By 2030, older adults will account for roughly 20% of the U.S. population. [3] The aging population of these regions comes with a variety of economic consequences. [1, 2] Projections suggest that health and long-term care will account for about half of the increase in age-related social expenditures by 2050. [4] Improving quality of life and providing adequate medical care for the rising number of elderly while keeping health care costs under control has, in recent years, become a major problem. [5] The rising cost of health care potentially represents a significant threat to the long-term economic security of workers and retirees. [6] The costs associated with the health and long-term care of older adults can be brought down by appropriate and well-coordinate health and social policies that keep down the required amount of health services. [7]

Preventive healthcare seeks to avert or avoid disease. We can divide preventive healthcare into three kinds of disease prevention: Primary prevention – modifying unhealthy behaviors, Secondary prevention – detecting diseases or their risk at early stages, Tertiary prevention – the effort to avoid or divert the complications from diseases after they have developed. [8] Current, institution-centered, medical care focuses on tertiary prevention. [8] A well-defined and effective package of services promoting primary and secondary prevention at reasonable cost should offer good economic value. [8] In the cases of dementia and Alzheimer's disease, the expected benefits of early detection and intervention would make up for the expected costs of putting a system in place to perform early detection and intervention in the projected savings across the disease course. [9-11]

1.2.2 Institution-Centered Model of Preventive Healthcare

The current model for providing healthcare is institution-centered and requires a trained-professional to meet with the subject and make performance measurements. [12] Clinical evaluation of cognitive and motor performance suffers from a number of drawbacks. Frequent visits to the clinic for assessment are impractical as they are of prohibitive cost and it is difficult for subjects to make frequent trips to a clinic. Infrequent measurements report only the net change between measurement times and cannot distinguish between functional changes occurring slowly over time and abrupt functional changes, which may have different causes. Infrequent measurements do not detect changes when they happen which may reduce the ability of a clinician to provide intervention or reduce the effect of an intervention. Performance in the clinic may be atypical and not representative of the subject's everyday performance.

1.2.3 Institution-Centered Measurement Example: Walking Speed

One commonly used clinical measure of performance is the walking speed. We provide an extended description of the walking speed at this point both to illustrate clinical evaluation techniques through a specific example as well as to provide relevant clinical background for the technique of measuring walking speed continuously in the home that we present in Part I Chapter 2.

A clinician measures the walking speed by observing the time the subject takes to walk a fixed distance along a straight line. The most used walking speed tests use: 2.44 m, 4 m, and 6 m, carried out at usual walking speed. [13] The walking speed is simply the distance walked divided by the observed time taken.

Walking speed has been found to decline as adults age, [14, 15] and has been shown to be associated with survival in older adults. [16, 17] Evidence supports the use of walking speed tests as predictors of adverse results related with health in older adults, [13] and has shown walking speed to be a quantitative estimate of risk of future hospitalization. [18] Slower walking speed has been demonstrated in dementia patients compared to controls [19] and has been shown to precede cognitive impairment [20] and dementia [21], and timed walk has been used as a partial characterization of lower extremity function which has been shown to predict disability [22, 23]. The slowing of walking speed appears to take place secondary to the slowing of processing speed in the path leading to dementia. [24] Other studies have shown a relationship between walking speed and cognition. [25, 26]

1.2.4 Institution-Centered Measurement Example: Trail-Making Test (TMT)

Another commonly used clinical measure of performance is the Trail-Making Test. We provide an extended description of the walking speed at this point both to illustrate clinical evaluation techniques through a another specific example as well as to provide relevant clinical background for the techniques of measuring cognitive performance continuously in the home through interactions with a computer that we present in Part II Chapters 3, 4, and 5.

TMT consists of two connect-the-dots tasks (TMT-A and TMT-B) which the subject completes by using a pen to draw a single line through a series of targets on a test page. Each test takes the form of a standard 8.5”x11” sheet of paper on which is printed 25 small (12mm diameter) targets, seemingly randomly scattered circles containing a label that may be a letter or a number. For TMT-A, the targets are labeled with numbers from 1 to 25, with one number labeling each circle, while in TMT-B targets are labeled with all letters from A to L and all numbers from 1 to 13 with one letter or number labeling each circle. The individual completes the TMT-A by using a pen to draw a line (the “trail”) through all the circles in ascending numerical order of the labels (i.e. ‘1,2,3,…,24,25’), while the TMT-B is completed by drawing the line through the circles in ascending alphanumeric order (i.e. ‘1,A,2,B,…,L,13’). The score on each part of the test is the time the subject needs to complete each task (there is no time limit). If the subject makes an error on the test (drawing the line through an incorrect target), the test administrator stops the subject as soon as the error is noted by the administrator and returns the subject to the last correctly selected target; timing of the subject is not stopped during this error recovery process. The total numbers of errors made on each part are included with the test score. The difference between TMT-A and TMT-B is the use of the numeric and alphanumeric sequence of labels respectively. The alphanumeric label sequences introduce the additional complication of set-switching in which the subject must not only recall the next element in an alphabetic or a numeric sequence, but must also switch sets between the alphabetic and numeric sequences.

Normative TMT data give scores of 42 s on TMT-A and 100 s on TMT-B for ages 75-79, and 55 s on TMT-A and 130 s on TMT-B and for ages 80-84. [27] The test re-test reliabilities for TMT have been observed to be $R^2 = 0.56$ for TMT-A and $R^2 = 0.72$ for TMT-B for a cohort of normal adult controls. [28] These controls had observed scores of 47 ± 25 s on TMT-A and 120 ± 86 s on TMT-B. [28] Guidelines for the administration of TMT are provided in [29]. A neuropsychologist normally administers TMT in an office setting once every 6 to 12 months to reduce practice effects associated with repeated completion of standardized tests. [30-32]

TMT is one of the most clinically useful neuropsychological tests and is used routinely in the diagnosis of many neurological conditions (Parkinson’s, Alzheimer’s and dementias, and general cognitive decline). [33] TMT measures sensorimotor ability, working memory, and set-switching ability. [34, 35] TMT-A indicates mainly sensorimotor abilities, while the TMT-B indicates working memory and set-switching abilities over and above what is indicated by TMT-A. [34] The difference of TMT-A and TMT-B, S^A and S^B respectively, given by $S^B - S^A$ is considered to provide a measure of cognitive and set-shifting ability, [36] while the ratio given by S^B / S^A has been shown to provide an index of executive function. [37]

TMT performance has been found to decline as adults age. [38-43] Performance on the TMT is a strong, independent predictor of mobility impairment, accelerated decline in lower extremity function, and death in older adults living in the community. [44] In older adults, performance on the TMTs has been associated with gambling problems [45], as well as being a predictor of failure on standard driving tests. [46] Poor performance on TMT has been associated with altered dual-task prioritization in older adults. [47]

Normal adult controls do make errors on TMT, with 12% and 35% of normal controls observed to make at least one error on TMT-A and TMT-B respectively. [48] TMT scores and error counts have been shown to be independently meaningful and both to be of clinical utility for assessing individuals for dementia. [49]

1.3 Introduction

1.3.1 User-Centered Model of Preventive Healthcare

The user-centered model of healthcare is one providing for overall lifestyle health management using technology to implement a system of pervasive healthcare. [12] Pervasive healthcare seeks to apply principles of pervasive computing to healthcare and make techniques of preventive healthcare appear everywhere and anywhere. [50] It addresses new emerging research questions, represents a novel approach, designs new types of technologies, and applies a new kind of research method. [51] Several methodologies have been proposed to address the application of user-centered healthcare to the problem of providing cost-effective, preventive healthcare to a growing population of older adults through the use of technology to develop systems that promote aging in place [52] and the use of pervasive healthcare [53] to help alleviate the burden placed on health care providers. One of the underlying themes of these approaches is to employ technology such as wireless networks combined with novel sensing systems to gather and interpret data in non-health care settings such as the home environment. By virtue of its ubiquitous presence, pervasive healthcare provides an alternative to infrequent clinical measurement capable of providing continuous measurement of real-life behaviors. [53, 52]

We can apply the ideas behind pervasive healthcare to address the problems inherent in using clinical measurements of performance to detect disease by placing technology in the subject's home to make continuous measurements of the subject's performance. Continuous in-home measurement can alleviate the costs associated with frequent trips to the clinic while at the same time providing frequent measurements of performance. They can detect functional changes occurring slowly over time as well as abrupt functional changes. Finally, they are representative of typical subject performance.

1.3.2 User-Centered, In-Home Cognitive Monitoring of Older Adults

Older adults want to maintain their independence as long as possible, [54] and decline in cognitive performance is a major concern for people as they age. [54, 8] Measurable decline in cognitive performance has been observed in nearly half of all people over age 85. [55] In the institution-centered model, cognitive performance may be screened at a physician's clinic, though the results are coarse and do not perform well as an early detector of problems. [56]

The user-centered model of preventive health care provides a technological platform for the long-term monitoring of cognitive performance in older adults. It allows for frequent measurement of cognitive performance using everyday behaviors. Thus, the measured cognitive performance represents typical performance rather than the (possibly somewhat different) performance displayed in the clinic setting. Cognitive monitoring allows not only for the early detection of cognitive decline but also allows one to track the efficacy of interventions [57] used to reverse detected cognitive decline. Such interventions include forms of cognitive health coaching [58] including: (1) cognitive exercise, [59, 58, 60-62] (2) physical exercise, [60, 61, 63, 62] (3) sleep management, [64] (4) socialization, [61, 65] or (5) diet. [61] Studies of potential pharmacological treatments of cognitive decline can also benefit from user-centered cognitive monitoring as a way to measure the efficacy of the drug. [60]

1.3.3 Computational Models in User-Centered, In-Home Cognitive Monitoring

The application of computational models to in-home monitoring has largely centered on the problem of organizing and presenting the data to clinicians or care-givers (see e.g. [66-70]). Our interest is not in the application of computational modeling techniques for making sense of data coming from multiple sources. Instead, our interest is in using computational models to develop a detailed, physical description of the behavior that we are measuring.

Researchers have applied a variety of technologies to user-centered, in-home monitoring of older adults. A sample of these technologies include: motion sensors placed in the home for the monitoring of activity [71, 69, 70], activity monitoring using various wearable sensors [72-77], balance assessment using a Nintendo Wii Fit [78], gait measurement using a Microsoft Kinect [79] or a webcam [80], monitoring of breathing during sleep using sensors attached to the bed [81]. In addition, many smart home technologies involve monitoring resident behavior and appropriately responding to residents' prompts. [82, 83] A related application of user-centered monitoring to the care of older adults is the placement of sensors in the home for the purpose of detecting falls. [84, 85] A survey of further wearable and mobile sensors may be found in [86].

For the application of any of these technologies to user-centered, in-home monitoring to be immediately clinically useful, one must show that one can use the technologies to derive estimates of established clinical measures. Thus, a key problem in making the user-centered healthcare model work for in-home monitoring is that of relating the quantities that can be measured continuously to clinically established measures of subject performance. A computational model that describes both the behavior that is measured in the home and a related behavior that is measured in the clinic provides a principled way to establish such a relationship between in-home and in-clinic measurements.

A computational (or mathematical) model of a behavior allows one to calculate how a subject carries the behavior out given a description of the task the subject is trying to perform. For a specified task, we are able to compare the behavior predicted by the model to the observed behavior and quantify how well the model performs. In general, a computational model will contain a number of free parameters. The model should predict somewhat different performances of the behavior depending on the values of the free parameters. We can use a computational model to characterize a subject by finding the values of the free parameters in the model that cause the behavior predicted by the model to approximate most closely the behavior measured for the subject for a given specified task.

In a good model, the values of the free parameters should remain essentially constant across a range of specified tasks so that the same model closely approximates the observed behaviors for a number of tasks using the same free parameter values. Thus, in the case of a good model, the free parameters provide a characterization of the subject. When a good model also describes a behavior used in performing a clinical measurement, then we can use the measured parameter values to predict performance on the clinical measurement. By providing a detailed description of the behavior being measured using user-centered, in-home monitoring techniques, a good computational model facilitates a more detailed analysis of the observations by providing a set of free parameters that can be fit to the data and so used to characterize the subject and estimate performance on related clinical measures. The computational model also allows us to put a principled structure on the data so we can make the best use of the available data for making performance estimates.

1.4 Thesis Structure

In this thesis, we look at techniques for user-centered, in-home monitoring of cognitive performance using available cost-effective technologies. We use the cost-effective technologies to produce cognitive performance estimates in terms of the two clinical measures that we gave detailed descriptions for above: (1) walking speed, and (2) the Trail-Making Test. We make measurements of the walking speed in the home using an inexpensive system of motion sensors placed in the home. We make measurements from which we can estimate TMT performance in the home by observing the subject's interactions with a personal computer.

1.4.1 Part I – In-Home Monitoring of Walking Speed

In Part I, we develop a technique for making measurements of walking speed in the home using a system of passive infrared motion sensors. This technique produces a continuous measurement of a subject's in-home walking speeds.

In Chapter 2 in Part I, we develop the technique for measuring walking speed in the home using passive infrared motion sensors. In this Chapter, we develop a computational model of the process by which the motion sensors detect the subject walking beneath them and use the model to produce an estimate of the walking speed. We validate the walking speed estimates by comparing the estimates to measurements of walking speed made using a GAITRite® Walkway System gait mat.

My specific contributions in Chapter 2 are the setting up and running of the empirical study and the computational modeling of the process by which the system of motion sensors estimate the walking speed.

1.4.2 Part II – In-Home Monitoring of Trail-Making Test Performance

In Part II, we develop two techniques for estimating performance on TMT in the home using measurements of subjects' interactions with a computer. These techniques produce continuous estimates of cognitive performance as described by sets of several measured parameters. We also show that the data obtained from in-home measurements of computer usage support a model of TMT in which the subject dual-tasks set-switching and movement during TMT-B.

In Chapter 3 in Part II, we develop a computational model of the process a subject goes through when playing a simple computer game that was designed to mimic TMT. We use this model to derive a set of several parameters that we can measure by observing how a subject plays the game and that we can use to characterize the subject's cognitive performance. We validate the clinical utility of the measured parameters by constructing a model of TMT and using that model together with the measured parameters to generate an estimate of a subject's performance on TMT. We compare these estimates of subjects' performances on TMT to measurements of actual performances on TMT.

My specific contributions in Chapter 3 are the construction of the computational model that describes TMT and the computer game (the connect-the-dots model), the analysis of the subjects' play of the computer game to produce measurements of the various parameters present in the computational model, and the validation of the technique by producing an estimate of TMT performance.

In Chapter 4 in Part II, we develop a technique to store and analyze mouse position data observed during a subject's everyday (real-life) computer usage. We use this technique to derive a set of several parameters that we can measure by observing how a subject uses the computer mouse. We use the model that we have developed in Chapter 3 to provide a qualitative model of the cognitive process that a subject uses when going about using a computer. The model indicates how we can relate measurements obtained from a subject's everyday computer usage to that subject's performance on TMT. We validate the clinical utility of the measured parameter values by comparing these estimates of subjects' performances on TMT to measurements of actual performances on TMT. We observe that the measured parameter values perform much better in producing an estimate of performance on TMT-B than in producing an estimate of performance on TMT-A.

My specific contributions in Chapter 4 are the technique to identify individual mouse movements, the analysis of the resulting mouse movement data to produce performance metrics related to mouse movements, and the validation of the performance metrics by producing an estimate of TMT performance.

In Chapter 5 in Part II, we provide an improvement to the computational model that we have used in Chapters 3 and 4 based on observations made when applying the model to the data that we have obtained in Chapters 3 and 4. We observe that the parameters measured in Chapter 4 perform significantly better when used to estimate subjects' performances on TMT-B than they do when used to estimate performances on TMT-A. As the parameters measured in Chapter 4 are derived from observing how a subject uses a computer mouse, we argue that the simplest model that we can use to account for the observation is one in which subjects move the hand slower on TMT-B than on TMT-A. We argue that this effect is due to movements begin performed as a single-task during TMT-A, and as a dual-task during TMT-B. We proceed to revisit the measurements that we have made in Chapter 3 and show that they are consistent with a model in which the subject is single-tasking during movements in TMT-A and dual-tasking during movements in TMT-B.

My specific contributions in Chapter 5 are the modification of the computational model developed in Chapter 3 to include dual-tasking of the set-switching and motor stages, and the analysis of the data from Chapter 3 to show that data support a model in which set-switching and motor are dual-tasked during TMT-B.

Part I – In-Home Monitoring of Walking Speed

Chapter 2 – Unobtrusive and Ubiquitous In-Home Monitoring: A Methodology for Continuous Assessment of Gait Velocity in Elders

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2.0 Abstract

Gait velocity has been shown to quantitatively estimate risk of future hospitalization, has been shown to be a predictor of disability, and has been shown to slow prior to cognitive decline. In this paper, we describe a system for continuous and unobtrusive in-home assessment of gait velocity, a critical metric of function. This system is based on estimating walking speed from noisy time and location data collected by a "sensor line" of restricted view passive infrared (PIR) motion detectors. We demonstrate the validity of our system by comparing with measurements from the commercially available GAITRite® Walkway System gait mat. We present the data from 882 walks from 27 subjects walking at three different subject-paced speeds (encouraged to walk slowly, normal speed, or fast) in two directions through a sensor line. The experimental results show that the uncalibrated system accuracy (average error) of estimated velocity was

7.1cm/s (SD = 11.3cm/s), which improved to 1.1cm/s (SD = 9.1cm/s) after a simple calibration procedure. Based on the average measured walking speed of 102 cm/s our system had an average error of less than 7% without calibration and 1.1% with calibration.

2.1 Introduction

Improving quality of life and providing adequate medical care for the rising number of elderly while keeping health care costs under control has in recent years become a major problem [87]. Several methodologies have been proposed to address this problem that include the use of technology to develop systems that promote aging in place [52] and the use of pervasive healthcare [53] to help alleviate the burden placed on health care providers. One of the underlying themes of these approaches is to employ technology such as wireless networks combined with novel sensing systems to gather and interpret data in non-health care settings such as the home environment.

One specific measure of particular interest for unobtrusive assessment for health monitoring is walking speed. Walking speed has been shown to be a quantitative estimate of risk of future hospitalization [18]. Slower walking speed has been demonstrated in dementia patients compared to controls [19] and has been shown to precede cognitive impairment [20] and dementia [21], and timed walk has been used as a partial characterization of lower extremity function which has been shown to predict disability [22, 23]. Other studies have shown a relationship between walking speed and cognition [25, 26]. Current evaluation of walking speed is typically done both infrequently and in the clinic setting which suffers from at least five shortcomings. First, frequent assessment visits are impractical and cost prohibitive since either it is difficult for patients to make frequent trips to a doctor's office or other clinical settings or in the case of research assessments, inconvenient for the research team to visit homes frequently. Second, for longitudinal study each testing session is typically scheduled in increments of six months or a year after a baseline visit making it difficult both to evaluate the validity or stability of baseline measurements and to detect short and long term variability [88]. Third, there may be an intentional [18] change in walking speed in the clinical setting or an unintentional [88] change in abilities during a single assessment. These pacing considerations themselves may have important implications for predicting outcomes [26]. Fourth, infrequent measurements report only the net change between measurement times and cannot distinguish between functional changes occurring slowly over time and abrupt functional changes, which may have different causes. Fifth, infrequent measurements do not detect changes when they happen which may reduce the ability of a clinician to provide intervention or reduce the effect of an intervention. By shifting to continuous in-home monitoring of walking speed from the current paradigm, the effect of all of these short comings can be significantly reduced or removed.

There have been several systems proposed for monitoring walking speed and other gait features outside of the clinical setting [89-91]. These systems typically consist of some wearable combination of gyroscopes and/or accelerometers and have demonstrated accuracy and precision in the field. However, these systems suffer from several limitations such as short battery life, the need to download the data or introduce additional hardware and complexity for wireless data collection, and the inconvenience of both a wearable device and having to remember to wear a device. For these reasons the wearable devices are currently inadequate for long-term, in-home, unobtrusive monitoring.

In order to address these concerns and to improve diagnostic ability for clinicians and researchers, we propose a methodology for continuous in-home monitoring of walking speed using passive infrared motion sensors. Specifically, we describe the hardware preparation and deployment, the techniques for data collection, and the data processing algorithms for continuous in-home assessment of walking speed in elders. Finally, we validate our approach by comparing the results of our method for walking speed estimation with the commercially available GAITRite® Walkway System gait mat.

2.2 System Description and Data Collection

In this section, we describe the hardware and methodology used to deploy the walking speed measurement system in a residence. A partial description of this system has been described elsewhere [92, 93] in the more general context of total activity monitoring, as has a simpler version of the proposed approach [94]. Here we specialize and describe in more detail the specific nature of the walking speed measurement system. We begin by describing the sensors and how they are placed in a residence and follow with a description of the wireless network based data collection.

To detect motion we used the X10 model MS16A (X10.com) passive infrared motion sensor which emits a unique programmable bit code at 310 MHz when motion is detected. We restricted the field of view of each motion sensor to ±4 degrees and installed four sensors sequentially on the ceiling (average height of 2.54 m) approximately 61cm apart in a confined area such as a hallway or other corridor. This combination tends to force a resident to walk linearly through each sensor pair in the sensor line and ensures that each sensor will only fire when someone passes directly below. Limiting the field of view precisely and placing sensors in exact locations is not possible, and therefore there is some variability in the physical locations which cause the sensors to fire, as will be discussed shortly. Figure 2.1 shows how these sensors look from a resident's point of view when entering the sensor line.

Figure 2.1. A motion sensor line for measuring walking speed where the four sensors are placed 0.61 m apart and are installed on a ceiling typically 2.54 m high.

To collect the wirelessly transmitted sensor firings, we use a WGL 800 wireless transceiver connected to a desktop computer installed in the residence. Simultaneous sensor firings or other interfering sources can result in lost data due to collisions at the wireless transceiver. However, these have been shown to be minor, with a less than 2% overall data loss [93]. The computer timestamps the sensor firings and the data pair is both stored locally and sent via a secure Internet connection to a central database for analysis.

Our experience with the described technology comes from the deployment and monitoring of approximately 250 Portland (OR, USA) metropolitan area homes and retirement community dwellings from between 6 months to over 2 years in ongoing studies. We have instrumented both single and multi person dwellings and have collected data from over 1,200,000 walking events from single person homes with minimal technical challenge or sophistication needed for setup. Installation of the complete system (including additional technologies described elsewhere [93]) takes an average of 1.5 to 2 hours with 2 people. Deploying only the equipment necessary to measure walking speed (computer, sensors, wireless transceiver, and internet) is estimated to take 1 person approximately 1 hour – if the home already contains an Internet-connected computer, this could be done in 20 min. The technologies are managed remotely using custom systems management software that supports data viewing, remote software updates, and remote computer reboots if needed. Other issues, such as replacing motion sensor batteries (battery life is about 1 year) or changing sensors if they become unreliable or defective can typically be handled in a very short visit to the residence, typically 10-15 min. Overall, we have found the system has been simple to install, unobtrusive in the sense of both passive sensor technology and minimal outside intervention, and easy to maintain.

2.3 Data Modeling and Analysis

In this section, we introduce and discuss both the proposed linear model and the estimator for determining the gait velocity from noisy motion sensor data. We start by describing how to determine the precise spatial separation of the sensors from the sensor firings since they will not, as mentioned, be the same as the measured values due to a combination of installation variability and differences between individual sensors. We then use this information to model the walking speed as a linear function of the measured data degraded by two sources of additive noise. The first source of noise is in units of distance and is due to the sensor firing in slightly different locations during each pass through the sensor line. This error is based on the field of view and sensitivity of an individual sensor. The second source of error is in units of time and is due to the discrepancy between when a sensor fires and when the computer timestamps the firing, which generally causes positive time errors. We conclude the section by proposing a walking speed estimator that minimizes the combination of these errors followed by a discussion of model calibration in the presence of ground-truth data versus estimating the calibration factor when ground-truth data is unavailable.

2.3.1 The Linear Model

We start by assuming the sensors are placed at physical positions $\{\tilde{x}_i\}$ in some spatial coordinate system. For a particular walking event the sensors fire at times $\{t_i^k\}$ where k indexes the particular sensor line walking event and i indexes the particular sensor which fired. We then define $\{x_i\}$ to be the average position at which the walker is when the ith sensor fires. In other words, for a particular walking event the ith sensor fires when the walker is at some random location $\{x_i + \varepsilon_i\}$ with the errors $\{\varepsilon_i\}$ being independent random variables with zero expected value. Figure 2.2 illustrates this arrangement.

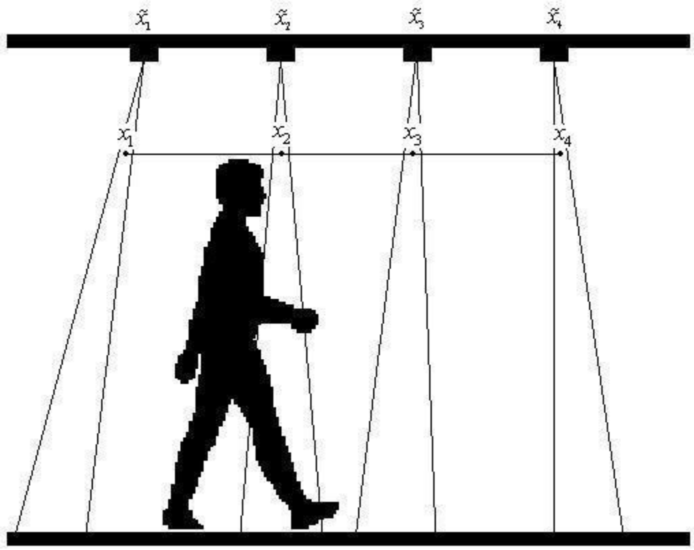

Figure 2.2. Schematic of a person walking through a sensor line containing four sensors with the fields of view and the locations of the $\tilde{x}_i$ and x_i shown.

The differences $\{x_i - \tilde{x}_i\}$ represent likely biases due to the field of view of the sensor and the direction of movement as shown in Figure 2.2. For the sake of simplicity we restrict the present discussion to the analysis of movement in one direction.

Now assuming a walker moves with some known velocity v through a sensor line and we have some absolute reference time, $\{\tau_i\}$ can be defined as the time at which the walker is expected to be at location $\{x_i\}$ and trigger the *i*th sensor. If we now include the errors in detection location $\{\varepsilon_i\}$ explicitly in the measured time we find that the measured times should be $\{\tau_i + \varepsilon_i / v\}$.

By further assuming that there is some random delay $\{\eta_i\}$ between when a sensor fires at location $\{x_i + \varepsilon_i\}$ and when the computer time-stamps the sensor firing data, the measured time can be written as $\{t_i^k\}$ = $\{\tau_i^k + \varepsilon_i^k / v^k + \eta_i^k\}$ where the $\{\eta_i\}$ are independent random variables with some common non-negative expected value and the explicit dependence on the measured time from both position errors and time errors is shown.

Now, consider an event k to comprise a person walking past the line of sensors with a constant, but unknown velocity v^k. Then for any pair of sensors, i,j we have $x_j - x_i$ = $v^k\left(\tau_j^k - \tau_i^k\right)$, from which we find:

$$\left(x_j + \varepsilon_j^k\right) - \left(x_i + \varepsilon_i^k\right) = v^k\left[\left(t_j^k - \eta_j^k\right) - \left(t_i^k - \eta_i^k\right)\right]. \tag{2.1}$$

Using (2.1) we can solve for the velocity v^k, for any three sensors i, j, m:

$$v^k = \frac{\left(x_j - x_i\right) + \left(\varepsilon_j^k - \varepsilon_i^k\right)}{\left(t_j^k - t_i^k\right) + \left(\eta_i^k - \eta_j^k\right)} = \frac{\left(x_m - x_j\right) + \left(\varepsilon_m^k - \varepsilon_j^k\right)}{\left(t_m^k - t_j^k\right) + \left(\eta_j^k - \eta_m^k\right)}. \tag{2.2}$$

We now economize the notation and define $\varepsilon_{ji}^k \equiv \varepsilon_j^k - \varepsilon_i^k$ and $\eta_{ij}^k \equiv \eta_i^k - \eta_j^k$ for i, j, m. Rewriting (2.2) yields:

$$\begin{aligned}&\left(x_j - x_i\right)\left(t_m^k - t_j^k\right) + \left(x_j - x_i\right)\eta_{jm}^k + \left(t_m^k - t_j^k\right)\varepsilon_{ji}^k + \varepsilon_{ji}^k\eta_{jm}^k \\ &= \left(x_m - x_j\right)\left(t_j^k - t_i^k\right) + \left(x_m - x_j\right)\eta_{ij}^k + \left(t_j^k - t_i^k\right)\varepsilon_{mj}^k + \varepsilon_{mj}^k\eta_{ij}^k.\end{aligned} \tag{2.3}$$

Taking the expectation of both sides and using the facts that: $E_k\left\{\varepsilon_{ij}^k\right\}$ = 0, $E_k\left\{t_i^k\varepsilon_j^k\right\}$ = 0, and $E_k\left\{\varepsilon_j^k\eta_i^k\right\}$ = 0 for $i \neq j$, results in:

$$\begin{aligned}&\left(x_j - x_i\right)E_k\left\{t_m^k - t_j^k\right\} - E_k\left\{t_j^k\varepsilon_j^k\right\} + E_k\left\{\varepsilon_j^k\eta_j^k\right\} \\ &= \left(x_m - x_j\right)E_k\left\{t_j^k - t_i^k\right\} - E_k\left\{t_j^k\varepsilon_j^k\right\} + E_k\left\{\varepsilon_j^k\eta_j^k\right\},\end{aligned} \tag{2.4}$$

which simplifies to:

$$\frac{\left(x_j - x_i\right)}{\left(x_m - x_j\right)} = \frac{E_k\left\{t_j^k - t_i^k\right\}}{E_k\left\{t_m^k - t_j^k\right\}}. \tag{2.5}$$

From this we may conclude that:

$$\left(x_j - x_i\right) \propto E_k\left\{t_j^k - t_i^k\right\} = E_k\left\{\Delta t_{ij}^k\right\}. \tag{2.6}$$

The expected value of the random variable Δt_{ij}^k can therefore be used to estimate the spatial separation of the sensors up to a scale factor by computing the average values over a large number of events.

By explicitly writing (2.6) with the proportionality constant c we have:

$$\left(x_j - x_i\right) = cE_k\left\{\Delta t_{ij}^k\right\}. \tag{2.7}$$

Here c has a ready interpretation as the speed a person would have to walk in order for the sensors to register time differences equal to the average time differences calculated from the training data set.

Let us look more closely at the estimated spacings $\left(x_j - x_i\right)$. Considering Figure 2.2 again, we see that the sensor-line is effectively hovering at some height between the ceiling and the floor. In the figure it has been drawn at the top of the head. Let us imagine that we knew the actual mean firing position for each sensor as a function of the height above the floor, so that if the sensor is triggered by motion at a height h it will typically be triggered at a position $x_i\left(h\right)$. In addition, the body itself does not move at a single constant velocity v during gait, but rather different segments move with various velocities over the course of the gait cycle. The effect of this is that the values $\left\{\tau_i\right\}$ (which are the actual measurements) reflect triggering at various heights due to different body segments. In effect, all these factors are averaged over to produce effective sensor spacings based on the subject's height and style of walking together with the sensor characteristics. We expect that for people of similar heights, as well as reasonably similar styles of gait, that the estimated effective sensor spacings $\left(x_j - x_i\right)$ should be close in value.

2.3.2 Estimation of Gait Velocity

When we estimate the gait velocity we must consider two sources of measurement error. First, there is the combined error for sensors i, j resulting from detecting the walker at positions away from the mean detection locations x_i, x_j which we denote by ε_{ij}. Second, there is the combined error for sensors i, j resulting from errors in time-stamping the moments at which each sensor fired. This is represented by η_{ij}. In general, these two types of errors should be given different weights in accordance with the relative variability captured by the spatial and temporal covariance matrices of the error terms ε_{ij} and η_{ij} [95]. The relative weighting of the temporal error term relative to the spatial error term is represented by the parameter ρ. We proceed initially by assuming that the calibration factor c and the weighting factor ρ are known values and derive an estimator for the walking velocity, $\hat{v}$ through the sensor line. With this estimator, we then proceed to consider situations in which we know the actual walking velocity, v and consider the estimator now as a function, $\hat{v}(c,\rho)$, which arises when one calibrates the line using a set of data where the velocities are known. Finally we consider the case where c, ρ are not known and use information from the physical set up of the sensors to estimate a value of c. In this last case we assume that weighting of the errors is a general value across all reasonably similar sensor lines and so take the value for ρ obtained from our calibrated experiment described in the next section.

In a sensor line of four sensors i, j, l, m:that fire sequentially when a subject walks along the sensor line, we can estimate the walking speed by minimizing the overall error in the dependent and independent variables using the method of total least squares [96] applied to the model:

$$\left(\begin{bmatrix}\rho E_k\left\{\Delta t_{ij}^k\right\}\\ \rho E_k\left\{\Delta t_{jl}^k\right\}\\ \rho E_k\left\{\Delta t_{lm}^k\right\}\end{bmatrix}+\begin{bmatrix}\frac{\rho}{c}\varepsilon_{ij}^k\\ \frac{\rho}{c}\varepsilon_{jl}^k\\ \frac{\rho}{c}\varepsilon_{lm}^k\end{bmatrix}\right)\left(\frac{c}{\rho\hat{v}^k}\right)=\begin{bmatrix}\left(t_j^k-t_i^k\right)\\ \left(t_l^k-t_j^k\right)\\ \left(t_m^k-t_l^k\right)\end{bmatrix}+\begin{bmatrix}\eta_{ji}^k\\ \eta_{lj}^k\\ \eta_{ml}^k\end{bmatrix}, \tag{2.8}$$

where we have rewritten the linear equations in matrix notation , used the fact that η_{ji}^k = $-\eta_{ij}^k$ to keep the noise term in (2.8) in the standard additive form, and used the estimate of the spatial sensor separation as in (2.7). We proceed assuming that c, ρ are fixed and known constants for the sensor line.

