DESIGNING TACTILE INTERFACES FOR ABSTRACT INTERPERSONAL COMMUNICATION, PEDESTRIAN NAVIGATION AND MOTORCYCLISTS NAVIGATION

A Dissertation

by

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ABSTRACT

The tactile medium of communication with users is appropriate for displaying information in situations where auditory and visual mediums are saturated. There are situations where a subject's ability to receive information through either of these channels is severely restricted by the environment they are in or through any physical impairments that the subject may have. In this project, we have focused on two groups of users who need sustained visual and auditory focus in their task: Soldiers on the battlefield and motorcyclists.

Soldiers on the battlefield use their visual and auditory capabilities to maintain awareness of their environment to guard themselves from enemy assault. One of the major challenges to coordination in a hazardous environment is maintaining communication between team members while mitigating cognitive load. Compromise in communication between team members may result in mistakes that can adversely affect the outcome of a mission.

We have built two vibrotactile displays, Tactor I and Tactor II, each with nine actuators arranged in a three-by-three matrix with differing contact areas that can represent a total of 511 shapes. We used two dimensions of tactile medium, shapes and waveforms, to represent verb phrases and evaluated ability of users to perceive verb phrases the tactile code. We evaluated the effectiveness of communicating verb phrases while the users were performing two tasks simultaneously. The results showed that performing additional visual task did not affect the accuracy or the time taken to perceive tactile codes.

Another challenge in coordinating Soldiers on a battlefield is navigating them to respective assembly areas. We have developed HaptiGo, a lightweight haptic vest that provides pedestrians both navigational intelligence and obstacle detection capabilities. HaptiGo consists of optimally-placed vibro-tactile sensors that utilize natural and small form factor interaction cues, thus emulating the sensation of being passively guided towards the intended direction. We evaluated HaptiGo and found that it was able to successfully navigate users with timely alerts of incoming obstacles without increasing cognitive load, thereby increasing their environmental awareness. Additionally, we show that users are able to respond to directional information without training.

The needs of motorcyclists are different from those of Soldiers. Motorcyclists' need to maintain visual and auditory situational awareness at all times is crucial since they are highly exposed on the road. Route guidance systems, such as the Garmin, have been well tested on automobilists, but remain much less safe for use by motorcyclists. Audio/visual routing systems decrease motorcyclists' situational awareness and vehicle control, and thus increase the chances of an accident. To enable motorcyclists to take advantage of route guidance while maintaining situational awareness, we created HaptiMoto, a wearable haptic route guidance system. HaptiMoto uses tactile signals to encode the distance and direction of approaching turns, thus avoiding interference with audio/visual awareness. Evaluations show that HaptiMoto is intuitive for motorcyclists, and a safer alternative to existing solutions.

DEDICATION

This dissertation is dedicated to my teachers, who inspired me to pursue Science.

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NOMENCLATURE

DOT	Department of Transportation
TxDOT	Texas Department of Transportation
ATIS	Advanced Traveller Information System
IRANS	In-vehicle Routing and Navigation System
ATMS	Advanced Traffic Management System
IMSIS	In-vehicle Motorists Services Information System
ISIS	In-vehicle Signing Information System
IVSAWS	In-vehicle Safety Advisory and Warning System
ITS	Intelligent Transport System

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1. INTRODUCTION

Visual, auditiory, and tactile are the three primary senses that we use to assimilate information. While user interfaces largely use visual and audio channels to communicate with users, the tactile medium is also used, although to a lesser extent. The tactile medium is appropriate for displaying information in situations were visual and auditory mediums are degraded or saturated [78]. The saturation of the visual and auditory mediums for information transmission could be due to a number of factors such as cognitive overload and information clutter, attention tunneling owing to repetition of the same task for a prolonged period of time, and fatigue or tiredness [78]. The tactile medium is commonly used in situations where users are multi-tasking. It is used to prime users' attention to a secondary task and not disrupt the visual and audio information flow in the primary task. For instance, Van Erp et al. [99] tested the use of vibrotactile feedback as a means of sending warning signals to drivers, Rupert et al. [74]used vibrotactile feedback to convey flight orientation to pilots. Rupert et al. [74], and Lindeman et al. [41] tested Soldiers' ability to navigate through a stimulated environment using a tactile vest [41]. In all these instances, the researchers found that the vibrotactile signals did not disrupt the subjects' primary task performance. The motivation behind the use of vibrotactile signals in these interfaces was to change the focus of the user's attention to a specific object or direction and represent more than one bit of information. This use of the tactile medium is called priming.

In this dissertation, we have focused on two groups of users who require sustained use of visual and auditory channels to maintain awareness of environment: Soldiers on the battlefield and motorcyclists. Soldiers on the battlefield face a situation where their visual and auditory capabilities are saturated. Soldiers use their visual and auditory capabilities to maintain awareness of their environment to guard themselves from enemy assault. This research focuses on the use of tactile medium to communicate verb phrases without disrupting the users' primary function. Motorcyclists, similar to Soldiers, require their complete visual and auditory focus to maintain situational awareness. Motorcyclists are highly exposed while riding and are required to maintain their focus on the road to reduce the risk of accidents. Current navigation systems use audio/visual interfaces to provide assistance to riders, therefore increase the risk of accidents to riders. We have developed HaptiMoto, a wearable haptic navigation device for providing motorcyclists with navigation assistance.

1.1 Communicating Verb Phrases with Tactile Codes

Typically Soldiers complete missions in teams. In a battlefield scenario, the environment and operating constraints do not allow for direct contact between Soldiers. In such scenarios, team coordination is vital for the success of a mission. One of the major challenges to coordination in a hazardous environment is maintaining communication between team members while mitigating cognitive load [54, 75]. Compromise in communication between team members may result in mistakes that can adversely affect the outcome of a mission [21, 75]. Maintaining communication requires multi-tasking from each Soldier to maintain an awareness of the environment and communicate with other team members. Soldiers use a common vocabulary for communication which is in the form of simple imperative sentences (e.g, "Need Ammo", "Move to Bravo") [94]. In the English language, the syntax of imperative sentences is similar to verb phrases [12, 13]. Our motivation is to enable communication of a vocabulary of verb phrases through the tactile medium.

Our tactile sense can be stimulated using a variety of inputs: pressure, flutter, temperature, electricity, and vibration. Vibrotactile stimulation is widely used in input devices like cellphones, and gaming controllers. These devices have a single actuator that delivers one bit of information about the occurrence of a specific event. For example, with regard to cellphones, the actuator is used to deliver an incoming call event. Use of a single actuator restricts the amount of information that can be sent through the vibrotactile channel. Communication of verb phrases involves more than a single bit of information. One method of accommodating more information through a vibrotactile medium is to increase the number of actuators, hence permitting the use of different patterns (i.e., shapes) to represent information [5]. Usability of the tactile medium depends on the ability of users to distinguish different tactile shapes [45].

We have built a tactor array, Tactor I, with nine vibration motors [84] arranged in the form of a three-by-three matrix. A pilot study with five users showed that prolonged use of a tactile display built with vibrotactile motors caused discomfort to users due to heat generated from the motors. In order to stop the conduction of heat from the motors to users' skin, we present a novel method for designing a tactile display, Tactor II, which involves attaching a carbon fiber rod to the vibration motors to not only stop the conduction of heat but also to linearise the tactile stimulation. We used Tactor II in our research for all data collection purposes. The tactile display could be used to present a total of 512 tactile shapes. We studied the users' perception of shapes on Tactor II to assess the usability of each tactile shape. The perception of a tactile stimuli is influenced by the rendering method. There are five parameters that largely determine the effectiveness of rendering: amplitude, frequency, location, pattern, and timing of the stimuli. Frequency encoding and temporal order manipulation [5, 44] have been used to render shapes. We identified four different forms of presenting shapes with the tactor array—constant stimuli, temporal ordering or drawing, square wave, and pattern masking. We evaluated how the vibrotactile stimuli are perceived in terms of the perception rate, perceived intensity, and decision latency. We used a variation of A/B testing to determine the users' ability to distinguish between two shapes. Using the results from the test, we state a measure of distinguishability between two shapes, a graph model with shapes as nodes, distinguishability between shapes as weights of edges, and an algorithm to cluster distinguishable shapes. We compared the distinguishability of shapes from the clustering algorithm with the experimenter's choice of shapes for tactile codes with eight users.

The usability of a tactile medium also depends on the number of tactile codes used in the interface. Using waveforms and shapes of tactile codes to represent information has a limitation on the total number of codes that can be represented [44, 98]. This limitation affects the usability of tactile codes since the increase in number of tactile codes in one dimension reduces the users' ability to perceive a code, and can be overcome by using more than one dimension. We tested the feasibility of using two dimensions of tactile codes with a ringtone scenario. In this scenario, incoming call information is represented as a verb phrase which in turn is encoded in two dimensions of tactile code: shape and waveform. We compared the performance of subjects in identifying caller information presented as tactile ringtone as against information presented as audio ringtone. To test the usability of tactile medium in a multi-tasking scenario, we evaluated users performance in recognizing the ringtone task while simultaneously performing a visual task. In a multi-tasking scenario, users performance in the visual and ringtone task was better when the audio channel was used for ringtones as against the tactile channel. This difference in performance can be attributed to the familiarity of users with perceiving information from audio channel.

1.2 HaptiGo: A Navigational 'Tap on the Shoulder'

We developed HaptiGo, a lightweight haptic vest for providing navigation intelligence. HaptiGo tactilely guides subjects to their intended destinations and away from potential obstacles. Our haptic vest features optimally-placed vibro-tactile actuators that provide intuitive and small form factor interaction cues emulating the invisible sensation of being passively guided.

Our system is designed for scenarios where the users are engaged in multitasking while navigating. The following scenarios illustrate the situations where a user could take advantage of our system.

1. George is a military paratrooper of airborne troops. He is on an operation that involves him parachuting into enemy territory with other soldiers. Once he lands, he has to reorient himself and find his way to the rendezvous point. Since he is in a hostile terrain, he must be aware of the environment around him, maintain his stealth, and navigate through unfamiliar terrain. George could use HaptiGo to offload the cognitive task of navigation while maintaining an awareness of the space around him [15].

2. Maggie is a university undergraduate student. She just finished her class in building A and has another class in building B. She receives an important text from her friend. While she is typing a reply to her friend, she walks to building B through a route that is congested with other students. Maggie would benefit from a system to help her multi-task while walking from building A to B. HaptiGo can help her navigate through the crowded route while her awareness of the environment is impaired due to texting.

3. Stacey is a player in a geocaching game. The game involves Stacey finding

hidden treasure at a given location. The latitude and longitude of the treasure is specified in the game. Stacey would have to navigate to this location and search for treasure in an unfamiliar terrain. Stacey could use HaptiGo to help her find obstacles in her path and navigate through the terrain while she is engaged in finding the treasure given at the location.

Pedestrians often tap into existing knowledge of their surroundings to guide them while walking to familiar destinations. They may therefore be encouraged to take on a more passive awareness of their surroundings while performing group (e.g., engaging in conversation with colleagues) and individual (e.g., listening to music with headphones) activities during the journey. As people become accustomed to multi-tasking while navigating, their habits subsequently introduce several challenges such as inconvenience, where people must become aware of both their surroundings and navigation tools in unfamiliar environments due to lack of prior knowledge; and the more serious aversion of danger, which stems from navigating in more active environments [46]. While the former challenge is readily apparent, the latter is latent and occurs especially with individuals who are either momentarily situationally impaired, which occurs when an individual loses awareness of their immediate surroundings; or otherwise distracted for extended periods of time during pedestrian navigation [37]. This phenomenon of situational impairment is widespread and readily apparent; people collide with objects or other people while distracted with mobile device usage [46]. A loss of awareness (i.e., *iPod Zombie trance*) often also accompanies individuals listening to loud music, with some cases even leading to pedestrian fatalities [65].

Conventional navigation systems found on many mobile devices—especially those driven by visual or auditory modalities—prove lacking in addressing the specifics from these particular challenges. In response, various studies have shown the effectiveness of navigation solutions that instead utilize alternative tactile modalities, especially when users are cognitively occupied in performing other tasks [20]. Moreover, touch is highly appealing in communicating navigation information without simultaneously introducing mental distraction, since tactile sensory channels are barely affected when utilized to observe one's surroundings [65]. In related theoretical frameworks such as Wicken's Multiple Resource Theory [20, 105], tactile modality has great appeal in serving to "guide, reduce workload, and support situation and navigation performance".

We evaluated our haptic vest on a group of pedestrians tasked with navigating through several different waypoints while engaged in cognitively demanding tasks, and our results demonstrated that users navigated to their destinations effectively and enjoyed our haptic interface solution.

1.3 HaptiMoto: Wearable Tactile Navigation System for Motorcyclists

Fatalities from motorcycle accidents are significantly higher than those from automobile ones [2]. Motorcycle fatalities represent approximately 5% of all highway deaths each year, yet motorcycles represent just 2% of all registered vehicles in the United States [55]. The United States Center for Disease Control and Prevention (CDC) report on motorcycle accidents shows that more than 34,000 motorcyclists were killed and an estimated 1,222,000 persons were treated in American emergency department (ED) for non-fatal motorcycle-related injuries between 2001 and 2008 [10]. Navigation support has always been necessary for automobilists and motorcylists alike. The paper map was the status quo for many years, but in an attempt to improve navigation and safety, modern technical solutions using global positioning system (GPS), virtual displays, and turn by turn audio and visual directions have been developed.

Navigation systems (e.g., Garmin [26]) provide information to vehicle drivers ranging from route planning and traffic density to points of interest en route [8]. In-vehicle route guidance and navigation system (IRANS) is the primary feature of the navigation system [2]. IRANS is used for two purposes: route planning and route guidance. Route planning is used to plan a driving route between two known locations. Route guidance is used to provide turn-by-turn guidance to drivers while driving. Dynamic visual maps and voice guidance are the most common methods for guiding drivers with a navigation system. For instance, Google Maps [27] uses dynamic visual maps to show the location of the user, the upcoming turn, and the distance to that turn. The application also uses audio guidance to direct the drivers attention to an approaching turn.

Audio/visual navigation interfaces affect the drivers attention by obstructing vision and decreasing acoustic awareness. The distraction caused by these interfaces increases the chances of the driver's involvement in accidents [2, 7]. The human auditory system is very good at focusing on certain sounds and blocking out others, which can be detrimental in cases when outdoor sounds are crucial for motorcyclists, but not automobile drivers whom are accustomed to being blocked from outdoor noise while driving. Additionally, current smartphone navigation systems encourage touch interaction. Any touch interaction is hazardous for the motorcyclist, who must keep one hand on the brake and the other on the gas at all times.

We developed a vest called HaptiMoto that can communicate direction signals using the tactile channel. The vest in combination with a smartphone acts as a route guidance system. The smartphone app is used to access route information, get current location of the rider, calculate the distance to an upcoming turn and communicate the tactile direction signals through the tactile vest. Upon receiving the tactile signals from the smartphone app, the vest can activate one or two of the three tactile actuators located at the shoulders and center of the back of the rider to provide vibrotactile signals. The vibrotactile signals are designed to provide a tap on the shoulder or nudge/pull the users in the back with vibrotactile signals.

We conducted three user studies to evaluate the usability HaptiMoto. The first study evaluated if the HaptiMoto increased the workload of riders while riding a motorcycle. The second study compared the usability of HaptiMoto to usability of Google Maps audio guidance. The usability was compared with a NASA TLX workload survey [28] and the time taken to drive a 0.5 mile circuit. The third study evaluated the ability of riders to follow HaptiMoto driving directions over a long circuit. Our hypotheses are HaptiMoto does not increase the workload of riders significantly when compared to riding without any navigation system, HaptiMoto is more usable than Google Maps audio guidance for motorcyclists, and the driving directions from HaptiMoto are usable over long circuits.

1.4 Contributions

The contribution of our work include the following

1.4.1 Communication Verb Phrases with Tactile Codes

1. Develop a three-by-three tactile array that provides discrete vibrotactile sensation without conducting heat to the user's skin.

2. Develop a quantitative metric of dissimilarity between tactile shapes and model to determine distinguishable tactile shapes.

3. Evaluate the graph model of choosing tactile shapes against the experimenter's intuition.

4. Develop a method to encode components of verb phrases in two dimensions of tactile code.

5. Show the ability of users to perceive two dimensions of tactile information – shapes and waveform – of the tactile code and decode verb phrases from the perceived tactile code.

6. Compare the performance of users in identifying tactile and audio ringtones while performing a visual object tracking task.

7. Measure the change in performance of users while simultaneously performing two tasks: visual object tracking task and tactile/audio ringtone recognition.

