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The Design and Development of a Perceptual-Based Haptic Display Device

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A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University.

by

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Abstract

THE DESIGN AND DEVELOPMENT OF A PERCEPTUAL-BASED HAPTIC DISPLAY DEVICE

By Sohaib Akhter, BS Electrical Engineering

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Graphical information presented as pictures, graphs, maps, and the like are an important media for relaying knowledge and are a fundamental means of education rarely experienced by people who are blind or have a severe visual impairment. This thesis presents the design, development and testing of a multiple finger, haptic matrix dynamic display device capable of relaying graphical information through simulated textures. The design is based on user perception studies that determined which hand constraints provided the best tradeoff between simplicity of design, accuracy and time to answer. The best design was one that incorporated multiple fingers in close proximity to each other and restricted wrist rotation. Upon further

testing after the development of the device, evidence was gathered to show its effectiveness. Although subjects could determine key information from the simulated textures, there is a clear mismatch between the simulated representations of the objects and their tactile or embossed counterparts. There is some evidence that shows that the spatial resolution of the actuators may be a source of this error and also some evidence to state that it is the inability to track the edges that causes the difference between determining the physical diagrams and the simulated. On the other hand, results on determining locations using simulated maps were far closer to the control texture maps used than the results for object diagrams. Further studies could be done to determine the effect of higher actuator spatial resolution on object identification and edge tracking.

1. Introduction

One of the fundamental means of conveying unfamiliar information is through graphical representation. Whether it be teaching children how a horse or apple looks like or determining where you are in a mall, understanding graphics is important. Users who are blind or visually impaired have little to no experience using graphics and there is a lack of tools which can effectively allow such users to access graphical information. This has most likely contributed to an unemployment rate of over 70% [20] for the working age adult blind population.

Individuals with severe vision impairment have used their sense of touch to substitute for the lack of visual perception and thus most visual information is converted to tactile form for such users. To relay text, a system of dots called Braille is used, and for pictures, static raised-line diagrams or texture embossed paper help relay the information. Considering the explosive advancement of digital processing techniques and computer processers through every walk of life, rehabilitation for people with visual disabilities is a field which is relatively untouched. The commercial actuator for haptics technology hasn't really changed from the piezoelectric bimorphs used in 1969 by Linvill, J.G. and associates in their studies [18]. Linvill had made an analog Braille translator that would turn a physical picture into a tactile stimulation by raising and lowering pins that are connected to the bimorphs. As time moved on and dynamic computer user interfaces played increasingly important parts in sighted people's lives, Rotard et al. [23] decided to make a web interface consisting of a huge matrix of pins. There hasn't been an in-depth study on whether the algorithms they developed were feasible for users, but from a technical standpoint there is too much unnecessary power consumption and the device would have a lower refresh rate because it simulates a lot of pins that won't be felt by the user.

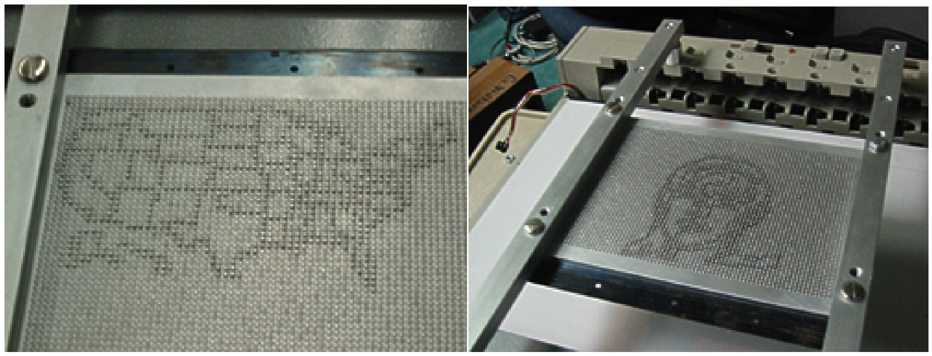

Figure 1. NIST Tactile Graphic Display [22]

Owen et al. [21] decided to simulate graphics on a mouse where the actuators lay right under the user's index finger. Owen's device however, was not the first mouse-based peripheral that incorporated tactile pins. The first commercially available mouse device was the VirTouch player as used by Walls and his associates [27], but Owen's device improved on the ability to track edges and distinguish different frequencies of bimorph vibrations. On a side note, there were actuators being tested other than the tactile array of bimorphs. One such actuator was the piezoelectric speaker, like the ones used by Burch et al. [2], where he placed small analog speakers under the index, middle and ring fingers of a user coupled with an analog RGB sensor per finger. This translated color to frequencies that simulate different textures, and the results of his study found that the response time decreases and that the users are more accurate if they use multiple fingers as opposed to one, and even more so when using two hands.

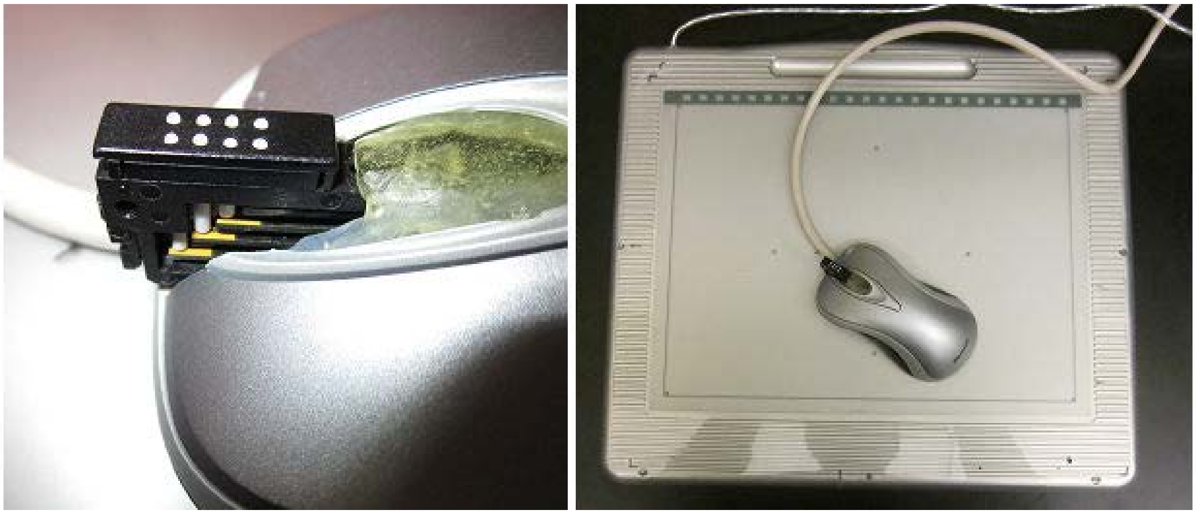

Figure 2. Owen's Refreshable Haptic Display Mouse [21]

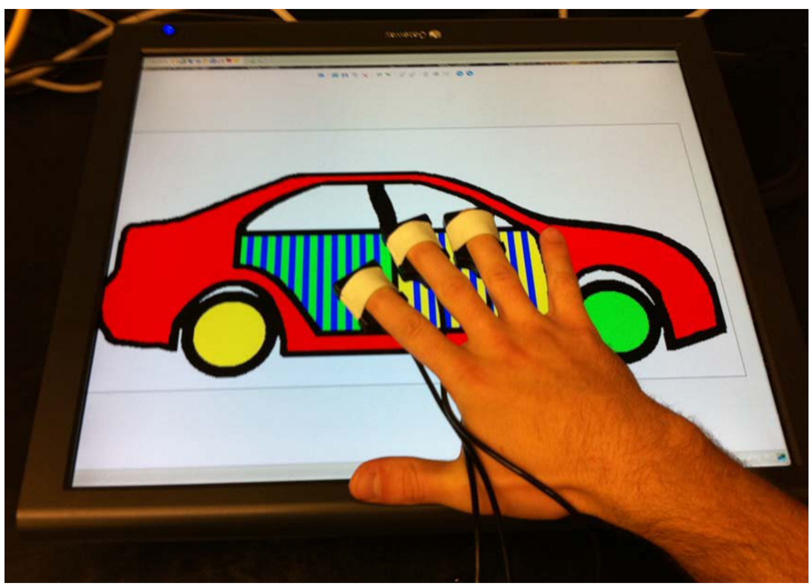

Figure 3. Burch's Multiple Finger Piezoelectric Haptic Display [2]

The objective of this thesis is to determine what user motions are necessary to obtain the major features of graphical information yet not be overly complicated to be difficult to design around. Is independent, individual finger motion relative to other fingers important in determining an image's identity? Does rotating the hand around the wrist help trace edges? Is most of the identification done through cutaneous processes or is kinesthesia the more dominant factor? To test these hypothesizes, several tests were performed where users had to identify textured fabric diagrams and maps under different hand constraints. The results of that study were used to make a new haptic refreshable display device and the resulting product was tested to determine what assumptions were correct, what weren't, and what to do next.

2. Background

Vision or visual perception is an unique sense that allows an organism to survey the entire environment though parallel processing of photoreceptors in the eye. A large set of information is received by the optic nerve at once and can paint a full picture in the occipital lobe of the brain. The array of retinal photoreceptors and the ganglions layers create receptor fields with high acuity and resolution leading to a crisp image that allows the organism to recognize objects and navigate its surroundings with ease. It is one of the fundamental five senses that everyone learns as a child. All the other senses, be it auditory, olfactory, haptic or gustatory have either very little spatial dimensions or have masking effects where channels bleed into each other reducing acuity and salience. Thus sight is a hard sense to substitute for, yet there are over 39 million people who are blind worldwide and about 284 million who are severely vision impaired [19] and have to make do without.

So how do these people live without this seemingly vital sense? The problem had existed ever since humans walked the earth so some of the solutions are still very primitive. Companionship with a human or a dog, who can act as a guide, was one of the simplest solutions for individuals with visual disabilities to accomplish everyday tasks. A second solution was to use a stick or cane to act as an extension of one's arm allowing the user to "feel" things at a distance. More descriptive sensory substitution could be obtained through the auditory system. For example, the location of objects can be encoded in the 3D spatial positioning of sound sources in a room as long as there aren't too many sources to make the task overwhelming. Lastly, haptic sensations allow people who have lost their vision to determine finer spatial details of certain objects that they come into physical contact with.

Braille, a tactile system of writing using raised dots on a 2x3 dot cell created by Louis Braille in 1821, was the first foray into tactile representation of words and letters that had previously only been used by people with sight. Braille determined that raised text could not give information of a whole symbol without moving the finger and so users couldn't move quickly from one letter to the next. Since the creation of Braille, a multitude of text was translated. In addition, raised outline pictures were embossed [8] to give people who were blind the ability to visualize graphical information. It is clear from the story of the adoption of Braille that there should be a user centered approach when designing haptic technology. For the development of a refreshable display to present textured tactile diagrams, which are more effectively used than raised line drawings: (1) the users must first be understood according to the nature and variety of their impairments and their haptic behavior when feeling texture embossed diagrams classified, and (2) other haptic display devices and their performances can also be scrutinized to determine what would be the most cost-effective means of developing the device.

2.1 Degrees of Visual Impairment

One of the most challenging design requirements in tailoring a refreshable displays to the population of the visually impaired is accounting for the wide range of disabilities they have and prior visual experiences. The disabilities could be congenital, occurring from birth, or adventitious, occurring later in life. They also could be from a traumatic injury, a disease, or a birth defect and could be static, like in the case of a scotoma, or degenerative, such as Retinitis Pigmentosa or macular degeneration. A portion of individuals who are visually impaired still have the ability to see silhouettes or basic shapes with blurred edges, while others do not. This results in a wide range of visual experiences that users might have and could affect their performance on the controlled experiment to be conducted.

The Center for Disease Control and Prevention [4] has classified visual disability into four groups: partially sighted, low vision, legal blindness and totally blind. Partially sighted people have some visual problems that requires them to receive special education. Low vision can be anything from Myopia, or near-sightedness, Hyperopia, far-sightedness or presbyopia, increased stiffness of the lenses resulting in a lower diopter due to old age. Legal blindness is when a person has lower than 20/200 vision, which means text need to be 10 times closer for them to recognize it, or other fine edged symbols, as compared to a normal sighted person. Total blindness is, as the name implies, the inability to see light of any kind. This type of classification is used in schools and many other educational institutions. However, another important classification is whether individuals have prior visual experience or not. Users in this type of classification are categorized as congenitally blind (CB) or adventitiously/late blind (LB). The LB group consist of people who have lost sight later on in life and have prior visual experiences that might help them comprehend the tactile representation presented with the device, whereas the CB group have a birth defect resulting in blindness from birth or unfortunate trauma in the first years of life so understanding 2D diagrams may present a challenge.

Heller et. al [10] did a number of experiments requiring users who are blind to understand tactile diagrams of real-world objects and he determined that the CB group usually lacks experience with drawings and prior interpreting of raised-line diagrams, which gives a heavy advantage to the LB group. Jansson and Holmes [13] did a more in-depth study of the perception differences between CB and LB groups using texture gradients and determined that many CB participants perceived linear changes in distance as slightly exponential due to the body-centric warping of the individuals kinesthetic map. This makes representing any perspective in an image extremely difficult for these users. Heller [11] also found a number of illusions that present themselves as a result of this mismatch. One example is the Mueller-Lyer illusion where two lines of equal lengths appear to be different lengths due to the orientation of the flanges on either end. Another is a horizontal-vertical illusion on arches and T-shapes where the vertical height seems longer than the horizontal width when both width and height are the same length. Other studies by Wijntjes and his associates [29] show that CB can overcome most of these shortcomings by learning how to sketch, draw and interpret those drawings.