To compute the velocity estimates, we now construct a matrix containing as column vectors the distances between adjacent sensors, and the time differences between adjacent sensor firings:

$$M^k\left(\rho\right)=\begin{bmatrix}\rho E_k\left\{\Delta t_{ij}^k\right\} & \left(t_j^k-t_i^k\right)\\ \rho E_k\left\{\Delta t_{jl}^k\right\} & \left(t_l^k-t_j^k\right)\\ \rho E_k\left\{\Delta t_{lm}^k\right\} & \left(t_m^k-t_l^k\right)\end{bmatrix}. \tag{2.9}$$

This matrix may be factored per the singular value decomposition into a trio of matrices $A^k\left(\rho\right)$, $B^k\left(\rho\right)$, $\Sigma^k\left(\rho\right)$ so that the equation $M^k\left(\rho\right)$ = $A^k\left(\rho\right)\Sigma^k\left(\rho\right)B^{k*}\left(\rho\right)$ is satisfied. Letting $B_{12}^k\left(\rho\right)$, $B_{22}^k\left(\rho\right)$ denote the appropriate elements of the matrix

$B^k(\rho)$, the estimated velocity is given by:

$$\hat{v}^k = -\frac{c}{\rho}\frac{B_{22}^k(\rho)}{B_{12}^k(\rho)}. \qquad (2.10)$$

2.3.3 The Calibrated Sensor Line

Taking the weighting factor ρ still to be fixed and known, we now treat the calibration factor c as a variable whose value we may estimate using known velocity data. We are given a set of training data consisting of sensor firing times $\{t_i^k\}$ and true gait velocities $\{v^k\}$ for a sample set of walks through the sensor line. We assume the actual walking speeds and the estimated walking speeds satisfy the linear model:

$$v^k + \omega^k = -\frac{\hat{c}}{\rho}\frac{B_{22}^k(\rho)}{B_{12}^k(\rho)}, \qquad (2.11)$$

where the $\{\omega^k\}$ are independent random variables with zero expected value. By collecting all the measurements v^k, $b^k(\rho) = B_{22}^k(\rho)/B_{12}^k(\rho)$ into vectors v, $b(\rho)$, we can estimate the calibration factor with linear least squares:

$$\hat{c} = -\rho\frac{v^T v}{v^T b(\rho)}. \qquad (2.12)$$

If we knew the actual value ρ we would be done at this point as we could estimate the calibration factor c given the measured time and velocity values. However, where we do not know the actual value of ρ, we would like to choose a value which yields the best performance of the method for estimating velocities. In particular we would like to find a value of ρ which gives the best performance across many sensor-lines. Let us consider the calibration factor for the *n*th sensor-line as a function of ρ, that is:

$$\hat{c}_n(\rho) = -\rho \frac{v_n^T v_n}{v_n^T b_n(\rho)}. \tag{2.13}$$

We may consider the set of velocity estimates also as functions of ρ:

$$\hat{v}_n^k(\rho) = -\frac{\hat{c}_n(\rho)}{\rho} b_n^k(\rho) = \left(\frac{v_n^T v_n}{v_n^T b_n(\rho)} \right) b_n^k(\rho). \tag{2.14}$$

This expresses the estimated velocity for the *k*th walk along the *n*th sensor-line $\hat{v}_n^k(\rho)$ entirely in terms of the measured time, the measured velocity, and the unknown parameter ρ. The weighting factor may now be found as a value which gives the best sensor-line performance on average.

In practical situations where calibration data are not available we use an average value of ρ determined from existing data. In particular, we found that the average value that minimized the estimation error in our controlled experiments, described in the next section, was ρ = 0.75.

2.3.4 The Uncalibrated Sensor Line

If the velocity is not known, then the training data set will contain only the sensor firing times $\{t_i^k\}$. In this case we must estimate the value for c using the values for the physical sensor positions $\{\tilde{x}_i\}$. Choosing any pair of sensors i, j we may make the estimate:

$$\hat{c} = \frac{\tilde{x}_j - \tilde{x}_i}{E_k\{\Delta t_{ij}^k\}}. \tag{2.15}$$

We would like to choose our pair of sensors so that the expected value $\tilde{x}_j - \tilde{x}_i$ is as near in value as possible to the distance between mean detection positions $x_j - x_i$. In general the expected error will be minimized by choosing the pair consisting of the outermost sensors of the line.

We do note that care should be taken when using the uncalibrated sensor line cross-sectionally, especially over small samples, as the individual instantiations of a sensor line can have sizable differences between $\hat{c}$ and c as shown in Figure 2.5.

2.4 Experimental Verification

2.4.1 Experimental Description

27 subjects (9 male and 18 female, aged 75 to 95 years, mean age 85.2 years, 145cm to 185cm in height, average height 164.8 cm) participated in the experiment; all provided informed consent. The experiment was conducted in a common use room at the facility where the participants live. A single sensor line of eight (8) restricted-field PIR motion sensors was placed on the ceiling with sensors physically spaced at 61cm (2ft) intervals. The ceiling height was 240cm (7.8ft). Beneath the sensor line an 854cm (14ft) long GAITRite® Walkway System gait mat was placed so that the ends of the mat aligned with the outermost sensors. Participants were instructed to walk at self-determined “slow”, “normal”, and “fast” walking speeds. A total of 30 walks were recorded for most participants such that each participant walked five times at each of the three speeds in the two directions available along the sensor line. Five participants did a larger number of walks (36, 42, 42, 44, and 46) but their larger group of walks included the basic 30 which all participants did. Their precise walking speed for each trial was calculated using the gait mat data. Firing times were collected for each PIR sensor during each trial and used to determine the accuracy of the PIR sensors for measuring walking speed.

Based on our experience with several hundred homes, a reasonable sensor line configuration which may be installed under the space constraints of typical small homes consists of four sensors placed in a line at approximately 61cm (2ft) intervals. The choice of four sensors was influenced by a few different factors. First, since the sensors are known to be noisy, we wanted multiple measurements of the walking speed to use in our estimator to reduce estimator variance. Experiments showed, for example, that moving from three sensors to four sensors reduced variance by a factor of approximately 3.8. Second, due to space constraints in the homes and retirement communities we found that four sensors are all that would reliably fit in most homes. Third, the probability of an individual sensor firing is approximately 0.937. With four sensors in place and assuming we use walks where either three or four sensors fire, we can capture almost 98% of walking events in the home. Finally, we note that using two sensors in not sufficient as this causes equation (2.8) to reduce to a single equation with a single unknown which can be solved exactly, and therefore does not allow mitigation for known noise effects. In accordance with this we have considered sensor data in groups of four adjacent sensors. Thus our line of eight sensors is treated as five individual sensor lines. Furthermore as there is no reason to suppose that the effective sensor spacing is the same in the two directions along which the line may be walked, – in the “forward” or “return” direction through the line (with respect to the experimenter) – we evaluated each direction independently.

For each sensor line of four sensors in each direction only those walking events in which all 4 sensors fired were considered for the purposes of calculating the effective sensor spacing and calibration factor. However, to estimate the velocity for walking events we used all the sensor line data in which 3 or 4 of the 4 sensors fired.

2.4.2 Experimental Results

A total of 882 walks from the 27 participants (mean age 85.2 years) were recorded during this experiment with 441 in the "forward" direction and 441 in the "return" direction (as referenced by the experimenter). The numbers of "slow", "normal", and "fast" speed walks were the same in either direction for each given participant. The 8 ceiling-mounted PIR sensors were divided into 5 sensor lines of 4 sensors with a regular 61cm (2ft) physical spacing for analysis. In the "forward" direction the sensor lines had all four sensors fire 350 ± 36 times, and in the "return" direction all 4 sensors fired 330 ± 29 times. The effective sensor spacing for each sensor line was calculated and normalized as in the foregoing using only the events where all 4 sensors fired.

Participants walked in the "forward" direction with a speed of 104 ± 30.6cm/s, and in the "return" direction with a speed of 100 ± 29.3cm/s as measured by the gait mat. We estimated velocity using a sensor line only in those cases where 3 or 4 of the 4 sensors in the line fired. Figure 2.3 shows the directional walking speed estimates versus the measured values for the combined sensor line data after calibration using velocity data from the gait mat. Figure 2.4 shows the directional walking speed estimates using estimated calibration factors. In both figures the "return" direction is differentiated from the v^k "forward direction" by introducing a negative sign on all the velocity estimates. Additionally, in both figures the line $x = y$ (corresponding to perfect estimation) has been plotted as a dashed line to demonstrate that both calibrated and uncalibrated estimates are distributed around the correct values. Further, the distribution of points in Figure 2.4 is wider than in Figure 2.3 demonstrating that the calibration procedure does improve estimation. Also, of particular note is the fact that distribution of estimates in both figures is more centered and densely packed around the true value in the ”return” direction, indicating that velocity estimates in the “return” direction are better than in the ”forward” direction (i.e., the same sensors performed better in one direction than in the other).

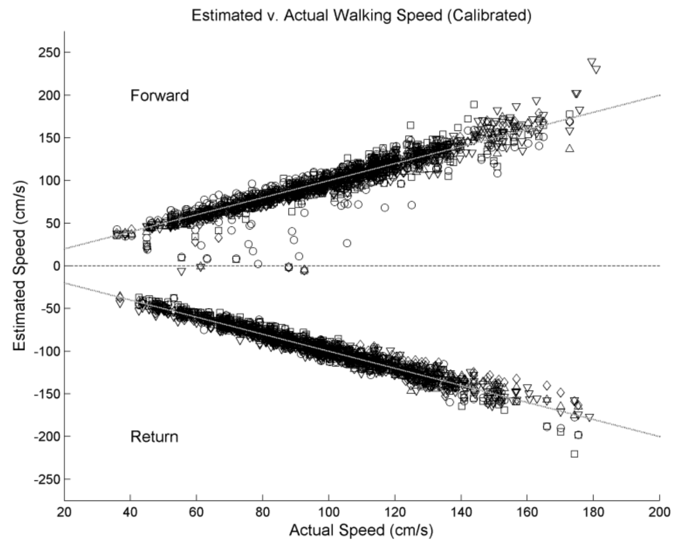

Figure 2.3. Combined walking speed data for all subjects for the 5 sensor lines of 4 sensors (the various shapes indicate data from different sensor lines), using a calibration factor calibrated to the walking speed measured by the gait mat. The sign of the estimated speed differentiates “forward” walks (positive values) versus “return” walks (negative values).

To be more precise about the discussion of the walking speed estimates, we denote the estimated speed for the *k*th walk through sensor line i for both directions by $\hat{v}_i^k$ and the actual speed by . The accuracy of the system was evaluated by computing the average difference $\left\{\hat{v}_i^k - v^k\right\}$. For the case of the calibrated sensor lines the mean of this difference is 1.1cm/s and the standard deviation is 9.1cm/s. In the case of the uncalibrated sensor lines the mean is 7.1cm/s, and the standard deviation is 11.3cm/s.

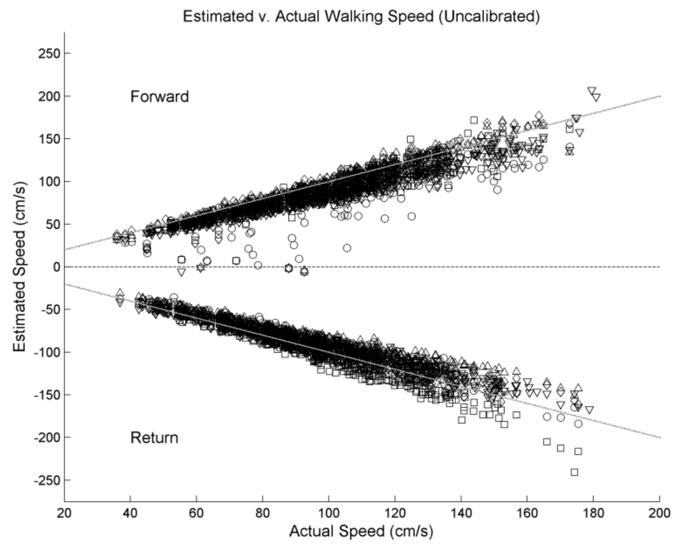

Figure 2.4. Combined walking speed data for all subjects for the 5 sensor lines of 4 sensors (the various shapes indicate data from different sensor lines), using estimated calibration factors. The sign of the estimated speed differentiates "forward" walks (positive values) versus "return" walks (negative values).

Figure 2.5 shows the relationship of the estimated calibration factors to the true (measured) calibration factors, with the line $x = y$ drawn for comparison. This shows that the uncalibrated sensor line with $\hat{c}$ as in (2.15) tends to underestimate the true calibration factor, this making the velocity estimates slightly higher than in the calibrated case. This also demonstrates the need to be careful when comparing uncalibrated sensor line estimates cross-sectionally.

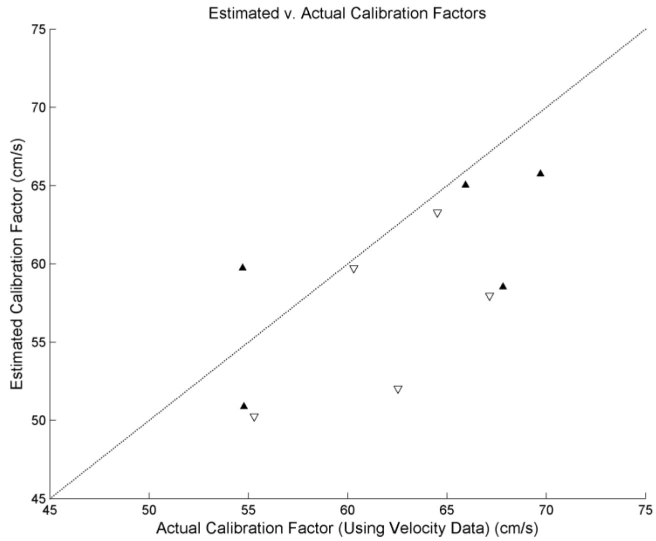

Figure 2.5. Combined calibration factor data (c value) for the 10 possible sensor lines (5 "forward" and 5 "return"). The direction the triangle is pointing indicates whether the direction is "forward" (up) or "return" (down).

2.5 Discussion

The proposed system for unobtrusive and continuous monitoring of in home walking speeds has been shown to accurately estimate velocity when compared to the GAITRite® Walkway System gait mat standard. The mean estimation errors of 7.1cm/s and 1.1cm/s for the uncalibrated and calibrated sensor lines when compared to the average speed of 102cm/s result in average errors of 6.96% and 1.08%, respectively. Further, the standard deviations of the error distributions for the uncalibrated and calibrated sensor lines are 11.1% and 8.92% when compared to the average speed of walking. This shows that each individual estimate is accurate, and local averaging and other statistical techniques can be used to increase precision (reduce the error variance further).

These positive results demonstrate the feasibility of the proposed method and address several deficits in the current paradigm of assessing gait episodically or in clinic settings. First, with this system the variability of walking speed can now be monitored continuously over the short term (e.g., walk-to-walk variability) in addition to longer time scales (e.g., month-to-month, yearly) without expensive and inconvenient clinic visits. Second, subjects in high-risk groups can be monitored more closely and rapidly than is currently feasible. Third, researchers can have access to more frequent measurements of walking speed, which facilitates the refinement and better understanding of walking speed as it relates to health outcomes and correlations presently in the literature that are based on single or infrequent measurements. Fourth, wide scale analysis of multiple subjects can be performed relatively easily which we anticipate will open further areas of population-based research and diagnostic ability not discussed here. We do note that while our proposed system is less expensive than repeated clinical visits, the cost of the sensors, computer, internet service, and transceiver may currently be cost prohibitive for studies that might involve thousands of subjects who are widely dispersed. However, since historically the cost of equipment and services has continued to drop as better and faster technology becomes available in the marketplace, it is likely that deployment of these kinds of systems to larger cohorts will be facilitated. In addition, less expensive motion sensors may work adequately and simple application specific computers may be built cheaper than off the shelf models which could be deployed today. Further work is needed to identify the most cost efficient approaches to maximize scalability of in-home assessment platforms.

One of the largest challenges to the broad use of our approach to continuous monitoring of walking speed, and to in-home monitoring in general, is the differentiation of multiple residents. This problem is typically addressed by requiring the participants to wear or care some type of radio frequency identification (RFID) tag. We are currently working on both pattern recognition and model-based approaches to distinguish between multiple residents based on the walking events. This will allow the expansion of this methodology from single resident homes to multiple resident dwellings without the need for additional equipment or hardware.

Future work will address comparisons of the in-home continuous method with standard clinical tests of walking, mobility, and physical performance such as the Short Physical Performance Battery, Unified Parkinson's Disease Rating Scale, and various other timed walks of different durations (e.g., 4-meter, 10-meter, 400 meter) thus facilitating interpretation of these established clinical metrics with our new framework. Other future work will include relaxing the assumption that velocity is fixed over a walking event in order to measure the step-to-step variability in each walking event. In this case the velocity of the *k*th walking event becomes some function of time $v(t)$. Retaining our definition of the error $\{\varepsilon_i\}$ above we find that the time at which the sensor fires may be expressed as $\{\tau_i + \upsilon_i\}$, where $\{\upsilon_i\}$ satisfies:

$$\varepsilon_i = \int_{\tau_i}^{\tau_i+\upsilon_i} v(t')dt'. \tag{2.16}$$

The values $\{\eta_i\}$ are still defined as above which gives a relation to the measured time values of $\{t_i^k\} = \{\tau_i^k + \upsilon_i^k + \eta_i^k\}$. Finally, for any pair of sensors we have the relation:

$$\left(x_j + \varepsilon_j^k\right) - \left(x_i + \varepsilon_i^k\right) = \int_{t_i^k-\eta_i^k}^{t_j^k-\eta_j^k} v^k(t')\,dt'. \tag{2.17}$$

which generalizes (2.1). We anticipate that adjusting the model along the lines of (2.16) will allow us to derive additional gait parameters from the current and future data.

2.6 Conclusion

In this paper we have proposed a new system for continuous in home assessment of walking speed based on PIR sensors and a wireless network for data collection. We have shown that this method is both accurate and precise when compared to the standard of the GAITRite® Walkway System gait mat. This method allows the convenient in home collection of a large number of walking events otherwise gathered infrequently in a clinical setting. Since walking speed has been shown to be an indicator or predictor of many diseases and other health issues such as cognitive decline and hospitalization, we feel that the continuous monitoring of this measure and its applications is an important and useful area of future research.

Part II – In-Home Monitoring of Trail-Making Test Performance

Chapter 3 – Assessing Executive Function Using a Computer Game: Computational Modeling of Cognitive Processes

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3.0 Abstract

Early and reliable detection of cognitive decline is one of the most important challenges of current healthcare. In this project we developed an approach whereby a frequently played computer game can be used to assess a variety of cognitive processes and estimate the results of the pen-and-paper Trail-Making Test (TMT) – known to measure executive function, as well as visual pattern recognition, speed of processing, working memory, and set-switching ability. We developed a computational model of the TMT based on a decomposition of the test into several independent processes, each characterized by a set of parameters that can be estimated from play of a computer game designed to resemble the TMT. An empirical evaluation of the model suggests that it is possible to use the game data to estimate the parameters of the underlying cognitive processes and using the values of the parameters to estimate the TMT performance.

Cognitive measures and trends in these measures can be used to identify individuals for further assessment, to provide a mechanism for improving the early detection of neurological problems, and to provide feedback and monitoring for cognitive interventions in the home.

3.1 Introduction

Quantitative assessment of cognitive function is an important component of caring for the aging as well as those with other dysfunctions such as traumatic brain injury and many other conditions affecting cognitive functions. The goal of this study is to find ways to assess and monitor subjects' cognitive performance in the subjects' home using information technology. In this paper, we show how a simple computer game in conjunction with computational model can be used for sensitive assessment and monitoring of components of executive function in individual subjects.

The computer game we consider in this paper bears a close relationship to a commonly administered, neuropsychological test – the (pen-and-paper) Trail-Making Test (TMT). Typically administered as one test in a larger battery of tests, TMT is made up of two parts – TMT-A and TMT-B – each resembling a child's connect-the-dots puzzle. Each part, as with the puzzle, is completed by drawing a single, continuous line through all the "dots" in a specified order. The subject's score on each part of TMT is the time the subject took to draw the line to the last "dot." TMT is known to measure visuo-perceptual ability, working memory, and set-switching ability. [34, 35]

Computer-based implementations of neuropsychological tests, such as TMT, have potentially many advantages over traditional, pen-and-paper implementations, including: (1) uniformity of administration across subjects, and (2) more consistent scoring of performance. They also allow the possibility of decomposing performance on the test into performance on individual parts of the test. Researchers have examined the use of computer-based neuropsychological testing [97-99] and have found them to be promising for the cognitive assessment of older adults. [98, 99] In particular, computerized implementations of TMT have been developed (e.g., [100, 101]), however differences between performance on a computerized implementation of TMT and the standard pen-and-paper TMT, as measured by the scores on TMT-A and TMT-B, have been shown. [101] An alternative to simply implementing a computer-based TMT is to have the subject perform the pen-and-paper TMT while the test administrator notes the duration of the subject's moves the pen to each "dot" by selecting a button on a computer GUI each time a "dot" is selected. [102] This approach allows the performance on TMT to be decomposed into performance on each movement to a "dot."

Our approach is to focus on the time taken to make each move to each "dot" rather than on the time taken to draw the line through the whole set of "dots." Given the information about subject performance gained by examining all the individual moves to "dots" we can then estimate the time the subject would need to draw a line through a set of dots – such as those given on TMT. To obtain sufficiently accurate estimates of the underlying processes requires data for a large number of moves. To acquire the needed move data, we have constructed a simple computer game in which the subject completes a series of rounds each of which consists of a set of randomly placed "dots" which the subject connects by using a computer mouse to select the "dots" in a specified sequence.

We develop a model for each move to a "dot" assuming a sequence of the three independent processes based on Donders' additive stages: [103, 104] recall, search, and motor. The motor stage, describing the movement of the pen or mouse from one “dot” to the next, is based on Fitts’ law, characterizing rapid movements into specified target regions. [105-107]

3.2 Overview of Two Connect-the-Dots Tasks

TMT is a pen-and-paper neuropsychological test that measures a subject’s visuo-perceptual ability (ability to interpret visual information), working memory (ability to hold items in memory while completing a complex task), and set-switching ability (ability transition from a task involving one class of objects to a task involving a different class). [34, 35] Scavenger Hunt (SH) is a point-and-click, mouse-driven computer game with game mechanics designed to mimic the testing mechanics of TMT and yet be both challenging and fun so that people are willing to play it routinely over time in a home environment. Both TMT and SH are built around the *connect-the-dots task* that forms the basis of the child’s puzzle giving the task its name. In this task, the subject must select a number of “dots” in sequence by drawing a line through them. We used both TMT and SH to validate our model of the connect-the-dots task given in Section 3.3. The following sections provide an overview of TMT and SH.

We call the interval from the selection of one “dot” to the selection of the next “dot” a *move*.

3.2.1 Trail-Making Test

The pen-and-paper TMT is comprised of two separate tests: TMT-A and TMT-B. TMT-A and TMT-B are printed on a standard 8.5”x11” sheet of paper with 25 small (12mm diameter) circles, the *targets*, placed in a seemingly random pattern on the sheet. All targets in both tests have the same diameter or *width*, and contain a *label* which may a letter or a number. In TMT-A, a label is a number from 1 to 25, while in TMT-B a label is a letter from A to L or a number from 1 to 13. Labels only appear once on the test page. In addition, two targets on each test page are indicated by the presence of the words "Begin" and "End" near to (but outside of) these targets. TMT-A and TMT-B refer to test pages each with a specific arrangement of targets, and the same test pages are used every time TMT is administered. Figure 3.1 shows a portion of TMT-A.

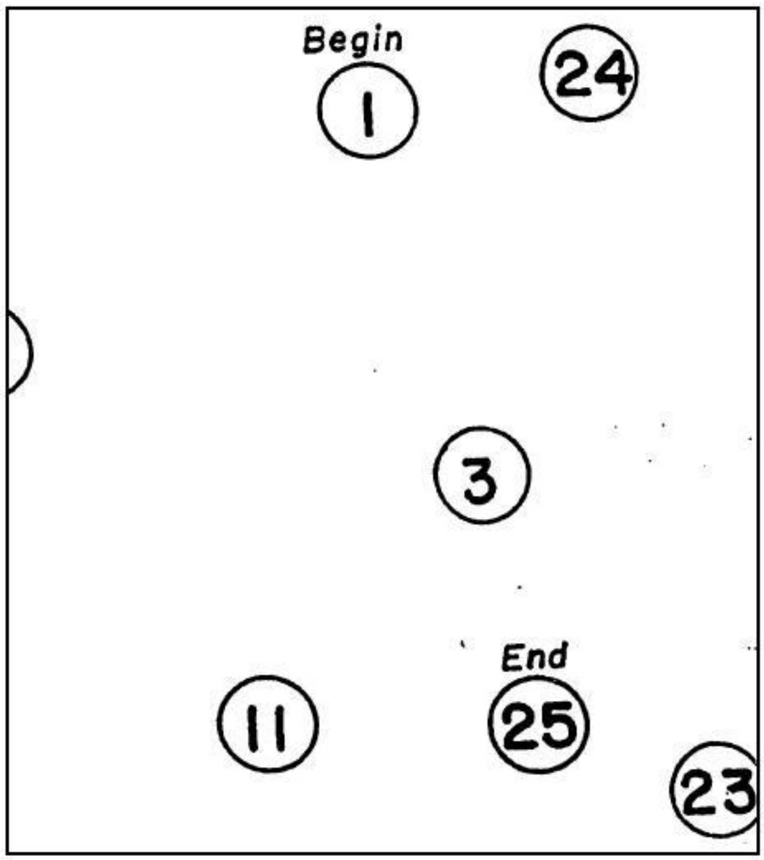

Figure 3.1. A section of the TMT-A neuropsychological test. Note the words "Begin" and "End" indicating the locations of the first and last targets.

Prior to beginning TMT-A or TMT-B, the test administrator instructs the subject on how to correctly complete the test. This is done by walking the subject through a shorter – 8 target – sample test.

TMT-A and TMT-B each start with the subject being given the test page face down, the subject not having seen the test page. The test begins when the test administrator instructs the subject to start the test, and the subject turns over the test page and begins. The subject completes each test by drawing a single line, the *trail*, through all 25 targets in the specified order. In TMT-A, the targets are selected in ascending numerical order of the target labels (i.e. '1,2,3,…,24,25'), while in TMT-B, the order is ascending alphanumeric order of the target labels (i.e. '1,A,2,B,…,L,13'). The "Begin" is printed on the test page lies near the first target of the sequence and the "End" near the last.

The subject's performance on TMT is given in the form of a *score* on each of TMT-A and TMT-B, that is, the time taken to correctly draw a line through all targets on the test page in the specified order beginning when the test administrator instructs the subject to begin, and ending when the test administrator notes that the subject has reached the last target.

The test administrator also makes sure that the subject completes the test correctly, interrupting the test whenever the subject is observed to make an incorrect target selection (i.e. selecting a target out of sequence), as soon as the test administrator notices the error. Whenever such an *error* occurs, the test administrator instructs the subject to return to the last correctly selected target. Timing is not suspended during this process, and is included in the total time and thus in the test score, although, the number of errors for TMT-A and TMT-B are recorded by the test administrator. We call the sequence just outlined, the process of *recovering* from the error.

Guidelines for the administration of TMT are provided in [29]. TMT is normally administered in an office setting by a neuropsychologist once every 6 to 12 months to reduce practice effects associated with repeated completion of standardized tests. [30-32] Normative data for subjects with education in the range of the subject used in our study show TMT scores for ages 75-79 of 42 s on TMT-A and 100 s on TMT-B, and for ages 80-84 of 55 s on TMT-A and 130 s on TMT-B. [27] TMT is one of the most clinically useful neuropsychological tests and is routinely used in the diagnosis of many neurological conditions (Parkinson's, Alzheimer's and dementias, and general cognitive decline). [33] However, it is an expensive test and the infrequent assessment leads to delays in the detection of cognitive issues.

3.2.2 Scavenger Hunt

The point-and-click, mouse-driven SH computer game is intended to mimic the mechanics of TMT while presenting the subject with arbitrary target configurations rather than the two fixed target configurations present on TMT-A and TMT-B test pages. SH was designed to be more engaging and fun, and yet present cognitive tasks that would test cognitive functions similar to those of TMT. We have been able to demonstrate that older adults are able to learn the game and play it routinely on computers in their homes. [67]

The subject plays SH by completing a series of *rounds* each being a single connect-the-dots task. SH rounds must be completed in 30 s (imposing a speed-accuracy tradeoff); if the subject fails to do so the round is lost and the game of SH ends. SH play continues from round to round until either a round is lost, or the subject elects to stop playing.

Figure 3.2 shows a typical SH round. We call the large pane within the GUI containing the words "Scavenger Hunt" the *board.* The upper left hand corner of the board shows the amount of time left in the round. The upper right hand corner of the board shows the cumulative *score* for all the rounds completed so far. The box in the center of the upper center of the board contains the *search string* ‘B,2,A,1’. The remainder of the board shows the array of *markers* for this round. The set of markers includes both *targets*: ‘1’, ’2’, ’A’, and ‘B’, and additional *distractors*: ‘5’, ‘C’, and ‘L’. The *number* of markers on the board for the round shown is 7. The subject would *play* this round of SH by using the computer mouse to connect-the-dots by *selecting* targets the targets ‘B’, ‘2’, ‘A’, ‘1’, in that order, by clicking on them. The *trail* made by the subject in SH is path taken by the mouse in the course of selecting the targets.

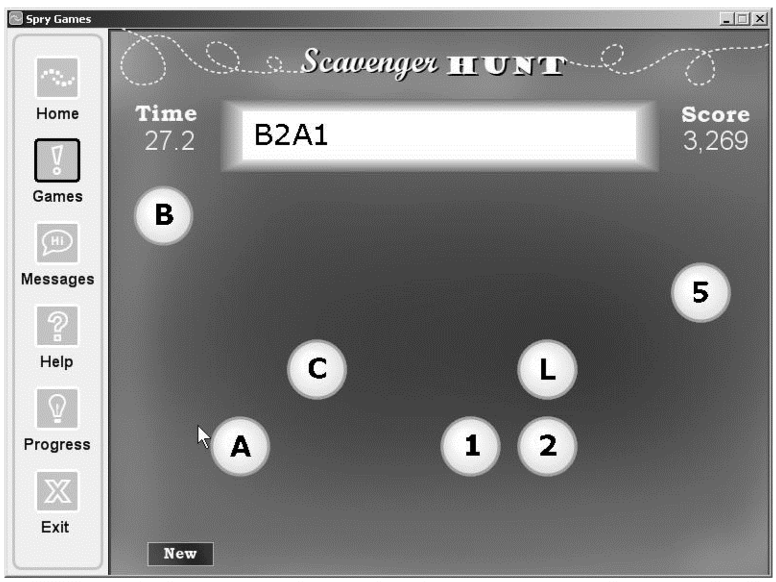

Figure 3.2. A typical Scavenger Hunt round. The board for a round of Scavenger Hunt showing the time remaining in the game (27.2 s), search string (‘B2A1’), cumulative game score (3269), targets (‘1’,’2’,’A’,’B’), and distractors (‘5’,’C’,’L’).

SH indicates correctly selected markers by coloring them green for the remainder of the round; no line indicating a trail is drawn. A subject makes an error when playing a round of SH by selecting any marker other than the one currently being looked for (i.e. the lowest unselected marker in the search string). SH indicates that an error has occurred by drawing a red “X” over the selected marker which remains until another marker is selected.

SH displays the subject’s cumulative score on the game board for the rounds that have been completed. This score is used as feedback and motivation for the subject and not used to infer cognitive function or predict TMT scores. In this paper, we only refer to TMT-A and TMT-B test scores.

Search strings in SH may be ascending or descending alphabetical sequences (e.g., ‘A,B,C,…’ or ‘…,C,B,A’), ascending or descending numeric sequences (e.g., ‘1,2,3,…’ or ‘…,3,2,1’), ascending or descending alphanumeric sequences (e.g., ‘1,A,2,B,…’ or ‘…,B,2,A,1’), and English language words selected out of a fixed lexicon (e.g., ‘H,O,R,S,E’).

A marker in SH appears as a circle containing a single letter or number. The centers of the markers are arranged on the board in a 4x8 grid with a spacing of 80 pixels. We refer to the position of all the markers on the board in this grid as the *layout* of the markers. Markers may have a diameter of 63 pixels or 77 pixels. At the normal viewing distance of about 25 cm, the markers subtend approximately 3 degrees of visual angle. This size assures 100% recognition for subjects with corrected vision to 20/20. In any round, all the markers have the same *width* (diameter). SH has two types of markers: (1) targets, and (2) distractors. *Targets* are those markers containing a character that appears in the search string and that the subject must select in the course of completing the connect-the-dots task for the round. *Distractors* are markers that contain characters not appearing in the search string.

A SH round has a variable number of targets, typically about 4 to 10, as well as additional distractors. The board for each SH round is generated at random. In order to track accurately the subject's performance over time, SH has a particular type of test pattern that appears regularly and often to serve as a baseline reference on a subject's performance over time; these rounds have the search string '1,2,3,4', and no distractors. These rounds make up about one in four SH rounds.

SH was designed to try to make the repetition of a very simple task as interesting to the subject as possible. The use of a smaller number of targets was believed to make the game faster, and the variability of the number of targets together with additional distractors was believed to add more variety to the game. Ascending numeric and alphanumeric sequences were included to facilitate comparison to TMT, and descending numeric and alphanumeric sequences as well as ascending and descending alphabetic sequences and lexical sequences were included to add further variety to the game.

3.2.3 Differences Between SH and TMT

While SH was designed to mimic TMT, the two tasks are clearly not identical, with differences including: (1) SH is played in-home at the subject's leisure, while TMT is an in-clinic test, (2) SH is a computer game while TMT is a pen-and-paper test, (3) a SH round has a 30 s time limit while the subject is instructed to complete TMT-A or TMT-B as quickly as possible, (4) in SH the search string remains visible to the subject for the duration of the round while in TMT the subject is told the search string verbally before beginning the test, (5) the presence of the words "Begin" and "End" on TMT, (6) that SH marks a selected target by changing the color to green where TMT marks a selected target by trail passing through it, (7) SH boards can contain both targets and distractors while TMT contains only targets, and (8) SH board typically contain about 4-10 markers while TMT always contains 25. In Section 3.3.1 – 3.3.4, we develop a model of the connect-the-dots task that is intended to produce a set of performance measures for each subject based on analysis of moves made playing SH. It is expected that these performance measures would be related to comparable measures based on analysis of moves made in TMT (were the move data available). However, comparison of the resulting performance measures between SH and TMT is complicated by the differences listed here. Instead of assuming that the performance measures are the same in the two cases, we suppose some set of transformations exist relating each performance between the cases of SH and TMT, and, for simplicity, that these transformations are the approximately the same for all subjects. These transformations are developed in detail in Section 3.3.5, and given in Eq. (3.4).

3.3 Connect-the-Dots Model

The connect-the-dots task is completed by drawing a single line through a sequence of "dots" in a specified order. On a high level, performance on the connect-the-dots task can be characterized by the time taken to complete the entire task and the number of errors made in the course of completing the task (as is done in TMT); however, we choose to characterize subject performance by characterizing the performance across each individual move the subject makes in the course of completing the task.

The particular goal in the present paper is to show that measuring subject performance on moves observed in SH play can be used to estimate the subject's scores on TMT. The connect-the-dots model we develop in this section describes each move in the connect-the-dots task. By applying the model to the SH we can take all the observed moves from

SH rounds and estimate a set of parameters characterizing how a subject makes a move in connect-the-dots tasks like those in SH. Conversely, given a set of parameters characterizing how a subject makes a move during TMT, we can construct an estimator of the TMT score in the case where no errors are made.

For the sake of simplicity, the proposed model does not characterize errors or the process of recovering from errors; consequently, in our analysis, we ignore the small proportion of rounds of SH in which the subject made any error. We ignore whole rounds to avoid any affects of the error on other moves, whether the error was due to something happening during an earlier move, or caused the subject to carry out subsequent moves differently than they otherwise would. Unfortunately, subjects do make errors on TMT, and we have to account for those errors in the estimators of the TMT-A and TMT-B scores (see Section 3.4 for information on the numbers of errors made). We account for the observed errors by estimating the time delays due to the errors and including these in the prediction of the TMT-A and TMT-B scores. This approach is useful in estimating the relative contribution of the correctly executed moves and errors in the final test scores.