1.4.2 HaptiGo: A Navigational 'Tap on the Shoulder'

1. Develop a wearable haptic vest that navigates pedestrians with a "tap on the shoulder".

2. Optimally place ultrasonic sensors [58] and vibration motors to signals pedestrians of potential obstacles.

3. Demonstrate the ability of users to perceive direction and obstacle signals, and navigate through a route.

4. Compare performance of users using HaptiGo against performance of users using PocketNavigator.

1.4.3 HaptiMoto: Wearable Haptic Navigation System

1. Enumerate the differences in haptic interface design requirements between pedestrian route guidance and motorcyclist route guidance.

2. Design a wearable haptic solution for motorcyclists route guidance.

3. Design a set of tactile signals to encode direction and distance to approaching turns.

4. Identify driving scenarios capable of evaluating a route guidance system for motorcyclists.

5. Demonstrate the effectiveness of tactile medium to communicate turn-by-turn directions to motorcyclists, including the ability of users to perceive and understand tactile signals, react appropriately to direction cues and perform appropriate turns while driving with HaptiMoto.

6. Measure a subject's effort required to use HaptiMoto while riding a motorcycle.

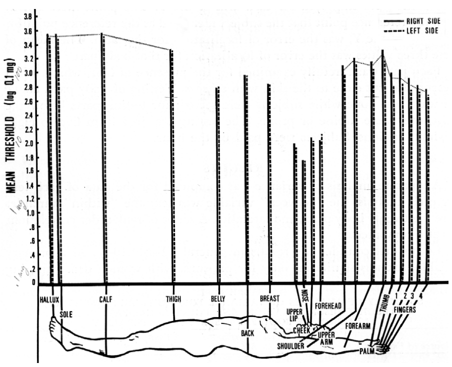
7. Compare subjects' effort required to use HaptiMoto against the effort required to use Google Maps audio guidance.

8. Test the ability of subjects to complete a two-mile circuit with HaptiMoto driving directions.

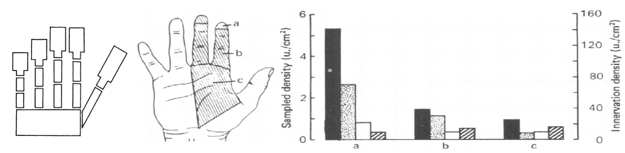
2. RELATED WORK

2.1 PsychoPhysical Research on Tactile Perception.

Tactile information transmission has been studied in the fields of psychophysics and computer human interaction. There are two types of receptors in our skin that can sense vibrations, specifically Pacinian corpuscles and Meissner corpuscles [52]. The Meissner corpuscles are sensitive to vibrations of low frequency of range 20 – 40 Hz and the Pacinian corpuscles are sensitive to vibrations of high frequencies of range> 100 Hz [52]. The sensitivity of skin to vibration differs at different locations on our body (Figure 2.1(a)). The variation is due to the difference in the density of the receptors. The density of receptors in the hand is particularly high when compared to other parts of the body. Figure 2.1(b) shows the density of receptors on the human hand [33]. The perception of vibratory signals depends on the following factors—amplitude, frequency, location, contact area and the waveform of the stimulus. The amount of contact area affects the minimum signal amplitude threshold required to sense vibration (Figure 2.2). The minimum signal threshold is the minimum amount of tactor displacement that is required for a subject to feel a stimulus. The greater the minimum signal threshold, greater is the difference between the stimulus ON and OFF state. Figure 2.2 shows minimum signal threshold as a function of frequency of tactile signal in cycles per second and the contact area of the tactor in sq. mm. The minimum signal threshold decreases by 3db for every doubling of the contact area. Both the graphs illustrate that reducing the contact area increases the minimum threshold [102, 103, 104].



(a) Sensitivity measurements at different parts of the body [52].



(b) Map of receptor density and tactile sensitivity in hand [33].

Figure 2.1: Sensitivity measurements.

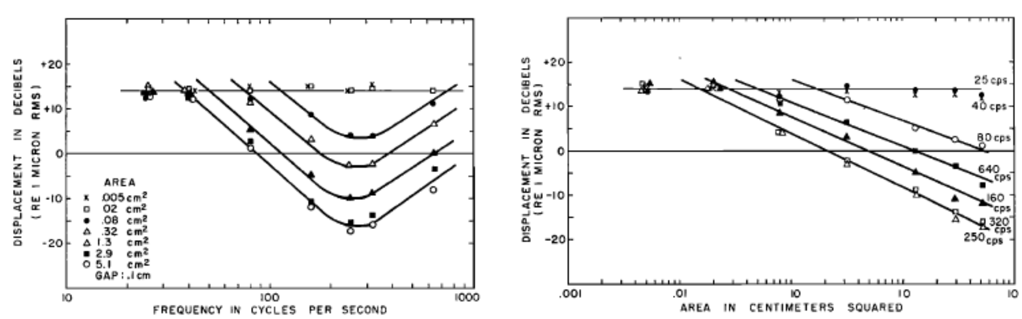
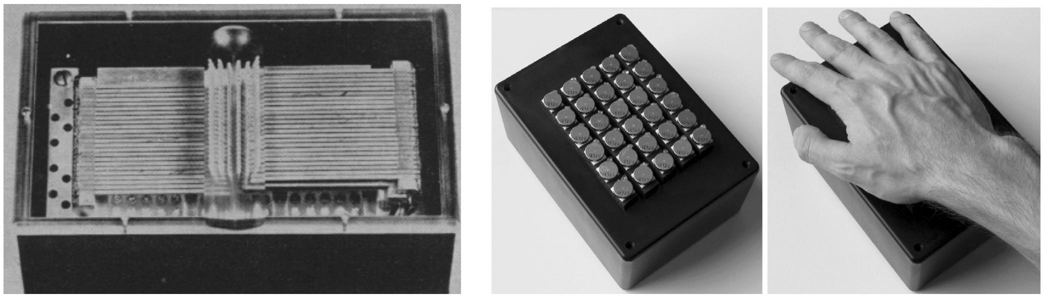


Figure 2.2: The image on the left shows the effect of increasing contact area on the minimum threshold of the perceived vibration frequency (in cycles per second). The image on the right is a graph of contact area versus the minimum amplitude threshold for perceiving vibration. [102, 103]



(a) Optacon by Bliss et al. [3] (b) vibrotactile array by Borst et al. [4]

Figure 2.3: Tactile array devices built for communicating synthetic codes.

2.2 Tactile Display Devices

Estimated bandwidth of tactile perception is 10^6 bits/second and that of auditory perception is 10^5 bits/second. A tactile channel can receive ten times more information than an audio channel [57]. We have the ability to discriminate tactile patterns, as well as process and learn them just as we do for letters or words in speech and vision [79]. Initial research in the usability of a tactile medium was focussed on constructing tactile arrays that can stimulate vibrotactile sensation (Figure 2.3). Bliss [3] built an array of 144 mechanical pins in a twelve by twelve matrix to create vibrotactile sensation for use by the blind. Borst et al. [4] constructed a low resolution vibrotactile array with a vibration motor [84] as a means to communicate a sense of touch. They constructed a thirty-element vibrotactile array as a means to communicate sketches which act like touch [5, 42]. We have used vibration motor and a methodology similar to one developed by Borst et al. [4] to construct our tactile display. Prolonged use of this tactile display causes discomfort to users due to the heat it generates. In this dissertation, we have proposed design improvements to the construction of tactile display targeted to reduce the user discomfort and make it suitable for long data collection studies.

2.3 Tactile Code Design

Recent research in tactile interfaces provides insights into tactile codes with a single vibrotactile actuator. Maclean [44] studied semantic tactile messages, called haptic icons, created by varying the signals across the following dimensions - frequency, amplitude, and waveform (sine, square, and triangle). The subjects could consistently distinguish two dimensions of the data: the frequency and the waveform. The frequency range of 10 – 20 Hz was optimum for user perception of signals. Van Erp [98] conducted similar studies with a single actuator that presented tactile messages, called tactile melodies. They created 250 tactile melodies of 15 seconds in length. The subjects were presented with 59 randomly selected tactile melodies. They could consistently rate the melodies based on two dimensions—intrusiveness and tempo. These researchers showed the ability of users to understand different dimensions of tactile codes with one actuator but did not provide interface designers with a formal approach to design tactile codes [45]. Ternes [91] provided a heuristic approach to choose tactile codes with rhythms from a set of 84 codes. He uses a multi dimensional scaling (MDS) plot to recognize clusters of similar codes. The measure of dissimilarity used in a MDS plot is calculated from subjective ratings of six expert users on the similarity between codes. A/B testing used in traditional phychophysical experiments provides a quantitative method to measure dissimilarity between two stimuli. Performing A/B tests provides us with the time taken and the errors performed by users in distinguishing between two tactile shapes. In our model, we have used a linear combination of these two quantities to calculate measure of dissimilarity between two shapes.

There exist five models to recognize clusters of distinguishable shapes in a graph—spring-electrical, stress, strain, MDS and Hall. Each technique represent the edge as a force/stress between nodes and optimizes graph structure to minimize the overall force/stress in the graph [32]. We use the spring-electrical technique to represent the edge weights as repulsive forces between nodes. We use Hu's fast force approximation algorithm [32] to perform clustering. We used the spring-electrical model because it works for sparse incidence matrices and scales better than other models for large graphs [32]. In other words, the model does not require a dissimilarity measure between each shape in a code space to form clusters of distinguishable shapes and it also provides valid solutions for large code spaces.

2.4 Interfaces for Automobile Navigation

Human factors research on orienting users in using tactile interfaces includes conveying driving directions [16, 31, 90, 100] and pedestrian navigation [15, 65]. Van Erp examined the navigation of pilots, car drivers, and soldiers, and devised a theoretical framework to decide the appropriateness of a communication modality based on the primary and secondary task [97]. Van Erp [97] suggests the use of tactile modality in such circumstances, including dual-task environments (navigation and driving). The workload for the cueing task is less when tactile cues are used in combination with audio or visual cues rather than audio or visual alone [18, 100]. Additionally, research comparing tactile and auditory modalities to convey driving directions in cars shows tactile input works better than auditory [9], further motivating the use of haptics for motorcycle navigation.

Augmented Reality (AR) interfaces form good alternate solutions for situations where a user has visual overload of information. Medenica et al. [51] have compared the advantages of AR maps over street view interfaces in navigation. They showed a 6.5% improvement in visual attention of users on roads when an AR interface is used for navigation over street view map interface. The users spent 4 – 5 seconds seeing the road ahead for AR Heads Up Display (HUD) when compared to street view map interface. We chose not to use an AR interface for motorcycle navigation because automobile navigation requirements are different from those of motorcyclists. Motorcyclists are often part of accidents due to lane intrusion from automobiles. The small size of motorcycles makes them less visible in rear view mirrors. This results in lane intrusions from automobiles. The consequences are that motorcyclists cannot afford to take eyes of the road since they need to keep their complete focus on the road ahead. AR/HUD display overlays information on a part of riders visual field and impairs them of the events in that field. This visual impairment adds risk to motorcyclists while riding.

Tactile direction cueing for car drivers has been shown to be effective, and has been tested in several manners, including using a three-by three array of tactors on a chair [90], an eight-by-eight array tactors on a seat [16, 100] and left-right haptic sensations on steering wheel [18, 38]. An *"on-thigh"* vibro-tactile belt containing eight tactors around the thigh successfully alerts pilots of the plane's orientation, with two tactors specifying the line representing the direction of gravity [77, 76]. Researchers have found haptic driving modalities to be safer than electro-tactile or force-feedback systems while driving cars [11]. When compared to a visual navigation display, the tactile navigation display did not increase the mental workload of the auto drivers. We contend that car drivers have a lesser workload while driving than do motorcyclists. Our motivation is to focus on building a usable vibro-tactile guidance system that does not increase the workload for motorcyclists.

2.5 Tactile Interfaces for Pedestrian Navigation

Research work as far back as over a decade ago [71] has focused on the development of pedestrian navigation systems that either additionally included or alternatively incorporated tactile modalities. While not primarily targeting people with situation-induced impairments, such systems have been developed to accommodate various other pedestrian types such as tourists in unfamiliar environments (e.g., [65, 89]), soldiers in sensitive environments (e.g., [15, 20]), and vision-impaired individuals in bustling environments (e.g., [34, 60]). Furthermore, these systems propose diverse solutions which take full advantage of tactile modalities in pedestrian navigation, ranging from mobile user interfaces which exploit mobile communication devices' vibration alerts to wearable tactile displays such as vibrotactile belts and vests.

The global ubiquity of mobile devices (such as the recent generation of smartphones) have motivated researchers to build multitudes of mobile navigation apps with tactile feedback support by those mobile devices' built-in vibrating alert feature. These various solutions provide their own approaches that build upon the existing capabilities of mobile phone technologies and can be categorized into two different types: *magic wand* and *sixth sense* [22].

2.5.1 Magic Wand Navigation Metaphor

Mobile user interfaces which incorporate *magic wand* functionality, take their cues from the metaphor of pointing the device at a distant object to learn more about its presence and access its corresponding information [22], and have been made specifically more feasible with recent mobile devices such as smartphones due to increased built-in digital compass capabilities [65]. In the context of pedestrian navigation, mobile user interfaces that incorporate *magic wand* functionality have recently been utilized to actively scan the user's surroundings, by physically waving the mobile device with their arms stretched out forward or turning their bodies around with the mobile device in their possession [48, 49], and for different purposes, such as better guidance for the visually-impaired individuals [47], more flexible routes for exploring tourists [70], and improved streamlined meetups for social groups [107].

These *magic wand* interfaces have proven successful in terms of intuitiveness from user feedback, and evaluations from these cited examples have demonstrated that users are able to reach target destinations effectively (e.g., [48, 70, 107]). While these systems benefit pedestrians through more intuitive navigation, this intuitiveness comes at the cost of requiring users to be actively engaged with these interfaces [70]. Consequently, not only would this type of interaction be cumbersome and exhausting to users over prolonged use as they adjust their limbs or bodies while locating their target destinations, but users with situation-induced impairments (e.g., Soldiers and motorcyclists) would not be able to benefit from such interfaces as they would require active engagement with these interfaces. The *sixth sense* metaphor is often used with wearable devices including multiple vibrating tactors, enabling users to derive the location or navigation of their target destinations in relation to their current location and orientation [15, 40, 63, 64, 65, 68, 73, 89]. *Sixth sense* interfaces benefit users through more passive interaction (no additional user motion), but sometimes possess a steeper learning curve to understand the directional meaning of feedback before successful navigation.

2.5.2 Sixth Sense Navigation Metaphor

In the context of pedestrian navigation, *sixth-sense*-based interfaces enable users to derive the location of their target destinations in relation to their current location and orientation [65]. Techniques that rely on the *sixth sense* metaphor have provided their own implementations either through turn-by-turn-based vibration patterns (e.g., [40, 68]) or compass-based directional vibration cues (e.g., [15, 63, 64, 73, 89]). In comparison to *magic wand* interfaces, *sixth sense* interfaces benefit users through more passive interaction; in other words, users are not required to search for spatial entities by explicitly performing pointing gestures. Consequently, the lack of such active gesturing to physical directions in *sixth sense* interfaces means that these interfaces are less intuitive and possess a steeper learning curve. As a result, users must first understand the directional meaning of the mobile devices' vibration feedback (e.g., meaning of vibration patterns, context of vibration cues) before they may be able to successfully navigate to their target destinations.

2.5.3 Magic Wand + Sixth Sense

Insights extracted from the contributions of these existing tactile-based mobile user interfaces have enabled researchers to explore possible synergies in a hybrid technique of both *magic wand* and *sixth sense*, such as applying vibration patterns from *magic wand* techniques that also expressed the direction of target destinations relative to the mobile device found in *sixth sense* techniques (e.g., [48, 62, 63]). Efforts from these explorations demonstrated that improvements were achievable for interfaces combining the strengths of both *magic wand* and *sixth sense* techniques; these subsequent interfaces accomplished the intuitive strengths of *magic wand* techniques with the passive capabilities of *sixth sense* interfaces without requiring that pointing gestures be executed.

While more recent navigation interfaces enjoy the benefits of *magic wand* and *sixth sense* techniques, one limitation that the hybrid technique possessed stemmed from evaluations which demonstrated lingering intuitiveness issues such that users required further training in order to utilize tactile feedback for pedestrian navigation [65]. Moreover, theoretical frameworks revealed that the placement of tactile information was critical to be intuitively comprehended by users [20, 95]; in the case of the hybrid technique, this tactile information is singularly expressed from the vibrating alarm of the mobile device which less effectively and intuitively conveys navigation information when carried by hand or in clothing compared to techniques that incorporate additional and more optimally placed tactile sensors (e.g., tactile displays). An additional limitation of the hybrid technique stems from the hardware (i.e., the mobile device's vibrating alarm) used for expressing tactile information when additionally including obstacle detection; further intuitiveness issues may develop from the ambiguity of determining whether cues from the vibration alarm indicate either navigation guidance or obstacle detection.