2.2 Haptic User Behavior

The haptic behavior varies with the level of instruction that the user has received and is another variable that would affect the design of the haptic display. Apart from the different constraints that will be tested in the experiments mentioned in this thesis, there are a lot of techniques users who are visually disabled developed to feel texture diagrams. Jansson and Holmes also discovered through their experiments, that participants not experienced in identifying haptic raised-line diagrams would commonly not explore the entire diagram before making a judgment. They coin this premature judgment phenomenon the "Haptic glance" that doing such improves the accuracy at determining small representations but adversely affects larger diagrams; it is about 20% less accurate than fully explored diagrams.

With embossed diagrams more experienced users would first explore the edges or borderlines before exploring the textures, and the index fingers typically run along the edges whereas multiple fingers would be used to explore the textures. The haptic acuity of users also plays into their behavior as determined by Joseph Stevens and his associates [26]; it seems that haptic acuity decreases with age as well as discrimination for gaps, lines and orientation which are also compromised. Older individuals are also slower in reading text and are more likely to experience tactile adaptation effects. People with resting tremors or blindness due to diabetes may resort to using the mid regions of the finger instead of just the tip or wiggle the fingers to understand an object.

It should also be noted that most of these tests deal with raised-line diagrams of actual 3D objects and utilize active touch, where the finger moves on the texture, as opposed to passive touch, where the texture changes but the finger is stationary. For moving tactile displays, there is an interesting combination of the two: the hands do move over the virtual diagram but the tactile display remains in a fixed relationship to the finger (i.e., there is no movement between the device and the fingers, although the display itself will act as if it is moving). Davidson, Appelle and Haber [6] did a number of experiments with Braille cells with CB and LB subjects and found that using two hands are about twice as fast in identifying textures and text as compared to one hand. Subjects would usually use the index fingers of each hand and use the left index finger for line positioning if they were skilled Braille readers.

2.3 Haptic Display Classification

Traditionally tactile diagrams were made using embossing techniques, silk-screening, thermoforming, or multiple materials to generate the edges and textures of haptic diagrams, however most information nowadays is dynamic. Text on a computer screen can change location when scrolling through a website revealing new text or pictures; as visual reading has moved on from static books to on-screen text, so too is Braille transitioning to a more dynamic form with the use of Haptic displays. These display devices come in many sizes and shapes, and use different types of actuators to simulate textures in many different ways. The classifications types of dynamic displays on the market are Force Feedback devices (like the Logitech Wingman or the PHANTOM), Localized Contact displays, like the VirTouch Player [16] or the STReSS2 Display [28], and Distributed Contact displays, like the one Rotard made [23]. Force feedback devices restrict motion to simulate forces, Point Contact displays only actuate the region under the fingers whereas Distributed Contact displays actuate and the entire area meant to be explored.

We can also classify the displays in terms of the actuators used where the actuation technologies commercially available are the piezoelectric bimorphs, piezoelectric films, Eccentric Rotating Mass (ERM) motors, Linear Resonant Actuators (LRA)/Shaftless Motors, and Electro-Active Polymers (EAP) [12].

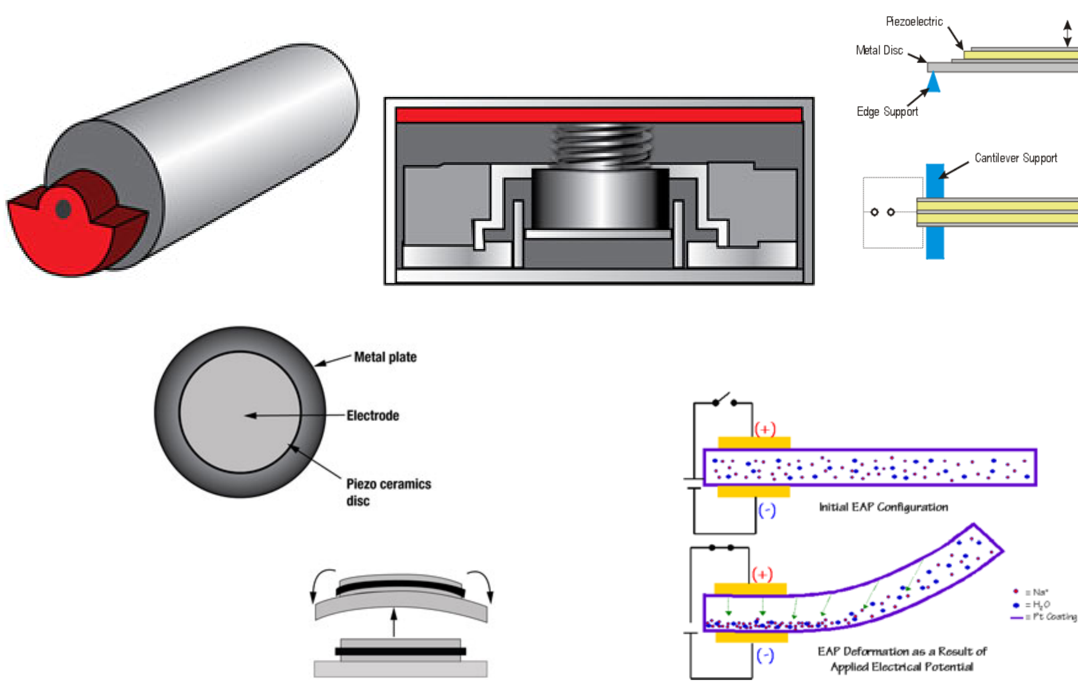

Figure 4. Types of actuators (from top-left to bottom-right): ERM, LRA, Piezoelectric Bimorph, Piezoelectric Film, EAP[24]

ERM and LRA motors are the cheapest actuators but have poor spatial resolution and longer rise and fall times, reducing the bandwidth of frequencies available for texture simulation. Piezoelectric bimorphs have a slightly wider bandwidth depending on the amplitude required for the texture and piezoelectric film have the best frequency response. Piezoelectric technology also has a higher spatial resolution but it depends on the construction of the actuator; Braille cells have thin bimorphs which can actuate independently, Piezoelectric films under the touch-screens of modern Smartphones can be synchronized to localize the stimulation with a high degree of accuracy. However, the films in old toy speakers have distributed stimulation because of its size and construction. Another difference between the bimorphs and the films is that there is a lot less work required into building a bimorph array device as opposed to a film array device. For the film array, a filter layer must be placed on top of the elements to transmit vibrations between the piezoelectric elements for a localized summated effect. It must not be too taught and held lightly above the array; moisture must be removed; and other controls must be in place to simulate the proper displacement for the virtual texture. EAPs [1] have approximately the same mechanical rise and fall times of piezoelectric but have a slightly smaller bandwidth; 200Hz maximum as opposed to a 300Hz maximum in piezo-actuators. It also has a high fidelity of sensation, again depending on its construction.

Lastly a haptic display can be classified in the way it transfers information to the user. Piezoelectric bimorphs and EAPs raise and lower pins to simulate textures. The STReSS2 tactile display [28] uses lateral bimorphs which can deflect left to right whilst directly contacting the finger to simulate textures. Both can use a variety of techniques such as varying spatial and/or temporal frequencies.

Outline of Thesis

This thesis follows a traditional top-down design approach to developing a haptic device. Institutional Review Board (IRB) reviewed studies were first conducted on a portion of the population of people who are blind or visually impaired. The first tests were used to standardize a set of 51 textured diagrams, 14 textured maps and 6 scenes in terms of complexity and time taken, down to six counter-balanced sets containing seven diagrams, a map, and a scene each. The second subject experiments constrained the users' motions in different ways whilst the user was trying to identify the tactile representation of the objects or features of the maps from one of the standardized sets. Section 3 elaborates on the way the experiments were prepared, conducted and a brief discussion of the results. These results were then used to determine the design requirements for a new device that both simplified the design space while trying to improve on the results from previous single-finger Localized Contact display devices. The complete design and revision procedure is documented in Section 4. Once the design was completed, a pilot study was conducted to determine the effectiveness of the new device against a constraint used in previous devices and the textured diagrams, which is considered to be the current standard when it comes to visualizing tactile graphics. The procedure and results of this final testing are presented in Section 5 followed by a discussion and conclusion.

3. Preliminary Research and Testing

Following the questions posed in Section 1, the hypothesis was formed that developing a multi-touch device, like the one shown in Figure 3, with a multiple pin actuator for each finger (as opposed to a single contact point) would give better performance results in terms of high accuracy and faster response times. However, to allow for multiple pin actuators on each finger when each finger (and the hand) is able to move freely is a very difficult design problem. Simple alternatives were investigated on whether or not they could potentially provide the same performance. To do this without building actual devices, participants were allowed to use their actual hands and fingers on a diagram, but constrained them in such a way as to mimic different constraints of the alternative devices. A number of cases were developed with single finger and multiple finger constraints in addition to other simplifying assumptions that needed to be tested. In total there were 5 constraints numbered in the following order: Index finger unconstrained, multiple fingers unconstrained, multiple fingers with constrained finger articulation but wrist rotation permitted, index finger constrained to move only in an X-Y direction, and multiple fingers constrained to X-Y motion.

Constraints 1 and 2 can determine quantitatively how much does multiple fingers improve on a single finger. Comparing 2 and 3 shows whether or not independently moving fingers are required for the difference between single finger and multiple finger exploration (Constraint 3 being easier to design). Constraint 4 and 5 looks into restricting both finger articulation and wrist rotation, either of which will greatly simplify the design and to see whether it positively or negatively affects the identification compared to the previous experiments.

For constraint 3, a plastic mold made of thermoplastic was generated to fit each subjects' hands and they moved the mold similar to moving a mouse on top of the diagrams tested. Constraints 4 and 5 used a specially designed 2-dimensional rig that was built using Polyoxymethylene (Delrin) sliders and industrial grade bearing slides, as well as a translational element where the final device was to be mounted as shown in Figure 5. More of the design and development of this rig will be explained in Section 4, but for these experiments, a combination bowling brace with a thermoplastic mold was used to constrain the wrist, keep the fingers from articulating, and attach it to the translational slider so that any other potential movements would be suppressed.

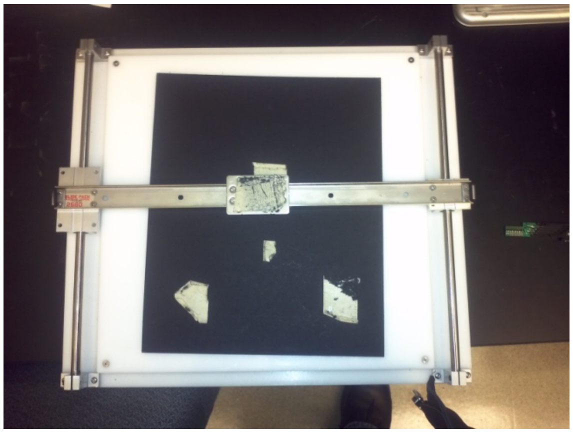

Figure 5. Two-Dimensional Constraining Rig

3.1 Procedure

To test the different constraints, and increase statistical power, it was preferable to use the same subject for all constraints. However, reusing the same pictures from constraint to constraint was expected to create strong order effects. Instead, a sufficient number of pictures for six different sets were developed. They were then rated by subjects on their complexity and divided into six sets to form sets of approximately equal complexity.

This set of experiments had a subject pool of 10 subjects, all students of the local Virginia Department for the Blind and Vision Impaired rehabilitation program, of them, 6 were congenitally blind and 4 were adventitiously/late blind. Proper counter balancing other factors like level of visual experience or tactile education couldn't be attained due to the limited pool of subjects. Participants were also blindfolded to avoid any use of residual vision.

This set of experiments had each subject try to identify 51 tactile pictures of everyday objects, animals, vehicles and other common pictures extracted from Snodgrass and Vanderwart's [25] set of standardized set of 260 pictures. These pictures were modified to remove any 3D perspective as that might be a problem for individuals who are blind, and to use texture encoding as in Burch's[3] TexyForm diagrams (but using actual materials with different textures to denote different parts of the objects rather than simulated textures on a haptic display). In the case that all the 3D perspective couldn't be removed, layered textures (horizontal, vertical and curvature) using fabric paint was used to describe the 3D orientation, for example polka dots on top of a texture indicated that the part of the object is curved. Only 3 underlying material textures were used per diagram for ergonomic purposes, to be within the limits of human short-term memory [5].

The pictures were presented in random order. The time to respond was recorded, and once the subject identified the object, they were told if they got it right or wrong and asked to rate the diagram based on the complexity of the task on a Likert scale from 1 to 10 where 1 is the easiest and 10 is the hardest. In the case where the answer was not correct, the complexity would be noted as a 12.

In addition to the pictures, the subjects were also required to interpret a total of 14 maps that were of three types: Position maps, Agricultural maps, and Temperature maps. Position maps used different textures to represent different attractions and feature of a small geographical region like parks, ponds, mountains and forests. Agricultural Maps used rougher textures to represent a larger density of vegetation and softer textures to represent scarcity. Temperature maps used rougher textures to denote hotter regions and vice versa. The subjects were asked 4 questions about each map after given half a minute to get accommodated. The map was given a score between 0 and 4 based on the answers. Six object scenes were also constructed and presented to the subjects for interpretation. The object scenes consisted of multiple objects in a particular setting and a similar set of 4 questions were asked per scene.

Once all the results were collected, 6 sets of 7 pictures, one map, and one object scene each were generated to be used with the different constraints. Each set was counter-balanced with some easy and hard diagrams, and either an easy map with a hard object scene or a hard map with an easy object scene.

The main experiment was to compare the performance of subjects for the five different constraints that could be used to simplify the development of a haptic display device. This test had a subject pool of 12 users from the local National Federation of the Blind (NFB) Chapter, who had to answer questions about a set (7 objects, 1 map and 1 object scene) for each of the different constraints. Each constraint received a different set to avoid learning effects. The sets and constraints were counterbalanced across subjects to the extent capable for the small number of subjects (i.e., the counterbalancing was only partial), and were not correlated with each other. For the maps and object scenes, subjects were required to name the object. For the maps and object scenes, subjects were asked four questions about the diagram. The response time, whether the answer was correct and the complexity on a scale of 1 to 10 were recorded. Participants were blind folded to avoid the use of any residual vision. The results of this experiment are presented in section 3.2 below.