The connect-the-dots model decomposes a move into a sequence of three statistically independent stages as shown in Figure 3.3: (1) the *recall and update* stage during which the subject calls to mind the next target in the search string, (2) the *search* stage during which the subject searches among the unselected targets game board to locate the current target, and (3) the *motor* stage during which the subject moves the mouse or pen to the located target to select it. The general methodology corresponds to Donders' additive stages. [103, 104]

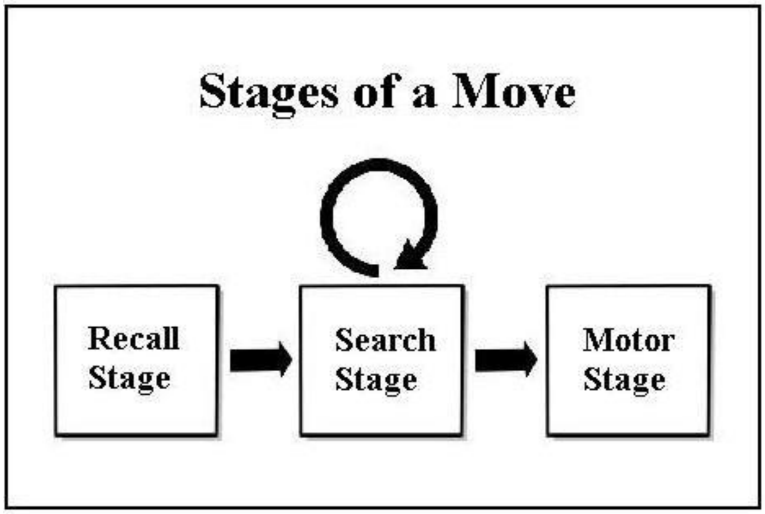

Figure 3.3. Additive stages move model. The process of selecting the next target in the sequence involves three sequential stages of (1) recalling the next target, (2) serially searching for the next target by considering the available targets one after another, and (3) physically moving the mouse so that the cursor is on the target and clicking.

The statistical independence is based on the idea that each stage is affected by different aspects of the task and that the effect is limited to that stage. We expect that the duration of the recall and update stage would vary with the type of the search string (i.e. it should take a different amount of time to recall the next target when the search string is purely alphabetic or numeric as opposed to an alphanumeric search string). The duration of the search stage should depend on the number of additional distractors and unselected targets on the board, with the time spent in search decreasing on average as the subject moves to the end of the round. [108] Finally, the length of the motor stage should depend only on the distance on the board from the previously selected target to the new target – assuming that the target size is constant.

We now describe the detailed characterization of the stages of the model: recall and update, search and motor.

3.3.1 Recall and Update Stage

The recall and update stage is characterized by the *recall time* T_R required by the subject to recall the next target in the search string. The recall time is a random variable (RV) with expected value $\langle T_R \rangle = \tau_R$, and some standard deviation. We suppose that the time T_R spent by the subject recalling the next target in a sequence may vary across the classes of search strings available in SH (i.e. alphabetic, numeric, alphanumeric, and lexical), but is assumed to be the same for all the targets in sequences of a given class. We denote values for τ_R intended to estimate recall for TMT-A-like connect-the-dots task by τ_R^A, and for TMT-B-like tasks by τ_R^B.

3.3.2 Search Stage

The search stage is characterized by the *search time* T_S required by the subject to locate the next target in the search string after it has been recalled. We treat search as a series of discrete steps, [108] where the total number of steps in any search is a RV. In each step, the subject considers a different marker (a target or a distractor) on the board. The subject compares the marker being considered during that step to the target being searched for. If the subject decides that the marker being considered is the same as the target they are searching for, they select the marker; otherwise the subject continues the search to another step and considers another marker. Each step of search takes some fixed time τ_S . We suppose that the time τ_S spent by the subject on each step of search may vary across the classes of search strings available in SH (i.e. alphabetic, numeric, alphanumeric, and lexical), but is assumed to be the same for all the targets in sequences of a given class. We denote values for τ_S intended to estimate search step time for TMT-A-like connect-the-dots task by τ_S^A, and for TMT-B-like tasks by τ_S^B.

The number of steps in a given search depends on the number of markers remaining on the board (i.e. the initial number of markers less the number of targets that have been selected thus far). We suppose that the subject searches the remaining markers at random, with no memory of any of the remaining markers from searches made in previous moves in the same round; we further suppose that during the search stage, the subject has perfect memory and considers each marker only once (we discuss the validity and utility of these assumptions in Section 3.7). Let us consider a SH round with n targets and d distractors. Suppose the subject is searching for the $\nu - th$ target. The subject has already found $\nu - 1$ targets, so there are $n - \nu + 1$ targets still on the board. The expected number of steps for the search is $(n - \nu + d + 1)/2$. The expected value for the total search time T_S for this target is given by:

$$\langle T_S \rangle = \left((n - \nu + d + 1)/2 \right) \tau_S. \tag{3.1}$$

The distribution of T_S for a given value $n - \nu + d$ is uniform on the discrete values τ_S, …, $(n - \nu + d + 1)\tau_S$.

3.3.3 Motor Stage

The motor stage is characterized by the *motor time* T_M, required by the subject move the mouse or pen from one target to the next. We suppose it to be independent of the search string. The movement made by the mouse or pen is a rapid movement into a target area given by the size of the marker being selected, and is expected to be consistent with Fitts' law. [105-107] We treat the motor time as a RV whose mean value satisfies

Fitts' law and has some standard deviation. Fitts' law expresses the relationship between the distance D from the initial position to the center of the target, the target width W, and the expected motor time, T_M, required to complete the move. Defining D_ν to be center-to-center distance between the $\nu-1-th$ and $\nu-th$ targets, assuming a common width W for all targets, the expected motor time taken to move from the $\nu-1-th$ to the $\nu-th$ target is given by:

$$\langle T_M \rangle = a + b\log_2\left(D_\nu / W + 1\right). \tag{3.2}$$

The value $\log_2\left(D/W+1\right)$ provides a measurement of the amount of information the subject must process to complete the movement as measured in bits; so the value b provides a measure of how much time the subject spends processing each bit of information.

3.3.4 Total Time

The expected time needed to complete an error-free connect-the-dots task with n targets and d distractors is simply the sum of the expected times for all of the component moves (we use the dot to distinguish multiplication $a\cdot(b)$ from the expression of a function $a(b)$):

$$\begin{aligned} &T = n\cdot\left(\tau_R + a\right) + \kappa\left(n,d\right)\tau_S + \chi\left(D_1,\ldots,D_\nu,W\right)b, \\ &\kappa\left(n,d\right) = \sum\nolimits_{\nu=1}^{n}\left(\left(n-\nu+d+1\right)/2\right), \\ &\chi\left(D_1,\ldots,D_\nu,W\right) = \sum\nolimits_{\nu=1}^{n}\log_2\left(D_\nu / W + 1\right). \end{aligned} \tag{3.3}$$

We can see that the expected time required to complete a connect-the-dots task is linear in the parameters characterizing the subject's cognitive and motor abilities: τ_R, τ_S, a, and b. We call $\kappa(n,d)$ and $\chi(\{D_v\},W)$ the *search complexity*, and the *motor complexity* respectively.

Due to the way in which τ_R and a appear in Eq. (3.3), their values cannot not be estimated separately. Instead, the best we can do is to estimate their sum $\tau_R + a$.

3.3.5 Relating SH to TMT

Due to the differences between SH and TMT outline in Section 3.2.3, we do not expect the values τ_R, τ_S, a, and b to relate trivially to their counterparts $\tau_R{}'$, $\tau_S{}'$, a', and b'. Differences 7 and 8 from Section 3.2.3, the presence of distractors and the numbers of targets, have already been handled in the model developed in this section. We suppose that the differences between SH and TMT do not affect the search or motor stages, so difference 6 regarding how selected targets are indicated is assumed not to affect search, and difference 2 regarding SH being a computer game and TMT being a pen-and-paper test is assumed not to effect movement from one target to the next. The remaining differences – 1, in-home versus in-clinic, 2, presence of time limit, 4, visibility of the search string, and 5, the presence of the words "Begin" and "End" – are assumed to only affect recall. We model the net effect of these differences on recall using the linear transformation $\tau_R{}' = \alpha + \beta\tau_R$. However, as a practical matter, we cannot separate the values τ_R and a, but rather we must work with $\tau_R + a$, so we use the approximate transformation $\tau_R{}' + a' \approx \alpha + \beta \cdot (\tau_R + a)$. The full set of transformations is:

$$\begin{aligned} &\tau_R{}' + a' \approx \alpha + \beta \cdot (\tau_R + a), \\ &\tau_S{}' = \tau_S, \\ &b' = b. \end{aligned} \tag{3.4}$$

This set of transformations is assumed to be the same for all search strings (i.e. the values α and β are the same when relating SH to TMT for TMT-A-like search string and for TMT-B-like search strings). We also assume that our subject population is sufficiently homogeneous that we can use the same transformation for every subject.

3.4 Analyzing SH Play

We validated the model of connect-the-dots tasks developed in Section 3.3 by constructing an estimator of the subject's scores on the TMT-A and TMT-B using measurements taken from that subject's play of SH. We used SH data from rounds using ascending and descending alphabetic and numeric search string to construct the TMT-A estimator and data from rounds using ascending and descending alphanumeric search string to construct the TMT-B estimator. We chose to combine round data in this way so that more data would be available for each subject and we would be able to retain as many subjects as possible for analysis (see Section 3.4 for more information).

We now consider how to estimate a subject's cognitive and motor parameters $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, τ_S^B, and b using the SH move data which consists only of timestamps indicating when buttons were selected by the subject and the relative positions of the buttons on the board. We produce the estimates in a two-step process. In the first step, we estimate the subject's motor performance as described by the Fitts' law b parameter, from the time and position data, using SH rounds with search string '1,2,3,4' and no distractors using the model developed in Section 3.3. In the second step, we use the estimated motor performance from the first step to remove the effect of motor performance from observed moves in SH rounds with alphabetic, numeric, and alphanumeric search strings (i.e. rounds with search strings of the same classes as that in the TMT-A and TMT-B respectively), and then estimate the subject's cognitive recall and search parameters $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, and τ_S^B also using the model developed in Section 3.3.

3.4.1 Estimating Motor Parameters

The first step in our two step process of estimating a subject's cognitive and motor parameters is to estimate the subject's Fitts' law motor parameter b. We use a data set consisting only of moves from SH rounds with the search string '1,2,3,4' and no distractors. As there is some uncertainty in the position of the mouse at the beginning of the round, we ignore the move to the first target for each round.

For each move, we know the inter-target distances D_i, target widths W_i, observed move times t_i, numbers of targets n_i, and the position of the target in the search string ν_i (so for the string '1,2,3,4', the target '1' has $\nu = 1$, the target '2' has $\nu = 2$ and so on). So, for a particular move, the expected total time taken to move is:

$$\begin{aligned}\langle t_i \rangle = (\tau_R + a) + \left((n_i - \nu_i + 1)/2\right)\tau_S \\ + b\log_2\left(D_i / W_i + 1\right).\end{aligned} \tag{3.5}$$

As the values $\tau_R + a$, τ_S, and b are unknown at this point, we have to fit all three to the data. We can estimate their values by finding the values c_0, c_1, and c_2 that minimize the total squared error given by:

$$\begin{aligned}\varepsilon = \sum_i \Big(\langle t_i \rangle - c_0 - |c_1|\left((n_i - \nu_i + 1)/2\right) \\ - |c_2|\log_2\left(D_i / W_i + 1\right)\Big)^2.\end{aligned} \tag{3.6}$$

We constrain the result so that c_1 and c_2 are non-negative. From this step, we only retain the estimated value $b = |c_2|$.

3.4.2 Estimating Cognitive Parameters

The first step in our two step process of estimating a subject's cognitive and motor parameters is to use the subject's Fitts' law motor parameter b estimated in the first step to remove the motor component of the move time and estimate the subject's cognitive parameters $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, and τ_S^B. For estimation of $\tau_R^A + a$ and τ_S^A, we use a data set consisting only of moves from SH rounds with the ascending or descending alphabetic or numeric search strings excluding SH rounds with search string '1,2,3,4' and no distractors; and for estimation of $\tau_R^B + a$ and τ_S^B, we use a data set consisting only of moves from SH rounds with ascending or descending alphanumeric search strings. As there is some uncertainty in the position of the mouse at the beginning of the round, we ignore the move to the first target for each round.

As we did above in Eq. (3.5), we estimate the expected time taken for each move by summing the expected times for each of the three additive stages. In this case, however, we must also include values for the numbers of distractors d_i present for each move, giving the expected move time:

$$\begin{aligned} \langle t_i \rangle = & (\tau_R + a) + ((n_i - \nu_i + d_i + 1)/2)\tau_S \\ & + b\log_2(D_i / W_i + 1). \end{aligned} \tag{3.7}$$

As the values $\tau_R + a$ and τ_S are unknown at this point, we have to fit both to the data. We can estimate their values by finding the values c_0 and c_1 that minimize the total squared error given by:

$$\begin{aligned} \varepsilon = \sum_i \Big(& \langle t_i \rangle - c_0 - |c_1| ((n_i - \nu_i + d_i + 1)/2) \\ & - b\log_2(D_i / W_i + 1) \Big)^2. \end{aligned} \tag{3.8}$$

We constrain the result so that c_1 is non-negative. From this step, we retain the estimated values $\tau_R + a = c_0$ and $\tau_S = |c_1|$.

3.5 Estimating TMT Scores

Using the procedure given in Section 3.4, we can produce estimates for the cognitive and motor parameters $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, τ_S^B, and b for each subject using data from play of SH. We now use these estimates to produce estimators of performance on TMT-A and TMT-B for each subject.

3.5.1 TMT Score Estimator

We begin our construction of the estimators for the performance on TMT by assuming we had the actual values of the cognitive and motor parameters $\tau_R^{A\prime} + a'$, $\tau_R^{B\prime} + a'$, $\tau_S^{A\prime}$, $\tau_S^{B\prime}$, and b' that describe the subject's performance on TMT. Let us consider first the time spent completing TMT-A or TMT-B after the first target has been selected. The search complexity $\tilde{\kappa}$ for this portion of the test can be calculated from the definition in Eq. (3.3); while the motor complexities $\tilde{\chi}^A$, and $\tilde{\chi}^B$ for this portion of the test can be found using the definition in Eq. (3.3) and direct measurement of the layout of the markers on the test page. Using the superscript X as a place-holder for either A or B, indicating whether TMT-A or TMT-B is being considered, the expected total time spent completing the test after the first target has been found when no errors are made is:

$$\langle T^X \rangle = 24\left(\tau_R^{X\prime} + a'\right) + \tilde{\kappa}\tau_S^{X\prime} + \tilde{\chi}^X b'. \tag{3.9}$$

One aspect of difference 2 in Section 3.2.3 is that the subject begins the test by turning over the test page. This adds some amount of amount T^0 to the final time. We suppose

T^0 is the same for all subjects for both parts of TMT. In addition, the move to the first target begins at some unknown position. We suppose that the motor portion of the time taken to make the move to the first target is about average for the motor times on the test, or $a + (1/24)\tilde{\chi}^X b'$. When the first move is included, the search complexity is now κ as given in Eq. (3.3) for the full test rather than $\tilde{\kappa}$. The expected total time spent completing the entire test when no errors are made is:

$$\langle T^X \rangle = T^0 + 25\left(\tau_R^{X\prime} + a'\right) + \kappa \tau_S^{X\prime} + (25/24)\tilde{\chi}^X b'. \tag{3.10}$$

We denote the number of errors the subject made on the TMT-A and TMT-B respectively by N^A and N^B and treat time required by the subject to make and recover from an error as a random variable with mean θ; we further assume that the random variable is the same for all subjects. Thus, the expected test score (or expected total time spent completing the test when errors are made) given a expected numbers of errors $\langle N^A \rangle$ and $\langle N^B \rangle$ is:

$$\begin{aligned} \langle S^X \rangle = \langle T^X \rangle = T^0 + 25\left(\tau_R^{X\prime} + a'\right) + \kappa \tau_S^{X\prime} \\ + (25/24)\tilde{\chi}^X b' + \theta \langle N^X \rangle. \end{aligned} \tag{3.11}$$

Finally, we must replace the cognitive and motor parameters $\tau_R^{X\prime} + a'$, $\tau_S^{X\prime}$, and b' describing performance on TMT by their counterparts that have been estimated from SH. Replacing the TMT cognitive and motor parameters $\tau_R^{X\prime} + a'$, $\tau_S^{X\prime}$, and b' by their SH counterparts $\tau_R^X + a$, τ_S^X, and b using the transformation between the two connect-the-dots tasks is given in Eq. (3.4) gives the estimator for expected scores on TMT given expected numbers of errors:

$$\left\langle S^X \right\rangle = \left(T^0 + 25\alpha\right) + 25\beta \cdot \left(\tau_R^X + a\right) + \kappa\tau_S^X \\ + \left(25/24\right) \tilde{\chi}^X b + \theta \left\langle N^X \right\rangle. \tag{3.12}$$

3.5.2 Estimating Global Parameters

The subject-specific cognitive and motor parameters $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, τ_S^B, and b appearing in Eq. (3.12) have been estimated using SH move data. The global parameters $T^0 + 25\alpha$, β, and θ (assumed to be the same for all subjects) now need to be estimated. We estimate the global parameters by finding the values of $T^0 + 25\alpha$, β, and θ that cause our estimators given in Eq. (3.12) to have optimal performance combined for both TMT-A and TMT-B across all subjects.

We index our subjects so that every subject has some index i in the data related to TMT-A, and some index j in that related to TMT-B. For each subject we have measurements average test scores $\left\langle S_i^A \right\rangle$ and $\left\langle S_j^B \right\rangle$, and the average numbers of errors made in each part $\left\langle N_i^A \right\rangle$ and $\left\langle N_j^B \right\rangle$. As the values $T^0 + 25\alpha$, β, and θ are unknown at this point, we have to fit all three to the data. We can estimate their values by finding the values c_0, c_1, and c_2 that minimize the total squared error given by:

$$\begin{aligned} \varepsilon = \sum_i \Big(\left\langle S_i^A \right\rangle - c_0 - 25\left|c_1\right| \cdot \left(\tau_R^A + a\right)_i \\ - \kappa\tau_{S,i}^A - \left(25/24\right) \tilde{\chi}^A b_i - \left|c_2\right| \left\langle N_i^A \right\rangle \Big)^2 \\ + \sum_j \Big(\left\langle S_j^B \right\rangle - c_0 - 25\left|c_1\right| \cdot \left(\tau_R^B + a\right)_j \\ - \kappa\tau_{S,j}^B - \left(25/24\right) \tilde{\chi}^B b_j - \left|c_2\right| \left\langle N_j^B \right\rangle \Big)^2 . \end{aligned} \tag{3.13}$$

We constrain the result so that c_1 and c_2 are non-negative. We retain the estimated values $T^0 + 25\alpha = c_0$, $\beta = \left|c_1\right|$, and $\theta = \left|c_2\right|$.

3.6 Empirical Study

30 older adults (25 female and 5 male, average age 80 ± 6.0 years, average level of education 15 ± 2.7 years, MMSE = 28 ± 1.1, ADL = 0.071 ± 0.30) participated in a one year study in which a set of computer games that included SH was placed into their homes.

SH was developed along with 8 other adaptive computer games to measure cognitive performance of individuals on a regular basis by monitoring their computer interactions during game play on their home computers. [109, 59] The set of computer games, including SH, was placed in subjects' homes for a period of one year. Subjects were encouraged to play all the games often, but were free to play the games as little as they wanted. Play of the computer games by the subjects was monitored, and the relevant information needed to reconstruct a subject's play in any of the games was recorded in a central database in a format allowing us to reconstruct any round of SH played. Subjects were given a battery of cognitive tests, including TMT, administered by trained clinical staff according to standard administrations procedures, at the beginning of the study, 6 months into the study and at the end of the study.

We restricted the analysis to those subjects for whom, when only error-free rounds of SH with alphabetic, numeric, and alphanumeric search strings were considered, we could find at least 25 moves total (across all such rounds) for rounds using alphabetic or numeric and at least 25 moves total for rounds using alphanumeric search strings. Data from SH rounds with alphabetic and numeric search strings were combined in the analysis. Rounds with search string '1,2,3,4' and no distractors, were excluded, as were the first moves within each round for the purpose of determining whether a subject had enough data. This restriction left a cohort of 23 older adults (20 female and 3 male, average age 81 ± 6.8 years, average level of education 15 ± 2.9 years, MMSE = 28 ± 0.89, ADL = 0.058 ± 0.16).

The numbers of moves across the remaining cohort 23 subjects for SH rounds with the search string '1,2,3,4' and no distractors ranged from 24 to 1236 (median of 108), for rounds with alphabetic or numeric search strings (not including moves from rounds with search string '1,2,3,4' and no distractors) the numbers of moves ranged from 35 to 4618 (median of 259), and for rounds with alphanumeric search string ranged from 43 to 4819 (median of 273). Data for rounds ascending and descending alphabetic or numeric search strings were pooled together for estimating TMT-A performance as were data for ascending and descending alphanumeric search strings for estimating TMT-B performance so that as many subjects as possible could be retained for analysis.

Following the first step of our two step procedure for estimating subject cognitive and motor parameters from SH data given in Section 3.4, for each subject we estimated the value for the Fitts' law parameter b (Eq. (3.2)) by minimizing the total error expressed in the model given in Eq. (3.6) using all observed error-free SH rounds with search string '1,2,3,4' and no distractors. The observed means and standard deviations for the values of R^2 and p for the fit of the model given in Eq. (3.6) across the 23 subjects were $R^2 = 0.26 \pm 0.11$ and $p = 0.0080 \pm 0.028$, and the mean and standard deviation of the numbers of moves available for each subject for the estimation was $n = 590 \pm 810$. The observed mean and standard deviation of the estimated Fitts' law parameter b across the full cohort of 23 subjects was:

$$b = 300 \pm 110 \, \text{ms} / \text{bit}. \tag{3.14}$$

The SH rounds chosen for the estimation of the Fitts' law parameter b were intended to be those for which the motor component would be strongest. The model fit all subjects at a significance level of $p < 0.05$. The low R^2 values are expected due to the uniform distribution of the number of search steps given a number of unselected targets on the board described in Section 3.3.2. Our average value for b is close to the independently measured value of 166 ms/bit measured for point-select methods of selecting icons in a computer interface, [110] with the measured value being about one deviation below our average b. We consider this further in Section 3.7.

Continuing to the second step of our two step procedure for estimating subject cognitive and motor parameters from SH data, we estimated the recall and search performances $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, and τ_S^B for each subject using the previously estimated values of b by minimizing the total error expressed in the model given in Eq. (3.8) using data from alphabetic and numeric search strings to estimate $\tau_R^A + a$ and τ_S^A, and alphanumeric search strings to estimate $\tau_R^B + a$ and τ_S^B. The observed means and standard deviations for the values of R^2 and p for the fit of the model given in Eq. (3.8) across the 23 subjects for estimation of the parameters $\tau_R^A + a$ and τ_S^A were $R^2 = 0.097 \pm 0.061$ and $p = 0.065 \pm 0.17$ with the number of moves available use in the estimation having mean and standard deviation $n = 670 \pm 1200$, and for estimation of the parameters $\tau_R^B + a$ and τ_S^B were $R^2 = 0.087 \pm 0.050$ and $p = 0.049 \pm 0.12$ with the numbers of moves available use in the estimation being $n = 730 \pm 1300$. In the case of the estimation of $\tau_R^A + a$ and τ_S^A, four of the subjects had fits with $p > 0.05$, and among these subjects the numbers of moves available for estimation had means and standard deviations of n = 52 ±

19; similarly for the case of the estimation of $\tau_R^B + a$ and τ_S^B, four of the subjects had fits with p > 0.05, and among these subjects the numbers of moves available for estimation had means and standard deviations of n = 82 ± 38. Two subjects had fits with p > 0.05 in both cases. Removing the appropriate four subjects with poor fits in the each of the two cases gives, for the remaining 19 subjects, in the former case R^2 = 0.11 ± 0.057, p = 0.0032 ± 0.0077, and n = 800 ± 1300, and, for the remaining 19 subjects, in the latter case R^2 = 0.10 ± 0.043, p = 0.0039 ± 0.0095, and n = 830 ± 1300. The observed means and standard deviations of the estimated cognitive parameters across the full cohort of 23 subjects were:

$$
\begin{aligned}
\tau_R^A + a &= 380 \pm 250\,\text{ms}, \\
\tau_R^B + a &= 660 \pm 280\,\text{ms}, \\
\tau_S^A &= 96 \pm 43\,\text{ms}, \\
\tau_S^B &= 110 \pm 41\,\text{ms}.
\end{aligned}
\tag{3.15}
$$

The model, again, fit most subjects to a statistical significance level of $p < 0.05$, and the cases where this level of significance was not met appear to be attributable to the smaller amount of data available. Again, the low R^2 values are expected due to the uniform distribution of the number of search steps given a number of unselected targets and distractors on the board described in Section 3.3.2. Due to the fact that we are measuring combined cognitive and motor values $\tau_R^A + a$ and $\tau_R^B + a$ rather than the purely cognitive values τ_R^A and τ_R^B, we could not compare the measured values to existing research. However, we could estimate the set-switching (the time needed for the subject to switch from considering the sequence of numbers to considering the sequence of letters and vice versa in TMT-B) by taking the difference of $\tau_R^A + a$ and $\tau_R^B + a$. The average estimated set-switching time of 280 ms compared well with independently measured values of about 200 ms. [111] The average estimated values for τ_S^A and τ_S^B for each step in visual search differed from the independently measured value of 240 ms [112] by about a factor of two. We consider these further in Section 3.7.

The observed TMT-A and TMT-B scores and numbers of errors across all the tests taken by the subjects being included in this analysis and their standard deviations were S^A = 45 ± 11 s and N^A = 0.0073 ± 0.14, and S^B = 100 ± 28 s and N^B = 1.0 ± 0.64. The observed scores are near those given in Section 3.2.1 (i.e. [27]) for subjects around the age and education of those used in our study. The observed TMT test-retest reliability for the test pairs: (1) beginning and 6 months, (2) beginning and 1 year, and (3) 6 months and 1 year, was observed to have R^2 of 0.32, 0.20, and 0.13 for TMT-A, and R^2 of 0.43, 0.30, and 0.59 for TMT-B. As we used the full year's worth of data to estimate subject performance, we characterized subject performance on TMT using averages of the test scores over the year.

We next constructed estimators of the mean TMT scores given the mean numbers of errors made on the tests using the procedure given in Section 3.5. The motor complexities for the TMT-A and TMT-B for all moves after the first target has been selected were measured from the test pages using a ruler, giving $\tilde{\chi}^A$ = 66 bits, and $\tilde{\chi}^B$ =74 bits. Using the values of the cognitive and motor parameters $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, τ_S^B, and b that we estimated for the 23 subjects (Eqs. (3.14) and (3.15)), we estimated the global parameters $T^0 + 25\alpha$, β, and θ by minimizing the total error expressed in the model given in Eq. (3.13) using, for each subject the means of the three test scores and the means of the numbers of errors made in the course of each test administration. The model was fit with $R^2 = 0.82$ and $p < 0.0001$, and the estimated global parameter values were:

$$\begin{aligned} &T^0 + 25\alpha = -9.1\text{s}, \\ &\beta = 2.2, \\ &\theta = 30\,\text{s}. \end{aligned} \tag{3.16}$$

For comparison, we looked at the performance of a simple linear regression of the test scores on the number of errors; the fit in this case had $R^2 = 0.58$ and $p < 0.0001$.

Inspection of the 95% confidence intervals for the coefficient estimates showed that the estimates of β and θ were statistically significant, while that of $T^0 + 25\alpha$ was not. The values in Eq. (3.16) suggested that subjects required 30 s to recover from an error. We consider this further in Section 3.7. In Figure 3.4, we show how the estimated average TMT-A and TMT-B test scores using these values of the global parameters compared to the actual average test scores for each subject.

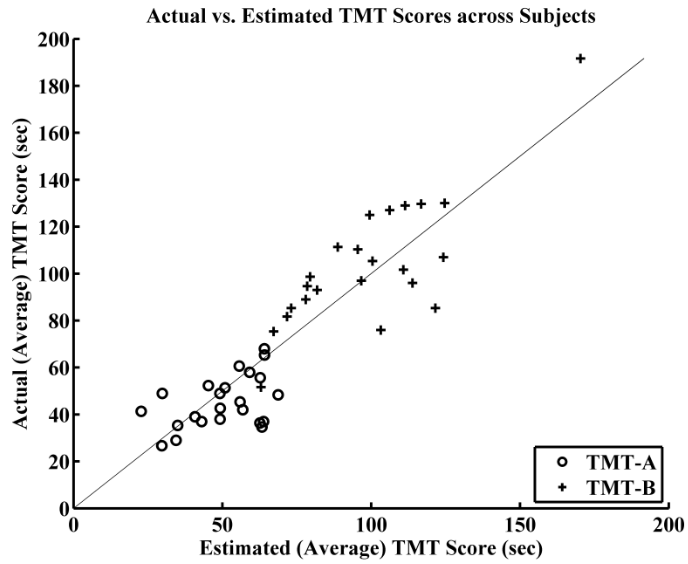

Figure 3.4. Actual vs. estimated TMT scores across subjects. Each of the 23 subjects has two values shown, one for TMT-A and one for TMT-B, each representing the average of the three administrations of TMT. The model fit has $R^2 = 0.82$ and $p < 0.0001$. A line with slope one passing through the origin is shown for reference.

It was of interest to see how the model developed in this paper would perform in the case where no errors were made on TMT. We restricted the analysis to only include administrations of TMT in which both TMT-A and TMT-B had no errors. There were 16 subjects who had at least one error-free administration of TMT. We fitted a truncated version of our model in Eq. (3.13) lacking the terms in θN^A and θN^B, and used the average of all error-free TMT administrations for the test scores. The model fit with $R^2 = 0.55$ and $p < 0.0001$, and estimated global parameter values of $T^0 + 25\alpha$ = -9.1 s and β = 3.1. Inspection of the confidence intervals for the coefficient estimates showed that the estimate of β was statistically significant while that of $T^0 + 25\alpha$ was not. The results were close to those found by retaining tests where errors were made in Eq. (3.16).

If the subject whose data give the outlier is removed from the data set, and the procedure repeated, the fit became $R^2 = 0.73$ and $p < 0.0001$, and the global parameters were found to be $T^0 + 25\alpha =$ -6.3 s, β = 2.0, and θ = 29 s, with β and θ being statistically significant while $T^0 + 25\alpha$ was not. These results were very close to those found when retaining the outlier in Eq. (3.16), so we retained the outlier in our analysis. The linear regression of the test scores on the number of errors had $R^2 = 0.51$ and $p < 0.0001$. When we limited ourselves to error-free administrations of the TMT, we were left with the same set of 16 subjects as in the previous paragraph.

3.7 Discussion

The connect-the-dots model developed in this study is a very simple model of the connect-the-dots task, and incorporates a number of simplifying assumptions, particularly in the search stage. Our simple model relating the measurements from SH to the case of TMT using a single set of transformations taken to be approximately the same for all subjects is based on the assumption of a relatively homogeneous set of subjects. A broader range of subjects may need to be grouped into classes each with a different set of transformations. A further limitation to our analysis presented here is the exclusion of SH rounds with errors, possibly limiting our ability to collect data for (mildly) cognitively impaired subjects.

We treated the time spent recalling the next target in the sequence as a single RV that appears once in each move. Because our empirical measurements did not allow to separate the effects of cognitive and motor segments, we were unable to estimate the recall times τ_R, but had to measure a combined cognitive and motor parameter $\tau_R + a$. As a result, we could only average estimated set-switching time of 280 ms measured by taking the difference of $\tau_R^A + a$ and $\tau_R^B + a$ to independent measurements; though they compared well to the independently measured value of about 200 ms. [111] The model we developed to describe the transformation from the SH case to the TMT case should have taken the form $\tau_R{}' = \alpha + \beta\tau_R$, but, since we could only use values $\tau_R + a$, we had to make the approximation $\tau_R{}' + a' \approx \alpha + \beta \cdot (\tau_R + a)$ which causes the motor parameter a to change value between the two cases. Even were this not a problem, the transformation $\tau_R{}' = \alpha + \beta\tau_R$ causes the set-switching time to change between the SH case and the TMT case, where it seems reasonable that the set-switching time would not change.

The model we use for visual search is that of a serial search that does not benefit from the memory from previous search stages for previous “dots,” during any given round, but has perfect memory within the search stage for the current “dot.” Using this model, we estimated times spent on each step of search of about 100 ms in both cases (τ_S^A and τ_S^B). The natural sequence of images produced by the eye during visual search has been independently measured to be about 240 ms per image. [112] This suggests that our model over-estimates the average number of steps in the visual search for a given target by about a factor of two. A more sophisticated model of search would include aspects related to: (1) visual acuity and how much target information the subject can take in at each search step, (2) the ability of the subject to remember target locations from previous searches, (3) the degree to which the subject becomes confused and considers the same target multiple times during a single search, and (4) the ability of the subject to ignore already selected targets and whether they spend much time considering these targets in later searches. What our simple model of search does capture is the observation that the total search times for moves are, on average, longer earlier in the connect-the-dots task than they are later in the task. [102]

We used Fitts' law to describe the motor portion of a move. An average value for the Fitts' law parameter of $b \approx 300$ ms/bit was measured across the subjects analyzed. We can compare this value to independently measured values for Fitts' law for several methods of using a computer mouse to select a icon: (1) a = 135 ms and b = 249 ms/bit for drag-select, (2) a = 230 ms and b = 166 ms/bit for point-select, and (3) a = 135 ms and b = 249 ms/bit for stroke-through. [110] Point-select should be closest to the button selection process happening in SH, so our average value of b is roughly twice as large of the independently measured value (although that value is approximately one standard deviation below our average b).

We included the time spent recovering from an error as a single global parameter with the same value for all subjects. The estimated 30 s recovery time for each error is somewhat long (we do not have data on the duration of errors during the administrations of TMT). However, the average number of errors on TMT-A was near zero and that on TMT-B near one, so it is likely that the value estimated for θ largely reflects the time needed to recover from errors during TMT-B. The value for θ may well be inflated by a correlation where subjects making more errors also require more time to recover from each one. Alternatively, it is possible that, when taking the TMT, subjects also made a number of "near errors" in which they came close to selecting and incorrect "dot," but corrected the error themselves. If the number of these "near errors" is correlated to the number of actual errors, then the large error recovery time may reflect time taken up in a "near error" process as well.

Possibly related to variability in the numbers of errors between administrations of TMT and variability in the error-recovery time is the low test-retest reliability observed in

Section 3.6. It appears from our results that errors can contribute a large amount of time to the test scores, and errors are discrete events, so differing numbers of errors from one test to another appear to be able to result in substantially different scores from one test to another.

Moving forward, it is important to better understand the process of making errors in the course of the connect-the-dots task, and there are a variety of approaches to doing this. There are four approaches one might take in considering the errors. (1) Look at the rate at which errors are made in playing SH and see whether this rate predicts the average number of errors made on TMT, or allows us to produce good estimates of the average TMT score without using the observed number of errors on TMT. (2) Look at how observed errors in SH relate to moves made immediately before and after. In our analysis, we have dropped all SH rounds in which any errors were made. The amount of data available, particularly for (mildly) cognitively impaired subjects, would be increased by dropping moves expected to be affected by observed errors from the data set rather than whole rounds. (3) Look at the moves in SH in which errors are made and see if the time spent recovering from the error can be used to predict error recovery times in TMT. (4) Look at outliers in the move times and see if the frequency and average duration of these outliers could be related to the number of errors or error recovery time in SH or TMT, suggesting that the outliers may be "near errors."

3.8 Conclusion

The key objective of this work included (1) the development of techniques that would allow frequent assessment of cognitive functions of individuals at risk, for example associated with aging and (2) the demonstration of the utility of computational modeling in assessment of cognitive function. The general approach was based on using computer games that would enable neurophysiologic assessments comparable to those obtained with traditional neuropsychological tests such as the TMT. In this study, we used a simple game that is similar to the TMT and was developed for this purpose as a part of prior study. [109, 59, 67] In addition to the estimation of the TMT performance, the objective of using the game was to derive a more refined assessment of the various cognitive components recruited in the execution of TMT.

