ABSTRACT

LI, YINGJIE. Development of a Haptic-based Rey-Osterrieth Complex Figure Testing and Training System with Computer Scoring and Force-feedback Rehabilitation Functions. (Under the direction of Dr. Yuan-Shin Lee and Dr. David B. Kaber.)

This research develops a new system for assessment and rehabilitation of motor skills in Traumatic Brain Injury (TBI) patients. By using contemporary computing technologies, including virtual reality (VR), haptic devices and telecommunications, the system can work as an alternative to traditional labor intensive and expensive diagnosis and rehabilitation procedures for TBI patients. This study also introduces a general approach to the design and prototyping of a haptic-based VR System for motor skill assessment and rehabilitation.

The Rey-Osterrieth Complex Figure (ROCF) is a neuropsychological test that has been used to manually assess various cognitive operations, such as perceptual apprehension, attention and control, graphomotor coordination, etc. The focus of this research was on developing a VR-based ROCF test system incorporating a haptic interface with functions to support testing protocols, based on specific user requirements, and to facilitate automated scoring of tests and quantitative test result output. Computer-based tests have advantages over traditional paper-based tests for motor skill assessment including automated recording of complete behavior information in the drawing process, simplifying the job of examiners, and reducing biases in evaluations.

Haptic technology was used in the simulator as both an input and force feedback device. Haptic devices have the capability of recording user performance in six degrees of freedom (6 DOF) in the drawing process and providing force feedback in 3 DOF. This means they have the potential to provide user performance data on the traditional three dimensional

(3D) method of ROCF testing. Also users may experience a more realistic feeling of drawing when using the haptic device versus using a tablet or tablet PC.

To develop the ROCF scoring system, advanced technologies of handwriting/pattern recognition were reviewed and adapted. A software application was created for recording of freehand drawings, recognition of strokes and normalization of strokes for unit scoring. ROCF scoring and analysis reports can be generated automatically with the system.

The haptic-based VR system was extended in capability for motor skill rehabilitation. Numerical models were used to describe motor skill assessment results and to parameterize the rehabilitation training application. The prototype system demonstrates the potential for using advanced information and VR technology to build more effective and intelligent tools for healthcare.

This study identified the major challenges in developing a fully automated ROCF test system, including hardware options and criteria for choosing the proper devices for human performance. The software challenges are also identified and algorithms were developed for use in the system. The prototype system is expected to change the process of motor-skill evaluation in clinical practice.

Development of a Haptic-based Rey-Osterrieth Complex Figure Testing and Training System with Computer Scoring and Force Feedback Rehabilitation Functions

by
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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Industrial Engineering

Raleigh, North Carolina

2010

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DEDICATION

I dedicate this dissertation work to my parents, Jiawei Li and Xifen Bao, for their endless love and support. And this dissertation would be incomplete without mention of the support given me by my husband, Xuezhong Wang, to whom this work is also dedicated.

BIOGRAPHY

Yingjie Li was born in Jiangsu province in China in 1980. She received her B.S. (2003) degree in Mechanical Engineering and Automation from Shanghai Jiaotong University, Shanghai, P.R. China. In the fall of 2004, she began her doctoral studies in the Edward P. Fitts Department of Industrial and Systems Engineering at North Carolina State University, in the USA. Her research interests include haptic-based VR development, application of virtual reality (VR) in healthcare, computer aided design and manufacturing (CAD/CAM), 3D modeling for design and manufacturing, and human-computer/ haptic interface.

ACKNOWLEDGMENTS

I would like to express my deep appreciation and gratitude to my advisors, Dr. David B. Kaber, and Dr. Yuan-Shin Lee for their patience, suggestions, and encouragement during my academic and research work at North Carolina State University. Without their guidance and continuous support, I would never have finished my studies. I would like to thank Dr. Larry Tupler, Dr. Simon Hsiang, and Dr. Christopher G. Healey who served on my committee. I would also like to thank Dr. Rob St. Amant for his support and suggestions during my doctoral examination. I appreciate the committee's time and comments given to me to improve the quality of this dissertation. Their knowledge and commitment to the highest standards inspired and motivated me.

I wish to thank Prithima Reddy Mosaly and Wu Chen for their help on the study. I greatly appreciate and would like to thank my fellow students in both the manufacturing and ergonomics research groups: Yongfu Ren, Susana Lai-Yuen, Shiyong Lin, Deyao Ren, Apichart Boonma, Plawut Wongwiwat, Manida Swangnetr, Eui Seok Kim, Sathish Meenakshisundaram, Plamen Velinski, Yu Shu, Zongliang Jiang, Mohamed Sheik-Nainar, Xu Xu, Tao Zhang, Yulan Liang, Yu Zhang, Biwen Zhu, Jing Xu, Guk-Ho Gil, Shruti Bharat Gangakhedkar, and Michael Clamann for their valuable consultation, suggestions, advice and help during my research. Special thanks goes to Darrel Rice for his appreciated help during my experiment setup machining and assembling, and my TA assignment in the manufacturing lab.

I would also like to thank the National Science Foundation (NSF) for providing the grant to support part of the study. Although the views and opinions expressed in this paper are those of the author and do not necessarily reflect the views of the NSF.

My sincere thanks are also extended to my friends here at NCSU. Their support and friendship have enriched my years at NC State University, making my time here that much more wonderful and joyful.

Finally, I greatly appreciate my grandparents, parents, and Xuezhong for their love and support all these years. Their encouragement and inspiration have benefited and enriched my entire life.

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ACRONYMS

2D	2- Dimensional
3D	3-Dimensional
ANOVA	Analysis of Variance
APL	Abductor Pollicis Longus Muscle
BP	Back Propagation
DOF	Degree of Freedom
DoG	Difference of Gaussians algorithm
DTP	Digitizer Tablet/PDA
ECU	Extensor Carpis Unaris Muscle
EDM	Extensor Digitorum Muscle
EMG	Electromyograph
EMR	Electronic Medical Record
FAST	Feature from Accelerated Segment Test corner detection
FD	Flexor Digitorum Superficialis Muscle
GUI	Graphic User Interface
HCI	Human Computer Interaction
HMM	Hidden Markov models
ID3	Iterative Dichotomiser 3 algorithm
MIS	Minimally invasive surgery
MLP	Multi-Layer Perception

NA	Neuropsychological assessment
PCM	Programmable Constraint Machine
PD	Proportional/Derivative control
PDA	Personal digital assistant
PNN	Probabilistic Neural Networks
RBF	Radical Basis Function
RID	Immediate Recall and Delayed Recall test
ROCF	Rey-Osterrieth Complex Figure
SUSAN	Smallest Univalue Segment Assimilating Nucleus(SUSAN) algorithm
TBI	Traumatic Brain Injury
VR	Virtual Reality
VRE	Virtual Reality Environment

CHAPTER 1. INTRODUCTION

1.1. Motivation and Objective

1.1.1. Introduction to VR for TBI Patient Diagnosis and Treatment

Virtual reality (VR) was introduced into healthcare in the early 1990s, when people recognized the technology had the potential to provide assistance with complex medical data visualization during surgery and surgery planning [15]. Now the scope of VR applications in medicine has broadened to the areas of neuropsychological assessment and rehabilitation [8, 64, 66]. This study demonstrates how available, advanced VR technology can be used in healthcare for traumatic brain injury (TBI) patient diagnosis and rehabilitation.

With the rapid progress of haptic and computer recognition technology, development of a computer-based system for neuropsychological testing can make diagnosis processes much more accurate and easier to use. Computer-based tests have substantial advantages over traditional paper-based tests due to the fact that the computer can record complete information in a motor-control process, including variables that cannot be easily seen in traditional paper-based tests. Such a system can also simplify the job of examiners and reduce the affects of subjectivity in patient assessment. For example, time-to-task-completion can be accurately recorded by a computer program in real-time, so uneven pacing in skill execution and the rate of production over time can be captured and analyzed later. In paper based testing, this type of measurement can be accomplished by asking subjects to use different task implements and to switch implements at fixed intervals.

With this in mind, the objective of this work was to develop a VR-based computerized testing and training system. The system development was also motivated by the following:

- Current diagnosis and rehabilitation therapies for brain injured patients are costly. Professionally trained neuropsychologist and therapists are needed. The work time for each patient is long and depends on the nature of the assessment procedure and therapy.
- Major aspects of the professional work are knowledge-based and repetitive. A computer system has enormous potential in adapting comprehensive expert knowledge into a software system and providing assistance to clinicians in diagnosis and support for decision making process.

TBI patients typically go through a series of neuropsychological tests to specify impairment level attributable to their injury in various cognitive domains, including attention, memory, executive control, language, constructional praxis and motor functioning. Some tests include the Grooved Pegboard, Purdue Pegboard, Finger Oscillation Test, Serial Reaction Time Test, Handgrip Strength Test, Rey-Osterrieth Complex Figure (ROCF) (see Figure 1-1), Wechsler Adult Intelligence Scale-Third Edition Block Design and Digit Symbol Substitution Test, Behavioral Dyscontrol Scale, and the Halstead-Reitan Tactual Performance Test [41]. The new system renders and provides objective and effective scoring capability for the ROCF Test. This test requires patients to reproduce a complicated line drawing, first by copying and then from memory. Different motor skill functions, such as perceptual apprehension, visual construction, attention, planning, and spatial memory, can be evaluated based on the drawing result.

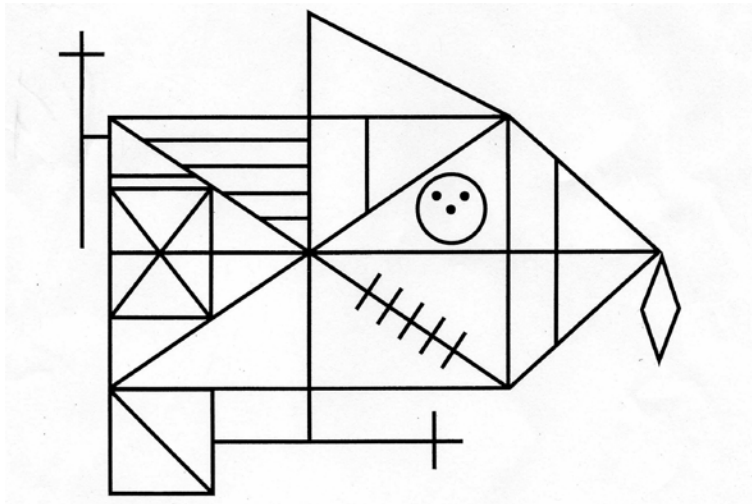


Figure 1-1. Rey-Osterrieth Complex Figure.

Yet another benefit of developing a VR-based haptic simulation for presenting the ROCF is that the evaluation of subject accuracy in motor tasks can be performed automatically by the computer system; whereas, in conventional paper and pencil tests, subject performance must be manually scored against a template.

1.2. Specific Aims

The specific aims of this project include developing a computer system that can record and score ROCF drawing results. With the rapid progress of haptic and computer recognition technology, development of a computer-based ROCF testing system may make the test more accurate and easier to use. The system also provides special features, such as scale, quantification, feature angles, deviations in line drawings etc., for diagnoses by neuropsychologists. With respect to drawing functions, the system allows for representation of the drawing task with different levels of difficulty and it can provide different levels of haptic force feedback assistance. By repeating drawing tasks with the system, it is expected that compensatory brain mechanisms may be triggered and reinforced to help TBI or stroke patients in recovery.

In this study, the functions of neuropsychological assessment and therapy have been integrated in the prototype system. This integration may benefit the treatment therapy in terms of patient progress tracking and support flexible, customized therapy design. It may also save time and money by reducing the information communication costs between diagnosis and rehabilitation processes. Figure 1-2 shows how the computerized system can reduce repetitive work of neuropsychologists (grey blocks). More importantly, it presents how various data can be organized in a database in order to support accuracy in communication between physicians. In this way, the developed system can be considered as a communication tool.

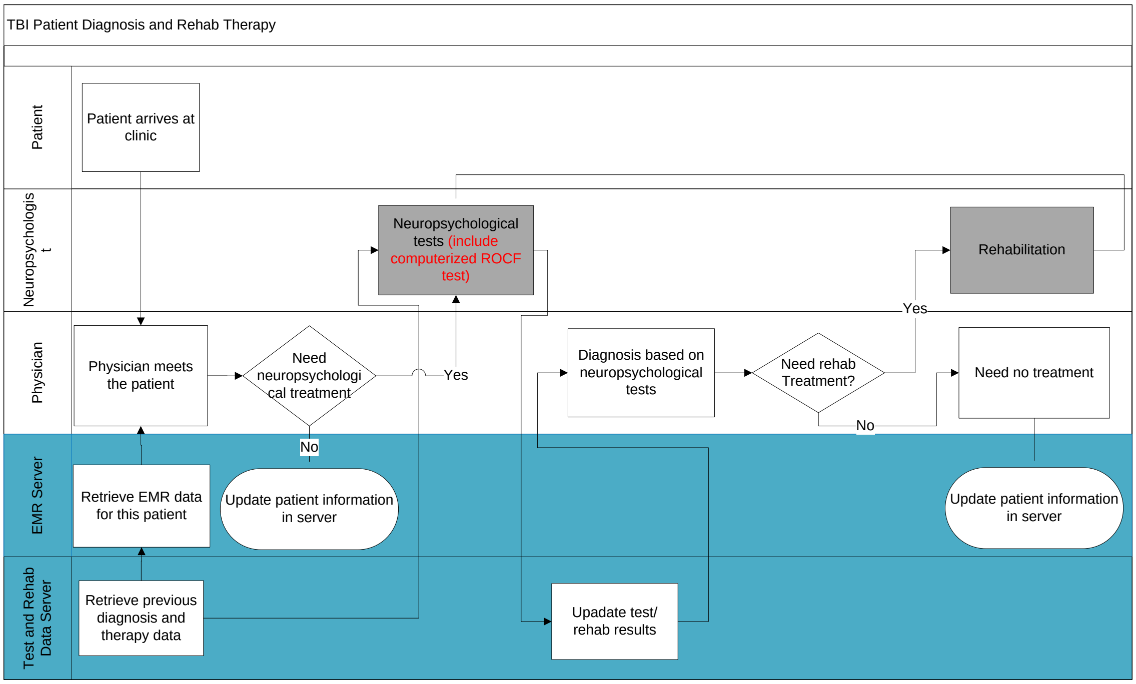


Figure 1-2. Data flow for patient diagnosis and rehabilitation therapy using computer-based system.

For the neuropsychologists, workload is reduced by automating testing and scoring processes. When performed on the VR system, the therapy process is simplified by the use of programmable parameter controls. The results of these processes can be sent to an external server and provide an extension to current Electronic Medical Record (EMR) systems content. Physicians can then review these data, along with the all other important medical information for a patient in order to prescribe a therapy regimen. The parameters of the system can then be set for a patient's therapy programming.

For physicians, this system provides assistance in two ways: (1) diagnosis data is more objective and accurate; and (2) communication with neuropsychologists is more effective. Physicians can retrieve data to support their decision making from the EMR system directly.

They can also monitor a patient's progress and adjust the treatment accordingly, on a regular basis. Beyond this, from the medical record management point of view, parameterized / computerized diagnoses and treatment plans are superior to paper records for documentation and organization of the medical records database.

1.3.Dissertation Organization

The remaining sections of this dissertation are organized as ten chapters. Chapter 2 discusses the research challenges of the project. Chapter 3 provides a literature review on VR in healthcare, the ROCF scoring system, current work of input devices in clinical practice and haptic-based medical-related applications, and online handwriting/pictogram recognition. Chapter 4 presents the hardware components and workstation design of the computer-based ROCF test system. The advantages of each device are also discussed. Chapter 5 presents an experiment comparing various haptic devices in the VR-based ROCF test. Chapter 6 presents the drawing recognition and scoring algorithm developed as part of the new system. Chapter 7 provides an introduction on how the software part of the system is used by clinicians. Chapter 8 presents a rehabilitation interface for use of the system with TBI patients. Chapter 9 presents a second experiment for validation of the software for scoring ROCF tests and facilitating data analysis. Finally, Chapter 10 presents the conclusion and future work.

CHAPTER 2. RESEARCH ISSUES

The system developed in this research includes two major parts: (1) the testing and rehabilitation interface, which is designed to support interaction with patients; and (2) the scoring and diagnosis interface, which supports interaction with clinicians. There are several research issues that need to be addressed in both parts of the system for operation.

2.1. Intuitive Interaction

The construction of a hardware setup should allow patients to interact with the computer system in an intuitive way. Current TBI diagnosis tests have been standardized based on research on human performance and motor skills required in those tests, as well as the mechanisms for performing the tests. The new system should not require user motor skills beyond those necessary to complete the tests. The physical performance and motor skill required to accomplish the VR-based test tasks should be similar to the performance requirements of the existing physical tests.

2.2. User Interface Design for Patients

The current ROCF drawing tests are conducted with pencil and paper. The test results are drawings on paper. One solution to automated scoring for clinicians is to digitize the test document by scanning paper drawings. However, this requires extra labor in hospitals or clinics for the scanning operation. Furthermore, diagnosis based on scanning results does not provide certain performance information, including drawing time, speed, feature sequencing, etc.

In the computer-based version of the ROCF, patients are required to draw directly on a display screen. The interface between the computer and the patients needs to support two-way interaction, which means the computer responds with visual feedback and haptic feedback in real time and patient performance can be recorded and quantified by the computer. The interaction the computer can develop with patients, in drawing includes providing realistic haptic sensations as part of drawing with paper and pencil.

2.3.Parameterization of Rehabilitation Process

The ROCF drawing and the training tests conducted using any computer workstation should be customized for patients through adjustable parameters of the system. Therefore, clinicians should be able to implement customized treatment regimens for each patient by defining system parameters settings for them. The types of parameters that can be customized are identified in this research. The implementation of controls for the parameters is also addressed.

2.4. Segmentation of User Input

For the automated ROCF scoring process, the first research challenge comes in the segmentation of user input in reproducing the figure. The recorded data is a series of points and times. It is possible to group the points into drawing strokes, which start from a virtual pen touching the drawing surface and end with the virtual pen being lifted from the drawing surface. However, scoring of more detailed segments is required.

As an example of the segmentation process, in Figure 2-1 the stroke from Point 1 to Point 4 is drawn continuously without the pen leaving the drawing surface. However, the line segment from Point 2 to Point 3 is part of scoring Unit 6, which is the small rectangle sharing the left side with the large rectangle (Unit 2). Therefore, the line segment between Point 2 to Point 3 must be identified.

2.5. Imprecision and Variation in Freehand Drawings

The ROCF scoring process relies on the identification and examination of very detailed features, such as figure corner angles, relations between specific lines, etc. The objective of computer-based recognition is to identify each drawing feature for scoring. This can be very demanding from programming and computational perspectives, as features in freehand drawings can be imprecise. For example, in Figure 2-1 the intersection of the top of the large rectangle and the side lines are major scoring points. However, in the example drawing, there are more than one unwanted intersections in the circled area close to the desired intersection. This makes the recognition process very difficult for a computer system.

Another common imprecision in ROCF testing occurs in the circle drawing. The recognition of this unit relies on pattern matching of a circle, and the circle can be irregular in shape in freehand drawings (see Figure 2-3 for another example). Finally, variations in drawing position, scale and proportion can also be critical factors in automated feature recognition. Compare Figure 2-1 and Figure 2-2 as an example, the features or units are similar; however, the two subjects used different scaling in the reproduction.

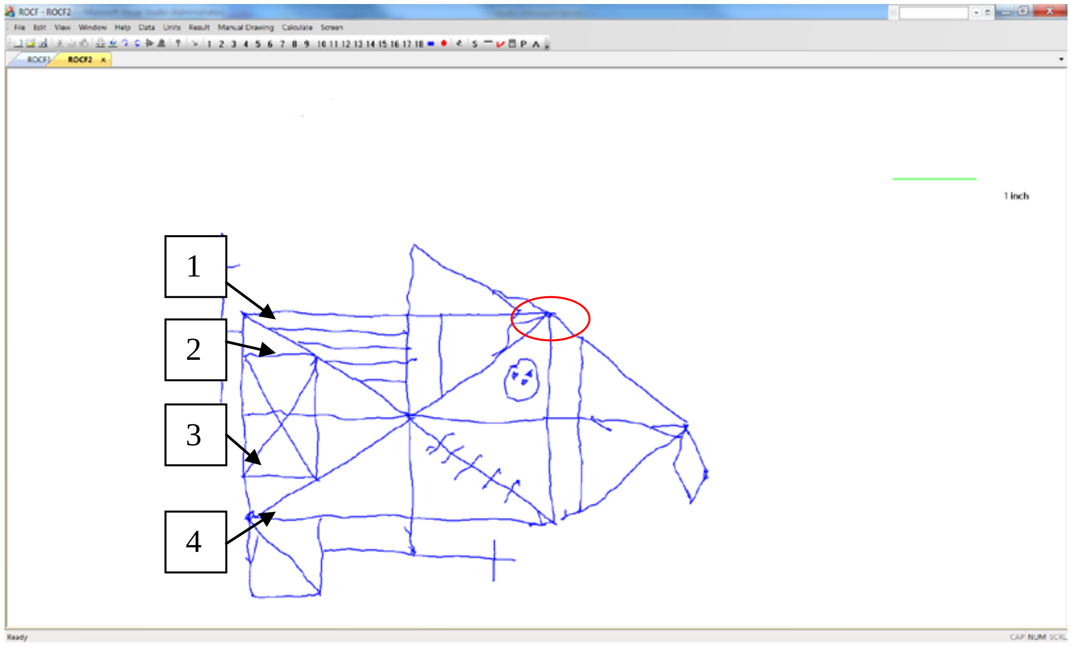


Figure 2-1. Example of freehand drawing.

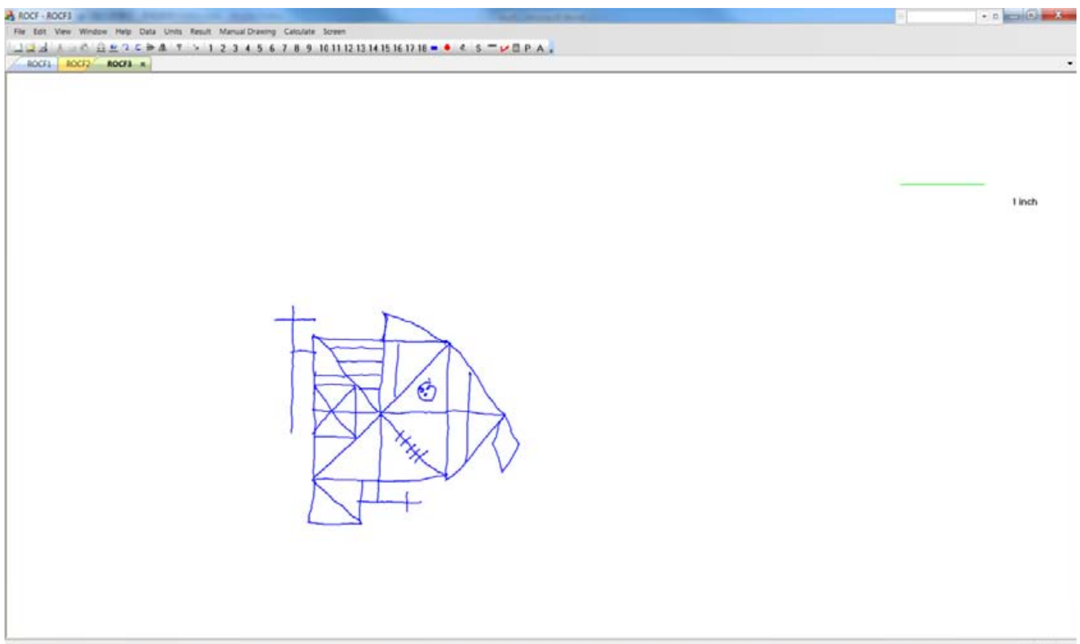


Figure 2-2. Variation of drawing.

2.6.Drawing Habits, Overtracing and Sketching

Generally, freehand drawings are not comprised of single strokes for single feature representation. They include many overlapping strokes and they may reflect unwanted tails or turns of a writing utensil (see Figure 2-3). This “noise” can be due to user’s unintentionally touching the drawing surface, or some habits in drawing. For example, the subject that produced Figure 2-3 has a habit of ending a horizontal line by drawing a small upward turn, such drawing idiosyncrasy further complicates the feature recognition process. Overtracing is another common issue in computer-based drawing feature recognition. Figure 2-3 shows two types of typical overtracing examples. The overtracing of Point 1 reveals a subject drawing multiple lines to represent one feature segment. In this case, ideally the system should identify one target line and ignore the multiple lines close to it. The overtracing of Point 2 represents a case of two strokes to represent one feature segment, but the system cannot ignore any of the lines drawn by the subject. The lines need to be combined to together to form a single line (see Figure 2-4).

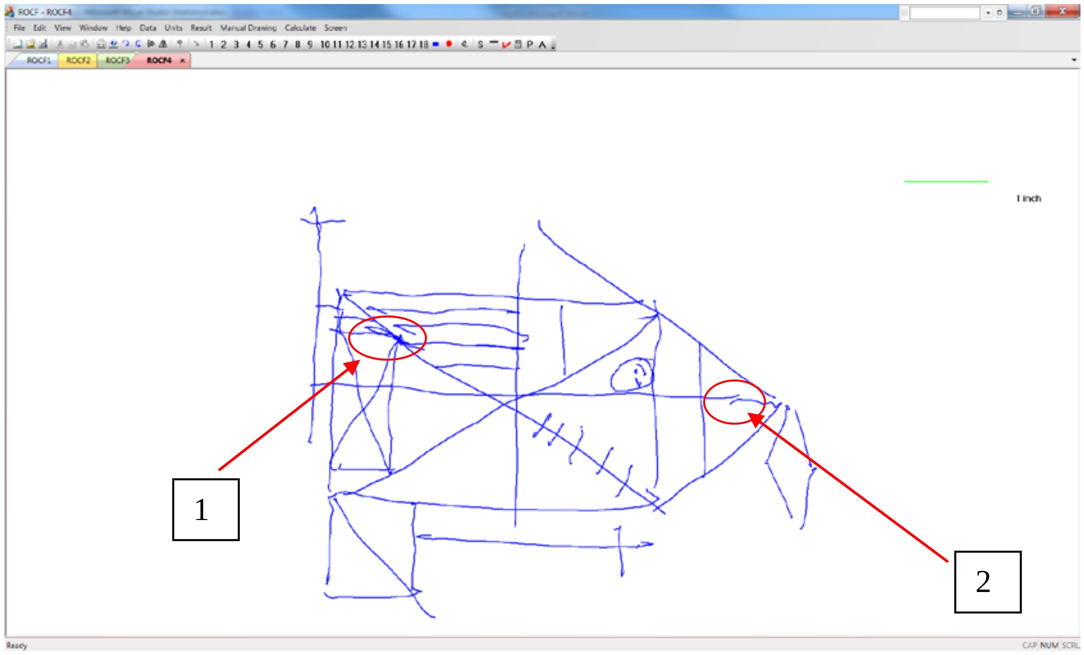


Figure 2-3. Overtracing examples.

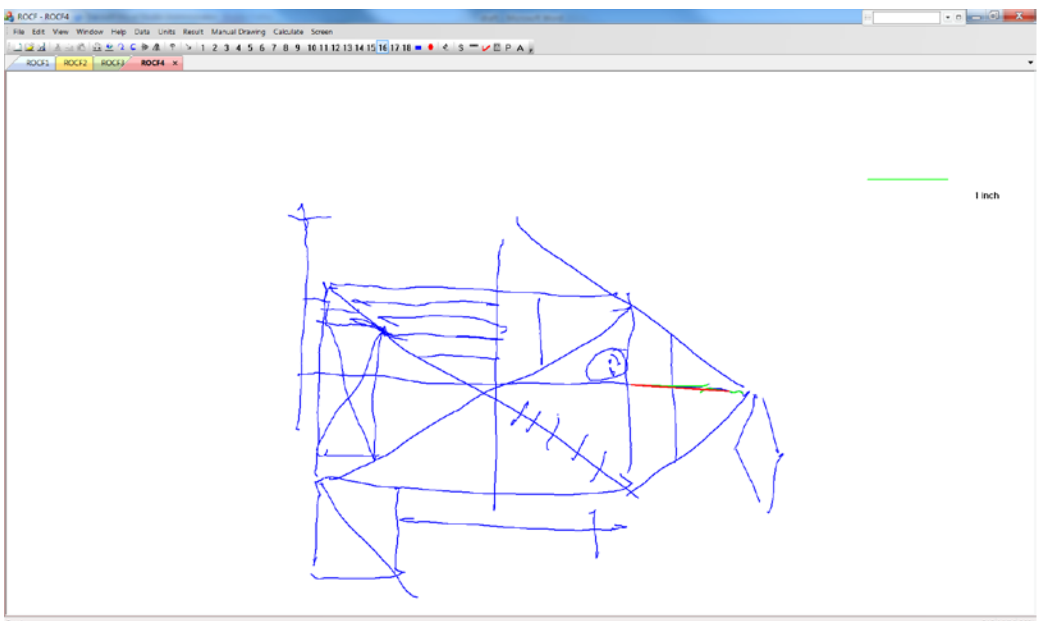


Figure 2-4. Identified overtracing stroke.

Lastly, the lines in a drawing can be categorized into three groups: horizontal lines, vertical lines and diagonal lines. However, in freehand drawings, directional deviations of lines can be large. For example, in Figure 2-5, the left most vertical line reflects a major direction change. Although the vertical line can be perceived by human observation, it is challenging for a computer system, to identify the existence of a vertical line based on defined recognition criteria.

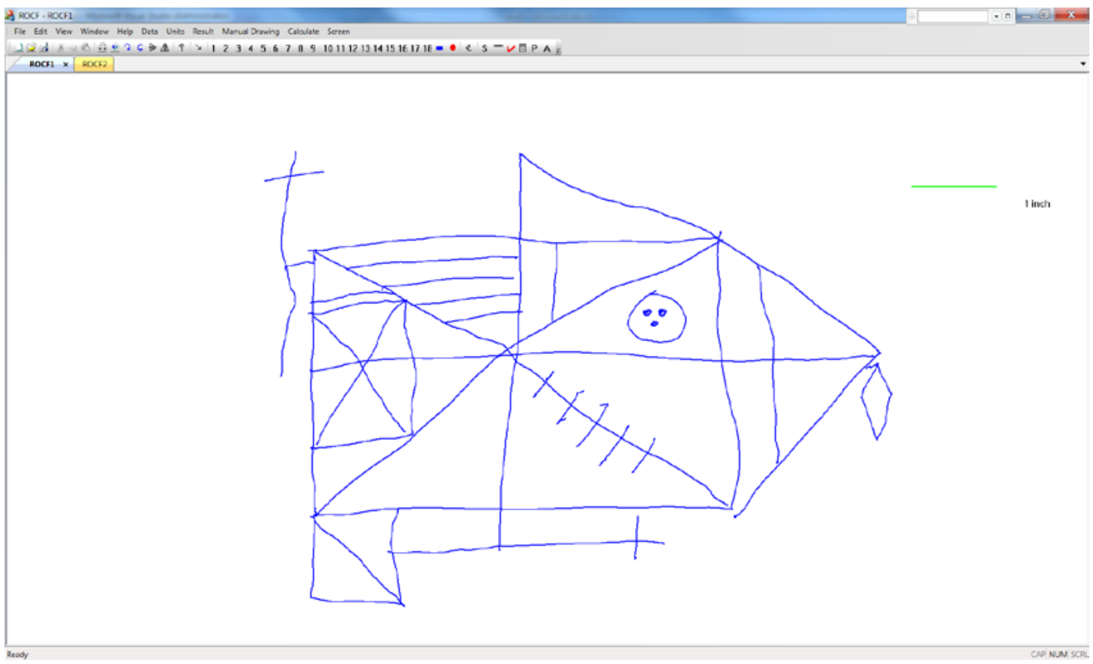


Figure 2-5. Example of direction deviation.

CHAPTER 3. LITERATURE REVIEW

This literature review provides an introduction to current studies that have used the ROCF along with different protocols and scoring systems to assess particular neurocognitive functions. In general, current applications and studies of the ROCF reveal potential users and groups that may benefit from the development of the system presented in this work. The most widely used protocols and scoring systems are identified and have been integrated into the new system.