2.5.4 Tactile Belts

Various proposed tactile belt systems for pedestrian navigation share similar characteristics in embedding vibrotactile sensors around the waist that generate absolute point pulses analogous to receiving visual cues from a compass [85]. Earlier tactile belt prototypes [101, 34, 53, 93] provided tactile feedback on larger, protruding belts that guided users with navigational feedback from a backpack-carried laptop or a nearby server. More recent tactile belt systems [60, 61] achieved small form factors similar to clothing belts and with navigational guidance from smartphones.

Some of the advantages demonstrated by tactile belt designs included users intuitively understanding the direction cues from the tactile feedback [101] and performing better as compared to wearing early-generation pattern-based tactile vests in controlled studies [85]. An observation we made with tactile belt designs involved additionally incorporating obstacle detection functionality; since sensors on existing tactile belt systems are equally-spaced around the user's waist, this introduced the possibility of usability issues of interpreting what tactile feedback would indicate navigational cues and what would indicate obstacle avoidance.

Tactile Vests Wearable tactile interfaces for pedestrians that are an alternative to tactile belts are tactile vests, which consist of torso vests embedded with a set of vibrotactile sensors; early-generation vests were bulkier and supported sensors that generated straight-line patterns (e.g., directional gestures) [35, 72] which functioned as pulsating sequences, while more recent vests were better streamlined and supported relative point vibrations on the backside of the user (e.g., left, forward, right) [15, 20, 19] during navigation.

Recent tactile vest approaches have demonstrated advantages including their effectiveness in displaying direction cues based on both controlled and preliminary field studies [20] f in navigating users without distracting them [60]. Moreover, various theoretical frameworks (e.g., Wickens' Multiple Resource Theory [105], van Erp's Prenav model [95]) provide supporting evidence on the effectiveness of tactile vests in improving various aspects of navigation. The Prenav model particularly theorizes that simply providing tactile information in navigation is not enough, and observations have shown that direction information can be intuitively comprehended with torso-placed sensors such as on tactile vests [20]. While the cited works on tactile vests focus specifically on pedestrian navigation tasks, the tactile vest approach specifically appealed to us due to its supported intuitive benefits.

In general, haptic belts [101, 61, 85] outperform [85] early haptic vests that generated straight-lined patterns [35, 72], as tactile belts allow for 360 degrees of location feedback. Recent vest improvements support relative point vibrations on the backside of the user (e.g., left, forward, right) [15, 20, 19] during navigation, allowing for more sophisticated navigation. We have experimented with both belts and vests in our work with motorcycles, and found that hips and waist get a significant amount of vibrational noise from the motorcycle, making a tactile belt impractical for our use, and thus chose a tactile vest that affords the "tap on the shoulder" analogy [6].

2.6 Navigation Interfaces for Cyclists, Segway Riders and Motorcyclists

There are a number of approaches proposed for guiding cyclists and segway riders: tactile waist belt [87], tactile steering wheel [66, 67], and a combination of AR and tactile steering wheel interface [39]. Steltenpohl and Bouwer proposed a vibro-tactile belt with eight tactors around the waist to provide turn-by-turn navigation signal for bicyclists. The signals are provided at 50m and 10m before a turn. Distance to a turn is encoded with rhythm; faster the rhythm closer is the turn. Pielot et al. [66, 67] propose a combination of visual and tactile approach to navigate cyclists. This interface uses both visual and tactile medium to provide location and destination information. They have used a drift towards the destination approach to provide directions. The system provides the direction of destination with respect to location and orientation of bicyclists just like a compass that provides direction to North. The system uses two tactors each placed at left and right handles of the steering handle. The intensity of each of the tactors is varied to state the direction towards destination. Drift towards a destination works well for slower modes of navigation and does not work well for motorcyclists. Motorcyclists require turn-by-turn navigation and providing orientation of destination relative to them does not provide appropriate route guidance. The waist of a rider is prone to vibrational noise from the frame of the motorcycle [80].The choice of handle bars for the placement of tactors is not appropriate for motorcyclists because they can increase change blindness [24]. The handle bars vibrate and interfere with vibrational stimuli [80]. The effect of change blindness in perceiving tactile signals is explained detail in the next section of this chapter. Li et al. [39] have proposed a system similar to the AR interface mounted on the center of the handlebar of a segway and the tactors are fitted to left and right of the handle bars. The directions are presented on AR and tactile interfaces before the turn. Tactile pulses of 500ms length mark the arrival of turn. A pulse of 5000ms suggests the users to make the next turn. One user study compares the reaction time for AR + Audio and AR + tactile interface and finds that tactile interface takes less reaction time. Another compares the navigation and workload for Maps + audio, AR + audio, and AR + tactile. These studies prove that the workload is the least for AR + tactile mode.

Li et al. [39] support the use of speed based lead distance calculation which is used in HaptiMoto. Segway navigation is similar to bicycle navigation as noted by Li et al. [39] and is different from requirements for motorcyclists. The difference between motorcyclists requirements and bicyclists are similar to difference between pedestrians and motorcyclists requirements. Bicyclists travel at much slower speeds when compared to motorcyclists. These slower speeds provide bicyclists ample time to perform both riding and responding to navigation cues. Motorcyclists travel, on the other hand, can not afford to be distracted by navigational cues. The range speeds travelled by motorcyclists and bicyclists are also different. The speed of the vehicle determines the time before which a rider needs to be warned of an approaching turn. Low speeds and small variations in travelling speed of bicyclists allow designers to signal riders at predefined distances before a turn (50m before turn for Vibrobelt [87]). The motorcyclists can travel anywhere up to 75mph, the range of the travelling speeds, warning distance required to make appropriate turn, and the distance between intersections all become critical factor in deciding the timing of a direction signal before an approaching turn.

2.7 Psychophysical Research on Tactile Navigation Interface

2.7.1 Psychological Refractory Period (PRP)

Auditory directional signals are better than visual directional signals for drivers, as they reduce visual overload [17, 43, 88] and still present high priority and intermittent information [8]. For motorcyclists, the use of auditory channel comes with certain limitations and increased risk for users as it reduces accoustic awareness. Motorcyclists need to have acoustic awareness in order to respond to unexpected events [7]. Additionally, external noise, such as engine or wind turbulence noise could make the directional signals inaudible. At 100 km/h (70 mph) the wind turbulence is approximately 100 db and is the major source of noise at high speeds [7]. The Psychological Refractory Period (PRP) states that when two tasks require simultaneous response, the users decide on performing one task and queue the response for the secondary task. The delay in performing the queuing task is called PRP period, and reduce attention on detecting critical events is called the PRP effect [30]. The PRP effect provides additional motivation for us not to overload the visual or auditory channels of the driver.

2.7.2 Change Blindness

The effectiveness of tactile medium depends on the perceptability of tactile stimulus, depending on the stimulus strength, count, location, environmental change blindness, and user sensitivity [23]. The HaptiMoto vest provides tactile signals behind the two shoulders and in the center of the lower back and is shown to be effective by other experiments [6]. Humans can distinguish up to twelve different angles of direction information with errors in judgment within $10 - 17°$ [96].

Change blindness is induced when multiple stimuli are presented simultaneously on similar mediums, can reduce commuincation effectiveness. Driving involves both visual and auditory input mediums of the user, so change blindness will be higher when the user is given audio/visual direction cues. Change blindness is higher for tactile stimulus when it is applied to moving parts of the body or close proximity other tactile stimulus [24, 80]. For example, motorcyclists use their arms to steer motorcycles and their arms and legs are close to vibrational noise from the motorcycle. Thus, it is ineffective to provide tactile direction stimulus to either arms or legs of a motorcyclist. The tactors in HaptiMoto vest are located on the upper part of the body, away from moving parts of the body or those close to motorcycle vibration (such as the hips or waist). Errors caused due to change blindness can be further reduced by repeating the tactile signals [23] as we do in HaptiMoto.

2.7.3 Navigation Signal Processing

Navigation research supports the use of turn-by-turn route guidance for navigating users Turn-by-turn signals can be associated to view-action pairs where a driver gets a direction signal for a turn and performing the corresponding turning action [17, 92]. According to Dingus, the directional information is enough for route guidance and any other information is potentially disruptive. Information about a turn signal should contain three important parts to it: the directional turn left/right, the turn distance, and the specific road to turn onto [17]. HaptiMoto is designed to deliver the minimum required information for navigation: the direction of the upcoming turn and the distance to that turn.

2.8 Evaluation Techniques for Navigation Systems

Given a driving task for a certain distance and a route to travel, several standard measures exist to determine effectiveness and the attentional demands of the task at hand, including, the NASA TLX Subjective Workload Test [28, 59, 86], reaction time required to respond to direction cue [86], the Subjective Workload Assessment

Test (SWAT) [43, 69], number of correct turns, number of wrong turns, number of missed turns and number of near miss [43], mean velocity, absolute deviating in velocity, variance in acceleration (higher variation means the navigation cues take more attention disrupting the speed of the vehicle [43]), and the total travel time to complete driving a route [59]. In our evaluation, we measure the driver's workload while through the NASA TLX workload survey, we measure the completion time, number of correct turns made, wrong turns, and near misses.

3. THREE-BY-THREE TACTILE DISPLAY DESIGN

3.1 Control Circuit of Tactile Display

We have created two versions of a tactor array during our experiment. Both the versions use the same control circuit (Figure 3.1). The circuit serves as a digital amplification interface between the pulse wave modulated (PWR) outputs of the microcontroller and the rotary vibration motors. The use of PWR output enables the amplitude of each motor to be controlled independently by the microcontroller. There are three components to the circuit:

1. The Arduino microcontroller is a serial interface with a controlling computer. It is the source of low current and PWR voltage controlling the rotary vibration motors.

2. The optical isolators separate the control circuit and the power circuit. The isolators protect the low current circuit of the microcontroller from transient noise.

3. The power circuitry drives the rotary vibration motors using power transistors and diodes. The power transistors are used to supply a greater current to the motors and diodes are used to protect the power circuit components against back EMF from the motors. Two separate 5V power sources are used to power microcontroller and the vibrator motors.

3.2 Tactor I - Constructing Display with Vibration Motor

The first version of the tactile array (Tactor I) is built with nine vibration motors arranged in a three-by-three matrix on a soft sponge block. They are embedded with

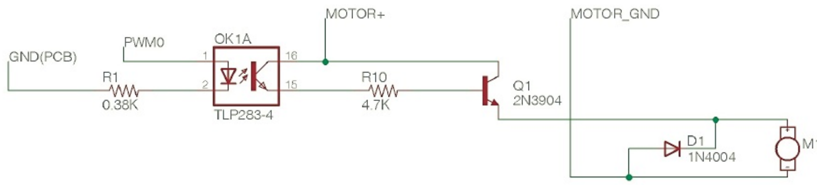
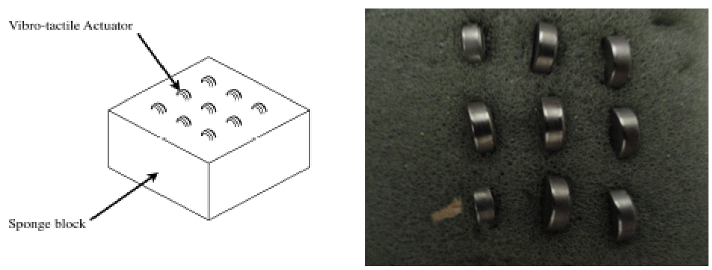


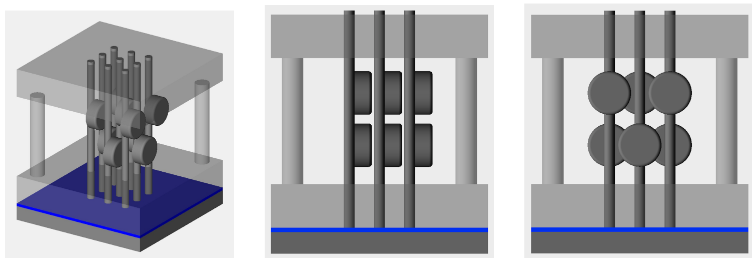
Figure 3.1: The circuit diagram of the control circuit used in tactor array.



(a) Schematic Diagram (b) Original Diagram

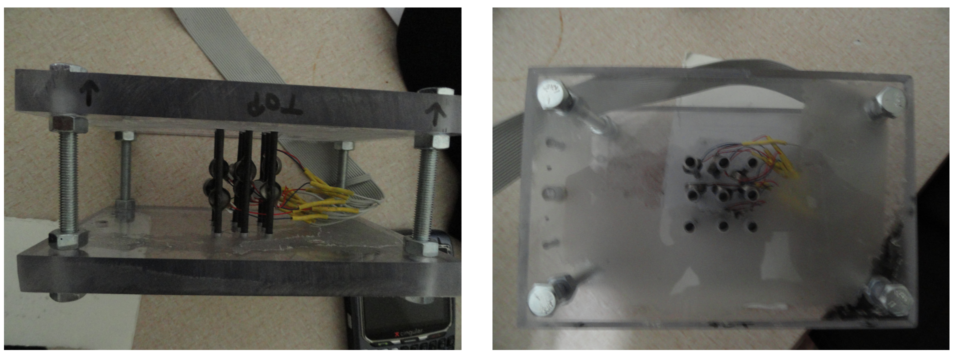
Figure 3.2: An illustration of the first version of the tactor array.

12mm spacing. The vibrator motors are DC rotary eccentric weight type motors which can generate a maximum vibration amplitude of 90db. Figure 3.2 illustrates the first of version of the tactor array. A pilot study with five users showed that continuous and prolonged use of the tactors caused discomfort for the users. The discomfort is caused due to heat generated by the motor and heat generated from the friction between the vibration motor and the skin when used for a long time. We required the users to use the tactile array continuously for more than an hour collecting A/B test data. In practice, we expect the users to use the technology only intermittently. However, we wanted to create a version that would allow for long term use without discomfort.



(a) (b) (c)

Figure 3.3: CAD diagrams illustrating the front and side views of tactor array II.



(a) Side View (b) Front View

Figure 3.4: Pictures of the side view and the front view of tactor array II.

3.3 Tactor II - Constructing the Display with Vibration Motor & Carbon Fiber Rods

The second version of the tactile array (Tactor II, Figures 3.3 & 3.4) was constructed to reduce the discomfort for users during prolonged usage. The goal of the design was to create a method of delivering a more discrete stimulus than is possible with the vibration motors directly, while simultaneously reducing heat from the vibration motor and heat due to friction.

The eccentric weight in the vibration motor generates a rotary motion. A carbon fiber shaft was attached to each motor to linearize the motion. This procedure limits the shaft movement to the vertical dimension resulting in a linear reciprocating action. The diameter of the individual carbon fiber shaft defines the individual area of tactile stimulation. The use of carbon rods reduced the contact area from, previously, greater than $3.4 * 5$ sq. mm for the vibration motors in Tactor I, to $2 * 2$ sq. mm. for the carbon fiber rods in Tactor II.

The alternating vertical placement of the vibration motors on the carbon fiber shafts gives us the ability to increase the density of the vibration stimuli in the array by reducing the space between the shafts. These improvements allow a discrete haptic stimulation presentation, limiting the vibration to the vertical dimension, and enable a higher resolution of the tactile array using the same vibration motors. The carbon fiber rods eliminate the conduction of heat from the motor to the user's hand. The vertical movement and the reduced surface contact area of each carbon fiber rod reduces the friction generated heat between carbon fiber rod and the user's hand.

4. FACTORS THAT AFFECT TACTILE SHAPE RECOGNITION

The first step in developing a model for selecting tactile codes is to understand the factors that affect the perception of a code in tactile medium. In this chapter, we discuss the factors that affect tactile perception, and explain two user studies conducted to understand the effect of these factors on tactile perception. Additionally, we discuss the data collection user study conducted to understand the relationships between each tactile shape based on the perception accuracy, time taken, number of active tactors and the waveform. The data collected from this user study forms the basis of the graph model for tactile shapes, described in the next chapter.

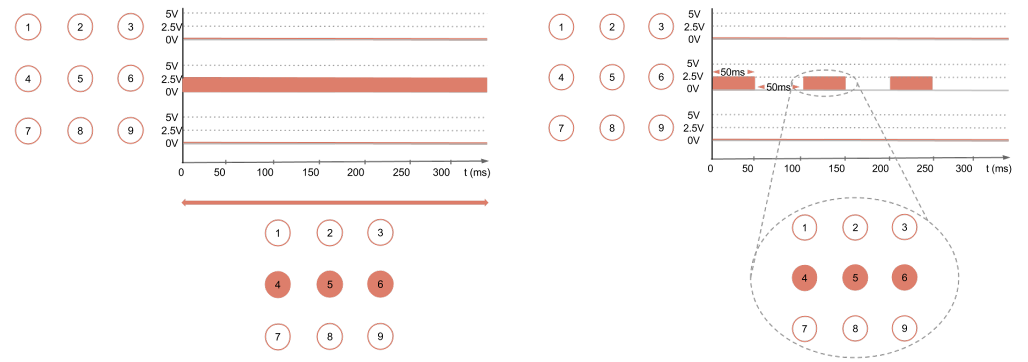
We have studied four factors that affect a user's tactile shape recognition:

Modes of Tactile Perception There are two modes of perceiving touch—active and static search. Active search exploration involves probing with fingers and static search involves static touch with a palm. Both forms of search are common in tactile perception with hands. The sensitivity of palm and fingers depend on the density of the touch receptors in them. The fingers have a very high density of touch receptors when compared to the density of the touch receptors in palm [33].