The potential benefit of our approach to modeling computer interactions is that we can model cognitive performance over time for individuals in the home in a more scalable and less expensive manner than current standard practice. Cognitive measures and trends in these measures can be used to identify individuals for further assessment, to provide a mechanism for improving the early detection of neurological problems, and to provide feedback and monitoring for cognitive interventions in the home.

The following appendix was not included in the published version of this Chapter

3.9 Appendix

We can analyze the model in Eq. (3.13) further using the same set of 23 subjects analyzed in Section 3.6. Rather than fitting the model in Eq. (3.13) once for all 23 subjects, we fit it 23 times, once for each subset of 22 subjects. These models fit with a mean and standard deviation of R^2 of $R^2 = 0.82 \pm 0.013$ and in all cases $p < 0.0001$. The means and standard deviations of the estimated global parameter values were:

$$\begin{aligned} T^0 + 25\alpha &= -9.1 \pm 1.0\,\text{s}, \\ \beta &= 2.2 \pm 0.096, \\ \theta &= 30 \pm 1.2\,\text{s}. \end{aligned} \tag{3.17}$$

The global parameter values estimated for each of the 23 models in Eq. (3.17) are close to those estimated in the single model using all 23 subjects in Eq. (3.16). We arrive at the same model using any set of 22 subjects that we do when using all 23 subjects.

We define S^X to be the actual average TMT scores and $\tilde{S}^X$ to be the estimated average TMT scores for the individual subject left out of the estimation of the global parameter values in Eq. (3.17). The means and standard deviations of the resulting differences in the actual and estimated average TMT scores $S^X - \tilde{S}^X$ using the estimated global parameter values for each of the 23 subject for TMT-A and TMT-B were:

$$\begin{aligned} S^A - \tilde{S}^A &= -5.0 \pm 14\text{s}, \\ S^B - \tilde{S}^B &= 5.0 \pm 19\text{s}. \end{aligned} \tag{3.18}$$

We can compare the values in Eq. (3.18) to the means and standard deviations of the errors when all 23 subjects are fit using a single model:

$$\begin{aligned} S^A - \tilde{S}^A &= -5.0 \pm 13\text{s}, \\ S^B - \tilde{S}^B &= 5.0 \pm 17\text{s}. \end{aligned} \tag{3.19}$$

The errors in the case where the model is fit using 22 subjects and the estimated global parameters were used to estimate TMT performance for the remaining subject were comparable to the errors when all 23 subjects were used to estimate the global parameter values.

Chapter 4 – Towards the Unobtrusive and Ubiquitous In-Home Monitoring of Cognitive Performance Using Mouse Dynamics

4.0 Abstract

Early detection of decline in cognitive performance in older adults facilitates early medical intervention to treat the decline. Detection of decline requires on-going monitoring cognitive performance by which a baseline level of performance is established and decline from the baseline is noted. Detection of cognitive decline can be made earlier as the monitoring becomes more frequent. We look at the unobtrusive and ubiquitous monitoring of in-home (computer) mouse dynamics during everyday computer usage as a means of monitoring cognitive performance. We characterize cognitive performance by executive function as measured by the Trail-Making Test (TMT), and use measures derived from mouse dynamics to estimate cognitive performance by estimating performance on TMT. We further attempt to indicate the direction of future work to improve the measures we use here and to derive further measures from mouse dynamics.

4.1 Introduction

Early detection of declines in cognitive performance is an important component of providing proper medical treatment for maintaining the health and well-being of an older adult. Detection of decline requires regular measurement of cognitive performance by which a baseline level of performance is characterized and declines from the baseline can be detected. As it takes several measurements of cognitive performance to overcome noise in the measurements and definitively detect cognitive decline, the frequency of the measurements of cognitive performance place a limit on how early a decline in cognitive performance can be detected. Currently, medical professionals perform regular measurements of cognitive performance during regular visits to a clinic. Clinical visits are infrequent and of short duration, limiting how quickly cognitive decline can be detected. An alternative to clinical visits is unobtrusive in-home monitoring through the placement of sensors in the subject's home. Unobtrusive in-home monitoring can produce measurements of cognitive performance more frequently and so provide for earlier detection of decline.

Unobtrusive in-home measurements of cognitive performance for older adults have been developed using measurements of in-home activity. [71, 69, 70] Some in-home measurements of specific sorts or aspects of activity that have been developed include walking speed [Chapter 2, [79, 80]], time spent using a computer [113], typing speed [114], time away from home [115], and sleep [116, 117]. Unobtrusive, in-home measurement techniques have also been applied to fall risk assessment and fall detection for older adults. [84, 85]

A further, potentially rich, source of information about the subject that one can measure unobtrusively in the home is how the subject moves a computer mouse. The measurement of (computer) mouse dynamics (MD) as an unobtrusive in-home measure of performance has been explored in a limited way in [118]. Measurements of MD have been explored for use as a biometric for authenticating a computer user's identity. To this end, variety of methods have been put forward which characterize mouse movements by a number of geometrical (the shape of the path of the mouse movement) and dynamical measurements (the timing of the mouse movement), and use machine learning techniques to create classifiers capable of identifying individual subjects. The verification of the subject's identity can be done statically (i.e. the subject completes a set of specified tasks which are compared to recorded previous performances of the same tasks) (e.g. [119]), or continuous (i.e. the subject uses the computer normally and measurements of how the computer is used are compared to characteristic data for the subject) (e.g. [120-122]). The continuous techniques for verification of a subject's identity during computer usage are a form of unobtrusive monitoring.

Rather than identify the subject using MD, we would like to use MD as a measure of subject performance. Cognitive performance and motor performance have been shown to be intertwined, with seemingly motor-only tests functioning as predictors of cognitive decline. The timed up and go test, in which the subject rises from a chair, walks three meters, turns around, returns to the chair and sits down, has been shown to predict cognitive decline; [123, 124] declining walking speeds [20, 125, 126] and motor speeds as characterized by finger-tapping speeds [20, 127] have been shown to indicate cognitive impairment. Measurements of MD during controlled experiments have been used to investigate a variety of cognitive processes, including the cognitive dynamics of the negation-operator in linguistics, [128] the cognitive dynamics in shape and pigment processing in face categorization, [129] and the underlying response confidence during recognition decisions, [130] as well as the effect of semantic priming on mouse movements. [131]

In the present paper, we begin the process of developing techniques to use in-home measurements of MD to monitor the cognitive and motor performance of a subject. We provide solutions to practical problems related to recording and storing large amounts of raw mouse position data for the purpose of on-going analysis. We also provide an algorithm for identifying individual mouse movements within the stored raw data. We show that we can use the mouse movements identified by the algorithm to produce performance metrics, and that these performance metrics capture some amount of inter-subject variability by using them to predict subject performance on the Trail-Making Test (TMT) – a standard clinical test in which the subject draws a line through a series of targets printed on a page. To provide a conceptual schema for understanding the MD data and how best to analyze it, we use a mathematical model that describes how a subject completes TMT. We suggest that the process of drawing a line through a series of targets bears a resemblance to the process of navigating a computer by moving a mouse cursor through a series of control widgets.

The data available for analysis cover 210 older adults observed over a period of 6 years. The very large quantity of mouse data available necessitated that the techniques developed require as few computational resources as possible so that our computer could perform the calculations in a reasonable amount of time. The solution of these problems only constitutes the first steps of a wider program of measuring cognitive performance from MD. In addition to looking at these three problems, we indicate possible directions for carrying out the next steps for improving the measures of cognitive performance we develop here and producing further measures from in-home MD.

4.2 Cognitive Performance (Executive Function)

We begin by presenting a conceptual schema for understanding MD and its relationship to cognitive and motor performance. We characterize cognitive performance using executive function, and, in turn, characterize executive function using the score on TMT, a clinical neuropsychological test known to measure executive function. [37, 34, 35] The subject completes TMT by drawing a line through a series of targets printed on a page. We can analyze the TMT score into performance on component tasks using the connect-the-dots model developed in Chapter 3. In this model, we decompose the process of drawing the line from one target to the next into a series of three additive stages. The first two stages are purely cognitive in nature, while the third describes the physical movement to the next target using Fitts' law. [105-107] The third stage relates TMT to the MD of physically moving the mouse. In the interest of making the present treatment as self-contained as possible, we reproduce the model here in detail.

The remainder of Section 4.2 provides a review of material appearing in Chapter 3

4.2.1 Trail-Making Test

TMT is one of the most clinically useful neuropsychological tests and is used routinely in the diagnosis of many neurological conditions (Parkinson's, Alzheimer's and dementias, and general cognitive decline). [33] As we show, the process by which a subject completes TMT resembles the way subject controls a computer using a computer mouse. A natural way of constructing a measure of executive function from MD is to construct an estimator of a subject's score on TMT using MD; and this is how we approach the analysis of subjects' MD. So in order to better understand how to approach the MD data in order to estimate cognitive performance using executive function, we begin by looking in detail at the structure of TMT.

TMT consists of two connect-the-dots tasks (TMT-A and TMT-B) which the subject completes by using a pen to draw a single line through a series of targets on a test page. Each test takes the form of a standard 8.5"x11" sheet of paper on which is printed 25 *targets* – small (12mm diameter), seemingly randomly scattered circles containing a label that may be a letter or a number. For TMT-A, the targets are labeled with all numbers from 1 to 25, with one number labeling each circle, while in TMT-B targets are labeled with all letters from A to L and all numbers from 1 to 13 with one letter or number labeling each circle. The individual completes the TMT-A by using a pen to draw a line (the "trail") through all the circles in ascending numerical order of the labels (i.e. '1,2,3,…,24,25'), while the TMT-B is completed by drawing the line through the circles in ascending alphanumeric order (i.e. '1,A,2,B,…,L,13'). We call the process of drawing a line from one target to the next in the sequence a *move*. The *score* on each part of the test is the time the subject needs to complete each task (there is no time limit). If the subject makes an error on the test (drawing the line through an incorrect target), the test administrator stops the subject as soon as the error is noted by the administrator and returns the subject to the last correctly selected target; timing of the subject is not stopped during this *error recovery* process. The total numbers of errors made on each part are included with the test score. The difference between TMT-A and TMT-B is the use of the numeric and alphanumeric sequence of labels respectively. The alphanumeric label sequences introduce the additional complication of *set-switching* in which the subject must not only recall the next element in an alphabetic or a numeric sequence, but must also switch sets between the alphabetic and numeric sequences.

TMT characterizes the subject's executive function using two pairs of numbers: (1) the scores on each of the two parts, and (2) the numbers of errors made in completing each of the two parts. Normative data for subjects with education in the range of the subject used in this study show TMT scores for ages 75-79 of 42 s on TMT-A and 100 s on TMT-B, and for ages 80-84 of 55 s on TMT-A and 130 s on TMT-B. [27] The test re-test reliabilities for TMT have been observed to be $R^2 = 0.56$ for TMT-A and $R^2 = 0.72$ for TMT-B for a cohort of normal adult controls, scores of 47 ± 25 s on TMT-A and 120 ± 86 s on TMT-B. [28] Guidelines for the administration of TMT are provided in [29].

4.2.2 Connect-the-Dots Model

The connect-the-dots model developed in Chapter 3 describes the process by which a subject makes each move in TMT by dividing the move into a sequence three additive stages. [103, 104] The stages are (1) *recall and updating*, in which the subject recalls the next target in the target sequence, (2) *search*, in which the subject searches for the recalled target, and (3) *motor*, in which the subject moves the mouse to the target according to Fitts' law.

The recall and updating stage is characterized by the *recall time* required by the subject to recall the next target in the sequence. We treat the recall time as a random variable (RV) T_R with expected value $\langle T_R \rangle = \tau_R$ (the *characteristic recall time*), and some standard deviation.

The search stage is characterized by the *search time,* T_S, required by the subject to locate on the test page the next target in the sequence after it has been recalled. Search is treated as a series of discrete steps. [108] We assume that each step of search takes some fixed time τ_S (the *characteristic search time*) and that the variation in search time is due to each search taking a variable number of steps; we treat the number of steps as a RV. At each step of search, the subject considers a randomly chosen unselected target on the test page; if that marker is the desired target, the subject ceases search and moves on to the motor phase, otherwise the subject considers another randomly chosen unselected target. We assume that the subject does not consider any unselected target twice during a particular search. For a move during a part of TMT, the subject is searching for the $\nu - th$ of 25 targets, the subject has already found $\nu - 1$ targets, and there are $26 - \nu$ targets still on the board. The expected number of steps for the search is $(26 - \nu)/2$, so the expected value for the search time for this target is given by:

$$\langle T_S \rangle = ((26 - \nu)/2)\tau_S. \tag{4.1}$$

The distribution of T_S for a given value ν is uniform on the discrete values τ_S, …, $(26 - \nu)\tau_S$.

The motor stage is characterized by the *motor time* T_M, a RV representing the time the subject takes to move the mouse to the next target. We assume that the time taken to make each move is consistent with Fitts' law. Defining D_ν to be center-to-center distance between the $\nu - 1 - th$ and $\nu - th$ targets, assuming a common width W for all targets, the expected time taken to move from the $\nu - 1 - th$ to the $\nu - th$ target is given by:

$$\langle T_M \rangle = a + b \log_2 (D_\nu / W + 1). \tag{4.2}$$

The value $\log_2 (D / W + 1)$ provides a measurement of the amount of information the subject must process to complete the movement as measured in bits; so the value b

provides a measure of how much time the subject spends processing each bit of information.

The expected total time $\langle T \rangle$ required to complete TMT-A or TMT-B where no errors are made is the sum of the expected times spent making moving to each target in turn, that is:

$$\begin{aligned} &\langle T \rangle = 25(\tau_R + a) + \kappa\tau_S + \chi(D_1,\ldots,D_{25},W)b, \\ &\kappa = \sum_{\nu=1}^{25}((26-\nu)/2), \\ &\chi(D_1,\ldots,D_{25},W) = \sum_{\nu=1}^{25}\log_2(D_\nu / W + 1). \end{aligned} \tag{4.3}$$

We call κ the *search complexity*, and $\chi(D_1,\ldots,D_\nu,W)$ the *motor complexity*. We note that the estimate for expected total required to complete the task is linear in the cognitive and motor parameters τ_R, τ_S, a, and b.

Eq. (4.3) provides an estimate of the expected time required to complete one part of TMT without any errors using the cognitive and motor parameters τ_R, τ_S, a, and b. We allow that different values may apply to each part of TMT and characterize subject performance on TMT as a whole by the set of parameter values τ_R^A, τ_R^B, τ_S^A, τ_S^B, a^A, a^B, b^A, and b^B where the superscript indicates whether the parameter is for TMT-A or TMT-B. When the subject makes no errors, TMT characterizes executive function by two values – the two test scores – the connect-the-dots model characterizes executive function by up to eight values. The search complexity κ for TMT-A or TMT-B (they are the same value) can be calculated from the definition in Eq. (4.3); while the motor complexities $\tilde{\chi}^A$, and $\tilde{\chi}^B$ for the remainder of the test after the first target has been selected can be calculated using the definition in Eq. (4.3) and direct measurement of the layout of the targets on the test page.

In practice, we must modify the estimate in Eq. (4.3) to include times related to other effects present in the test-taking process. When errors are allowed to occur on either part of TMT a parameter θ giving the expected time needed to recover from an error must also be included. The act of turning over the test page and moving to the first target adds some time T^0 in addition to the recall, search and motor times to the total time. Using X as a place-holder for either of superscripts A or B, given a number of errors N^X, a subject's expected score on TMT-A or TMT-B (the expected time required to complete the test) $\langle S^X \rangle$ is:

$$\begin{aligned} \langle S^X \rangle &= T^0 + 25\left(\tau_R^X + a^X\right) + \kappa\tau_S^X \\ &+ \left(25/24\right)\tilde{\chi}^X b^X + \theta N^X. \end{aligned} \tag{4.4}$$

4.3 Measuring In-Home MD

In Section 4.2, we provided a conceptual schema for understanding the in-home MD and its relationship to cognitive performance. The schema characterizes cognitive performance as the score on TMT, that is, the time taken to complete a sequence of simple motor tasks. It uses the connect-the-dots model that decomposes each of the simple motor tasks as an additive sequence of cognitive and motor stages. We would like to estimate cognitive performance using in-home MD by deriving estimates of performance for each of the cognitive and motor stages from measurements made from in-home MD. To begin this process of producing estimates of cognitive and motor performance on TMT, we must first put some structure on the raw mouse data by identifying the individual mouse movements and (implicitly) the intervals between mouse movements when the mouse is idle. Once we have this structure, we can begin to do a more sophisticated analysis of the stored mouse data.

In this Section, we develop a technique for parsing the raw mouse data into a sequence of movements and idle intervals between movements. We also show how to estimate the motor parameters for Fitts' law using the identified mouse movements. We expect the motor parameters to provide an estimate of performance during the motor stage in TMT. We further begin the process of providing a more sophisticated analysis of the stored mouse data by deriving a simple physical model of mouse movements and using it to derive a simple, initial division of the mouse movements into two classes.

4.3.1 Preliminaries

A subject uses a computer in a series of *sessions* that begin when the subject logs-on to the computer and ends when the subject finally logs-off or leaves for an extended period. Within each session, the subject controls the computer by a series of movements made by the computer mouse. During a computer session, the mouse to alternates between intervals in which it is *idle* (not moving), and periods in which it is *active* (moving).

MD occurs in two spaces related by a non-linear transformation: (1) the first is the *pointer-space*, which involves movement of the pointer on the computer screen (2) the second is the *mouse-space,* which involves movement of the computer mouse on the tabletop. Distances in the former are expressed in *pixels* (distances on the computer screen), while those in the latter are expressed in *counts* (distances on the tabletop). One count indicates the smallest distance the mouse must travel before the computer recognizes that it has moved. The physical distance of movement corresponding to one count varies with the mouse hardware. The analysis of computer mouse movement in

[118] mistakes what are, in fact, mouse-space measurements for pointer-space measurements.

The transformation relating the pointer- and mouse-spaces is given by the *pointer ballistics* that relates the pointer velocity $\vec{v}_{\text{pointer}}$ in the pointer-space to the mouse velocity $\vec{v}_{\text{mouse}}$ in the mouse-space by a transfer function $\vec{v}_{\text{pointer}} = G(\vec{v}_{\text{mouse}})$, which appears roughly quadratic. [132] The intent of the transfer function is to facilitate the subject's ability to make both small and large movements of the pointer using reasonable movements of the mouse. [132]

4.3.2 Storing Mouse-Position Data

We think of MD over the course of a session as being a stream of regularly sampled data. This is a very large amount of data, and we would like to store it as compactly as we reasonably can while being able to use it to recover as much information about the mouse movements as we can. The way we do this is to store the data with a variable sampling rate so that we sample the mouse-position more frequently when there is activity and less frequently when there is little activity.

The algorithm that we implement to record the mouse-position data uses event-triggered sampling. We record the initial mouse-position (in mouse-space) at the beginning of data acquisition. We record subsequent mouse-positions and times whenever the event occurs that the mouse's position exceeds a distance of five counts from the last recorded position along a Manhattan metric in the mouse-space coordinate system for the duration of data acquisition.

4.3.3 Identifying Mouse Movements

The event-triggered sampling procedure in Section 4.3.2 records the mouse movement during the session as an irregularly sampled time series of mouse-positions $\vec{x}(t_n)$. We would like to characterize MD during the session by identifying individual mouse movements in $\vec{x}(t_n)$. First, we interpolate a regularly sampled time series of mouse-positions $\vec{X}(t_k)$ that approximates the original raw mouse data. The sampling rate of the interpolated time series $\vec{X}(t_k)$ is taken to be the highest observed sampling rate in the irregularly sampled time series $\vec{x}(t_n)$, typically 16 ms. We interpolate by assuming the mouse moved with constant velocity along a straight line between recorded data-points. From $\vec{X}(t_k)$, we construct a mouse speed time series $|\vec{v}(t_k)|$ using $\vec{X}(t_k)$ by taking $|\vec{v}_k|$ = $|\vec{v}(t_k)|$ = $|\vec{X}(t_{k+1}) - \vec{X}(t_k)| / \Delta t$. Using the speeds that occur in the time series $|\vec{v}(t_k)|$, we can estimate the distribution of the logarithm of the mouse speeds over the course of the session. Figure 4.1 shows the kernel-smoothed density estimate of a typical distribution of the logarithm of the mouse speeds $\{|\vec{v}_k|\}$ for a session lasting 12 min. The data are analyzed on the logarithm of the speed domain $\{\log_{10}(|\vec{v}_k| / v_0)\}$ where v_0 = 1 count/s. We observe that the distribution of the logarithm of the mouse speeds in Figure 4.1 is multimodal; this is typical for the distribution the logarithm of the mouse speeds in a computer session. We use the modes of this distribution to distinguish active intervals from idle intervals in the session. We identify time intervals associated with speeds in the highest mode of the distribution as being "active," and all other intervals as being "idle." To do this we associate the *cut speed* v_{cut}, which demarcates the boundary between active (higher velocity) intervals and idle (lower velocity) intervals, with the local minimum in the distribution between the mode containing the highest velocity intervals and the next lower mode. In Figure 4.1, the cut speed is the local minimum at about 67 count/s.

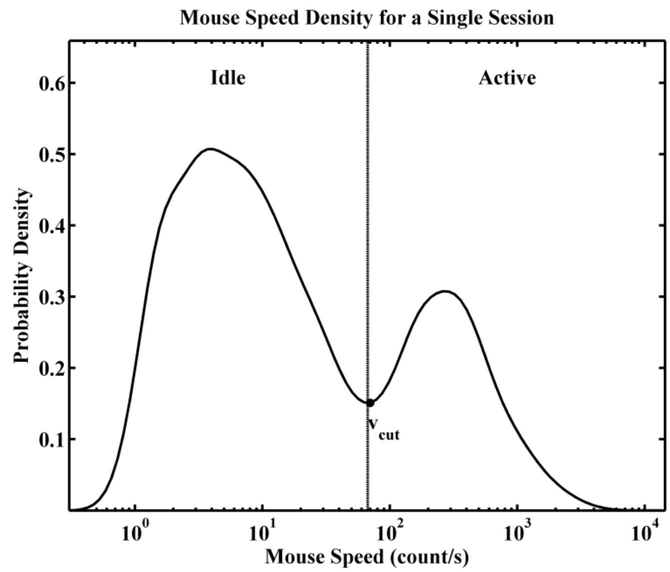

Figure 4.1. Mouse speed density for a single session. The kernel smoothed density of the interpolated regularly sampled mouse speed time series for a single computer usage session by a single subject. The speed v_{cut} = 67 counts/s separates velocities associated with mouse activity with those associated with the mouse being idle. The session lasted about 12 min and 544 mouse movements were identified by the procedure.

We now return to the irregularly sampled time series of mouse-positions $\vec{x}(t_n)$. We can construct a mouse speed time series $|\vec{v}(t_n)|$ for $\vec{x}(t_n)$ just as we did for $\vec{X}(t_k)$ albeit with a variable Δt. In this way, we associate a speed with the interval between any two consecutive mouse-position samples. We identify as "idle" any intervals with speed less than v_{cut} and as "active" those with speed greater than or equal to v_{cut}. We then identify a mouse movement with any consecutive sequence of active intervals between two idle intervals. Figure 4.2 shows horizontal and vertical mouse-position data (in mouse-space) for a 5 s period. The mouse movement data (dots) have been parsed into five separate movements (indicated by alternating series of grey and black dots) after the calculation of v_{cut}. The intervals between the separate movements correspond to intervals with speeds below v_{cut}.

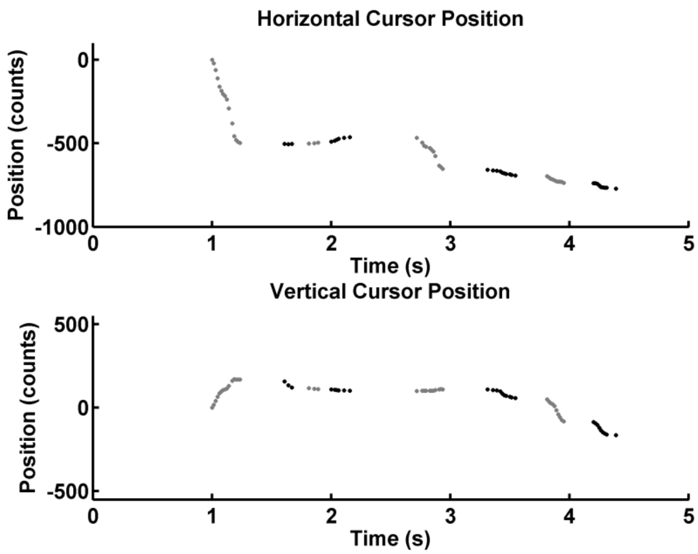

Figure 4.2. Sample mouse-position data. A sample segment of horizontal and vertical mouse-position data (in mouse-space) covering a 5 s period. The dots correspond to individual mouse-position measurements. There are 8 separate mouse movements indicated by alternating series of grey and black dots. The intervals between the separate movements correspond to intervals with speeds below v_{cut}.

We have observed that the distribution of the logarithm of the velocity is multimodal. It appears that we can use this observation to divide the raw mouse data into individual mouse movements. If this holds, then we have a way of identifying individual mouse movements using information contained in the stored mouse data itself without introducing any further arbitrary assumptions about how the subject carries out the mouse (such as how long the shortest idle interval between movements can be). The reader can view the remainder of this paper as laying out the structure of the mouse data when one identifies individual mouse movements by this technique. We consider limitations of this technique for identifying mouse movements in Section 4.6.

4.3.4 Estimating Motor Parameters

The procedure given in Section 4.3.3 parses the raw mouse data for a computer session into a sequence of mouse movements and idle intervals between mouse movements. Each identified mouse movement has an associated time interval T – the time taken to make the movement – and an associated distance D_{mouse} that the mouse travelled in mouse-space. We can now use this parsed mouse movement data to estimate the portion of the executive function performance of the subject associated with the motor stage of the connect-the-dots model given in Section 4.2.2 as characterized by the motor parameters a and b in Fitts' law.

We assume that all identified mouse movements satisfy Fitts' law, the parameters a and b in Fitts' law are the same for all identified mouse movements, and that each identified mouse movement is a movement to a target of (unknown) width W. We also assume that Fitts' law is related to the visual feedback given by the pointer on the screen and that Fitts' law holds in pointer-space. Thus, each identified mouse movement satisfies the equation.

$$T_M = a + b\log_2\left(D_{\text{pointer}}/W\right). \tag{4.5}$$

The parameters a and b in Eq. (4.5) apply to all identified mouse movements, and each mouse movement is has its own values T_M, D_{pointer}, and W. We would like to estimate the motor parameters a and b of Fitts' law in pointer-space using the observed times T_M and distances moved D_{mouse}.

We assume that, for typical mouse movements, the relationship between D_{pointer} and D_{mouse} is approximately linear and can be approximated by $D_{\text{pointer}} \approx \eta D_{\text{mouse}}$. This gives an approximate expression for Fitts' law in the mouse-space:

$$T_M \approx \left(a + b\log_2\left(\eta / W\right)\right) + b\log_2 D_{\text{mouse}} \\ + b\log_2\left(1 + \left(W / \eta\right) / D_{\text{mouse}}\right). \quad (4.6)$$

To simplify Eq. (4.6) further, we suppose that:

$$\left|\left(W / \eta\right) / D_{\text{mouse}}\right| < 1. \quad (4.7)$$

We confirm the validity of this supposition in Section 4.5. As we do not know the target width W for a given mouse movement we replace the target width with an approximate typical value $\tilde{W}$; thus, we arrive at the following approximate expression for Fitts' law in mouse-space:

$$T_M \approx \tilde{a} + b\log_2 D_{\text{mouse}} + \left(b\tilde{W} / \eta\right) / D_{\text{mouse}}. \quad (4.8)$$

The parameter $\tilde{a}$ is related to the motor parameter a by the expression:

$$a = \tilde{a} - b\log_2\left(\eta / \tilde{W}\right). \quad (4.9)$$

It turns out empirically that $\eta / \tilde{W}$ is much less than one and thus $\log_2\left(\eta / \tilde{W}\right)$ is a negative number. As a result, estimated values of $\tilde{a}$ are negative numbers.

In principle, we can estimate the motor parameters a and b for a computer session by taking the measured movement times T_M and distances moved D_{mouse} for all the identified mouse movements and calculating the values $\tilde{a}$, b, and $b\tilde{W} / \eta$ that minimize the differences between the left-hand side (LHS) and right-hand side (RHS) of Eq. (4.8) in the ordinary least squares (OLS) sense. We can then use Eq. (4.9) to calculate a. In practice, to avoid numerical problems, it is preferable to ignore the value estimated for $b\tilde{W}/\eta$ using Eq. (4.8), and instead estimate the value $\log_2\left(\eta/\tilde{W}\right)$ across the population of subjects by fitting a linear model to the measured values of $\tilde{a}$ and b.

4.3.5 Modeling Mouse Movements

In Section 4.3.4, we achieved our goal for the present paper of estimating the portion of the executive function performance of the subject associated with the motor stage of the connect-the-dots model. This is the first step to using in-home MD to estimate executive function as characterized by TMT. Future steps involve estimating the subjects' performance of the search and recall stages of the connect-the-dots model. We now try to derive more information from individual mouse movements beyond Fitts' law with the idea that a better understanding of individual mouse movements may help construct measures of search and recall. Also a better understanding of individual mouse movements may allow us to restrict the mouse movements we use in Section 4.3.4 to estimate Fitts' law to a set that gives better estimates of the motor parameters $\tilde{a}$ and b.

Each identified mouse movement consists of a time series of position values. The data available for each mouse movement has additional structure beyond the distance moved and the time taken to make the movement. We can potentially gain more information about what was happening during the movement by looking at this structure for each movement. To do this, we fit a simple mouse movement model to each identified mouse movement. In the present paper, we use the model for the purpose of dividing mouse movements into two classes and seeing whether Fitts' law differs across the two classes or one class is more useful for making estimates of Fitts' law for estimating executive function using the TMT scores.

We construct the model of mouse movements by first assuming that the movements subjects make are, in some sense, better than the alternative movements. We formulate this mathematically by saying that the movements subject make minimize the value of some cost functional. [133-138] There must be some aspect of the movement (e.g., position, velocity, acceleration, etc.) that the subject has complete control over. By this, we mean that there is some aspect of the movement whose value the subject can choose at will, discontinuously. We assume the subject controls the jerk – $\dddot{x}$ – and that the subject makes the movement in a way that keeps the magnitude of the jerk relatively small. [134-137] We write the cost functional associated with the movement that takes a time T_M in the form:

$$\begin{aligned} J[x] &= \int_0^{T_M} L(x,\dot{x},\ddot{x},\dddot{x})\,dt, \\ L(x,\dot{x},\ddot{x},\dddot{x}) &= (1/2)\dddot{x}^2 - \Phi(x,\dot{x},\ddot{x}). \end{aligned} \tag{4.10}$$

The minus sign appears in the RHS of Eq. (4.10) by analogy with the Lagrangian formulation of classical mechanics (see e.g., [139] Chapter 2); since the function $\Phi(x,\dot{x},\ddot{x})$ may take on both positive and negative values the minus sign in Eq. (4.10) places no restriction on the model being used. The movement the subject makes, the optimal orbit $x(t)$ is the one that minimizes Eq. (4.10). We treat a mouse movement as beginning at rest at a position $-D_{\text{mouse}}$ and travelling along an approximately straight line for the movement time T_M to the origin where it returns to rest. We express these initial and final conditions by requiring that the movement satisfy:

$$\begin{aligned} x(0) &= -D_{\text{mouse}}, \quad & x(T_M) &= 0, \\ \dot{x}(0) &= 0, & \dot{x}(T_M) &= 0, \\ \ddot{x}(0) &= 0, & \ddot{x}(T_M) &= 0. \end{aligned} \tag{4.11}$$

The term in the jerk $\dddot{x}$ in the integrand of Eq. (4.10) represents the cost associated with the value of the jerk in making the movement; the term in $\Phi(x,\dot{x},\ddot{x})$ represents any other costs associated with the movement. We assume the only cost represented by $\Phi(x,\dot{x},\ddot{x})$ is associated with ending in the target region. As the target is a purely geometric object, we expect the cost $\Phi(x,\dot{x},\ddot{x})$ to be approximately a function of position alone, that is $\Phi(x)$. We approximate the unknown cost $\Phi(x)$ using a Taylor series expansion truncated to second-order in x:

$$\Phi(x) \approx \phi_0 + \phi_1 x \pm (1/2)\phi^{\pm} x^2, \quad \phi^{\pm} \geq 0. \tag{4.12}$$

The super script of $\phi^{\pm}$ simply indicates whether sign of the second term on the RHS in Eq. (4.12) is positive or negative. The target is located at the end of the movement, that is, the origin. As the subject simply needs to end the movement within the target region, any point within the target region is as good a place to end the movement as any other. We model this by taking $\Phi(x)$ to be approximately constant over the target region; this is done by taking ϕ_1 = 0, giving:

$$\Phi(x) \approx \phi_0 \pm (1/2)\phi^{\pm} x^2, \quad \phi^{\pm} \geq 0. \tag{4.13}$$

We do not try to impose any further physical requirements on the cost represented by $\Phi(x)$, and leave it in this general mathematical form.

The cost functional in Eq. (4.10) is minimized by setting the first variation to zero, that is (see e.g., [140] part I, Chapter 4):

$$\frac{d^3}{dt^3}\frac{\partial L}{\partial \dddot{x}} - \frac{d^2}{dt^2}\frac{\partial L}{\partial \ddot{x}} + \frac{d}{dt}\frac{\partial L}{\partial \dot{x}} - \frac{\partial L}{\partial x} = 0. \tag{4.14}$$

The L in Eq. (4.14) is the Lagrangian of the system, that is, it is the integrand of the cost functional in Eq. (4.10). The solution to Eq. (4.14) is the Euler-Lagrange equation, Taking the Lagrangian in Eq. (4.10) and using the form of $\Phi(x)$ in Eq. (4.13) and plugging this into Eq. (4.14), we find the Euler-Lagrange equation for the model of mouse movements:

$$\overset{\cdot\cdot\cdot\cdot\cdot\cdot}{x} \approx \mp\phi^{\pm}x. \tag{4.15}$$

Eq. (4.15) gives the general form of an optimal orbit $x(t)$ that minimizes the cost functional in Eq. (4.10). The orbit of a particular mouse movement is found by calculating the solution of Eq. (4.15) using the conditions given in Eq. (4.11). The solution to Eq. (4.15) can be found using the standard technique of assuming the solutions have the form $x = \exp(rt)$, plugging this form of the solution into Eq. (4.15) and calculating the values of r needed to satisfy the conditions in Eq. (4.11). We denote the orbits that solve Eq. (4.15) by $x_{\phi}^{\pm}(t)$ according to the sign associated with the RHS in Eq. (4.15). Denoting by c_i constant values that are determined by the conditions in Eq. (4.11), and by $R_i^{\mp}$ the sixth-roots of -1 and +1 respectively, these solutions take the form:

$$x_{\phi}^{\pm}(t) = \sum_{i=1}^{6} c_i \exp\left(R_i^{\mp}\left(\phi^{\pm}\right)^{1/6} t\right). \tag{4.16}$$

We call orbits of the form $x_{\phi}^{-}(t)$ *class I movements*, and orbits of the form $x_{\phi}^{+}(t)$ *class II movements*. In Figure 4.3, we show the data and fit of the models for mouse movements for example class I and class II movements traversing approximately the same distances in approximately the same times. It can be seen that class I movements reach the peak velocity nearer the beginning of the movement while class II movements reach the peak velocity nearer the end.