3.1. Introduction to the ROCF, Procedures and Implementation

Neuropsychology is an applied science that evaluates how specific activities in the brain are expressed in observable behaviors [39]. Neuropsychological assessment (NA) uses psychometric evaluation tools to diagnose dysfunction and specify cognitive strengths and types of dysfunction. Design of rehabilitation systems to address dysfunction focuses on three key features: (1) repetition of activity, (2) feedback, and (3) motivation [29, 30, 67, 69]. Repeated practice must be linked to incremental success at some task or goal. This is achieved by trial and error with feedback on performance facilitated via the senses; e.g., visual feedback, force feedback, etc. Motivation is the reason for patients to tolerate extensive practice periods. Feedback has been extensively investigated and there is general agreement that it improves learning rates [57]. A VR system that can provide patients with repetitive training, while providing feedback and maintaining attractive features may achieve the three key aspects of rehabilitation system design and effectively support neuropsychologists and clinicians. Typically VR systems are able to provide different kinds of feedback, including augmented feedback, “knowledge of results feedback” or real-time feedback. In this way, users can see the task results immediately, and tend to be more motivated to continue performance, as compared to the situation without immediate feedback.

3.1.1. Motor Skill Assessment Methods

Effective neuropsychological assessment is a prerequisite for the treatment and scientific analysis of any neurologically based cognitive impairment, for example, patients with TBI. The neuropsychological assessment for these patients serves a number of functions including: (1) assisting in determining a diagnosis; (2) provision of normative information on the status of cognitive and functional abilities; (3) assistance in producing guidelines for the design of rehabilitative strategies; and (4) creation of data for the scientific understanding of brain functioning through the examination of different types of brain damage or dysfunction [90].

In certain medical centers, a commonly used diagnosis tool for TBI patients is the ROCF. The ROCF (Figure 1-1) is composed of approximately 34 lines of varying length, plus three dots inside a circle. Patients copy the complex figure during a test trial and this experience may serve as a basis for later recall trials in which an examinee may be asked to draw the figure from memory. The determinants of ROCF drawing performance are multifactorial and reflect integrated contributions of many neurocognitive functions. Therefore, varieties of cognitive operations have been measured by the ROCF Test and results have been presented in the literature [36], such as perceptual apprehension, attention and control, visual mnestic power [58], visual and perceptual organization [40], visualconstructive function and long-term spatial memory [7], motor functioning and memory [14], planning and organization [28], and graphomotor coordination [9].

A growing interest in use of the ROCF is reflected in recent research and contemporary ROCF applications are expanding. On this basis, a formal sampling of potential ROCF use is warranted [36]. The ROCF is being used to examine varieties of clinical conditions in children and/or adult nervous systems, including acute Lymphoblastic Leukemia [38] for children, amnestic disorders in adults [35, 85], psychological causes/characteristics of rapists [25], alcoholism [18], drug abuse [75], solvent exposure [51], asymptomatic HIV-seropositive status [49], etc.

Even in light of all the applications, both the administration of test procedures and scoring systems of the ROCF can be complicated and time-consuming [36]. The protocols include: single-trial protocols, two-trial protocols, three- and four- trial protocols. The options for scoring systems vary in complexity from unstructured and brief to comprehensive, standardized systems. Scoring systems can be generally grouped into two categories: “quantitative” and “qualitative”. Many scoring systems have been proposed in each of these categories. For example, the quantitative category includes the Rey-Osterrieth 36 point scoring system, the L. B. Taylor Scoring Criteria, the Denman Scoring System, etc. In the qualitative category, there are also many options, including a Typology approach developed by Rey [62], another typology approach proposed by Bennett-Levy [7] and Visser’s Complex Figure Test scoring system [87]. Beyond scoring system complexity and labor, subjective judgments and biases of examiners are other concerns with traditional scoring systems.

3.1.2. Standard ROCF Scoring System

A standard approach to scoring the ROCF is described below and was used in the new system development. In general, a score of 0, 0.5, 1 or 2 is assigned to each unit of the figure based on accuracy and placement criteria. Unit scores are then summed to obtain the raw score for the drawing. The same scoring criteria apply to multiple drawing trials. Thus, raw scores ranging from 0.0 to 36.0 may be obtained for all 18 units of the ROCF in copy, immediate recall, and delayed recall trials. For each unit of the figure, a score of 2 is assigned if the unit was drawn accurately, and placed correctly. A score of 1 is assigned if the unit was drawn inaccurately, but was placed correctly. A score of 1 is also assigned if the unit was drawn accurately but placed incorrectly. A score of 0.5 is assigned if the unit was drawn inaccurately and was placed incorrectly. (The unit must be recognizable.) A score of 0 is assigned if the unit was omitted altogether or was drawn inaccurately and placed incorrectly, and was not recognizable.

Table 3-1. Scoring criteria for ROCF drawings.

	Scoring Criteria	
Score	Accuracy	Placement
2	Accurately drawn	Correctly placed
1	Accurately drawn	Incorrectly placed
1	Inaccurately drawn	Correctly placed
0.5	Inaccurately drawn, but recognizable	Incorrectly placed
0	Inaccurately drawn and unrecognizable	Incorrectly placed

3.1.3. Summary of ROCF studies

Many clinical studies have employed the ROCF qualitative and/or quantitative scoring systems. Many research groups have developed scoring systems for different types of applications of the figure. The more comprehensive systems require more time-consuming procedures in clinical practice in order to meet diagnosis requirements. Consequently, some systems have limited popularity in clinical usage.

A tremendous number of ROCF clinical applications have been studied and published. Outside of hospitals and clinics, the ROCF has been used by police and law enforcement organizations for in-depth understanding of criminals, for example, distinguishing rapists from other offenders [25]. The ROCF has also been used for understanding both the long-term and short-term effects of drug abuse on neuropsychological functioning [75], or predicting the memory performance of alcoholics [18].

For most published studies, replicated experiments and extended clinical populations are needed to demonstrate reliable results and provide a basis for wider application of the ROCF. This type of work requires a great amount of time and labor in use of existing methods, for example, use of pen or pencil, stop watch, etc.

This provides further motivation for the development of a computer-based ROCF testing system with the following features:

- Programmable testing protocols - Copy, Immediate Recall and Delayed Recall tests are used by many studies, and delay times vary among applications. Users require features to program protocols.

- Tracking drawing procedures - Qualitative scoring plays an important role in different studies and in most cases, colored pencils are used with the ROCF for recording drawing patterns and qualitative characteristics (e.g., to determine whether or not one feature is drawn before another one). Computers can do the job of capturing qualitative features, including orders and patterns, and make testing easier for examiners, especially when applying comprehensive scoring systems, such as the Boston Qualitative Scoring.
- Detailed measurement standards - Larger sample sizes and more diverse populations can be tested with a computer-based system and detailed measurement standards can be applied in order to meet a variety of research needs.
- Easy modification for scoring systems – A computerized version of the ROCF can allow for changes in the presentation of stimuli, modification of task difficulty, parameters and changes to scoring criteria.

3.2. Technology Related to Computerized ROCF Test System

The second part of this literature review focuses on current techniques related to design of the computerized ROCF system.

3.2.1. Virtual Reality

Virtual reality, including 3D visual rendering, haptic interfaces and deformable object modeling, is a technology with the potential to bring radical innovation to healthcare. According to the research groups of Rubino and McCloy, virtual reality is defined as, “a collection of technologies that allow people to interact efficiently with 3D computerized databases in real time using their natural senses and skills” [48, 71]. Aukstakalnis and Blastner defined VR as, “a way for humans to visualize, manipulate and interact with computers and extremely complex data” [6] .

The user interface to a VR system can include vision, hearing, touch, proprioception and smell stimuli. A fast computer with powerful video cards (that can do fast computation and generate 3D images) is one of the most critical components of a VR system. Regarding visual displays, computer monitors (CRT, LCD or LED displays), 2D/3D projectors and stereoscopic goggles have been used in prior research. Motion trackers and haptic devices are often used as input devices to transfer user motion behaviors to the computer. Haptic devices can also be used as output devices to provide force feedback sensations to users. Special software is needed to make all of the components in a VR system work together [12, 22, 81].

Visual rendering is a key element to provide users with realistic sensations and perceptions in using VR. Both 2-dimensional and 3-dimensional displays can be used. For 2D visual feedback, additional depth cues need to be carefully designed, for example, perspective, relative motion, occlusion and aerial perspective can be used. 2D displays are good for some applications, because they are easy to use, cheap and may not cause occurrences of cybersickness in research studies. However, 3D displays, including flicker glasses, head-mounted displays, large stereo projection systems/monitors, and polarizing glasses are used for immersive virtual reality applications. 3D displays can provide users with immersive experience, but can be more expensive. Such displays may also cause symptoms of cybersickness, including nausea, vomiting, headache, somnolence, loss of balance and altered eye-hand coordination [31].

Mice and joystick interfaces have been widely used in many kinds of VR applications. They are easy to use, and do not have many limitations in setup. Electromagnetic tracking devices have the advantages of low cost and are impervious to optical occlusion problems. Such devices are good for VR applications, which are typically not designed for users sitting in front of a computer screen[77]. The limitation of electromagnetic tracking devices are signal distortion from large metal objects or from electromagnetic fields generated by nearby electronic devices.

Haptic devices have been widely used for many surgical simulation, handwriting training and recognition studies [54, 79, 83]. Haptic devices can be categorized as ground-based and body-based devices [11, 81]. Ground-based haptic devices are usually attached to a base, and can be further categorized according to different control elements, including force-feedback joysticks, pen-based masters, robot arms, floor-grounded exoskeletons, etc. Body-based haptic devices are usually portable and smaller compared with ground-based devices, including arm exoskeletons, hand masters, and cyberforce gloves. etc. They are mounted on the user [4, 27].

Customized software need to be developed for each VR application. In the next paragraph, examples of developed software in healthcare will be introduced, including applications for surgery planning, surgical training, rehabilitation etc.

3.2.2. Virtual Reality in Healthcare

Starting in the 1990s, VR was used in healthcare systems to visualize complex medical data, particularly during surgery and for surgery planning [15]. Subsequently, the application of VR in medicine has mainly focused on three areas: surgery training, surgery planning and augmented reality for open surgical procedures, and endoscopy and radiosurgery. In recent years, the scope of VR applications in medicine has been broadened to include neuropsychological assessment and rehabilitation [42, 43, 52, 63].

The importance of surgical simulation has already been recognized in medical education programs [45, 76]. VR is a good alternative to on-the-job training in surgical tasks for three reasons: First, traditional surgical training involves training-by-opportunity. There is no guarantee that all surgeons-in-training will have the opportunity to participate in addressing all kinds of disease states related to their chosen surgical specialty. Simulation can ensure that certain kinds of training are available at any time for those trainees. Second, the rising costs of healthcare motivate the use of VR simulation in medical applications. Third, the rapid expansion of minimally invasive surgery (MIS) has reduced the applicability of traditional models of training surgical skills [45]. VR can be effectively used to train MIS.

Now, more and more researchers have begun to recognize the potential of applying VR technologies to neuropsychological assessment and rehabilitation [11, 74, 82]. According to projections on the future of psychotherapy, the use of VR and computerized therapies are ranked third and fifth, respectively, out of 38 psychotherapy interventions predicted to increase within the next 10 years (from 2002) [56]. For any motor skills or psychological tests or treatments, VR has advantages, including: supporting a variety of procedures of interventions for psychological distress, the possibility of structuring a large number of controlled stimuli for psychological tests and simultaneously monitoring user responses to test stimuli generated by the VR systems [65]. In this study, the VR system for neuropsychological assessment is intended to be an example of radical innovation in healthcare applications.

3.2.3. Devices Used for Computerization of Neuropsychological Tests

The choice of a proper HCI interface for the new computerized ROCF system is important. The reasons to use HCI interfaces as input devices, versus using scanned images of pencil-paper results, are as follows: (1) For current recognition methods, on-line recognition has a higher success rate than off-line. (2) As reviewed above, qualitative characteristics, such as the order of drawing procedures, are important in many ROCF scoring systems, and direct input from HCI devices provides a solution to capturing this kind of information.

Most popular devices for on-line handwriting recognition can be grouped into three categories:

- A digital pen on patterned paper
- A pen-sensitive surface, such as a touch screen
- A haptic device

Digital pens have been evaluated and tested for clinical applications for medical staff usage [19, 20]. Results have shown that "natural" technologies such as the digital pen are good tools for use in stressful clinical environments that do not interfere with normal workload or increase the time of data acquisition. However, designing acquisition forms specifically for the use of digital pens can be time consuming and costly. Figure 3-1 shows an example digital pen.

Figure 3-1. EPOS Digital Pen (http://www.epos-ps.com/products.asp?pid=1275&ppid=1278).

According to a study conducted by Cole and Pisano, tablet PCs and digital pens were statistically equivalent to conventional pen and paper in initial data entry speed and in the collection of mammography clinical trial data [16]. Users were equally satisfied with the d-pen and Tablet PC according to a survey, and more satisfied with those two platforms than with a PDA and digitizer Tablet/PDA (DTP) hybrid alternatives. Nowadays, most tablet PCs are pre-installed with the handwriting software, such as the built-in handwriting recognition module of Windows XP [88]. Tablet PCs with handwriting recording and recognition functions are a mature technology and have been widely implemented in commercial applications.

Haptic devices have been widely used for many handwriting training and recognition studies [55, 80, 84]. Srimathveeravalli and Thenkurussi's study used a haptic device for skill training by developing a virtual writing testing bed (see Figure 3-2). The interaction force between the virtual pen and virtual paper was simulated in the program. There were three writing modes in Srimathveeravalli and Thenkurussi's system, including: a basic mode, a proportional/derivative (PD) position control and a force control mode. The basic mode was a simulation of traditional pencil-paper writing. In the PD position control mode a reference trajectory was provided to the user for practice and the position control assisted the user in the training process. The force control mode provided users with the opportunity of sharing haptic sensations between two people over a network. Experiment results revealed that with haptic force-feedback information, users achieve better training than with position information. Hand-writing rehabilitation exercises with haptic devices have also been developed for users with hand dysfunctions [33].

Figure 3-2. Srimathveeravalli and Thenkurussi's virtual writing testing bed [80].

3.2.4. Mechanisms of Haptic Device

Haptic devices have been used in various clinical practices. Commercialization of haptic devices makes it possible to familiarize users in hospitals and clinics with such devices in an easy way without special training.

The degrees of freedom of movement of haptic devices, as well as the force feedback, are some of the major concerns in selecting a device for particular applications. The SenSable Phantom Desktop device is a widely used commercial haptic device, providing 5-DOF movement and 3-DOF force feedback. In earlier research by Lee et al., a 5-DOF haptic force-torque feedback device was developed [91, 92]. Figure 3-3 shows the lab-built haptic device, which was designed and manufactured by Suzuki Inc. (Japan). Its controller system and software driver program were developed by Lee et al. Further discussion of the selection of a haptic device for this project is presented in a later chapter.

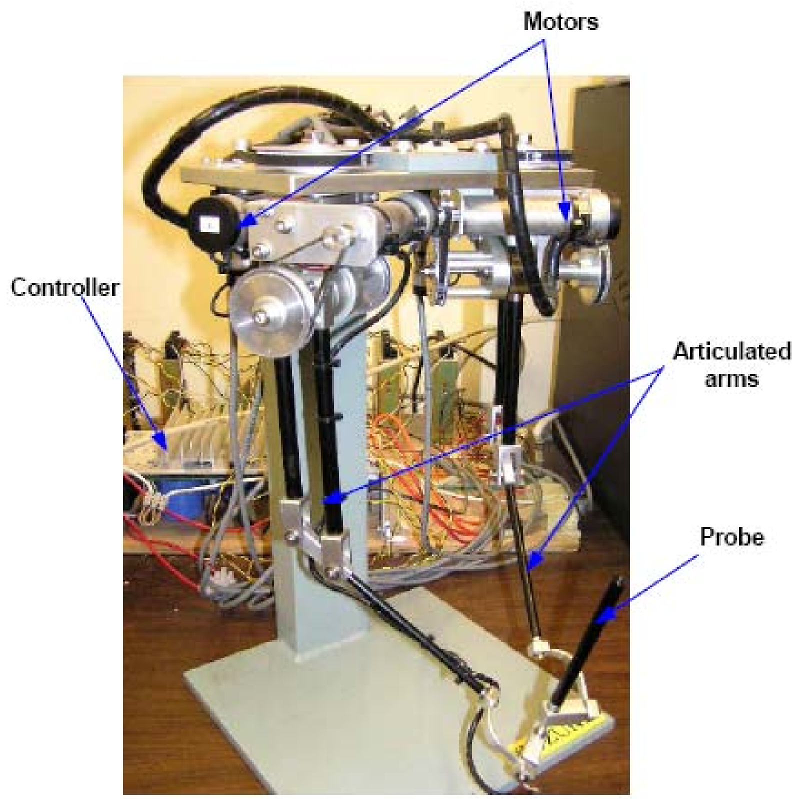


Figure 3-3. Lab built 5-DOF haptic devices [44].

3.2.5. Force Rendering

Force rendering refers to the process by which desired sensory stimuli are imposed on a user to convey information about a virtual haptic object. Realistic force rendering can allow users to perceive a virtual object better, and as a result, user performance in the virtual reality environment (VRE) may more closely approximate real world performance. Figure 3-4 shows the basic architecture of a VR application with haptic force feedback. A human operator interacts with a simulation engine through a haptic device driven by a force rendering algorithm. The algorithm is important for providing a realistic “feeling”. Section

3.2.3 addresses selection of the device for the VR system and this section focuses on the algorithm selection. It is important to note that visual presentation of an object in VR determines whether or not the virtual object/environment “looks” realistic.

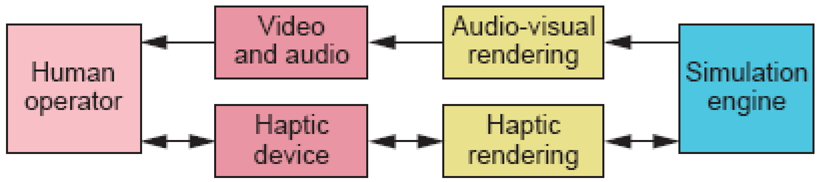


Figure 3-4. Architecture of VR application with haptic force feedback [72].

In this study, three-DOF force interaction has been used. In this literature review, force rendering is introduced in terms of one-DOF, two-DOF, three-DOF and more than three-DOF interaction.

One-DOF interaction: One-DOF interaction is the simplest way of providing force rendering; that is, force-feedback along one spatial dimension. The application of one-DOF interaction is limited; however, many interesting effects can be simulated. For example, the operation of pressing a syringe piston can be simulated with one-DOF interaction. Rendering a virtual wall is a very basic one-DOF interaction application, and it serves as a benchmark for haptic system stability [2, 17, 26]. Figure 3-5 shows a virtual wall rendering example.

$$F_{reaction} = \begin{cases} 0 & \text{if } x > x_w \\ K(x_w - x) & \text{if } x \le x_w \end{cases} \tag{3-1}$$

K is the stiffness of the wall.

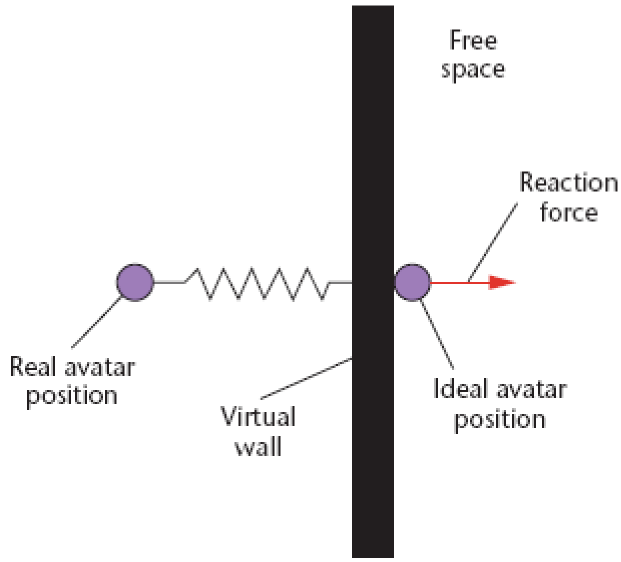


Figure 3-5. Virtual wall using one-DOF interaction.

Two-DOF interaction: There are examples of two-DOF control everywhere, such as the mouse; however, two-DOF force feedback devices are not very commonly used. Figure 3-6 shows an example of a two-DOF PCM (programmable constraint machine) [59]. The wheel is free to roll in response to forces applied to the handle by the user. The steering motor sets the available rolling direction. Strain gauges measure lateral forces perpendicular to the rolling direction. When in contact with a virtual wall, the wheel is simply steered tangent to the wall. Away from virtual walls, the wheel is steered so as to null lateral forces. It acts as an “electronic caster”, and appears to the user to move freely in two dimensions.

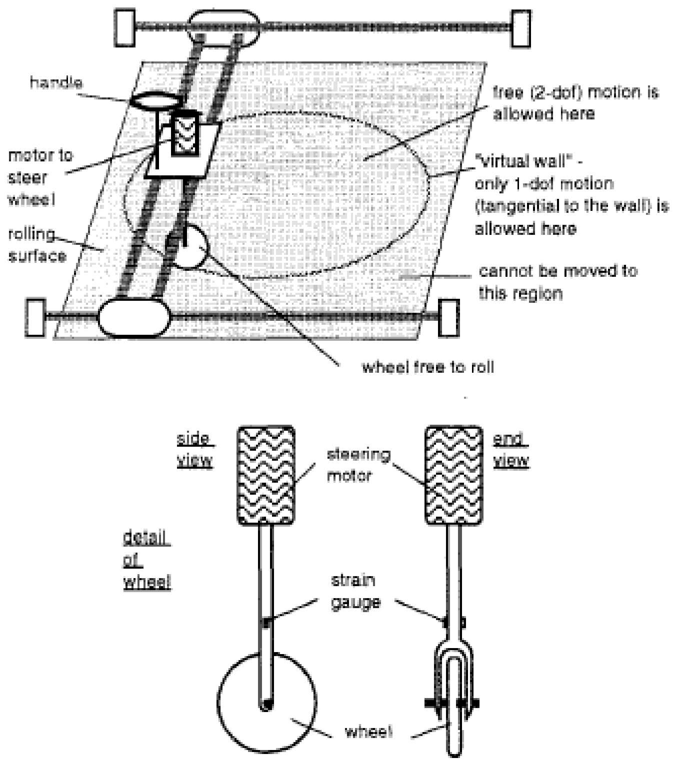


Figure 3-6. Two-DOF planar PCM.

Three-DOF interaction: This is most commonly used control for the majority of commercial haptic devices today. Through three-DOF control, users can intuitively manipulate virtual objects in 3D space. At the same time, three-DOF force-feedback makes it possible to simulate material properties of virtual objects, including stiffness and friction on the virtual object surface. Furthermore, complicated simulations, including deformable objects, can be rendered [44].

- *More than three-DOF interaction*: Torque calculations and rendering is required by some applications, like virtual sculpting, and these capabilities are not available with many commercial haptic devices. Previous research with the lab-built 5-DOF haptic device accomplished a realistic object simulation [91]. In the present study, we did not use the five-DOF force-feedback device; however, the availability of the technique provides a basis for future research on advanced applications of haptic interaction in clinical practice, especially for rehabilitation systems integrating haptic devices.

3.3. Handwriting/Drawing Recognition

Computer recognition of handwriting or drawings is one of the most successful applications in computer vision [46]. It is an automated process that uses pattern recognition and machine learning techniques to recognize the written/drawn content. There are two major problem domains in handwriting recognition: on-line and off-line.

On-line recognition: Data are collected while a user is writing on a digitizing surface. The data recorded include the spatial positions (x, y) as well as the velocity v(t) and acceleration α(t) of pen/stylus movement. Based on {(x, y), v(t), α(t), t}, a recognition algorithm infers written characters or words in real time [46].

Off-line recognition: Only digitized spatial information is available, for example, a scanned letter. Thus, compared with on-line recognition, off-line recognition has much lower recognition rates.

3.3.1. Feature Extraction

There are two major steps for handwriting/drawing recognition: feature extraction and pattern recognition. There are two major purposes served by feature extraction: (1) extracting the most representative features that are used by classifiers, and (2) reducing redundancies in data [46]. For on-line recognition, input is composed of line-segments with dynamic information, so feature extraction is a relatively easy task. However, for off-line systems, feature extraction needs to overcome the following challenges: different document backgrounds, non-uniform illumination of scans, convolution distortion due to the point spread function of a scanner, noise introduced by electronics and writing tools, and different qualities of paper and types of ink. These problems further motivate the use of on-line recognition methods.

3.3.2. Pattern recognition

There are three basic approaches for pattern recognition: (1) statistical pattern recognition, (2) structural pattern recognition, and (3) soft computing for pattern recognition.

Statistical Pattern Recognition: Recognition is based on decision boundaries established in the feature space by statistical distributions of the patterns [61]. A decision is usually made by maximizing a *posteriori* probability, where the recognition error of this approach is called Bayes error. The observations can be represented as a set of random variables and the density function of the observation depends on its class. The classification of a pattern is based on minimizing the overall Bayes error. Hidden Markov models (HMM) are widely used to exploit sequential properties of data and to reduce classification errors.

HMMs were first developed in the 1960s by Baum and his colleagues and popularized in the mid 70s. A hidden Markov model (HMM) is a statistical model in which the system being modeled is assumed to be a Markov process with unknown parameters. The challenge is to determine hidden parameters from observable parameters. This modeling method has been widely used for both speech recognition and handwriting recognition. It was first used for on-line recognition with dynamic information [23]. HMMs are well suited for modeling sequential features in writing. Now, HMMs are also widely used for off-line handwriting recognition.

The general architecture of an instantiated HMM is shown in Figure3-7. Each oval shape represents a random variable that can adopt a number of values. The random variable x(t) is the hidden state at time t (with the model from the below diagram, $x(t) \in \{x_1, x_2, x_3\}$). The random variable y(t) is the observation at time t ($y(t) \in \{y_1, y_2, y_3, y_4\}$). The arrows in the diagram (often called a trellis diagram) denote conditional dependencies.

From the diagram, it is clear that the value of the hidden variable x(t) (at time t) only depends on the value of the hidden variable x(t− 1): the values at time t − 2 and before have no influence. This is called the Markov property. Similarly, the value of the observed variable y(t) only depends on the value of the hidden variable x(t) (both at time t).

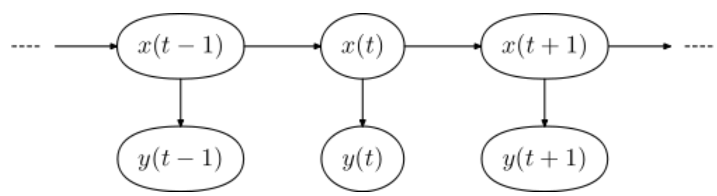


Figure 3-7. Probability of an observed sequence.

The probability of observing a sequence $Y = y(0), y(1), \ldots, y(L-1)$ of length L is given by

$$P(Y) = \sum_{x=0}^{L-1} P(Y|X)P(X) \qquad (3\text{-}2)$$

Where the sum runs over all possible hidden node sequences $X = x(0), x(1), \ldots, x(L-1)$. Brute force calculation of P(Y) is intractable for most real-life problems, as the number of possible hidden node sequences is typically extremely high. The calculation can however be sped up enormously using the forward algorithm or the equivalent backward algorithm [89]. This methodology was not applied in the present system development because application of

HMM methods requires the preprocessing of raw data and feature extraction. The freehand drawing of ROCF with shared features and noises, make the feature extraction for HMM a very challenging problem.

Structural Pattern Recognition: In this method, each pattern class is defined by using structural descriptions or representations [13, 24]. The recognition is performed according to structural similarities. Regarding specific methods, analysis-by-synthesis was an important early approach proposed by Eden (1968). Recently, fuzzy grammars and graph trees have been widely used for handwriting recognition. Abuhaiba and Ahmed proposed to use a set of 105 fuzzy constrained character graph models, which can tolerate large variations in writing styles, to recognize unconstrained off-line handwritten numerals [1]. Matching graphic structures and relationships between components without parsing is also a popular approach in handwriting recognition. Rocha and Pavlidis developed a character recognition system based on graph transformations [68]. Recently, structural classifiers have also been used in handwritten word recognition.

Neural Networks for Pattern Recognition: Neural networks have also been popular in handwriting recognition since the mid 1980s. Feed-forward neural networks remain dominant because well-known training methods, including back propagation (BP) of errors and function approximation, are available. There are three types of neural network classifiers: multi-layer perception (MLP), radical basis function (RBF) and probabilistic neural networks (PNNs). Research shows that the probabilistic neural network (PNN) outperforms MLP and RBF in both speed and recognition rates for handwriting [10].

Soft Computing in Handwriting Pattern Recognition: Soft computing is a new problem-solving paradigm that combines emerging techniques and theories such as fuzzy logic, neural networks, genetic algorithms, evolutionary computation, and probabilistic methods for complex problems that cannot be solved by conventional mathematical methods. There are two categories: (1) Pattern recognition is based on a single classifier that is formed by combining different soft computing methods, which may include neural networks, fuzzy logic, genetic algorithms, and probabilistic modeling. (2) Pattern recognition is based on the results of several classifiers used together [46].

3.3.3. Circle Recognition

Shifting from handwriting recognition, the Hough transformation is a well-established method for shape detection in drawings. It can be used to detect arbitrary shapes [3]. It is very effective for circle detection. In the ROCF, drawing Unit 11 is one circle with three dots in it. The circle is the most distinguishable object in the drawing. If it can be recognized, Unit 11 can be isolated from the rest of the drawing.

Duda and Hart proposed to use the Hough transformation to detect circles in digitized pictures in 1972 [21]. Kimme, Ballard and Sklandsky proposed a more effective algorithm in 1975 by adding directional information to Duba and Hart's algorithm [34].

The application of Hough Transformation is described as follows:

P(**X**) contains lines and circles in a digitized picture

$\boldsymbol{X} = (x, y)$ are the coordinates of one pixel

Xp is the set of points $\{\boldsymbol{X} | p(x) \neq 0\}$

$\boldsymbol{C}x$ is a set of circles passing through X a(X) and r(X) are the centers and radii of each member of $\boldsymbol{C}x$, respectively.

Then, for each $\{(a,r)|X \in Xp\}$, an accumulator at (**a(x), r(x)**) in (a,r) space is incremented by unity. The process is performed for all members of Xp and (**a(x), r(x)**) contains the number of points lying on the circle of radius r(x) and center a(x).

Subsequently, the picture is turned into a grey scale image. An empirical threshold (T) is applied to the content of the accumulator to detect those points, which are likely to be the centers of circles in p(**x**).

Let's use f(x) as the gray level in the picture, G(x) is the digitized gradient of f(x), and g(x) and (x) are the modulus and direction of G(x). $g_1(x)$ and $g_2(x)$ represent the horizontal and vertical components respectively.

So

$$\boldsymbol{g_1}(\boldsymbol{X}) = \frac{1}{2s}[\boldsymbol{f}(\boldsymbol{X} + (\boldsymbol{s},\boldsymbol{0})) - \boldsymbol{f}(\boldsymbol{X} - (\boldsymbol{s},\boldsymbol{0}))] \qquad (3\text{-}3)$$

$$\boldsymbol{g_2}(\boldsymbol{X}) = \frac{1}{2s}[\boldsymbol{f}(\boldsymbol{X} + (\boldsymbol{0},\boldsymbol{s})) - \boldsymbol{f}(\boldsymbol{X} - (\boldsymbol{0},\boldsymbol{s}))] \qquad (3\text{-}4)$$

Where s is a positive integer.

$$\boldsymbol{g}(\boldsymbol{X}) = [\boldsymbol{g}_1^2(\boldsymbol{X}) + \boldsymbol{g}_2^2(\boldsymbol{X})]^{\frac{1}{2}} \qquad (3\text{-}5)$$

$$(\boldsymbol{X}) = \boldsymbol{tan^{-1}}(\boldsymbol{g_2}(\boldsymbol{X})/\boldsymbol{g_1}(\boldsymbol{X})) \qquad (3\text{-}6)$$

If **X**1 is on a circle embedded in f(**X**), then the gradient of f(**X**) at **X=X**1 will point to the center of the circle. Kimme, Ballard and Sklandsky's algorithm only selects the member of Cx that G(**X**) points to $\{(a,r)|X \in Xp\}$ within a range of angle ΔΦ to make the processing more effective.