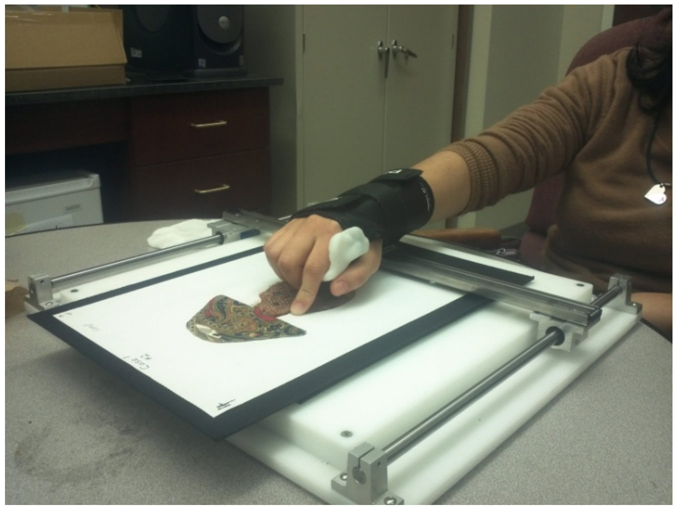

Figure 6. Testing the Single Finger X-Y Constraint

3.2 Results

Once the data was collected, it was analyzed with a repeated measures design using generalized estimating equations. Data for the tactile diagrams, maps and object scenes were separated into 3 different subsets and analyzed individually. For each subset, the time taken, complexity and number of correct were analyzed individually and pairwise comparisons were made between each constraint and the rest of the constraints to see if the difference in means were significant. The full analysis of the data is given in Appendix A.

For diagrams, the response time was modeled using a normal distribution with a log-link function with a model consisting of main effects for constraint and diagram set and a constraint by diagram set interaction. Constraints were numbered 1 through 5, with:

Constraint 1 = index finger only, unconstrained

Constraint 2 = multiple fingers, unconstrained

Constraint 3 = multiple fingers, constrained finger articulation, but unconstrained wrist

Constraint 4 = index finger only, movement constrained to an X-Y direction

Constraint 5 = multiple fingers, movement constrained to an X-Y direction.

Although the effect of constraint was not significant, both set and the set-constraint interaction were ($p = 0.0001$ in both cases). The 95% confidence interval showed that each diagram took around 55-125 seconds to identify. Nominally, constraint 3 had the lowest mean of 79.7s followed by constraint 2, 5, and 4; constraint 1 had the slowest response time with a mean of 90.6s. However, it is also important to mention here that although constraint 3 shows the lowest mean, the difference between constraints was not statistically significant overall.

The analysis of complexity was modeled using a normal distribution with a log-link function; it consists of main effects from the constraints, diagram sets, and constraint by set interaction. For complexity, both the main effect of constraint and the constraint-set interaction were significant ($p < 0.0001$). Pairwise comparisons showed that the results for constraint 3 were significantly different than that for constraint 1 ($p=0.22$), constraint 2 ($p=0.001$) and constraint 4 ($p < 0.0001$), with the task being considered less complex with constraint 3. Constraint 5 was also significantly different from constraint 2 ($p=0.22$) and constraint 4 ($p = 0.006$). Constraints 3 and 5 were not considered significantly different from each other. 95% of the diagrams had a complexity between 5.3 and 9.5. Constraints 3 and 5 had the lowest mean of 6.79 and Constraint 4 had the highest mean of 7.8.

Lastly, the analysis of the number of correct used a Poisson distribution with a log-linear link function, as is typical for count data, and with main effects for constraint, diagram set and constraint by diagram set interaction. Both the main effects of constraint and set, and the interaction of constraint-set, have statistically significant effects on the data ($p<0.0001$ in all cases). In pairwise comparisons, Constraint 5 was significantly different than Constraint 1 ($p=0.042$), Constraint 2 ($p=0.005$) and Constraint 4 ($p < 0.0001$). Constraint 4 was also significantly different from Constraint 3 ($p < 0.0001$) which was in turn, significantly different from Constraint 2 ($p = 0.023$). The 95% Wald confidence intervals showed that out of 7 pictures, typically 2 to 5 pictures were correctly identified. Constraint 5 had the highest mean of 4.29 correct followed by constraint 3 with a mean of 4.14 and the lowest mean was constraint 4 with 3.11.

Together, results for the diagrams suggest that using Constraints 3 or 5 (multiple fingers, constrained finger articulation, with or without constrained wrist rotation) resulted in the best performance. These results were interesting as they were statistically better than for Constraint 2 (all five fingers, no constraints). This suggests that constraining motion of the fingers (and hand) may actually improve performance, possibly due to an increased motor control.

For object scene and map analysis, the results were close to 100% correct for the number of correct questions and, therefore, there was not enough variability to properly analyze the response as a function of constraint or set. The scenes/maps took anywhere between 165 and 280 seconds. Using a model similar for the response time for pictures of objects: there was a statistically significant effect for constraint ($p < 0.0001$), set ($p = 0.002$) and a constraint-set interaction ($p< 0.0001$) for object scenes. For the object scenes (only), Constraint 3 was significantly different from Constraint 1 ($p = 0.013$), Constraint 2 ($p = 0.036$) and Constraint 4 (p

< 0.0001). No other pairwise comparisons were significant. In this case, Constraint 3 actually had a significantly higher response time than the other constraints (except for Constraint 5).

Although, constraints 1 and 4 consistently had the lowest mean times with about 195s to analyze a scene and about 220s to analyze a map, and constraint 3 and 5 had the highest mean times with about 220s to analyze a scene and 235s to analyze a map.

For the rating of complexity, the typical complexity was between 3.7 and 7.3 for object scenes and 3.5 to 7.2 for maps. The analysis preformed for complexity was similar to that preformed for complexity for pictures of objects. There were no significant effects of constraint, although Constraint 3 had the nominally lowest complexity (4.79) followed by Constraint 5 (5.26). Both set ($p = 0.002$) and the set-constraint interaction ($p < 0.0001$) were significant. For maps, there was an effect of constraint ($p = 0.026$), set ($p < 0.0001$) and constraint-set interaction ($p < 0.0001$). The results for Constraint 1 were significantly different from Constraint 2 ($p = 0.011$), Constraint 4 ($p = 0.009$) and Constraint 5 ($p = 0.072$). Constraint 2 was also significantly different form Constraint 3 ($p = 0.095$) which was, in turn, significantly different from Constraint 4 ($p = 0.030$). The least complex was Constraint 4 (4.30), followed by Constraints 2 (4.71) and 5 (4.85) which were not statistically significantly different from Constraint 4.

3.3 Conclusion

In conclusion, using Constraints 3 and 5, where multiple fingers were used but were constrained to moving together, with or without constraining wrist rotation, showed the best performance. In the case of maps and object scenes, although both didn't perform as well with time taken, the pairwise comparisons did not show Constraint 5 to be statistically different from any of the other constraints. For complexity there was either not a difference in performance between the constraints (object scenes) or Constraint 5 was not considered statistically different from the other constraints. Therefore, the results suggest that developing a device following Constraint 5 will result in the best performing system.

The design requirements suggest developing a device using the X-Y constraining rig as a foundation, with the fingers fixed in relationship to each other, and incorporate high acuity actuators to simulate textures would be the best course of action. The placement of actuators on the device should restrict articulation, but accommodate for users with different sized hands. There are other requirements for the software end of the device to be as fast as possible in order to reduce mismatches between the frequency simulated and that observed, as well as to give the largest possible dynamic range in frequency to simulate 4 or 5 perceivably different textures.

4. Design of a Perceptual Haptic Device

The technical solution designed in this paper involves the use of computer controlled set of Braille cell actuators to simulate tactile textures on a virtual diagram that give the user an indication of objects or maps that are on the screen. In the following sections, the functional units of design will be explained and the reason as to why they were chosen. This will be followed by the hardware and software design considerations and implementations, and finally any revisions that were made to the device.

4.1 Design Architecture

The black-box diagram has one input and one output; the objective of the device was to take an image rendered as a digital format on the computer and process it such that users could feel different textures and explore it just as they would a tactile diagram. Digging a little deeper to a level 1 architecture, the image must be fed through a means of interpretation, a way the computer would know how to generate the textures, and an additional digital-to-analog stage is necessary as any of the commercial actuators rely on analog voltage. The device is a Localized Contact display device so there must also be a feedback mechanism to tell the computer which sub-region of the image to generate textures for. The full level 1 system architecture is shown in Figure 7.

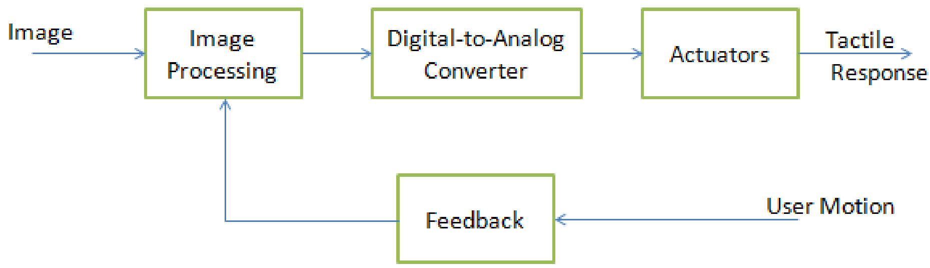

Figure 7. Level 1 Design Architecture

The software used for instrumentation and prototyping in an academic institution have been either MathWorks MATLAB or National Instruments Labview. As this project requires some digital-to-analog and potentially analog-to-digital channels, Labview was chosen as MATLAB doesn't provide its own data acquisition hardware and driver compatibility could be an issue with third party hardware. The actuators that will be used are Braille Cells because the piezoelectric bimorphs can simulate the widest depth of frequencies and provide high enough acuity to simulate high resolution textures. Three Braille cells will be used for the multiple fingers approach, and be built to the two-dimensional constraining rig used in the previous experiments. For feedback, linear motion sensors will track the users distance relative to the dynamic range of the device to determine the appropriate location on the virtual image to display.

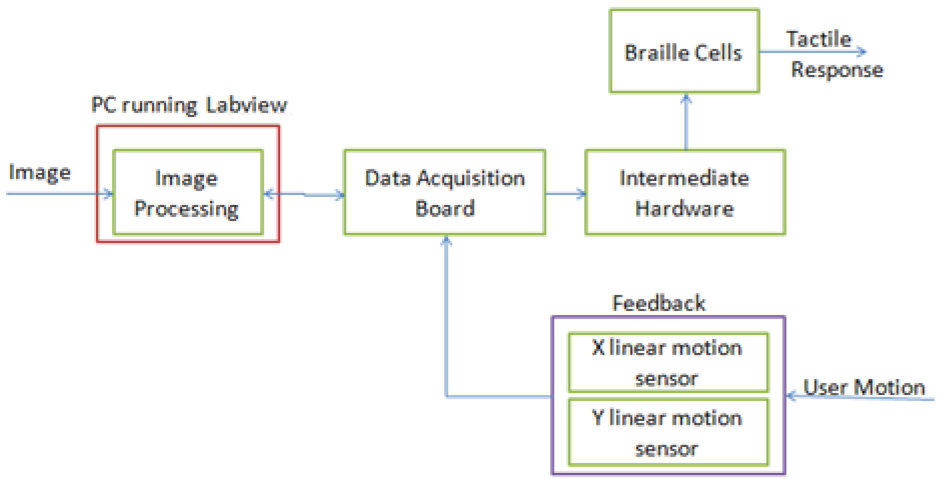

Figure 8. Level 2 Design Architecture

4.2 Hardware Design

The mechanical hardware design started as a means to constrain subjects' hand motions to only the X-Y directions in the previous experiments involving hand constraints. The constraining rig design iterated from using X- and Y-axis bars with the translational element to one that used an industrial slide for the X-axis and bars for the Y-axis. The first design had the translational element twisting a bit when sliding, causing it to stick in places and prevent itself from moving diagonally. The new design uses ball bearings on the slide that makes moving left to right smooth, and the Delrin sliders with Teflon inserts works reasonably well for the vertical axis. This mismatch between the ease of horizontal and vertical motions makes diagonal movement less intuitive but still doable compared to the previous design. Figure 9 shows the differences between the first and second iterations of the rig.

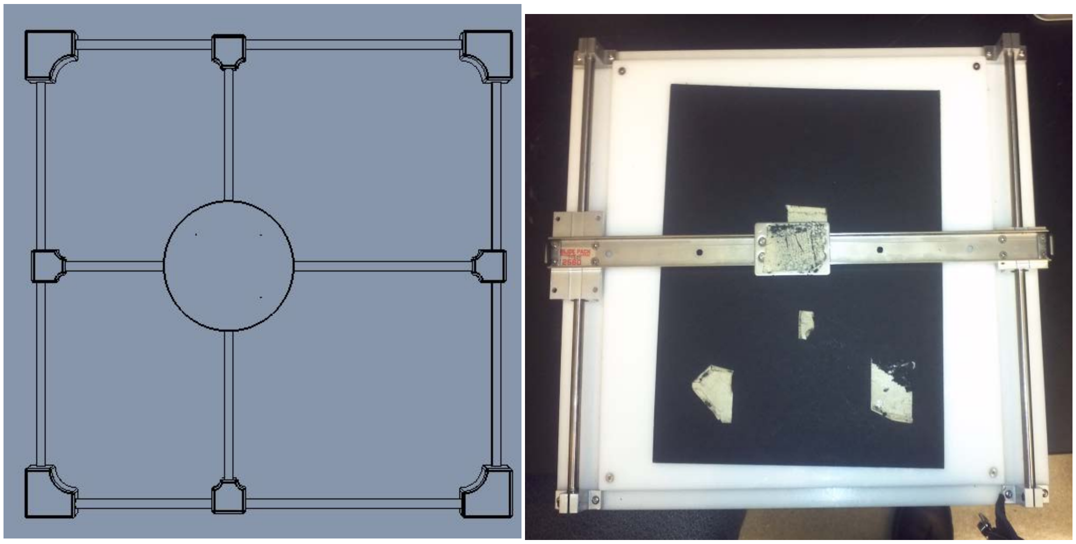

Figure 9. Two-Dimensional Constraining Rig Revisions

For the tactile feedback component, there were several considerations that went into design. First the Braille cells need to be able to electronically activate each tactile pin independently and for this reason the Metec P16 Braille cell was chosen as it required a common ground and a +200V input but also had 8 inputs, one for each pin. The 200 Volts required for the actuation is standard for bimorphs, but it only requires 1-2μA per pin so it's about 1.6 mW of maximum power consumption per cell. In order to source the cells, a Metec driver circuit was used which took in 5V and stepped it up using a boost configuration of a switched-mode power supply to the required 200V. To control the rising and falling of the pins, a set of SPST high-speed digital photorelays (TLP4227G-2) were placed on a breadboard. The pins had to be switched from 200V to ground for one oscillation and thus one 8 pin Dual In-line Package chip was used per pin, one relay to connect it to 200V and another to send it to ground. A layer of 74LS04 NOT gates take digital signals from the Data Acquisition (DAQ) board and invert them for the alternative relay on every chip reducing the number of necessary digital output channels to 24.