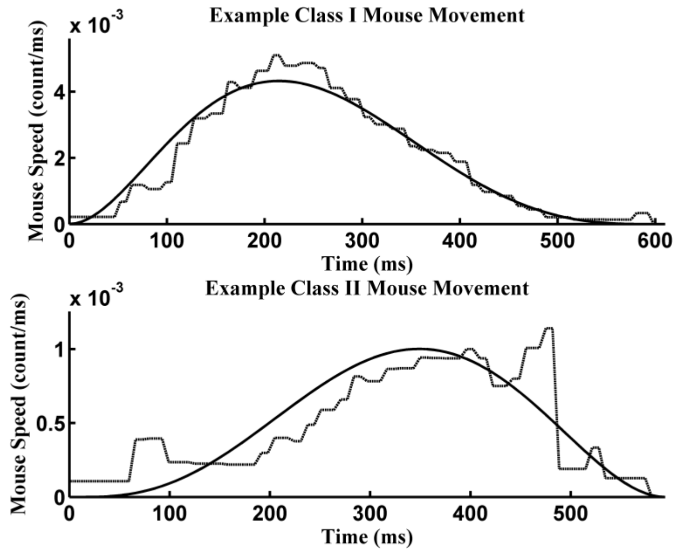

Figure 4.3. Example class I and class II mouse movements. The dashed line indicates the observed mouse speed time-course of the movement, and the solid line indicates the time-course of the fitted model. Due to the way in which mouse movements are stored and estimated (see Section 4.3) the observed mouse speeds appear as a sequence of average velocities over time intervals. Note that for class I movements, the peak speed is nearer to the beginning of the movement and for class II movements, the speed is nearer to the end.

The cost $\Phi(x)$ has a somewhat different functional form depending on the sign in Eq. (4.13), and it is the different sign and corresponding functional form of $\Phi(x)$ that drives the division of mouse movements into two classes. An understanding of the circumstances in which a subject makes a class I or class II movement is needed in order to better understand what the cost $\Phi(x)$ means. Additionally, the class of a movement may inform the analysis of the idle intervals preceding and following the movement.

4.4 Proxies for Recall and Search Performance

In Section 4.3, we have provided a technique for parsing the raw mouse data into mouse movements and idle intervals between mouse movement, and a simple division of mouse movements into two classes. We have also shown how to estimate the parameters of Fitts' law for the mouse movements. We expect the estimated Fitts' law parameters to provide an estimate of performance of the motor stage in TMT. In the model we have developed to describe TMT, there are two cognitive stages, recall and search, in addition to the motor stage. In lieu of explicit measurements of the performance of these stages from the mouse data, we provide two proxy values that provide information about these two stages. The first is derived from in-home MD in the process that we used to identify the individual mouse movements. The second is the score on a further standard clinical neuropsychological test. We include the second proxy for the light it might shed on future work for extracting measures of recall and search stages from in-home MD.

4.4.1 Cut Speed

In Section 4.3.3, we defined the cut speed v_{cut} and used it as a means to parse the raw mouse data into individual computer mouse movements. We can think of the cut speed v_{cut} as determined by two quantities. The first is a rough threshold indicating the lowest speed at which meaningful, controlled MD occurs during a computer session. The second is the length of the shortest idle intervals between movements. Looked at this way, we expect that the cut speed v_{cut} contains some information about cognitive performance. We define a measure related to the cut speed v_{cut} to use as a measure of cognitive performance. The measure of cognitive performance we use is the quantity that we actually measure in Section 4.3.3 and from which we derive the cut speed v_{cut}, namely:

$$\rho = \log_{10}\left(v_{cut} / v_0\right). \tag{4.17}$$

The constant in Eq. (4.17) is v_0 = 1 count/s.

4.4.2 Digit Symbol Test

Another standard clinical instrument used to measure executive function is the Digit Symbol Test (DST). [141] In this test, the subject is given a set of symbols to each of which a single digit has been assigned, and containing a list of the symbols (with symbols repeated) next to a blank space. For each symbol, the subject write in the blank space the digit associated with the symbol. The assignment of digits to symbols remains visible to the subject during the test. The score on this test is the number of correct digit assignments the subject makes in 90 s. DST tests the subject's ability to remember an assignment of arbitrary symbols to digits. We expect DST to provide information about the recall stage of TMT (where the subject must remember the next target in the sequence), and how quickly a subject recalls the next needed control widget (e.g., icons, buttons etc.) to use when navigating a computer application.

4.5 Empirical Study

210 older adults (121 female and 89 male, average age 83 ± 5.4 years, average level of education 16 ± 2.6 years, MMSE = 28 ± 1.9, ADL = 0.51 ± 1.2 for the first year on record for the subject) were observed over a period of 6 years during which their computer usage was monitored. [114, 126] The subjects' computers ran using the Microsoft Windows XP operating system. We recorded and stored computer mouse-position data for all subjects in a database following the procedure described in Section

III.B. TMT and DST were administered as part of a battery of neuropsychological tests to each subject once each year. The observed means and standard deviations of the scores and numbers of errors on TMT-A and TMT-B across all administrations were S^A = 46 ± 22 s and N^A = 0.16 ± 0.93, and S^B = 120 ± 58 s and N^B = 1.3 ± 2.0. As data for neuropsychological tests were only available for each year, we reduced the measures for in-home MD to characteristic values for each (calendar) year; so the data we analyzed were the set of available one-year periods across all subjects. There were 929 one-year periods across subject with 4.4 ± 1.5 one-year periods per subject.

Our aim was to validate the measurements made using in-home MD by estimating cognitive performance using executive function as characterized by the TMT scores. In order to perform this validation in a meaningful way, we limited our data set to those one-year periods in which we expected that the fraction of the TMT scores attributable to the motor stage (cf. Section 4.2.2) was largest. That is, we limited the data set to those one-year periods in which the subjects indicated the highest level of cognitive performance. We retained in the data set only those one-year periods in which the subject had perfect scores on MMSE (MMSE = 30) and ADL (ADL = 0), and made no errors on TMT-A and no errors on TMT-B. In addition, two one-year periods had exceptionally large scores on TMT, one having S^A = 91 s and the other having S^B = 201 s. We excluded these two one-year periods as outliers.

These restrictions left a cohort of 55 older adults (30 female and 25 male, average age 83 ± 5.8 years, average level of education 16 ± 2.5 years, for the first year on record for the subject in the restricted set). There were 102 one-year periods across subject with 1.9 ± 1.1 one-year periods per subject. The observed means and standard deviations of the scores on TMT-A and TMT-B across these one-year periods were S^A = 35 ± 9.4 s, S^B = 76 ± 22 s. Of the 55 subjects, 27 had more than one one-year period among the 102 one-year periods used for analysis, and the total number of one-year periods associated with these 27 subjects were 74 one-year periods. We used these 74 one-year periods to estimate how well the score on one completion of TMT estimated the score on the next completion on TMT available within the 74 one-year periods. The correlations were, for TMT-A, $R^2 = 0.43$ and $p < 0.0001$, and, for TMT-B, $R^2 = 0.43$ and $p < 0.0001$.

4.5.1 Measures of Motor Performance

We first look at the application to the technique presented in Section III of identifying individual mouse movements within the raw mouse data to observed in-home MD data. The aim is to show that identified mouse movements have the expected properties (e.g., they have reasonable time durations, and they yield the expected values for the motor parameters in Fitts' law). We then calculate the measures of motor performance (i.e. the motor parameters in Fitts' law) from the identified mouse movements.

We applied the technique presented in Section 4.3.3 of identifying the individual mouse movements within the raw mouse data to the monitored in-home MD to the full set of 929 one-year periods for the full cohort of 210 subjects. For any computer session that exceeded one hour, we analyzed only the first hour of the session. We did this because we found that the computer we were using to analyze the data had memory problems when the length of the sessions being analyzed became too long.

A total of 130446 computer sessions were observed over the full set of 929 one-year periods for the full cohort of 210 subjects. In order to keep the amount of data analyzed in each session manageable, we only considered session data up to the end of the first hour of usage in a given session. The procedure to find a cut speed v_{cut} was applied to all sessions. It failed to find a value in 4850 cases. So, in about 96% of sessions, an appropriate v_{cut} was found and mouse data from the session could be divided into mouse movements. The means and standard deviations of observed cut speeds across subjects were $v_{cut} = 67 \pm 19$ count/s.

We applied the techniques presented in Sections 4.3.4 and 4.3.5 of quantifying motor performance using Fitts' law and modeling the time-course of the identified mouse movements themselves to the restricted set of 102 one-year periods for the restricted cohort of 55 subjects.

For each one-year period, we separated the identified mouse movements into two sets corresponding to the class I and class II mouse movements defined in Section 4.3.5. We fit the optimal orbits $x_{\phi}^{\pm}(t)$ calculated from Eq. (4.16) to each identified mouse movement and associated with each identified movement a value $\phi^{\pm}$. To improve the fit, for each movement additional initial and final measurements were interpolated for each movement and assigned an average velocity of zero. Solutions were required to satisfy Eq. (4.11) where the time T_M was the total movement time including the interpolated initial and final measurements, and D_{mouse} was the total distance traveled by the mouse (i.e. not the simply the distance between the initial and final positions Δ_{mouse}). In practice, we found it better to normalize the time in Eq. (4.16) so that it ran from 0 to 1. When this is done, a parameter $\left(\phi^{\pm}\right)^{1/6} T_M$ naturally appears in the exponential terms. As the c_i in Eq. (4.16) are determined by the conditions in Eq. (4.11), the parameter

$\left(\phi^{\pm}\right)^{1/6} T_M$ is what is actually fit to the data. As very large numbers of individual mouse movements were fit to the model, we sped up the process by choosing $\left(\phi^{-}\right)^{1/6} T_M^I / 2\pi$ and $\left(\phi^{+}\right)^{1/6} T_M^{II} / 2\pi$ being elements of the set $\{0.2, 0.25, \ldots, 2.0\}$. We chose the ranges after considering a subset of the data and calculating values $\phi^{\pm}$ using a fitting technique with no constraint on the frequency values. Each movement was classified as being class I or class II movements according to whether a model in ϕ^{-} or ϕ^{+} gave a better fit to the data. We carried out subsequent analysis separately for each of the two sets of mouse movements.

For each one-year period, we calculated the ratio of the number of class I movements to the total number of movements. The mean and standard deviation of this ratio across one-year periods was 0.73 ± 0.035.

Models of Fitts' law (see e.g. [142]) use a motion that accelerates quickly to a peak speed and spends that larger part of the movement slowing while approaching the target (i.e. class I movements in our terminology). As one of the two movement classes arising from the model in Section 4.3.5 produced movements of the form expected for Fitts' law, and the other did not, we analyzed the data separately for the two classes of movements.

The sets of movements for each one-year period classified as class I movements had the following properties. We began by trying to characterize the fits of the model given in Section 4.3.5 to classify the mouse movements to evaluate how well that model was working. For each one-year period, we calculated the medians (M{·}) and interquartile ranges (IQR{·}) of $(R^I)^2$ and p^I values (i.e. R^2 and p values for class I movements) for each fit. We then took the means and standard deviations of the medians and interquartile ranges across all one-year periods, and found $M\{(R^I)^2\} = 0.40 \pm 0.069$ and $IQR\{(R^I)^2\} = 0.45 \pm 0.026$, and $M\{p^I\} = 9.2 \cdot 10^{-5} \pm 2.7 \cdot 10^{-4}$ and $IQR\{p^I\} = 0.016 \pm 0.018$. Although the fits are largely statistically significant, it appears we need a more sophisticated model of mouse movements to capture the variety of mouse movements. We next looked at the distributions of the time durations of the identified mouse movements. The means and standard deviations of the medians and interquartile ranges of the movement times T_M^I were $M\{T_M^I\} = 390 \pm 92$ ms, $IQR\{T_M^I\} = 370 \pm 97$ ms. For comparison, the lower limit of applicability of Fitts' law occurs at $D_{\text{pointer}}^I / W = 1/2$, which, for these subjects, corresponds to a movement time of about 190 ms. So, the middle 50% of the identified mouse movements had reasonable time durations. We consider the distribution of the movement times further in Section 4.6. Finally, we looked at how straight the movements were. The means and standard deviations of the medians and interquartile ranges of the total distances the movements travelled D_{mouse}^I were $M\{D_{\text{mouse}}^I\} = 110 \pm 31$ count, $IQR\{D_{\text{mouse}}^I\} = 190 \pm 58$ count. The means and standard deviations of the medians and interquartile ranges of the ratios of the net distance travelled Δ_{mouse}^I to the total distance travelled were $M\{\Delta_{\text{mouse}}^I / D_{\text{mouse}}^I\} = 0.91 \pm 0.022$, $IQR\{\Delta_{\text{mouse}}^I / D_{\text{mouse}}^I\} = 0.10 \pm 0.028$. So, most of the identified mouse movements were relatively straight.

The sets of movements for each one-year period classified as class II movements had the following properties. The means and standard deviations (across all one-year periods) of the medians and interquartile ranges of $(R^{II})^2$ and p^{II} values for each fit (in each one-year period) of the model given in Section 4.3.5 used to classify the movements were $M\{(R^{II})^2\} = 0.43 \pm 0.068$ and $IQR\{(R^{II})^2\} = 0.47 \pm 0.036$, and $M\{p^{II}\} < 0.001$ and $IQR\{p^{II}\} = 0.010 \pm 0.012$. The means and standard deviations of the medians and interquartile ranges of the movement times T_M^{II} were $M\{T_M^{II}\} = 340 \pm 61$ ms, $IQR\{T_M^{II}\} = 320 \pm 91$ ms. Again, the lower limit of applicability of Fitts' law occurs at $D_{\text{pointer}}^{II}/W = 1/2$, which, for these subjects, corresponds to a movement time of about 300 ms. So, the middle 50% of the identified mouse movements had reasonable time durations. We consider the distribution of the movement times further in Section 4.6. The means and standard deviations of the medians and interquartile ranges of the total distances the movements travelled D_{mouse}^{II} were $M\{D_{\text{mouse}}^{II}\} = 92 \pm 19$ count, $IQR\{D_{\text{mouse}}^{II}\} = 160 \pm 45$ count. The means and standard deviations of the medians and interquartile ranges of the ratios of the net distance travelled $\Delta_{\text{mouse}}^{I}$ to the total distance travelled were $M\{\Delta_{\text{mouse}}^{II}/D_{\text{mouse}}^{II}\} = 0.94 \pm 0.010$, $IQR\{\Delta_{\text{mouse}}^{II}/D_{\text{mouse}}^{II}\} = 0.077 \pm 0.040$. Again, the movements are relatively straight.

We next used the two sets of identified mouse movements to estimate the motor performance for each one-year period as characterized by Fitts' law using Eq. (4.8). As Fitts' law is a description of rapid, targeted mouse movements, we limited the data sets to movements that we expected Fitts' law to describe, those that were (1) relatively straight ($\Delta_{\text{mouse}}/D_{\text{mouse}} \geq 1/2$) and (2) not too long in duration ($T_M \leq 4$ s, corresponding to five times the average expected duration of each movement in TMT or $D_{\text{pointer}}/W \approx 7$ million). We characterized the motor performance for each one year period separately for class I and class II movements by estimating the parameters $\tilde{a}$, b, and $\tilde{W}/\eta$ in Eq. (4.8) using OLS regression on all the remaining identified mouse movements of the given class. The means and standard deviations of the R^2 and p values for the fits were $(R^I)^2$ = 0.66 ± 0.079 and $p^I < 0.0001$, and $(R^{II})^2$ = 0.54 ± 0.092 and $p^{II} < 0.0001$, and the means and the standard deviations of the estimated parameters were:

$$\begin{aligned} \tilde{a}^I &= -710 \pm 180\,\text{ms}, \\ b^I &= 160 \pm 36\,\text{ms / bit}, \\ \tilde{W}^I / \eta &= 14 \pm 2.5\,\text{count}, \\ \tilde{a}^{II} &= -800 \pm 360\,\text{ms}, \\ b^{II} &= 170 \pm 61\,\text{ms / bit}, \\ \tilde{W}^{II} / \eta &= 17 \pm 32\,\text{count}. \end{aligned} \tag{4.18}$$

The average values for b^I and b^{II} were close to the independently measured value of 166 ms/bit for point-select methods of selecting icons. [110] We consider this further in Section 4.6. We also note that the mean values of $\tilde{W}^I / \eta$ and $\tilde{W}^{II} / \eta$ are close to the same value.

We confirmed the data supported the linear relationship between $\tilde{a}$ and b expressed in Eq. (4.8) by performing a linear regression using all one-year periods with the appropriate model separately for class I and class II movements. The R^2 and p values for the fits were $(R^I)^2$ = 0.97 and $p^I < 0.0001$, and $(R^{II})^2$ = 0.99 and $p^{II} < 0.0001$, and the resulting models were:

$$\begin{aligned} \tilde{a}^I &= [96\,\text{ms}] - [4.9\,\text{bit}]\, b^I, \\ \tilde{a}^{II} &= [200\,\text{ms}] - [5.8\,\text{bit}]\, b^{II}. \end{aligned} \tag{4.19}$$

Examination of the 95% confidence intervals showed that all the fitted parameters in Eq. (4.19) were statistically significant. We used Eq. (4.19) to estimate the values of the motor parameters a^I and a^{II} that appear in Fitts' law, these were:

$$\begin{aligned} a^I &= 96 \pm 31\,\text{ms}, \\ a^{II} &= 200 \pm 42\,\text{ms}. \end{aligned} \tag{4.20}$$

The average values for a^{I} and a^{II} were close to the independently measured value of 230 ms for point-select methods of selecting icons. [110] We consider this further in Section 4.6.

Finally, we looked at the relationship of class I to class II movements as characterized by the parameters b^{I} and b^{II} by performing linear regression using a simple linear model with all one-year periods. The R^2 and p values for the fits were $R^2 = 0.79$ and $p < 0.0001$, and resulting model was:

$$b^{II} = -[77\,\mathrm{ms/bit}] + [1.5]b^{I}. \tag{4.21}$$

Examination of the 95% confidence intervals showed that all the fitted parameters in Eq. (4.21) were statistically significant. By the measures we have looked at here, the two classes of mouse movements do not appear to differ appreciably. They have approximately the same distributions of time durations and straightness, and have about the same values for the motor parameters in Fitts' law with those motor parameters strongly correlated with each other.

We looked again at the set of 27 subjects that had more than one one-year period in the data set. We used these 74 one-year periods to estimate how well the estimates of $\tilde{a}^{I}$, b^{I}, $\tilde{a}^{II}$, and b^{II} in one one-year period estimated the value of the same quantity on the (chronologically) next one-year period in the set by the same subject. The correlations were, for $\tilde{a}^{I}$, $R^2 = 0.82$ and $p < 0.0001$, for b^{I}, $R^2 = 0.86$ and $p < 0.0001$, for $\tilde{a}^{II}$, $R^2 = 0.93$ and $p < 0.0001$, and, for b^{II}, $R^2 = 0.94$ and $p < 0.0001$.

4.5.2 Measures of Cognitive Performance (Executive Function)

We have shown in Section 4.5.1 that the identified mouse movements look, on average, like what we expect mouse movements to looks like in terms of the time durations and straightness of the movements, and the estimates of the motor parameters of Fitts' law. We next look at how well the identified mouse movements found using the technique presented in Section 4.3 capture subject-to-subject variability in executive function as characterized by TMT. We do this by using the recall and search performance proxy ρ that is also measured from the in-home MD data. We also look at the effect of including a second recall and search performance proxy, the DST score, to suggest directions for future work extracting recall and search performance measures from the MD data. This analysis continued the use of the restricted set of 102 one-year periods for the restricted cohort of 55 subjects.

We first looked at the ability of the motor parameters estimated from MD to estimate the TMT scores S^A and S^B. Using the superscript X as a placeholder for A or B indicating the test score being fit, and the superscript Y as a place holder for I or II indicating the class of mouse movements used in estimating the motor performance, we fit four models of the form:

$$S^X = c_0^{X,Y} + c_1^{X,Y} \tilde{a}^Y + c_2^{X,Y} b^Y. \tag{4.22}$$

The fits had R^2 and p values of $(R^{A,I})^2 = 0.037$ and $p^{A,I} = 0.15$, $(R^{B,I})^2 = 0.071$ and $p^{B,I} = 0.027$, $(R^{A,II})^2 = 0.066$ and $p^{A,II} = 0.034$, and $(R^{B,II})^2 = 0.16$ and $p^{B,II} = 0.00020$. Examination of the 95% confidence intervals showed that all the fitted parameters except $c_1^{A,I}$ and $c_2^{A,I}$ were statistically significant.

We next modified the model in Eq. (4.22) by including ρ (see Eq. (4.17)) as a proxy for recall and search performance. As ρ is measured using only in-home MD measurements, the resulting models generate estimated of TMT performance using only information from in-home MD.

We characterized each one-year period by the mean value of ρ across all sessions in the one-year period; we denote this value by $\langle\rho\rangle$. The mean and standard deviation of $\langle\rho\rangle$ across all one-year periods was:

$$\langle\rho\rangle = 1.8 \pm 0.044. \tag{4.23}$$

We also looked at the relationship between $\langle\rho\rangle$ and $\tilde{a}$ and b using linear models; the R^2 and p values for the fits of the best performing models were $(R^I)^2 = 0.58$ and $p^I < 0.0001$, and $(R^{II})^2 = 0.64$ and $p^{II} < 0.0001$, and the resulting models were:

$$\begin{aligned}\langle\rho\rangle &= [2.0] - \left[5.0\cdot10^{-4}\,\mathrm{ms}\right]a^I - \left[8.2\cdot10^{-4}\,\mathrm{bit/ms}\right]b^I,\\ \langle\rho\rangle &= [2.0] - \left[3.0\cdot10^{-4}\,\mathrm{ms}\right]a^{II} - \left[5.4\cdot10^{-4}\,\mathrm{bit/ms}\right]b^{II}.\end{aligned} \tag{4.24}$$

Examination of the 95% confidence intervals showed that all the fitted parameters in Eq. (4.24) were statistically significant. In Section 4.4.1, we describe ρ as being the logarithm of the lowest speed at which meaningful, controlled MD occurs. There appears to be a strong relationship between this lowest speed and the motor parameters of Fitts' law. We consider this further in Section 4.6.

We looked again at the set of 27 subjects that had more than one one-year period in the data set. We used these 74 one-year periods to estimate how well the estimate of ρ in one one-year period estimated the value of the same quantity on the (chronologically) next one-year period in the set by the same subject; the correlations for ρ were $R^2 = 0.82$ and $p < 0.0001$.

The connect-the-dots model tells us that estimates for cognitive performance using the scores on TMT-A and TMT-B should include the motor parameters a and b, or equivalently, $\tilde{a}$ and b to account for the movement of the hand. Combining Eqs. (4.4) and (4.9), we find that the form of the connect-the-dots model indicates that $\tilde{a}$ and b should appear linearly in the estimators of either TMT score. In the absence of other measurements of recall and search performance we use average value $\langle \rho \rangle$ for each one-year period and the score on DST for the one-year period as proxies for recall and search performance.

We fit four models of the form:

$$S^X = c_0^{X,Y} + c_1^{X,Y} \langle \rho \rangle + c_2^{X,Y} \tilde{a}^Y + c_3^{X,Y} b^Y. \tag{4.25}$$

The fits had R^2 and p values of $(R^{A,I})^2 = 0.11$ and $p^{A,I} = 0.0083$, $(R^{B,I})^2 = 0.27$ and $p^{B,I} < 0.0001$, $(R^{A,II})^2 = 0.14$ and $p^{A,II} = 0.0024$, and $(R^{B,II})^2 = 0.29$ and $p^{B,II} < 0.0001$. Examination of the 95% confidence intervals showed that all the fitted parameters were statistically significant. The effect sizes associated with the addition of $\langle \rho \rangle$ to the models in Eq. (4.22) were $(f^{A,I})^2 = 0.068$, $(f^{B,I})^2 = 0.27$, $(f^{A,II})^2 = 0.12$, and $(f^{B,II})^2 = 0.18$.

We chose the 102 one-year periods used to produce these models with the intent of identifying those periods corresponding to high cognitive performance by the subjects. We made this choice to produce a set of one-year periods where we could attribute the greatest amount of variation in TMT scores to differences in motor performance. If we assume that outliers to the model in Eq. (4.25) indicate one-year periods that nevertheless have poor cognitive performance, then trimming these one-year periods produces a better version of the intended data set. We trimmed the one-year periods for each model-case (i.e. A,I, B,I, A,II, or B,II) by looking at the residuals of the fit and trimming those one-year periods with residual values larger than expected in 95% of new observations for which the actual test score was larger than that predicted by the model. From the 102 one-year periods, we trimmed 3 one-year periods from the A,I model-case, 5 one-year periods from the B,I model-case (there was one one-year period that was trimmed from both), 3 one-year periods from the A,II model-case, and 4 one-year periods from the B,II model-case (there was one one-year periods that was trimmed from both). For the A,I model-case, the mean and standard deviation of the actual test scores of the 3 trimmed one-year periods were 64±4.9 s and those of the model estimates were 39±2.9 s. For the B,I model-case, these were 120±19 s and 73±15 s, for the A,II model-case, these were 62±7.8 s and 38±3.5 s, and for the B,II model-case, these were 125±14 s and 77±9.1 s. The fits on the trimmed data sets had R^2 and p values of $(R^{A,I})^2 = 0.070$ and $p^{A,I} = 0.074$, $(R^{B,I})^2 = 0.37$ and $p^{B,I} < 0.0001$, $(R^{A,II})^2 = 0.13$ and $p^{A,II} = 0.0045$, and $(R^{B,II})^2 = 0.37$ and $p^{B,II} < 0.0001$. Examination of the 95% confidence intervals showed that all the fitted parameters except $c_0^{A,I}$ and $c_0^{A,II}$ were statistically significant. In Figure 4.4, we compare the TMT scores estimated using class II movement data the actual TMT scores using the trimmed data sets.

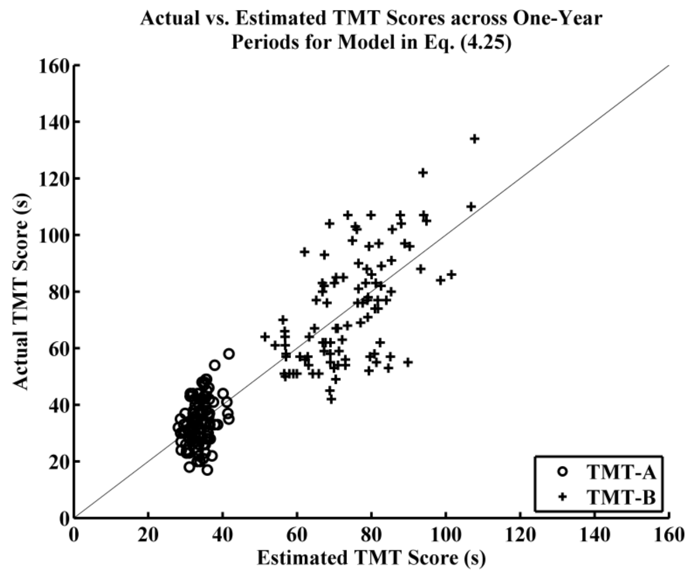

Figure 4.4. Actual vs. estimated TMT scores across one-year periods for model in Eq. (4.25). Comparison of actual and estimated scores for TMT-A and TMT-B (estimated separately) for high performing subjects (MMSE = 30, ADL = 0). Scores were estimated using class II movement data and outliers with high test scores were trimmed (3 for TMT-A and 4 for TMT-B). The model for TMT-A fit with $R^2 = 0.13$ and $p = 0.0045$, and the model for TMT-B fit with $R^2 = 0.37$ and $p < 0.0001$.

TMT was designed so that the scores on TMT-A and TMT-B, S^A and S^B respectively, would be used together in the form $S^B - S^A$ to arrive at an estimate of cognitive performance. [36] We next modified the model in Eq. (4.25) to produce an estimate of the difference in TMT scores $S^B - S^A$.

We fit two models of the form:

$$S^B - S^A = c_0^Y + c_1^Y \langle \rho \rangle + c_2^Y \tilde{a}^Y + c_3^Y b^Y. \qquad (4.26)$$

The fits had R^2 and p values of $(R^I)^2 = 0.22$ and $p^I < 0.0001$, and $(R^{II})^2 = 0.23$ and $p^{II} < 0.0001$. Examination of the 95% confidence intervals showed that all the fitted parameters were statistically significant.

We trimmed the data for Eq. (4.26) using the same criteria we used to trim the data for Eq. (4.25). From the 102 one-year periods, we trimmed 3 one-year periods from the I model-case, and 4 one-year periods from the II model-case (there were no one-year periods that were trimmed from both). For the I model-case, the mean and standard deviation of the actual values $S^B - S^A$ of the 3 trimmed one-year periods were 93 ± 13 s and those of the model estimates were 43 ± 9.3 s. For the II model-case, these were 87 ± 15 s and 40 ± 6.2 s. The fits on the trimmed data sets had R^2 and p values of $(R^I)^2 = 0.27$ and $p^I < 0.0001$, and $(R^{II})^2 = 0.33$ and $p^{II} < 0.0001$. Examination of the 95% confidence intervals showed that all the fitted parameters were statistically significant. In Figure 4.5, we compare the $S^B - S^A$ values estimated using class II movement data the actual $S^B - S^A$ values using the trimmed data sets.

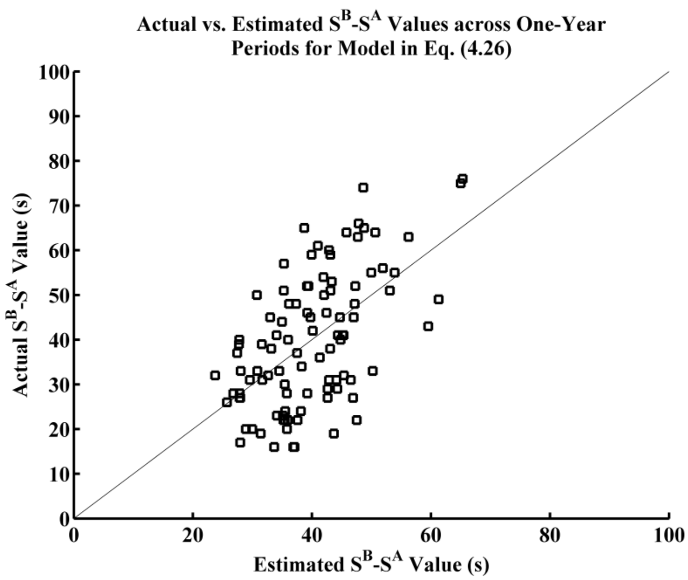

Figure 4.5. Actual vs. estimated $S^B - S^A$ values across one-year periods for model in Eq. (4.26). Comparison of actual and estimated values for $S^B - S^A$ for high performing subjects (MMSE = 30, ADL = 0). Scores were estimated using class II movement data and DST scores with no outliers trimmed. The model fit with $R^2 = 0.33$ and $p < 0.0001$.

We repeated the analysis of how well the score on one completion of TMT estimated the score on the next completion on TMT available that was done with 27 subject and 74 one-year periods above with the trimmed data sets. For the trimmed sets for the models using $\tilde{a}^I$ and b^I, we found that, for TMT-A, we had 26 subjects, 71 one-year periods, $R^2 = 0.35$, and $p < 0.0001$, for TMT-B, we had 25 subjects, 70 one-year periods, $R^2 = 0.43$, and $p < 0.0001$. For the trimmed sets for the models using $\tilde{a}^{II}$ and b^{II}, we found that, for TMT-A, we had 26 subjects, 71 one-year periods, $R^2 = 0.34$, and $p < 0.0001$, for TMT-B, we had 25 subjects, 70 one-year periods, $R^2 = 0.42$, and $p < 0.0001$.

We finally modified the model in Eq. (4.25) by including S^{DS} as a proxy for recall and search performance. As S^{DS} is measured in the clinic, the resulting model produces estimates that we cannot make using in-home MD measurements alone. However, the development of future techniques that estimate S^{DS} using in-home measurements would provide an estimate of TMT performance entirely using in-home measurements.

The observed mean and standard deviation of scores on the DST across one-year periods was $S^{DS} = 45 \pm 7.1$. S^{DS} did not show any statistically significant ($p < 0.05$) correlations with the motor parameters $\tilde{a}^I$, b^I, $\tilde{a}^{II}$, and b^{II} with $R^2 > 0.05$. S^{DS} had a statistically significant ($p < 0.05$) correlation with $\langle \rho \rangle$ with $R^2 > 0.072$.

We looked at how well the score S^{DS} on DST estimates the TMT scores using models:

$$S^X = c_0^X + c_1^X S^{DS}. \tag{4.27}$$

The fits had $(R^A)^2 = 0.18$ and $p^A < 0.0001$, $(R^B)^2 = 0.27$ and $p^B < 0.0001$. Examination of the 95% confidence intervals showed that all the fitted parameters were statistically significant.

We fit four models of the form:

$$S^X = c_0^{X,Y} + c_1^{X,Y} \langle \rho \rangle + c_2^{X,Y} S^{DS} + c_3^{X,Y} \tilde{a}^Y + c_4^{X,Y} b^Y. \tag{4.28}$$

We fit the models to the entire set of one-year periods rather than to random subsets. The fits had R^2 and p values of $(R^{A,I})^2 = 0.23$ and $p^{A,I} < 0.0001$, $(R^{B,I})^2 = 0.42$ and $p^{B,I} < 0.0001$, $(R^{A,II})^2 = 0.25$ and $p^{A,II} < 0.0001$, and $(R^{B,II})^2 = 0.44$ and $p^{B,II} < 0.0001$. Examination of the 95% confidence intervals showed that all the fitted parameters were statistically significant except for the leading constant coefficients in the case of both TMT-A models. The effect sizes associated with the addition of S^{DS} to the models in Eq. (4.25) were $(f^{A,I})^2 = 0.16$, $(f^{B,I})^2 = 0.26$, $(f^{A,II})^2 = 0.15$, and $(f^{B,II})^2 = 0.27$.

We trimmed the data for Eq. (4.28) using the same criteria we used to trim the data for Eq. (4.25). From the 102 one-year periods, we trimmed 3 one-year periods from the A,I model-case, 4 one-year periods from the B,I model-case (there were no one-year periods that were trimmed from both), 2 one-year periods from the A,II model-case and 3 one-year periods from the B,II model-case (there were no one-year periods that were trimmed from both). For the A,I model-case, the mean and standard deviation of the actual test scores of the 3 trimmed one-year periods were 64 ± 4.9 s and those of the model estimates were 42 ± 1.0 s. For the B,I model-case, these were 117 ± 23 s and 76 ± 20 s, for the A,II model-case, these were 67 ± 0.71 s and 42 ± 2.0 s, and for the B,II model-case, these were 120 ± 21 s and 78 ± 19 s. The fits on the trimmed data sets had R^2 and p values of $(R^{A,I})^2 = 0.18$ and $p^{A,I} = 0.0010$, $(R^{B,I})^2 = 0.48$ and $p^{B,I} < 0.0001$, $(R^{A,II})^2 = 0.22$ and $p^{A,II} = 0.00011$, and $(R^{B,II})^2 = 0.49$ and $p^{B,II} < 0.0001$. Examination of the 95% confidence intervals showed that all the fitted parameters except $c_0^{A,I}$, $c_1^{A,I}$, $c_0^{A,II}$, and $c_1^{A,II}$ were statistically significant. In Figure 4.6, we compare the TMT scores estimated using class II movement data the actual TMT scores using the trimmed data sets.