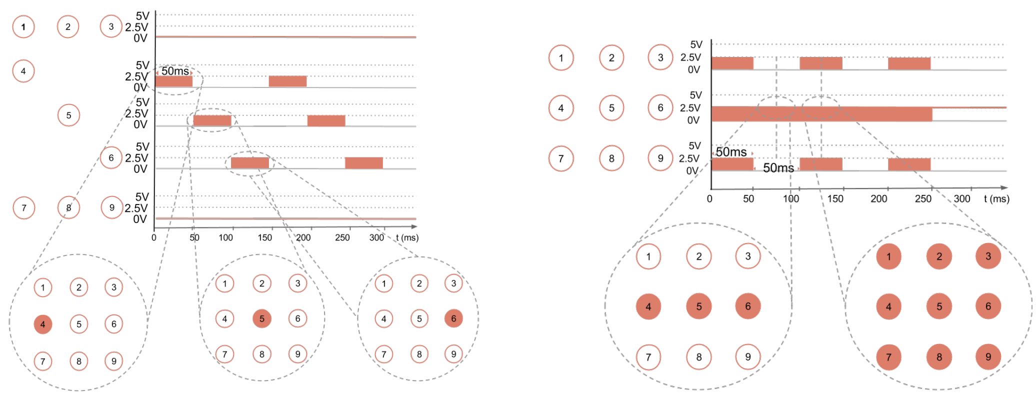
Amplitude of Vibrotactile Signal The amplitude of the vibrotactile signal affects the perception of the signal in two ways. First, it determines a minimum threshold of amplitude, below which the users cannot perceive a vibrotactile signal. Second, the amplitude determines the area of localization of the vibrotactile signal. A large area of localization causes overlap between two adjacent signals and cause errors in recognizing a tactile shape [102, 104].

Stimulus Contact Area The stimulus contact area is the surface area of a tactor that is in contact with the skin when a tactile stimulus is applied. The area of localization of the stimulus presented with the tactor is directly proportional to the contact area of the tactors [103]. Actuators in Tactor I have a larger contact area than actuators in Tactor II. We have observed the differences in tactile perception when shapes are presented with Tactor I and Tactor II.

Waveform is the rendering method used in presenting the tactile shape with Tactor I and Tactor II. We have used four waveforms for rendering shapes on a tactile display—constant [3], pulsed [44, 98], sketched [4], and pattern masked (BasePulse) [14]. An illustration of the four rendering methods is shown in Figure 4.1 with a horizontal line shape.



(a) Constant (b) Pulsed



(c) Sketch (d) Pattern Mask

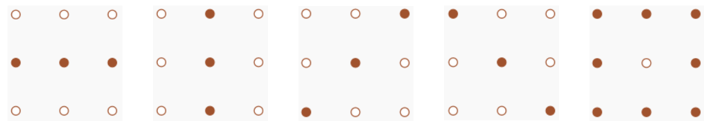
Figure 4.1: The four rendering methods used in the user study. Each image above shows the representation of a horizontal line when rendered with a particular waveform. The graph shows the pulse length and time between pulses for the waveforms. In the example above, all of the above wavelength forms show the same ‘shape’, that of a straight line down the middle. In the constant waveform (a), the shape is continuously displayed to the user. In the pulsed wave form (b), the shape is displayed all at once as in (a), but it is pulsed, so that no input (quiet) is interspersed with the signal. In the sketched waveform (c), each tactor is turned on, one at a time from left to right. In the pattern mask waveform (d), this is similar to (b) but instead of turning everything off, all of the tactors are turned on in between pulses.

We have conducted two user studies with Tactor I and Tactor II to study the effects of the four variables in the perception of tactile shapes. The first study was conducted to compare the modes of recognition used by subjects to perceive shapes. The study was conducted using Tactor I. This study was also used to set the amplitude level for a vibrotactile signal. The second user study was conducted to study the effect of waveforms and the area of stimuli on tactile perception. The second study used four waveforms for presenting ten shapes. Tactors I and II have been used to study the effect of change in the stimulus contact area on tactile perception.

4.1 Study on Amplitude of Vibrotactile Signal and Active vs Passive Tactile Search

In the first user study, the independent variables are the tactile shape, signal waveform, and the signal amplitude. We presented five different shapes (shown in Figure 4.2) at two amplitude levels (L1 and L2). We presented the shapes in either a continuous or a pulsed mode. L1 was a low amplitude signal which was equal to half of the highest actuator amplitude. L2 was a high amplitude signal which was equal to the highest actuator amplitude. The presentation of the pattern in either mode continued until the subject made a response. The dependent variables are the response time and accuracy.

We presented each of the five patterns four times in each of the four experimental conditions resulting in 80 presentations and tested each subject twice. The total number of subjects in the study were ten. All the subjects were male of age between 20 and 30. Considering that there are differences in sensitivities in palm and finger tips, we observed the methods used by the subjects to search the patterns. The subjects scanned the tactile array with their fingers (active tactile search) or placed



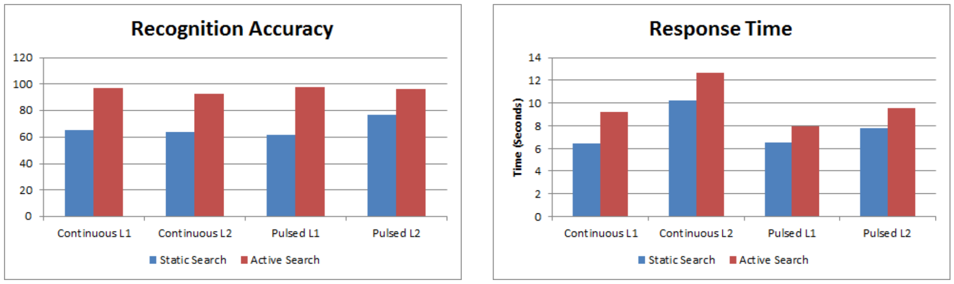
(a) Horizontal Line (b) Vertical Line (c) Forward Slash Line (d) Backward Slash Line (e) Square

Figure 4.2: Five Shapes used in User Study I

the tactile array against their palm and held it stationary (static tactile search). We altered the testing for different individual subjects, providing a total of 160 pattern presentations and recorded the number of correct identifications and response latencies throughout the experiment.

The significant effect was found to be the difference between finger (active search) and palm (passive search) acuity. Figure 4.3(a) shows an average of 96% correct identification for finger perception, as compared to 67% for palm perception. Response latencies for pattern identification are presented in Figure 4.3(b) for all experimental treatment conditions. An Analysis of Variance (ANOVA) with a repeated measures test was performed on the data. The $F_{(1,79)}$ score from the test is 0.3087 for $p < 0.01$ which illustrates that the latencies from the different probing modes and levels of vibration are not significantly different from each other. These results clearly demonstrate that response latencies are not affected by any experimental treatment. In particular there is no difference between finger and palm perception groups in terms of latency.

The difference in performance between finger and palm pattern recognition could be due to physiological factors. The finger tip has a higher density of touch receptors than the palm surface. As the area density of receptors determines regional cutaneous sensitivity, this would imply that the finger tip had a higher sensory resolution



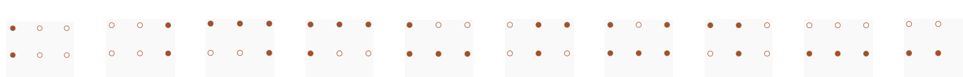
(a) (b)

Figure 4.3: Graphs illustrating the response time and accuracy of pattern perception.

than the palm surface. There was no significant difference in latency or recognition accuracy for different levels of signal amplitude.

4.2 Study on Stimulus Contact Area and Signal Waveform

In the second user study, the independent variables are the tactile shapes, the signal waveform, and the stimulus contact area. We presented ten shapes to the users. The shapes presented are shown in Figure 4.4. We presented each shape in four waveforms—Constant, Pulsed, Sketched and BasePulse. Figure 4.1 shows an illustration of variation of a shape for different waveforms. We used Tactor I and II to change the stimulus contact area. The stimulus contact area for Tactor II (3mm) is less than that of Tactor I (10mm). The amplitude of the vibrotactile signal is controlled through the experiment. The dependent variables that were measured are response time and number of errors.

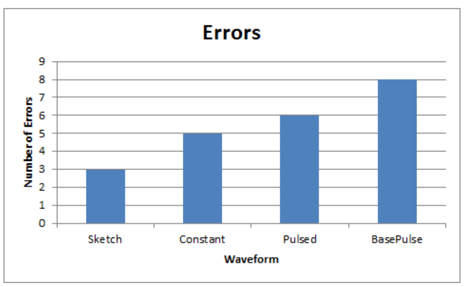


(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

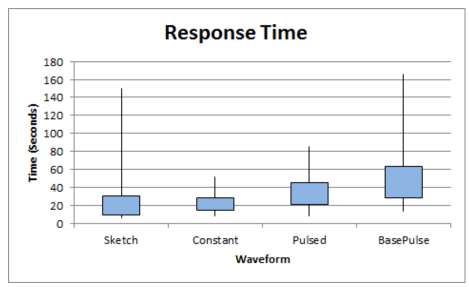
Figure 4.4: Ten Shapes used in User Study II

The user study was conducted in two sessions one for each tactor array. We had ten subjects in each session. All the subjects were male of age between 20 and 30. In each session, each subject was given training with five shapes and all four waveforms. The subject was then tested with ten shapes and four waveforms. Each combination of shape and waveform was presented to subject once. Each subject was presented with total of 40 vibrotactile shapes.

The number of errors and the response time for Tactor I is presented in Figure 4.5 and for Tactor II is presented in Figure 4.6. The average response time for each waveform and the standard deviation are tabulated in Table 4.1.



(a)

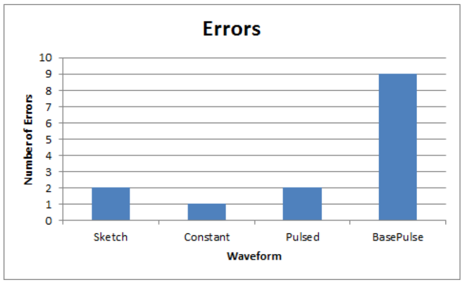


(b)

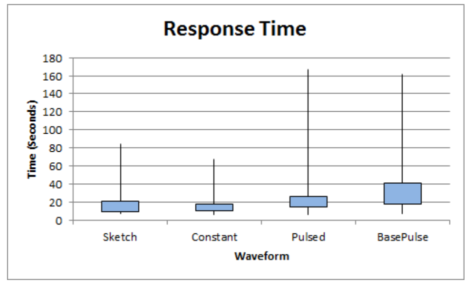
Figure 4.5: Number of errors and reponse time for perceiving shapes using Tactor I.

The F scores ($F_{(1,399)} = 0.0088$) and T Test ($T_{(T<t,alpha<0.05)} = 0.04$) performed on the data show that the number of errors in perceiving tactile shapes is less in Tactor II than Tactor I. The subjects stated difficulty in perceiving shapes due to overlap between adjacent stimuli in Tactor I. The subjects stated perceiving shapes was easier with Tactor II when compared to Tactor I because it was easier for them to perceive the ON and OFF state of each actuator.

The subjects were also asked to rank the waveforms based on ease of use. The



(a)



(b)

Figure 4.6: Number of errors and reponse time for perceiving shapes using Tactor II.

Table 4.1: Mean (M) and standard deviation (SD) of time taken to recognize a shape for Tactor I and II.

Waveforms	Tactor I		Tactor II	
	M	SD	M	SD
Sketch	25.28	23.61	18.51	14.51
Pulse	22.82	9.57	15.91	9.91
Constant	35.38	18.06	22.43	18.02
BasePulse	49.76	32.29	32.17	21.46
Overall	32.89	24.47	22.00	17.47

order of preference was

1. Sketch
2. Pulsed
3. Constant
4. Pattern Mask/BasePulse

The BasePulse was least preferred and the number of errors and the response time were the highest for this waveform. We believe the use of the pattern mask makes the recognition of tactile shape difficult. The sketched waveform was the preferred waveform. The number of errors in recognition was the least for this waveform. The response time for recognizing a tactile shape was as high as the BasePulse waveform. The high response time is due to the time required for the shape to be presented. The presentation time for each shape in sketch waveform was found to be five times more than the presentation time required for the same shape in other format. Figure 4.1 shows variation of a shape with time for sketched waveform.

4.3 Data Collection for Tactile Shapes Distinguishability

A total of $2^9 - 1 = 511$ tactile shapes can be represented using nine tactors. To find the shapes that are easy to distinguish, we used two measures - time required to distinguish between two shapes and number of errors while distinguishing two shapes. We designed an application which is a variation of A/B testing to calculate these two measures for each pair of tactile codes in the tactile code space. The total number of pairwise comparisons required from each user was $511 * 510$ and users took an average of $10 - 20$ seconds to recognize a shape from a pair of shape. Performing such a task required a huge amount of time from each user. In order to decrease the amount of time taken to collect data, users were asked to recognize the stimuli from four options rather than two options used in A/B testing. A/B testing with two options yielded a response time and error relationship between two tactile codes for every user response. Each user response in A/B testing with four options yielded a response time and error relationship between four tactile codes, an example of which is shown in Figure 4.7. The increase in number of options decreased the number of comparisons required to create relationships between each of the 511 shapes by four fold. The user was presented with a tactile code on Tactor II. The user then selected a tactile code from the list of four shapes and a *None of the above* option presented by the application and the response time and the error in recognition was recorded.

The *None of the above* option was included in the study in order to restrain the users from using the option elimination method to recognize the shape presented on the array.

A user study to collect this data was conducted with eight users—one female and seven male. The age of the users was between ages 20 – 25. The time taken for each user was between 8 – 10 hours broken into sessions of one hour each. The data collected from the study yielded the time taken to distinguish each pair of tactile code and the number of errors that the user committed when distinguishing a tactile code from other. We used four rendering methods in this study—constant, pulsed, sketched, and pattern mask with a total of 511 possible tactile shapes. Therefore, each user was presented with 511 shapes at four instances throughout the study. Thus each user was required to recognize and distinguish the tactile code for 2044 instances.

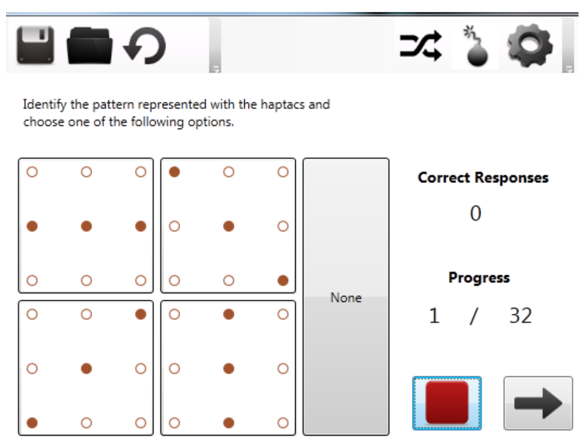


Figure 4.7: A screenshot of the tactile game. The game presents a shape on the tactor array and shows five options for the user to choose from including the "None of the above" option.

4.4 Distinguishability Data - Error and Response Time

The data collected from the study provided insights into the recognition behavior of users. When a shape was presented to users, the users perceived the shape presented to them using the following steps:

1. Determine the intensity of the vibrotactile shape

2. Determine the number of tactors present in the shape

3. Determine the location of the tactors in the shape

The intensity of the vibrotactile signal varies with the rendering method used for the shape. Users used intensity to determine the waveform of the tactile signal. The intensity of the shape also varies with the number of tactors in the shape. When the number of tactors activated for a shape increases, the intensity of the vibrotactile increases. In order to perceive the shape in the vibrotactile signal, the users first perceived the number of tactors activated on Tactor II, then they perceived the location of the tactors that was activated on the array. We have analyzed the effect of the rendering method and number of active tactors in a shape on recognition of the shape.

4.4.1 Waveform - Rendering Method of a Shape

The time taken to recognize a shape and the accuracy of shape recognition data were calculated for each of the rendering method. The recognition accuracy and response time of each user per waveform is listed in table A.6 under appendix A and the summary of the results (mean and standard deviation) is listed in table 4.2. Figures 4.8(a) & figure 4.8(b) show the box plot of recognition accuracy and time taken for recognition respectively. Comparing the variance in accuracy of recognition, F ratio was 1.1062 and $F_{(3,31)} = 0.4003$. The analysis of variance on accuracy was not significantly different. We performed a t-test to compare shape recognition accuracy for each pair of waveforms. Table A.8 lists the results of all pair t-test. The results indicate that rendering shapes with pattern mask waveform caused more errors than any of the other rendering methods. We then compared the recognition time of shapes for the four waveforms. The F ratio of 172.5753 and $F_{(3,31)} = 0.0001$ show that the variation in shape recognition time for the four waveforms are different. Pairwise t-test on shape recognition time (listed in table A.7) indicates that constant waveform required the least time to recognize a shape and pattern mask waveform required the most recognition time. The increasing order of waveforms in terms of recognition time is:

1. Constant
2. Pulsed
3. Sketched
4. Pattern Mask

The results from this study support the results from our first study comparing the performance of users in recognizing a shape with different rendering methods.