3.3.4. Corner detection in Drawing

Corner detection is a very important step in image processing and drawing recognition. The quality of corner detection will affect the quality of image processing and drawing recognition directly.

There are different types of corners:

- the intersection of two edges
- line endings
- a point on a curve where the curvature is locally maximum
- an isolated point

There are many existing methods for corner detection. The Moravec corner detection algorithm was one of the earliest methods [53]. In this study, we used a method developed by Rosten and Drummond called Feature from Accelerated Segment Test (FAST) corner detection [70]. The FAST corner detection method starts with a circle of 16 pixels around a corner candidate p. If there are a set of n contiguous pixels in the circle that are all brighter than the intensity of the candidate pixel I_p plus a threshold t, or all darker than I_p-t, p will be defined as a corner. All 16 locations on the circle around the candidate points will be tested. Then, each location on the circle relative to p will have one of the three states: darker, similar, or brighter. If p is a corner, then at least n of the locations must all be brighter than I_p+t or darker than I_p-t, otherwise p can't be a corner. Then Iterative Dichotomiser 3 (ID3) algorithm [60] is used to optimize the order, in which pixels are tested. It is reported that this method is the most computationally efficient feature detector, compared with the Harris, DoG and SUSAN methods [70].

3.3.5. Shape Recognition

Recognizing simple geometries, such as lines, arcs and ellipses, can also be an ambiguous parsing problem. Shileman et al. used a hand coded visual grammar to describe shapes [78]. Alvarado and Davis proposed using dynamically constructed Bayesian networks to parse a drawing, using both bottom-up and top-down interpretations [5].

Shilman's method inspired the recognition method used in this study. Due to the nature of freehand drawing, ambiguity of features is inevitable. Popular recognition methods (identified in the last section) suffer from fundamental limitations. The accuracy they can achieve is limited due to the fact that most existing ink parsing approaches are adapted from algorithms designed to operate on unambiguous tokens, such as typed text. In freehand drawing recognition, there is inherent ambiguity, for example, the multiple lines in Figure 2-3 as a result of the subject sketching a single line segment. It is also possible that the subject actually means to draw multiple lines. A curved line may represent a curve drawing, or the subject's original intention may have been to draw a straight line.

In order to accurately deal with such ambiguity in drawings, a recognizer must use context. To use visual language is one of the existing disambiguation techniques [47]. Statistical models are common disambiguation techniques, for example, HMMs. A hand coded visual language was used for shape recognition in this study.

3.4. Summary

In this chapter, related research and techniques were reviewed, including the ROCF scoring system, haptic devices, haptic force rendering algorithms, information design methods for systems design and pattern recognition techniques. All the techniques have their own strengths and limitations. In the development of the VR-based ROCF system, design requirements were determined based on user needs and task analyses. The scoring techniques, haptic rendering and pattern recognition best suited for the system were used in this study. Further justification is provided in later chapters.

CHAPTER 4. HAPTIC DEVICE AND WORKSTATION PROTOTYPING

This chapter presents the prototype workstation designed for the ROCF test system, including the design methodology, the design dimensions, device selection and setup assembly.

4.1. Introduction

At the beginning of this study, it was decided that the automated ROCF test system would capture user drawings, in real-time, instead of using scanned images of paper-pencil drawings. The reasons for this decision are as follows:

- The automated ROCF test system is demanding in terms of pattern recognition, as accurate assessment of drawings by users with varying abilities must be made for neuropsychological inference.
- As mentioned in the last chapter, on-line pattern recognition has much higher recognition rates than off-line recognition.
- Based on the literature review of ROCF scoring systems, sequential information is important for interpreting ROCF performance; therefore, real-time recognition is useful for qualitative feature extraction (e.g. drawing ordering).

On this basis, a workstation capable of on-line recognition of user drawings of the ROCF was prototyped for automated recording and scoring.

4.2.Haptic Device Selection

The main reason to use a haptic device, instead of a digitizer (tablet), as the input device was that the haptic device has the ability to record user performance in 3D space along with sequential drawing information. This can provide neuropsychologist with data that can be used to build patient performance models in 3D. Another reason for using the haptic device is that the technology has proved to be useful for handwriting training and rehabilitation applications [80]. Research on persons with motor function disabilities reveals that force-feedback functions in hand control provide unique advantages for upper-limb rehabilitation therapy. With this in mind, and considering that ROCF performance is multifactorial in nature and reflects the integrated contributions of many neurocognitive functions, the capability of several haptic-based controls for the ROCF test system was evaluated.

We choose two kinds of haptic devices for comparison:

The first one was the Sensable Technologies Desktop Phantom haptic device. It has been widely used in many research labs and R&D departments in industry. Figure 4-1 shows the phantom device being used in a VR-based surgery simulation [42].

Figure 4-1. Sensable Technologies Desktop Phantom haptic device.

The other device examined for the system was the Novint Falcon, which was originally developed for gaming purposes. These two kinds of haptic devices have their own advantages and disadvantages. Characteristics commonly considered desirable for haptic interface devices include:

- low back-drive inertia and friction;
- minimal constraints on motion imposed by the device kinematics, such that free motion feels “free”;
- symmetric inertia, friction, stiffness, and resonate frequency properties (regularizing the device so users do not have to unconsciously compensate for parasitic forces);

- balanced range, resolution, and bandwidth of position sensing and force reflection;
- proper ergonomics that let the human operator focus on the task “at hand” when wearing or manipulating the haptic interface (pain, or even discomfort, can distract a user from a virtual task, reducing overall performance).

Table 4-1 shows a comparison of the two haptic devices (blank cells indicates specification information was not released by the manufacturer). The Phantom device is superior to the Falcon on every parameter, but the Falcon also costs 1/100 of the Phantom device. This means the Falcon could make the new ROCF system accessible to many more potential users. The selection of the input device is validated in the next chapter.

Figure 4-2. Novint Falcon haptic device.

Table 4-1. Comparison of two haptic devices.

	Phantom	Falcon
Force feedback workspace	~6.4 W x 4.8 H x 4.8 D in.	4" x 4" x 4"
	> 160 W x 120 H x 120 D mm.	
Footprint (Physical area device base occupies on desk)	5 5/8 W x 7 1/4 D in.	9" x 9" x 9"
	~143 W x 184 D mm.	
Weight (device only)	6 lbs. 5oz.	6 lbs
Range of motion	Hand movement pivoting at wrist	
Nominal position resolution	> 1100 dpi.	>400 dpi
	~ 0.023 mm.	
Backdrive friction	< 0.23 oz. (0.06 N)	
Maximum exertable force at nominal (orthogonal arms) position	1.8 lbf. (7.9 N)	2lb
Continuous exertable force (24 hrs.)	0.4 lbf. (1.75 N)	
Stiffness	X axis > 10.8 lbs. / in. (1.86 N / mm.)	
	Y axis > 13.6 lbs. / in. (2.35 N / mm.)	
	Z axis > 8.6 lbs. / in. (1.48 N / mm.)	
Inertia (apparent mass at tip)	~0.101 lbm. (45 g)	

Table 4-2. Continued

Force feedback	x, y, z	
Position sensing	x, y, z (digital encoders)	
[Stylus gimbal]	[Pitch, roll, yaw (± 3% linearity potentiometers)	
Interface	Parallel port	
Supported platforms	Intel-based PCs	
OpenHaptics™ toolkit compatibility	Yes	
Applications	Selected Types of Haptic Research, the FreeForm® Modeling™, and the FreeForm® Modeling Plus™ systems	
Degrees of Freedom of Positional Sensing	6	3

4.3. Workstation Design

Figure 4-3 presents the design of the workstation with the Falcon haptic device. In order to make it possible for users to draw the ROCF in an intuitive way, the visual feedback display needs to be aligned with the haptic feedback. This means, the hand position in the drawing process needs to be aligned with the graphic drawing output. For the Phantom haptic device, prior research has been conducted on embedding a computer monitor in a desk surface, so the Phantom can be intuitively operated above the display. However this method is not applicable to the Falcon’s ball-shaped hand-control (Figure 4-2). Consequently, a semi-transparent rear projection screen was used for the image display. In this way, users can see the projected image of drawing results and through the image they can see the movement of their hand at the same time.

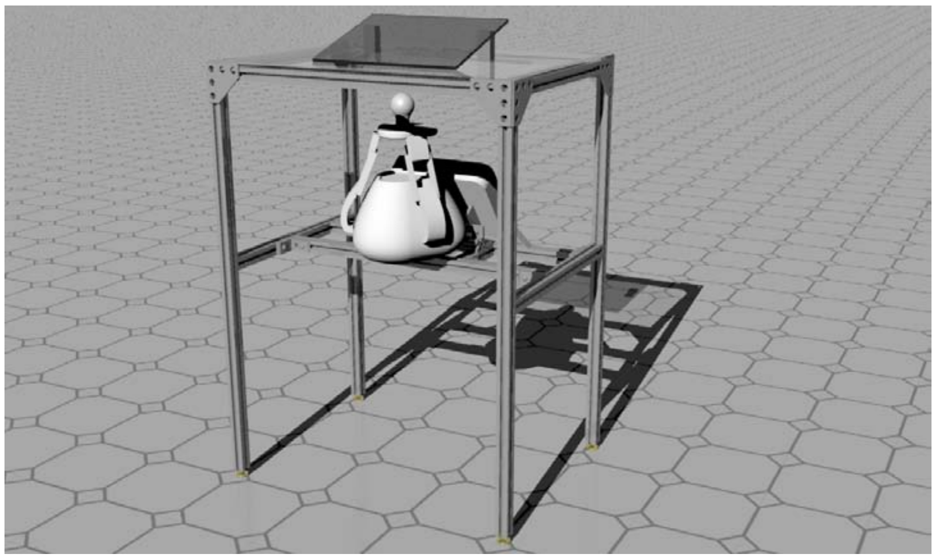


Figure 4-3. Design of workstation based on user physical and cognitive information requirements.

In using the Falcon device, the ball-shaped control makes the drawing task different from the pen-style stylus of the Phantom. Drawing with the Falcon is more difficult than using the Phantom due to the lack of support of the elbow. A lab-built, fully adjustable chair was modified and used to provide elbow support for different users. Figure 4-4 presents the lab-built chair with the adjustable height, inclination, tilting, and elbow support panel. Users can adjust the chair to optimize fit when they use the workstation, especially in terms of proper elbow support for handling the Falcon device.

Figure 4-4. Lab-built chair.

4.4.Summary

The usage of a haptic device is physically different from using a real pen. This chapter presented a new prototype workstation design to make drawing with a haptic device more closely approximate using a pen/pencil in the drawing process. How any differences between haptic device use and pen-paper drawing affect user performance in the ROCF test is assessed in the next chapter.

CHAPTER 5. A COMPARISON OF HAPTIC DEVICES FOR COMPUTER-BASED REY-OSTERRIETH COMPLEX FIGURE TESTING

5.1. Introduction

In this study, two commercially available interactive haptic devices were evaluated including the Phantom, manufactured by SensAble Technologies (see Figure 5-1, the device on the top of the rack) and the Falcon, manufactured by Novint Technologies (also see Figure 5-1). In order to compare the devices with pen-paper drawing, a Wacom Cintiq tablet was also used, covered under paper to which the Wacom inking pen was applied (Figure 5-2). This allowed for accurate recording of the pen drawing procedure and time. The ROCF drawing system ran on a high-performance Dell graphics workstation.

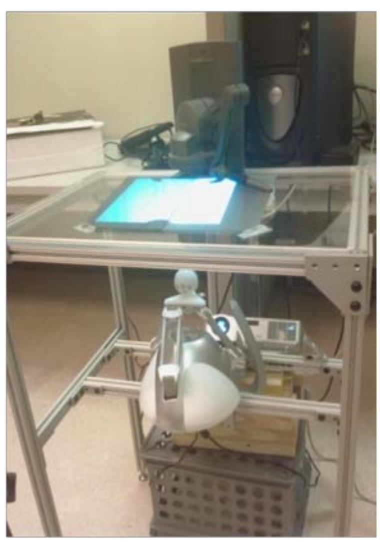


Figure 5-1. Phantom haptic device (upper) and Falcon haptic device (lower).

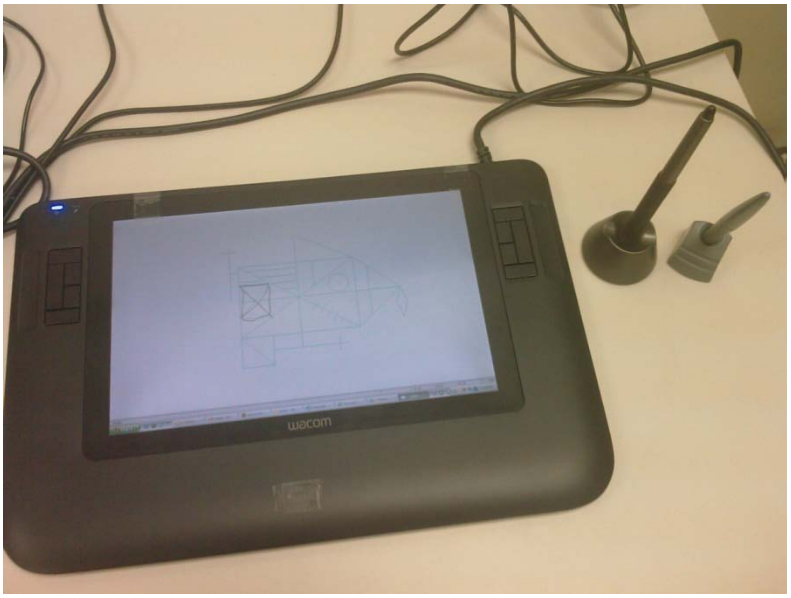


Figure 5-2. Wacom Cintiq Tablet used to record pen-paper drawing.

Users of the Novint Falcon haptic device and the SensAble Technology haptic device were compared with pen-paper users in terms of three aspects of performance:

- Physical behavior
- Time to completion
- Drawing accuracy and placement

The physical performance of users was assessed based on a fuzzy model of handwriting proposed by Sano and Kishibe [73]. Time to completion was recorded (in real time) by computer program. Drawing accuracy and placement was graded using the graphic results and following the rules of the standard ROCF manual.

In the following sections, the fuzzy model of handwriting is described, as background material. The experiment environment and protocol are presented, followed by the experimental results and statistical analysis. Finally, a discussion and suggestions for future work are provided.

5.2.Related work

5.2.1. Fuzzy Model for Handwriting

In 1962 Denier Van der Gon proposed a physical model of the handwriting process as a basis for ergonomic intervention in the design of writing tasks [86].

Figure 5-3 shows the model of the hand and muscle system in the human being for handwriting movement. The stiffness coefficient of the hand corresponds to the stiffness coefficient of the spring γ. The internal friction associated with handwriting movement is considered to be equivalent to the viscosity coefficient λ. The relation between handwriting movement and output of EMG signals supposes that the forces needed for handwriting processes are expressed as linear combinations of muscle signal obtained from EMG measurement equipment. The parameters μ, λ and k expressed are used in the dynamic model.

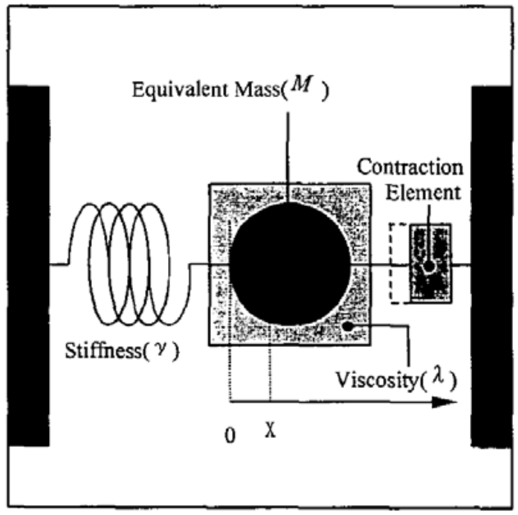


Figure 5-3 Model of hand and muscle system

The above research demonstrated that EMG signals of muscles during handwriting processes can be used to represent the physical performance of subjects in drawing tasks.

5.2.2. ROCF Scoring System

A standardized approach to the scoring of the ROCF, based on the criteria developed by Rey [62] and presented in Lezak [40], was used for user performance assessment in the present study. Table 3-1 presents the general scoring criteria for the ROCF test. Unit 6 in the ROCF was used as the test unit in this study (see Figure 5-4). The specific scoring criteria were as follows:

> ***Accuracy:*** *A small rectangle should be drawn within the area defined by the left vertical side of the Large Rectangle and the two lines that form the Diagonal Cross. The small rectangle should be composed of four line segments. The line segments should form four right angles at the corners. The lines should extend past any*

intersection no more than 1/8 inch. The lines should fail to intersect at a corner by no more than 1/8 inch. The height of the small rectangle should be greater than its width and generally proportional to the complex figure stimulus. Within the Small Rectangle are two diagonal lines that connect adjacent corners of the small rectangle. These lines should not overshoot or undershoot the corners by more than 1/8 inch.

Placement. *The midpoint of the Small Rectangle should not deviate from the Horizontal Midline by more than 1/4 inch. The intersection of the two small diagonals within the Small Rectangle should not deviate from the area defined by the left vertical side of the Large Rectangle and the Diagonal Cross more than 1/4 inch at any point.*

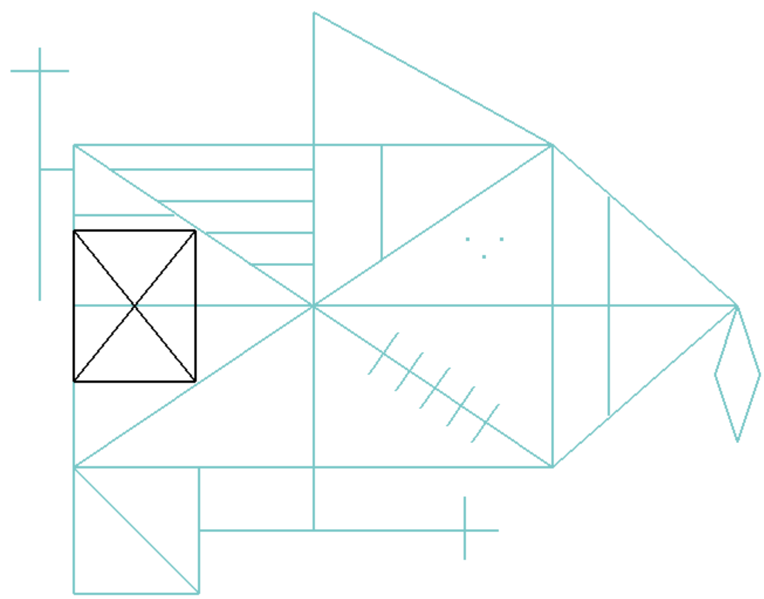


Figure 5-4. Rey-Osterrieth Complex Figure with Unit 6 highlighted.

5.3. Experiment

5.3.1. Participants

Three (3) subjects were recruited as participants for the experiment through word of mouth and email. All participants were from the North Carolina State University student population.

Subject visual acuity was a selection criterion. Any volunteer indicating a corrected visual acuity less than 20/20 was excluded from participation in the experiment. This was due to the visual requirements of the simulated task and the need for all visual display information to be perceived by subjects to effectively perform the ROCF reproduction. Personal computer experience was also used as a selection criterion. All subjects were required to have some basic computer experience such that they were familiar with typical control devices, including a mouse and keyboard. These criteria were verified through use of a subject survey (presented in Appendix B) administered at the start of the experiment.

5.3.2. System Setup and Apparatus

The experiment setup included a high-performance Dell graphics workstation, the Wacom Cintiq 12wx Tablet with inking pen, the Novint Falcon haptic device and the Sensable Technologies PHANTOM® Desktop™ haptic device. A computer interface was developed for each device in order to facilitate the ROCF testing. An EMG system was used to collect EMG signals on multiple forearm muscles. EMG was used to monitor muscle activity during each trial of the ROCF test. Figure 5 shows the forearm muscles used in drawing activities.

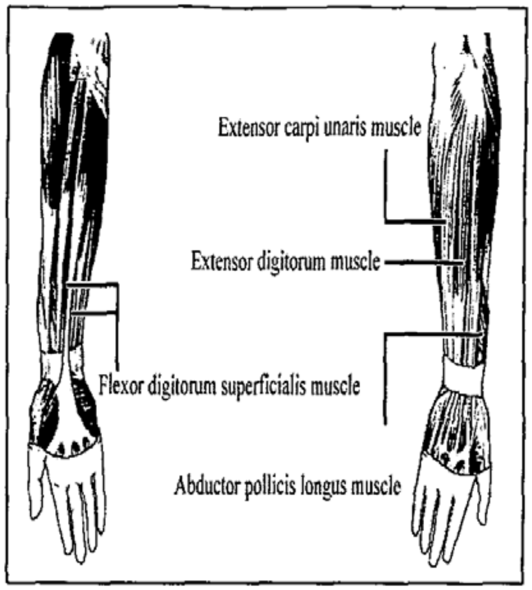


Figure 5-5. Muscles monitored by EMG.

5.3.3. Procedure

After completing the consent forms and survey, participants were asked to don four (4) pairs of electrodes. Base line force (relaxed muscles) and maximum force exertion were recorded. Subjects were then asked to practice drawing with the Wacom tablet covered by paper, the Novint haptic device and the Phantom haptic device.

Two training trials for each device were conducted. Subjects were asked to draw Unit 6 of the ROCF with each device. Extra training trials were provided if a subject asked for more practice to become familiar with a device.

After the training trials, subjects were asked to make pairwise comparisons of task workload demand factors as part of the NASA-TLX (task load index) survey, which is a subjective workload assessment tool (presented in Appendix D). This was followed by the experiment trials. The experiment was designed as a Latin Square:

Table 5-1. Experiment design following a Latin Square.

Subject	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6
Subject 1	Paper	Paper	Falcon	Falcon	Phantom	Phantom
Subject 2	Falcon	Falcon	Phantom	Phantom	Paper	Paper
Subject 3	Phantom	Phantom	Paper	Paper	Falcon	Falcon

5.4.Results

5.4.1. Physical Performance

Analysis of the EMG signals for the four muscles revealed that muscle activity of Phantom users more closely approximated pen-paper users (Figure 5-6). A MANOVA on the APL, ECU, EDM and FD activity levels indicated differences among devices were significant for all muscles (Wilks's Lambda=0.003692, p<0.0001). A one-way ANOVA was used to identify statistically significant differences among the three devices in terms of the EMG signal for each of the four muscles. ANOVA results revealed that the Falcon was not significantly different from pen-paper ("green" bars in Figure 5-6) in terms of the ECU, EDM and FD EMG responses. However, the Falcon did differ from pen-paper for the APL response and the Phantom was different from the other conditions for all other muscles responses. This is explained below.

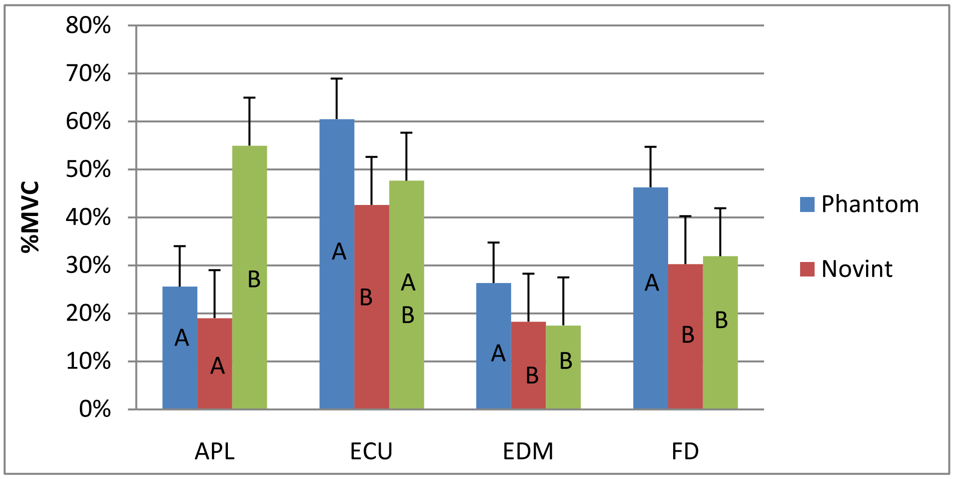


Figure 5-6. Average muscle activity for four muscles using different drawing devices.

Table 5-2. ANOVA results on EMG responses.

Muscle	ANOVA
Abductor Pollicis Longus Muscle (APL)	F(2,13)=52.48, p<0.0001***
Extensor Carpis Unaris Muscle (ECU)	F(2,13)=4.04, p=0.04*
Extensor Digitorum Muscle (EDM)	F(2,13)=14.13, p=0.0005***
Flexor Digitorum Superficialis Muscle (FDS)	F(2,13)=9.78, p=0.0026***

Correlation analysis showed that subject performance with the Novint device was less related to performance with the pen-paper than the Phantom haptic device (see Table 5-3).

Table 5-3. Correlation analysis for devices.

	Novint	Paper	Phantom
Novint		0.0702	0.2776
Paper	0.0702		0.4583
Phantom	0.2776	0.4583	

5.4.2. Time–to-Completion

ANOVA results revealed that the device had a significant influence on the task completion time (see Table 5-4). The time spent in performing the task with both the Novint Falcon and the Phantom haptic device was longer than for the pen-paper drawing (see Figure 5-7). Completion times for the Novint and Phantom devices were similar.

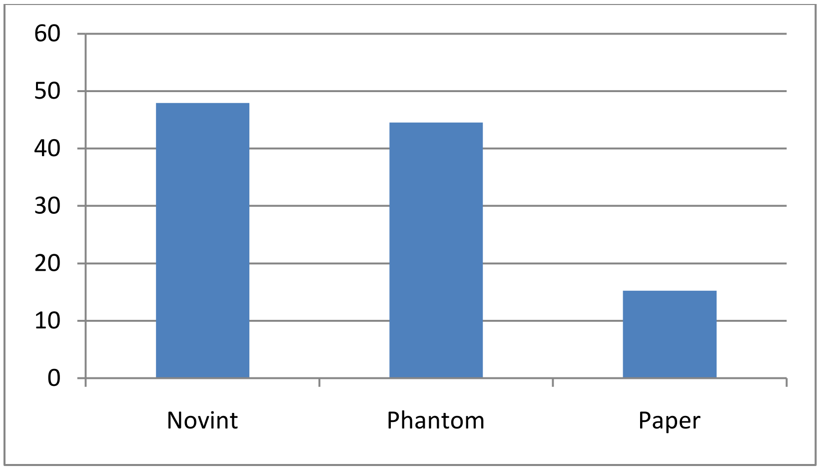


Figure 5-7. Time to Completion (second).

Table 5-5 reveals the influence of the device completion time. Table 5-5 shows that there was no significant difference between time-to-completion with the Phantom haptic device vs. Falcon haptic device, but the completion time for drawing on paper was significantly different.

Table 5-4. ANOVA results on completion time with three devices.

Source	DF	Sum of squares	Mean Square	F Value	Pr>F
Model	2	4.04161428	2.02080714	11.40	0.0010
Error	15	2.65871998	0.17724800		
Corrected Total	17	6.70033426			

Table 5-5. Tukey Test results on time-to-completion (log transformed) with three devices.

Tukey Grouping	Mean	N	Device
A	3.7570	6	Phantom
A	3.5536	6	Novint
B	2.6657	6	Paper

5.4.3. Accuracy and placement

Subjects complained about difficulty in controlling the Novint Falcon device, due to the fact that tiny adjustment movements were exaggerated by the device. The low resolution of the control translated into a zigzag pattern in line drawing and overshoots or undershoots at intersections/corners.

The graphic drawing results of the Phantom haptic device were similar to pen-paper drawing. Figures 5-8 and 5-9 show the drawing results of one subject. Figure 5-9 reveals an overshoot at the upper left corner, which is a major scoring point for the ROCF testing.

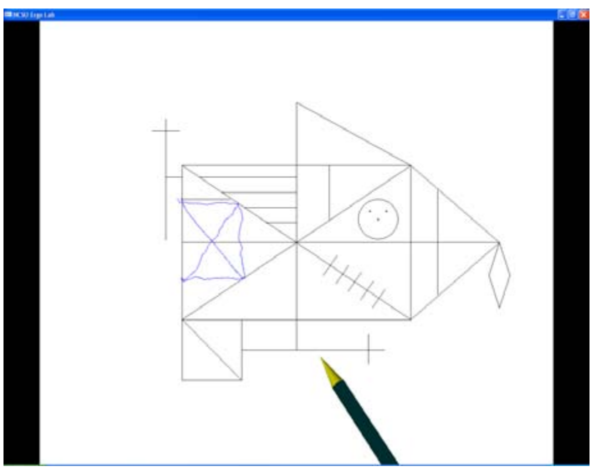


Figure 5-8. Drawing with Novint Falcon haptic device.

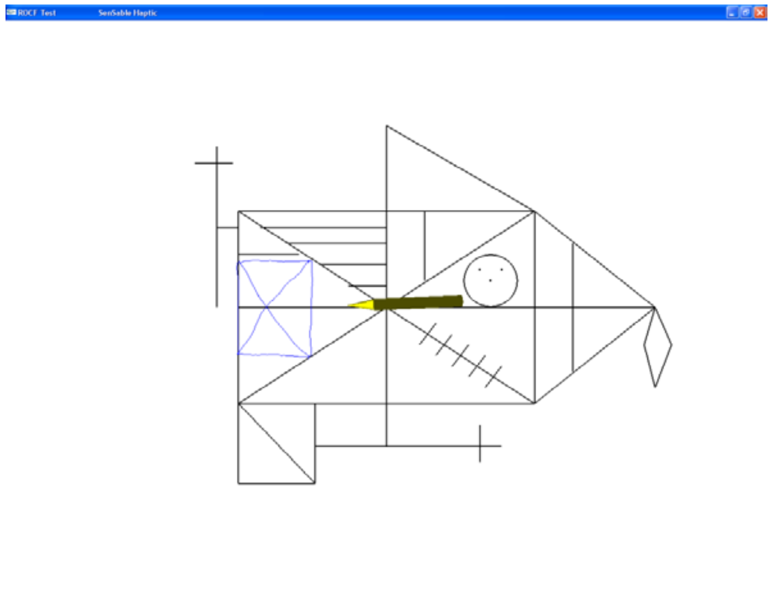


Figure 5-9. Drawing with SensAble Phantom haptic device.

5.4.4. Post-experiment Questionnaire

Subjects were asked to rate the realism of drawing with the Phantom device and Falcon device, as compared to real pen-and-paper drawing, on a scale from 1-7 (where 1=not useful at all and 7=extremely useful). The Phantom was rated as 6.33 and the Falcon as 3.67. Two out of three subjects thought that the Phantom haptic device had no negative influence on the accuracy of drawing, while the Falcon device did. One subject thought that neither of the haptic devices had a negative influence on drawing. Two out of three subjects thought the training trials were long enough to allow them to become comfortable with using the haptic device. One subject was not sure whether training was sufficient.

5.4.5. NASA-TLX Survey Results

At the close of each test trial, ratings of the workload demand components as part of the TLX were conducted. These ratings were integrated with the demand component rankings completed at the beginning of the study as a basis for calculating a composite workload score. The NASA-TLX workload assessment showed that the average workload score was 49.96. The lowest score was 35.33 and the highest was 65.72. The hypothesis was that subjects who had prior experience with haptic devices would produce lower workload scores. The subject with experience in using haptic device for research gave the lowest score, which supported the hypothesis.

5.5. Discussion and Conclusion

This study showed that both haptic devices, the SensAble Phantom and Novint Falcon, caused forearm muscle activity levels in the ECU, EDM and FD comparable to those observed in pen-paper based drawing tests. There was higher muscle activity in the EDM and FD when using the Phantom device compared to Novint falcon and pen-paper drawing. One possible explanation for this finding is that the Phantom device stylus tip is connected to a robotic arm, which is also connected to the base of the device. The arm rotates around the tip during the drawing process. Consequently, subjects frequently lifted their hand or tilted their wrist, for a better viewing angle on the drawing or a better holding position to avoid the influence of the stylus arm.

Since the APL muscle is used to stabilize the grip of the stylus and is not affected by frequent lifts, no significant difference was seen between the Phantom and Novint Falcon devices for this muscle. However, there was a significant difference in APL activity for paper drawing compared with the haptic devices. This can be attributed to the frictional force of the tablet stylus on the paper surface and the need to maintain a greater APL muscle force to stabilize the implement relative to stabilizing the Phantom stylus or Falcon ball in free space. In general, the limited differences in muscle activities using different drawing methods suggests that from a biomechanical perspective the haptic devices may be considered as alternate equipment for delivering the ROCF test.