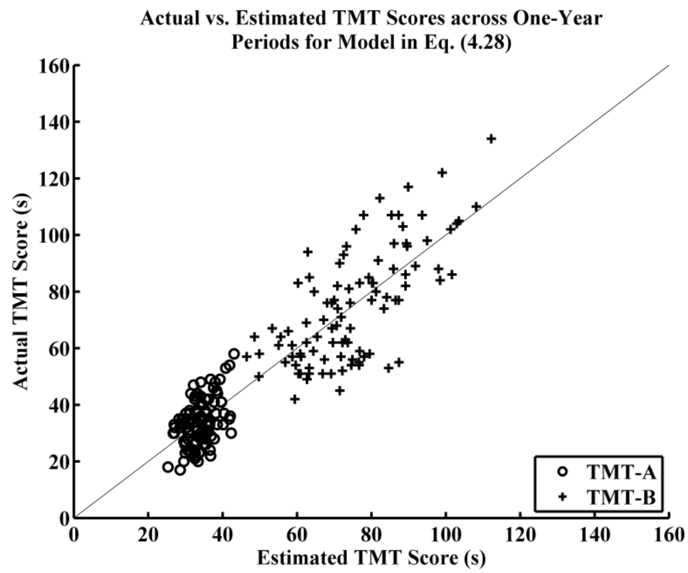

Figure 4.6. Actual vs. estimated TMT scores across one-year periods for model in Eq. (4.28). Comparison of actual and estimated scores for TMT-A and TMT-B (estimated separately) for high performing subjects (MMSE = 30, ADL = 0). Scores were estimated using class II movement data and DST scores with no outliers trimmed. The model for TMT-A fit with $R^2 = 0.22$ and $p < 0.0001$, and the model for TMT-B fit with $R^2 = 0.49$ and $p < 0.0001$.

4.6 Discussion

Discussion of the modeling decisions made in the connect-the-dots model (Section 4.2.2), its application to TMT (Section 4.2.1), and empirical validation of the model using TMT is given in Chapter 3.

We have provided a technique for recording and storing large amounts of computer mouse-position data and identifying individual mouse movements using that data. We designed the techniques given in this paper for identifying individual mouse movements, and fitting a mouse movement model to each identified mouse movement to be computationally fast. Nevertheless, even the restricted data set of 55 subjects that we used for the bulk of the analysis in Section 4.5 was very large (102 years of mouse movements) and required substantial computer time to perform all the required calculations. The results that we have presented represent about the limit of what we could reasonably do with the computational power we had available for this project. We expect that with more computational power available, we may obtain better results.

The observation that drives the analysis in this paper is that illustrated in Figure 4.1, namely the multimodal nature of the distribution of the logarithm of the mouse speed. Using this observation, we are able to impose a mathematical structure on the raw mouse data that appears, on average, to correspond to actual mouse movements as characterized by time duration and straightness of the movements, and the motor parameters of Fitts' law. We expect, however, that this simple procedure misclassifies a number of mouse movements. Likely, there are a number of cases where what should be a single mouse movement is divided into a number of smaller movements and where individual, consecutive movements have been combined into a single larger movement. Further refinements of the procedure given here may allow one to correct some of these misclassifications of movements. However, such refinements require a better understanding of how mouse movements are made, which we argue should proceed from a principled mathematical model of mouse movements.

We estimate the motor parameters a and b by fitting a set of observed movements to the empirical form of Fitts' law. The estimated values for the motor parameters of Fitts' law across the restricted set of subjects for the two classes of mouse movements were a^I = 96 ± 31 ms and b^I = 160 ± 31 ms/bit, and a^{II} = 200 ± 42 ms and b^{II} = 170 ± 61 ms/bit. We can compare these values to independently measured values for Fitts' law for several methods of using a computer mouse to select an icon: (1) a = 135 ms and b = 249 ms/bit for drag-select, (2) a = 230 ms and b = 166 ms/bit for point-select, and (3) a = 135 ms and b = 249 ms/bit for stroke-through. [110] The observed class I and class

II movements appear, on average to more nearly resemble the point-select movements rather than drag-select or stroke through movements measured in [110].

Using the regression model in Eq. (4.25), the untrimmed data set was observed to fit with R^2 values of $(R^{A,I})^2 = 0.11$, $(R^{B,I})^2 = 0.27$, $(R^{A,II})^2 = 0.14$, and $(R^{B,II})^2 = 0.29$. The trimmed data was observed to fit with R^2 values of $(R^{A,I})^2 = 0.070$, $(R^{B,I})^2 = 0.37$, $(R^{A,II})^2 = 0.13$, and $(R^{B,II})^2 = 0.37$. Using the regression model in Eq. (4.28), the untrimmed data set was observed to fit with R^2 of $(R^{A,I})^2 = 0.23$, $(R^{B,I})^2 = 0.42$, $(R^{A,II})^2 = 0.25$, and $(R^{B,II})^2 = 0.44$. We can compare these R^2 values to the observed test-retest reliabilities for a cohort of normal adult controls with scores of 47 ± 25 s on TMT-A and 120 ± 86 s on TMT-B. For this cohort, the test-retest reliabilities were observed to be $R^2 = 0.56$ for TMT-A and $R^2 = 0.72$ for TMT-B. [28] The test-retest reliabilities provide a rough indication of how much noise there is inherent to TMT. We observe that our models for TMT-B account for roughly one-third to one-half the size of the total variation that one administration of TMT-B accounts for in another administration of TMT-B.

The simple model of computer mouse movements that we developed in Section 4.3.5 is only sufficient to analyze the mouse movements into the two classes of mouse movements that we have used. The model is only sufficient to determine whether the peak speed occurs in the first or second half of the mouse movement. For the high performing (MMSE = 30, ADL = 0) cohort of subject analyzed in this study, there appears to be no information gained by making the classification that is made in this study into class I and class II movements. We have retained the classification scheme in this study for two reasons related to future work. First, although this high performing cohort does not exhibit any significant difference in the measures values of the motor parameters a and b between the two classes, there is the possibility that other cohorts may show a difference. Second, the classification may prove useful in putting a classification on the idle intervals between movements.

If the movement classification scheme presented here proves inadequate, we can generalized the reasoning to produce a more sophisticated model of mouse movement both to generate better fits of the model to the identified mouse movements and to identify more classes of mouse movements. We can obtain a more general model by retaining the general form of $\Phi(x,\dot{x},\ddot{x})$ in Eq. (4.10). If we suppose that we can approximate $\Phi(x,\dot{x},\ddot{x})$ using a Taylor series to second-order, then we find:

$$\Phi(x,\dot{x},\ddot{x}) \approx \phi_{00} + \begin{bmatrix} 0 \\ \phi_{02} \\ \phi_{03} \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix} + \frac{1}{2} \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ 0 & \phi_{22} & \phi_{23} \\ 0 & 0 & \phi_{33} \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix}. \tag{4.29}$$

The zero appears in the place of ϕ_{01} in Eq. (4.29) for the same reason that the comparable term in Eq. (4.12) is set to zero in Eq. (4.13). Taking the Lagrangian in Eq. (4.10) and using the form of $\Phi(x,\dot{x},\ddot{x})$ in Eq. (4.29) and plugging this into Eq. (4.14), we find the Euler-Lagrange equation for the more general model of mouse movements:

$$\ddddot{x} + \phi_{33}\dddot{x} - (\phi_{22} - \phi_{13})\ddot{x} + \phi_{11}x = 0. \tag{4.30}$$

There are now three parameters available to fit the identified mouse movements and to use to divide the identified mouse movements into classes. This model should also allow us to correct the classification of the raw mouse data into movements using the distribution of the logarithm of mouse speeds by providing a principled description of computer mouse movements.

We have argued that the shorter idle intervals between consecutive mouse movements should contain information about a subject's recall and search performance. We did attempt to derive measures of recall and search performance using simple mathematical operations on the observed idle interval data (e.g., the median, the mode, or the minimum value of the time durations). For the operations we considered, the resulting measures did not appear to contain any information not already contained in the recall and search performance proxy ρ and, in all cases, did not perform as well as ρ for the purpose of estimating TMT scores.

4.7 Conclusion

In-home MD during everyday computer usage potentially provides a rich and easily unobtrusively and continuously monitored source of information about the cognitive performance of a subject. We have presented the foundation for a methodology of estimating cognitive function using in-home MD measured during everyday computer usage. We characterize cognitive function in terms of TMT and use a model of how a subject completes TMT to motivate the choice of what to measure from in-home MD. We have shown how to record and store computer mouse-position data reasonably compactly, how to identify individual mouse movements using the stored data, and how to measure motor performance from the identified mouse movements. Finally, we have outlined a program for making further measurements from in-home MD to estimate other, non-motor aspects of TMT performance.

Chapter 5 – On the Relationship of Set-Switching, Movement Times, and Errors in Trail-Making Test Part B for Older Adults

5.0 Abstract

Early detection of decline in cognitive performance in older adults allows early medical intervention to treat the decline. One way to detect performance changes earlier is though unobtrusive and ubiquitous monitoring of subject behavior in the home. For monitoring to be useful, we must relate the resulting measurements to clinically useful quantities. One way to establish these relationships is through models of the phenomena that we are measuring. Naturally, better models produce better clinical estimates of performance from the in-home measurements. Elsewhere, we have constructed the connect-the-dots model to describe the neuropsychological Trail-Making Test (TMT) and used it to derive estimates of TMT performance using measurements from a computer game and from everyday in-home computer usage. We revisit the model with the aim of improving it to produce better clinical estimates from the in-home measurements. We look at the data available from in-home measurements made using the computer game and every-day computer usage and show they are consistent with physical movements taking longer on TMT-B than on TMT-A. We make the connect-the-dots model consistent with this observation by allowing the subject to perform set-switching as a dual-task with movement on TMT-B causing movements to slow. We also note that

subjects make more errors on TMT-B than on TMT-A, and look at how errors relate to set-switching and movement.

5.1 Introduction

Early detection of declines in cognitive performance is an important component of providing proper medical treatment for maintaining the health and well-being of an older adult. One way of facilitating early detection is to make clinically useful measurements by from behaviors observed in the home. However, relating measurements that one can feasibly make in the home to established clinical values is often non-trivial. One approach to the problem of relating feasible in-home measurements to established clinical measurements is to use a mathematical model of the phenomenon that one is measuring. Naturally, one would like to use the most accurate model that one can as a more accurate model is expected to produce an estimation of established clinical measurements from in-home measurements.

Researchers have developed in-home measurements of cognitive performance for older adults using measurements of in-home activity. [71, 69, 70] Some in-home measurements of specific sorts or aspects of activity that have been developed include walking speed [Chapter 2, [79, 80]], time spent using a computer [113], typing speed [114], time away from home [115], and sleep [116, 117]. Researchers have also applied unobtrusive, in-home measurement techniques to fall risk assessment and fall detection for older adults. [84, 85] In each case, the quantity that is measured is a form of everyday behavior that one can measure in the background with the subject having to do as little as possible to facilitate the measurement process. The aim of in-home measurement techniques is to produce a clinically useful measurement within the practical limitations of what one can feasibly measure in the home. However, to be immediately useful to the clinician, we must relate the in-home measurements to established clinical values. Producing such a relationship is typically a non-trivial task.

We have put forward in-home monitoring techniques involving measurements made from the play of a computer game [Chapter 3], (computer) mouse dynamics [Chapter 4]. In both cases, we relate the measurements made from the techniques to an established clinical measurement, the Trail-Making Test (TMT), a standard pen-and-paper neuropsychological test. Also in both cases, we establish the relationship between the in-home measurement and TMT using a mathematical model (the connect-the-dots model) that describes how a subject completes TMT. The ability of the two techniques to use in-home measurements to estimate performance on TMT is as good as the connect-the-dots model used describe TMT and relate the in-home measurements to TMT, and otherwise understand the phenomena that we are measuring. One way to improve performance of the techniques is to improve the connect-the-dots model so that it more accurately describes the connect-the-dots task.

In the present paper, we look at the relationship of the in-home measurements from Chapters 3 and 4 to the connect-the-dots model and to TMT. We proceed by observing that the data in Chapter 4 appear to indicate a correlation between set-switching on TMT and motor speed. We argue that the simplest mechanism for producing such a correlation is a dual-tasking of set-switching and movement causing a slowing down of movement when set-switching is present. The connect-the-dots model, as developed in Chapter 3 assumes that the motor speed is the same whether or not set-switching is present. We look at modified forms of the connect-the-dots model using the data from [Chapter 3] and show that those data support the supposition that motor speed is slower when set-switching is present. Finally, we note that errors are more likely on TMT when set-switching is present. We look at data from Chapter 3 where the subjects make errors and begin developing a form of the connect-the-dots model that addresses errors on TMT.

5.2 Background

The techniques put forward in Chapters 3 and 4 relate measurements made in the home to the established clinical measurement of the score on TMT using a mathematical model, the connect-the-dots model. Before looking the data from Chapters 3 and 4, we provide descriptions of TMT and the connect-the-dots model. We have slightly modified the form of the connect-the-dots model presented here from that given in Chapter 3. The model presented in Chapter 3 describes movement using a two-parameter form of Fitts' law. Here we replace that form of Fitts' law with a single parameter approximation that simplifies the analysis we use to relate set-switching to motor speed.

Section 5.2.1 provides a review
of material appearing in Chapters 3 and 4

5.2.1 Trail-Making Test

TMT consists of two connect-the-dots tasks (TMT-A and TMT-B) which the subject completes by using a pen to draw a single line through a series of targets on a test page. Each test takes the form of a standard 8.5"x11" sheet of paper on which is printed 25 *targets* – small (12mm diameter), seemingly randomly scattered circles containing a label that may be a letter or a number. For TMT-A, the targets are labeled with numbers from 1 to 25, with one number labeling each circle, while in TMT-B targets are labeled with all letters from A to L and all numbers from 1 to 13 with one letter or number labeling each circle. The individual completes the TMT-A by using a pen to draw a line (the "trail") through all the circles in ascending numerical order of the labels (i.e. '1,2,3,…,24,25'), while the TMT-B is completed by drawing the line through the circles in ascending alphanumeric order (i.e. '1,A,2,B,…,L,13'). We call the process of drawing a line from one target to the next in the sequence a *move*. The *score* on each part of the test is the time the subject needs to complete each task (there is no time limit). If the subject makes an error on the test (drawing the line through an incorrect target), the test administrator stops the subject as soon as the error is noted by the administrator and returns the subject to the last correctly selected target; timing of the subject is not stopped during this *error recovery* process. The total numbers of errors made on each part are included with the test score. The difference between TMT-A and TMT-B is the use of the numeric and alphanumeric sequence of labels respectively. The alphanumeric label sequences introduce the additional complication of *set-switching* in which the subject must not only recall the next element in an alphabetic or a numeric sequence, but must also switch sets between the alphabetic and numeric sequences.

5.2.2 Connect-the-Dots Model

The connect-the-dots model developed in Chapter 3 describes the process by which a subject makes each move by dividing the move in TMT into a sequence three additive stages. [103, 104] The stages are (1) *recall and updating*, in which the subject recalls the next target in the target sequence, (2) *search*, in which the subject searches for the recalled target, and (3) *motor*, in which the subject moves the mouse to the target according to Fitts' law. [105-107]

We characterize the recall and updating stage by the *recall time* required by the subject to recall the next target in the sequence. We treat the recall time as a random variable (RV) T_R with expected value $\langle T_R \rangle = \tau_R$ (the *characteristic recall time*), and some standard deviation.

The search stage is characterized by the *search time*, T_S, required by the subject to locate on the test page the next target in the sequence after it has been recalled. We treat search as a series of discrete steps. [108] We assume that each step of search takes some fixed time τ_S (the *characteristic search time*) and that the variation in search time is due to each search taking a variable number of steps; we treat the number of steps as a RV. At each step of search, the subject considers a randomly chosen unselected target on the test page; if that target is the desired target, the subject ceases search and moves on to the motor phase, otherwise the subject considers another randomly chosen unselected target. We assume that the subject does not consider any unselected target twice during a particular search. In the $\nu-th$ move during a part of TMT, there are 25 targets on the page, the subject is searching for the $\nu-th$ target, and the subject has already found $\nu-1$ targets. Thus, there are $26-\nu$ targets unselected targets on the test page. The expected number of steps for the search is $(26-\nu)/2$, so the expected value for the search time for this target is given by:

$$\langle T_S \rangle = \left((26-\nu)/2\right)\tau_S. \tag{5.1}$$

The distribution of T_S for a given value ν is uniform on the discrete values τ_S, …, $(26-\nu)\tau_S$.

The motor stage is characterized by the *motor time* T_M, a RV representing the time the subject takes to move the mouse to the next target. We assume that the speed of the movement is consistent with Fitts' law. Defining D_ν to be center-to-center distance between the $\nu-1-th$ and $\nu-th$ targets, assuming a common width W for all targets, the expected time taken to move from the $\nu-1-th$ to the $\nu-th$ target is given by:

$$\langle T_M \rangle = a + b\log_2\left(D_\nu / W + 1\right). \tag{5.2}$$

The value $\log_2\left(D/W+1\right)$ provides a measurement of the amount of information the subject must process to complete the movement as measured in bits; so the value b provides a measure of how much time the subject spends processing each bit of information.

The form of Fitts' law in Eq. (5.2) as the sum of two independent parameters presents technical difficulties for the present analysis. Eq. (5.2) is a standard form of Fitts' law, [105-107] and is the form used in Chapters 3 and 4. However, in the analysis in Chapter 3, we found we could not distinguish the parameters a and τ_R, and instead could only measure $\tau_R + a$. In the present paper, we avoid this problem by using a single-parameter approximation to Eq. (5.2). For typical empirical values of a and b, over the range of typical distances and target widths for TMT, we can approximate Eq. (5.2) using the single parameter model:

$$\langle T_M \rangle \approx \tau_M \cdot \left(D_\nu / W\right)^{1/3}. \tag{5.3}$$

Eq. (5.3) is a special case of Kvålseth's law for rapid, targeted movements. [143] In [110], the Fitts' law parameters a and b are measured for two classes of movements. The first class are movements made where the mouse button is not held down during the movement; these are point-select movements and have parameter values a = 230 ms and b = 166 ms/bit. The second class are movements made where the mouse button *is* held down during the movement; these are drag-select and stroke-through movements and have parameter values a = 135 ms and b = 249 ms/bit. The choice of the power of 1/3 provides an average functional form of Fitts' law able to approximate the forms of Fitts' law for point-select, drag-select, and stroke-through movements reasonably well using a single free parameter τ_M.

The expected total time $\langle T \rangle$ required to complete TMT-A or TMT-B where no errors are made is the sum of the expected times spent making moving to each target in turn, that is:

$$\begin{aligned} &\langle T \rangle \approx 25\tau_R + \kappa\tau_S + \xi\left(D_1,\ldots,D_{25},W\right)\tau_M, \\ &\kappa = \sum\nolimits_{\nu=1}^{25}\left(\left(26-\nu\right)/2\right), \\ &\xi\left(D_1,\ldots,D_{25},W\right) = \sum\nolimits_{\nu=1}^{25}\left(D_\nu / W\right)^{1/3}. \end{aligned} \tag{5.4}$$

We call κ the *search complexity*, and $\xi\left(D_1,\ldots,D_{25},W\right)$ the *motor complexity*. We note that the estimate for expected total time required to complete the task is linear in the cognitive and motor parameters τ_R, τ_S, and τ_M.

Eq. (5.4) provides an estimate of the expected time required to complete one part of TMT without any errors using the cognitive and motor parameters τ_R, τ_S, and τ_M. We allow that different values may apply to each part of TMT and characterize subject performance on TMT as a whole by the set of parameter values τ_R^A, τ_R^B, τ_S^A, τ_S^B, τ_M^A, and τ_M^B where the superscript indicates whether the parameter is for TMT-A or TMT-B. Whereas, when the subject makes no errors, TMT characterizes executive function by two values, the two test scores, the connect-the-dots model characterizes executive function by up to eight values. The search complexity κ for TMT-A or TMT-B (they are the same value) can be calculated from the definition in Eq. (5.4); while the motor complexities $\tilde{\xi}^A$, and $\tilde{\xi}^B$ for the remainder of the test after the first target has been selected can be calculated using the definition in Eq. (5.4) and direct measurement of the layout of the targets on the test page. Although we do not know where the hand begins before moving to the first target, we assume that the movement to the first target is typical for movements on the test and approximate the values ξ^A and ξ^B by $\xi^A \approx (25/24)\tilde{\xi}^A$ and $\xi^B \approx (25/24)\tilde{\xi}^B$.

In practice, we must modify the estimate in Eq. (5.4) to include times related to other effects present in the test-taking process. When we allow errors to occur on either part of TMT, a parameter θ giving the expected time needed to recover from an error must also be included. In addition, the act of turning over the test page and moving to the first target adds some time T^0 in addition to the recall, search and motor times to the total time. Using X as a placeholder for either of superscripts A or B, given a number of errors N^X, a subject's expected score on TMT-A or TMT-B (the expected time required to complete the test) S^X is:

$$\begin{aligned} S^X &\approx T^0 + 25\tau_R^X + \kappa\tau_S^X \\ &+ (25/24)\tilde{\xi}^X\tau_M^X + \theta N^X. \end{aligned} \tag{5.5}$$

5.3 In-Home Mouse Dynamics and TMT

In Chapter 4, we put forward a method for using measurements of in-home (computer) mouse dynamics (MD) made from everyday computer usage to estimate subject performance on TMT. That is, we observe how the subject moves the computer mouse during normal, free computer usage and produce measurements based on how the subject moves the mouse. The measurements we make from MD are estimates of the parameters in Fitts' law in the form given in Eq. (5.2), and a further value that is related to both the lowest speed at which the subject makes meaningfully controlled movements of the mouse and the shortest interval with which the subject typically pauses between mouse movements. Using these measurements taken from MD, we found we were able to fit simple linear models using ordinary least squares to TMT-A with $R^2 = 0.13$ and $p = 0.0045$, and to TMT-B with $R^2 = 0.37$ and $p < 0.0001$. Thus, the MD measurements were able to account for twice the observed variation in TMT-B as the observed variation in TMT-A.

The difference between TMT-A and TMT-B is that TMT-B includes set-switching while TMT-A does not. As we have shown in Chapter 3 the lengths of the trails in TMT-A and TMT-B do not differ considerably. This suggests that the results in Chapter 4 indicate a relationship between the measurements made from in-home MD and set-switching during TMT-B. Although we might postulate a variety of mechanisms to account for such a relationship, a particularly simple mechanism is to suppose that set-switching for the move to a target during TMT-B is performed in part as a dual-task with the motor stage of the movement to the previous target (i.e. the set-switching is performed while the motor stage is proceeding). The dual-tasking of set-switching and movement would be expected to cause the movement to be made slower than a comparable movement on TMT-A. The lengthened movement times on TMT-B would correspond to larger variations in the time associated with movement on TMT-B and so measures related to mouse movements would be able to account for a larger amount of the total variation in score on TMT-B than on TMT-A.

The remainder of this paper concerns itself with showing that the data from the computer game in Chapter 3 are consistent with a form of the connect-the-dots model in which the set-switching and motor stages are dual-tasked.

5.4 Single-Task and Dual-Task in TMT

We have allowed that the motor parameters τ_M^A and τ_M^B on TMT-A and TMT-B respectively, may differ between the two parts of the test. However, the motor tasks in TMT-A and TMT-B are the same – drawing a line from one target to the next. Since the motor tasks are the same, we would expect to find that $\tau_M^A = \tau_M^B$ (which we assumed to be the case in Chapter 3). For the motor tasks to be carried out differently in the two cases, that is for $\tau_M^A \neq \tau_M^B$ we need a model that makes the motor tasks in TMT-A and TMT-B differ in some way. One way to do this is to have the motor task occur in parallel with a cognitive task; that is have the motor task take place as part of a dual-task. We then allow that the subject carries out the motor task differently depending on the cognitive task. In this vein, poor performance on TMT has in fact been associated with altered dual-task prioritization in older adults. [47]

For movement a distance D to a target of width W, we define the motor parameter τ_M to be the motor parameter value for the single-task case, that is, the case in which there is no cognitive dual-task with the motor task. The form of Fitts' law in this case is approximately:

$$T_M \approx \tau_M \cdot \left(D/W\right)^{1/3}. \tag{5.6}$$

The average velocity of the movement is approximately:

$$\langle v \rangle \approx D / T_M = W^{1/3} D^{2/3} / \tau_M . \tag{5.7}$$

The motor time T_M changes when the subject performs a cognitive dual-task in parallel with the motor task. We assume that the dual-task lasts at least as long as the time taken to complete the motor task. We assume that the affect of the dual-task is to slow the movement by lowering the average movement speed. We model this by supposing that the dual-task lowers the average movement speed by a factor $1/\gamma$. We suppose that the value of the multiplicative factor γ is determined by the specific cognitive dual-task so that it takes about the same value across a population of subjects having a range of single-task motor times T_M for the same motor task. The average movement velocity when the cognitive dual-task is present is approximately:

$$\langle v \rangle \approx D / T_M \approx W^{1/3} D^{2/3} / \gamma \tau_M . \tag{5.8}$$

Thus, when a cognitive dual-task is present, Eq. (5.7) becomes:

$$T_M \approx \gamma \tau_M \cdot \left(D / W \right)^{1/3} . \tag{5.9}$$

We assume that the effect of any cognitive dual-task associated with the motor stage of TMT-A or TMT-B is constant across the subject population in the sense given in deriving Eq. (5.9). We also assume that we know the motor parameter τ_M for the single-task case for each subject in the population. Characterizing the presence of a cognitive dual-task in TMT-A or TMT-B by the parameters γ^A and γ^B, respectively, we may rewrite the TMT scores estimator in Eq. (5.5) as:

$$\begin{aligned} S^X &\approx T^0 + 25\tau_R^X + \kappa \tau_S^X \\ &+ \left(25/24 \right) \tilde{\xi}^X \gamma^X \tau_M^X + \theta N^X . \end{aligned} \tag{5.10}$$

In Section 5.2.2, we have given a model for TMT that divides the process of moving from one target to the next into the three additive stages of (1) recall, (2) search, and (3) motor. In this model, we have merged the set-switching into the recall stage. If we separate set-switching out into its own stage we find we have still have the three additive stages model for TMT-A , but now have a four additive stages model for TMT-B of (1) set-switching, (2) recall, (3) search, and (4) motor. We would like a mechanism that causes the motor parameter τ_M^A to take on a different value τ_M^B through the presence of a cognitive dual-task during the motor stage. A simple mechanism is to have the set-switching stage take place as a cognitive dual-task with the motor stage whenever possible (i.e. for every set-switching stage except the first one). As there is no set-switching stage for TMT-A, we find the motor stage during TMT-A is a single-task and γ^A = 1. All motor stages in TMT-B, except the very last one, are dual-tasks. We illustrate the sequence of stages for all but the last move in TMT-B in Figure 5.1.

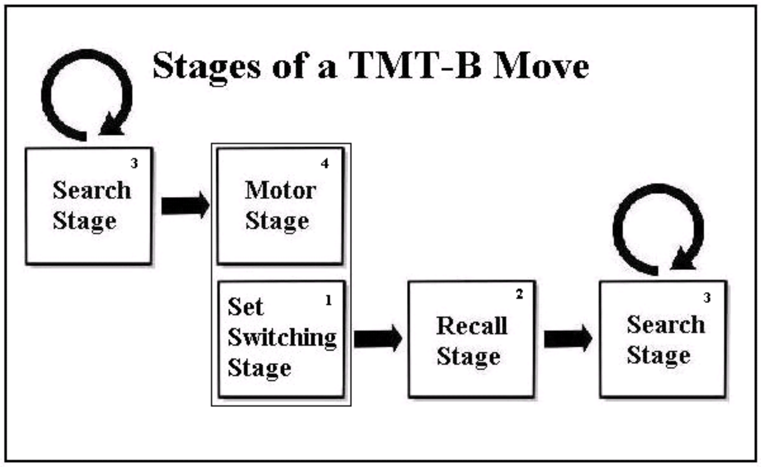

Figure 5.1. Stages of a TMT-B move. The process of selecting the next target in the sequence for TMT-B involves four sequential stages of (1) switching sets (2) recalling the next target, (3) serially searching for the next target by considering the available targets one after another, and (4) physically moving the mouse so that the cursor is on the target and clicking. The set-switching stage is made a secondary cognitive task with the motor stage whenever possible.

5.5 Cognitive Performance and Scavenger Hunt Computer Game

In Chapter 3, we used Scavenger Hunt (SH), a simple computer game designed to mimic TMT, to estimate subjects' performance on TMT. We based the analysis relating SH to TMT on a slightly modified form of the connect-the-dots model presented in Section 5.2.2. In the treatment in Chapter 3, we assumed that the motor parameters during TMT-A and TMT-B were the same (i.e. $\tau_M^A = \tau_M^B$). In the present treatment, we reconsider the data from Chapter 3 to see whether they provide any evidence of dual-tasking in TMT. In the interest of making the present treatment as self-contained as possible, we provide a brief review of the analysis in Chapter 3.

The subject plays SH by completing a series of self-contained rounds. Each round presents the subject with a board containing variable number of *markers* including both *targets* (typically about 4 to 10) and *distractors* that appear as circles containing a letter or number. The subject selects the targets in sequence by clicking each target in the order given by the *search string* that appears at the top of the board. Search strings used in SH include: ascending or descending alphabetical sequences (e.g., 'A,B,C,…' or '…,C,B,A'), (ii) ascending or descending numeric sequences (e.g., '1,2,3,…' or '…,3,2,1'), and (iii) ascending or descending alphanumeric sequences (e.g., '1,A,2,B,…' or '…,B,2,A,1'). The search string and layout of targets and distractors on the SH board for each round is generated at random.

A marker in SH appears as a circle containing a single letter or number. The centers of the markers are arranged on the board in a 4x8 grid with a spacing of 80 pixels. Markers may have a diameter of 63 pixels or 77 pixels. The largest value D/W possible in SH as measured between the centers of targets is D/W = 11.

We make estimates of subject performance from play of SH using the connect-the-dots model given in Section 5.2.2. In the Sections 5.5.1 and 5.5.2, we provide a brief account of how we make the measurements. Section 5.5.3 provides a brief account of how TMT scores are estimated using measurements made from SH. The reader interested in the rationale behind the analysis in these sections can consult Chapter 3.

5.5.1 Estimating Motor Performance

We estimate SH motor performance using the subset of rounds with search string '1,2,3,4' and no distractors. These rounds make up about one in four SH rounds. We only use rounds in which the subject made no errors. We calculate motor performance by looking at the individual physical movements of the mouse made to select the four targets ignoring the movement to the first target. For each of the remaining three movements, we know the movement time t_i, distance moved D_i, and target width W_i, the number of targets in the search string n = 4, and the place of the target being searched for during that move $\nu_i \in \{2,3,4\}$. We calculate the values c_0, $|c_1|$, and $|c_2|$ that minimize the total squared error given by:

$$\varepsilon = \sum_i \left(t_i - c_0 - |c_1| \left((5 - \nu_i) / 2 \right) - |c_2| \left(D_i / W_i \right)^{1/3} \right)^2 . \tag{5.11}$$

We constrain the result so that c_1 and c_2 are non-negative; we retain the estimated motor parameter value $\tau_M = |c_2|$.

In [110], the Fitts' law parameters a and b are measured for two classes of movements. The first class are movements made where the mouse button is not held down during the movement; these are point-select movements and have parameter values a = 230 ms and b = 166 ms/bit. The second class are movements made where the mouse button *is* held down during the movement; these are drag-select and stroke-through movements and have parameter values a = 135 ms and b = 249 ms/bit. The motor performance estimates are made for SH for the range of values D/W = 3.5 ± 1.7. Over this range, the estimated values for the characteristic motor time is τ_M = 390 ms for movements of the first class, and τ_M = 440 ms for movements of the second.

We may compare these values to the values we would estimate for the characteristic motor time τ_M from typical moves in TMT. Typical values for TMT-A are D/W = 6.1 ± 2.6, and, over this range, the estimated values for the characteristic motor time is τ_M = 380 ms for movements of the first class, and τ_M = 450 ms for movements of the second. Typical values for TMT-A are D/W = 8.2 ± 3.6, and, over this range, the estimated values for the characteristic motor time is τ_M = 380 ms for movements of the first class, and τ_M = 460 ms for movements of the second. The largest value occurring on TMT is D/W = 17.

5.5.2 Estimating Recall and Search Performance

For SH, we characterize recall and search performance using the parameters τ_R, and τ_S. We do this using all the games played by the subject with search string belonging to some set. For each move we know the movement time t_i, distance moved D_i, and target width W_i, the number of targets in the search string n_i, the number of distractors in the search string d_i, and the place of the target ν_i being searched for during that move. To accommodate the varying number of targets and the presence of distractors, we replace Eq. (5.1) in Section 5.2.2 with the expected search time:

$$\langle T_S \rangle = \left(\left(n_i - \nu_i + d_i + 1\right)/2\right)\tau_S. \tag{5.12}$$

Given the value of the motor parameter b estimated in Section 5.5.1, we calculate the values c_0, and $|c_1|$ that minimize the total squared error given by:

$$\varepsilon = \sum_i \left(\langle t_i \rangle - c_0 - |c_1|\left(\left(n_i - \nu_i + d_i + 1\right)/2\right) - \tau_M \cdot \left(D_i / W_i\right)^{1/3}\right)^2. \tag{5.13}$$

We constrain the result so that c_1 is non-negative; we retain the estimated values $\tau_R = c_0$ and $\tau_S = |c_1|$.

We make estimates using Eq. (5.13) separately for two sets of SH rounds. The first is the set of rounds with ascending or descending alphabetic or numeric search strings. The second is the set of rounds with ascending or descending alphanumeric search strings. This gives four recall and search parameters τ_R^A, τ_R^B, τ_S^A, and τ_S^B.

5.5.3 Estimating TMT Performance

The procedure in Sections 5.5.1 and 5.5.2 for measuring cognitive and motor performance using play of SH characterizes a subjects performance in terms of five cognitive and motor parameters τ_R^A, τ_R^B, τ_S^A, τ_S^B, and τ_M. We assume the subject completes TMT using the related parameters $\tau_R^{A\prime}$, $\tau_R^{B\prime}$, $\tau_S^{A\prime}$, $\tau_S^{B\prime}$, and $\tau_M{}'$ so that the expected scores on TMT given numbers of errors N^X are given by Eq. (5.10) in the form:

$$\begin{aligned} S^X &\approx T^0 + 25\tau_R^{X\prime} + \kappa\tau_S^{X\prime} \\ &+ (25/24)\tilde{\xi}^X \gamma^X \tau_M{}' + \theta N^X . \end{aligned} \tag{5.14}$$

We would like to estimate the TMT scores using the cognitive and motor parameter values measured in SH. Following Chapter 3, we assume that the parameters in TMT relate to those in SH by the set of transformations:

$$\begin{aligned} \tau_R^{X\prime} &= \alpha + \beta\tau_R^X , \\ \tau_S^{X\prime} &= \tau_S^X , \\ \tau_M^{X\prime} &= \tau_M . \end{aligned} \tag{5.15}$$

Eq. (5.15) assumes that the characteristic search time and the motor parameters for the single-task case are the same for TMT and SH. It allows that the characteristic recall time may differ between TMT and SH due to the subject being more careful in one than in the other. These assumptions are justified in more detail in Chapter 3. The final estimator for the expected TMT scores in terms of the cognitive and motor parameters estimated in SH is:

$$\begin{aligned} S^X &\approx \left(T^0 + 25\alpha\right) + 25\beta\tau_R^X + \kappa\tau_S^X \\ &+ (25/24)\tilde{\xi}^X \gamma^X \tau_M + \theta N^X . \end{aligned} \tag{5.16}$$

5.6 Errors in TMT and SH

As we show in Section 5.8, subjects make larger numbers of errors during TMT-B than during TMT-A. We have argued that the difference between TMT-A and TMT-B comes down to the presence of set-switching in TMT-B and its absence in TMT-A. This suggests that the increased rate of making errors during TMT-B is related to set-switching and the dual-tasking of the set-switching and motor stages. As we also show in Section 5.8, this observation holds in SH as well, with subjects making larger numbers of errors during SH rounds with ascending or descending alphanumeric search strings than during SH rounds with ascending or descending alphabetic or numeric search strings.