For obtaining an accurate measurement of the X and Y positions of the device, a Spectra Symbol SoftPot linear motion potentiometer was used. A 300mm potentiometer was set as the Y-axis and a 400mm potentiometer was used for the X-axis; they were set up in a potential divider configuration with a regulated 5V source and fed to the analog inputs of the DAQ board.

For the DAQ board, the total number of Digital I/Os on the board needed to be greater than 24 and it had to have at least 2 Analog Input ports on the device, therefore, the NI USB-6212 was chosen which has 32 digital outputs and 16 16-bit analog inputs that can sample at 400kS/s allowing for quick measurement of the X,Y position. A section schematic shown in Figure 11 illustrates how one input and one output channel are wired.

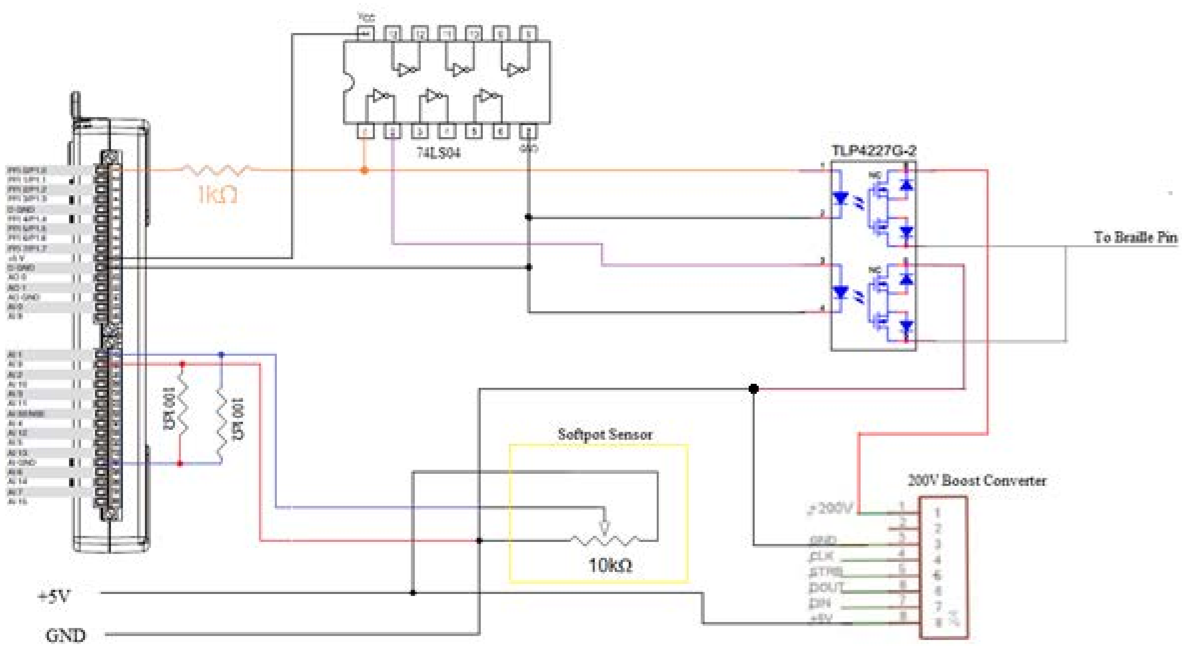

Figure 10. Preliminary Circuit Schematic with one Input(bottom) and Output(top) Channel

To decide how the Braille cells would be mounted to the translational element (Figure 11) to allow contact with the distal pads of the fingers, anthropomorphic data was researched on human finger lengths [7]. If there is no disfiguring disability in the user, 95% confidence interval shows that a hand length could be 173mm to 209mm for males and 159mm to 191mm for females. The index finger lengths range from 64mm to 79mm for males and 60mm to 74mm for females. The average ratios from the index finger to the middle finger is 1.16 and for index to ring finger it is 1.06. The length of a Braille cell is 84mm, which suggests simple positioning on the translational element. The mechanical diagram of the haptic interface is shown below; a circular aluminum disc of 0.1m diameter is used as the base and the Braille cells extrude from underneath giving a place for the palm and fingers to rest. All of this is mounted to the translational element.

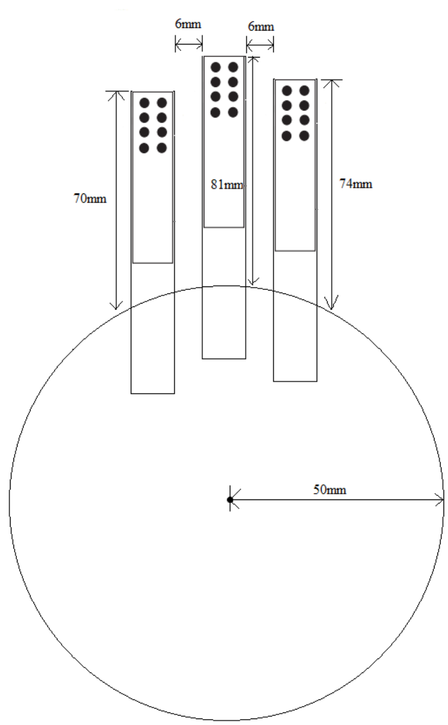

Figure 11. Haptic Translational Element Interface Design

A few more modifications were made to the rails to hold the linear potentiometers and spring loaded set screws were placed on the sliders to apply about 2N of force where the slider contacts the potentiometer on the rails. The tip material, Delrin, has a low coefficient of friction so it doesn't prevent smooth movement the device.

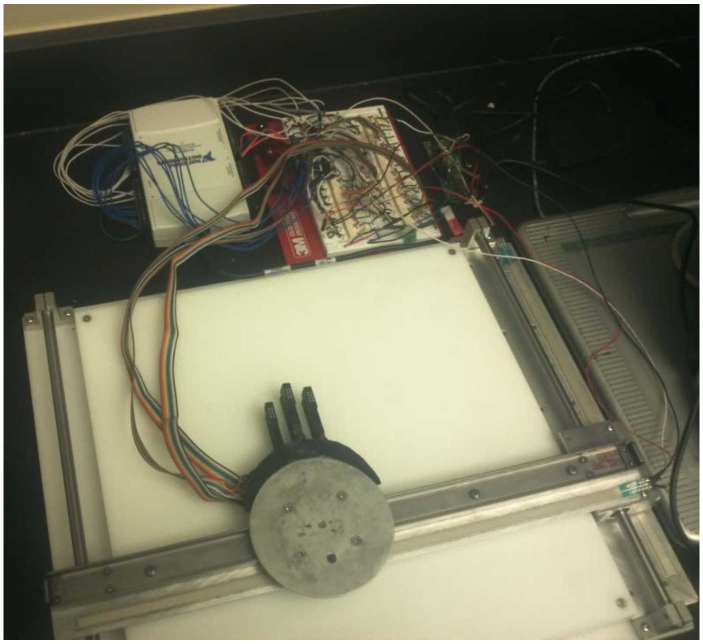

Figure 12. The Perceptual-Based Haptic Display Prototype

4.3 Software Design

The entire software developed for the device was built using Labview Virtual Instruments (VIs). A VI is a graphical program that runs instructions represented as blocks and transfers data from one instruction to the next using connections. A loop is often used keep the program continuously running, but because these loops have to wait for all the instructions inside them to finish before iterating through the loop again, it is a better idea to have a separate input and output loop. The input stage only reads in the two analog channels from the sensors which would be quite fast in its own loop without having to wait for the image processing and output stages.

To calibrate the device before it is used, the software needs to translate the physical distance on the device to that of the virtual picture. On the input stage, a task is created to read in the Analog ports from the DAQ and run it through an 'if' box controlled by a "Calibrate On/Off" toggle switch to determine if the VI is in calibration mode or not. If the switch is on, the 'if' statement is True and the data runs through another set of 'if' boxes to see if it is setting the initial or final values for the dynamic range of the device. The analog port reads the voltage as type double, and the voltage corresponds to the distance moved. One way of calibrating the device is to take voltage difference when the element is at two extremes (i.e. initial subtracted from final values) and divide that by the dynamic range in either the X or Y direction in millimeters. The Volts/mm would then be divided with the scaling factor in pixels/mm to get the Volts per pixel. The calibration procedure in the input stage is shown below in figure 14. To calibrate the device, the 'Calibrate On/Off' switch must be switched on and the translational element must be moved to the top-left most corner and the 'Initial Set' button must be pressed. The element must then be moved to the bottom-right and the 'Final Set' button must be pressed, the Calibrate button can then be turned off and the device is calibrated.

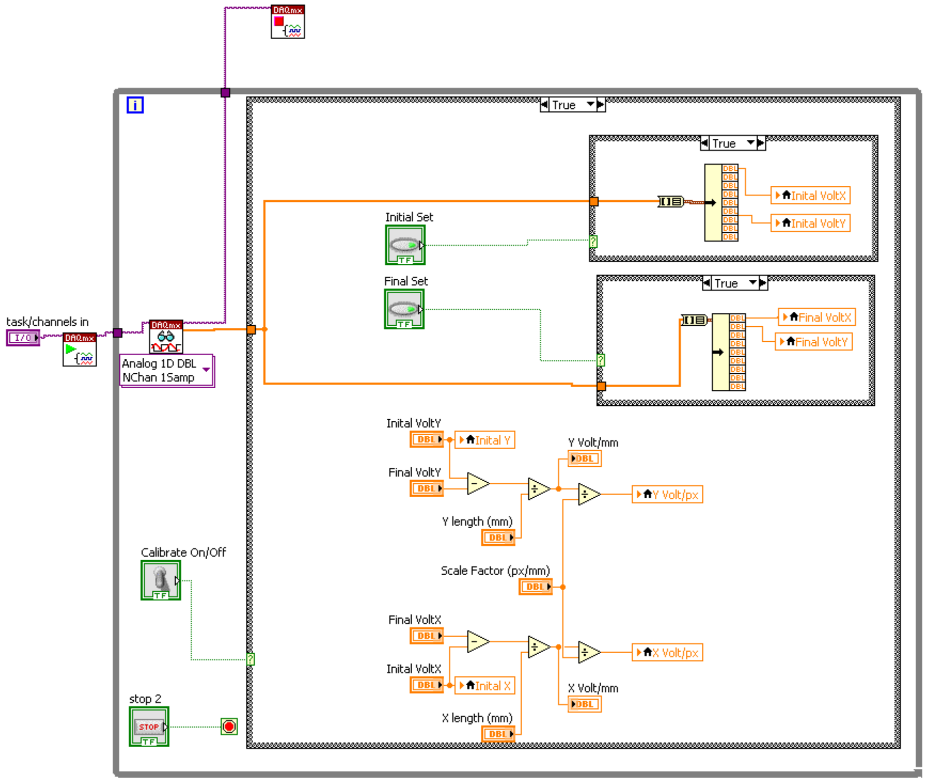

Figure 13. Input Stage and Calibration Labview VI

When the calibration is turned off, the volts from the analog ports are divided by the Volts/px to get the pixel location on the image. The set screws contact the linear sensors at the center of the translational element, so the variables are called 'X Center Ref' and 'Y Center Ref'. These references are then used to determine the pixel locations of the top-right pin of each Braille cell.

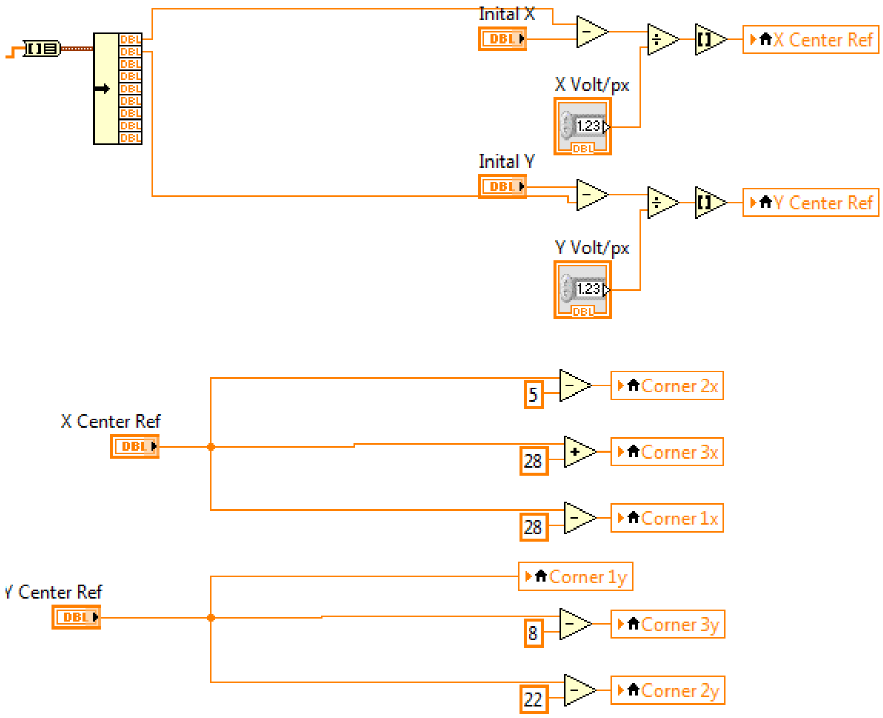

Figure 14. Calculations of Braille Cell Locations at Input Stage Post-Calibration

On the output stage, the picture is first selected as a PNG file and it is parsed into a 24-bit 2D pixmap array. The array is then sent along with the corner coordinates to a 'Cell Driver' VI which does the image processing and then writes it to the DAQ's 3 digital output ports, each consisting of 8 lines controlling all 24 output channels.