However, it was also observed that the two devices caused significant increases in task completion time compared with the pen-paper tests. The reasons for the extra task time with the haptic devices may include the following:

- A lack of depth cues - Subjects said that they felt they needed to slow down their movement when the virtual pen started to get close to the virtual writing surface, until the pen actually touched the writing surface. Since subjects had to constantly lift the pen and move to a certain point for the next stroke trajectory, the overall completion time increased.
- Different control methods - The Falcon haptic device was controlled by holding a ball in the hand, which is very different from normal writing/drawing movements. In order to achieve reasonably good drawing performance, subjects had to slow down their normal hand motions. Although the SenSable Phantom is built with a stylus-type control mechanism, the stylus is much thicker than a standard pen used in pen-paper drawing. The stylus pointing position also occurs in virtual space; consequently good eye-hand coordination skills matter. The reason why drawing took longer with the Phantom was that it was possible to obtain better drawing results by sacrificing drawing speed.

However, with the Novint device, the ball shaped controller and low control resolution were major problems, which could not be compensated for by slowing drawing movements. In general, the ball shaped controller was not designed for delicate control. Intuitively, subjects felt that slowing down was not as helpful with the Novint as with the Phantom, and they started to draw faster with the Novint.

On one hand, the tablet PC or tablet (Wacom Cintiq) is a good alternative to pen-paper-based ROCF testing. This is due to the physical similarity of the task with the tablet and the pen and paper. On the other hand, the ability of the Phantom haptic device to provide similar accuracy and placement results, as pen-paper drawing, and its ability to be add extra force assistance in rehabilitation applications make it a versatile tool for clinical test applications.

The low-end Falcon haptic device was not able to deliver reasonably good results in terms of accuracy and placement in drawing feature reproduction for clinical testing; however, based on its price and portable design, we believe it could be used for applications where general force-feedback is needed but accuracy is not a major concern. Rehabilitation application development may be an appropriate area. An example would be upper-limb stroke therapy, as studied by Lam′s group [37].

The results of this study provide some insight into the influence of haptic devices on user performance in medical evaluation applications. The results indicate that advanced VR technologies, like the Phantom haptic device, may be used to replace traditional pen-paper-based tests, specifically for ROCF testing, to assess motor-control disabilities.

CHAPTER 6. ON-LINE DRAWING RECOGNITION AND SCORING

6.1. Introduction

As previously stated, the main purpose of this study was to develop an automated scoring system for the ROCF test. This application poses very high accuracy and robustness requirements for drawing recognition and scoring, particularly in use as a diagnosis tool in hospitals and clinics. The accuracy of recognition was the highest priority in the system development. Multiple information resources, including human assistance, are used to guarantee the most effective and accurate drawing recognition and scoring.

The contributions of this work in terms of the software development for drawing recognition include:

- Successful recording of freehand drawings and recognition of strokes - The recorded data from testing is point data. Effective data processing and recognition of drawing features and strokes are critical to accurate scoring results.
- Normalization of strokes for unit scoring - The scoring requirements for specific units in the ROCF are very detailed and need to be strictly implemented. Each component of units needs to be recognized and identified. For example, Unit 2 is a large rectangle. Top horizontal line, bottom horizontal line, left vertical line and right vertical line are required to be identified respectively.

6.2.Sample size

In the new prototype system, original drawing data are recorded every 0.015 seconds. However, the required sampling rate for drawing analysis is much lower. The prototype system samples drawing data at a fixed frequency when patients are taking the ROCF test. The more slowly patients draw, the more data points are recorded. There may be great individual differences between patients; therefore, choosing an optimal number of sampled points can save processing time and maintain the effectiveness of the system. Referring to Figures 6-1 - 6-4, when the sample size is as small as 500 points in total, scoring elements may be missing. For example, Figure 6-1 is missing a short line as marked by the arrow. However, Figures 6-2, 6-3 and 6-4 are not very different, although there are 10 times more points presented in Figure 6-4 as compared with Figure 6-2.

Figure 6-5 is a picture saved from an original drawing test. It can be seen that graphics generated from the data text file, and presented in Figure 6-2, 6-3 and 6-4, are exactly the same as Figure 6-5. A clinician can choose the optimal sample size that is large enough to display all features for scoring and still small enough for fast processing.

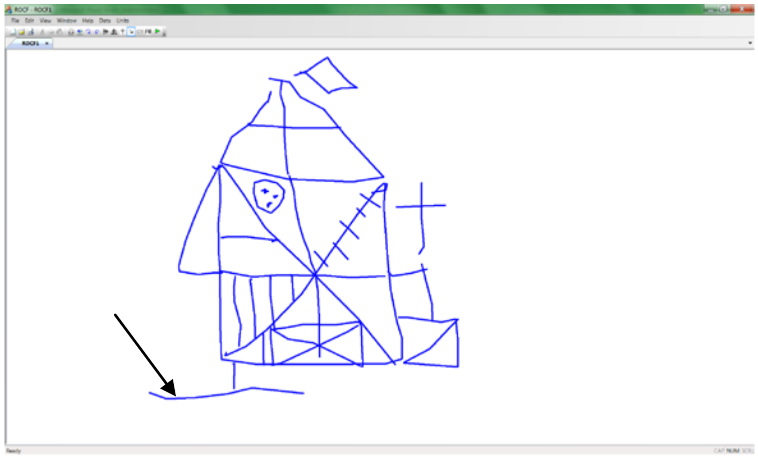


Figure 6-1. 500 sample points for entire drawing.

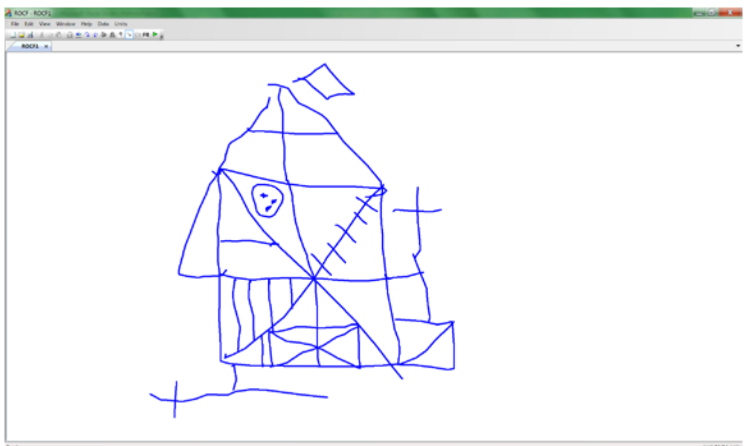


Figure 6-2. 1000 sample points for entire drawing.

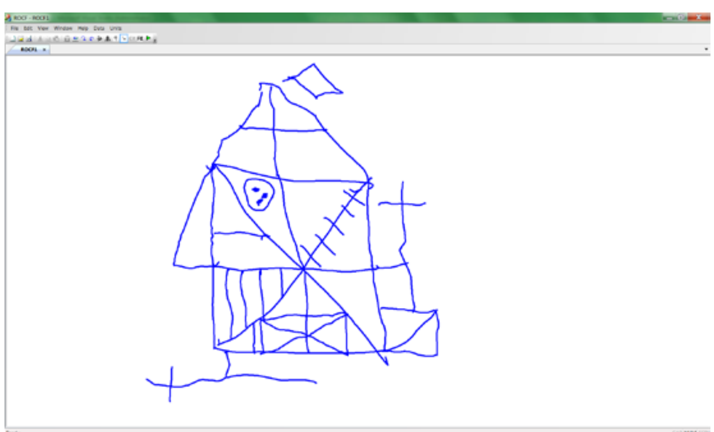


Figure 6-3. 5000 sample points for entire drawing.

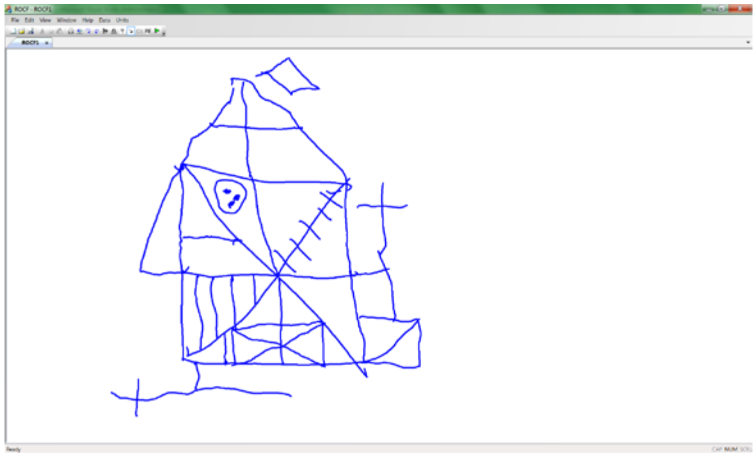


Figure 6-4. 10000 sample points for entire drawing.

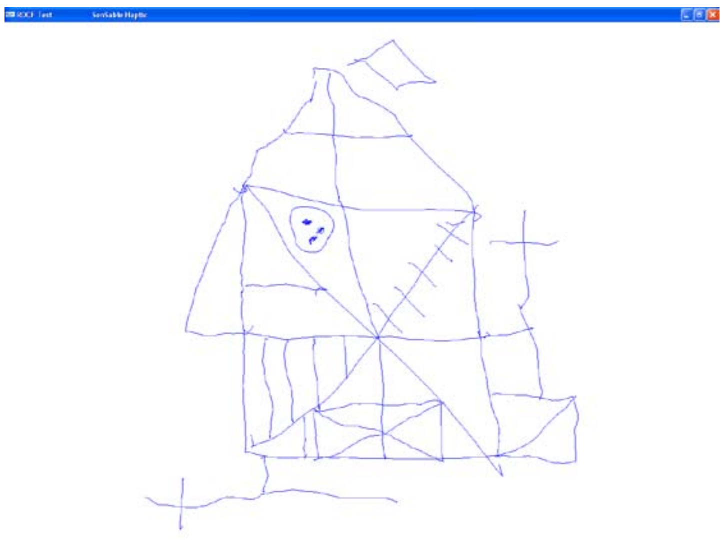


Figure 6-5. Original graphic drawing screenshot.

6.3. Stroke Forming

In the new prototype system, drawing strokes are simply isolated points. Points are represented by 3D coordinates, which provide enough information to infer user drawing movements. Figures 6-6 through 6-10 show “stroke-by-stroke” drawings. In Figure 6-6, the entire large rectangle is drawn with one stroke. This means it is drawn continuously without the pen being lifted from the drawing surface. The first step in identifying strokes is to group data points. Although strokes may ultimately be further divided into line segments, stroke information is very useful for optimizing the drawing feature recognition process. For example, Figure 6-11 presents the bounding boxes for each stroke that is recognized in the drawing. The boxes can also be used to facilitate quick selection of features by a clinician in the scoring process.

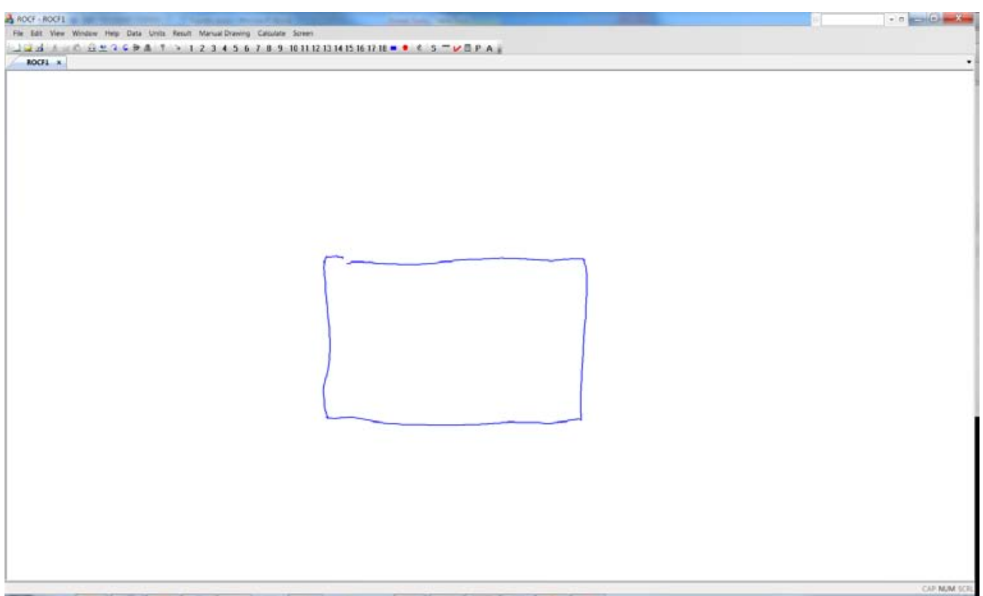


Figure 6-6. First stroke in drawing.

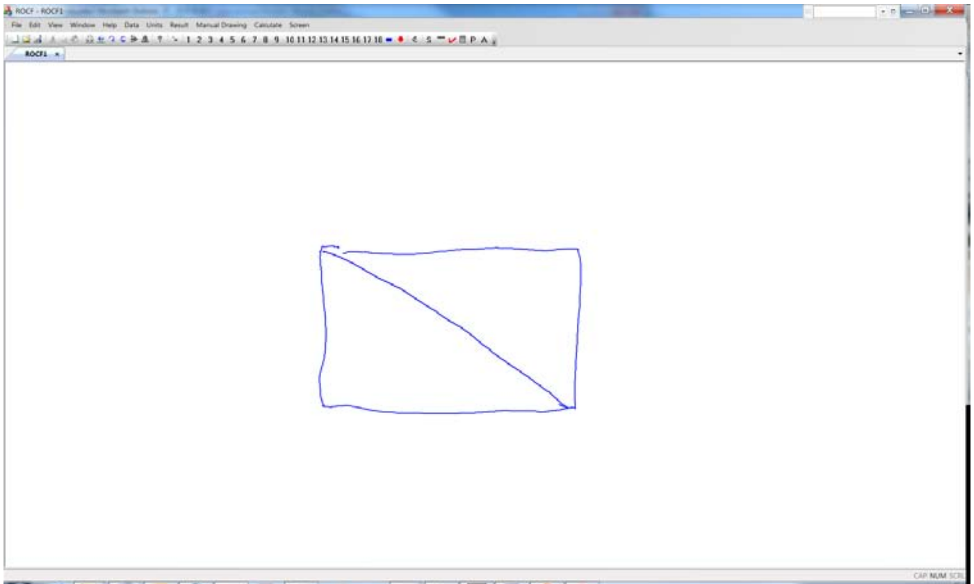


Figure 6-7. First two strokes in drawing.

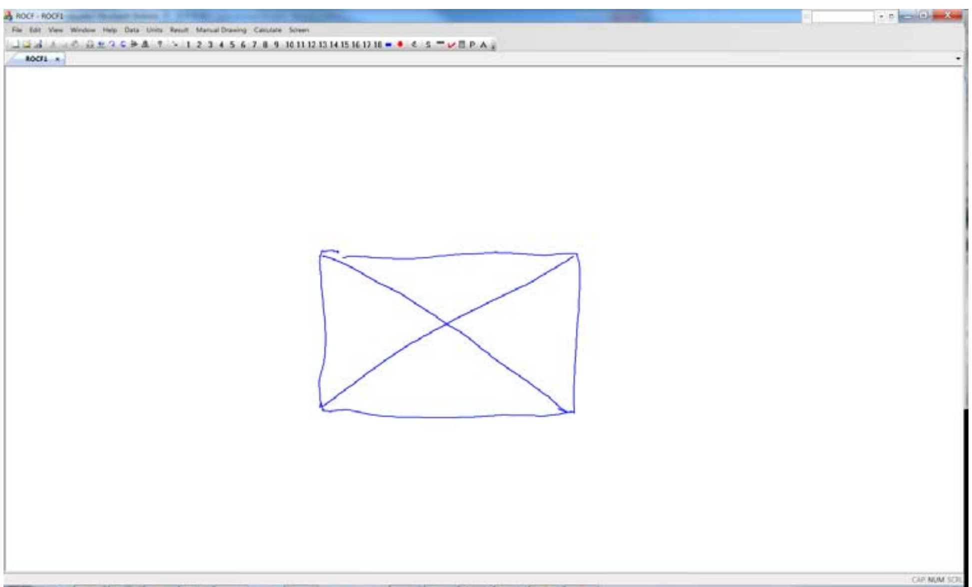


Figure 6-8. First three strokes in drawing.

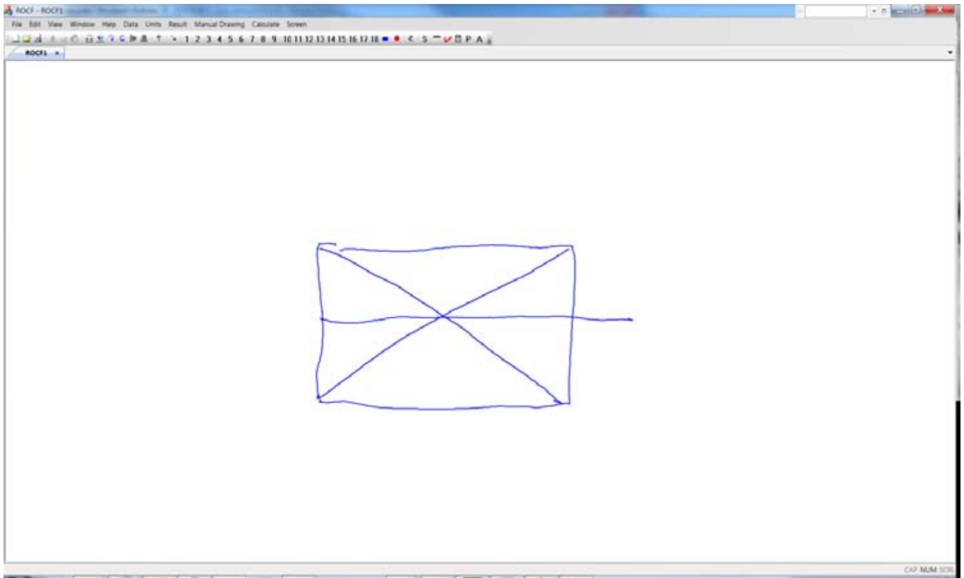


Figure 6-9. First four strokes in drawing.

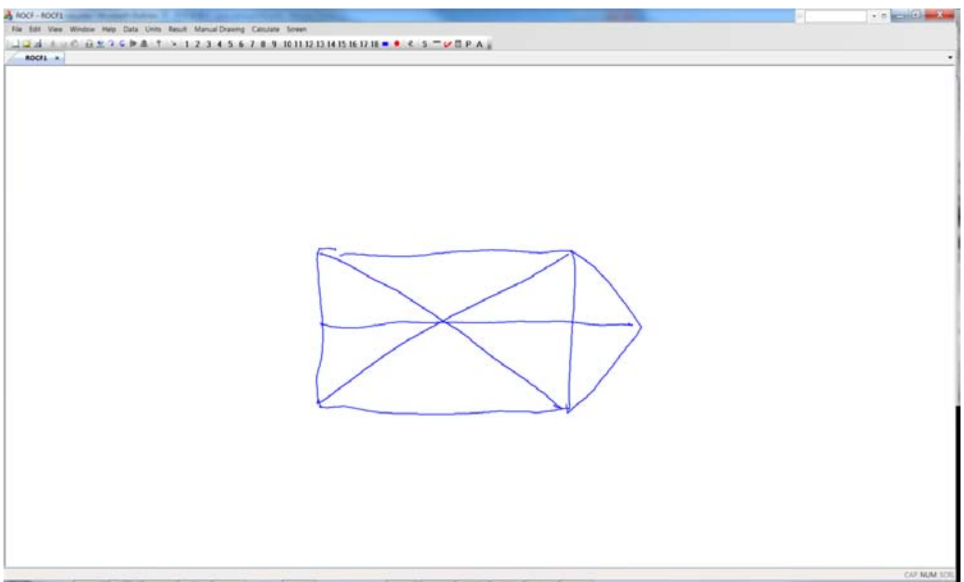


Figure 6-10. First five strokes in drawing.

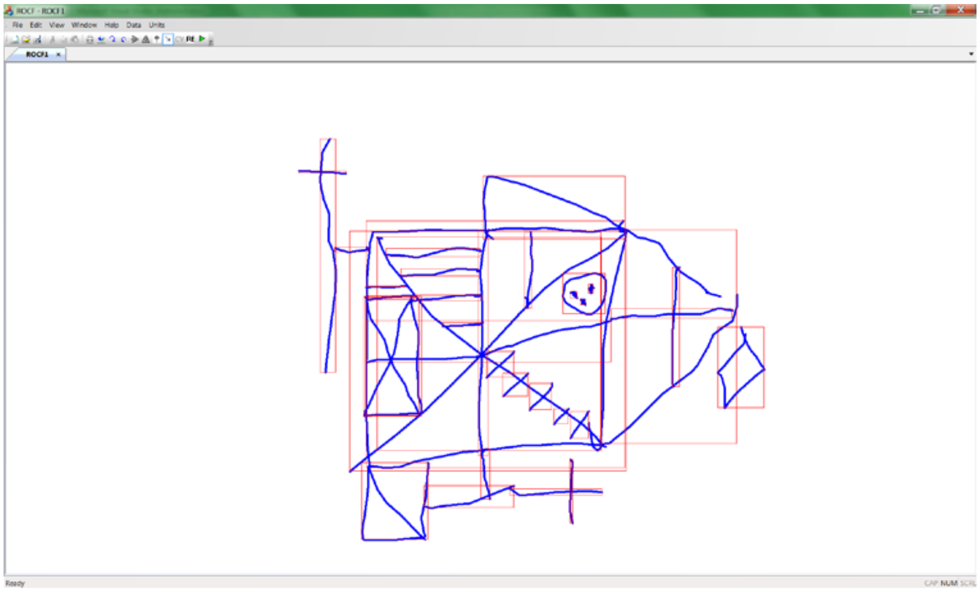


Figure 6-11. Bounding boxes for strokes in drawing.

6.4.Corner Detection

Corner detection is often used as a first step in imaging processing, drawing/handwriting recognition and figure fitting. The purpose is to further divide strokes into line segments. For example, Figure 6-10 shows that two sides of the triangle on the right are drawn with one stroke. However, later in the analysis of the drawing, the angle of each side is needed for scoring. Consequently, corner detection is necessary to find the rightmost point of each side of the triangle.

As mentioned in the literature review, the FAST feature detector was used for corner detection in the prototype system. In order to obtain better results in the detection process, the drawing graphic was converted to a grey scale image. Figure 6-12 shows the detected corners in the image displayed with neighbor pixels.

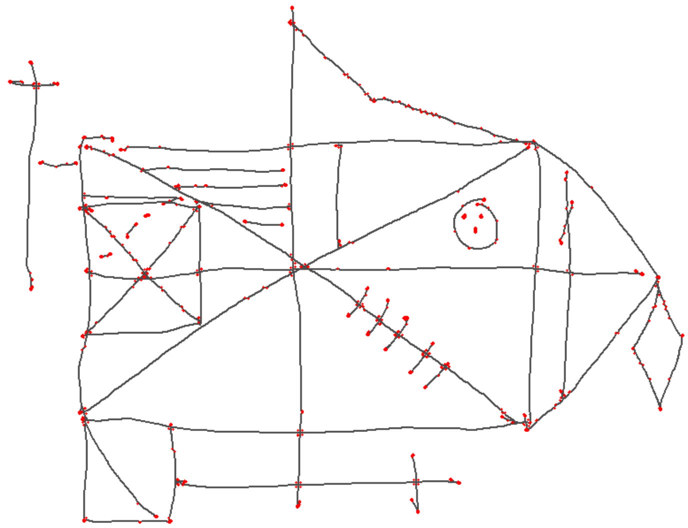


Figure 6-12. Corner detection results.

6.5. Circle Detection

The Hough transformation circle detection algorithm was used to find Unit 11 (see Figure 6-13). For the Hough Transformation detector, we need to assume that Unit 11 is a circle. However, as previously mentioned, in the ROCF test, users may draw imperfect circles, which are more like ellipses. If Unit 11 is drawn as an ellipse, it is important to know the proportion of the two axes of the ellipse. On this basis, further processing is needed to fit the circle. Specifically, the bounding box of the circle is inflated to encompass the longest possible axis. All points in the bounding box are then checked to find the ellipse, that is the best fit of Unit 11 (see Figure 6-14).

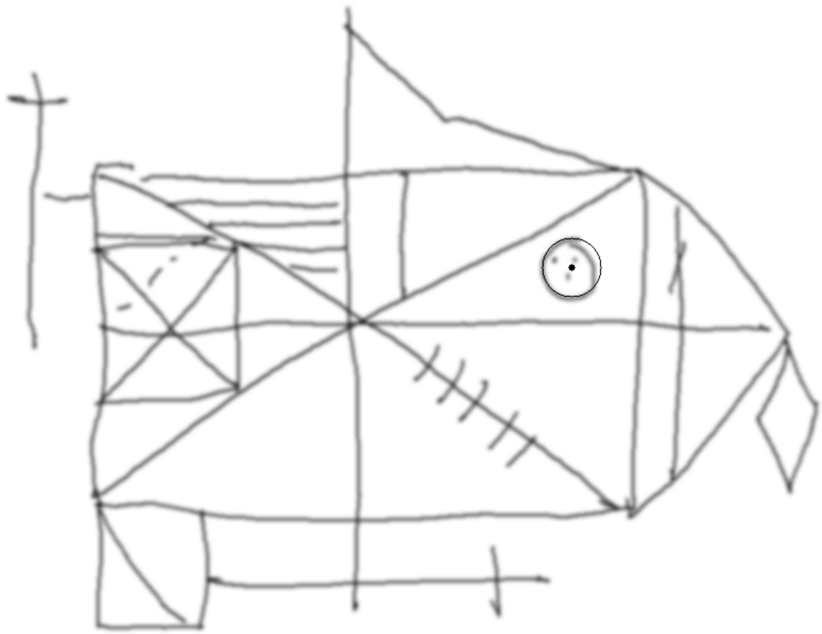


Figure 6-13. Results of the Hough Transformation corner detection.

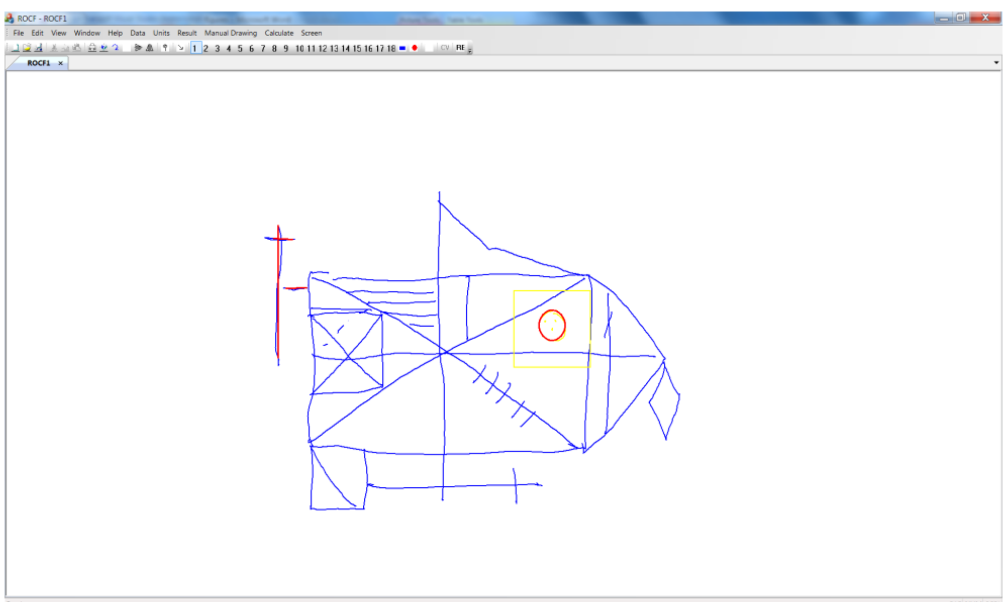


Figure 6-14. Fitting an ellipse to Unit 11.

6.6. Line Segmentation

For each stroke in a drawing, small line segments are formed based on the corner detection results. As shown in Figure 6-12, some detected corners result from noise and unintentional movements (e.g., shaking of the hand). Consequently, it is important to filter out unwanted corners as a basis. Below is the list of processing steps in identifying line segments within one stroke:

```
Start
Declare variables
    LineSegment
    Point
    StartPoint
    EndPoint
Do While Not End of Stroke
    Read point from Stroke
    If Point is corner
        StartPoint =Point
    Endif
    Do While EndPoint=NULL
        If Point is Corner
            EndPoint=Point
        Endif
    EndDo
```

```
    Construct LineSegment with StartPoint, EndPoint
EndDo
Record New Line Segment
End
```

Subsequently, within each stroke, line segments are rearranged to form new segments:

```
Start
    Declare variables
        LineSegment
        NextSegment
        NewLineSegment
        AngleThreshold
        LengthThreshold
    Read LineSegment from Stroke
    Do While Not End of Stroke
        Read NextSegment from Stroke
        If LineSegment's Angle- NextSegment<AngleThreshold
        or NextSegment <LengthThreshold
            NewLineSegment=combine LineSegment and NextSegment
      Endif
    EndDo
```

End

By controlling the minimum acceptable angle-change threshold and length threshold, lines with zigzags or curves can still be recognized, without being divided into very short segments. Figure 6-15 shows an example of this recognition capability in the new system. Although subject hand trembling resulted in many short line segments being identified in the first step of the segmentation process, there in the second step, those lines shorter than the line length threshold were used to form a longer line segment, as marked by the arrow. Line deviation information, including the degree of trembling as a reference of drawing quality, is saved with the line. For Figure 6-16, if we want to make sure the line identified by the arrow can be formed, verses identification of two small line segments, the angle threshold value must be increased in order to accommodate the degree of difference between the two small lines.

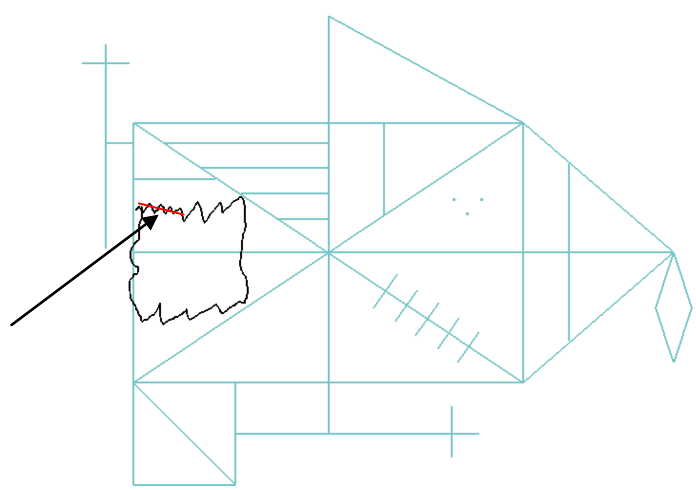


Figure 6-15. Trembling/shaking effects filtered out by segment length control.

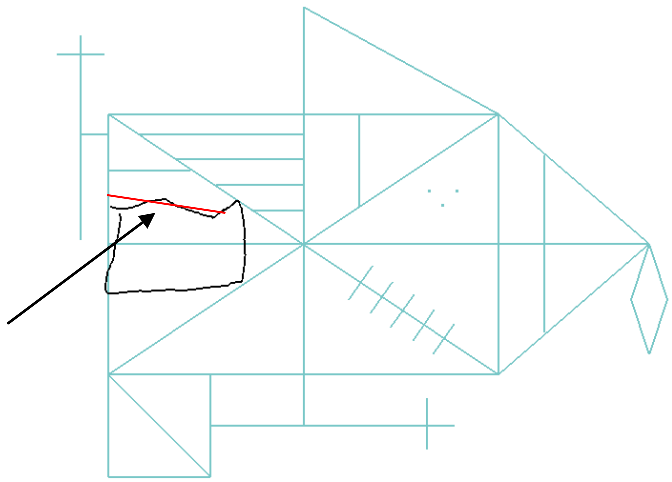


Figure 6-16. Identification of line segments based on angle control.