4.4.2 Number of Active Tactors in a Shape

The data collected (number of errors and the time taken to recognize a shape) from individual users is listed under Appendix A in table A.1. The summary of the results, number of shapes, number of errors, accuracy and response time, is listed in table 4.3. The variance in response time for recognizing shapes with different number of tactors was compared with F Test. The F ratio was 3.320 and the probability that

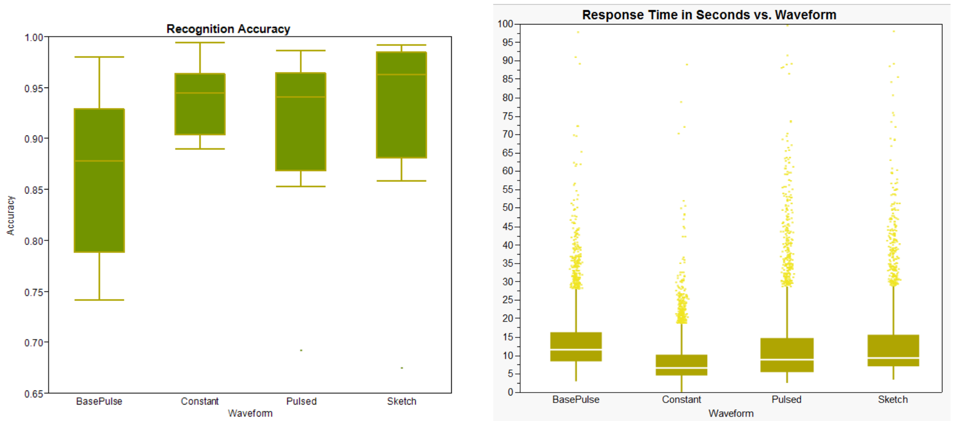
Table 4.2: Mean and standard deviation of accuracy and response time for recognizing tactile shapes. The tactile shapes are rendered in one of the four rendering methods listed in the below table.

Waveform	**Accuracy**		**Response Time**		**Number of Errors**
	Mean	**SD**	**Mean**	**SD**	
Pattern Mask	0.87	0.08	13.83	10.99	536
Constant	0.94	0.04	8.63	11.74	243
Pulsed	0.91	0.10	12.16	12.34	380
Sketch	0.92	0.11	12.98	10.52	324

the variations in response time were equal was $F_{(8,16351)} = 0.0008, \alpha = 0.05$. The test showed that the variances are significantly different. We performed an all pair t-test to rank the effect of number of tactors in the shape based on the time taken to recognize the shape. The results of the test (table A.4 in appendix A) indicate that the shapes with 1, 2, 3, 8 or 9 tactors activated in them are recognized faster than shapes with 4, 5, 6 or 7 tactors activated in them.

The mean and variance of accuracy data for shapes were then compared. Figure 4.9(b) shows the box plot of the mean and variation in accuracy of user response for shapes with different number of tactors. F ratio was 2.4479 and probability that variation in accuracies based on number of tactors were equal was $F_{(8,71)} = 0.0225, \alpha = 0.05$. The F test implies that the variations in response accuracies for shapes with different tactors are different. We then performed an all pair t-test on the accuracy data (table A.5 in appendix A). The results indicate that the shapes with 1, 2, 3, 8 or 9 tactors activated in them are recognized more accurately than shapes with 4, 5, 6 or 7 tactors activated in them.

The errors made by the users in recognizing shapes are shown in the form of correlation matrix in figure 4.10(a) and heat map in figure 4.10(b). Analysis of the

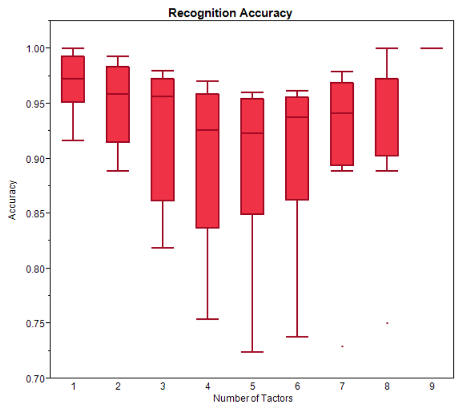


(a) Recognition Accuracy (b) Time Taken to Recognize Shape

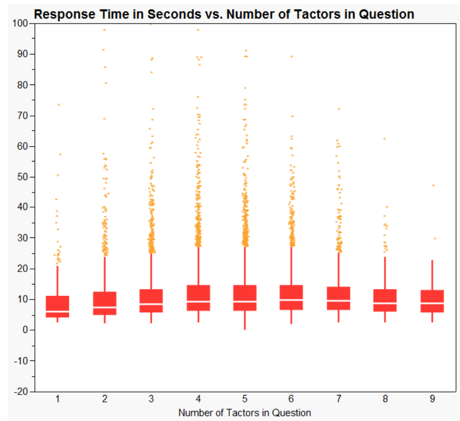
Figure 4.8: Illustration of performance of users in recognizing the tactile shapes grouped by rendering method used in the shape. Chart (a) is a box plot of user response accuracy and Chart (b) is a box plot of user response time in recognizing tactile shapes.

Table 4.3: Performance of users in recognizing tactile shapes grouped by number of tactors in a shape. Mean and standard deviation (SD) of accuracy and response time for recognizing tactile shapes. The number of tactors activated for each shape is between one and nine.

Number of Tactors	**Number of Shapes**	**Number of Errors**	**Accuracy**		**Response Time (s)**	
			Mean	**SD**	**Mean**	**SD**
1	288	9	0.97	0.03	11.49	38.52
2	1152	56	0.95	0.04	10.76	9.93
3	2688	200	0.93	0.06	11.36	9.72
4	4032	410	0.90	0.08	12.07	9.97
5	4032	431	0.89	0.08	12.26	11.58
6	2688	261	0.90	0.08	12.25	11.32
7	1152	97	0.92	0.08	11.95	9.06
8	288	19	0.93	0.08	10.95	7.48
9	32	0	1.00	0.00	10.97	8.76



(a) Recognition accuracy



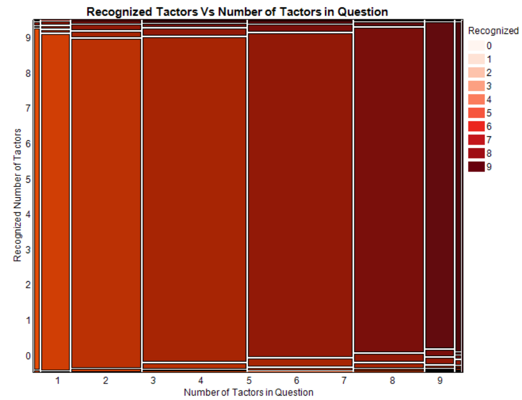
(b) Time taken to recognize shape

Figure 4.9: Illustration of performance of users in recognizing the tactile shapes grouped by number of tactors in the shape. Chart (a) is a box plot of user response accuracy and Chart (b) is a box plot of user response time in recognizing tactile shapes.

errors in recognition suggests that the users are prone to make mistakes when the options provided in A/B testing have shapes with a similar number of tactors. For example, a shape with 5 active tactors is most likely to be confused with shapes with 4, 5 or 6 active tactors in them.

The results in comparison of response time and accuracy data can be attributed to the way users recognize tactile shapes. Users count the number of active tactors and locate them on a tactile display to recognize a shape. They find the number of active tactors by counting the number of tactors that are active or counting the number of tactors inactive and substracting them from nine. When the number of active or inactive tactors for a shape is less than three, users find it easy and take less time to find the number of active/inactive tactors than when the number of active or inactive tactors for a shape is greater than three. The results from the data support choosing shapes with 1, 2, 3, 8 or 9 active tactors over shapes over shapes with 4, 5, 6 or 7 active tactors but the errors in recognition of shapes suggests the code

(a) Error correlation matrix between number of tactors in question and number of tactors in user responses



(b) Error correlation heat map between number of tactors in question and number of tactors in user responses. The area of each box shows the proportion of number of shapes that can be represented using a particular number of tactors to the total number of shapes (511).

Figure 4.10: Charts showing the correlation between the number of tactors in question with the number of tactors in the answers. This matrix shows the user responses that were wrong and how the number of tactors in an answer affected the user response.

set containing shapes with similar number of active tactors will cause inaccurate recognition of shape. Therefore, the number of active tactors in the shape alone cannot be used to select a set of shapes for tactile code.

5. GRAPH MODEL OF TACTILE SHAPES

The previous chapter discussed in detail the factors that affect tactile perception. In this chapter, we build on the results of the data collection user study described in the previous chapter. We propose a graph representation of tactile shapes, and a clustering algorithm to form clusters of good tactile shapes. This chapter describes the graph models generated based on the results of data collection user study, the choice of the clustering algorithm used to find tactile code clusters, the measures used to evaluate the effectiveness of the graphs, and the choice of graph representation for selecting tactile codes. The validation of the chosen graph representation is discussed in the next chapter.

5.1 Graph Representation of Tactile Codes

We represented the tactile shapes as nodes and the relationship between them as edges in a undirected graph. In order to construct a graph with 512 nodes, we need a incidence matrix of size $511 * 511$. Since differentiating shape i from shape j is the same as differentiating shape j from shape i, the edges of the graph are symmetric and undirected. So to construct a graph with 511 shapes, we require $511 * 256$ incidence matrix. The data collection study was performed with eight users. From each response provided by a user, we can determine the relationship between one tactile code and four other tactile codes. Each tactile code was presented four times to a user. Thus, for each tactile code in the code space, the data collection study yielded a relationship between that code and $8 * 4 * 4 = 128$ other codes in the graph. The study yielded eight response time (RT) matrices and eight perception error matrices (E). To combine the partial incidence matrix from eight users to create a final incidence matrix, we have used the approach proposed by Ternes [91].

Ternes approach calculates a final incidence matrix of perceptual difference from partial incidence matrices of six users by finding the average of the edge weights from six incidence matrices. We have used the same approach to calculate the average response time to distinguish two shapes and the average number of perception errors between two shapes.

In a undirected graph, the relationship between tactile shapes was represented by the weight of the edge connecting the nodes. The weight of the edges can be represented in one of the following three methods:

1. Error matrix (E) - The number of errors in distinguishing the shapes(nodes) connected by an edge

2. Response time matrix (RT) - The time taken to distinguish shapes(nodes) connected by an edge

3. Error + Response time matrix (E + RT) - The combination of the number of errors and the time taken to distinguish the shapes(nodes) connected by an edge

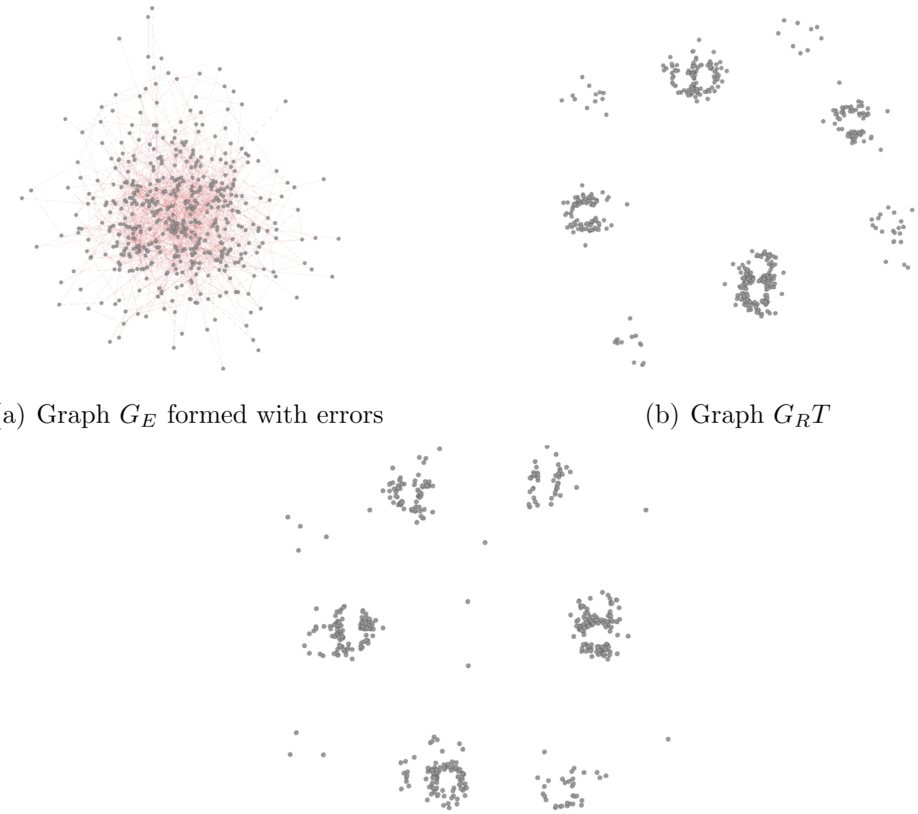
Given the graph representation of tactile codes, our goal of finding a good tactile code is defined as finding a cluster of nodes in the graph that minimizes the number of high weight edges and maxmizes the low weight edges between nodes. We use the spring-electrical technique to represent the edge weights as repulsive force between nodes and Hu's fast force approximation algorithm [32] to perform clustering. The spring-electrical model is proven to work well for sparse incidence matrices and scales better than other models for large graphs [32].

We created two separate graphs G_E and G_RT. Graph G_E was formed with an error incidence matrix (E). Applying Hu's algorithm on the graph resulted in figure 5.1(a). The output clusters the shapes that were distinguished without errors. The clustering algorithm was evaluated based on four parameters: network diameter, modularity, average clustering coefficient, and average path length. Table 5.1 shows the values of four parameters used to evaluate the three graph models. The network diameter (8), average path length (3.811) and Modularity (0.393) of G_E were high, and the average clustering coefficient (0.013) was low, showing that the error data alone did not suffice in creating a good cluster of shapes.

G_RT was formed with a response time incidence matrix (RT). Figure 5.1(b) shows the output of Hu's algorithm on G_RT. The algorithm clustered the shapes that were easily distinguished. The time taken to distinguish two shapes within a cluster is much smaller than the time taken to distinguish two shapes from two different clusters. The resulting graph had a low network diameter (2), average path length (1.772), and modularity (0.084) were low, and the average clustering coefficient (0.227) was high, showing that G_RT formed clusters of shapes. The disadvantage of using clustering on G_RT is that it does not take into account the errors in perceiving the difference between two shapes. The shapes that are hard to distinguish can also be easily mistaken for each other. Such shapes will have low response time and will fall in the same cluster.

Table 5.1: Network Diameter, Modularity, Average Clustering Coefficient and Average Path Length of the Graph Models.

Cluster Type	**Network Diameter**	**Modularity**	**Average Clustering Coefficient**	**Average Path Length**
Error	8	0.393	0.013	3.811
Time Taken	2	0.084	0.227	1.772
Time Taken + Error	2	0.201	0.23	1.769



(a) Graph G_E formed with errors

(b) Graph G_RT

(c) Graph G_C

Figure 5.1: Figures show the visualization of three graph G_E, G_RT and G_C formed with the error matrix (E), the response time matrix (RT), and the combination of the error matrix and the response time matrix (E + RT) respectively. The figures also illustrates the visualization of the graphs after the application of Hu's fast force algorithm.

We used a linear combination of the average response time by users to distinguish the tactile codes and the number of errors committed by users while distinguishing the codes to form graph G_C. For any pair of tactile codes i and j in the code space, the weight *W(i,j) or W(j,i)* of the edge between the nodes is given by the following equation:

$$W(i,j) = RT(i,j) + E(i,j) * C \tag{5.1}$$

RT(i,j) is the average response time taken by users to distinguish i and j during the user study, *E(i,j)* is the number of errors committed by users while distinguishing the codes, and C is a constant value equal to 100s. The weight of an edge is the time taken to distinguish codes i and j. Each error committed adds a 200ms response time to the edge weight. This equation is chosen to guarantee the following two properties:

1. If two tactile codes i and j are easy to distinguish, the value of *W(i,j)* is small due to one or both of the following reasons. The users take less time to distinguish i from j and/or commit no errors in distinguishing i and j.

2. If two tactile codes i and j are hard to distinguish, the value of *W(i,j)* is large because users take more time to distinguish i from j and/or commit more than one error in distinguishing i and j. The penalty (C) of 100 seconds guarantees *W(i,j)* is a large value when there is more than one error to distinguish i and j.