We treat errors as a probability for each move of moving to an incorrect target. When error probabilities are small, we can construct an approximate model in which the probability of making an error P during TMT or SH is the sum of the rates of making different types of errors, that is $P \approx \sum_i P_i$. Researchers have identified three types of TMT errors. [144, 145] The first type is *perseverative errors* in which the subject fails to alternate between the categories of letters and numbers in TMT-B. The second type is *sequential errors* in which the subject omits next element in the search string in either TMT-A or TMT-B. The third type is *proximity errors* in which the subject proceeds to an incorrect nearby target in either TMT-A or TMT-B. We assume that errors in set-switching appear only as additional perseverative errors (we consider this further in Section 5.9). Instead of using these three types of TMT errors, we divide the probability of making an error into two components. The first component is P_0, the baseline error probability (i.e. the probability of making an error on TMT-A, or the probability of making sequential or proximity errors). The second component is P_{Sw}, the additional probability of error due set-switching (i.e. the difference of the probability of making an error on TMT-B and the probability of making an error on TMT-A). The baseline error probability represents the baseline probability of making sequential and proximity errors while the additional probability of error due to set-switching represents the presence of perseverative errors. So the probabilities P^A and P^B of making an error on TMT-A and TMT-B respectively, when the probability of making an error is small, are approximately:

$$\begin{aligned} P^A &\approx P_0, \\ P^B &\approx P_0 + P_{Sw}. \end{aligned} \tag{5.17}$$

We provide a discussion of potential ways of performing a more detailed analysis of errors during SH in Chapter 3.

5.7 Notation Convention

In the models we use in Section 5.8, we fit a single model to both TMT-A and TMT-B. However, we sectors of the model describing TMT-A and TMT-B may differ somewhat. In order to indicate clearly and compactly the way we calculate the model parameters in Section 5.8, and to make clear how the TMT-A and TMT-B sectors of the model differ, we adopt a convention for denoting the way we use ordinary least squares (OLS) regression to fit the scores on TMT. We assume we dependent variables y and Y, and independent variables x_n and X_n. From the dependent and independent variables, we calculate the parameters $c_0,\ldots,c_n$ that minimize the square error:

$$\varepsilon = \sum_i \left(y_i - c_0 - \sum\nolimits_{n=1}^{N} c_n x_{n,i} \right)^2 + \sum_j \left(Y_j - c_0 - \sum\nolimits_{n=1}^{N} c_n X_{n,j} \right)^2. \tag{5.18}$$

We denote the problem of finding the parameters $c_0,\ldots,c_n$ that minimize Eq. (5.18) by:

$$\begin{cases} y = c_0 + \sum_{n=1}^{N} c_n x_n \\ Y = c_0 + \sum_{n=1}^{N} c_n X_n. \end{cases} \tag{5.19}$$

For the models used in Section 5.8, the first equation in the formalism indicated in Eq. (5.19) corresponds to the TMT-A sector, and the second equation to the TMT-B sector of the model.

5.8 Empirical Study

To provide a self-contained account of the analysis relevant to investigating evidence for dual-tasking in SH and TMT, we reproduce the portion of the analysis in Chapter 3 that is relevant to the present analysis. The reader can consult Chapter 3 for further information.

23 older adults (20 female and 3 male, average age 81 ± 6.8 years, average level of education 15 ± 2.9 years, MMSE = 28 ± 0.89, ADL = 0.058 ± 0.16) participated in a one year study in which a set of computer games that included SH was placed into their homes. Subjects were given a battery of cognitive tests, including TMT, administered by trained clinical staff according to standard administrations procedures, at the beginning of the study, 6 months into the study and at the end of the study. The observed TMT-A and TMT-B scores and numbers of errors across all the tests taken by the subjects being included in this analysis and their standard deviations were S^A = 45 ± 11 s and N^A = 0.0073 ± 0.14, and S^B = 100 ± 28 s and N^B = 1.0 ± 0.64.

We looked at whether the measured SH motor performances indicated both single-tasking and dual-tasking during SH. More specifically, we looked at whether the motor parameters estimated using only rounds with alphabetic or numeric search strings indicated significantly quicker motor performance than motor parameters estimated using only rounds with alphanumeric search strings.

For each subject, we estimated the motor parameter τ_M in three ways. We measured a value τ_M using Eq. (5.11) and data from rounds with search string '1,2,3,4' and no distractors (the method used to estimate the motor parameter τ_M in Chapter 3). We measured a value τ_M^A using a modified Eq. (5.11) that accounts for varying target numbers and the presence of distractors (see Eq. (5.13) for how distractors are accounted for) and data from rounds with alphabetic or numeric search strings (excluding rounds with search string '1,2,3,4' and no distractors). We measured a value τ_M^B using a modified Eq. (5.11) that accounts for varying target numbers and the presence of distractors and data from rounds with alphabetic or numeric search strings. The means and standard deviations of the estimated values were:

$$\begin{aligned} \tau_M &= 670 \pm 240\,\text{ms}, \\ \tau_M^A &= 890 \pm 350\,\text{ms}, \\ \tau_M^B &= 780 \pm 460\,\text{ms}. \end{aligned} \tag{5.20}$$

Although both the estimates τ_M^A and τ_M^B were somewhat larger than the estimate τ_M, the estimates τ_M^A and τ_M^B gave comparable values. We consider these values and their relationship to the measurements further in Section 5.9.

An important difference between the SH rounds used to estimate τ_M and those used to estimate τ_M^A and τ_M^B in Eq. (5.20) is that those used to estimate τ_M contain no distractors, while those used to estimate τ_M^A and τ_M^B do contain distractors. To better understand the effect of distractors (if any), we restricted the analysis to SH rounds containing at most one distractor (limiting to zero distractors left too few subjects). We only performed the analysis on a subject if that subject had at least 15 moves total for rounds with alphabetic or numeric search strings and at most one distractor (excluding rounds with search string '1,2,3,4' and no distractors), and at least 15 moves total for rounds with alphanumeric search strings and at most one distractor.

This restriction left a cohort of 15 older adults (13 female and 2 male, average age 82 ± 6.6 years, average level of education 15 ± 2.9 years, MMSE = 29 ± 0.78, ADL = 0.044 ± 0.12). The observed TMT-A and TMT-B scores and numbers of errors across all the tests taken by the subjects being included in this analysis and their standard deviations were S^A = 45 ± 12 s and N^A = 0.044 ± 0.12, and S^B = 100 ± 23 s and N^B = 0.98 ± 0.62.

We estimated the values τ_M, τ_M^A, and τ_M^B in the same way as in Eq. (5.20); the means and standard deviations of the estimated values were:

$$\begin{aligned} \tau_M &= 650 \pm 220\,\text{ms}, \\ \tau_M^A &= 720 \pm 240\,\text{ms}, \\ \tau_M^B &= 620 \pm 330\,\text{ms}. \end{aligned} \tag{5.21}$$

In this case, all three estimates τ_M, τ_M^A, and τ_M^B give comparable values.

We observe in Eqs. (5.20) and (5.21) that the characteristic motor times τ_M^B for movements during TMT-B-like rounds of SH are about the same as the characteristic motor times τ_M^A for movements during TMT-A-like rounds (in fact, they are slightly smaller in both cases). This observation suggests that it is not the case during SH that moves during TMT-A-like rounds are made using single-tasking while moves made during TMT-B-like rounds are made using dual-tasking. Rather, moves in both types of rounds are made in approximately the same way. As set-switching only occurs in TMT-B-like rounds, this means that subjects are not dual-tasking set-switching with movement during play of SH.

We continued our analysis using the original set of 23 older adults.

SH characterizes a subject's cognitive performance with five measured parameters: τ_R^A, τ_R^B, τ_S^A, τ_S^B, and τ_M. We calculated these using Eqs. (5.11) and (5.13). We estimated the motor parameter τ_M as in Eqs. (5.20) and (5.21) using rounds with search string '1,2,3,4' and no distractors. The superscripts A and B denote estimates made using rounds with alphabetic and numeric, or alphanumeric search strings respectively. The means and the standard deviations of the parameter estimates across all subjects were:

$$\begin{aligned} \tau_R^A &= 110 \pm 270\,\text{ms}, \\ \tau_R^B &= 410 \pm 330\,\text{ms}, \\ \tau_S^A &= 96 \pm 45\,\text{ms}, \\ \tau_S^B &= 110 \pm 40\,\text{ms}, \\ \tau_M &= 670 \pm 240\,\text{ms}. \end{aligned} \tag{5.22}$$

If we assume that the difference of values between τ_R^A and τ_R^B in Eq. (5.22) are due to set-switching, we estimate the average set-switching time to be 290 ms which compares well with independently measured values of about 200 ms. [111] We looked at the correlations of the parameter τ_M with parameters measured in Eq. (5.22). We also looked at the correlation of the parameter τ_M to the estimated characteristic set-switching time $\tau_R^B - \tau_R^A$. We summarize the correlations in Figure 5.2.

Parameter correlated to τ_M	R^2	p
τ_R^A	0.18	0.044
τ_R^B	0.35	<0.01
τ_S^A	0.10	0.13
τ_S^B	0.056	0.28
$\tau_R^B - \tau_R^A$	0.17	0.053

Figure 5.2. Correlations of τ_M with other parameters measured from Scavenger Hunt.

The stronger correlations between τ_M, and τ_R^A and τ_R^B were expected due to the method by which the estimates are made. We note that τ_M had no statistically significant correlation with τ_S^A and τ_S^B and a weak (but statistically significant in the sense of $p < 0.05$) correlation with the estimated characteristic set-switching time $\tau_R^B - \tau_R^A$. The correlation between b and $\tau_R^B - \tau_R^A$ is negative. We consider this further in Section 5.9.

We began by repeating the analysis in Chapter 3 but characterizing motor performance using Eq. (5.3) rather than Eq. (5.2). We used the characterization of subject cognitive performance given by SH in Eq. (5.22) to estimate TMT scores in the case where the motor stages of both TMT-A and TMT-B were assumed to be single tasks, that is $\gamma^A = \gamma^B = 1$. We calculated the TMT scores estimator by finding the global parameters $T^0 + 25\alpha$, β, and θ using OLS regression with the model (following the notation convention in Section 5.7):

$$\begin{cases} \left\langle S^A \right\rangle - \kappa\tau_S^A - \left(25/24\right)\tilde{\xi}^A \tau_M \\ = \left(T^0 + 25\alpha\right) + 25\beta\tau_R^A + \theta\left\langle N^A \right\rangle \\ \left\langle S^B \right\rangle - \kappa\tau_S^B - \left(25/24\right)\tilde{\xi}^B \tau_M \\ = \left(T^0 + 25\alpha\right) + 25\beta\tau_R^B + \theta\left\langle N^B \right\rangle . \end{cases} \tag{5.23}$$

We measured values for the motor complexities $\tilde{\xi}^A$ and $\tilde{\xi}^B$ from the TMT of $\tilde{\xi}^A$ = 43 and $\tilde{\xi}^B$ = 47. The model fit with $R^2 = 0.80$ and $p < 0.0001$. Inspection of the 95% confidence intervals for the coefficient estimates showed that the estimates of β and θ were statistically significant, while that of $T^0 + 25\alpha$ was not. The parameter values were:

$$\begin{aligned} &T^0 + 25\alpha = 1.9\,\text{s}, \\ &\beta = 1.7, \\ &\theta = 32\,\text{s}. \end{aligned} \tag{5.24}$$

The model performance and estimates for β and θ were comparable to those in Chapter 3.

As we observed in Chapter 3, there was a subject that produces a notable outlier in the data. Again, as in Chapter 3, removal of the outlier subject does not produce a notable change in the performance of the model or the estimated parameter values. We retain this subject for the analysis, as in Chapter 3. In the models analyzed here, removal of the outlier subject produced comparable or slightly better results than those produced while retaining the outlier.

As in Chapter 3, it was of interest to see how the model would perform in the case where subjects made no errors on TMT. We restricted the analysis to include only administrations of TMT in which both TMT-A and TMT-B had no errors. There were 16 subjects that had at least one error-free administration of TMT. We fitted a truncated version of the model in Eq. (5.23) lacking the terms in θN^A and θN^B, and used the average of all error-free TMT administrations for the test scores. The model fit with $R^2 = 0.54$ and $p < 0.0001$, and estimated global parameter values of $T^0 + 25\alpha$ = 12 s and β = 2.7. Inspection of the confidence intervals for the coefficient estimates showed that the estimates of β and $T^0 + 25\alpha$ were both statistically significant.

Having established that using Eq. (5.3) to characterize motor performance provides comparable results to those obtained when Eq. (5.2) is used (as is done in Chapter 3), we next looked at whether the available data provided evidence that movement times were longer during TMT-B than during TMT-A.

To estimate values for γ^A and γ^B, we weakened the model in Eq. (5.23) to allow us to fit values for γ^A and γ^B to the data. We calculated the new TMT scores estimator by finding the global parameters $T^0 + 25\alpha$, β, γ^A, γ^B, and θ using OLS regression with the model:

$$\begin{cases} \langle S^A \rangle - \kappa \tau_S^A = \left(T^0 + 25\alpha\right) + 25\beta\tau_R^A \\ +\left(25/24\right)\tilde{\xi}^A \gamma^A \tau_M + \theta \langle N^A \rangle \\ \langle S^B \rangle - \kappa \tau_S^B = \left(T^0 + 25\alpha\right) + 25\beta\tau_R^B \\ +\left(25/24\right)\tilde{\xi}^B \gamma^B \tau_M + \theta \langle N^B \rangle. \end{cases} \tag{5.25}$$

This model fit with $R^2 = 0.87$ and $p < 0.0001$; inspection of the 95% confidence intervals for the coefficient estimates showed that the estimates of β, θ, γ^A, and γ^B were statistically significant, while that of $\left(T^0 + 25\alpha\right)$ was not. The parameter values were:

$$
\begin{aligned}
&T^0 + 25\alpha = -9.1\text{s},\\
&\beta = 2.1,\\
&\gamma^A = 1.2,\\
&\gamma^B = 1.8,\\
&\theta = 21\text{s}.
\end{aligned}
\tag{5.26}
$$

We repeated this analysis 10000 times using the data for 12 randomly selected subjects each time. In this way, we estimated the means and standard deviations for parameters γ^A and γ^B of γ^A = 0.79 ± 0.42 and γ^B = 1.6 ± 0.31. The smallest observed value for $\gamma^B - \gamma^A$ was $\gamma^B - \gamma^A$ = 0.15.

To reduce any effects due to the observed correlations between τ_M, and τ_R^A and τ_R^B, we weakened the model in Eq. (5.25) to use the estimated characteristic set-switching time $\tau_R^B - \tau_R^A$ rather than the recall times τ_R^A and τ_R^B. We calculated the new TMT scores estimator by finding the global parameters $T^0 + 25\alpha$, β, γ^A, γ^B, and θ using OLS regression with the model:

$$
\begin{cases}
\quad\left\langle S^A \right\rangle - \kappa\tau_S^A = \left(T^0 + 25\alpha\right) \\
\quad + \left(25/24\right)\tilde{\xi}^A \gamma^A \tau_M + \theta\left\langle N^A \right\rangle \\
\left\langle S^B \right\rangle - \kappa\tau_S^B = \left(T^0 + 25\alpha\right) + 25\beta \cdot \left(\tau_R^B - \tau_R^A\right) \\
+ \left(25/24\right)\tilde{\xi}^B \gamma^B \tau_M + \theta\left\langle N^B \right\rangle.
\end{cases}
\tag{5.27}
$$

This model fit with R^2 = 0.79 and $p < 0.0001$; inspection of the 95% confidence intervals for the coefficient estimates showed that the estimates of β, θ, and γ^B were statistically significant, while those of $\left(T^0 + 25\alpha\right)$ and γ^A were not. The parameter values were:

$$
\begin{aligned}
&T^0 + 25\alpha = 11\text{s}, \\
&\beta = 2.5, \\
&\gamma^A = 0.56, \\
&\gamma^B = 1.1, \\
&\theta = 20\text{s}.
\end{aligned}
\tag{5.28}
$$

We repeated this analysis 10000 times using the data for 12 randomly selected subjects each time. In this way, we estimated the means and standard deviations for parameters γ^A and γ^B of γ^A = 0.26 ± 0.29 and γ^B = 0.99 ± 0.22. The probability that $\gamma^B - \gamma^A$ was less than zero was p = 0.011.

The model that we have developed in Chapter 3 is approximately Eq. (5.23) which is Eq. (5.23) with γ^A = γ^B = 1. In the models in Chapter 3 and Eq. (5.23), we assume that movements in both TMT-A and TMT-B are made as single-tasks and that the motor parameters that we measure in SH are measurements for single-task movements. The simplest improvement of the models in Chapter 3 and Eq. (5.23) is to include dual-tasking during TMT-B is to maintain that the assumptions we have made in Chapter 3 and Eq. (5.23) still hold in the case of TMT-A, but allow γ^B to assume a larger value to reflect dual-tasking. We do this by allowing γ^B to be a parameters that we fit to the data while holding γ^A = 1. This provides us with a better model to use to estimate TMT performance from SH data to replace the one used in Chapter 3. The new model is able to include the dual-tasking effect with the addition of only one additional free parameter over the model used in Chapter 3, and constitutes the simplest model that can replace that used in Chapter 3 while including dual-tasking.

We strengthened and simplified the weakened form the model in Eq. (5.23) by fixing the value γ^A to one. The TMT scores estimator was found by calculating the global parameters $T^0 + 25\alpha$, β, γ^B, and θ using OLS regression with the model:

$$\begin{cases} \left\langle S^A \right\rangle - \kappa\tau_S^A - \left(25/24\right)\tilde{\xi}^A \tau_M \\ \quad = \left(T^0 + 25\alpha\right) + 25\beta\tau_R^A + \theta\left\langle N^A \right\rangle \\ \left\langle S^B \right\rangle - \kappa\tau_S^B = \left(T^0 + 25\alpha\right) \\ +25\beta\tau_R^B + \left(25/24\right)\tilde{\xi}^B \gamma^B \tau_M + \theta\left\langle N^B \right\rangle . \end{cases} \tag{5.29}$$

The model fit with $R^2 = 0.87$ and $p < 0.0001$; inspection of the 95% confidence intervals for the coefficient estimates showed that the estimates of β, θ, and γ^B were statistically significant, while that of $\left(T^0 + 25\alpha\right)$ was not. The effect size associated with the addition of γ^B to the model in Eq. (5.23) was $f^2 = 0.54$. The parameter values were:

$$\begin{aligned} &T^0 + 25\alpha = -3.0\text{s}, \\ &\beta = 1.9, \\ &\gamma^B = 1.6, \\ &\theta = 21\text{s}. \end{aligned} \tag{5.30}$$

The lower bound for the 95% confidence intervals for γ^B was 1.3. This model is a simple modification of the model in Chapter 3 to allow for dual-tasking during TMT-B. We illustrate the performance of this model in Figure 5.3.

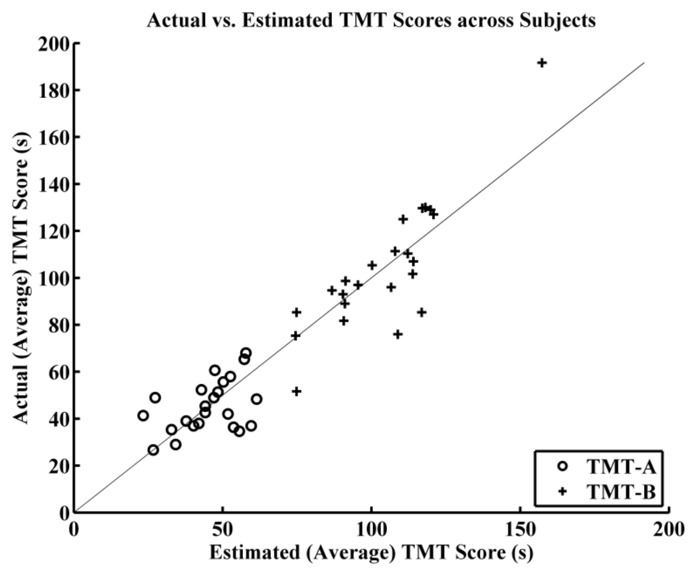

Figure 5.3. Actual vs. estimated TMT scores across subjects. Each of the 23 subjects has two values shown, one for TMT-A and one for TMT-B, each representing the average of the three administrations of TMT. The model fit has R^2 = 0.87 and p < 0.0001. A line with slope one passing through the origin is shown for reference.

As we did for the model in Eq. (5.23) above, we looked at how the model would perform in the case where subjects made no errors on TMT. We again restricted to the 16 subjects that had at least one error-free administration of TMT. We fitted a truncated version of the model in Eq. (5.29) lacking the terms in θN^A and θN^B, and used the average of all error-free TMT administrations for the test scores. The model fit with R^2 = 0.80 and p < 0.0001, and estimated global parameter values of $T^0 + 25\alpha$ = -1.9 s, β = 1.9, and γ^B = 1.9. Inspection of the confidence intervals for the coefficient estimates showed that the estimates of β and γ^B were statistically significant while $T^0 + 25\alpha$ was not.

Again, to reduce any effects due to the observed correlations between τ_M, and τ_R^A and τ_R^B, we weakened the model in Eq. (5.29) to use the estimated characteristic set-switching time $\tau_R^B - \tau_R^A$ rather than the recall times τ_R^A and τ_R^B. The new TMT scores estimator was found by calculating the global parameters $T^0 + 25\alpha$, β, γ^B, and θ using OLS regression with the model:

$$\begin{cases} \qquad \left\langle S^A \right\rangle - \kappa\tau_S^A - \left(25/24\right)\tilde{\xi}^A\gamma^A\tau_M \\ \qquad = \left(T^0 + 25\alpha\right) + \theta\left\langle N^A \right\rangle \\ \left\langle S^B \right\rangle - \kappa\tau_S^B = \left(T^0 + 25\alpha\right) + 25\beta\cdot\left(\tau_R^B - \tau_R^A\right) \\ +\left(25/24\right)\tilde{\xi}^B\gamma^B\tau_M + \theta\left\langle N^B \right\rangle. \end{cases} \tag{5.31}$$

This model fit with $R^2 = 0.78$ and $p < 0.0001$; inspection of the 95% confidence intervals for the coefficient estimates showed that the estimates of β, θ, and γ^B were statistically significant, while that of $\left(T^0 + 25\alpha\right)$ was not. The parameter values were:

$$\begin{aligned} &T^0 + 25\alpha = -1.6\text{s}, \\ &\beta = 2.9, \\ &\gamma^B = 1.4, \\ &\theta = 21\text{s}. \end{aligned} \tag{5.32}$$

The lower bound for the 95% confidence intervals for γ^B was 1.0.

We finally looked at the rates at which the subjects made errors on TMT and SH. For SH rounds with ascending or descending alphabetic or numeric search strings (excluding rounds with search string ‘1,2,3,4’ and no distractors) the range of the total number of errors observed for each subject across subjects was 0 to 70 with a median of 6.5. For SH rounds with ascending or descending alphanumeric search strings the range of errors across subjects was 0 to 127 with a median of 12. To compare the two rates of errors we looked at the probability of making an error each time a subject makes a movement to a target. For TMT, this was defined to be the total number of errors observed divided by the total number of movements made, and denoted the probabilities for TMT-A and TMT-B by P^A and P^B. For SH, we used all the observed rounds of SH, including those in which errors were made, these probabilities, defined for SH rounds with ascending or descending alphabetic or numeric search strings (excluding ‘1,2,3,4’ and no distractors) and ascending or descending alphanumeric search strings; these probabilities of error are denoted by p^A and p^B respectively. The observed means and standard deviations were:

$$\begin{aligned} P^A &= 0.0028 \pm 0.0054, \\ P^B &= 0.037 \pm 0.022, \\ p^A &= 0.022 \pm 0.019, \\ p^B &= 0.048 \pm 0.026. \end{aligned} \tag{5.33}$$

The observed means and standard deviations values of the errors due to set-switching P_{Sw} = $P^B - P^A$ and p_{Sw} = $p^B - p^A$ were:

$$\begin{aligned} P_{Sw} &= P^B - P^A = 0.034 \pm 0.023, \\ p_{Sw} &= p^B - p^A = 0.026 \pm 0.021. \end{aligned} \tag{5.34}$$

We did not find any statistically significant relationships among the probabilities P^A, P^B, p^A, and p^B except for the linear model:

$$p^B = [0.031] + [0.81]\, p^A. \tag{5.35}$$

The model in Eq. (5.35) fit the data with $R^2 = 0.37$ and $p < 0.0022$. Inspection of the 95% confidence intervals indicted that both parameters were statistically significant. The coefficient value of 0.81 multiplying p^A is close to the value of 1.0 predicted by the model in Eq. (5.17).

5.9 Discussion

The study presented in Section 5.8 is discussed more fully in Chapter 3. We restrict the present discussion to issues related to the observed correlation of the total set-switching and motor times, evidence for dual-tasking of set-switching with movement during TMT-B, and their relationship to the making of errors.

In Chapters 3 and 4, we presented two techniques for in-home monitoring of subject performance using data obtained from interactions with a computer. In both cases, we used the obtained data to estimate performance on TMT. The aim of the present paper has been to modify the model developed in Chapter 3 so that it would be able to account for the observations in Chapters 3 and 4. When we monitor subjects in the home, we sacrifice some ability to control what the subjects are doing in order to gather large quantities of data over a long period. We make up for the loss of some amount of control over what the subjects are doing by using a mathematical model to understand how the in-home measurements relate to other quantities of interest (e.g. cognitive performance as characterized by the score on TMT). As a result, it is important to produce the most accurate model of what we are measuring as we can.

We measure a value for the characteristic motor time of τ_M = 730 ± 270 ms in Eq. (5.20) which differs from both the expected value of τ_M = 390 ms for point-select movements, and τ_M = 440 ms for drag-select and stroke-through movements. This result is comparable to the values of b = 300 ± 110 ms/bit for Eq. (5.2) measured in Chapter 3 using SH for in relation to the values of b = 166 ms/bit for point-select movements, and b = 249 ms/bit for drag-select and stroke-through movements measured in [110]. Using a comparable cohort of older adults in Chapter 4 we measured values of b = 160 ± 36 ms/bit and b = 170 ± 61 ms/bit using in-home measurement of MD. Point-select movements are made with the mouse button up, while drag-select and stroke through movements are made with the mouse button held down. The results in Chapter 4 suggest that most mouse movements during everyday computer usage resemble point-select movements, that is, the movements are made with the mouse button held up. However, the estimates of b or τ_M made using SH appear to be nearer to drag-select or stroke-through movements made with the mouse button held down. We note that when the mouse button is held down, it is also the case that there is a greater force by the hand pushing the mouse onto the table; thus the change in Fitts' law may not be due as much to the button being held down as the greater force associated with holding the button down. One interpretation for the larger values for b or τ_M is that the subjects push on the mouse with a greater force when playing SH than during everyday computer usage. This may relate to a general phenomenon of people pushing harder on controls when playing in video games.

In the SH computer game, Eqs. (5.20) and (5.21) indicate there is no change in the motor parameter τ_M between rounds with alphabetic or numeric search strings, and rounds with alphanumeric search strings. This suggests that rounds of SH with alphabetic or numeric search strings are completed according to the simple additive stages model with three stages: (1) recall, (2) search, and (3) motor; while rounds with alphanumeric search strings are completed according to the simple four stages model: (1) set-switching, (2) recall, (3) search, and (4) motor.

In Chapter 4, we observed that purely motor speed measurements were able fit TMT-A with $R^2 = 0.13$ and $p = 0.0045$, and TMT-B with $R^2 = 0.37$ and $p < 0.0001$. So the motor speed measurements were able to account for about twice as much of the total variation in TMT-B as in TMT-A. We have suggested that a simple explanation for this observation is that the subjects spends a longer time in the motor stage during TMT-B than during TMT-A. In the present paper, we wanted to see if the data from SH indicated a similar effect. We fit several models using the data for SH. The first model we fit (Eq. (5.23)) is a slightly modified version of the model used in Chapter 3 where we have replaced the original form of Fitts' law (Eq. (5.2) (used in Chapter 3) with an approximation (Eq. (5.3)). We have shown that this slightly modified model gives results comparable to the model that we actually used in Chapter 3. The next model we fit (Eq. (5.25) took the first model and allowed the total times spent in the motor stages to differ in TMT-A and TMT-B by allowing the model to fit the parameters γ^A and γ^B giving values γ^A = 1.2 and γ^B = 1.8. Thus, we have observed that the SH data appear to support a longer motor stage in TMT-B than in TMT-A in agreement with the observations in Chapter 4. In the fourth model (Eq. (5.29), we looked at the simplest extension of the first model that allows for the effect of more time being spent in the motor stage in TMT-B over TMT-A and have observed that it provides a significant improvement over the model used in Chapter 3. We also looked at two additional models, the third and fifth models, to determine whether the fit values γ^A and γ^B could be related to the presence of the recall time values. We found that the use of the characteristic recall times τ_R^X and the estimated characteristic set-switching times $\tau_R^B - \tau_R^A$ both show that the data are consistent with a longer motor stage in TMT-B than in TMT-A.

In the models in Eqs. (5.25), (5.27), (5.29), and (5.31), we included the characteristic recall times τ_R^X or the estimated characteristic set-switching times $\tau_R^B - \tau_R^A$ and allowed them to be fit to the models. The effect of the inclusion of these parameters in this way is that we are allowing additional time for set-switching beyond the time devoted to set-switching during dual-tasking with the motor stage. Physically, we can interpret these models as saying that the set-switching stage for a move begins when the movement to the target of the previous move begins and continues for some time after the movement is finished. The apparent extension of set-switching beyond the period spend dual-tasking with the motor stage taken together with the apparent increase in the motor times due to dual-tasking with set-switching would indicate that both the total time spent making movements and the total time spent in-between movements increase from TMT-A to TMT-B.

When set-switching is included in the connect-the-dots model explicitly as an additive stage, the recall and update stage becomes the process of recalling the next target in the sequence given that the current target in the sequence is in mind. In TMT-A, the current target in the sequence is in mind when the subject has just moved to the current target, while in TMT-B the subject has to switch-sets and recall the most recent target selected in the set before the current target in the sequence is in mind. The set-switching stage in the model contains all the processing that a subject does in a TMT-B move prior to the recall and update stage. In a simple formulation of the connect-the-dots model, we can suppose that the characteristic times associated with these more narrowly defined recall and update stages are the same for TMT-A and TMT-B and that the set-switching stage captures extra time needed to complete TMT-B.

Following [144, 145], we have divided errors on TMT into three types: perseverative, sequential, and proximity. The three types of errors correspond well with different stages of the connect-the-dots model. Perseverative errors, in which the subject fails to switch sets between letters and numbers, appear to be errors made during the set-switching stage. Sequential errors, in which the subject omits the next element in the search string in either TMT-A or TMT-B, appear to be errors made during the recall stage. Proximity errors, in which the subject proceeds to an incorrect nearby target, appear to be errors made during the search stage. We expect that the subject can reduce the probability of making an error during a particular stage by being more careful during that stage; that is by spending more time performing that stage. In relation to this, we note that in the fits of the models in Eqs. (5.25), (5.27), (5.29), and (5.31), that the time spent performing recall approximately doubles. This is consistent with the subjects spending more time performing the recall stage during TMT than during SH. We expect that subjects are less likely to make sequential errors during TMT than during SH, possibly accounting for the observed lower rates of errors during TMT than during SH. In the models in Eqs. (5.25), (5.27), (5.29), and (5.31), we have assumed that the time devoted to search does not change from SH to TMT. If we assume that changes in the times devoted to the various stages during TMT are in part chosen to lower the associated rates of error, this assumption is consistent with the assumption that the probability of making a proximity error is already very low in SH.

The probabilities of perseverative errors are comparable for TMT-B and SH. Although the data appear to indicate a higher probability of probability of perseverative errors on TMT-B the standard deviations of the two estimated probabilities of perseverative errors overlap. As it appears that subjects spend more time performing the set-switching stage in TMT-B than in SH, we would expect the probability of perseverative errors to be lower during TMT-B. If, in fact, it were to turn out that the probabilities of perseverative errors is higher during TMT-B, then it would seem that the longer time spent performing the set-switching stage, or the dual-tasking of the set-switching and motor stages increases the error probability. In this case, there would appear to be no benefit to lengthening the set-switching stage or dual-tasking set-switching with motor during TMT-B, so it would be of interest to determine why the subjects would do this. Alternatively, such a result may indicate that a model that assumes that set-switching introduces the possibility of perseverative errors, but does not affect other types of errors is incorrect.

We postulated that older adults dual-task the set-switching and motor stages during TMT-B as a way of modifying the connect-the-dots model to make the observations in Chapters 3 and 4 consistent with each other. We have argued that it is the simplest mechanism to account for the apparent relationship between set-switching and motor. One should be able to confirm or disprove this postulate simply by observing a cohort of older adults complete TMT and measuring the time they spend physically drawing the trail. This could be done by recording older adults completing the test or by using a computer-based annotation technique like that in [102]. It is still possible that there is no difference in the physical movement times between TMT-A and TMT-B. If this turns out to be the case, the measurements in Chapter 4 and the analysis presented in Section 5.8 that quantifies a relationship between the set-switching and motor stages still hold and a more complicated model that dual-tasking would have to be found to account for the observations.

5.10 Conclusion

In Chapters 3 and 4, we used a mathematical model describing how a subject completes TMT to make measurements using a simple computer game [Chapter 3], and in-home MD [Chapter 4] to provide estimates of subject performance on TMT. The performance of these techniques follows from both the quality of the measurements and the quality of the model used. We expect improvements in the model to yield better estimates of TMT performance. Data from Chapters 3 and 4 point to an improvement in the model in the form of allowing dual-tasking of set-switching and movement on TMT-B, although this remains to be confirmed by direct observation. By generating better models of the physical phenomenon being measured for clinical purposes we point the way to more clinically useful measurements of the physical phenomenon, not only in-home, but also in future clinical instruments which may improve upon TMT.

5.11 Appendices

5.11.1 Appendix 1

We can analyze the model in Eq. (5.29) further using the same set of 23 subjects analyzed in Section 5.8. Rather than fitting the model in Eq. (5.29) once for all 23 subjects, we fit it 23 times, once for each subset of 22 subjects. These models fit with a mean and standard deviation of R^2 of $R^2 = 0.93 \pm 0.0040$ and in all cases $p < 0.0001$. The means and standard deviations of the estimated global parameter values were:

$$
\begin{aligned}
&T^0 + 25\alpha = -3.0 \pm 0.54\,\text{s},\\
&\beta = 1.9 \pm 0.079,\\
&\gamma^B = 1.6 \pm 0.024,\\
&\theta = 21 \pm 1.4\,\text{s}.
\end{aligned} \tag{5.36}
$$

The global parameter values estimated for each of the 23 models in Eq. (5.36) are close to those estimated in the single model using all 23 subjects in Eq. (5.30). We arrive at the same model using any set of 22 subjects that we do when using all 23 subjects.