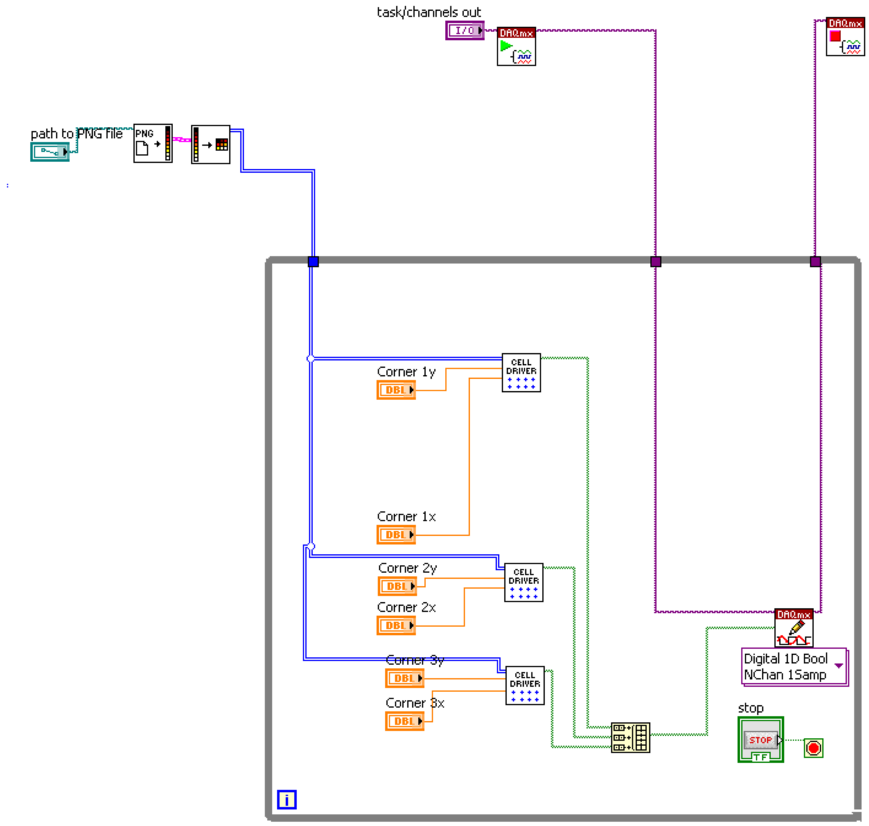

Figure 15. Output Stage of Main VI

The full dynamic range of the device is 376mm from left to right and 282mm from top to bottom. The device is supposed to distinguish sub-millimeter features of image so a good size image to load in would be double this, a 752x564 image. The pins of this particular Braille cell are separated by 2.5mm horizontal and vertically which equates to a 5 pixel difference. This is used in determining the rest of the pins' pixel coordinates given the corner pin's X and Y pixel location. In the 'Cell Driver' VI, a corner Y and X coordinates are taken in as inputs as well as the pixmap array and the pixels at each pin location are extracted from the array. These pixel values are in a 24-bit RGB format, 8-bits per color. The pixel values are then passed to a 'Pin Driver' VI that will output a Boolean telling the pin weather to rise or fall. The Booleans from all the pins are collected into an array and are passed back to the higher level VI.

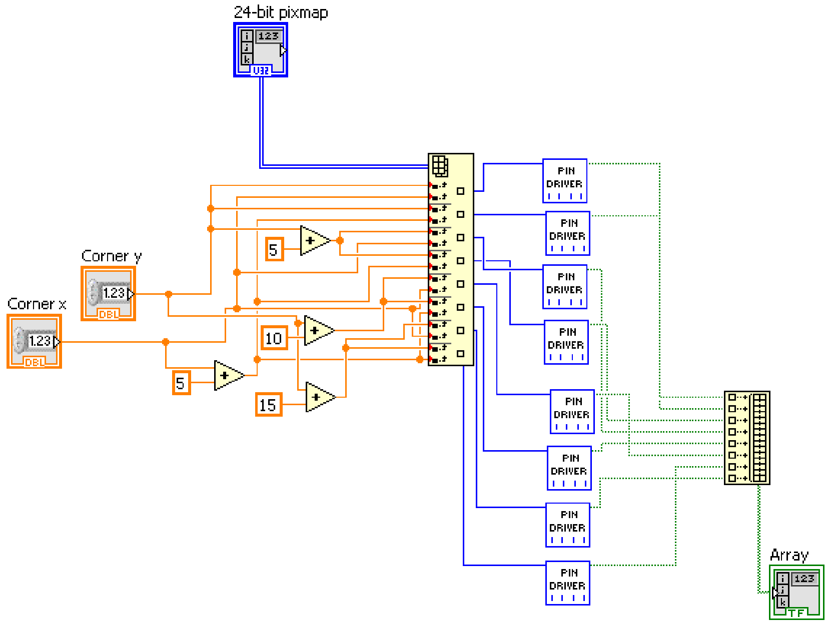

Figure 16. Virtual Graphic Parsing in Cell Driver VI

The 'Pin Driver' VI passes the color to a frequency encoder VI which outputs a numeric frequency and an enable signal. The Frequency generation algorithm is the same one used by Headley [9] and generates a 50% duty cycle Boolean pulse wave with the frequency specified to a reliable degree as long as its below the Nyquist rate of the 1kHz internal clock.

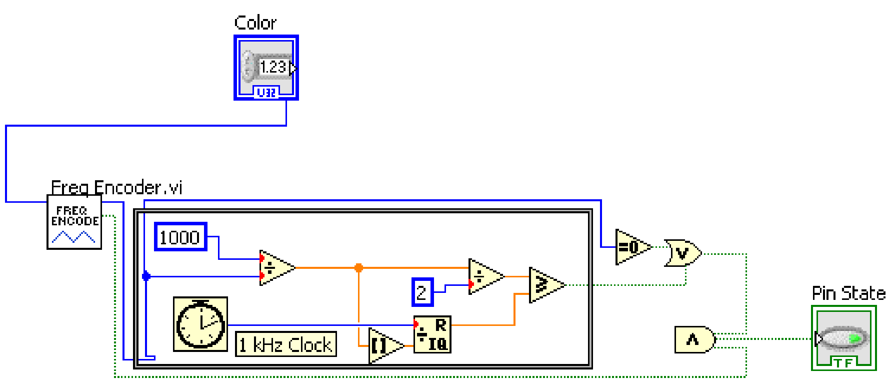

Figure 17. Pin Driver VI with Fundamental Frequency Generation Algorithm

The Frequency Encoder VI is the last of the sub VI's and its operation is to choose a frequency based on the color of the pixel. The Braille cell pins have a rise time of at least 24ms so a maximum frequency with full amplitude is around 42Hz; higher frequencies would result in a fall in amplitude as the pin doesn't have enough time to rise before it begins to fall. The 5 levels of frequency that the device simulates is a constant Low (black), low frequency of 8Hz (red), middle frequency of 16Hz (green), a high frequency of 64Hz reserved for edges (white) and finally a constant High (blue).

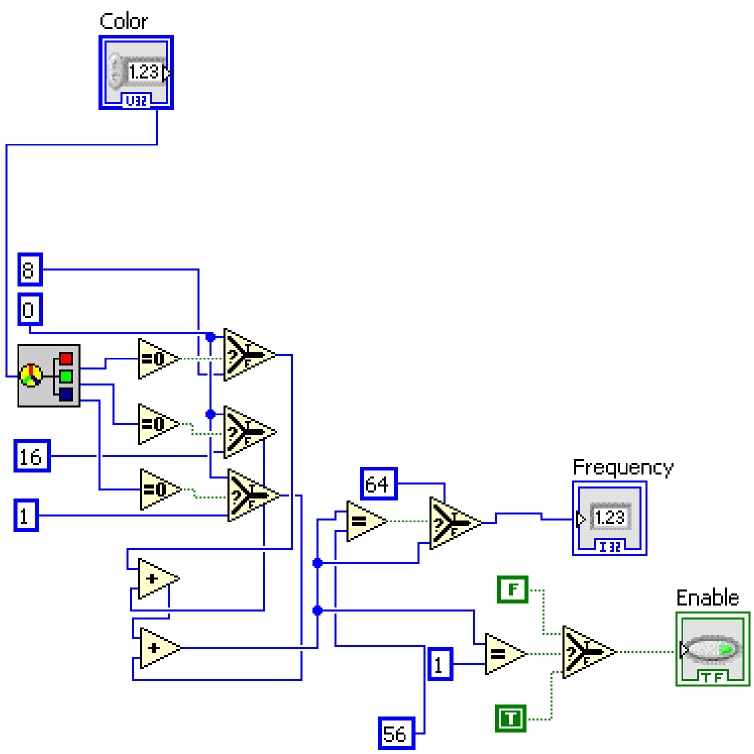

Figure 18. Color to Frequency Translation in Frequency Encoder VI

4.4 Testing and Revision

Two problems were encountered when conducting some validation tests with the device. First, when the translational element was moved to a location that bordered two different frequencies, it felt like the lower frequency was being modulated with the higher frequency. The problem was found to be that the TTL 74LS04 chip had a 5-15ns delay. During this delay, if the line from the DAQ and the inverted line are both high, the 200V source shorts to ground. To solve this, a set of DPST LLC110 relay ICs were ordered that had similar rise and fall times of the SPST Toshiba Photorelays. In the LLC110 ICs, when one pole is open, the other is closed thus there isn't any possibility for a short.

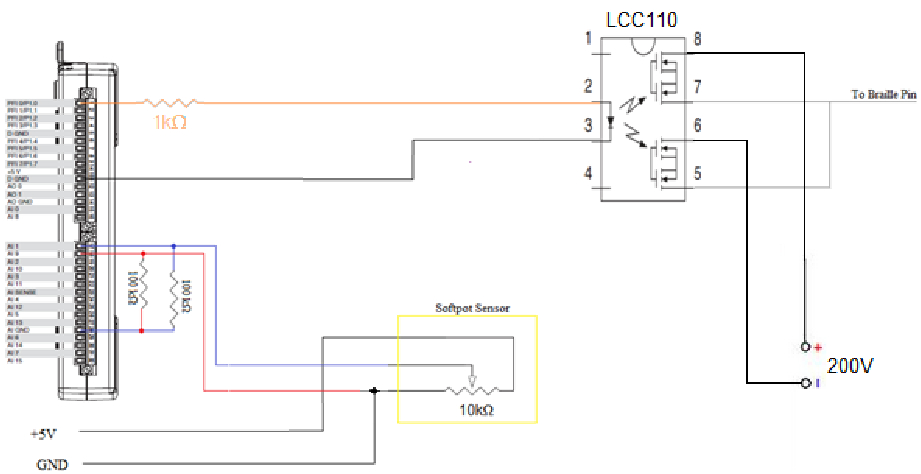

Figure 19. Final Circuit Schematic with one Input(bottom) and Output(top) Channel

The second problem was found in testing the device's software; initially a virtual canvas was used to show the position of the device and what texture was being simulated. However, refreshing the canvas was a processing intensive task and slowed the acquisition rate of the X,Y position. To solve this problem, the image was opened in Microsoft Paint to correlate the X and Y Center Ref variables to determine what the user was generally feeling. The final program interface is shown in Figure 21.

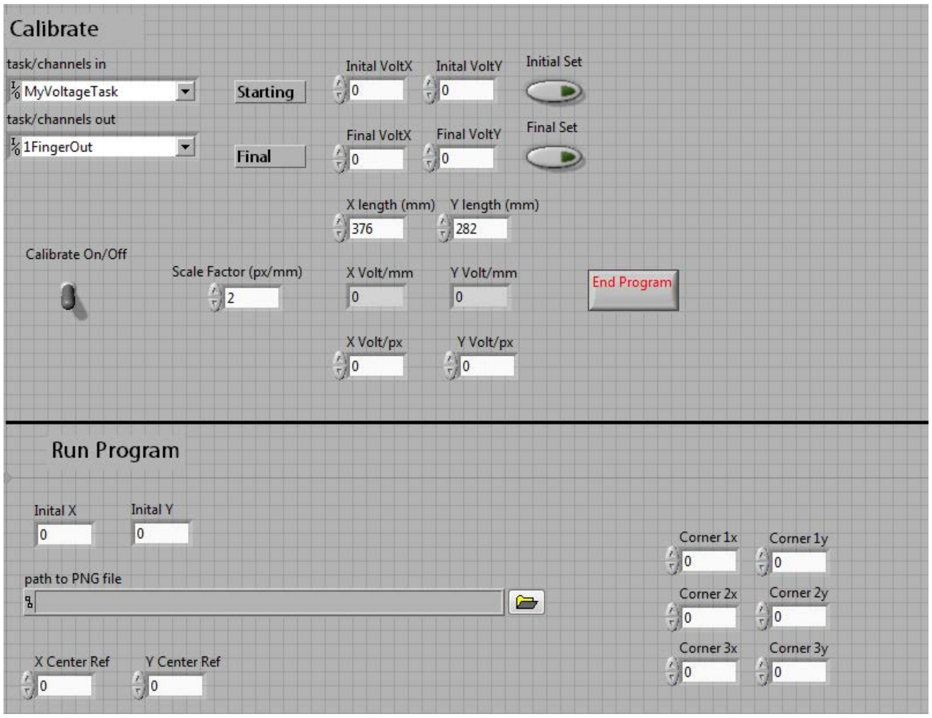

Figure 20. Final Software Interface

A final couple of usability tests were conducted on blindfold sighted individuals. These individuals had to use device to determine how many textures were presented in test virtual images and trace the textures edges of the texture around bends and curves to find out how well the device works with edge detection. The results found that all the frequencies chosen are very salient and that edge detection works in tracing big bends or curve in a diagram.