Equation 1 defines the relationship between the weight of each node in the graph, the average response time, and the average perception error. The output of the clustering algorithm is presented in the figure 5.1(c). The output combined the positives from graphs G_E and G_RT. It had a low network diameter(2), low modularity(0.201), low average path length(0.23), high average clustering coefficient(1.769), and also included the error information in clustering the shapes.

Based on the graph network measures—network diameter, modularity, average path length, and average clustering coefficient—we choose graph G_C over graphs G_E and G_RT. As discussed earlier in this chapter, G_C combines the information represented by both G_E and G_RT. In the next chapter, we discuss the validation of the model by selecting tactile codes from G_C clusters and assessing the perception rate and accuracy. Figure 5.2 shows a method of selecting tactile codes from G_C clusters. Each cluster represents shapes that are dissimilar and distinguishable from each other. The tactile codes selected from one cluster of the model represent easy to distinguish codes. We have selected ten shapes from one cluster to validate the output of the model in validation user studies. The ten shapes are highlighted as green nodes in figure 5.2.

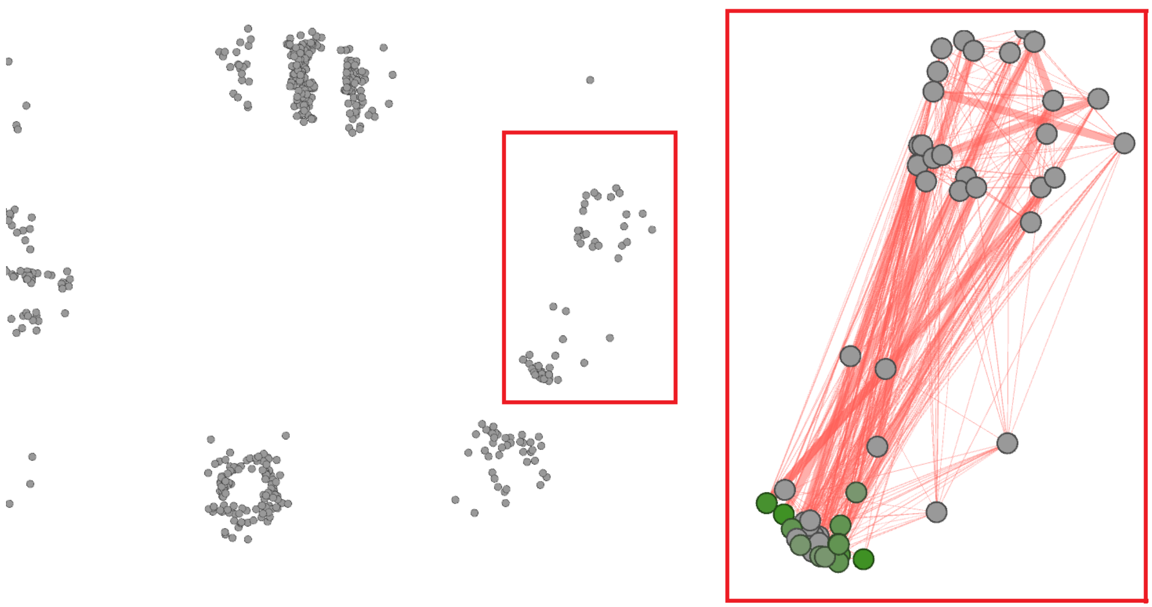


Figure 5.2: The graph shows the output of the clustering algorithm. Each node in the graph is one of the 512 shapes that can be presented with three-by-three tactile display. An edge between two shapes is weighted by the dissimilarity between the shapes. The weight *(i,j)* for an edge between node i and node j is calculated using equation 1. The red box on the right is zoomed in view of two clusters inside the red box on the left. The thickness of the edges correspond to the edge weight. The green nodes are marked to show the tactile codes selected for evaluation. The nodes that are closer to each other represent shapes that are easy to distinguish from each other.

6. EVALUATING GRAPH MODEL FOR SELECTING TACTILE CODES

We have thus far seen the factors affecting tactile perception, graph model to represent tactile shapes, a clustering algorithm to form tactile shape clusters and a method to select tactile shapes for interfaces. In this chapter, we discuss the user studies conducted to validate the model to choose tactile shapes. The design of the validation user studies is in line with the motivation for conducting this research, that is to develop semantic tactile codes for communication between Soldiers. The most common form of communication between Soldiers is imperative sentences [94]. In this chapter, we describe the following components as part of the graph model validation:

1. Syntactic representation of verb phrases in the English language.
2. Mapping components of a verb phrase to two dimensions of a tactile code.
3. A ringtone scenario that uses the vocabulary of verb phrases to communicate incoming calls to users.
4. Two user studies to validate the graph model of selecting shapes and ability of users to identify verb phrases from tactile codes using the proposed ringtone scenario.

6.1 Representing Verb Phrases with Tactile Codes

According to Chomsky's Syntactic theory [12, 13], a simple verb phrase (VP) is comprised of an optional adverb (A) and a verb (V) followed by a subject (N). According to a study by Urban [94], there are two common forms of verb phrases used in the communication vocabulary of Soldiers:

$VP - V + N$ – This vocabulary contains phrases formed from a finite set of verbs and a finite set of subjects, the number of verbs being comparatively smaller than the number of subjects. Figure 6.1(b) shows examples of such verb phrases. We have proposed a method to represent verb phrase with two dimensions of tactile code. To encode these verb phrases in shapes and waveforms of tactile codes, the verbs in the vocabulary can be represented in the form of a waveform of the tactile code, and the subjects can be represented in the form of shapes of the tactile code.

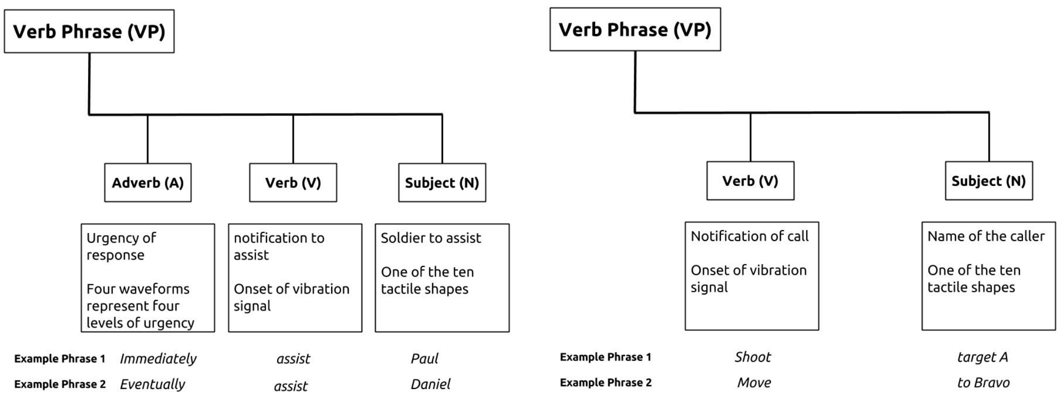
$VP - A + V + N$ – This vocabulary contains phrases formed from a finite set of adverbs, one verb and a finite set of subjects, and the number of adverbs being comparatively smaller than the number of subjects. *"Immediately assist Alpha unit"* is an example of a verb phrase used in communication [94]. To encode these verb phrases in shapes and waveforms of tactile codes, the verbs in the vocabulary can be represented in the form of a waveform of the tactile code and the subjects can be represented in the form of shapes of the tactile code. Figure 6.1(a) illustrates the syntax of verb phrase and the mapping of components of a verb phrase to tactile code dimensions.

We have designed two user studies to evaluate the following hypotheses

1. The recognizability of a set of shapes from the spring-electrical graph model is better than a set of shapes created from intuition *(E1)*.

2. The ability of the users to recognize the second dimension (waveform) of tactile code *(E2)*.

3. The ability of the users to form verb phrases from two dimensions of tactile code and acquire the information *(E3)*.



(a) Verb phrases comprising an adverb (A), a verb (V) and a subject (O). The vocabulary of such phrases contain a list of adverbs, a single verb and a number of subjects.

(b) Verb phrases comprising a verb (V) and a subject (O). The vocabulary of such phrases contain a list of verbs and a number of subjects.

Figure 6.1: Syntax and examples for the most common form of verb phrases used in communication between Soldiers [94].

4. The ability of the users to perceive information in tactile medium while performing visual tasks *(E4)*.

5. When performing two tasks simultaneously (visual task and haptic ringtone task), performing the visual task does not affect the performance of users in perceiving information from tactile medium *(E5)*.

6. When performing two tasks simultaneously (visual task and audio/haptic ringtone task), perceiving information from the tactile and audio medium equally affect the performance of users in visual task *(E6)*.

The first user study evaluated *E1, E2, & E3* — the recognizability of the shapes from the graph model, compared them against the recognizability of shapes from experimenters intuition, and determined if users can perceive information that is sent in the form of verb phrases in the form of shapes and waveforms of tactile codes. The second user study evaluated *E4, E5, & E6* — change in performance of users in individual task while performing the visual task and perceiving haptic/audio ringtones simultaneously.

6.2 Ability of Users to Recognize Verb Phrases from Tactile Codes

6.2.1 Procedure

We used a cellphone ringtone scenario in the first user study. The information represented by each haptic ringtone represents a verb phrase. Each haptic ringtone represented a call (verb) from a contact. A ringtone identified name of the caller (subject) and the priority (adverb) of the call. An example of the verb phrase represented by a haptic ringtone is *"Important call from Paul"* which can be translated to *"Immediately pick up call from Paul"*. The onset of tactile code represented the call event (verb), shape of tactile code represented the caller (subject) and the waveform of tactile code was the priority (adverb) of the incoming call. To test tactile codes as ringtones, the tactor array was attached to the rear side of a smartphone. This arrangement helped the users perceive the tactile codes while holding the phone. Figure 6.2 shows the tactor array attached to the rear side of an Android smartphone. We created an application that simulates incoming calls. The users were notified of the incoming calls by presenting a tactile code on Tactor I. The time between two incoming calls was controlled by the experimenter and the caller and the priority of the call was randomly generated by the application.

The users were asked to perform the experiment twice. In the first iteration, ten contacts were chosen from his/her existing contact list. Each of the ten contacts were assigned a tactile code selected from the proposed model (Figure 6.3) which remained constant throughout the experiment. The selected codes are highlighed in Figure 5.2. Additionally, each call was randomly assigned a priority presented by one of the four rendering methods shown in Figure 4.1—constant [3], pulsed [44, 98], sketched [4] or

Figure 6.2: Tactor array attached to rear side of HTC Android phone.

pattern mask [14]. Users performed the study twice (with the order randomized and counter-balanced) such that the shapes in one experiment were those chosen from our graph model, and the shapes in the other experiment were chosen from intuition (Figure 6.4). Everytime a user received a call from one of the ten contacts, the tactile array displayed the shape assigned. The dependent variables measured during the experiment were the response time to identify the friend and the number of correct responses to tactile codes. The total number of tactile presentations to the user was 40 in each of the iterations. Each tactile shape (caller) was represented four times in one iteration. Each waveform (priority) was presented ten times in one iteration. We have assumed that the errors caused due to learning would equally affect both conditions of the user study.

Our hypothesis was that the users would commit fewer errors in identifying tactile shapes from the model than recognizing the tactile shapes selected by experimenter. The second hypothesis was that the users would take less time to recognize the tactile shapes from the model than to recognize codes selected by experimenter. The third hypothesis was that the users can determine with high levels of accuracy the priority of the call from the waveform used to present the tactile code and the fourth hypothesis was that the users can form verb phrases from the recognized tactile shape and waveform thereby identify caller name and priority of a call from tactile code.

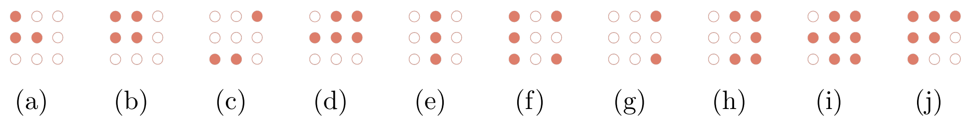


Figure 6.3: Ten tactile codes selected from the graph model. The selected codes are shown as green nodes in Figure 5.2.

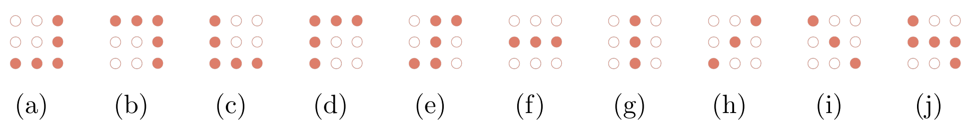


Figure 6.4: Ten shapes used in the evaluation. The ten shapes referred as experimenter's list is selected based on experimenter's intuition.

6.2.2 Results

Ten users participated in the user study—one female and nine male users and their ages were between 20 – 25. The number of correct responses was 31.5 ± 5 and the response time was 23.8 ± 14.7 seconds when the tactile shapes where chosen from the model. The number of correct responses was 29.3 ± 11 and the response time was 21.96 ± 13.11 seconds when the tactile shapes where chosen from the experimenter's list. Table 6.1 shows the mean response time and variation in response time to recognizing a tactile code and associating with a corresponding verb phrase.

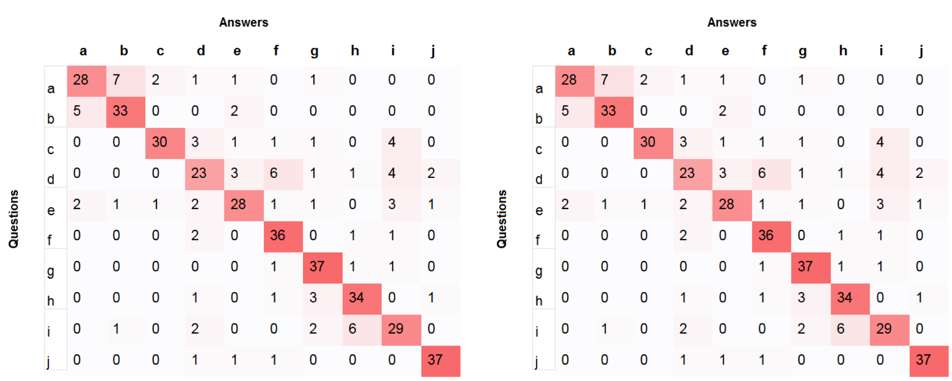
The users recognized the waveform of the code consistently. There were no mistakes in identifying the priority of the call. The users were able to recognize the waveforms (priority of the call) at each instance at 100% accuracy. Therefore, the response time and accuracy of recognizing the verb phrase from the tactile code is equal to response time and accuracy of recognizing the tactile shape (name of the caller). Table 6.1 shows the mean number of correct responses and the variation in the number of correct responses across the users. The variation in number of correct responses from users was less for tactile codes from the model when compared to that from the experimenter's intuition list. This was due to one user who was an outlier in the case of tactile code from the experimenter. The outlier user's responses were right 4 out of 40 instances. Our results do seem to show that the model is not only more accurate, but also more predictable in terms of a smaller standard deviation.

Table 6.1: Performance of users in identifying tactile code. M - Mean, SD - Standard Deviation.

Shape Set	**Response Time**		**Correct Responses**		**Errors**		**Accuracy (%)**	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Experimenter's List	21.97	14.01	28.22	11.27	11.78	11.27	70.56	28.17
Model	23.84	17.02	31.22	5.56	8.78	5.56	78.06	13.91

6.2.3 Discussion

We performed a student t-test to compare the number of correct responses for tactile codes from the model versus the tactile codes from the experimenter's list. The t-test — t(9) = -4.82, p = 0.68, $\alpha < 0.05$ — showed that the number of correct responses for codes from the model is not significantly greater than the number of correct responses for codes from the model. The F test showed that difference between the variance for the number of responses were not significant either — $F(1,19) = 3.2072, p = 0.63$. The data did not support our first hypothesis (*E1*) that the users would perform less errors in recognizing tactile codes from our model when compared to the codes from the experimenter's list. Figure 6.5 shows the confusion matrices generated from user responses for graph model shapes and experimenter's list of shapes. The confusion matrix for graph model shapes (figure 6.5(a)) shows that shapes a & b can be due to confusion in discriminating them. This proves there is a possibility of two shapes from a cluster of graph model can be confused with each other. The average accuracy for graph model shapes was 78% with users who are not expert in perceiving tactile shapes. The accuracy result is comparable to result from previous study by [56] conducted with ten expert braille readers on 26 braille shapes that yielded 82% accuracy.