By controlling the angle and length thresholds in the system software, common defects, such as trembling and unwanted curvature, can be filtered to assure unit recognition quality. Furthermore, drawing quality information is still saved for clinicians. Proper threshold setting should allow for actual defect information to be retained in the drawing recognition process and output. A clinician must decide if a threshold value is acceptable or not. For example, in Figure 6-17, the marked line segments are recognized as two small lines. With the new system, a clinician has the option to decide whether to accept them as one side of the triangle.

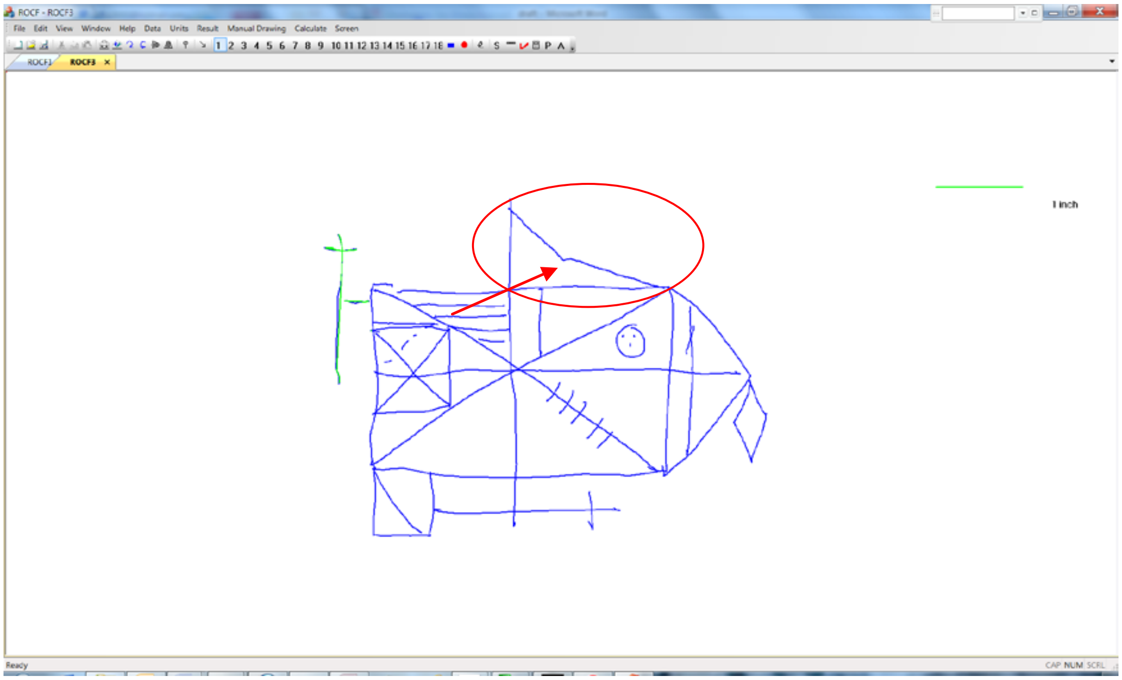


Figure 6-17. A drawing defect.

6.7. Unit Recognition

Unit recognition is the most challenging part of the ROCF analysis and scoring process. In the present application, it is necessary that not only can drawing units be recognized, but that the components of each unit, including lines, circles and points, can be recognized. Each component needs to be fitted with a drawing unit in an exact manner. The challenges in unit recognition include the following:

1. Each unit has a different number of components and each component has different geometric relations.
2. Substantial variations in drawings make component recognition difficult.
3. Many drawing units share components.

4. Minimum recognition success rates are required for scoring, etc.

Since the prototype system is intended to be used in hospitals and clinics, the stability and robustness of the system in unit recognition is critical. Even if the system can achieve a 95% or 98% success rate in matching each unit component to the correct line segment in a drawing, the application may still not be acceptable for clinical use. Consequently, human assistance in unit component identification may be necessary and even beneficial over using statistical model-based parsers of a drawing. However, the new system is also designed to minimize labor requirements in the unit recognition process. In every unit recognition process, clinicians are asked by the system to select candidate line segments for each unit. This approach can eliminate noise and effectively reduce unnecessary searching and processing requirements for the computer system. The system pattern-matching algorithm was developed to identify each unit component and to ensure the correct match with the candidate segments. A clinician also has the opportunity to visualize and confirm the recognition results for each unit.

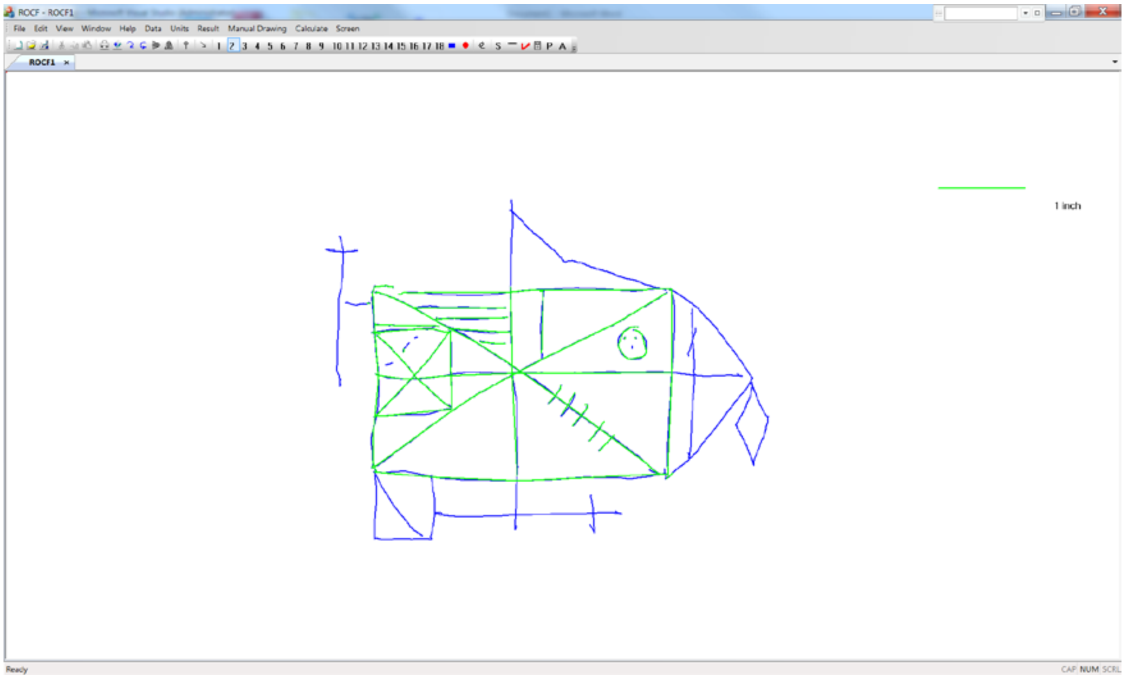


Figure 6-18. Candidate line segments selected for Unit 2 recognition.

As an example of the unit component recognition process, consider Unit 2, the largest rectangle in the drawing (see Figure 6-18). The user of the system is asked to identify the candidate lines by dragging a large rectangle to include all four sides of the drawn unit without excluding any components inside. The component matching algorithm works as follows:

Start

Declare variables

LineSegment

BoundingBox

TopLine

BottomLine

```
    LeftLine
    RightLine
Get Bounding Box of Selected lines
DoWhile Check all selected line segments
    If LineSegment is horizontal line
        If LineSegment close to BoundingBox Top
            Add LineSegment to TopLine
        Endif
        If LineSegment close to BoundingBox Bottom
            Add LineSegment to BottomLine
        Endif
    Endif
    If LineSegment is vertical line
        If LineSegment close to BoundingBox Left
            Add LineSegment to LeftLine
        Endif
        If LineSegment close to BoundingBox Right
            Add LineSegment to RightLine
        Endif
    Endif
EndDo
Form Unit 2 with LeftLine, TopLine, RightLine, BottomLine
```

End

Figure 6-19 shows the recognized Unit 2 after this process. In the next chapter, the system parameter setting interface is introduced as a basis for deciding if the upper-left corner is acceptable as a “no undershoot” situation or not. The parameter settings and such decisions can be controlled by clinicians.

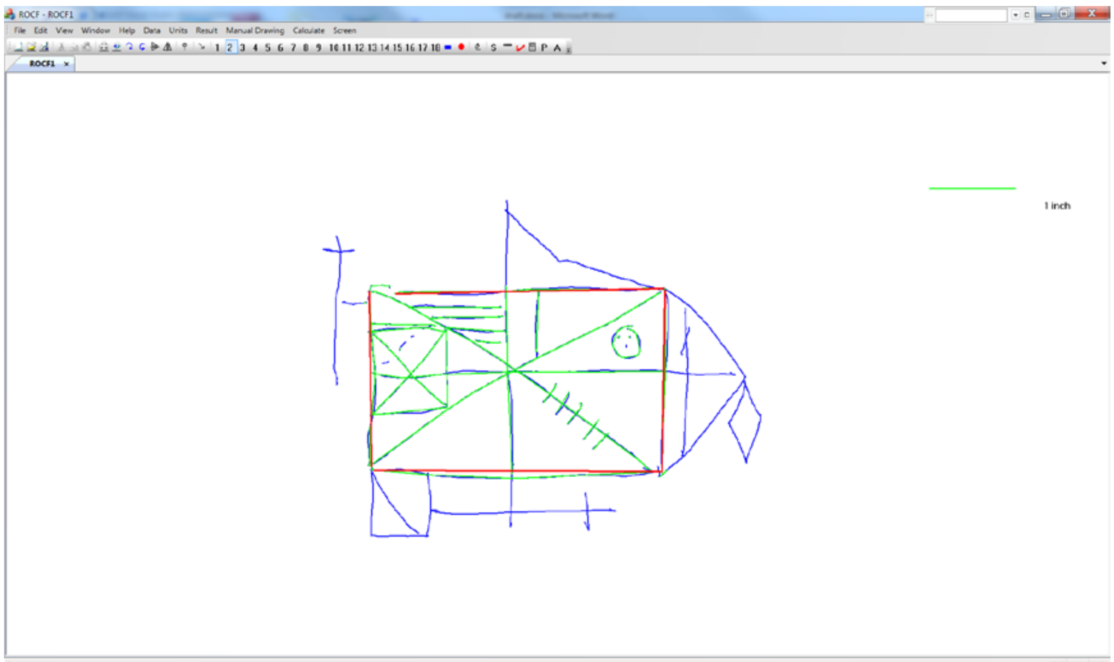


Figure 6-19. Recognized Unit 2.

6.8. Score Calculation

After each unit has been recognized, scores are calculated for each unit by the system. Appendix E lists the criteria that have been programmed in the software for scoring based on the published scoring manual [50]. The importance of the current work is that this part can be changed for implementation of other ROCF scoring systems. In order to demonstrate the scoring mechanism, Unit 4 is used as an example. The following is the scoring criteria for Unit 4.

Accuracy

04_A_1 - A horizontal line should be drawn between the vertical segments of the Large Rectangle (2).

04_A_2 - The line should not overshoot or undershoot the vertical segments of the Large Rectangle (2) by more than 1/8 inch.

04_A_3 - The line segment should be approximately straight.

Placement

04_P_1 - The Horizontal Midline (4) should be positioned no further than ¼ inch from the intersection of the two lines that form the Diagonal Cross (3) and should be within ¼ inch of bisecting the vertical sides of the Large Rectangle (2).

04_P_2 - If the Diagonal Cross (3) is not present, the Horizontal Midline (4) should be no further than ¼ inch from the midpoint of the Large Rectangle (2).

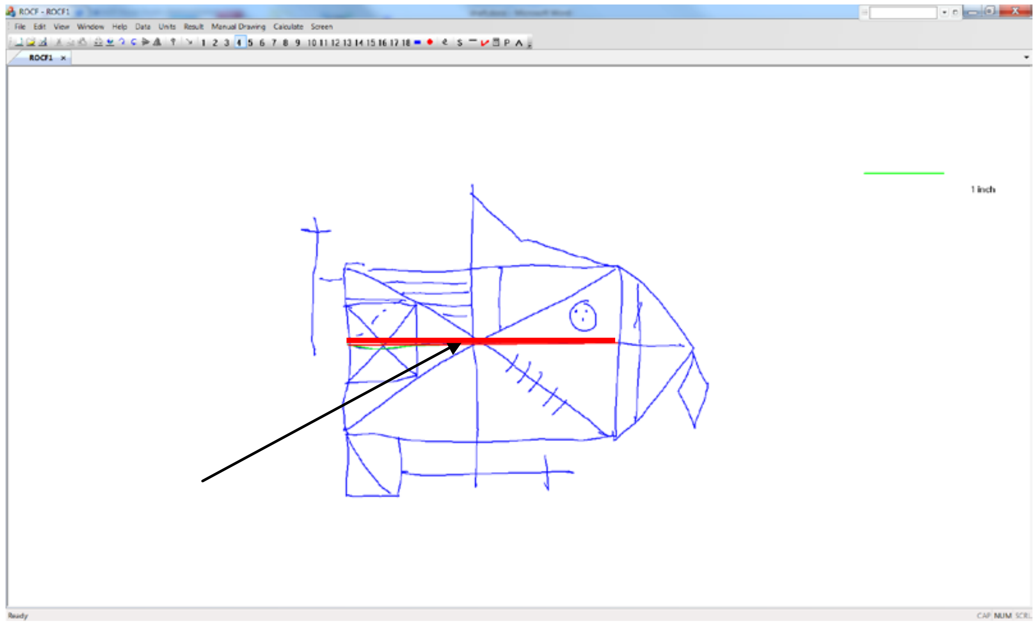


Figure 6-20. Unit 4 in ROCF (highlighted in bold)

Start

Declare Variable

Unit 4

Accuracy=1

Placement=1

TotalScore

If unit 4 not exist

Accuracy=0

Placement=0

TotalScore=0

Endif

```
If unit 4 not interaction with LeftLine of unit 2
  Accuracy=0.5
Endif
If unit 4 not interaction with RightLine of unit 2
  Accuracy=0.5
Endif
Calculate distance1 of unit 4 left end to LeftLine of unit 2
Calculate distance2 of unit 4 right end to RightLine of unit 2
If distance 1> 1/8 inch or distance1<-1/8 inch
    Accuracy=0.5
Endif
If distance 2> 1/8 inch or distance1<-1/8 inch
    Accuracy=0.5
Endif
If unit4 deviation >threshold
    Accuracy=0.5
End if
Placement=1
If unit 4 position –intersection of unit 3> ¼ inch or < - ¼  inch
    Placement=0
Endif
If unit4 position-midline of unit 2
```

```
        Placement=0
    Endif
    Total score=accuracy + placement
    If Totalscore=1.5
         Totalscore=1
    Endif
END
```

6.9. Conclusion

In this chapter, the algorithms to process drawing data and calculate ROCF scores were presented. The unit recognition process was designed to support high accuracy as a basis for accurate scoring. The scoring algorithms were developed to provide for complete and robust analysis of drawings. In future study, the code for these algorithms needs to be tuned based on feedback from clinicians. Functions can be modulated and added to support new scoring methods and features.

CHAPTER 7. ROCF SCORING SOFTWARE FOR CLINICIANS

This chapter presents the interface design for the new system to support clinician use. A graphical user interface (GUI) has been developed for clinicians to use the system to analyze drawing results. Clinicians can obtain files directly from the testing workstation. Graphic results are presented for clinician visual analysis. The system then automatically generates a score report in text format as an entity to the current EMR system.

7.1.User Operation

The test workstation is connected to a computer with software installed and CPUs for supporting the haptic and graphics rendering. However, the client terminal for clinicians can be installed in different computers in clinician offices, even on laptop computers. The flexibility and portability of this part of the system enables clinicians to replay and monitor the analysis process for a patient anywhere and anytime. They can also change the control parameters for scoring and diagnosis as needed.

After a subject completes a drawing with the haptic based ROCF system, the resuls are saved in the testing workstation and can be transferred to clinicians' computers through internet or portable storages devices. Figure 7-1 shows the flowchart of standard operations for clinician use of the system from opening the drawing raw data to generating complete drawing score reports. In the following paragraphs, each step of the operation is defined and explained.

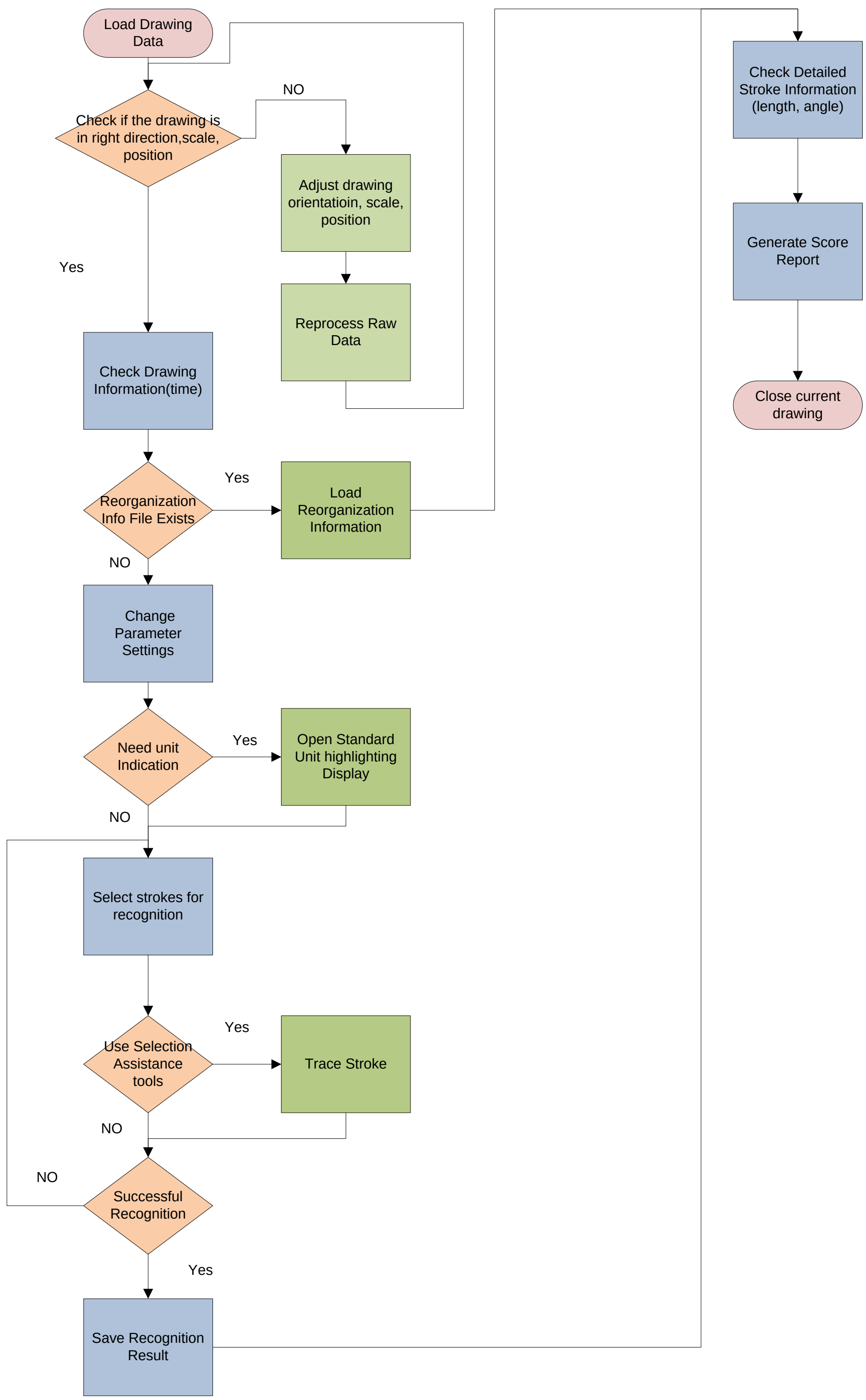


Figure 7-1. Flowchart of clinician user operations.

7.2. Client Software Interface for Clinicians

A Windows-style graphic user interface (GUI) was developed for clinicians (see Figure 7-2). Standard controls, for example, file open, save, print etc., are used, so minimal training is needed for clinicians to use the system. The main menus as part of the software are listed here:

- The "data" menu includes the necessary operations to open the raw data and adjust the graphic display of raw data.
- The "units" menu controls the selection of each unit for unit recognition. In the recognition of a particular unit, if the standard unit indication function is selected, the corresponding unit will be highlighted in the standard sample figure.
- The "calculation" menu includes operations for recognition and scoring processes and recognition data import/export.
- Screen menu options control turning on/off sample figure displays.
- A 1-inch long line is displayed on the screen to guarantee that the software is working with proper scaling factors on different computers and displays.

Tabs are shown for multiple document control. Clinicians can open more than one set of patient results at any time, and switch between results for checking and comparison (see Figure 7-3). As shown in Figure 7-3, when a clinician opens the client software, a standard ROCF is presented at 1:1 ratio as the background.

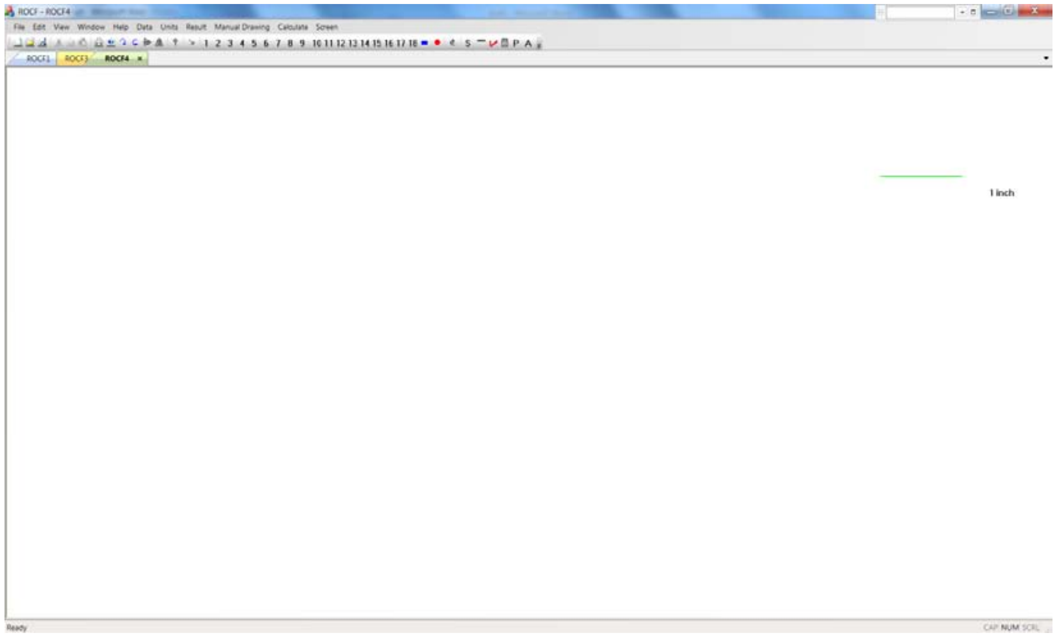


Figure 7-2. Windows interface for clinicians.

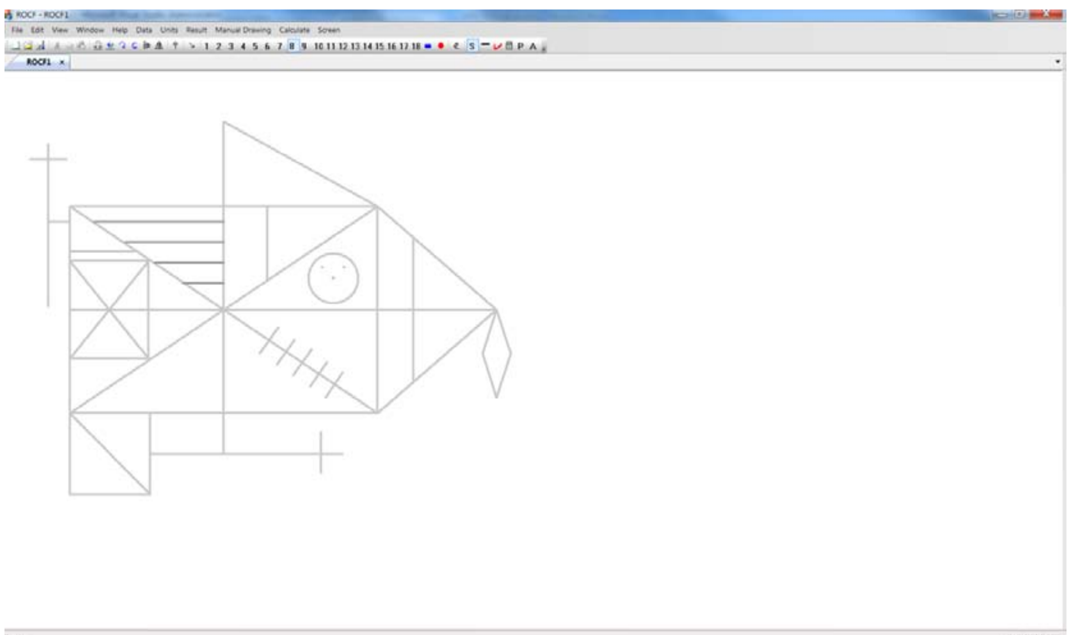


Figure 7-3. Standard ROCF (with Unit 8 highlighted).

7.3. Loading Drawing Data

Patient system drawing files are saved as text files. No graphical data are directly stored, so the required system storage is limited and file management, including file indexing, searching and transferring, is more efficient. Data files can be stored on a remote server or local machine. Clinicians can choose the “Open data file” from the data menu or tool bar to open the patient data (see Figures 7-4 and 7-5).

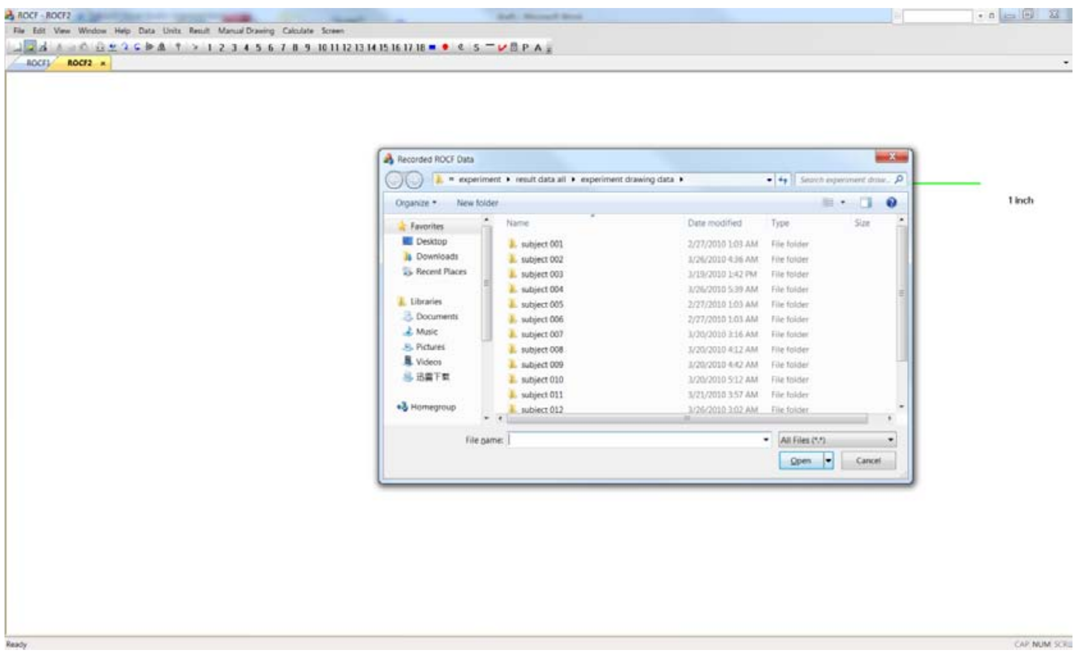


Figure 7-4. Open Data File dialog.

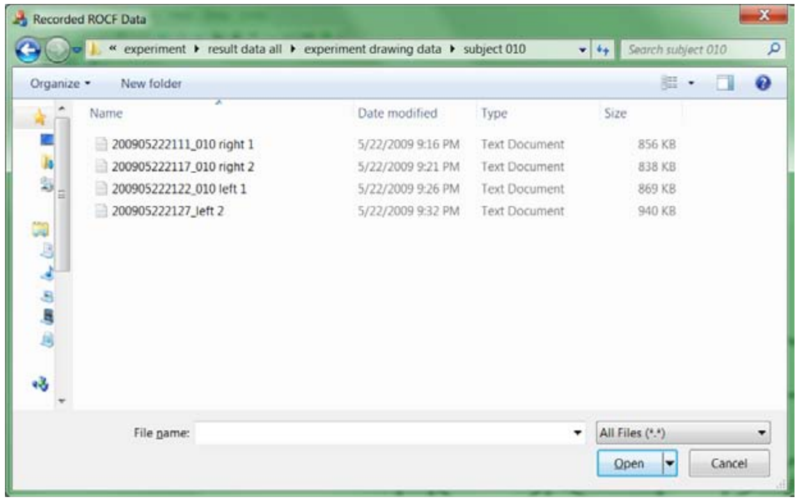


Figure 7-5. A list of data files for a specific patient.

Once a recorded file is opened, the graphic results are automatically generated, as shown in Figure 7-6.

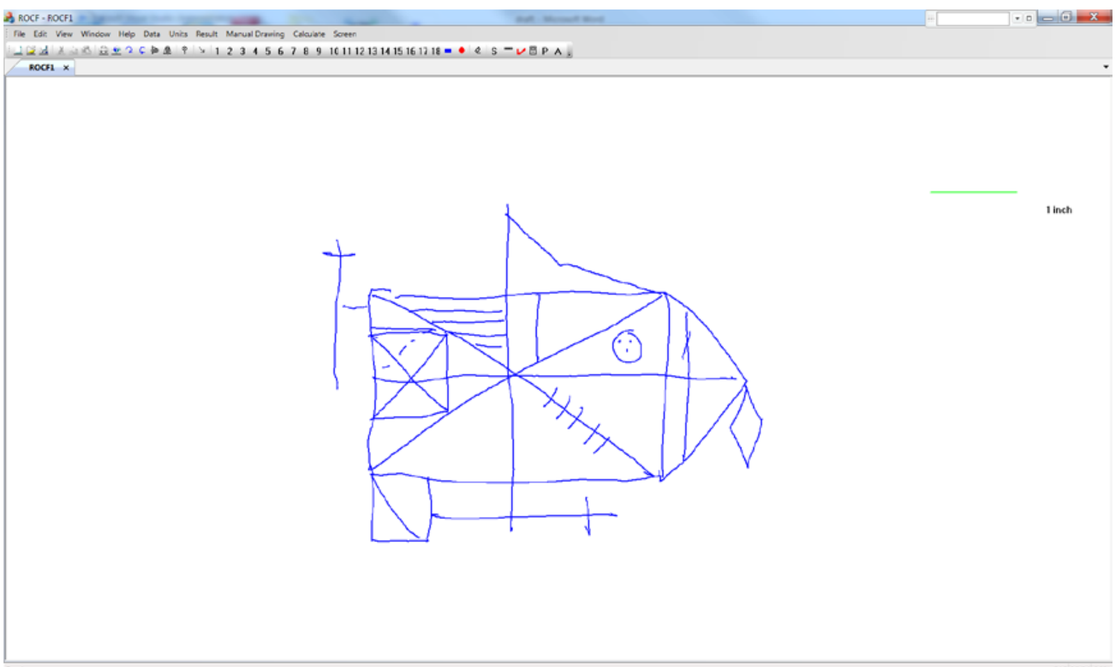


Figure 7-6. Graphic results generated from a data text file.

7.4.Scaling, Rotation and Translation

The ROCF scoring system considers the proportion of drawing units, as well as the scale of units. Although patients are instructed to copy the sample figure in the same size, certain factors may bias patient sizing of features. For example, patients with depression may tend to draw smaller figures. Thus, the drawing/unit scale can be an important parameter for clinician diagnosis. This system provides clinicians with the option to adjust the size of the figure to match the standard figure, and record the scale ratio as a parameter in a report.

Figure 7-7. shows a small drawing overlaid on the stimulus figure. This design of software makes it easy for a clinician to see that the drawing is too small by comparison to the sample figure. The size of the subject drawing can be adjusted as in Figure 7-8. The clinician can then see the drawing is not proportional to the sample figure. Clinicians can easily determine that the drawing is too short in width.