We define S^X to be the actual average TMT scores and $\tilde{S}^X$ to be the estimated average TMT scores for the individual subject left out of the estimation of the global parameter values in Eq. (5.36). The means and standard deviations of the resulting differences in the actual and estimated average TMT scores $S^X - \tilde{S}^X$ using the estimated global parameter values for each of the 23 subject for TMT-A and TMT-B were:

$$
\begin{aligned}
&S^A - \tilde{S}^A = 0.10 \pm 12\,\text{s},\\
&S^B - \tilde{S}^B = 0.017 \pm 18\,\text{s}.
\end{aligned} \tag{5.37}
$$

We can compare the values in Eq. (5.37) to the means and standard deviations of the errors when all 23 subjects are fit using a single model:

$$
\begin{aligned}
&S^A - \tilde{S}^A = -0.15 \pm 11\,\text{s},\\
&S^B - \tilde{S}^B = 0.15 \pm 15\,\text{s}.
\end{aligned} \tag{5.38}
$$

The errors in the case where the model is fit using 22 subjects and the estimated global parameters were used to estimate TMT performance for the remaining subject were comparable to the errors when all 23 subjects were used to estimate the global parameter values.

5.11.2 Appendix 2

We can reconsider the analysis in Chapter 3 and this paper using a simpler analysis of SH rounds. In the simpler analysis, we use only average observed movement times for the TMT-A-like and TMT-B-like rounds used for analysis in Chapter 3 and in this paper rather than characteristic recall, search, and motor times. We denote the average movement times by t^A and t^B. Using the notation in this paper, the model we fit is:

$$\begin{cases} \left\langle S^A \right\rangle = 25c_0 + 25c_1 t^A + \theta \left\langle N^A \right\rangle \\ \left\langle S^B \right\rangle = 25c_0 + 25c_1 t^B + \theta \left\langle N^B \right\rangle. \end{cases} \tag{5.39}$$

This model fit with R^2 = 0.82 and p < 0.0001; inspection of the 95% confidence intervals for the coefficient estimates showed that all the parameter values were statistically significant. The parameter values were:

$$\begin{aligned} c_0 &= -1.7\,\text{s}, \\ c_1 &= 2.5, \\ \theta &= 28\,\text{s}. \end{aligned} \tag{5.40}$$

So, denoting the average movement times during TMT by T^A and T^B, we find that SH movements transform into TMT movements according to the relationship:

$$T^X = [-1.7\,\text{s}] + 2.5t^X. \tag{5.41}$$

We observe that the model in Eq. (5.39) performs somewhat better than the model in Eq. (5.23) where $\gamma^A = \gamma^B = 1$ that had R^2 = 0.80 and p < 0.0001, but somewhat worse than the model in Eq. (5.29) where $\gamma^A = 1$ but γ^B is free that had R^2 = 0.87 and p < 0.0001.

As we did for the models in Eqs. (5.23) and (5.29) above, we can look at how the model would perform in the case where subjects made no errors on TMT. We again restricted to the 16 subjects that had at least one error-free administration of TMT. We fit a truncated version of the model in Eq. (5.29) lacking the terms in θN^A and θN^B, and used the average of all error-free TMT administrations for the test scores. The model fit with R^2 = 0.61 and p < 0.0001, and estimated global parameter values of c_0 = -2.5 s and

c_1 = 3.3. Inspection of the confidence intervals for the coefficient estimates showed that all the estimated parameter values were statistically significant. We again observe that the model in Eq. (5.39) performs somewhat better than the model in Eq. (5.23) where γ^A = γ^B = 1 that had $R^2 = 0.54$ and $p < 0.0001$. However, in this case, the model in Eq. (5.29) where γ^A = 1 but γ^B is free that had $R^2 = 0.80$ and $p < 0.0001$ performs substantially better. In this case, SH movements transform into TMT movements according to the relationship:

$$T^X = \left[-2.5\text{s}\right] + 3.3t^X. \tag{5.42}$$

The model using the average observed movement times in SH, t^A and t^B, performs better than the model in Eq. (5.23) for the purpose of estimating the TMT scores because the model in t^A and t^B, implicitly includes the contribution of dual-tasking during the motor stage while this is left out in the model in Eq. (5.23). However, the more detailed analysis developed in Chapter 3 and in this paper performs better for the purpose of estimating the TMT scores when dual-tasking is allowed as is the case in the model in Eq. (5.29). We can make sense of the forms of the transformations in Eqs. (5.41) and (5.42) in terms of the additive stages model we developed in Chapter 3 and this paper. The models in Eqs. (5.41) and (5.42) transform the averge SH movement times, while the models developed in Chapter 3 and this paper transform each of the stages separately to produce the estimated movement times in TMT. In terms of the additive stages model, we can identify the large negative value c_0 as a necessary correction for stages that have been transformed to too large of a value using the coefficient c_1.

The aim of developing the connect-the-dots model in Chapter 3 and of modifying it in this paper to make it consistent with the observations that we have made in Chapter 4 is not to simply produce an in-home estimator of TMT performance as represented entirely by the scores on TMT. The aim is to produce a physical model that can describe the entire behavior of the subject completing the connect-the-dots task as it appears in a number of situations (in particular in SH and TMT). This physical model takes the form of an additive stages model where we can monitor the performance of each stage separately. By monitoring the subject's performance of each of the stages through measurements of the cognitive and motor parameters τ_R^A, τ_R^B, τ_S^A, τ_S^B, and τ_M , we aim to arrive at a more detailed description of the subject than is available through simply monitoring the average movement times in SH, t^A and t^B. Nevertheless, it is important to show that we can produce an estimate of performance on TMT, as TMT is an established clinical instrument.

Conclusion

Chapter 6 – Conclusion and Future Directions

6.1 Conclusion

In this thesis, we have looked at three techniques for user-centered, in-home monitoring of cognitive performance using available cost-effective technologies. We have made measurements of the walking speed in the home using an inexpensive system of passive infrared motion sensors placed in the home. We have made measurements from which we can estimate TMT performance in the home by observing the subject's interactions with a personal computer using both a computer game and everyday, real-life computer usage. We have validated the in-home monitoring techniques using two established clinical performance measures: (1) the walking speed, and (2) the Trail-Making Test. Finally, we have shown that the data obtained by observing in-home computer usage support a model of TMT performance in which the subject dual-tasks set-switching and movement during TMT-B.

6.1.1 Part I – In-Home Monitoring of Walking Speed

In Part I, we have developed a technique for monitoring of walking speed in the home using a system of passive infrared motion sensors.

In Chapter 2, we have presented a technique for measuring the walking speed v in-home using a system of PIR sensors. As we have shown in Chapter 1, the walking speed has been shown to be an indicator of a variety of aspects of health and performance in older adults including: survival, [16, 17] health, [13] risk of future hospitalization, [18] risk of cognitive impairment [20] and dementia, [21] and disability. [22, 23] The technique that we have presented in Chapter 2 allows one to monitor the walking speed v continuously as an indicator of these various health and performance issues.

6.1.2 Part II – In-Home Monitoring of Trail-Making Test Performance

In Part II, we have developed two techniques of monitoring a subject's cognitive performance in the home using the subject's interactions with a computer. We have also shown that the data obtained using these techniques support a model in which the subject dual-tasks set-switching and movement during TMT-B.

In Chapter 3, we have presented a technique for measuring the cognitive and motor parameters $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, τ_S^B, and b^{SH} in-home using the SH computer game. We have facilitated the analysis of SH game-play by constructing a computational model – the connect-the-dots model – to describe the process of playing SH. We have also constructed estimators for performance on TMT using these cognitive and motor performance parameters. As we have shown in Chapter 1, the TMT performance has been shown to be clinically useful: in the diagnosis of many neurological conditions, [33] for measuring of cognitive and set-switching ability, [36] and for measuring executive function. [37] The technique that we have presented in Chapter 3 allows one to monitor the TMT performance continuously and thus monitor cognitive and set-shifting ability, and executive function continuously. It also allows for a more detailed diagnosis of observed problems by providing a more detailed analysis of a subject's performance than does TMT due to the separate measurement of each of the cognitive and motor parameters.

In Chapter 4, we have presented a technique for measuring the cognitive and motor parameters $\langle \rho \rangle$, $\tilde{a}^{I}$, $b^{MD,I}$, $\tilde{a}^{II}$, and $b^{MD,II}$ using in-home MD. We have also constructed estimators for performance on TMT using these cognitive and motor performance parameters. We have observed that the cognitive and performance parameters perform poorly in estimating performance on TMT-A but much better in estimating performance on TMT-B. The technique that we have presented in Chapter 4 allows one to monitor continually those aspects of TMT-B performance that are related closely to the control and movement of the hand.

In Chapter 5, we have argued that the reason that the parameters measured in Chapter 4 perform better in estimating TMT-B than in estimating TMT-A is due to the subjects dual-tasking set-switching with movement during TMT-B causing movements to be made more slowly. Following this observation, and after reviewing the data used in Chapter 3, we have modified the connect-the-dots model developed in Chapter 3 to allow the dual-tasking of the set-switching and motor stages during TMT-B. This has allowed the description of TMT made using the connect-the-dots model to capture the observations in both Chapters 3 and 4.

6.1.3 Connect-the-Dots Model

In Chapter 3, we have constructed the connect-the-dots model to understand how an older adults plays the SH computer game, and have used the model to generate measures of performance form play of SH. This initial version of the connect-the-dots model presented in Chapter 3 consists of three additive stages: (1) recall and update, (2) search, and (3) motor. In Chapter 4, we have used the connect-the-dots model as a model to understand in-home MD qualitatively. In Chapter 5, we have observed that the data we have appear to support the idea that mouse movements take longer during TMT-B than during TMT-A. To account for this observation, we have modified in Chapter 5 the connect-the-dots model by dividing the recall and update stage into two stages: (1) set-switching stage, and (2) recall and update stage. We have accounted for the longer movement times during TMT-B by allowing the subject to perform set-switching as a dual-task with the motor stage causing the subject to make the movements more slowly. We now summarize the final form of the connect-the-dots model developed over Chapters 3, 4, and 5 in detail.

We characterize a general connect-the-dots task as having n targets and d distractors arrayed on a page or computer screen. The targets are labeled using elements from some number of sets, and a trail must be drawn through the targets in an indicated order. In the sequence of targets, the transitions between some targets may involve set-switching, and the transitions between other might not. Elements from each set appear in a fixed ascending or descending sequence, we are simply allowing an interweaving of sets in the overall target sequence. The distances between consecutive targets in the sequence are values D_{ν} and the widths of the targets are (possibly varying) values W_{ν}. The task begins with the subject's pencil, pen, or computer pointer at a known position.

We describe the process of drawing the trail from target $\nu - 1$ to target ν. The process of selecting target ν requires the subject complete a sequence of four additive stages: (1) set-switching, (2) recall and update, (3) search, and (4) motor. We allow the subject to dual-task the set-switching stage with the motor stage from the previous movement to a target if the subject likes, bearing in mind that dual-tasking of set-switching and movement is optional.

The subject must perform set-switching if the labels of targets $\nu - 1$ and ν come from different sets. A subject switches sets when the subject changes focus from the set to which the label of target $\nu - 1$ belongs to the set to which the label of target ν belongs. This process takes some amount of time with an expected value of τ_{Sw}. The quantity τ_{Sw} is the *characteristic set-switching time*. We address this process with more detail in Chapter 5. The expected set-switching time is:

$$\langle T_{Sw} \rangle = \tau_{Sw}. \tag{6.1}$$

This stage may be dual-tasked with the motor stage of the previous movement. This dual-tasking is optional.

In Chapter 5, we attribute perseverative errors on TMT (i.e. errors in which the subject fails to alternate between the categories of letters and numbers in TMT-B) [144, 145] to a failure to carry out the set-switching stage correctly.

Once the subject is working with the correct set, the subject must determine the next element in the sequence for that set. This process takes some amount of time with an expected value of τ_R. The quantity τ_R is the *characteristic recall and update time*. We address this process with more detail in Chapters 3 and 5. In Chapter 3, we folded the set-switching stage into the recall and update stage, while in Chapter 5, we separated the two as we do here. The expected recall and update time is:

$$\langle T_R \rangle = \tau_R. \tag{6.2}$$

In Chapter 5, we attribute sequential errors on TMT (i.e. errors in which the next element in the search string in either TMT-A or TMT-B is omitted) [144, 145] to a failure to carry out the recall and update stage correctly.

Having decided what the next label in the target sequence is, the subject next searches for the next target. We assume the subject has perfect memory of previously selected targets but otherwise no memory of the positions of the remaining targets or the distractors. The subject searches the remaining targets and distractors at random until the next target is found. Each step of the search takes a time τ_S. The quantity τ_S is the *characteristic search time*. We address this process with more detail in Chapter 3. The expected search time is:

$$\langle T_S \rangle = \left((n - \nu + d + 1) / 2 \right) \tau_S. \tag{6.3}$$

In Chapter 5, we attribute proximity errors on TMT (i.e. errors in which the subject proceeds to an incorrect nearby target in either TMT-A or TMT-B) [144, 145] to a failure to carry out the search stage correctly.

Once the subject finds the next target, the subject must move from the present position to the target just located. The subject does this according to Fitts' law and is characterized by the Fitts' law motor parameters a and b. The expected motor time is:

$$\begin{aligned} \langle T_M \rangle &= a + b \log_2 \left(D_\nu / W_\nu + 1 \right) \\ &\approx \tau_M \cdot \left(D_\nu / W_\nu \right)^{1/3}. \end{aligned} \tag{6.4}$$

The two-parameters form of Fitts' law in Eq. (6.4) is the form used in Chapters 3 and 4, while the single-parameter approximation to Eq. (6.4) is an approximation that we have developed in Chapter 5.

We assume that, during the motor stage, the subject always moves to the target decided upon by the end of the previous stages. Motor stage errors involve failing to end the movement within the region of the target that the subject is moving to by either undershooting or overshooting the target during the movement.

6.1.4 Using the Three Techniques Together

Taken together, the three in-home monitoring techniques presented in Chapters 2, 3, and 4 provide a characterization of a subject's performance in terms of eleven measured parameters: v, $\tau_R^A + a$, $\tau_R^B + a$, τ_S^A, τ_S^B, $\langle \rho \rangle$, $\tilde{a}^I$, $\tilde{a}^{II}$, b^{SH}, $b^{MD,I}$, and $b^{MD,II}$. Although we have not done so in this thesis, we may modify the techniques used in Chapters 3 and 4 to use the approximate single-parameter form of Fitts' law given in Eq. (6.4). This form approximates the two parameter form of Fitts' law in the motor parameters a and b using a single parameter form with motor parameter τ_M., Using this approximation, the cognitive and motor parameters measured in the technique in Chapter 3 become: τ_R^A, τ_R^B, τ_S^A, τ_S^B, and τ_M^{SH}. The cognitive and motor parameters measured in the technique in Chapter 4 become: $\langle \rho \rangle$, $\tau_M^{MD,I}$, and $\tau_M^{MD,II}$. Using this approximation, a subject monitored using all three techniques would now be characterized by nine measured parameters: v, τ_R^A, τ_R^B, τ_S^A, τ_S^B, $\langle \rho \rangle$, τ_M^{SH}, $\tau_M^{MD,I}$, and $\tau_M^{MD,II}$.

When the three techniques presented in Chapters 2, 3, 4, and 5 are all used to monitor a single subject, we are able to combine the measurements made using the three techniques (either 11 or 9 cognitive and motor parameters) to produce a single picture of the subject's performance. The picture that we build is one that combines information about how subject walks with information about how a subject completes the connect-the-dots task. This information takes the form of how quickly the subject: (1) walks, (2) performs set-switching, (3) recalls a symbol in a sequence, (4) performs a visual search, (5) moves a pencil, pen, or computer mouse while playing SH, and (6) moves a pencil, pen, or computer mouse when going about everyday activities. Thus, the picture we build of the subject is one of the times the subject takes to carry out a variety of behaviors. The aim of monitoring, then, is to detect significant slowing in the performance of one or more of the monitored behaviors. By noting which activities have slowed significantly and which have not, we may arrive at a detailed description of the subject's decline in performance.

6.2 Future Directions

We conclude by going over a number of possible future directions for extending the research that we have presented in this thesis.

6.2.1 Measure Walking Cadence In-Home

Grieve's law [146] provides an empirical relationship between the walking speed and the step-size of the form:

$$s \sim v^{0.42}. \quad (6.5)$$

We can augment the technique for measuring walking speed by instrumenting shoes worn by the subjects in the home to measure when the subject takes a step. The measurement of the intervals between steps provides an in-home measurement of the walking cadence (the number of steps in a given time period). If these measurements of when the subject takes a step are time-aligned with the sensor data from the PIR sensor line, then we can obtain the cadences for walks through the sensor line. The walking speed v, step-size s, and cadence c must satisfy the relationship:

$$s = v / c. \quad (6.6)$$

Thus, by combining measurements of walking speed and walking cadence, we may obtain estimates of the parameters in Grieve's law.

6.2.2 Augment Computer Game Suite

We can augment the computer game suite that includes SH with further measures that we expect to relate to the various additive stages of the connect-the-dots model of SH. First, we can include a computer game designed to mimic DST, and create a model that relates performance on the computer game version of DST with performance on DST itself. As DST involves the remembering of an assignment of digits to symbols, we expect a model of DST to bear some relationship to the recall stage of the connect-the-dots model used to describe SH and TMT. Second, we can use a webcam to try to detect saccades of the eye during play of SH. By counting the saccades, we can produce an estimate of the actual number of steps in search during SH, and use this information to produce a better empirical estimate of the characteristic search time. Finally, one could add a further game that amounts to a straightforward implementation of a laboratory measurement of Fitts' law. The game would consist of targets of various widths appearing at various positions on the computer screen which the subject must click on. This would provide a more solid characterization of motor performance than that estimated using SH play, and would allow principled investigation of changes of motor performance during play of SH due to either dual-tasking or the presence of distractors.

6.2.3 Analyze Errors Made During SH

There is reason to believe that the numbers of errors made during TMT contain important information about subject performance, and we expect the probabilities with which a subject makes errors during SH contain related information. We have limited the use of the available data on errors made during SH to a quick summary in Chapter 5, where we have also related an existing classification of the types of TMT errors to stages in the connect-the-dots model. In Chapter 3, we have provided a number of avenues for exploring the SH error data.

6.2.4 Reduce In-Home MD Processing Time

We have designed the technique of measuring performance using in-home MD presented in Chapter 4 to work with the limited computational resources that were available for the analysis there. Improvements in the way the data are stored or are processed would lower the time required to analyze the data, as would the availability of more computational resources. Lowered processing times would allow more sophisticated analyses of the data to be completed in reasonable amounts of time. Potential improvements to the analysis given reduced processing times are given in Chapter 4.

6.2.5 Measure Dual-Tasking During Mouse Movement

For mouse-movements, we expect there to be a slowdown in the movement when dual-tasking is present. If we can classify mouse-movement times into those that take longer or shorter times given all other relevant factors (such as the distance moved for a mouse-movement), then we can potentially generate an estimate of how much a subject's movements slow when dual-tasking. In cases where we can assume the cognitive part of the dual-task is the same across subjects, then we try to differentiate subjects by the degree to which movement slows down when dual-tasking.

6.2.6 Optimal Control Model of Mouse Movements

In Chapter 4, we have used a simple optimal control model of computer mouse movements to divide the observed mouse movements into two classes. For the high performing older adults examined in that Chapter, the classification does not appear to be useful. However, the same sort of analysis used in Chapter 4 may prove useful for a lower performing set of older adults. The two classes may also prove useful for classifying pauses between mouse movements. In the discussion in Chapter 4, we have proposed using a more general model of mouse movements to provide a more detailed description of mouse movements in order to arrive at a better division of mouse movements into classes. We would like to use such a better classification of mouse movements to provide a more detailed description of how a subject uses a computer. However, as we have characterized mouse movements in Chapters 3, 4, and 5 using Fitts' law, it is important that we know how to relate a detailed model of individual movements to Fitts' law.

We can set out a brief outline of the optimal control formalism in which the model in Chapter 4 and generalizations of it fit. The movement problem is one of finding the movement orbit $x(t)$ that minimizes some cost functional $J[\cdot]$ subject to some set of initial and final conditions. In the case of mouse movements, the initial and final conditions are that the movement begin at rest at some position $-D$ and end at rest at the origin. Mathematically, we express the optimal control problem as:

$$
\begin{aligned}
J[x] = \int_0^T L(x,\dot{x},\ddot{x},\dddot{x})\,dt = \int_0^T \left(\frac{1}{2}\dddot{x}^2 - \Phi(x,\dot{x},\ddot{x})\right)dt,& \\
x(0) = -D, \quad x(T) = 0,& \\
\dot{x}(0) = v_0, \quad \dot{x}(T) = v_T,& \\
\ddot{x}(0) = a_0, \quad \ddot{x}(T) = a_T.&
\end{aligned}
\tag{6.7}
$$

The integrand $L(x,\dot{x},\ddot{x},\dddot{x})$ of the cost functional is the Lagrangian of the system. We minimize the cost functional in Eq. (6.7) by setting the first variation to zero. This is done by solving the following differential equation (see e.g., [140] Part I Chapter 4):

$$\frac{d^3}{dt^3}\frac{\partial L}{\partial \dddot{x}}-\frac{d^2}{dt^2}\frac{\partial L}{\partial \ddot{x}}+\frac{d}{dt}\frac{\partial L}{\partial \dot{x}}-\frac{\partial L}{\partial x}=0. \tag{6.8}$$

The orbit $x(t)$ of the movement is the solution to Eq. (6.8) that satisfies the initial and final conditions in Eq. (6.7). Eqs. (6.7) and (6.8) provide the Lagrangian formulation of the optimal control problem. There is an alternative formulation of the optimal control problem called the Hamiltonian formulation. This formulation is a mathematically dual and equivalent formulation to the Lagrangian formulation. We construct the Hamiltonian formulation by first defining the *generalized coordinates* vector $Q(t)$:

$$\begin{gathered} Q^{\mathrm{T}}=[q_1 \quad q_2 \quad q_3]=[x \quad \dot{x} \quad \ddot{x}], \\ \dot{Q}=\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} Q+\begin{bmatrix} 0 \\ 0 \\ u \end{bmatrix}. \end{gathered} \tag{6.9}$$

The quantity $u(t)$ is the control of the system and, in the case of Eq. (6.9), satisfies $u=\dddot{x}$. We next define the *generalized momenta* vector $P(t)$:

$$P^{\mathrm{T}}=[p_1 \quad p_2 \quad p_3]. \tag{6.10}$$

The vectors $Q(t)$ and $P(t)$ together provide a complete description of the state of the system at any time. We calculate the Hamiltonian by taking the Legendre transform (see e.g., [147]) of Eq. (6.7). The Legendre transform of the Lagrangian has the form:

$$H=P^{\mathrm{T}}\dot{Q}-L. \tag{6.11}$$

The optimal orbit $x(t)$ satisfies the equations (see e.g., [148] Chapter 5):

$$\dot{Q}=\frac{\partial H}{\partial P}, \quad \dot{P}=-\frac{\partial H}{\partial Q}, \quad \frac{\partial H}{\partial u}=0. \tag{6.12}$$

The first two equations in Eq. (6.12) are Hamilton's equations. Hamilton's equations provide a description of how the state of the system evolves in time. Given an expression for the Hamiltonian, we may use Eq. (6.12) to calculate the form of the generalized momenta of the system:

$$P=\begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}=\begin{bmatrix} \overset{\cdot\cdot\cdot\cdot\cdot}{x} \\ -\ddddot{x} \\ \dddot{x} \end{bmatrix}-\begin{bmatrix} 0 & 1 & -d/dt \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}\frac{\partial \Phi}{\partial X}. \tag{6.13}$$

Finally, Pontryagin's minimum principle (see e.g., [148] Chapter 5) tells us that the Hamiltonian takes a constant value when calculated along an optimal orbit.

$$H=\Psi. \tag{6.14}$$

We call the constant of the motion Ψ the *generalized energy*.

In the discussion of Chapter 4, we suggested a more general formulation of the optimal control movement of mouse movements of the form:

$$\begin{gathered} L=\frac{1}{2}\dddot{x}^2+\phi_{00}+\begin{bmatrix} 0 \\ \phi_{02} \\ \phi_{03} \end{bmatrix}^{\mathrm{T}}\begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix}-\frac{1}{2}\begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix}^{\mathrm{T}}\begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} \\ 0 & \phi_{22} & \phi_{23} \\ 0 & 0 & \phi_{33} \end{bmatrix}\begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix}, \\ x(0)=-D, \quad x(T)=0, \\ \dot{x}(0)=0, \quad \dot{x}(T)=0, \\ \ddot{x}(0)=0, \quad \ddot{x}(T)=0. \end{gathered} \tag{6.15}$$

We calculate the equation of motion for the system in Eq. (6.15) using Eq. (6.8) and find:

$$\overset{\cdot\cdot\cdot\cdot\cdot\cdot}{x}+\phi_{33}\ddddot{x}-\left(\phi_{22}-\phi_{13}\right)\ddot{x}+\phi_{11}x=0. \tag{6.16}$$

The Hamiltonian in this case is:

$$H=\frac{1}{2}P^{\mathrm{T}}\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}P+P^{\mathrm{T}}\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}Q+\frac{1}{2}Q^{\mathrm{T}}\begin{bmatrix} \phi_{11} & 0 & \phi_{13} \\ 0 & \phi_{22} & 0 \\ 0 & 0 & \phi_{33} \end{bmatrix}Q=\Psi. \tag{6.17}$$

Evaluating the Hamiltonian at time zero, we find:

$$\frac{1}{2}\dddot{x}(0)^2+\frac{1}{2}\phi_{11}D^2=\Psi. \tag{6.18}$$

The initial value of the jerk $\dddot{x}(0)$ is approximately (see Section 6.3):

$$\dddot{x}(0)\approx\left(60-24\phi_{33}T^2-\frac{\phi_{11}T^6}{120}+\frac{54\phi_{33}{}^2T^4}{5}+\frac{9\phi_{11}\phi_{33}T^8}{20}\right)\frac{D}{T^3}. \tag{6.19}$$

Combining Eqs. (6.18) and (6.19), we find the distance moved D and the movement time T satisfy the polynomial equation:

$$1800-1440\phi_{33}T^2+816\phi_{33}{}^2T^4-\frac{\Psi}{D^2}T^6+27\phi_{11}\phi_{33}T^8+\frac{\phi_{11}{}^2}{28800}T^{12}\approx 0. \tag{6.20}$$

We expect Eq. (6.20) to be consistent with Fitts' law. To do this, we must include the target width W in Eq. (6.20) so that every appearance of D becomes D/W. We can do this by requiring the generalized energy Ψ to satisfy:

$$\Psi=\frac{1800}{\tau_M{}^6}W^2. \tag{6.21}$$

Combining Eqs. (6.20) and (6.21) in the special case where $\phi_{11}\approx 0$ and $\phi_{33}\approx 0$, we arrive at an approximate form of Fitts' law:

$$T\approx\tau_M\cdot\left(\frac{D}{W}\right)^{1/3}. \tag{6.22}$$

Eq. (6.22) is a special case of Kvålseth law for rapid, targeted movements. [143] Eq. (6.22) provides a reasonably good approximation to Fitts' law in the form we have used in Chapters 3 and 4 and is the approximate form of Fitts' law that we have used in Chapter 5 and Eq. (6.4). We observe that models of the form given in Eq. (6.15) are consistent with Fitts' law given the assumption that mouse movements satisfy Eq. (6.21).

We have left open the nature of the cost represented by the functional $J[\cdot]$. One choice for the cost is the metabolic work of the movement. In this case the minimization of the cost corresponds to making the movement so that the minimal amount of metabolic work is expended. We look at a model of human movement describing an individual exercise in which $J[\cdot]$ represents the metabolic work in [149].

6.3 Appendix

We would like to find an approximation for the orbit $x(t)$ of a computer mouse movement that begins motionless at a position $-D$ and ends motionless at the origin at some time T. We begin with the equation of motion given in Eq. (6.16). Although Eq. (6.16) can be solved exactly using standard mathematical technique, it is more convenient to generate an approximate solution to Eq. (6.16) in the form of a truncated Taylor series expansion about time t = 0:

$$\begin{aligned} x(t) &\approx x(0) + \dot{x}(0)t + \frac{1}{2}\ddot{x}(0)t^2 + \frac{1}{6}\dddot{x}(0)t^3 \\ &+ \frac{1}{24}\ddddot{x}(0)t^4 + \frac{1}{120}x^{(5)}(0)t^5 + \frac{1}{720}x^{(6)}(0)t^6. \end{aligned} \tag{6.23}$$

The unknown coefficients on the RHS of Eq. (6.23) must satisfy Eqs. (6.15) and (6.16), and as there are seven unknown coefficients in Eq. (6.23) and seven equations in Eqs. (6.15) and (6.16), there is a unique solution. Combining Eqs. (6.15) and (6.23) using the conditions for time t = 0, and evaluating Eq. (6.16) at time t = 0 gives the following system of equations:

$$
\begin{aligned}
x(t) &\approx -D + \frac{1}{6}\dddot{x}(0)t^3 + \frac{1}{24}\ddddot{x}(0)t^4 + \frac{1}{120}x^{(5)}(0)t^5 + \frac{1}{720}x^{(6)}(0)t^6, \\
\dot{x}(t) &\approx \frac{1}{2}\dddot{x}(0)t^2 + \frac{1}{6}\ddddot{x}(0)t^3 + \frac{1}{24}x^{(5)}(0)t^4 + \frac{1}{120}x^{(6)}(0)t^5, \\
\ddot{x}(t) &\approx \dddot{x}(0)t + \frac{1}{2}\ddddot{x}(0)t^2 + \frac{1}{6}x^{(5)}(0)t^3 + \frac{1}{24}x^{(6)}(0)t^4, \\
x^{(6)}(0) &+ \phi_{33}\ddddot{x}(0) = \phi_{11}D.
\end{aligned} \tag{6.24}
$$

Evaluating Eq. (6.24) at $t = T$ gives:

$$
\begin{aligned}
D &\approx \frac{1}{6}\dddot{x}(0)T^3 + \frac{1}{24}\ddddot{x}(0)T^4 + \frac{1}{120}x^{(5)}(0)T^5 + \frac{1}{720}x^{(6)}(0)T^6, \\
0 &\approx \frac{1}{2}\dddot{x}(0)T^2 + \frac{1}{6}\ddddot{x}(0)T^3 + \frac{1}{24}x^{(5)}(0)T^4 + \frac{1}{120}x^{(6)}(0)T^5, \\
0 &\approx \dddot{x}(0)T + \frac{1}{2}\ddddot{x}(0)T^2 + \frac{1}{6}x^{(5)}(0)T^3 + \frac{1}{24}x^{(6)}(0)T^4, \\
x^{(6)}(0) &+ \phi_{33}\ddddot{x}(0) = \phi_{11}D.
\end{aligned} \tag{6.25}
$$

We can rewrite the system of equations in Eq. (6.25) compactly in matrix form as:

$$
\begin{bmatrix} 720D \\ 0 \\ 0 \\ \left(\phi_{11}T^6\right)D \end{bmatrix} \approx \begin{bmatrix} 120 & 30 & 6 & 1 \\ 60 & 20 & 5 & 1 \\ 24 & 12 & 4 & 1 \\ 0 & \left(\phi_{33}T^2\right) & 0 & 1 \end{bmatrix} \begin{bmatrix} \dddot{x}(0)T^3 \\ \ddddot{x}(0)T^4 \\ x^{(5)}(0)T^5 \\ x^{(6)}(0)T^6 \end{bmatrix}. \tag{6.26}
$$

We note that the values $\phi_{11}T^6$ and $\phi_{33}T^2$ are unitless, that is they are simply real numbers. We can simplify Eq. (6.26) using standard row operations. First, we use the third equation to eliminate terms in $x^{(5)}(0)$ from the first and second equations:

$$
\begin{bmatrix} 2880D \\ 0 \\ 0 \\ \left(\phi_{11}T^6\right)D \end{bmatrix} \approx \begin{bmatrix} 336 & 48 & 0 & -2 \\ 120 & 20 & 0 & -1 \\ 24 & 12 & 4 & 1 \\ 0 & \left(\phi_{33}T^2\right) & 0 & 1 \end{bmatrix} \begin{bmatrix} \dddot{x}(0)T^3 \\ \ddddot{x}(0)T^4 \\ x^{(5)}(0)T^5 \\ x^{(6)}(0)T^6 \end{bmatrix}. \tag{6.27}
$$

Next, we use the fourth equation to eliminate terms in $x^{(6)}(0)$ from the remaining equations:

$$
\begin{bmatrix} \left(2880+2\left(\phi_{11}T^{6}\right)\right)D \\ \left(\phi_{11}T^{6}\right)D \\ -\left(\phi_{11}T^{6}\right)D \\ \left(\phi_{11}T^{6}\right)D \end{bmatrix} \approx \begin{bmatrix} 336 & 48+2\left(\phi_{33}T^{2}\right) & 0 & 0 \\ 120 & 20+\left(\phi_{33}T^{2}\right) & 0 & 0 \\ 24 & 12-\left(\phi_{33}T^{2}\right) & 4 & 0 \\ 0 & \left(\phi_{33}T^{2}\right) & 0 & 1 \end{bmatrix} \begin{bmatrix} \dddot{x}(0)T^{3} \\ \ddddot{x}(0)T^{4} \\ x^{(5)}(0)T^{5} \\ x^{(6)}(0)T^{6} \end{bmatrix}. \tag{6.28}
$$

Finally, we use the second equation to eliminate terms in $\ddddot{x}(0)$ from the first equation leaving:

$$
\begin{aligned} &\left(336\left(20+\left(\phi_{33}T^{2}\right)\right)-120\left(48+2\left(\phi_{33}T^{2}\right)\right)\right)\dddot{x}(0)T^{3} \\ &\approx\left(\left(20+\left(\phi_{33}T^{2}\right)\right)\left(2880+2\left(\phi_{11}T^{6}\right)\right)-\left(48+2\left(\phi_{33}T^{2}\right)\right)\left(\phi_{11}T^{6}\right)\right)D. \end{aligned} \tag{6.29}
$$

This gives:

$$
\dddot{x}(0) \approx \left(\frac{7200+360\left(\phi_{33}T^{2}\right)-\left(\phi_{11}T^{6}\right)}{120+54\left(\phi_{33}T^{2}\right)}\right)\frac{D}{T^{3}}. \tag{6.30}
$$

The remaining terms $\ddddot{x}(0)$, $x^{(5)}(0)$, and $x^{(6)}(0)$ may be evaluated in a similar manner. If we assume that $\phi_{11}T^{6}$ and $\phi_{33}T^{2}$ is relatively small, then we can approximate Eq. (6.30) using a Taylor series expansion. Keeping to at most second order in $\phi_{11}T^{6}$ and $\phi_{33}T^{2}$, we find that Eq. (6.30) is approximately:

$$
\dddot{x}(0) \approx \left(60-24\phi_{33}T^{2}-\frac{\phi_{11}T^{6}}{120}+\frac{54\phi_{33}{}^{2}T^{4}}{5}+\frac{9\phi_{11}\phi_{33}T^{8}}{20}\right)\frac{D}{T^{3}}. \tag{6.31}
$$

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