(a) Response confusion matrix for shapes from graph model. a - j maps to shapes in figure 6.3

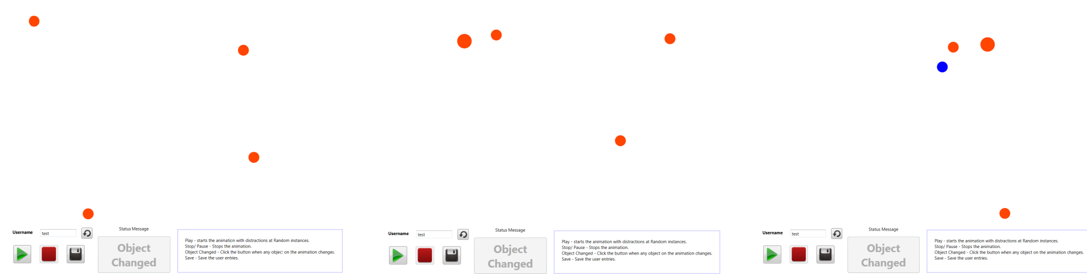
(b) Response confusion matrix for shapes from experimenter's list. a - j maps to shapes in figure 6.4

Figure 6.5: Confusion matrices of responses generated for the ten shapes from graph model and experimenter's list.

We also performed a student t-test to compare the response time for recognizing tactile codes. The t-test — t(9) = 1.79, p = 0.03, $\alpha < 0.05$ — that the response time for codes from the model is greater than the response time for codes from the experimenter's list. The F test — $F(1, 19) = 3.24, p = 0.07$ — showed that there is a significant difference between the variance for the response time. Based on the analysis, the average time taken to recognize codes from our model is greater than the average time taken to recognize codes from experimenter's list. Since there was no significant differences in number of correct responses from users for the two conditions, we concluded that the higher response time for model shapes did not directly reflect as higher number of correct responses for model shapes. Both recognition time and number of correct responses did not support our hypothesis that model shapes are more usable than experimenter's list. Analyzing the variations in number of correct responses showed that using model shapes would reduce the variations in responses from users and prime consistent recognition results than the shapes from experimenter's list. The ability of users to recognize waveforms consistently without any errors proves the second hypothesis (*E2*). Overall, the users could recognize verb phrases with an average accuracy of 83% which supports our third hypothesis (*E3*) that users can perceive verb phrases from tactile codes.

6.3 Comparing Tactile Code with Auditory Code

The second user study was designed primarily to understand performance of users in perceiving information in tactile medium while performing a visual task. Tactile interfaces are commonly used in situations where users are multi-tasking, also called dual-task scenarios. Dual task scenarios involve the users performing two tasks simultaneously—one primary task and one secondary task. In this user study, the visual task involved tracking changes in four circular objects moving at the rate of 3 pixels per second. The changes in circular objects could be change in diameter of the object or change in color of the object. The diameter changed between 10 pixels to 20 pixels. The color of the object changed between reddish orange and blue. No two objects changed simultaneously at any instant of time and no two object change both color and size at any instant of time. The changes in size and color of objects are shown in the Figure 6.6. The application primes the users to respond when there is a change in any object. The application keeps log of the changes noticed, changes missed and changes that have been falsely noted by the users.



(a) Initial state of four objects in visual task

(b) Change in size of the object from 10 to 20 pixel diameter. The diameter of the object highlighted with a square has increased from 10 pixels to 20 pixels.

(c) Change in color of the object from reddish orange to blue. The color of the object highlighted with a square has changed from orangish red to blue.

Figure 6.6: Illustration of the visual task used in the user study II.

6.3.1 Procedure

The secondary task in this user study is identifying caller name from either haptic or audio ringtone. The second user study was performed in four steps

1. The experimenter introduced the visual task to the user. The user was given ample time to train and familiarize herself with the visual task.

2. *Visual* – The users were asked to perform the primary visual task for two minutes. We use the results of this task as the baseline performance of users, and use it to understand the change in performance when performing the same visual task with haptic or audio ringtones.

3. *Visual + Haptic* – The users were then asked to map ten contacts to tactile shapes from the model. The users were given ample time to remember the mapping between a tactile shape and the corresponding contact. The users were then asked to perform the visual task while simultaneously recognizing tactile ringtone. An application simulated incoming call with tactile ringtones. The users were asked to perform both visual task and identify the caller from the tactile shape.

4. *Visual + Audio* – The users were then asked to map ten contacts to preloaded audio ringtones in an Android phone. The users were given time to train themselves listening to audio ringtones and remember the mapping between the ringtone and the corresponding contact. The users were then asked to perform the visual task while listening to audio ringtones. An application simulated incoming call with audio ringtones.

The steps 3 & 4 were shuffled in order to counterbalance the effects of learning. The independent variables in the user study are the change in color or size of the object in the visual task, and the type of tactile shapes used for haptic ringtone. The dependent variables are the precision, recall and time taken to note the change in objects, the accuracy of recognizing the caller and time taken to recognize the caller. According to Multiple Resource Theory by Wickens [105, 106] and human factors in tactile user interfaces by Van Erp [78], the use of audio/tactile medium of communication in secondary task breaks the attention fixation in primary task. In our dual task scenario, the visual task was primary task, and recognizing ringtones was the secondary task. The break of attention fixation in the primary task will reduce the performance of users in the primary task, and the secondary task performance will not be affected. The first hypothesis was that there will be a drop in the performance of users in the visual task while simultaneously recognizing haptic/audio ringtones, but there would be no significant difference between the drop in the performance of users in tracking objects while recognizing haptic ringtones and tracking objects while recognizing audio ringtones (*E5*). The second hypothesis was that the users performance in recognizing caller from a tactile medium did not change significantly.

6.3.2 Results

Nine users participated in the user study—all of them were male users, and their ages were between 20 – 25. The performance of users was measured in the primary visual task and the secondary ringtone task. Accuracy, precision, recall, and the reaction time of tracking objects in visual task were calculated. The results of the performance of the users in three steps (*Visual, Visual + Audio, and Visual + Haptic*) of the user study are listed in table C.5 (attached in Appendix). The table shows the mean and standard deviation of measures calculated from the user study data. From the calculated measures, we calculated the change in the performance of users in the visual task when performing the secondary ringtone task simultaneously. The change was calculated by subtracting the user performance in tracking objects with secondary task from the user performance in tracking objects without any secondary task. Table 6.2 lists the mean and standard deviation of the change in user performance in tracking objects and Figure 6.7 shows the box plot of the change in performance measures.

We measured the accuracy and response time of users in recognizing the caller

Table 6.2: The change in user performance in performing visual task while performing the ringtone recognition task simultaneously. M - Mean, SD - Standard Deviation.

Task	**Visual + Audio**		**Visual + Haptic**	
	M	**SD**	**M**	**SD**
Change in Accuracy	0.107884	0.14316	0.246892	0.075925
Change in Precision	0.029827	0.054859	0.041121	0.060991
Change in Recall	0.093997	0.130393	0.231801	0.072258
Change in Reaction Time	0.247192	0.224203	0.360033	0.238421

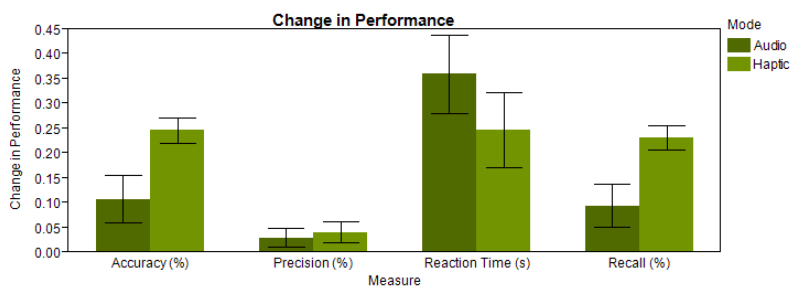


Figure 6.7: A plot showing the change in users performance of visual task while simultaneously performing the ringtone perception task. The mean and standard deviation of change in accuracy, precision, recall, and reaction time for visual task.

from haptic and audio ringtones. We have used the data to compare user performance in recognizing haptic or audio ringtones while performing a visual task. In order to evaluate the effect of performing a visual task on the perception of tactile codes, the accuracy and the response time of users to recognize haptic ringtones from User Study I was compared against the accuracy and the user response time to recognize haptic ringtones while performing a visual task. Table 6.3 lists the number of correct responses, errors, accuracy, and time taken to recognize audio ringtones (User Study II) and haptic ringtones (User Study I & II).

Table 6.3: The performance is measured in terms of response time (mean and standard deviation), number of correct responses, and the accuracy of the responses. The table reports the measurements for *Visual + Audio* task in User Study II, *Visual + Haptic* task in User Study II and *Haptic* task in User Study I. M - Mean, SD - Standard Deviation.

Task	**Response Time**		**Correct Responses**		**Errors**		**Accuracy**	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Visual + Audio	6.83	5.25	33.56	7.02	6.44	7.02	83.89	17.55
Visual + Haptic	10.67	8.60	29.67	8.08	10.33	8.08	74.17	20.19
Haptic	23.85	0.71	31.22	5.56	8.78	2.31	78.06	13.91

6.3.3 Discussion

The drop in user performance in *Visual + Haptic* task and *Visual + Audio* task were compared using Wilcoxon signed rank sum test. The comparison showed that the drop in accuracy ($Z(8) = 1.85$, $p = 0.06$) and recall ($Z(8) = 2.11$, $p = 0.03$) of users in the visual task was significantly greater when they performed the *Visual + Haptic* task than when they performed the *Visual + Audio* task but the drop in precision ($Z(8) = 0.72$, $p = 0.46$) was not significantly different. Increase in number of false negatives decreased the accuracy and recall but not the precision, that is, the number of object changes missed by users were higher when they were recognizing haptic ringtones than when they were recognizing audio ringtones.

Increase in reaction time for users doing the *Visual + Haptic* task was higher when compared to that for *Visual + Audio* task. The higher increase in reaction time could not be proved conclusively with the Wilcoxon signed rank sum test ($Z(8) = 1.05$, $p = 0.29$). The time taken by users in recognizing the ringtone is the amount of time where the users share their mental processing resources across two tasks - the visual task and the recognition task. The sharing of mental processing resources increases the reaction time of users in the primary visual task. The results (Z(8) = 9.25, $p < 0.0001$) from the user study showed that users require more time to recognize haptic ringtones as compared to time required to recognize audio ringtones. The familiarity of users with the audio channel, and their unfamiliarity with perceiving information from haptic codes is the reason behind the difference in performance. The higher time taken to recognize haptic ringtones than to recognize audio ringtones meant that the users shared mental processing resources longer when recognizing haptic ringtones than when recognizing audio ringtones. The greater mental resource sharing increased the reaction time of the visual task in the case of the *Visual + Haptic* task than for the *Visual + Audio* task. The data did not support hypothesis (*E5*). The performance of users in visual task dropped more when the users performed the *Visual + Haptic* task than when the users performed the *Visual + Audio* task.

We compared the recognition accuracy and the time taken to recognize haptic ringtones in *Visual + Haptic* task and *Haptic* task with Wilcoxon Rank Sum test. We found that there was no significant difference in accuracy or response time. The data supports our hypothesis *E6* that being involved in the visual task does not affect users haptic signal recognition. A haptic ringtone in the middle of the visual task causes the users to switch focus from the visual task to recognizing the haptic signal. While recognizing the haptic signal, the users reduce their mental processing resources applied to visual task and divert them to recognize the haptic signal. The shift in mental processing resources causes a drop in performance of the users in the visual task and the haptic signal perception is unaffected.

7. HAPTIGO DESIGN AND IMPLEMENTATION

The second part of this dissertation is the development of a haptic vest for pedestrian navigation. We have developed HaptiGo, a haptic vest designed to help pedestrians navigate and avoid obstacles in their path. The motivation behind the design of this system is to provide users with higher awareness of their surroundings in situations where they are under high cognitive load. In designing HaptiGo, we were inspired particularly by two human behavioral cues: the tendency to turn in the direction of where our shoulder is tapped (e.g., to gain someone's attention), and the tendency to halt when pushed back (e.g., to prevent an inattentive person from colliding into something). We adapted the former for navigational guidance and the latter for obstacle detection.

7.1 Navigational Guidance

We implemented tactile feedback on the HaptiGo vest's upper back area for navigational guidance based on the outcome of our pilot study: (1) the back area is effective in communicating navigational cues and (2) participants intuitively turn in the direction of where they feel the tactile feedback without any directional instruction. Figure 7.1 shows a schematic diagram of the vest's components. We used four vibrational tactors in a rectangular pattern from the LilyPad's Vibe Boards as tactile feedback for conveying the navigational information: one each for the vest's left and right rear shoulder, which indicated left and right turns respectively; and two located equidistantly from the vest's rear center, which indicated forward movement. We chose to use two tactors for forward movement to bolster the tactile feedback based on an observation that participants could not reliably perceive tactile feedback from a single tactor placed on the vest's rear back due to the gap between the vest's rear back and the natural curve of users' backs from their spine. The location of tactors on the shoulder provide direct mapping for two primary turn directions—left and right. The left and right shoulder signals are mapped to the left and right directions respectively. This is called *Co-location of Cue and Target*. Ho, et al. [31] showed that co-location decreases number of direction cueing errors committed by users. The pilot study conducted by Boxer, et al. [6] reveals that conveying tactile signals to the upper back of a user's body is effective in communicating navigational cues. The participants in our study intuitively turned in the direction of where they felt the tactile feedback without any directional instruction, and described the interaction as responding to a "shoulder tap" [6]. Figure 7.2 illustrates the position of the tactors on the torso's rear side on the vest, which also features an adjustable waist strap to ensure a proper fit between the tactors and user's torso.

There are three components in the HaptiGo—an Android smartphone, a bluetooth communication module and an Arduino microcontroller. For our system, a Nexus One Android smartphone provided location updates via GPS, measured the user's alignment via a magnetometer, and handled calculations of the directional cues.;a BlueSmirf Bluetooth communication module provided directional cues from the smartphone to the microcontroller; and a LilyPad Arduino microcontroller activated the vibrational tactors for directional cues and provided a low-cost and lightweight solution for sending signals into conductive threads.

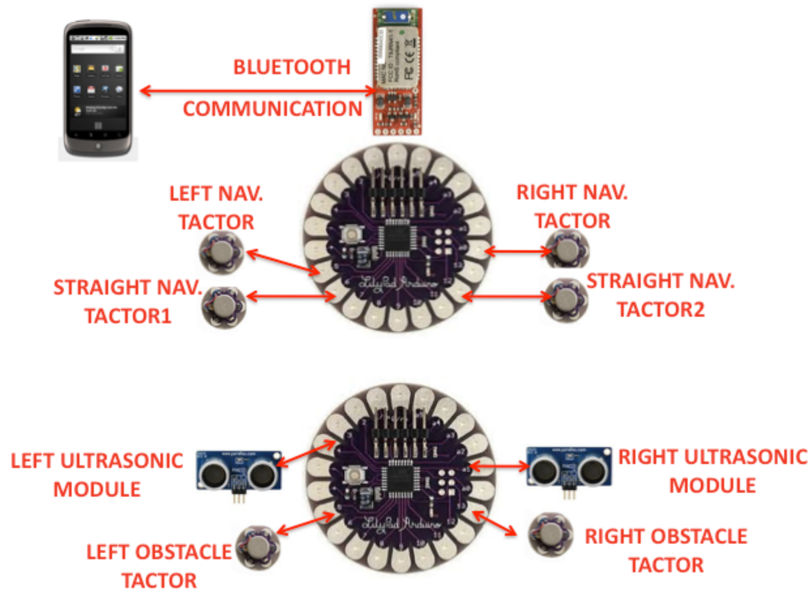


Figure 7.1: Schematic diagram of the components used in HaptiGo.

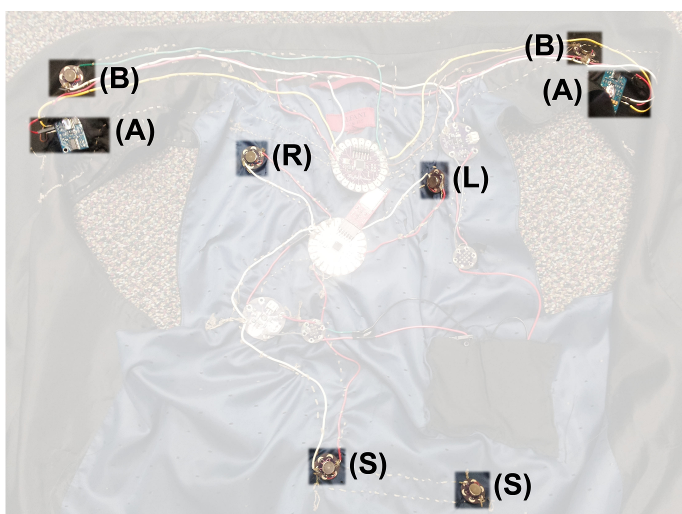


Figure 7.2: Rear inside view of HaptiGo vest: (A) obstacle sensors, (B) obstacle tactors, (L) left navigation tactor, (R) right navigation tactor, (S) straight navigation tactor

We conducted a pilot study to test the functionality of our system, evaluate/test the most responsive regions of the wearer's body to place tactors and to evaluate which haptic cues users found the most intuitive for both the navigation and obstacle functionalities of the system. This study was conducted with four users (three male, one female). Their feedback was used to design the haptic cues and tactor positions described in the implementation section. From participant responses in our initial user study, we encoded haptic cues as three distinct and consecutive vibrations pulsed 0.5 seconds apart, and conveyed turns to users through locations of the vibrating tactors (e.g., a vibrating tactor on the left shoulder prompts the user to start turning left). We further discovered that continuous signals longer than 1.0 seconds on one shoulder were interpreted as cues "pushing" users towards the side of the other shoulder (e.g., the "pushed" signal on the right shoulder would cue the user to turn counterclockwise to the left), while pulsed vibrational signals of no greater than 0.7 seconds on one shoulder were interpreted as cues "tapping" users towards the side of the same shoulder (e.g., the "tapped" signal on the right shoulder would cue the user to turn clockwise to the right). We used pulsed vibrational signals to improve user's reaction times in differentiating between shorter burst (e.g., 0.5 second intervals) and longer continuous (e.g., 1.5 second intervals) pulses, and to also better conserve battery power.