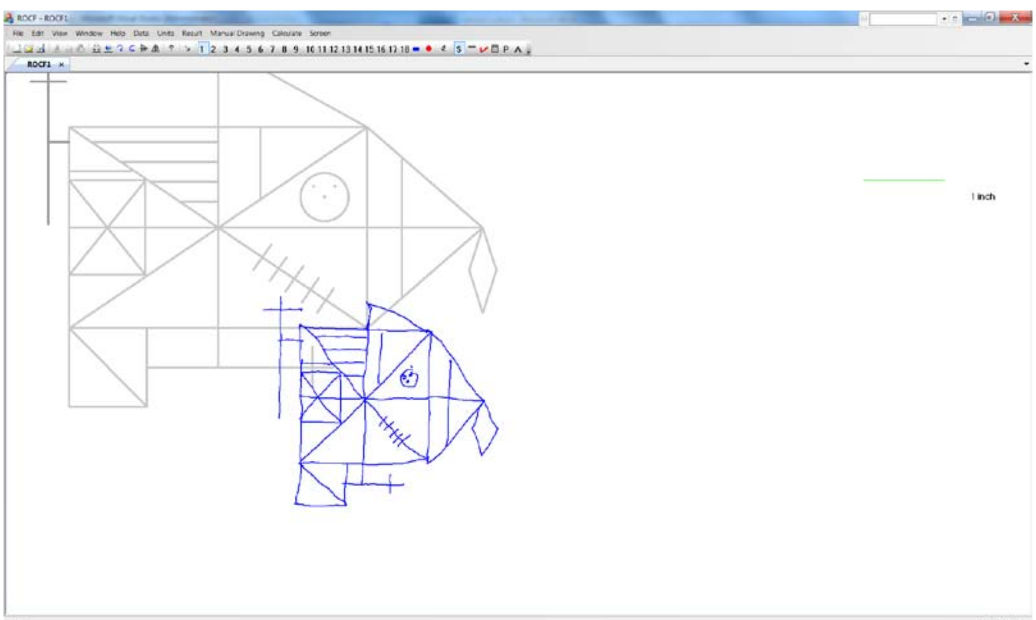


Figure 7-7. An example of a small drawing.

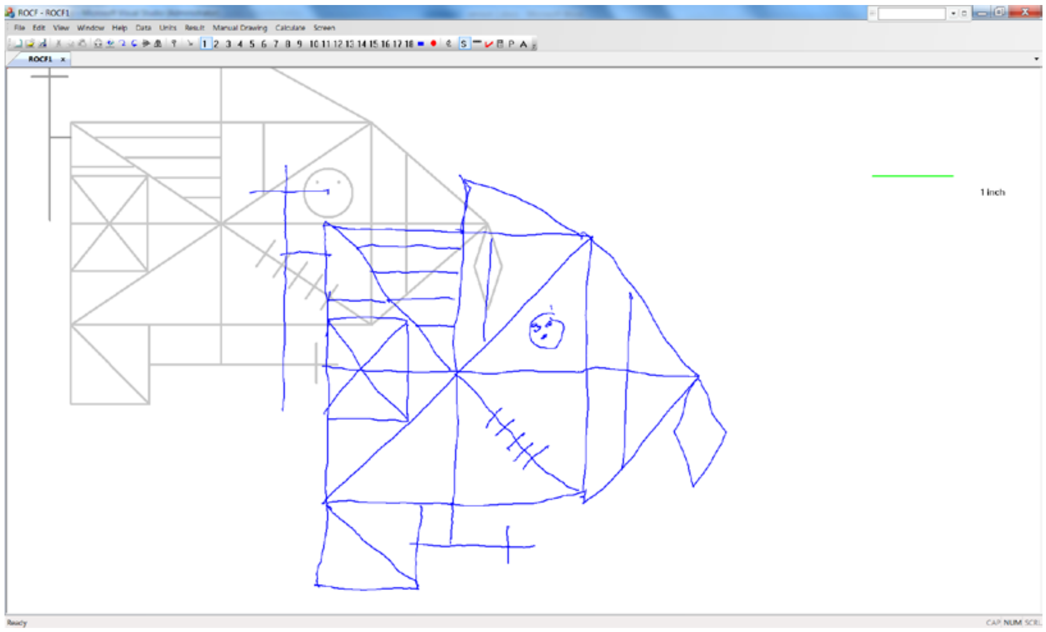


Figure 7-8. An example drawing which has been scaled to the correct size (relative to the stimulus).

Since patients may draw the ROCF in different directions and with different scales and positions, clinician adjustments of direction, scale and position need to be recorded. Adjustments ultimately do not affect the automated scoring of a drawing. They are intended to support clinician analysis. The adjustment options make the graphic presentation more conducive to clinician analysis (see Figure 7-9).

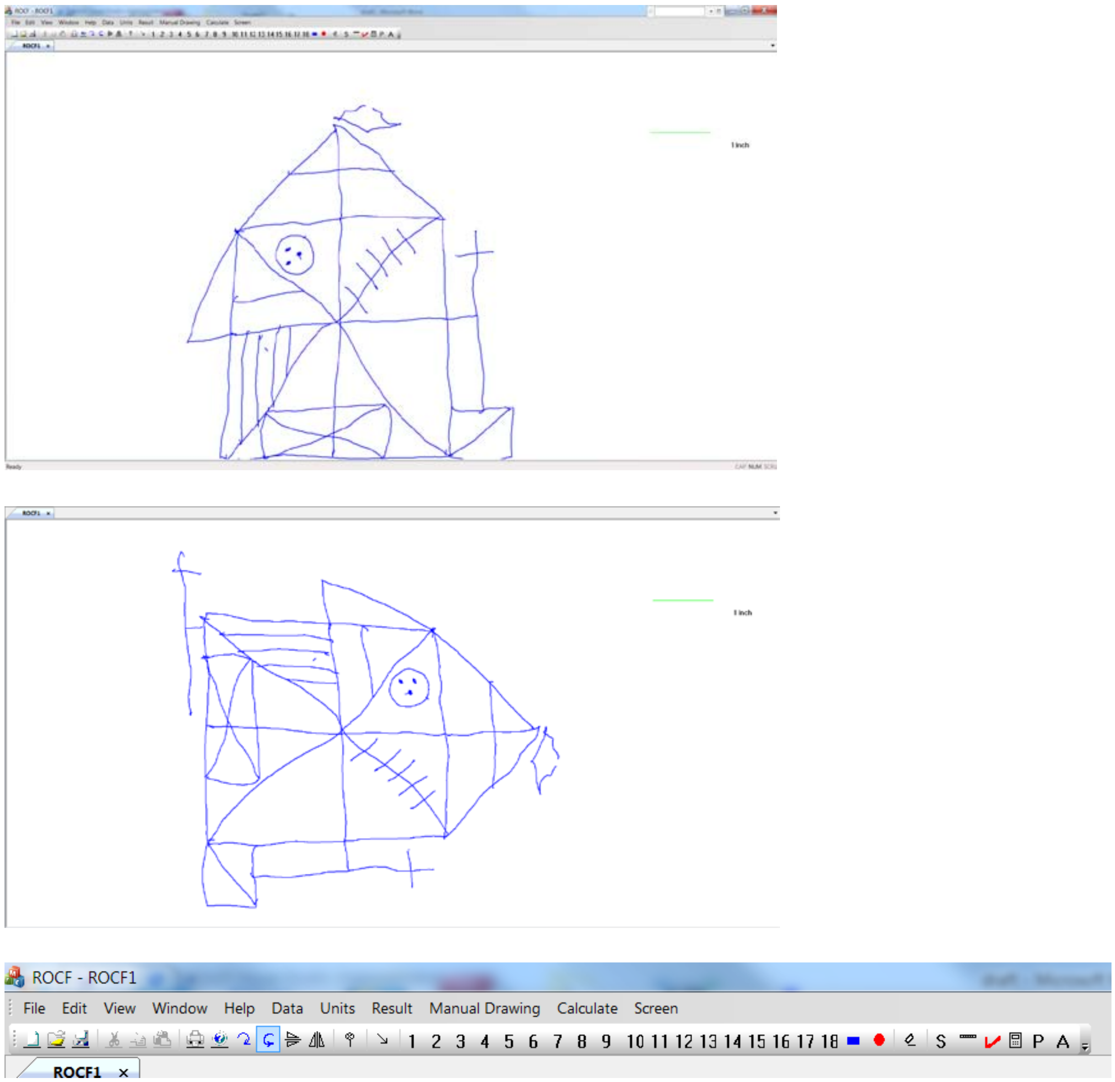


Figure 7-9. Drawing figure direction adjustment for analysis.

7.5.Checking Drawing Information

The computer system has an advantage over pen-paper testing in that it can capture sequential drawing information. Recording such information in traditional ROCF testing is difficult and time consuming. With the computer software, it is easy to check drawing time (see Figure 7-10) and sequence (Figure 7-11).

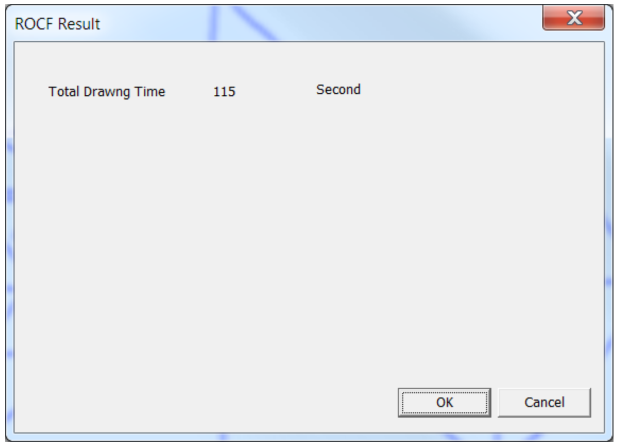


Figure 7-10. Drawing time dialog.

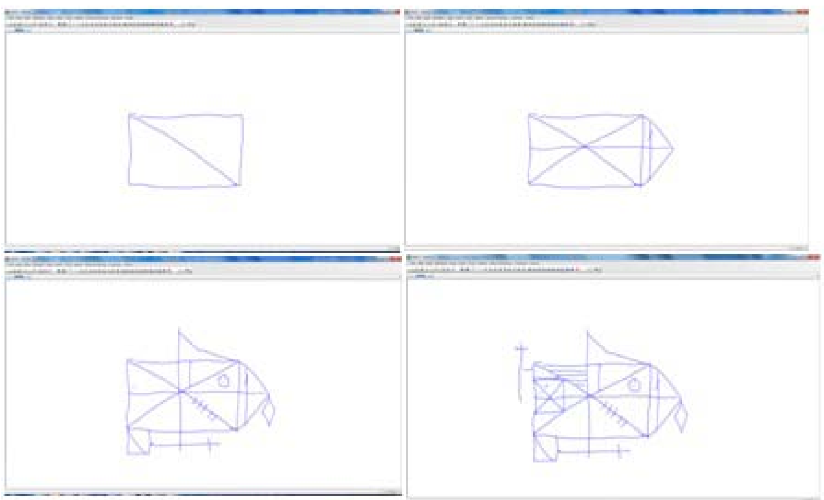


Figure 7-11. Images revealing drawing order.

7.6. Setting Parameters

Currently only part of the software parameters can be adjusted through visual controls in the user interface. Some parameters are designed for technical staff to adjust in order to obtain the most effective image processing results and best recognition rates. In Figure 7-12 , there are two types of parameters. Parameters in the "line segmentation" group are for raw data processing. The "corner effect area" parameter is for controlling the range of corner detection. This control allows for drawing strokes to be separated into individual lines. The Line Segmentation Length control is used to combine raw data points into line segments, as the smallest unit for recognition purposes. The line Segment Angle control is used to adjust the allowed angle variation for recognition purposes.

Parameters in the Scoring Unit Recognition group are for recognition processes. The "Unit 11 Inflate Control" allows for adjustment of the circle recognition result, when the drawing of the circle is actually irregular in shape. Vertical/Horizontal line angles are used to control the criteria for "recognizable" lines. Figure 7-13 shows an example drawing with "poor" vertical line reproduction. The angle control allows the clinician to establish if such reproduction should be recognized as acceptable. The "Line Curve Control" allows for adjustment of the acceptable degree of line waviness. The "Line Distance Control" is for identifying sketched lines. In this case, the control allows for multiple parallel strokes to be considered as one line. All parameters can be changed for each unit recognition operation.

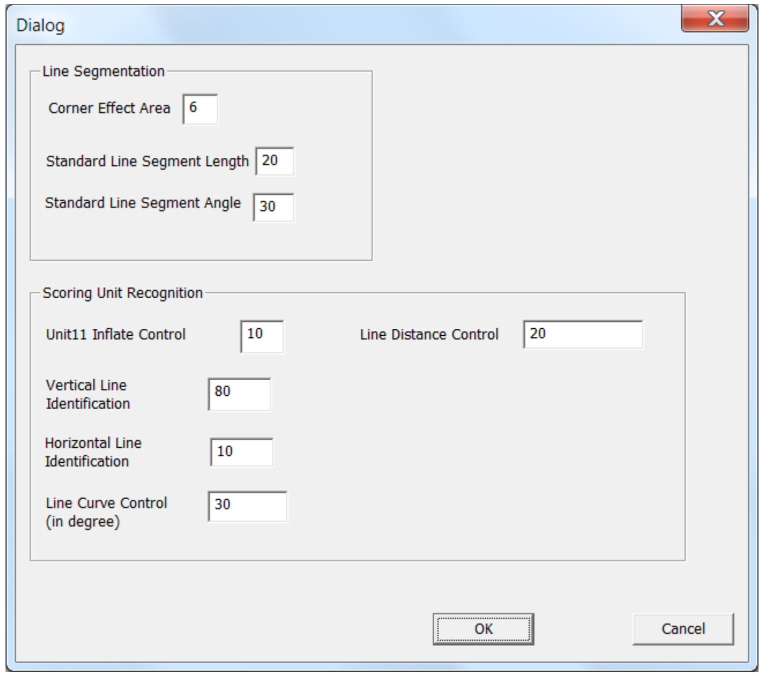


Figure 7-12. Parameter setting dialog.

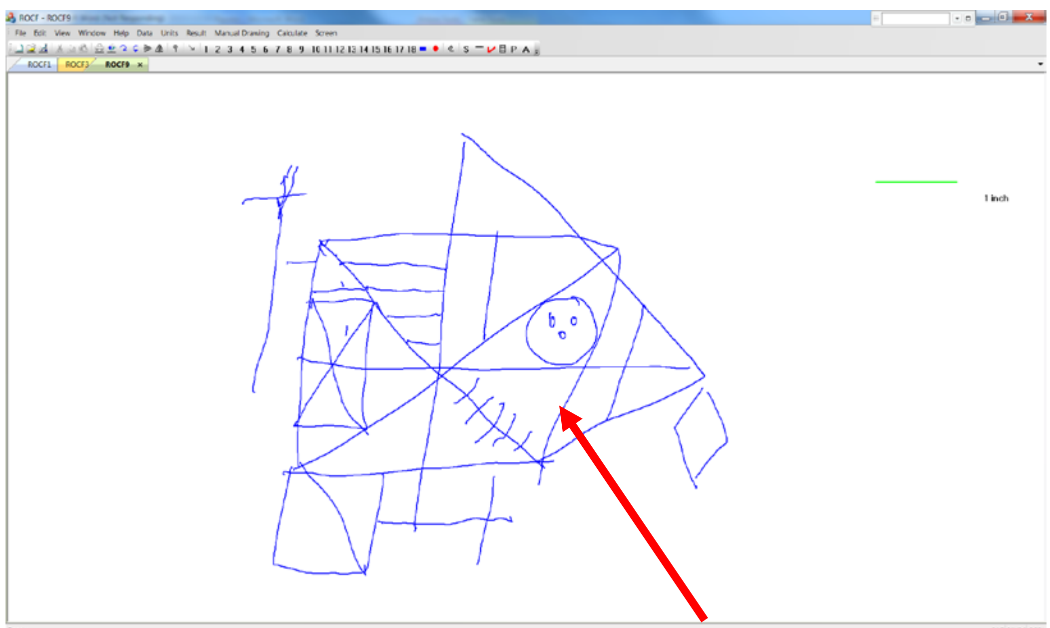


Figure 7-13. A sample figure with “poor” vertical line drawing.

7.7.Unit Recognition

The most critical part of the system development process was the capability to identify each unit for scoring. The system requires that a clinician select the area of each unit for recognition, and it allows the clinician to see the results of the processed unit. In Figure 7-14, the rectangle area is dragged by a clinician selection (all lines in this area turn “green” on software screen) and the bolded lines in Figure 7-15 are the recognized lines of Unit 1 (recognized lines appear in “red” on the software screen). In some cases, the lines are drawn as curves. When the system tries to fit a straight line to a curve, the result may not be accurate for scoring. Take Figure 7-16 as an example, the intersection, which is the major scoring point, has been shifted. In this case, a clinician can use the assistance tool to adjust the recognition result. In Figure 7-17, the result has been adjusted to position the intersection where it should appear in the context of the drawing (see Figure 7-17).

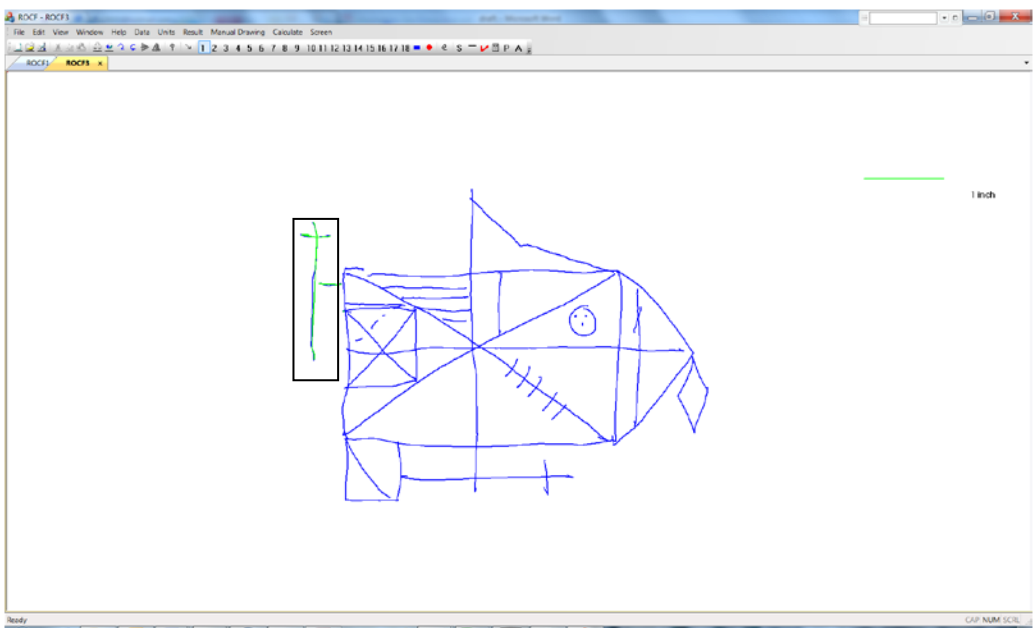


Figure 7-14. Selection of Unit 1.

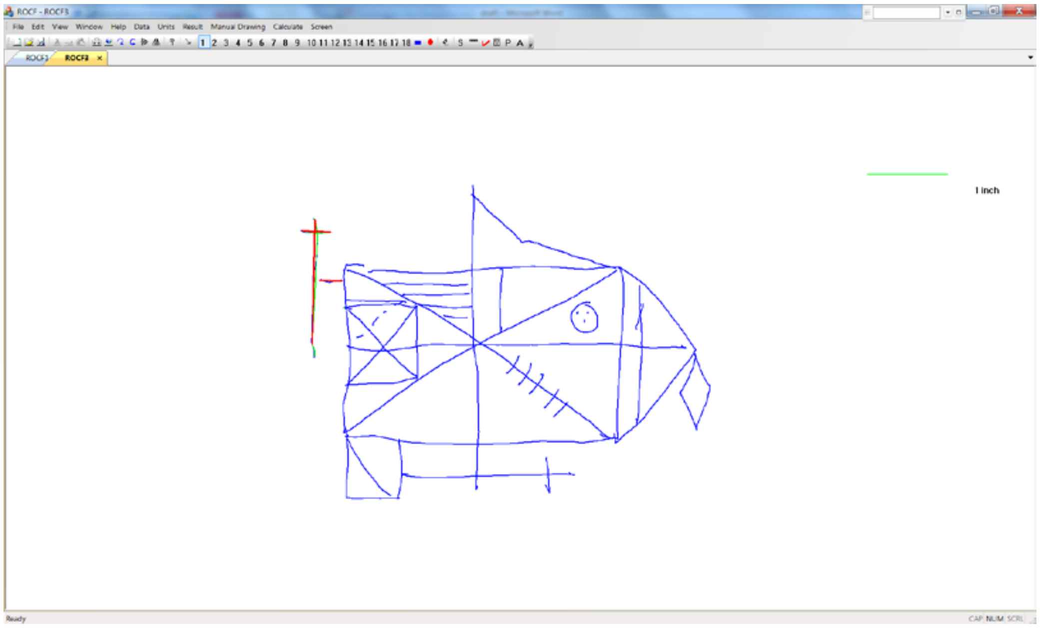


Figure 7-15. Recognized Unit 1.

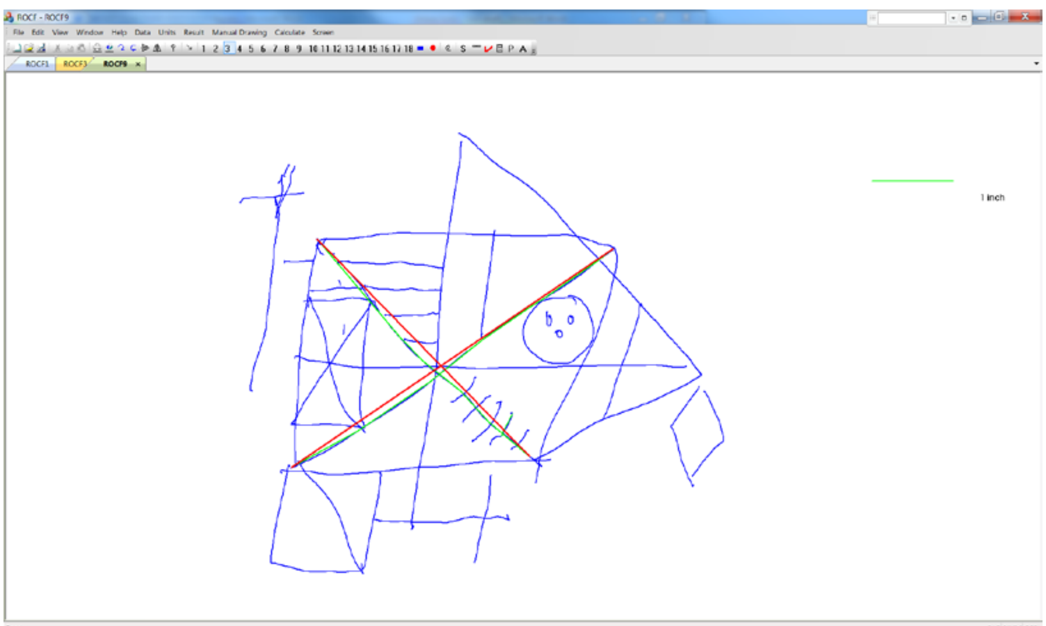


Figure 7-16. Automatically recognized lines.

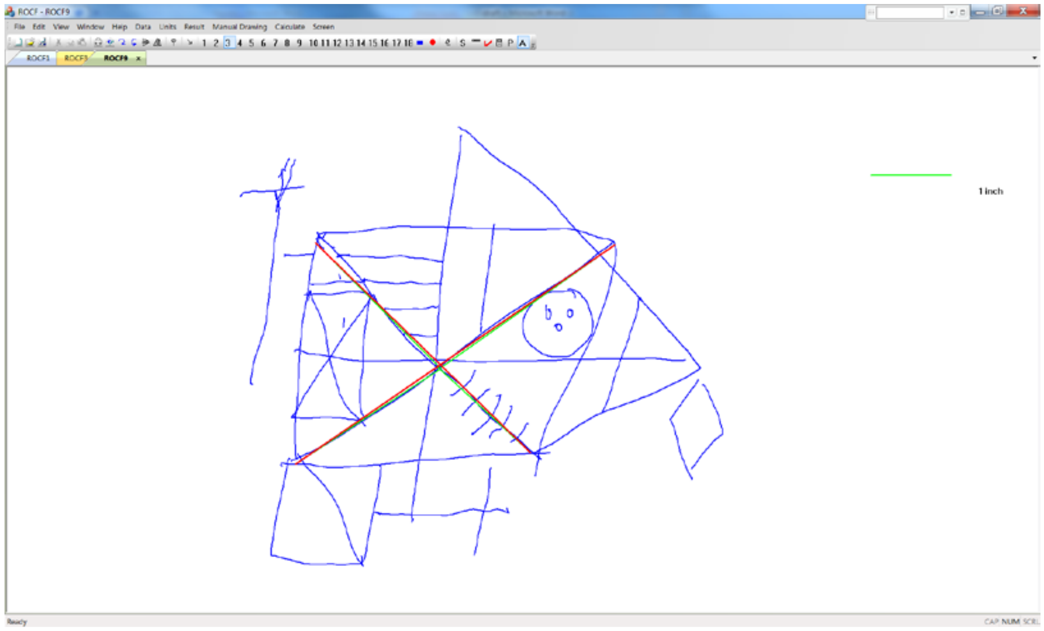


Figure 7-17. Adjusted Unit 3.

In the lower corner of the clinician GUI, the system displays recognized units. After all units have been recognized, the recognized results can be saved. When a clinician returns to the system, they do not need to repeat the recognition process for each unit (see Figure 7-18.).

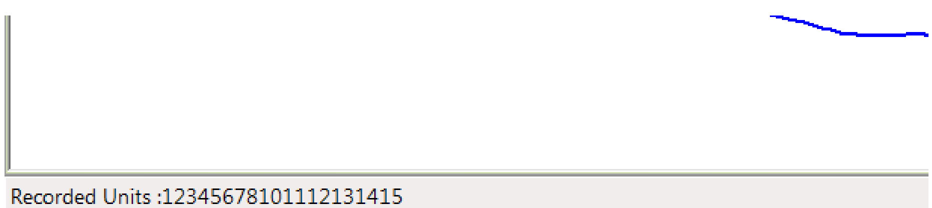


Figure 7-18. Recognized units indicator.

7.8. Checking Detailed Stroke Information

For each unit, the general length and angle information can be displayed. The length is displayed in inches and the angle is displayed in degrees. Degrees are in the range from (-90, 90) (see Figure 7-19).

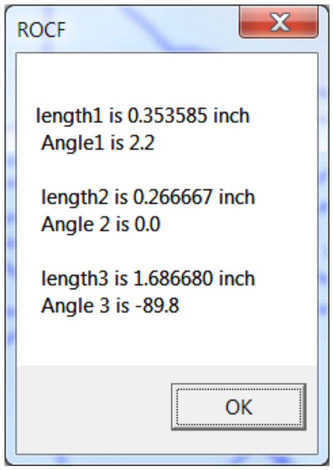


Figure 7-19. Stroke Information.

7.9. Generating a Score Report

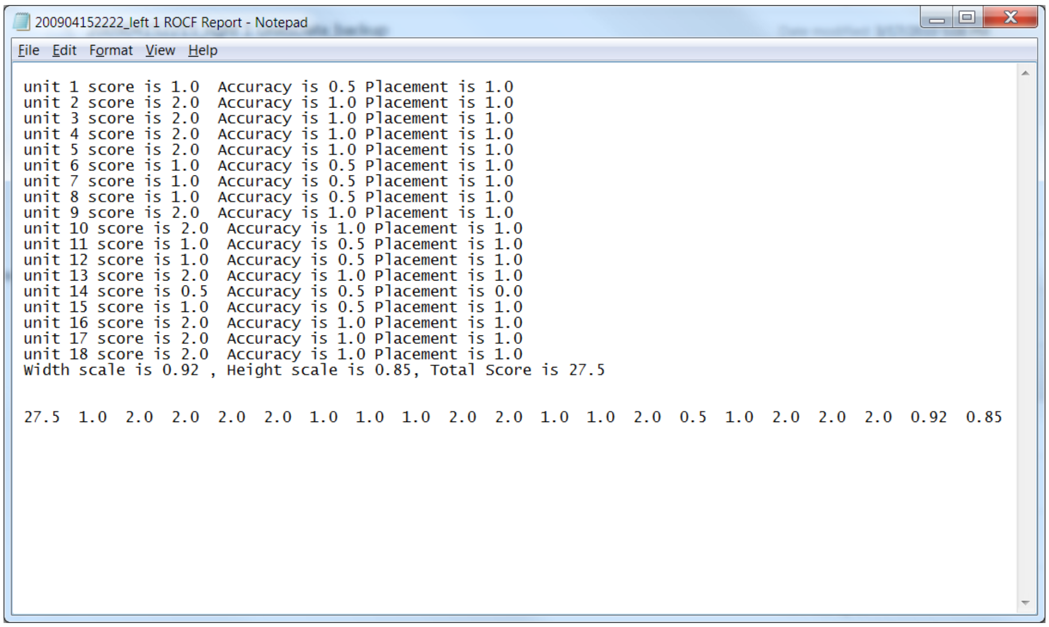
A clinician clicks the report icon to generate a score report. According to the scoring criteria for the ROCF drawing, presented in Table 3-1, accuracy has three levels:

- Accurately drawn (1 pt.)
- Inaccurately drawn, but recognizable (0.5 pts.)
- Inaccurately drawn and unrecognizable (0 pts.)

Placement has two levels:

- Correctly placed (1 pt.)
- Incorrectly placed (0 pts.)

Accuracy and placement are calculated separately by the scoring system. The total score is the sum of accuracy and placement, except in one case. Inaccurately drawn (0.5) and correctly placed (1) units result in a total score of 1 pt. Figure 7-20 presents a sample report.


200904152222_left 1 ROCF Report - Notepad

File Edit Format View Help

```
unit 1 score is 1.0  Accuracy is 0.5 Placement is 1.0
unit 2 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 3 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 4 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 5 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 6 score is 1.0  Accuracy is 0.5 Placement is 1.0
unit 7 score is 1.0  Accuracy is 0.5 Placement is 1.0
unit 8 score is 1.0  Accuracy is 0.5 Placement is 1.0
unit 9 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 10 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 11 score is 1.0  Accuracy is 0.5 Placement is 1.0
unit 12 score is 1.0  Accuracy is 0.5 Placement is 1.0
unit 13 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 14 score is 0.5  Accuracy is 0.5 Placement is 0.0
unit 15 score is 1.0  Accuracy is 0.5 Placement is 1.0
unit 16 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 17 score is 2.0  Accuracy is 1.0 Placement is 1.0
unit 18 score is 2.0  Accuracy is 1.0 Placement is 1.0
Width scale is 0.92 , Height scale is 0.85, Total Score is 27.5

27.5  1.0  2.0  2.0  2.0  2.0  1.0  1.0  1.0  2.0  2.0  1.0  1.0  2.0  0.5  1.0  2.0  2.0  2.0  0.92  0.85
```

Figure 7-20. A sample score report for all units in the ROCF.

7.10. Scores

According to the Standard ROCF manual, each unit is assessed for placement and accuracy. However, for each unit there are specific measurement requirements. Here, Unit 1 is used as an example again to show how the measurement requirements are implemented in the system.

7.10.1. General Scoring Principles

It is required that a vertical cross be drawn in the upper left of the large rectangle (Unit 1). If the intersected bounding boxes do not exist or are missing either the vertical or horizontal lines of the cross, the unit will be considered as inaccurately drawn and incorrectly placed. No points will be assigned for the unit. Otherwise, 0.5 points will be assigned.

7.10.2. Specific Scoring Criteria

For the scoring of Unit 1 in the ROCF, the following specific criteria have been defined:

Accuracy: The vertical segment of the vertical cross should be parallel to the left vertical segment of the large rectangle; the horizontal segment of the vertical cross should be short and should intersect the vertical segment near the top. The length of the horizontal and vertical segments of the vertical cross should be proportional to those of the complex figure stimulus.

Consequently the variables for Unit 1 accuracy assessment include: (1) the vertical angle (angle), (2) whether an intersection exists (If_intersected), and (3) the proportion (proportion). When all three of the variables fall in the acceptable range, the unit is considered to be accurately drawn.