5. Final Subject Testing

The last stage of the project was to test the new device on a pool of subjects who are blind or visually impaired to see how it compares to other devices, if the initial hypotheses obtained in the experiment involving different constraints were true, and what factors might not have been considered when designing the tactile display device.

5.1 Procedure

The subjects were drawn from members of the local National Federation of the Blind. They varied from 27-65 years of age, were mostly adventitiously blind and are were typically Braille literate. New sets of images were formed from the same images created for the experiment examining hand constraints. These sets consisted of a smaller set of images; there were three sets made up of 4 tactile images and 1 map each. The difficulty of these diagrams ranged from easy to medium (a average complexity between 2 to 7), and are all similar to the ones used by Burch [3]. In this experiment there were 3 new constraints to test:

Constraint 1 : use the device with multiple fingers

Constraint 2: use just the rig with a physical diagram (as in the previous tests)

Constraint 3: and use the device with only one finger on a Braille cell.

The latter configuration was similar to previously used methods involving a Braille cell mounted on a mouse case, using a graphics tablet to determine the position. The second configuration was meant to represent the best performance possible under the X-Y movement constraints as it used bare fingers (i.e., a tactile display of much higher resolution than a Braille cell).

A total of 9 blind folded subjects who have visual impairments, were used in this pilot study. Both the sets used and the constraints were counterbalanced between subjects and were not correlated with each other. At the start of the experiment, each subject was oriented to the use of the device by completing a couple of training sets where the edges and textures were explained, as well as 3D orientation using diagonal, vertical or horizontal patterns of alternating slow frequency (red) and solid Highs (blue) lines. Once the training sets were complete, the subject began the actual experiment. For each constraint and set, the subject had to explore the virtual tactile diagram, describe any information they were obtaining from the diagram and answer the question(s) about the diagram. The time taken was recorded, as well as whether the response was correct. Subjects were then asked to rate the complexity of the task (using the same Likert scale as before), which was also recorded. The subject was then allowed 10 minutes of break before returning to do another set with a different condition.

5.2 Results

Generalized Estimating Equations using a normal distribution model with a log link function was used to examine the data. The factors used as predictors of the model are the constraint and set. A separate analysis was conducted for the diagrams and for the maps; both were are analyzed for response time, complexity and number of correct responses.

In the time analysis for diagrams, the effect of constraint is more statistically significant on the response ($p < 0.001$) as compared to set which isn't statistically significant at all. This is mainly because of the second constraint that used the physical diagram and the subject's finger tips instead of a Braille cell. In all of the studies this is the case so a separate figure would be stated for the confidence between multiple fingers and single finger constraints (in there isn't any statistical significance between the two). The mean time using either a single finger or multiple fingers with the device to identify a diagram is about 200 seconds with a 28s std. error, whereas without the device the mean is 68s with a std. error of 14s. The sets all had around 120-160s averages with a 20-25s std. error.

For the diagram complexity, the effect of both constraint ($p < 0.0001$) and set ($p < 0.01$) are statistically significant. In addition, the difference between the single and multiple fingers constraint is closely statistically significant ($p = 0.011$) between Constraint 3 and 1. The mean for the multi-touch constraint is 9.72 with a 0.36 std. error, the mean for single finger is 10.35 with a 0.57 error, and with the physical diagrams, the mean is 3.92 with a 0.68 error. Just for comparison, the scale for complexity only goes as high as 10; a score of 12 is given to incorrect responses, so the majority of diagrams were incorrectly identified or very hard to identify using the device.

In the analysis for the number of correct with tactile diagrams, set plays absolutely no part in determining the result and multiple fingers vs. single finger constraints show strong statistical significance ($p < 0.0001$). The multi-touch constraint had a mean of 53% correct with a 2.8% error, the single finger constraint had a mean of 46% correct with a 1.6% error, and using no device showed 71% correct with a 1.9% error.

The map time analysis shows relatively strong statistical significance ($p < 0.095$) between multiple fingers and single finger and set isn't statistically significant enough. The mean time taken to answer all the questions of a map using the multiple fingers constraint is 337s with a 35s error, with a single finger it is 260s with a 28s error and using physical diagrams it is 179s with a 41s error. The sets averaged between 200-300s with a 25-40s error.

Map complexity analysis showed little statistical significance between the finger constraints ($p = 0.165$) and even less statistical significance for set; multiple fingers had a mean complexity of 5.9 with a 0.84 error, single finger had a mean of 6.74 complexity with an error of 0.60 error, and no device had a mean of 4.42 with a 0.83 error.

Lastly, studying the number of correct showed enough significance ($p = 0.001$) for all constraints, where even Constraints 3 and 1 had a strong significance ($p < 0.0001$) and between Constraints 3 and 2 a little less ($p = 0.007$). Out of 4 questions per map, multiple fingers averaged 3.30 with a 0.255 error, single finger averaged 2.24 with a 0.275 std. error, and using the physical tactile maps yielded a mean of 3.22 with a 0.243 error.

5.3 Experiment Conclusion and Validation

From the analysis of response times for both diagrams and maps, but mainly diagrams, it can be concluded without a doubt that using simulated textures takes a lot longer to work with than textured fabric. In the case of diagrams, it more than doubles the time taken from about 70 seconds to about 200 seconds and for maps it nearly doubles from 180 seconds to about 300 seconds. This could be due to the general unfamiliarity of simulated textures and because there is no proper classification for it; textures generated from vibrating pins cannot be classified solely as hard, soft, rough or smooth and are understood as being relatively different from other simulated textures. Also the device presents a problem in tracing edges continuously because of the mechanical features of the device but it's still possible due to the saliency of the texture, so it might have added to the time taken for identification.

From the complexity analysis, it can be found that the single finger condition is slightly more complex than the multiple fingers condition in both trying to identify diagrams and maps, usually harder by just under a complexity unit. The physical diagram or map in either case is significantly way easier, being about 6 complexity units under the device implementation for diagrams and about 1.5-2 units under the device for maps. Another point that could be made here is that it is easier to use the device to understand maps than diagrams, the complexity differences between diagrams and maps were generally 3.5 to 4 complexity points lower in both single finger and multiple finger device implementations. This could correspond to the repeating patterns of low-frequency and solid High lines that represent 3D orientation, that were used in the diagrams but weren't present in the maps. Determining the pattern orientation was a task on top of the task of separating out the different textures which made it more complex for the subjects.

In terms of the number of correct, the differences don't seem that great, even a single finger implementation of the device was able to get 46% of the diagrams right and a little over half the questions for each map right. In both map and diagram analysis, multiple fingers outdid the single finger implementation by about 7% more correct when trying to analyze diagrams and 1 more right answer when using maps. The physical diagrams beat both multi-touch and single finger use cases when it comes to diagrams by about 20% more correct, but when it comes to maps, it does slightly worse than the multiple finger condition by about 0.08 of a question which is well within the standard error. This can also be attributed to the extra orientation level that was added to the diagrams that increased its complexity, and that general localization tasks are usually easier than identification.

There is also another aspect that might be causing the wide divide between using the device and only using the rig with physical diagrams, which is that the subjects haven't been adapted to using this means of visualizing. Further research could show that users who have used this device through their education or rehabilitation process will do comparably well to those using physical diagrams.

6. General Discussion

The goal of this study was to compile what was currently known about the perception of virtual textures and effective haptic behavior to develop a dynamic haptic display device. The first set of experiments determined that using multiple fingers is better than a single finger. This may be due to parallel processing which has also been suggested by the results of other studies [3][14][17]. To this was added the findings that the fingers do not need to be independently articulated for this to be true and the wrist can be constrained to a X-Y direction.

These results suggested that a cost-effective, relatively simple device could be designed to take advantage of tactile processing both within a finger (i.e., having a matrix display on a finger tip) and between fingers. However, in order to validate these results, a device needed to be build and tested. The device was built to specification with 3 Braille cells and 8 individually actuated pins per cell. This allowed the user to detect transitions between textures, and a wide variety of textures using frequency and the drop of amplitude at higher frequencies to add dimension. However still, the identification rate for the objects still had the same identification rate that Burch [3] observed of around 50-60% although he used lower fidelity actuators. This raises the possibility that the constraining motion to the X-Y direction may not have an effect on direct finger use but may compound limitations of using a spatially restricted display. Perhaps the combination could be a cause for untraced edges, or the added complexity in determining 3D orientation from patterns, which a free motion device like Burch's may not have difficulties with. Burch conducted an experiment with 8 participants and had a mean identification time of 154s give or take 12s using his device and three finger constraint which is about 50s less than what was obtained in the final study for this experiment, thus there is some evidence that free motion is faster when identifying an object with virtual textures.

Possible suggestions for further experiments could be determining the effect actuator resolution has on the identification rate and the number of correct identifications, as well as whether a user gets more astute in operating the device, improving performance (with an additional question being what is the learning curve?)

7. Conclusion

There can be no doubt that there needs to be a new standard for haptic refreshable display devices to take in the needs of the target population. The inability of the rehabilitation industry to come up with a haptic device ensuring the best user experience has resulted in a generation of individuals who are visually impaired or blind and unable to utilize digital graphics, which are commonplace in today's world. This thesis goes through a complete top-down design process for a new device from determining the design parameters through user studies, developing the architecture, hardware and software prototyping and validation testing to see if the slightly novel idea of constraining motions could lead to a cost-effective device.

Constraining user motions simplifies the design space making it easier for both the users in terms of what they need to understand and for the designers to reduce the amount of research and potential end cost of the product. In the first set of experiments, it was concluded that it is both easier and faster for a user to have their identification motions constrained to moving only in a 2D plane, devoid of any rotation, wrist manipulation or finger articulation. This seemed like the easiest design requirements to design to and a device was developed using Braille cells to realize just that. When that was done a number of tests were conducted to make sure it operated as best it could, extending its potential bandwidth from only about 20Hz to about 125Hz, and out of that temporal frequency range, 5 distinct and salient textures were found.

In the final testing of this device, evidence concluded that it is a step above the current commercial Localized Contact haptic displays, which utilize a single finger, in relaying accurate information about tactile graphics to the user. There was a general reduction in the complexity of the identification task and an increase in the number of correct interpretations of objects.

However though, more research must be done to bring the identification rate of the device to usable levels. Firstly, understand the effect that training has on the usability of the device, and what feedback could be obtained from people who used the device regularly on how to improve it. Secondly, there is a limit to the number of salient textures that could be simulated by temporal stimulation alone. The effect of a higher resolution actuator or perhaps even using spatial frequencies in generating textures could be studied. Finally, the combination between constraining motions and actuators with different resolutions may result in a different solution to what would be the best design for a perceptual-based Haptic display. Hopefully, this thesis presents one step further in helping device manufacturers and the rehabilitation industry develop a standard to use with virtual tactile diagrams and open up more opportunities for people who are visually disabled.

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Appendix A

Preliminary Testing Full Results

Diagrams:

Analysis of Response Time:

Using Generalized Estimating Equations

Subject variables: Subject

Within-subject variables: constraint, set, description

Working correlation matrix: Exchangeable (compound symmetric)

Type of model: Normal distribution, log link function

Response: Time

Predictors: Constraint, Set, Description

Model: Constraint, Set, Constraint x Set

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	Df	Sig.
(Intercept)	774.998	1	.000
Constraint	4.152	4	.386
Set	67.313	5	.000
Constraint * Set	151402933449 654.250	13	.000

Dependent Variable: Time

Model: (Intercept), Constraint, Set, Constraint * Set

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1.00	90.6246	15.15917	65.2923	125.7854
2.00	82.0818	14.00801	58.7464	114.6865
3.00	79.7448	14.69423	55.5719	114.4325
4.00	87.1846	12.24897	66.1989	114.8231
5.00	86.1973	14.10092	62.5528	118.7793

Pairwise Comparisons

(I) Constraint	(J) Constraint	Mean Difference (I-J)	Std. Error	df	Sig.	95% Wald Confidence Interval for Difference	
						Lower	Upper
1.00	2.00	.099	.091	1	.278	-.080	.278
	3.00	.128	.085	1	.131	-.038	.294
	4.00	.039	.045	1	.388	-.049	.127
	5.00	.050	.051	1	.330	-.051	.151
2.00	1.00	-.099	.091	1	.278	-.278	.080
	3.00	.029	.058	1	.618	-.085	.142
	4.00	-.060	.065	1	.354	-.188	.067
	5.00	-.049	.069	1	.479	-.184	.086
3.00	1.00	-.128	.085	1	.131	-.294	.038
	2.00	-.029	.058	1	.618	-.142	.085
	4.00	-.089	.066	1	.180	-.220	.041

	5.00	-.078	.089	1	.382	-.252	.097
4.00	1.00	-.039	.045	1	.388	-.127	.049
	2.00	.060	.065	1	.354	-.067	.188
	3.00	.089	.066	1	.180	-.041	.220
	5.00	.011	.045	1	.800	-.077	.100
5.00	1.00	-.050	.051	1	.330	-.151	.051
	2.00	.049	.069	1	.479	-.086	.184
	3.00	.078	.089	1	.382	-.097	.252
	4.00	-.011	.045	1	.800	-.100	.077

Pairwise comparisons of estimated marginal means based on the linear predictor of dependent variable Time