Placement: The short horizontal line that connects the vertical cross to the large rectangle should be positioned within ¼ inch of the correct position above the small rectangle and the small horizontal line very near but below the upper left corner of the large rectangle. The height of the vertical cross should not extend more than ¼ above the top point of the small triangle or more than ½ inch above or ¼ inch below the horizontal midline. The cross should not be rotated or drawn upside down.

Thus, the variables for Unit 1 placement include: (1) the distance between the small horizontal line and small rectangle (dist_line_rectangle), (2) the distance between the small horizontal line and the corner of the large rectangle (dist_line_corner), (3) the difference between the top of the vertical cross and the top of the triangle (diff_top), and (4) the difference between the bottom of the cross and midline (diff_bottom). Only when all four variables fall within acceptable ranges is the placement of the unit considered to be correct .

When it is both accurately drawn and correctly placed, 2 points will be assigned for Unit 1, otherwise only 0.5 points are assigned for accurate drawing and 0.5 points for correct placement.

7.11. Conclusion and Future Work

This part of the study involved developing the interface for clinician use of the automated ROCF test system. The interface allows clinicians to see the drawing result and monitor the computer scoring process. Since patients with actual brain injuries may draw in less organized and recognizable ways, as compared to the subjects used in the present study, the system must be robust in drawing unit recognition and scoring in the presence of major individual differences. Beyond this, since the target users of the interface are clinicians, it is critical to make the system easy to use and to require only minimal input from them during the automated scoring process.

Currently, the system is adapted to scoring drawings of 15 different subjects. All of the subjects were healthy college students. Many of the automated scoring techniques have been improved during system testing and debugging with this data set. To test the system and to continue to address bugs, more patient data is needed. Future work is to involve making the system more robust in the scoring process.

CHAPTER 8. REHABILITAION INTERFACE DESIGN FOR PATIENTS

In this study, the system was designed with different interfaces for patients and clinicians. Patients use the workstation presented in Figure 4-3 for testing and training. The interface design includes visual feedback and force feedback for patients. As reported in Chapter 7, clinicians use different interfaces for report generation and diagnosis. Patient data is recorded in text files in the test system computer and transferred to doctors' computers through a network or simple standard file transfer protocol.

In this chapter, the software interface for patients is further described. The hardware design was introduced in a previous chapter. Force modeling for the drawing tasks and parameter control is also discussed in this chapter.

8.1.Modeling for Motor Skill Testing

A haptic based VR system was built for recording and scoring the ROCF complex figure test. Figure 8-1. shows the data flow in use of this system for patient diagnosis.

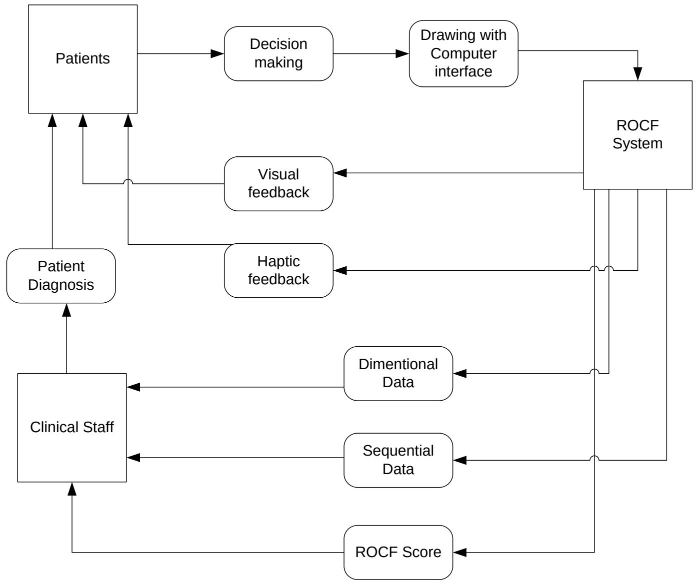


Figure 8-1. Automated ROCF system data flow analysis.

It is important that patients are able to draw with the haptic device, as in using pen and paper. Figure 8-2 and Figure 8-3 show the force models for the Phantom and Falcon devices respectively. Simulated frictional and normal forces are calculated as follows:

$$F_f = \mu F_k \tag{8-1}$$

$$F_n = \begin{cases} 0 & \text{if } L \geq L_0 \\ k * (L - r) & \text{if } L < L_0 \end{cases} \tag{8-2}$$

Where:

Ff is the simulated friction

μ is the coefficient of friction, which is a constant

Fn is the normal force

K is the spring constant (stiffness)

L is the spring length and r is the spring rest length

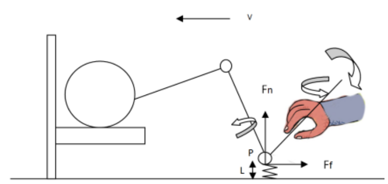


Figure 8-2. Force model of Phantom Desktop haptic device for the test application.

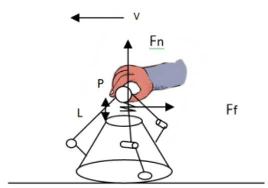


Figure 8-3. Force model of Novint Falcon haptic device for the testing application.

Figure 8-2 shows the force model of a simulated drawing application with the Phantom. The force model for the complex figure drawing application is not exactly same as the real-world force system, when drawing on a “hard surface”. For the haptic device, we calculated the normal force Fk based on the relevant position of the virtual cursor (in the 3D drawing space) to the defined drawing surface. The hard surface is simulated by a plane connected to a spring with a spring constant k applied to the surface.

Figure 8-3 shows the force-feedback model using the Novint Falcon haptic device. It is important to note that there are three extra rotational degrees of freedom in control, which are not represented in the force modeling. The Phantom Desktop haptic device provides 3 DOF in force feedback and 6 DOF in movement. Although using the pen-styled Phantom Desktop haptic device more closely approximates pen-paper drawing, the greater number of degree of freedom (compared with the Falcon haptic device) also adds complexity to force/control model. According to the earlier experiment, users of the Phantom device experience additional muscle activity in rotating, lifting and tilting the stylus [43]. In order to reduce muscle activity, it may be possible to introduce patient distraction and slow down the testing process. However, this might also affect drawing performance results. From the motor control point of view, patients need to constantly control and adjust the trajectory direction and the exerted force based on both the visual and haptic feedback in real time. This can make for a relatively complex control task, like real drawing.

Figure 8-4 presents a flow chart of the motor control process in patient drawing with the developed system. The traditional ROCF diagnosis is only based on the final output, which is a reproduction of Figure 1-1. For the neuropsychologist the control process in Figure 8-4 can be considered a “black box”. However, they must explain the inner connections between control functions and different forms of feedback that yield the static drawing results.

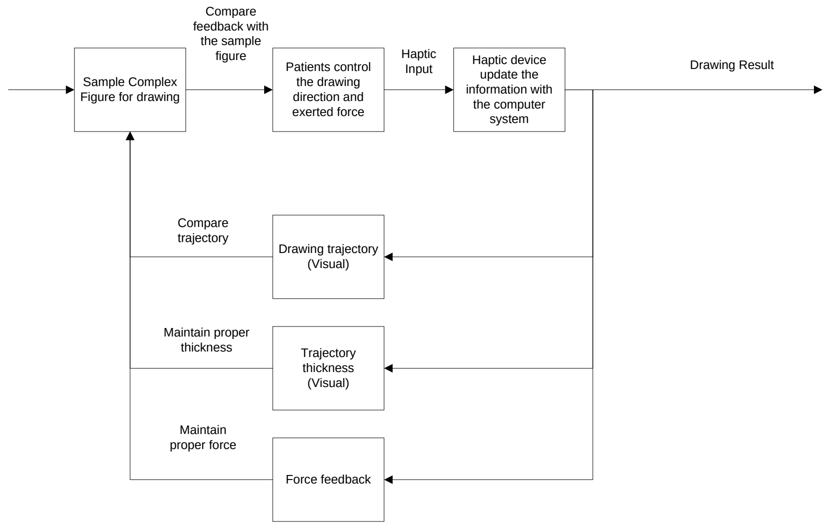


Figure 8-4. Motor control process model of haptic drawing.

With this in mind, the proposed system may increase clinician confidence in diagnosis. The current system is able to track and record dynamic information on stroke trajectory, changes in trajectory, thickness and force, etc. in real time. The equations below provide a way of modeling the patient behavior based on the force-feedback to users.

$\{M\} = \{P, F, t\}$ (8-3)

Where:

M is the quantified motor control model to be recorded in the database

P is the control point position

P=(x, y, z)   (8-4)

F is the force (in this example)

F= (Fn, Fk)   (8-5)

T is the time stamp

By extension of this model, the system can generate useful information for specialized diagnosis. Equation 8-6 represents sequential drawing information in terms of patient strokes and the velocity of stroking.

$$\{S\}=\{P, P', t\} = \{P, V, t\} \quad (8\text{-}6)$$

S is the sequential data. The neuropsychologist may query the system specifically for sequential information (S_1) based on the drawing speed V_1 and time t_1 at which the patient was drawing the area around P_1 (x_1, y_1, z_1). This may reveal whether the patient has difficulty in drawing certain parts of the ROCF. This extension of the motor control model allows for a more objective and accurate diagnosis.

P is the dimensional data of the drawing. By processing the data set $\{P\}$, the system can provide the clinician with drawing scale and deviation information. Ultimately, this analysis supports the standard ROCF scoring. These data provide neuropsychologists with extra information for assessing the patient's motor control process, including timing and sequential information.

8.2. Modeling for Motor Skill Training

As presented in Figure 8-4, the development of an explicit motor control model and generation of sequential drawing performance information allows for clinician explanation of the control process; that is, it is no longer a ”black box”. Theoretically, the weaknesses in the control loop can be identified. The quantitative results, $\{S\}$, $\{D\}$ and the ROCF score, can be used to set the parameters for the rehabilitation process. The rehabilitation process can then be enforced through repetitive motor skill training, focusing on the weakest part of the control loop. In general, it is anticipated that drawing simulation training would generalize to improved performance in the ROCF test. Related to targeting the weak part of the motor control loop, the training process can be assisted with extra visual feedback or force feedback (see Figure 8-5). For visual feedback assistance, a desired trajectory in drawing can be highlighted to guide patient control. If a patient is asked to draw different missing shapes from the ROCF, for example, highlighting of areas or line segments and augmented force-feedback may help in training for visual perception and cognitive planning. Highlighting the next line segment to be traced based on current drawing progress is one type of strategy to provide visual assistance to patients with cognitive planning problems. On-screen text instructions represent another kind of visual assistance, which has been tested and demonstrated to be effective in teaching children how to write letters [32].

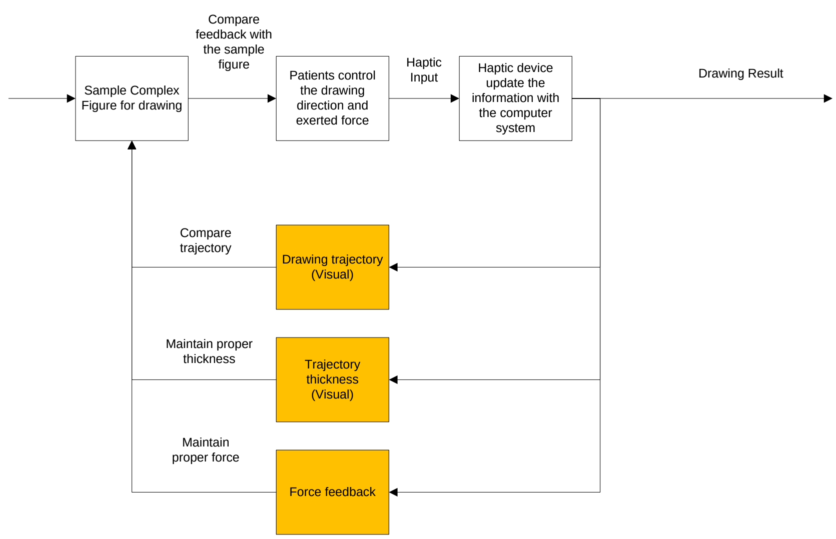


Figure 8-5. Motor control model for rehabilitation training.

Srimathveeravalli and Thenkurussi's [80] research on haptic training strategies for letter writing revealed that motor skill training using a haptic force profile was effective and was superior to training methods that used position–based aiding or no assistance whatsoever

[80]. In this study, three force control models were proposed and prototyped for motor skill rehabilitation. (An approach to extending the motor control model, identifying the parameters of the model, as well as testing the effectiveness of proposed force-feedback methods on TBI patient for rehabilitation will be described in the Future Research section.)

For the force feedback assistance, constraints can be either placed on dimensional $\{P\}$ or force feedback $\{F\}$ components. Figure 8-6 shows one possible force-assistance mode for guiding patient drawing in a desired direction. The equation describing the guiding force is:

$$\{F_a\} = s * \{q\} \qquad (8\text{-}7)$$

Where:

Fa is a force for directing the drawing on the designed trajectory

s is the strength of the force, which is a constant, set as a system parameter.

q is a vector defining the direction along with the trajectory. (This vector can be generated from a database.)

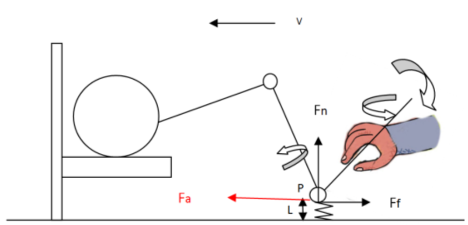


Figure 8-6. Force-feedback assistance model.

At any time t during the drawing process, the patient will be led by the force Fa (t) in the direction **q** (t).

Another mode for motor control training is to place a force constraint on the haptic device based on the position of the virtual cursor in drawing. $F_a(t)$ can be defined as the drag force on the virtual cursor at the closest point to the desired drawing trajectory.

$$F_a(t) = \begin{cases} 0 & \text{If } |d| = 0 \\ \frac{d}{|d|} * s & \text{If } |d| \neq 0 \end{cases} \quad (8\text{-}8)$$

Here, the force strength is constant and **d** is the vector to the closest point on the designed trajectory.

A third mode of haptic force feedback assistance is to set a virtual groove along with desired drawing trajectory (see Figure 8-7). The center point is the cross-section of the designed trajectory for copying, and the dashed lines are two virtual walls along with the trajectory. The virtual walls only exist on the surface adjacent to the trajectory. Patients can move the control point along the drawing trajectory without feeling any obstacles; however, once the copying of the drawing starts, patients can draw only freely in the space between the walls and cannot penetrate the walls without lifting the pen. The width (w) is a parameter defining the distance between walls that can be controlled through the software.

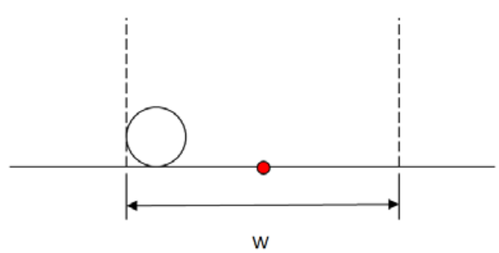


Figure 8-7. Virtual groove for tracing trajectory.

8.3.Conclusion

The prototype system for motor-skill training provides different training strategies for clinician use with controllable parameters. Table 8-1 lays out the possible motor skill training settings with parameters.

Table 8-1 Motor skill training setting with parameters

Training Assistance	Design	Parameter setting
Force Feedback	Mode 1	Force strength s
	Mode 2	Force strength s
	Mode 3	Groove width w
Visual Feedback	Highlighted cues	
	Geometry	Complexity

Table 8-2 presents how the recorded numerical models can be used to assess motor skill performance. It is important to note that both testing and diagnosis components and rehabilitation components can be parameterized and quantified by the system.

Table 8-2. Analyzing the model {M} for the drawing task.

Sub-model	Related Motor Skills Assessments
{**P**}	The final graphic results can be analyzed using the standard ROCF scoring system. Various cognitive-motor operations, such as visual perception, attention and control, graphomotor coordination, etc. can be assessed.
{**P**, **P'**,t}	Drawing speed tracking during the entire drawing process can be assessed. Detailed information on the time/effort distribution on various parts of the complex figure drawing can also be analyzed.
{**P**, t}	Drawing sequences, related to various planning and graphic perception skills can be recorded and analyzed.
{**t** }	Total drawing time can be analyzed.
{**F**, t}	Tracking of force control performance (e.g. eye-hand coordination, hand movement control) can be accomplished.

8.4. Discussion and future work

By developing the patient software interface and defining numerical models for motor skill assessment and training, the ROCF test system is able to record, track and manage large patient data sets. The system represents a preliminary step in building an effective healthcare technology based on VR. A database server can be connected to the system to store the testing and rehabilitation data. Such a dataset may ultimately be used to support the entire TBI patient treatment process. Applying VR and haptic technology to the TBI patient treatment process has many advantages: (1) motor skill testing is more objective and easier to implement; (2) comprehensive patient scoring strategies can be used because more detailed drawing information can be provided by the computer system; and (3) rehabilitation training can be designed, customized and controlled through parameters of the computer system. This chapter showed how patients can interact with the automated ROCF system, when the parameters are controlled by clinicians or therapists.

CHAPTER 9. SYSTEM VALIDATION

This chapter presents an experiment that collected drawing data from subjects and analysis of the data as a basis for assessment of the effectiveness of the automated ROCF system.

9.1. Introduction

The objective of the experiment was to validate the development of the ROCF system, including both the testing and scoring software. The experiment was designed to assess subject performance when using the haptic-based VR system for testing versus traditional paper-and-pencil tests, when using haptic-based VR system for ROCF test, instead of traditional paper-and-pencil tests. The experiment also sought to assess the effectiveness of the drawing recognition process and system scoring features. The outcome of the experiments was to provide a basis for further development and optimization of the system for clinical use.

Since we were not able to recruit TBI patients for the study, the original target users, healthy students were recruited to use the system. Subjects were asked to use their dominant and non-dominant hands to represent the average performance of a healthy population and functionally limited motor performance. In general, it was expected that the system would be sensitive to differences in completely functional vs. functionally limited in performance, as reflected by ROCF scores.

9.1.1. Participants

Fifteen (15) subjects were recruited for the experiment through word of mouth and email. All participants were from the North Carolina State University student population.

Subject visual acuity was used as a selection criterion. Any subject indicating a corrected visual acuity less than 20/20 was excluded from participation in the experiment. This was due to the visual requirements of the simulated task and the need for all visual display information to be perceived by subjects to effectively perform the ROCF reproduction. Personal computer experience was also used as a selection criterion. All subjects were required to have some basic computer experience such that they were familiar with typical control devices, including a mouse and keyboard. These criteria were verified through use of a subject survey administered at the start of the experiment.

9.1.2. System Setup and Apparatus

The system included two setups: (1) the workstation with haptic device for drawing tests; (2) and the computer with the custom software system for scoring. The test workstation included a high-performance Dell graphics workstation and the Sensable Technologies PHANTOM® Desktop™ haptic device (see Figure 4-3). The ROCF software was developed with c++ under VS.net 2003. The OpenGL SDK and OpenHaptics toolkits were used to provide the visual and force feedback during the figure drawing tests. The scoring system was developed on a DELL E6500 laptop computer in Windows 7. The software was developed with c++ under VS.net 2008. OpenCV was the open source library used for the pattern recognition program development. Subject drawings on paper were also recorded using a Logitech webcam for digital analysis.

9.1.3. Experiment Design and Variables

A randomized complete block design was used for the experiment, in which subjects served as the blocking factor. The sequence of combination of hand (dominant vs. non-dominant) and device (haptic vs. pen-paper) was balanced across subjects. Erasing was not an option, so drawing on paper was represented by use of a pen. Pencils are used clinically, however. There were two replications under each condition. The dependent variables recorded during the experiment included:

1. The total time to copy the ROCF. The pen-paper drawing time was captured based on the video recording. The drawing time with the haptic device was recorded by the computer.
2. The score for the ROCF reproduction. The pen-paper drawings were scored manually, following the instructions provided in the professional manual on the ROCF. The haptic drawing was scored using the new automated system. Screenshots of the drawings with haptic device were also manually scored by following the instructions in the professional manual for the ROCF.

There were three independent variables manipulated in the study including: (1) the drawing device, (2) the scoring method, and (3) the hand of the subject. Table 9-1 presents these variables and their settings.

Table 9-1. Independent variables.

Variables	Levels
Drawing device	0 - Haptic-based drawing 1 - Pen-paper drawing
Scoring method	0 - Computer scoring 1 - Manual scoring
Hand	0 - Dominant hand 1 - Non-dominant hand

9.2.Procedures

In general, the experiment included two parts: (1) test data collection; and (2) drawing scoring.

9.2.1. Test Data Collection

At the beginning of the experiment, subjects were required to read and sign an informed consent form and complete a short survey addressing their prior PC experience and drawing skills. Every subject in the experiment endorsed basic PC experience and drawing skills.

Subjects were permitted to practice drawing in the virtual environment (with their dominant hand) for as long as they felt necessary. Once they felt confident and comfortable with haptic drawing, a test was conducted. Subjects were asked to copy the simple house drawing presented in Figure 9-1 by using the haptic device. If they could draw the house with accuracy and correct feature placement, in a timely manner, then the training period was terminated.

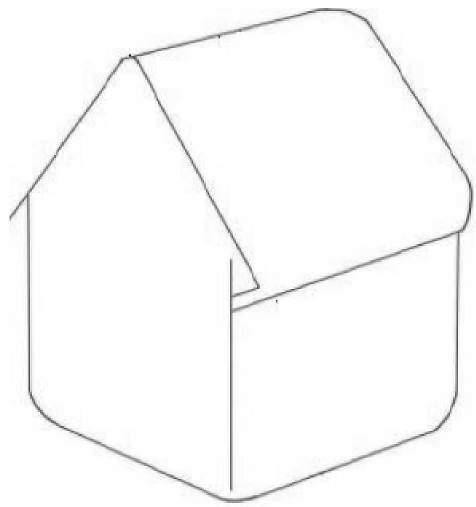


Figure 9-1. Simple figure for performance assessment after training trials.

Subsequently, the experimental trials were conducted. Subjects were presented with a sample ROCF and asked to draw it twice under each hand/device condition. There were four condition combinations, yielding eight drawings in total per subject.

9.2.2. Scoring

Computer generated scores were compared with manual scores. One rater manually scored the screenshots of haptic device drawings and the paper drawings. The rater was trained on ROCF scoring using the professional manual for the ROCF Test and Recognition Trials [50]. The manual was used as the standard for both the manual scoring and computer scoring. The author programmed the software to generate the scores for the haptic device drawings.

9.3. Data Analyses and Specific Hypotheses

For the experiment, the data for 10 out of 15 subjects was used for analysis. These 10 subjects drew the ROCF in landscape orientation. The other five subjects drew the ROCF in portraint orientation (counter to test instructions). The drawings by these subjects were, however, used to demonstrate the capability of the software to process and score drawings in different orientations. The data was not used for analysis purposes.

9.3.1. Hypotheses

Since all subjects were healthy students, functionally limited motor performance was assessed by evaluating the difference between drawing performance with the dominant and non-dominant hands. As mentioned, performance was measured by completion time and ROCF scores.

Hypothesis 1: The ROCF reproduction with pen and paper was expected to be sensitive to differences in hand dominance.

It was expected that subject performance with their dominant hand vs. non-dominant hand drawings would be significantly different. Dominant hand drawing was expected to be faster and to yield higher scores than the pen-paper drawing tests.

Hypothesis 2: The ROCF drawing with the haptic device was expected to be sensitive to differences in hand dominance.

It was expected that subject performance with their dominant hand and non-dominant hand would be significantly different when drawing with the haptic-based VR system. The dominant hand drawing was also expected to be faster and to yield higher scores in the haptic-based drawing tests.

Hypothesis 3: No significant differences were expected between drawing methods.

It was expected that subject performance would be consistent between the haptic device and pen-paper tests. In order to eliminate the effects of different scoring methods, the pen-paper drawings and screenshots of the haptic device drawings were manually scored for comparison. No significant differences were expected between the two types of test platforms.

Hypothesis 4: Positive linear correlations were expected between the scores generated by the different methods.

It was expected that the automated system would generate score reports consistent with manual scores. The drawings with the haptic device were scored manually based on the screenshots and by the computer. Correlation analyses were conducted on the scores generated by the software and manually by the trained rater.

9.4. Results

9.4.1. Effects of Hand Dominance on Pen-Paper Drawing Results

The completion time and scores for the dominant hand vs. non-dominant hand are shown in Tables 9-2 and 9-3. Generally, subjects took less time with the dominant hand to complete the drawings as compared with the non-dominant hand. In addition, the dominant hand resulted in higher drawing scores.

Table 9-2. Summary of completion time (in seconds) for pen-paper drawings.

	Dominant hand	Non-dominant hand
Mean	130.7	153.1
Std Dev	58.5	55.3
Std Err Mean	10.7	10.1
Upper 95% Mean	152.6	173.8
Lower 95% Mean	108.9	132.4
N	30	30

Table 9-3. Summary of scores for pen-paper drawings (max=36).

	Dominant hand	Non-Dominant hand
Mean	31.2	26.2
Std Dev	2.7	2.7
Std Err Mean	0.6	0.6
Upper 95% Mean	32.5	27.5
Lower 95% Mean	30.0	25.0
N	20	20

To further validate the difference in performance between the dominant hand vs. the non-dominant hand, an ANOVA was conducted using the following statistical model:

$$y = \mu + S_i + HD_k + \epsilon_{ik}$$

Where:

y is the completion time or score for pen-paper drawings

μ is the overall mean

S is the subject number, i=1, 2, 3,…10

HD is the hand dominance, k=0, 1The ANOVA model for completion time proved significant ($F(17, 22) = 30.1451$, $p<0.0001$). Effect estimates revealed that the non-dominant hand took significantly longer to complete the drawing ($p=0.0472$). This finding was in-line with hypothesis.

The ANOVA model for scores also proved significant ($F(17, 22) = 21.0467$, $p<0.0001$). The dominant hand produced significantly higher scores in the tests than the non-dominant hand ($p<0.0001$). This finding also supported expectation.

9.4.2. Effects of Hand Dominance on Haptic Device Drawing Results

The completion times and scores for dominant hand vs. non-dominant hand drawing with the haptic device are shown in Tables 9-4 and 9-5. Generally, it took subjects less time to complete the drawing with the dominant hand. The dominant hand also resulted in higher scores.

Table 9-4. Summary of completion times for haptic-based drawing tests.

	Dominant hand	Non-Dominant hand
Mean	184.3	211.9
Std Dev	88.7	62.3
Std Err Mean	19.8	13.9
Upper 95% Mean	225.8	241.0
Lower 95% Mean	142.7	182.7
N	20	20

Table 9-5. Summary of scores for haptic device drawing tests (max=36).

	Dominant hand	Non-Dominant hand
Mean	31.0	29.1
Std Dev	3.6	3.9
Std Err Mean	0.8	0.9
Upper 95% Mean	32.7	30.9
Lower 95% Mean	29.3	27.2
N	20	20

To further validate the difference in performance between the dominant and non-dominant hands in haptic device drawing, an ANOVA was conducted using the following statistical model.

$$y = \mu + S_i + HD_k + \epsilon_{ik}$$

Where:

y is the completion time or score of haptic drawings

μ is the overall mean

S is the subject number, i=1, 2, 3,…10

HD is the hand dominance, k=0, 1

The ANOVA model for completion time proved significant ($F(17, 22)=7.3248$, $p<0.0001$). Effect estimates revealed the non-dominant hand took significantly longer to complete the drawing than the dominant hand in using the haptic device ($p=0.0184$). This finding was in agreement with hypothesis 2.

The ANOVA model for scores also proved significant ($F(17, 22)=7.4788$, $p<0.0001$). The dominant hand produced significantly higher scores than non-dominant hand in haptic device drawing ($p=0.0034$). This finding also supported expectation and indicated that the new automated ROCF system was sensitive to functional limitations in motor skill, like the traditional pen-paper tests.

9.4.3. Drawing Method Differences

Based on the design of the new system, it was expected that when the pen-paper and haptic device drawing results were compared, there would be no significant difference in scores and completion times for different drawing methods. The following statistical model was used for ANOVAs on the two response measures.

$$y = \mu + S_i + D_l + HD_k + D_l * HD_k + \epsilon_{ikl}$$

Where:

y is the completion time or ROCF score

μ is the overall mean

S is the subject number i=1, 2, 3,…10

D is the drawing method, l=0, 1

HD is the hand dominance, k=0, 1

D*HD is the hand device interaction

The ANOVA model for drawing time proved significant ($F(12, 67) = 27.4733$, $p<0.0001$). Effect tests showed that the drawing time with the haptic device was significantly longer than the drawing time with the pen-paper ($p<0.0001$). Effect estimates also revealed the non-dominant hand took significantly longer to complete the drawing than the dominant hand in using the haptic device ($p=0.0023$). The interaction of hand and device was insignificant ($p=0.1898$). Figure 9-2 presents the interaction plot of time for drawing methods and hand dominance. For both haptic device drawing and pen-paper drawings, the non-dominant hand took significantly longer to complete the drawings. This finding was counter to expectation.

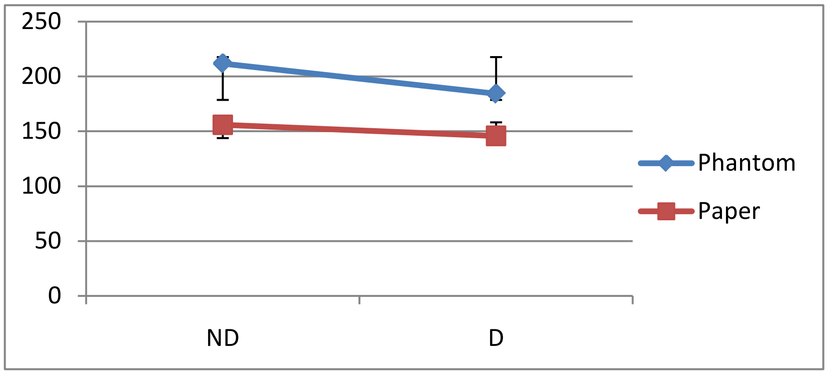


Figure 9-2 Drawing time (in sec.) interaction plot

The ANOVA model for drawing scores also proved to be significant ($F(12, 67) =11.1648$, $p<0.0001$). Effect tests showed that the average drawing score with the haptic device was significantly different from the average pen-paper drawing score ($p=0.0231$). The dominant hand produced significantly higher scores than the non-dominant hand in haptic device drawing ($p<0.0001$). The interaction between drawing methods and hands was also significant ($p=0.0059$). Figure 9-3 presents the interaction plot of score for drawing methods and hand dominance. Post-hoc tests were conducted to further analyze the effects of the drawing methods with the dominant and non-dominant hand. For drawings with dominant hand, there was no significant difference in scores when using the pen-paper or haptic device ($p=0.6207$). However, for the non-dominant hand, the pen-paper drawings realized significantly lower scores than the haptic device drawings ($p=0.0029$). The finding with the dominant hand supported expectation. The finding with the non-dominant hand was opposite to the hypothesis. However, it is possible that subjects took time in drawing with the phantom device with their non-dominant hand to achieve high ROCF reproduction accuracy (as observed in the first experiment).

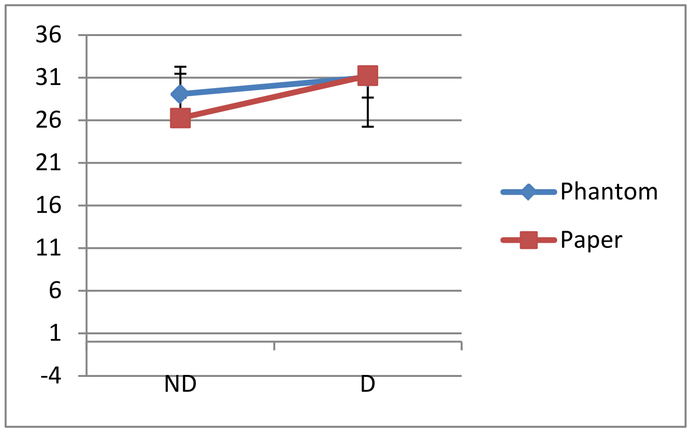


Figure 9-3 Drawing score interaction plot

9.4.4. Correlation Analyses

Correlation analyses were conducted on the manual scores for the pen-paper drawings, manual scores for the haptic device drawings and the computer generated scores for the haptic device drawings. Table 9-6 summarizes the non-parametric (Spearman's Rho) partial correlation analysis results and presents the statistical significance of the coefficients. The computer generated scores on the haptic device drawings were positively correlated with the manual scores on the same drawings (Spearman's ρ = 0.66729, $p<0.0001$). This result supported the validity of the automated scoring system. The manual scores for the pen-paper drawings were also positively correlated with manual scores of the screen shots of the haptic device drawings (Spearman's ρ = 0.43249, $p= 0.0060$). This result suggested reliability of rater performance across the type of drawings. The manual scores for the pen-paper drawings were also positively correlated with the computer generated scores on the haptic device drawings (Spearman's ρ = 0.02690, $p=0.8708$); however, the result did not achieve significance at the alpha = 0.05 level. This result indicated some reliability of the new automated ROCF test system relative to the traditional pen-paper method of testing and manual scoring. Due to limited number of observations in the present dataset, this finding should be further investigated with a larger sample size in order to determine if the new system is reliable.

Table 9-6. Nonparametric Spearman's ρ analysis results.

Variable	by Variable	Spearman's ρ	Prob>|an
computer-computer	manual-computer	0.66729	<.0001
manual-manual	manual-computer	0.43249	0.0060
manual-manual	computer-computer	0.02690	0.8708

9.5. Discussion

9.5.1. Dominant vs. non-dominant hand drawings

In general, both the pen-paper drawings and haptic-based drawings were sensitive to dominant and non-dominant hand performance. Subjects can draw the ROCF faster and obtain higher scores with the dominant hand vs. the non-dominant hand, no matter on paper or in a computer program. This result provides evidence that the new automated system can be used to identify motor impairments based on ROCF drawing times and scores.

9.5.2. Effects of drawing methods

The experiment results show that subjects drew faster and more accurately with pen on paper than when using the haptic device. This result was counter to expectation for the new system, but consistent with the result of the pilot study conducted earlier. There were two major reasons identified for the longer drawing times with the haptic device:

- A lack of depth cues - Subjects said that they felt they needed to slow down their hand motion when the virtual pen approached the virtual writing surface, until the pen actually touched the writing surface. Since subjects had to constantly lift the pen and move to a certain point for the next writing trajectory, the overall completion time became longer.
- Different control method- The stylus of the haptic device is much thicker than a standard pen used in pen-paper drawing. The stylus pointing position also occurs in virtual space; consequently, good eye-hand coordination skills matter. The reason why it took longer for drawings to be completed with the Phantom is that it was possible to achieve better drawing results by sacrificing drawing speed.

With respect to the drawing scores, the means for the dominant hand drawings with the pen-paper and haptic device were very close (31.2 vs. 31.0). For the dominant hand, effects tests showed that there was no significant difference in scores with the pen-paper or haptic device drawing. The mean score for the non-dominant hand drawing was actually higher using the haptic device than pen-paper (29.1 vs. 26.3). Based on the statistical test results, it can be inferred that subjects are capable of producing comparable drawing quality with the haptic device as with the pen and paper. The superior results with the non-dominant hand and haptic device may be the result of longer drawing times and slower speeds. It is possible that users found the VR system to be more engaging/interesting than the pen-paper drawing. Consequently, they might have explored the capabilities of the haptic device as a drawing tool and, thereby, traded speed for a better score. Since a time-dependence of drawing accuracy might have occurred, , it is suggested that future studies consider time-dependent measures of performance for evaluating accuracy (e.g., calculating a score/minute).

9.5.3. Correlation analyses for scoring methods results

It was expected that there would be positive correlations among the manual scores for pen-paper drawings, manual scores for haptic device drawings and computer scores for haptic device drawings. In other words, the following hypotheses were expected to be supported:

- Subject scores were expected to be consistent between pen-paper drawings and haptic device drawings. If a subject can obtain a high score in pen-paper drawings, they should also be able to obtain a high score in haptic device drawing, and vice versa.
- Scores generated manually and by the computer were expected to be positively correlated. Drawings with high manual scores should also yield high computer scores, and vice versa.

The above hypotheses were all supported by the data analyses. In this study, the manual scores were calculated by a graduate engineering student, following the instructions of the ROCF professional manual. In future research, expert scoring by a neuropsychologist should be used to generate scores, and parameter settings of the scoring software should be optimized by clinical users. As a result of higher accuracy and consistency in scoring by an expert, stronger positive correlations would be expected with the computer-based drawing scores.

9.6. Conclusion

Subjects were asked to use their non-dominant hand to simulate motor impaired users of the ROCF testing and scoring system. Results demonstrated that system was sensitive to functional differences between dominant and non-dominant hand use. The computer scoring software also appears to be valid for generating ROCF scores, which are consistent with manual (novice rater) scores.

CHAPTER 10. CONCLUSION AND FUTURE WORK

In this study, an automated system was successfully developed for use in hospitals and clinics for ROCF tests and rehabilitation therapy on brain injured patients. A series of experiments was conducted to validate the hardware selection, to guide the software development and validate the system by using human factors research methods. The system integrates technologies for haptic force modeling, pattern recognition in drawing analysis and solving many detailed technical problems to improve ROCF test efficiency and robustness.

The accomplishments of this research are summarized as follows:

- Software was developed for quick and accurate ROCF test result analysis. Not only can the computer-based system significantly reduce the workload of neuropsychologists, it can be used as an open source project for future research and development activities in TBI testing and rehabilitation.
- The research also demonstrated that the application of current VR technology to a complex healthcare process can make diagnosis more robust and objective.
- Human factors research methods yielded results indicating that haptic devices can be used for motor skill assessment and rehabilitation applications.
- Haptic force rendering and analysis techniques were presented for motor skill assessment and rehabilitation. Haptic force feedback was modeled and controlled through the new test system supporting rehabilitation application development.
- Human factors experiment methods tested and verified the reliability of the new system for field use.

10.1. Limitations and caveats

Participants in this study included student subjects and a rater trained based on the professional manual for ROCF scoring. At this stage of system prototyping, we were not able to recruit real patients for use of the system. Therefore, subjects were asked to use their non-dominant hand as a representation of TBI patient drawing ability. There was no feedback from a real clinician on the drawing results. The implications of these limitations include the following:

- Patients with real cognitive deficits may generate unanticipated drawing results not simulated in the current study. Consequently, the developed system may not be able to correctly recognize/score such drawings in field use.
- The current system parameters may not be set appropriately for expert decision making on TBI patient diagnosis. For example, the angle tolerance for right angle drawing and parallel line drawing might be too conservative, leading to generally lower patient scores. In addition, the tolerance for width-height proportioning and the tolerance for deviations from straight lines could be too liberal, leading to higher scores than an expert might assign.
- The usability and friendliness of the user interface needs to be approved by real clinicians.

10.2. Future work

The techniques presented in this study may lead to the development of more complicated and practical systems for medical diagnosis and rehabilitation in the future. This research may also serve as a basis for more engineers and researchers in engineering schools to conduct haptics research and develop applications in healthcare.

The system developed in this research was designed to be used in a hospital or clinic for TBI patient diagnosis and rehabilitation therapy. Once implemented, the system should be maintained and continually improved, based on the feedback from the facility. Future research on the system may extend in the following directions:

- Working with clinicians to further validate and tune the system to improve accuracy and robustness;
- New motor control testing systems may be developed using the current technology - other figure drawing-based tests can be easily accommodated by minimal modification to the existing system. Other types of tests can also be migrated to the VR environment;
- New functions can be added to the system - More parameter setting options for clinician control may make the system a more powerful tool for researchers to use in developing new clinical tests and rehabilitation therapies;
- Advanced computer graphics technologies can be integrated in the system-For example, immersive 3D vision and light-weight glove style haptic devices could be used, which can support larger varieties of motor skill tests and rehabilitation applications;
- Integration of the current system with an existing EMR system, and development of an online data server for data storage and communication - Computerized tests and therapies can be enabled in medical records in an electric format. Developing

an effective database system can help in better tracking and analysis of patient progress. Imagine that doctors can retrieve patient data at anytime and any place with accurate and comprehensive computer-generated report. This may not only improve the chance of patients receiving more accurate diagnoses and treatment, but it may also allow doctors to work more effectively.

- Develop haptic force profile and design experiments to establish an effective training strategy for motor skill rehabilitation. It is necessary to work with clinicians to solve training design issues, such as establishing specific condition presentation strategies, identification of system control parameters, customizing patient force training profile. These issues can be solved based on neuropsychological and engineering research. Experiments need to be designed and conducted to validate the effectiveness of training strategies.

In general, the new system is able to record patient data and clinician decisions. It is possible that a machine learning function could be implemented and could provide decision making support for patient diagnosis of similar drawing results. To support the implementation of these kinds of functions, a first step would be to identify those drawing features (individual components and patterns) that may be key to clinician decision making and could be quantified by the current system. The identification of features to support clinician decision making, development of a grammar for describing clinician decisions, and development of a machine learning method could be important research topics in future to expand the capabilities of the current setup.

There may be additional possible directions for future work in this area. It is expected that related research will continue to develop in applying new technologies in healthcare in order to make the current system more affordable and beneficial for all people.

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APPENDICES

Appendix A: Informed Consent form for research

NORTH CAROLINA STATE UNIVERSITY
INFORMED CONSENT FORM FOR RESEARCH

Title of Study Assessing the Utility of Haptic Devices for Medical Evaluations based on Models of Human Handwriting and Drawing Processes

Principal Investigator Yingjie Li and Prithima Mosaly Faculty Sponsor Dr. David B. Kaber

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We are asking you to participate in a research study. The purpose of this study is to validate the use of haptic devices for replacing traditional paper and pencil tests in medical evaluation applications. The results of the study will be used to predict the influence of the use of two popular haptic controls in reproduction of a complex drawing figure for motor control assessment. We also plan to use the results as a basis for developing other digital methods that allow for automation of medical evaluation processes in order to promote accuracy, reduce clinician workload, and reduce patient evaluation time.

INFORMATION

If you agree to participate in this study, you will be asked to perform drawing tasks in a virtual environment with the two kinds of haptic devices, as well as real pencil and paper. The virtual reality-based versions of the task will be presented to you with a high-performance graphics workstation and a desktop monitor, or overhead projection system. You will be asked to draw with a Sensible Technologies PHANTOM® Desktop™ device and a Novint Falcon 3D VR device by controlling a virtual pencil in the simulation environment. In each experiment trial, you will hold a stylus or pencil in your hand to sense the surface of virtual paper in VR or the surface of a real sheet of paper. Electromyography sensors (four) will be placed on your writing forearm and used to record your muscle activity during the test trials. (This will require cleaning of the skin with alcohol and a cotton pad. The electrodes will be attached using double-sided hypoallergenic tape.) You will complete two (2) test trials with method of drawing device. At close of each trial, you will be asked to complete a subjective workload rating form.

The entire experiment is expected to take approximately two hours to complete. The following steps are to be completed during this time: (1) 10 minutes for reading and signing of this informed consent; (2) 10 minutes for your completion of an anthropometric survey; (3) 20 minutes for training and warm-up trials; (4) 10 minutes for skin preparation and mounting of the electrodes; (5) 5 minutes to perform three maximum voluntary forearm muscle contractions (MVC) in a grip strength test with each MVC lasting no longer than 3 seconds; and (6) approximately 50 minutes for the 6 test trials. After the test trials, you will be debriefed and ask to complete a post-experiment questionnaire, which is expected to take 20 minutes.

RISKS

The risks associated with participation in this study are unlikely and minimal. They include potential visual strain and/or fatigue from viewing the virtual pencil and pen on the PC-monitor or projection image for extended periods. They also include skin irritation or reactions to the alcohol cleansing of your forearm and use of the hypoallergenic tape with the EMG electrodes. There is also the possibility of forearm muscle soreness due to the required MVCs. All these risks are expected to be unlikely. Beyond this, they are not substantially different from those associated with your everyday PC use, or the use of skin cleansing products in the home, and are reversible. In the event that you experience fatigue or discomfort during the described experiment, a rest period will be provided or you can terminate your participation. If abnormal physiologic conditions persist, your participation in the experiment will be terminated.

BENEFITS

There are no direct benefits of participation in this study. You may derive some indirect benefits, including an understanding of human factors research methods and insight into the design and development of VR applications.

CONFIDENTIALITY
The information in the study records will be kept strictly confidential. Only the anthropometric survey, completed at the beginning of the experiment, and the informed consent will carry your name and identifying information. You will be provided with a coded identifier and this will be used on all other data collection sheets. Data will be stored securely and will only be made available to persons conducting the study. No reference will be made to you in oral or written reports, which could link you to the study.

C**OMPENSATION** (if applicable)
Your participation in this study is completely voluntary. There will be no compensation provided for the experiment. You may withdraw at any time.

CONTACT
If you have questions at any time about the study or the procedures, you may contact Dr. David Kaber**, at** the Department of Industrial Engineering, Box 7906, North Carolina State University**, or** (919) 515 3086**. If you feel you have not been treated according to the descriptions in this form, or your rights as a participant in research have been violated during the course of this project, you may contact Dr. Matthew Zingraff, Chair of the NCSU IRB for the Use of Human Subjects in Research Committee, Box 7514, NCSU Campus (919/513-1834) or Mr. Matthew Ronning, Assistant Vice Chancellor, Research Administration, Box 7514, NCSU Campus (919/513-2148).**

PARTICIPATION
Your participation in this study is voluntary; you may decline to participate without penalty. If you decide to participate, you may withdraw from the study at any time without penalty and without loss of benefits to which you are otherwise entitled.

CONSENT
"I have read and understand the above information. I have received a copy of this form. I agree to participate in this study with the understanding that I may withdraw at any time."

Subject's signature____ Date _________________

Investigator's signature___________________________________ Date _________________

Appendix B: Subject Survey

Assessing the Utility of Haptic Devices for Medical Evaluations based on Models of Human Handwriting and Drawing Processes

Subject Survey

Name: _______________________

Age: ____________

Gender (circle one): Male Female

Handedness (circle one): Right Left

Corrected Visual Acuity: Left Eye: 20/________ Right Eye: 20/_________

For the following questions, please use this scale:

1	2	3	4	5
None		Occasional		Frequent

1. Rate your video gaming experience: ____________

2. Rate your PC experience: _____________

3. Rate your drawing skill: _______________

If you answered anything other than '1' for video gaming experience, please summarize the types and amount of games you play (e.g., 50% of time on car racing games; 25% of time on card games; 25% of time on adventure games):

If you answered anything other than '1' for drawing skill, please detail your experience below (any special training/education in painting, calligraphy), or identify any hobbies related to your drawing ability that might influence hand positioning accuracy or stability in performance:

Appendix C: Post-Experiment Questionnaire

Assessing the Utility of Haptic Devices for Medical Evaluations based on Models of Human Handwriting and Drawing Processes

POST-EXPERIMENT QUESTIONNAIRE

Please answer the following questions regarding your experience with the haptic devices throughout the experimental trials:

1. On a scale of 1-7 (where 1=not useful at all and 7=extremely useful), how realistic was the simulated drawing with the Phantom device as compared to real pencil and paper drawing? _____________

2. On a scale of 1-7 (where 1=not useful at all and 7=extremely useful), how realistic was the simulated drawing with the Flacon device as compared to real pencil and paper drawing? _____________

3. Do you think the Phantom haptic device had any negative influence on the accuracy of your drawing?

Yes No I Don’t Know

4. Do you think the Falcon haptic device had any negative influence on the accuracy of your drawing?

Yes No I Don’t Know

5. Do you think the training period before the test trials was long enough for you to fully understand and become comfortable with using the haptic devices for drawing?
Yes No I Don’t Know

6. Are there other types of feedback that you think might be helpful in a VR-based simulation of complex figure drawing? Please explain.

____

____

Appendix D: NASA-TLX Survey

NASA-TLX Workload Factor Definitions

Mental Demand

How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.) Was the task easy or demanding, simple or complex, exacting or forgiving?

Physical Demand

How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

Temporal Demand

How much time pressure did you feel due to the rate at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

Performance

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance?

Frustration

How insecure, discouraged, irritated, and annoyed versus secure, gratified, content and complacent did you feel during the task?

Effort

How hard did you have to work (mentally and physically) to accomplish your level of performance?

SUBJECTIVE COMPARISON OF DEMAND FACTORS: NASA-TLX SURVEY

Indicate the demand of greater importance by circling its label on each line directly below.

<u>Mental Demand / Physical Demand</u>

<u>Mental Demand / Temporal Demand</u>

<u>Mental Demand / Performance</u>

<u>Mental Demand / Frustration</u>

<u>Mental Demand / Effort</u>

<u>Physical Demand / Temporal Demand</u>

<u>Physical Demand / Performance</u>

<u>Physical Demand / Frustration</u>

<u>Physical Demand / Effort</u>

<u>Temporal Demand / Performance</u>

<u>Temporal Demand / Frustration</u>

<u>Temporal Demand / Effort</u>

<u>Performance / Frustration</u>

<u>Performance / Effort</u>

<u>Frustration / Effort</u>

SUBJECTIVE RATING OF PERCEIVED WORKLOAD: NASA-TLX SURVEY

Indicate the level of demand experienced during the drawing task for each of these factors by drawing a straight vertical line on the scale directly below.

Mental Demand

Low High

Physical Demand

Low High

Temporal Demand

Low High

Performance

Poor Good

Frustration

Low High

Effort

Low High

Appendix E: Rey-Osterrieth Complex Figure Scoring Criteria

Rey-Osterrieth Complex Figure Scoring Criteria

The scoring criteria are provided by Dr. Larry Tupler from Durham VA hospital. For each unit, accuracy and placement are scored based on each condition.

Unit 1

Accuracy

01_A_1 - The vertical segment of the Vertical Cross (1) should be parallel to the left vertical segment of the Large Rectangle (2).

01_A_2 - The horizontal segment of the Vertical Cross (1) should be short and should intersect the vertical segment near the top.

01_A_3 - The length of the horizontal and vertical segments of the Vertical Cross (1) should be proportional to those of the complex figure stimulus.

Placement

01_P_1 - The short horizontal line that connects the Vertical Cross (1) to the Large Rectangle (2) should be positioned within ¼ inch of the correct position above the Small Rectangle (6) and the Small Horizontal Line (7), very near but below the upper left corner of the Large Rectangle (2).

01_P_2 - The height of the Vertical Cross (1) should not extend more the ¼ inch above the top point of the Small Triangle (9), or more than ½ inch above or ¼ inch below the Horizontal Midline (4).

01_P_3 - The cross should not be rotated or drawn upside down.

Unit 2
Accuracy

02_A_1 - A large rectangle composed of four line segments should be drawn. These lines may be drawn discontinuously and still receive full credit for accuracy.

02_A_2 - The lines should extend past the corner intersections no more than 1/8 inch.

02_A_3 - The width of the Large Rectangle (2) should be greater than the height and generally proportional to the complex figure stimulus

Placement

02_P_1 - The Large Rectangle (2) should be drawn in the approximate center of the page.

02_P_2 - An edge of the page should not be used as a side.

Unit 3
Accuracy

03_A_1 - Two diagonal lines should be drawn from adjacent corners or the Large Rectangle (2).

03_A_2 - The lines should extend past the corners of the Large Rectangle (2) no more than 1/8 inch.

03_A_3 - The lines should be no more than 1/8 inch from intersecting the corners of the Large Rectangle.

03_A_4 - The two lines that form the Diagonal Cross should be approximately straight. These line segments may be drawn discontinuously and still receive full credit for accuracy.

03_A_5 - If only one diagonal line segment in one quadrant is drawn, a score of 0 is assigned.

Placement

03_P_1 - The two diagonal lines that form the Diagonal Cross (3) should intersect no more than ¼ inch from the midpoint of the Large Rectangle (2).

03_P_2 - The midpoint of the Large Rectangle (2) may be defined as the intersection of imaginary lines drawn from opposite corners of the Large Rectangle (2).

03_P_3 - A 0.5 is scored if only two quadrants have a diagonal.

Unit 4
Accuracy

04_A_1 - A horizontal line should be drawn between the vertical segments of the Large Rectangle (2).

04_A_2 - It should not overshoot or undershoot the vertical segments of the Large Rectangle (2) more than 1/8 inch.

04_A_3 - The line segment should be approximately straight.

Placement

04_P_1 - The Horizontal Midline (4) should be positioned no further than ¼ inch from the intersection of the two lines that form the Diagonal Cross (3) and should be within ¼ inch of bisecting the vertical sides of the Large Rectangle (2).

04_P_2 - If the Diagonal Cross (3) is not present, the Horizontal Midline (4) should be no further than ¼ inch from the midpoint of the Large Rectangle (2).

Unit 5
Accuracy

05_A_1 - The Vertical Midline (5) should be drawn perpendicular to each horizontal segment of the Large Rectangle (2).

05_A_2 - The line should not overshoot the horizontal segments of the Large Rectangle (2) more than 1/8 inch.

05_A_3 - The line segment should be approximately straight.

Placement

05_P_1 - The Vertical Midline (5) should be positioned no further than ¼ inch from the intersection of the two lines that form the Diagonal Cross (3).

05_P_2 - If the Diagonal cross (3) is not present, the Vertical Midline (5) should be positioned no further than ¼ inch from the midpoint of the Large Rectangle (2).

05_P_3 - The Vertical Midline (5) should be within ¼ inch of bisecting the horizontal segments of the Large Rectangle (2).

05_P_4 - It should connect with the vertical segment of the Small Triangle (9) and the vertical connecting line of the Horizontal Cross (17), but it may be drawn discontinuously, within ¼ inch, and still receive full credit for placement.

Unit 6

Accuracy

06_A_1 - A small rectangle should be drawn within the area defined by the left vertical side of the Large Rectangle (2) and the two lines that form the Diagonal Cross (3).

06_A_2 - The small rectangle should be composed of four line segments.

06_A_3 - The line segments should form four right angles at the corners.

06_A_4 - The lines should extend past an intersection no more than 1/8 inch.

06_A_5 - The lines should fail to intersect at a corner by no more than 1/8 inch.

06_A_6 - The height of the Small Rectangle (6) should be greater that its width and generally proportional to the complex figure stimulus.

06_A_7 - Within the Small Rectangle (6) are two diagonal lines that connect adjacent corners of the Small Rectangle (6).

06_A_8 - These lines should not overshoot or undershoot the corners by more than 1/8 inch.

Placement

06_P_1 - The midpoint of the Small Rectangle (6) should not deviate from the Horizontal Midline (4) by more than ¼ inch.

06_P_2 - The intersection of the two small diagonals within the Small Rectangle (6) should not deviate from the Horizontal Midline (4) by more than ¼ inch.

06_P_3 - The corners of the Small Rectangle (6) should not deviate from the area defined by the left vertical side of the Large Rectangle (2) and the Diagonal Cross (3) more than ¼ inch at any point.

Unit 7
Accuracy

07_A_1 - A Small Horizontal Line (7) should be drawn parallel to and directly above the Small Rectangle (6), crossing from the left vertical segment of the Large Rectangle (2) to the proximal Diagonal Cross (3) segment.

07_A_2 - It should not overshoot the endpoints on the Large Rectangle (2) and the proximal diagonal Cross (3) more than 1/8 inches.

Placement

07_P_1 - The line should deviate no more than ¼ inch from the proper location, defined as the area above the Small Rectangle (2) and below the short vertical line that connects the Vertical Cross (1) to the Large Rectangle (2).

07_P_2 - The line should be discontinuous with any segment of the Four Parallel Lines (8).

Unit 8
Accuracy

08_A_1 - Four lines must be present, with no fewer and no extra lines.

08_A_2 - The lines should not be rotated more than 30 degrees from the horizontal plane.

08_A_3 - Each line should be horizontal and drawn parallel to other three lines.

08_A_4 - The spacing between each line is scored liberally but should be generally proportional to the complex figure stimulus. No error is scored if disproportionate distance is between the top line and the top horizontal segment of the Large Rectangle (2).

08_A_5 - The lines should extend no more than 1/8 inch past the boundary of the Vertical Midline (5) or the upper left portion of the Diagonal Cross (3).

Placement

08_P_1 - Four evenly spaced horizontal lines should be drawn in the area defined by the upper left segment of the Diagonal Cross (3), the upper segment of the Vertical Midline (5), and the left proportion of the top horizontal segment of the Large Rectangle (2).

08_P_2 - The lines should be contained in the upper left quadrant of the Large Rectangle (2).

Unit 9
Accuracy

09_A_1 - A Small Triangle (9) should be a right triangle, with the 90-degree angle to the bottom left, the 60-degree angle at the top, and the 30-degree angle on the right.

09_A_2 - The hypotenuse should not be a continuation of the upper side of the Large Triangle (13).

09_A_3 - The lines that form the top (60 degree) corner of the Small Triangle (9) should extend past the point of intersection no more than 1/8 inch.

09_A_4 - The lines should be within 1/8 inch of intersecting at a corner.

Placement

09_P_1 - The Small Triangle (9) should be drawn immediately above the right portion of the top horizontal segment of the Large Rectangle (2).

09_P_2 - The horizontal segment of the Large Rectangle forms the bottom segment of the Small Triangle (9).

09_P_3 - The left vertical side of the Small Triangle should be within ¼ inch of connecting with the Vertical Midline (5).

09_P_4 - If the left vertical side of the Small Triangle (9) is correctly connected to the Vertical Midline (5), but the Vertical Midline (5) is itself misplaced (thereby distorting the Small Triangle [9]), score the Small Triangle (9) as correctly placed and score the Vertical Midline (5) as incorrectly placed.

09_P_5 - The hypotenuse of the Small Triangle (9) should connect with the upper right corner of the Large Rectangle (2).

Unit 10
Accuracy

10_A_1 - One, and only one, vertical line should be drawn.

10_A_2 - The line should not be rotated more than 30 degrees.

10_A_3 - The Small Vertical Line (10) should extend past the points of intersection no more than 1/8 inch.

Placement

10_P_1 - A vertical line should be drawn within the area defined by the upper right segment of the Diagonal Cross (3), the upper portion of the Vertical Midline (5), and the top right horizontal segment of the Large Rectangle (2).

10_P_2 - The Small Vertical Line (10) should be positioned within ¼ inch of the center point of the designated area with the Small Vertical Line (10) to the left of the center point.

Unit 11
Accuracy

11_A_1 - The circle should have three, and only three, dots.

11_A_2 - The dots must be oriented properly to be scored as accurate.

11_A_3 - The circle should be generally proportional to the complex figure stimulus.

11_A_4 - The dots should be dark (i.e., not overly light), but this may be scored somewhat liberally.

11_A_5 - A "smiley face" is scored as inaccurate.

Placement

11_P_1 - The Circle with Three Dots (11) must be placed within the area defined by the upper right segment of the Diagonal Cross (3), the proximal segment of the Horizontal Midline (4), and the top right vertical segment of the Large Rectangle (2).

11_P_2 - If any portion of the circle crosses these boundaries, it is scored as misplaced.

Unit 12
Accuracy

12_A_1 - Five lines of roughly equal length must be present along the lower right segment of the Diagonal Cross (3).

12_A_2 - They should form right angles with the Diagonal Cross (3).

12_A_3 - The lines should be evenly spaced and parallel to each other and generally proportional to the complex figure stimulus.

12_A_4 - Spacing and parallelism are scored liberally.

12_A_5 - In the event that the lower right segment of the Diagonal Cross (3) is not present, but the Five Parallel Lines (12) are drawn, the lines are scored as accurate if they meet the above criteria.

Placement

12_P_1 - The lines should be positioned on the lower right segment of the Diagonal Cross (3), within the lower right quadrant of the Large Rectangle (2).

12_P_2 - In the event that the lower right segment of the Diagonal Cross (3) is not present, the lines are scored as correctly placed if they meet the above criteria.

Unit 13
Accuracy

13_A_1 - Two line segments should originate from the two right corners of the Large Rectangle (2) and converge at a point to the right of the right vertical segment of the Large Rectangle (2).

13_A_2 - The size of the Sides of the Large Triangle should be generally proportional to the complex figure stimulus.

13_A_3 - The lines should not overshoot or undershoot the termination points by more than 1/8 inch.

13_A_4 - In the event that the right vertical segment of the Large Rectangle (2) is not drawn, the Sides of the Large Triangle (13) is scored as accurate if all other accuracy criteria are met.

Placement

13_P_1 - The lines should converge at a point no more than 1/8 inch from the endpoint of the Horizontal Line within the Triangle (16).

13_P_2 - The vertex of the triangle should be drawn opposite the mid-point of the right vertical segment of the Large Rectangle (2) and should not deviate from this position by more than ¼ inch.

13_P_3 - The base of the triangle should incorporate the right vertical segment of the Large Rectangle (2).

Unit 14
Accuracy

14_A_1 - This element must be a diamond shape with four sides of equal length. A round or triangle shape is scored as inaccurate.

14_A_2 - Although the shape of the diamond is scored somewhat liberally, the widest portion of the figure must be in the middle, and the width must taper at the top and bottom vertices.

14_A_3 - All lines of the Diamond (14) must be distinct from the segments that form the sides of the Large Triangle (13).

14_A_4 - The Diamond (14) must not be attached to the Sides of the Large Triangle (13) with another line segment (i.e., “stem”).

14_A_5 - The lines should extend past an intersection no more than 1/8 inch.

14_A_6 - The lines should be within 1/8 inch of intersecting at a corner.

14_A_7 - The vertical axis of the Diamond (14) should not be rotated more than 30 degrees from vertical.

Placement

14_P_1 - The top vertex of the Diamond (14) should connect with the vertex of the Sides of the Large Triangle (13).

14_P_2 - The bottom vertex of the Diamond (14) should not extend below the horizontal line of the Large Rectangle (2).

Unit 15
Accuracy

15_A_1 - A vertical line should be drawn that connects with the two line segments that form the Sides of the Large Triangle (13).

15_A_2 - The line should be rotated no more than 30 degrees. The line should extend past an intersection no more than 1/8 inch.

15_A_3 - The line should be within 1/8 inch of intersecting the Sides of the Large Triangle (9).

Placement

15_P_1 - The vertical line should be positioned to the left of the midpoint of the Horizontal Line within the Triangle (16).

Unit 16
Accuracy

16_A_1 - The Horizontal Line in the Triangle (16) should be within 1/8 inch of connecting with the Horizontal Midline (4).

16_A_2 - It should not overshoot the apex of the Sides of the Large Triangle (13) by more than an inch.

Placement

16_P_1 - The horizontal line should bisect the apex of the Large Triangle (13), and the endpoint should not fall more than ¼ inch above or below the appropriate intersection points.

Unit 17
Accuracy

17_A_1 - A horizontal cross with its vertical cross-piece should be present on the right side of the figure.

17_A_2 - A short vertical line should connect the horizontal cross to the Large Rectangle (2).

17_A_3 - The length of the lines that form the Horizontal Cross (17) should be generally proportional to the complex figure stimulus.

17_A_4 - The short vertical line that connects the Horizontal Cross (17) to the Large Rectangle (2) should also connect with the Vertical Midline (5).

17_A_5 - If the Vertical Midline (5) is not drawn, then this small vertical line should connect at the approximate center of the bottom horizontal segment of the Large Rectangle (2).

17_A_6 - The ¼ inch tolerance rule is used to score the accuracy of all closures.

Placement

17_P_1 - The cross should be within ¼ inch of connecting to the midpoint of the right side of the Square (18) (if drawn).

17_P_2 - The right end of the Horizontal Cross (17) should not extend more than ¼ inch past the right vertical side of the Large Rectangle (2).

17_P_3 - If the Vertical Midline (5) is drawn, then the small vertical line that connects the cross must be within ¼ inch of the Vertical Midline (5).

Unit 18
Accuracy

18_A_1 - A small square should be drawn that contains a diagonal line that extends from the upper left corner to the lower right corner of the square.

18_A_2 - The width of the Square (18) should be within ¼ inch of the approximate width of the Small Rectangle (6).

18_A_3 - The four lines of the Square (18) should meet to form right angles at the corners.

18_A_4 - The lines should extend past an intersection no more than 1/8 inch.

18_A_5 - The lines should be within 1/8 inch of intersecting at a corner.

18_A_6 - The end points of the diagonal line in the Square (18) should not overshoot or undershoot the adjacent corners by more than 1/8 inch.

Placement

18_P_1 - The Square (18) should be positioned below the lower left corner of the Large Rectangle (2).

18_P_2 - The top of the Square (18) should be within ¼ inch of connecting with the lower horizontal segment of the Large Rectangle (2).

18_P_3 - The left vertical segment of the Square should be within ¼ of connecting with the left vertical segment of the Large Rectangle (2).