Analysis of Complexity:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	393.526	1	.000
Constraint	20.848	4	.000
Set	8.471	5	.132
Constraint * Set	1092.095	11	.000

Dependent Variable: Complexity
Model: (Intercept), Constraint, Set, Constraint * Set

Estimated Marginal Means: Constraint

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1.00	7.4974	.73058	6.1939	9.0751
2.00	7.7701	.67000	6.5619	9.2008
3.00	6.7871	.76024	5.4492	8.4533
4.00	7.8489	.76455	6.4847	9.4999
5.00	6.8048	.85109	5.3255	8.6952

Pairwise comparison for linear predictor of complexity

Pairwise Comparisons

(I) Constraint	(J) Constraint	Mean Difference (I-J)	Std. Error	df	Sig.	95% Wald Confidence Interval for Difference	
						Lower	Upper
1.00	2.00	-.036	.034	1	.292	-.102	.031
	3.00	.100[a]	.043	1	.022	.015	.184
	4.00	-.046	.037	1	.213	-.118	.026
	5.00	.097	.067	1	.150	-.035	.229
2.00	1.00	.036	.034	1	.292	-.031	.102
	3.00	.135[a]	.042	1	.001	.052	.218
	4.00	-.010	.028	1	.723	-.066	.046
	5.00	.133[a]	.058	1	.022	.019	.246
3.00	1.00	-.100[a]	.043	1	.022	-.184	-.015
	2.00	-.135[a]	.042	1	.001	-.218	-.052
	4.00	-.145[a]	.032	1	.000	-.208	-.083
	5.00	-.003	.049	1	.957	-.098	.093
4.00	1.00	.046	.037	1	.213	-.026	.118
	2.00	.010	.028	1	.723	-.046	.066

	3.00	.145[a]	.032	1	.000	.083	.208
	5.00	.143[a]	.052	1	.006	.040	.245
5.00	1.00	-.097	.067	1	.150	-.229	.035
	2.00	-.133[a]	.058	1	.022	-.246	-.019
	3.00	.003	.049	1	.957	-.093	.098
	4.00	-.143[a]	.052	1	.006	-.245	-.040

Pairwise comparisons of estimated marginal means based on the linear predictor of dependent variable Complexity
a. The mean difference is significant at the .05 level.

Analysis of Number of Correct:

As GEE can have some problems for binary logistical data (which have been experienced),
We will do the GEE on the count data (number of correct) instead.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	111.007	1	.000
Constraint	50.441	4	.000
Set	23.797	5	.000
Constraint * Set	5253603358122.941	12	.000

Dependent Variable: NumCorrect
Model: (Intercept), Constraint, Set, Constraint * Set

Marginal Means based on Constraint:

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1.00	3.6800	.54989	2.7457	4.9322
2.00	3.5555	.42988	2.8054	4.5063
3.00	4.1409	.40606	3.4169	5.0184
4.00	3.1104	.49262	2.2804	4.2425
5.00	4.2863	.57524	3.2949	5.5759

Pairwise Comparison based on linear predictor of number correct

Pairwise Comparisons

(I) Constraint	(J) Constraint	Mean Difference (I-J)	Std. Error	df	Sig.	95% Wald Confidence Interval for Difference	
						Lower	Upper
1.00	2.00	.034	.074	1	.642	-.111	.180
	3.00	-.118	.100	1	.238	-.314	.078
	4.00	.168	.098	1	.085	-.023	.359
	5.00	-.153[a]	.075	1	.042	-.299	-.006
2.00	1.00	-.034	.074	1	.642	-.180	.111
	3.00	-.152[a]	.067	1	.023	-.284	-.021
	4.00	.134	.084	1	.110	-.030	.298
	5.00	-.187[a]	.066	1	.005	-.317	-.057
3.00	1.00	.118	.100	1	.238	-.078	.314
	2.00	.152[a]	.067	1	.023	.021	.284
	4.00	.286[a]	.070	1	.000	.149	.424
	5.00	-.034	.047	1	.467	-.127	.058

4.00	1.00	-.168	.098	1	.085	-.359	.023
	2.00	-.134	.084	1	.110	-.298	.030
	3.00	-.286[a]	.070	1	.000	-.424	-.149
	5.00	-.321[a]	.049	1	.000	-.418	-.224
5.00	1.00	.153[a]	.075	1	.042	.006	.299
	2.00	.187[a]	.066	1	.005	.057	.317
	3.00	.034	.047	1	.467	-.058	.127
	4.00	.321[a]	.049	1	.000	.224	.418

Pairwise comparisons of estimated marginal means based on the linear predictor of dependent variable NumCorrect
a. The mean difference is significant at the .05 level.

Object Scenes:

Analysis of Response Time:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	14926.549	1	.000
Constraint	30.742	4	.000
Set	18.730	5	.002
Constraint * Set	2829881383649738.000	12	.000

Dependent Variable: Time
Model: (Intercept), Constraint, Set, Constraint * Set

Marginal Means for Time as a function of constraint:

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1.00	208.0689	8.66349	191.7632	225.7612
2.00	201.9459	13.86744	176.5159	231.0395
3.00	236.9312	10.58155	217.0735	258.6054
4.00	185.3206	10.71841	165.4599	207.5653
5.00	210.5726	20.93383	173.2929	255.8722

Pairwise comparison using the linear predictor of time in model:

Pairwise Comparisons

(I) Constraint	(J) Constraint	Mean Difference (I-J)	Std. Error	df	Sig.	95% Wald Confidence Interval for Difference	
						Lower	Upper
1.00	2.00	.030	.068	1	.661	-.104	.164
	3.00	-.130[a]	.052	1	.013	-.232	-.028
	4.00	.116	.060	1	.053	-.001	.233
	5.00	-.012	.092	1	.896	-.192	.168
2.00	1.00	-.030	.068	1	.661	-.164	.104
	3.00	-.160[a]	.076	1	.036	-.309	-.010
	4.00	.086[a]	.037	1	.021	.013	.159
	5.00	-.042	.085	1	.622	-.208	.124
3.00	1.00	.130[a]	.052	1	.013	.028	.232
	2.00	.160[a]	.076	1	.036	.010	.309
	4.00	.246[a]	.066	1	.000	.116	.376

	5.00	.118	.115	1	.305	-.107	.343
4.00	1.00	-.116	.060	1	.053	-.233	.001
	2.00	-.086[a]	.037	1	.021	-.159	-.013
	3.00	-.246[a]	.066	1	.000	-.376	-.116
	5.00	-.128	.080	1	.109	-.284	.028
5.00	1.00	.012	.092	1	.896	-.168	.192
	2.00	.042	.085	1	.622	-.124	.208
	3.00	-.118	.115	1	.305	-.343	.107
	4.00	.128	.080	1	.109	-.028	.284

Pairwise comparisons of estimated marginal means based on the linear predictor of dependent variable Time

a. The mean difference is significant at the .05 level.

<u>Analysis of Response Complexity:</u>

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	458.644	1	.000
Constraint	7.805	4	.099
Set	18.775	5	.002
Constraint * Set	758440049037 0.494	12	.000

Dependent Variable: Complexity

Model: (Intercept), Constraint, Set, Constraint * Set

Constraint is <u>not</u> significant, but will include the estimated marginal means as a function of constraint:

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1.00	6.0339	.57359	5.0082	7.2697
2.00	5.3243	.49417	4.4387	6.3866
3.00	4.7932	.58029	3.7808	6.0769
4.00	5.5719	.72884	4.3119	7.2002
5.00	5.2647	.57510	4.2500	6.5216

Looking at the interaction between constraint and set, which is significant.

Marginal means for constraint x set:

Estimates

Constraint	Set	Mean	Std. Error	95% Wald Confidence Interval

				Lower	Upper
1.00	1.00	5.5000	2.47487	2.2769	13.2857
	2.00	5.0000	1.41421	2.8722	8.7041
	3.00	4.5000	.35355	3.8578	5.2492
	4.00	8.0000	.70711	6.7275	9.5132
	5.00	6.5000	1.06066	4.7208	8.9498
	6.00	7.5000	.35355	6.8381	8.2260
2.00	1.00	2.5000	.35355	1.8948	3.2985
	2.00	6.0000	1.63299	3.5195	10.2287
	3.00	4.5000	.35355	3.8578	5.2492
	4.00	7.5000	1.76777	4.7253	11.9040
	5.00	4.5000	1.76777	2.0837	9.7184
	6.00	10.0000	.00000	10.0000	10.0000
3.00	1.00	6.0000	.70711	4.7625	7.5590
	2.00	4.0000	.70711	2.8287	5.6563
	3.00	5.5000	1.06066	3.7689	8.0263
	4.00	3.5000	1.76777	1.3006	9.4187
	5.00	3.5000	.35355	2.8713	4.2663
	6.00	7.5000	3.18198	3.2653	17.2264
4.00	1.00	4.7500	.96014	3.1962	7.0591
	2.00	8.0000	.00000	8.0000	8.0000
	3.00	3.5000	1.76777	1.3006	9.4187
	4.00	5.0000	2.82843	1.6499	15.1524
	5.00	9.0000	.00000	9.0000	9.0000
	6.00	5.0000	.00000	5.0000	5.0000
5.00	1.00	7.0000	.00000	7.0000	7.0000
	2.00	5.0000	2.05480	2.2344	11.1887
	3.00	8.0000	.70711	6.7275	9.5132
	4.00	3.3333	.72008	2.1827	5.0905
	5.00	4.3333	1.18634	2.5339	7.4107

Maps:

Analysis of Response Time:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	24270.294	1	.000
Constraint	5.940	4	.204
Set	75.611	5	.000
Constraint * Set	100087634667698.800	12	.000

Dependent Variable: Time
Model: (Intercept), Constraint, Set, Constraint * Set

Constraint is not a significant effect, but will include the marginal means (as a function of constraint) anyway:

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1.00	213.7088	16.44878	183.7837	248.5065
2.00	234.9455	21.34319	196.6262	280.7327
3.00	226.8872	10.45566	207.2927	248.3339
4.00	225.0521	5.95993	213.6689	237.0419
5.00	245.5250	12.40436	222.3778	271.0815

We will also include the constraint x set interaction marginal means as that term was significant:

Estimates

Constraint	Set	Mean	Std. Error	95% Wald Confidence Interval	
				Lower	Upper
1.00	1.00	219.5000	74.59977	112.7569	427.2930
	2.00	262.0000	15.55635	233.2174	294.3349
	3.00	163.5000	6.71751	150.8501	177.2107
	4.00	308.0000	14.14214	281.4926	337.0036
	5.00	129.0000	3.53553	122.2533	136.1190
	6.00	255.0000	76.36753	141.7823	458.6258
2.00	1.00	256.0000	49.49747	175.2510	373.9550
	2.00	329.0000	67.66092	219.8573	492.3238
	3.00	263.0000	39.59798	195.7927	353.2766
	4.00	399.0000	62.22540	293.9173	541.6524
	5.00	86.5000	35.70889	38.5144	194.2714
	6.00	220.0000	.00003	220.0000	220.0000
3.00	1.00	215.0000	19.79899	179.4952	257.5278
	2.00	273.5000	55.50788	183.7396	407.1102
	3.00	187.0000	23.33452	146.4285	238.8128
	4.00	210.0000	3.53553	203.1836	217.0451
	5.00	278.0000	16.97056	246.6511	313.3333
	6.00	212.5000	18.03122	179.9418	250.9492
4.00	1.00	301.0000	35.33589	239.1331	378.8727
	2.00	334.0000	.00003	333.9999	334.0001
	3.00	226.5000	9.54594	208.5422	246.0042
	4.00	249.5000	10.96016	228.9173	271.9334
	5.00	148.5000	13.08148	124.9521	176.4857
	6.00	154.0000	.00001	154.0000	154.0000
5.00	1.00	526.0000	.00004	525.9999	526.0001
	2.00	161.6667	15.15354	134.5348	194.2703
	3.00	186.0000	7.77817	171.3631	201.8871
	4.00	327.3333	43.85414	251.7395	425.6269
	5.00	172.3333	32.39113	119.2287	249.0909

<u>Analysis of Response Complexity:</u>

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	596.644	1	.000
Constraint	11.073	4	.026
Set	97.371	5	.000

Constraint * Set	7376261019.145	12	.000

Dependent Variable: Complexity
Model: (Intercept), Constraint, Set, Constraint * Set

Marginal means as a function of constraint:

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1.00	5.9540	.60893	4.8725	7.2755
2.00	4.7177	.47982	3.8651	5.7584
3.00	5.8859	.57041	4.8677	7.1171
4.00	4.2953	.44502	3.5060	5.2624
5.00	4.8516	.39383	4.1380	5.6883

Pairwise comparison of constraints using linear predictor on complexity

Pairwise Comparisons

(I) Constraint	(J) Constraint	Mean Difference (I-J)	Std. Error	df	Sig.	95% Wald Confidence Interval for Difference	
						Lower	Upper
1.00	2.00	.233[a]	.091	1	.011	.054	.411
	3.00	.011	.090	1	.899	-.166	.189
	4.00	.327[a]	.125	1	.009	.082	.571
	5.00	.205	.114	1	.072	-.018	.428
2.00	1.00	-.233[a]	.091	1	.011	-.411	-.054
	3.00	-.221[a]	.095	1	.020	-.407	-.035
	4.00	.094	.122	1	.443	-.146	.333
	5.00	-.028	.118	1	.813	-.260	.204
3.00	1.00	-.011	.090	1	.899	-.189	.166
	2.00	.221[a]	.095	1	.020	.035	.407
	4.00	.315[a]	.145	1	.030	.030	.600
	5.00	.193	.109	1	.076	-.020	.407
4.00	1.00	-.327[a]	.125	1	.009	-.571	-.082
	2.00	-.094	.122	1	.443	-.333	.146
	3.00	-.315[a]	.145	1	.030	-.600	-.030
	5.00	-.122	.092	1	.187	-.302	.059
5.00	1.00	-.205	.114	1	.072	-.428	.018
	2.00	.028	.118	1	.813	-.204	.260
	3.00	-.193	.109	1	.076	-.407	.020
	4.00	.122	.092	1	.187	-.059	.302

Pairwise comparisons of estimated marginal means based on the linear predictor of dependent variable Complexity
a. The mean difference is significant at the .05 level.

Final Testing Full Results

Diagrams:

Analysis of Time Taken:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	1130.529	1	.000
Constraint	48.608	2	.000
Set	2.439	2	.295

Dependent Variable: Time Taken
Model: (Intercept), Constraint, Set

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	5.107	.2529	4.611	5.602	407.700	1
[Constraint=1]	.075	.1295	-.179	.329	.333	1
[Constraint=2]	-1.049	.1505	-1.344	-.754	48.570	1
[Constraint=3]	0[a]	.	.	.	.	.
[Set=1]	.296	.1931	-.082	.675	2.355	1
[Set=2]	.205	.1492	-.088	.497	1.883	1
[Set=3]	0[a]	.	.	.	.	.
(Scale)	8831.035					

Parameter Estimates

Parameter	Hypothesis Test	Exp(B)	95% Wald Confidence Interval for Exp(B)	
	Sig.		Lower	Upper
(Intercept)	.000	165.119	100.582	271.066
[Constraint=1]	.564	1.078	.836	1.389
[Constraint=2]	.000	.350	.261	.470
[Constraint=3]	.[a]	1	.	.
[Set=1]	.125	1.345	.921	1.964
[Set=2]	.170	1.227	.916	1.644
[Set=3]	.[a]	1	.	.
(Scale)				

Dependent Variable: Time Taken
Model: (Intercept), Constraint, Set
a. Set to zero because this parameter is redundant.

Estimated Marginal Means 1: Constraint

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	210.28	21.655	171.85	257.31
2	68.34	14.615	44.94	103.93
3	195.14	36.848	134.77	282.53

Estimated Marginal Means 2: Set

Estimates

Set	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	160.49	25.702	117.25	219.66
2	146.44	19.350	113.03	189.73
3	119.33	25.788	78.12	182.26

Analysis of Complexity:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	693.307	1	.000
Constraint	36.533	2	.000
Set	4.800	2	.091

Dependent Variable: Complexity
Model: (Intercept), Constraint, Set

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	2.352	.0440	2.266	2.438	2863.612	1
[Constraint=1]	-.065	.0407	-.145	.015	2.534	1
[Constraint=2]	-.974	.1612	-1.289	-.658	36.494	1
[Constraint=3]	0[a]	.	.	.	.	.
[Set=1]	.031	.0656	-.097	.160	.228	1
[Set=2]	-.071	.0390	-.148	.005	3.326	1
[Set=3]	0[a]	.	.	.	.	.
(Scale)	9.373					

Parameter Estimates

Parameter	Hypothesis Test	Exp(B)	95% Wald Confidence Interval for Exp(B)	
	Sig.		Lower	Upper
(Intercept)	.000	10.505	9.638	11.451
[Constraint=1]	.111	.937	.865	1.015
[Constraint=2]	.000	.378	.275	.518
[Constraint=3]	.[a]	1	.	.
[Set=1]	.633	1.032	.907	1.173
[Set=2]	.068	.931	.863	1.005
[Set=3]	.[a]	1	.	.
(Scale)				

Dependent Variable: Complexity
Model: (Intercept), Constraint, Set
a. Set to zero because this parameter is redundant.

Estimated Marginal Means 1: Constraint

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	9.72	.362	9.03	10.45
2	3.92	.680	2.79	5.50
3	10.37	.572	9.30	11.55

Estimated Marginal Means 2: Set

Estimates

Set	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	7.67	.674	6.46	9.11
2	6.92	.612	5.82	8.23
3	7.43	.522	6.48	8.53

Analysis of Number of Correct:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	18.565	1	.000
Constraint	90.492	2	.000
Set	.011	2	.994

Dependent Variable: Correct
Model: (Intercept), Constraint, Set

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	-.158	.1290	-.411	.095	1.501	1
[Constraint=1]	.277	.1079	.066	.489	6.614	1
[Constraint=2]	1.044	.1143	.820	1.269	83.434	1
[Constraint=3]	0[a]	.	.	.	.	.
[Set=1]	-.006	.1468	-.294	.282	.002	1
[Set=2]	.005	.1340	-.258	.267	.001	1
[Set=3]	0[a]	.	.	.	.	.
(Scale)	1					

Parameter Estimates

Parameter	Hypothesis Test
	Sig.
(Intercept)	.221
[Constraint=1]	.010
[Constraint=2]	.000
[Constraint=3]	.[a]
[Set=1]	.967
[Set=2]	.972
[Set=3]	.[a]
(Scale)	

Dependent Variable: Correct
Model: (Intercept), Constraint, Set
a. Set to zero because this parameter is redundant.

Estimated Marginal Means 1: Constraint

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	.53	.028	.47	.58
2	.71	.019	.67	.74
3	.46	.016	.43	.49

Estimated Marginal Means 2: Set

Estimates

Set	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	.57	.011	.55	.59
2	.57	.027	.52	.62
3	.57	.031	.51	.63

Maps:

Analysis of Time Taken:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	3245.299	1	.000
Constraint	4.732	2	.094
Set	3.997	2	.136

Dependent Variable: Time Taken
Model: (Intercept), Constraint, Set

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	5.426	.2000	5.034	5.818	735.983	1
[Constraint=1]	.259	.1550	-.045	.562	2.782	1
[Constraint=2]	-.374	.1879	-.742	-.005	3.955	1
[Constraint=3]	0[a]	.	.	.	.	.
[Set=1]	.076	.1734	-.264	.416	.193	1
[Set=2]	.335	.2423	-.139	.810	1.917	1
[Set=3]	0[a]	.	.	.	.	.
(Scale)	13609.778					

Parameter Estimates

Parameter	Hypothesis Test
	Sig.
(Intercept)	.000
[Constraint=1]	.095
[Constraint=2]	.047
[Constraint=3]	.[a]
[Set=1]	.660
[Set=2]	.166
[Set=3]	.[a]
(Scale)	

Dependent Variable: Time Taken
Model: (Intercept), Constraint, Set
a. Set to zero because this parameter is redundant.

Estimated Marginal Means 1: Constraint

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	337.64	35.024	275.52	413.76
2	179.41	41.485	114.03	282.27
3	260.72	28.703	210.12	323.50

Estimated Marginal Means 2: Set

Estimates

Set	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	236.04	25.723	190.64	292.24
2	305.90	35.126	244.25	383.11
3	218.73	42.837	149.00	321.07

Analysis of Complexity:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	240.246	1	.000
Constraint	10.887	2	.004
Set	3.303	2	.192

Dependent Variable: Complexity
Model: (Intercept), Constraint, Set

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	1.915	.1116	1.697	2.134	294.361	1
[Constraint=1]	-.133	.0959	-.321	.055	1.928	1
[Constraint=2]	-.423	.1623	-.741	-.105	6.780	1
[Constraint=3]	0[a]	.	.	.	.	.
[Set=1]	-.081	.1338	-.343	.182	.363	1
[Set=2]	.058	.1592	-.254	.370	.132	1
[Set=3]	0[a]	.	.	.	.	.

(Scale)	6.139						

Parameter Estimates

Parameter	Hypothesis Test
	Sig.
(Intercept)	.000
[Constraint=1]	.165
[Constraint=2]	.009
[Constraint=3]	.[a]
[Set=1]	.547
[Set=2]	.717
[Set=3]	.[a]
(Scale)	

Dependent Variable: Complexity
Model: (Intercept), Constraint, Set
a. Set to zero because this parameter is redundant.

Estimated Marginal Means 1: Constraint

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	5.90	.840	4.46	7.80
2	4.42	.825	3.06	6.37
3	6.74	.597	5.66	8.02

Estimated Marginal Means 2: Set

Estimates

Set	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	5.20	.754	3.92	6.91
2	5.98	.765	4.65	7.68
3	5.64	.720	4.39	7.24

Analysis of Number of Correct:

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	df	Sig.
(Intercept)	211.754	1	.000
Constraint	14.918	2	.001
Set	4.607	2	.100

Dependent Variable: Correct
Model: (Intercept), Constraint, Set

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test	
			Lower	Upper	Wald Chi-Square	df
(Intercept)	.865	.1202	.630	1.101	51.805	1
[Constraint=1]	.390	.1103	.174	.606	12.498	1
[Constraint=2]	.365	.1344	.101	.628	7.363	1
[Constraint=3]	0[a]	.	.	.	.	.
[Set=1]	-.111	.0771	-.262	.040	2.065	1
[Set=2]	-.072	.0662	-.201	.058	1.167	1
[Set=3]	0[a]	.	.	.	.	.
(Scale)	.748					

Parameter Estimates

Parameter	Hypothesis Test
	Sig.
(Intercept)	.000
[Constraint=1]	.000
[Constraint=2]	.007
[Constraint=3]	.[a]
[Set=1]	.151
[Set=2]	.280
[Set=3]	.[a]
(Scale)	

Dependent Variable: Correct
Model: (Intercept), Constraint, Set
a. Set to zero because this parameter is redundant.

Estimated Marginal Means 1: Constraint

Estimates

Constraint	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	3.30	.255	2.84	3.84
2	3.22	.243	2.78	3.73
3	2.24	.275	1.76	2.85

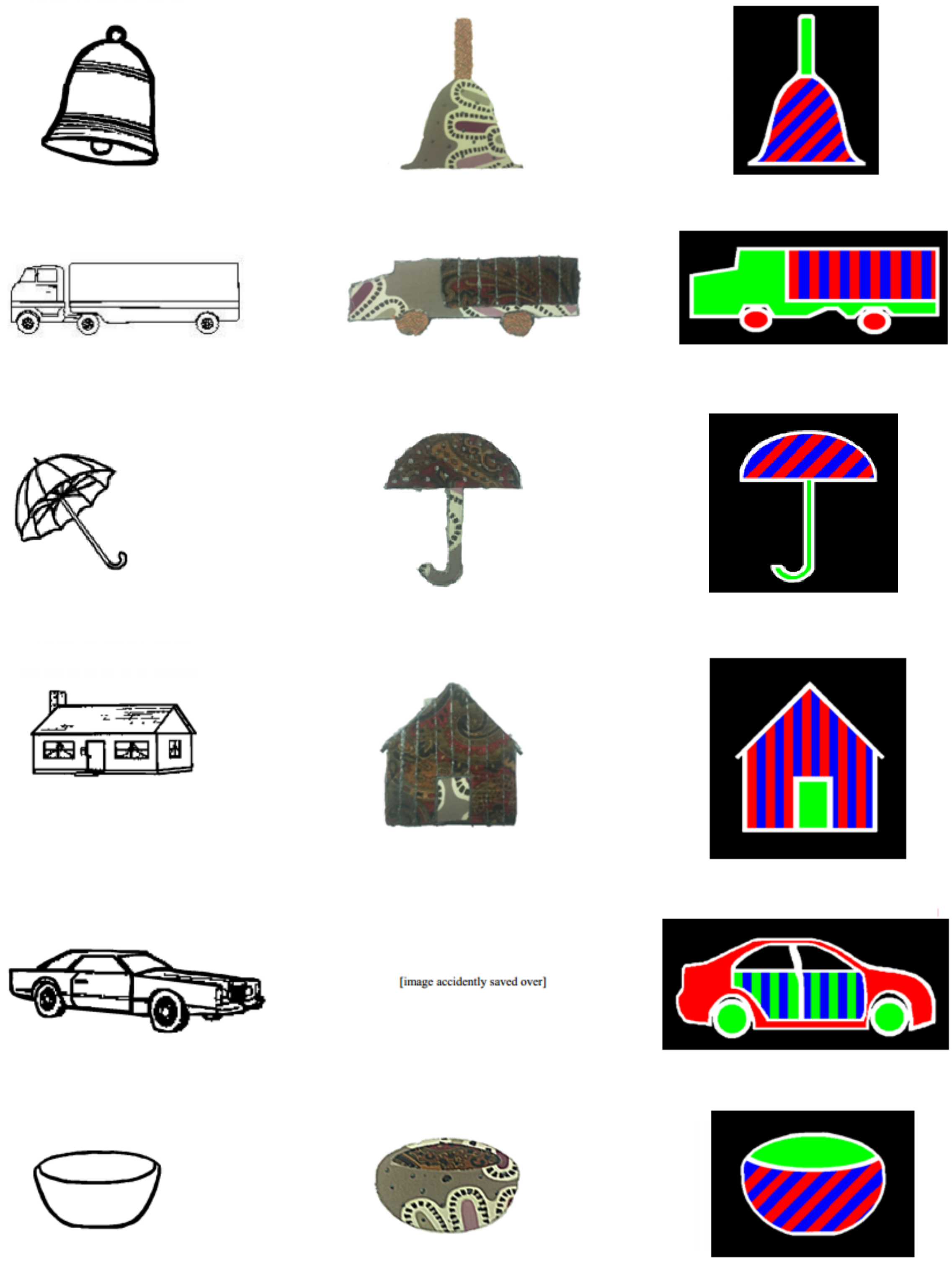
Estimated Marginal Means 2: Set

Estimates

Set	Mean	Std. Error	95% Wald Confidence Interval	
			Lower	Upper
1	2.74	.291	2.22	3.37
2	2.84	.215	2.45	3.30
3	3.06	.250	2.60	3.59

Appendix B

Set of Pictures and Tactile Representations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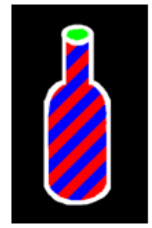

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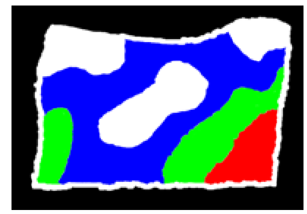

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