7.2 Obstacle Avoidance

Another feature of the HaptiGo is its capability to alert users of approaching obstacles within their immediate vicinity by employing two Parallax ultrasonic ping sensors. These sensors are placed just above the participants' chest area, one on the left and one on the right. These emit short 40 kHz ultrasonic signals, in order to receive distance measurements within a range of 2 cm to 5 m. Two vibrational tactors are placed below the ping sensors in order to alert users of approaching obstacles on the left and right sides respectively. The placement of these tactors is such that it ensures that users give higher priority to the obstacle avoidance feedback should it conflict with the navigational guidance feedback (i.e., users should avoid approaching obstacles before continuing with the received directions). Earlier iterations of HaptiGo placed obstacle tactors on the waist above the hips, but female participants expressed discomfort with tactors placed at that location.

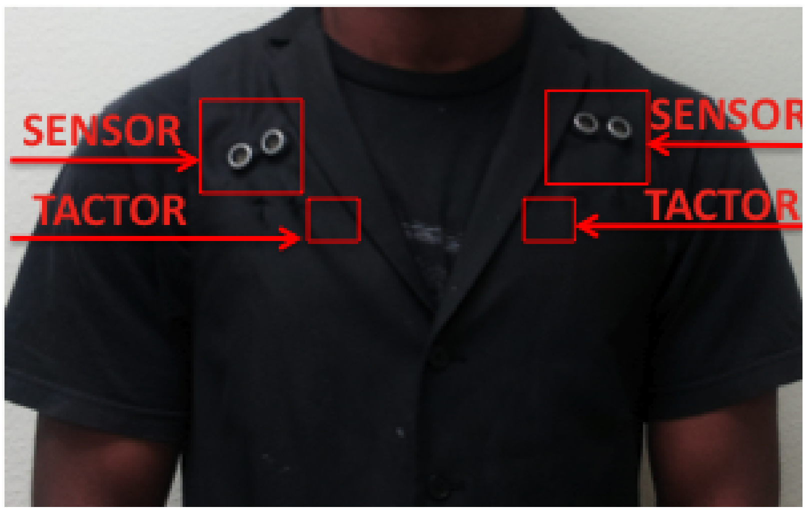


Figure 7.3: Front view of user wearing HaptiGo vest.

We used an additional LilyPad to read input from the ping sensors and relay the information to the user. The LilyPad activates either of the two obstacle tactors to signal the participants of obstacles. For example, if there is an approaching obstacle to the right of the participant, the right obstacle tactor will pulse. We encoded the obstacle haptic cue as a single vibrational pulse lasting 1.5 seconds based on participant feedback from our pilot study, and observed that participants successfully responded to long, continuous vibrational signals lasting over one second.

This feedback encouraged participants to shift directions in order to stop the stimuli, which was well-suited to the design of obstacle avoidance in HaptiGo. Figure 7.3 illustrates the position of the sensors and tactors on the user's frontal torso.

8. HAPTIGO USER EVALUATIONS

We evaluated HaptiGo with two user studies. This chapter provides a detailed description of the studies' design, the motivation behind them, and their results. The first study compares HaptiGo's navigational capabilities as against the PocketNavigator [62]. The second study evaluates the effects of HaptiGo's obstacle avoidance functionality on users' navigation time. Each study consisted of different participants.

We evaluated the following hypothesis in the studies:

1. The time taken to complete a route by a subject using HaptiGo sans obstacle detection is no less than the time taken to complete the same route using PocketNavigator system (*h1*)

2. Users' cognitive load while using HaptiGo sans obstacle detection is less than users' cognitive load while using PocketNavigator(*h2*)

3. Using obstacle detection along with HaptiGo does not increase the time taken by a user to complete a route when compared to users' using HaptiGo sans obstacle detection (*h3*)

4. Using obstacle detection along with HaptiGo increases users' cognitive load when compared to users' cognitive load while using HaptiGo sans obstacle detection. (*h4*)

The first user study evaluated the hypotheses *h1 & h2* and the second user study evaluated hypotheses *h3 & h4*.

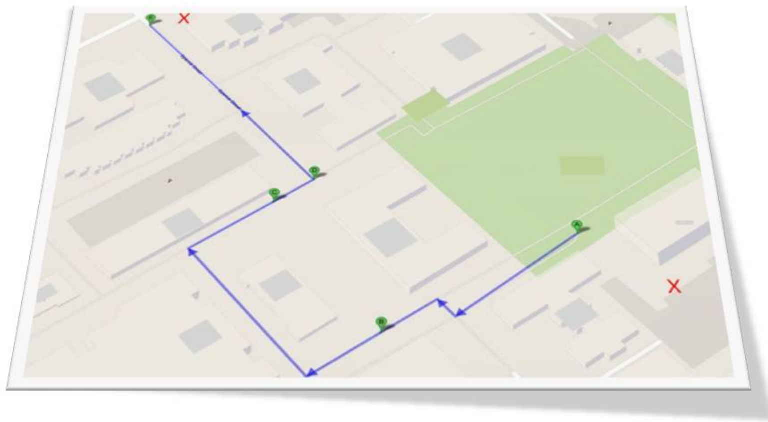


Figure 8.1: Routes taken by participants in user study.

8.1 HaptiGo versus PocketNavigator - Comparing Navigation Guidance

The PocketNavigator is an Android mobile app that uses a smartphone's built-in vibrational tactors to provide haptic cues for directions. In contrast to HaptiGo(described in previous chapter), PocketNavigator encodes its haptic cues as follows: forward direction, which consists of two short consecutive pulses; left turn, which consists of a single long pulse followed by a short pulse; right turn, which consists of a single short pulse followed by a long pulse; and U-turn, which consists of three consecutive short pulses.

8.1.1 Procedure

We began the studies by first surveying the participants on their demographic information and their familiarity of the location of the walking routes (Figure 8.1). We then surveyed them on their perceived sense of direction using the *Santa Barbara Sense of Direction Survey (SBSOD)* [29]. Lastly, we surveyed them on their familiarity of the Gyro mobile app [25], a pattern-based puzzle game where users rotate a color wheel to match approaching balls of the same color. After the initial surveys, we familiarized the participants with PocketNavigator and Gyro if they were not already so.

We selected the Gyro mobile app due to its high demands of user interaction and participation needed in order to successfully progress through the game. This app thus ensured the pedestrians needed to focus almost entirely on the game rather than on navigation. This design echoes the needs of the pedestrians in scenarios where navigation is a secondary task.

Participants were assigned one of the two navigation systems (PocketNavigator or HaptiGo sans obstacle detection) at random for the first round of the study. For the second round, they repeated the study with the second navigation system. Participants were instructed to follow the given navigation directions while playing Gyro. During the study, an experimenter accompanied the participants, first to ensure their safety, but also to answer any questions or concerns. The experimenter also recorded the participants' scores from Gyro and observed their behavior to emphasize the importance of a high score in the game and ensure its value as a distractor. The time taken for a user to complete a route during the study was automatically gathered from the smartphones assigned to the participants.

Following the study's navigation guidance activity, we surveyed each participant on the *NASA Task Load Index (NASA TLX)* in order to determine the total cognitive load imposed on them during the activity. We also surveyed each participant following the study for their feedback on the evaluated systems. We repeated the procedure for the participants on each evaluated system, albeit with different routes to ensure users could not predict where they were going. The independent variable of the study was the system selected for the first study's navigation guidance activity, while the control variables were the paths taken during the study. The dependent variables recorded during the study included the elapsed time required to complete the navigation guidance activity, subjective feedback from the participant on the usability of the evaluated system, and participants' cognitive load acquired from the NASA TLX survey administered after the activity.

8.1.2 Results

There were 12 participants in the study between the ages of 20-30 years. Participants reported a mean of 3.25 ± 1.88 for "sense of direction" on a Likert scale of 7, where 7 indicated great sense of direction; and a mean greater than 5 for good familiarity with mobile navigation apps on a Likert scale of 7, where 7 indicated great familiarity. Table D.1 lists the demography and familarity data collected from participants and Tables D.2, D.3, and D.4 list users' sense of direction data. The mean value calculated for PocketNavigator's cognitive load was 3.98 ± 1.14 out of a maximum score of 7, while the mean value calculated for HaptiGo was 3.52 ± 1.15 out of a maximum score of 7. Furthermore, the mean course completion time for PocketNavigator was 484.13 ± 253 seconds, while the mean course completion time for HaptiGo navigation system was 452.70 ± 183 seconds. Table D.7, Table D.6, and Table D.5 show course completion time, cognitive load, and usability data collected from each user respectively. Table 8.1 and Table 8.2 show the usability and the load data collected from the participants after user study respectively. The cognitive load and course completion time results for the navigational guidance activity are shown in Figure 8.2 and Figure 8.3.

Table 8.1: Usability rating for direction signals used in HaptiGo (H) and PocketNavigator (PN)

Direction Rating	**H**	**PN**	**F Test F(1,23)**	**T Test ($T > t$, $\alpha < 0.05$)**	**Wilcoxon Test (H)**	**Wilcoxon Test (PN)**
All Directions	5.83± 1.11	4.58± 1.56	0.0345	0.9828	188	112
Left	6.17± 0.94	4.25± 1.29	0.0004	0.9998	205	95
Right	6.17± 1.03	4.00± 1.28	0.0001	0.9999	208	92
Straight	5.17± 1.53	6.00± 1.48	0.1881	0.094	127	173

Table 8.2: NASA Tlx load data collected from participants in user study I. H - Haptigo and PN - PocketNavigator

Load Type	H	PN	F Test F(1,11)	T Test ($T > t$, $\alpha < 0.05$)	Wilcoxon Test (H)	Wilcoxon Test (PN)
Mental Demand	3.58± 1.00	5.00± 1.35	0.0078	0.0041	106.5	193.5
Physical Demand	2.58± 1.78	2.83± 1.40	0.7062	0.3532	139	161
Temporal Demand	2.67± 0.89	4.17± 1.53	0.0076	0.0044	108	192
Perfor-mance	6.00± 0.74	5.08± 1.38	0.0546	0.9708	178.5	121.5
Effort	3.08± 1.38	3.92± 1.31	0.1435	0.0718	124	175
Frustration	1.92± 1.44	2.83± 1.75	0.1754	0.088	121	179
Load Score	2.81± 0.81	3.99± 1.22	0.0103	0.0056	109.5	190.5

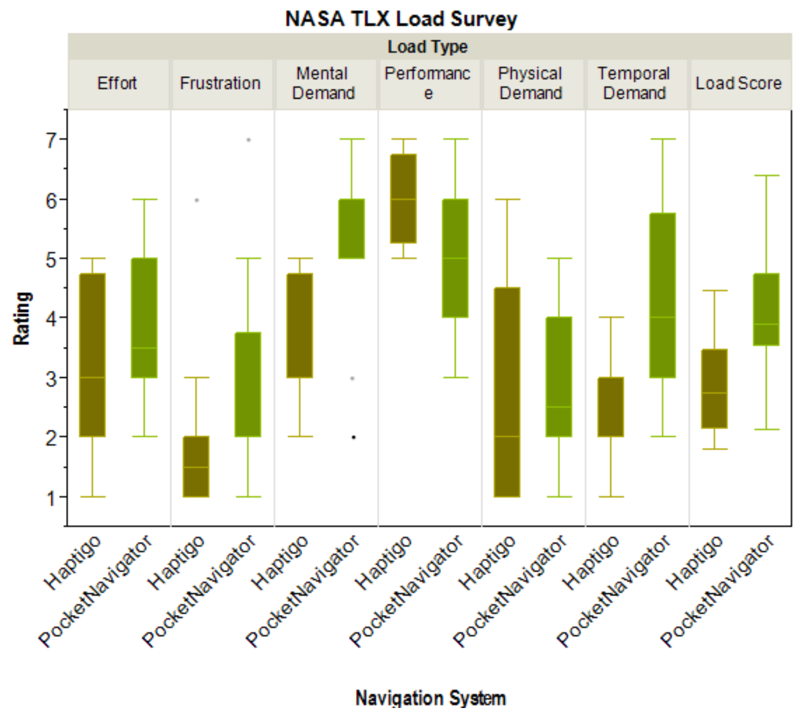


Figure 8.2: Comparison of NASA TLX indices for PocketNavigator and HaptiGo.

8.1.3 Discussion

The participants noted in the pilot study that the strength of HaptiGo's haptic cues for forward movement were weak and difficult to perceive. Additional testing showed that the original placement of the single vibrational tactor for forward movement did not firmly contact participants' bodies, due to the gap formed between the tactors' original placement on the vest and the region of participants' back where the spine dips inward. To address this, we revised the vest's design for forward movement by placing two vibrational tactors away from the back's dip. The number of tactors was increased to increase the tactile signal's strength. However, we discovered that participants found the tactile signals for forward movement in the revised vest design to still be weak, so we believe that the tactors' placement on the vest for this

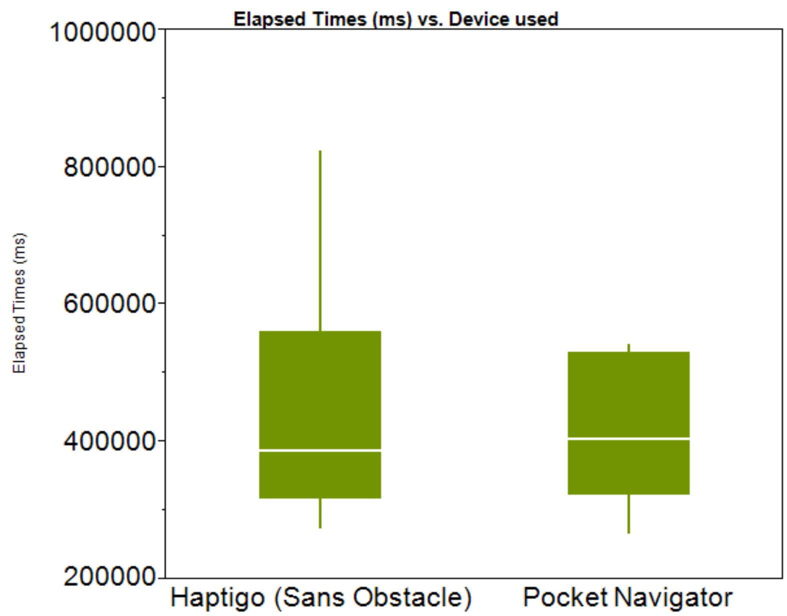


Figure 8.3: Comparison of course completion times for PocketNavigator and HaptiGo.

haptic cue still did not guarantee solid contact with a user's body, thus reducing their perceived strength of the signal. On the other hand, all the users in the pilot study were still able to successfully navigate the routes and perceive the navigational guidance and obstacle detection cues by relying on the stronger tactile signals from the left and right vibrational tactors.

We used a paired t-test to compare HaptiGo and PocketNavigator on course completion times, but it was inconclusive with t($\alpha < 0.05$) = 0.6343 for the hypothesis that the mean course completion time for HaptiGo was less than for PocketNavigator. We compared the variances in course completion time using F Test. The result of F Test – $F(1, 23) = 0.7311$ – showed that the completion times are not significantly different. The results did not support our hypothesis *h1* that HaptiGo users will be guided more efficiently than PocketNavigator. The differences in navigation system approaches used HaptiGo and PocketNavigator did not significantly affect the navigation time of pedestrians.

Comparisons of cognitive load (Table 8.2) and usability ratings (Table 8.1) for HaptiGo and PocketNavigator support hypothesis *h2*. The difference in the cognitive load is due to the type of tactile signals used by the system. Paired t-test on cognitive load showed that HaptiGo sans obstacle detection was able to navigate users to intended destinations with less cognitive load than PocketNavigator with $t(\alpha < 0.05) = 0.92$ and $F(1, 23) = 0.01$. Analyzing the load components showed that participants experience increased mental and temporal workload, and effort to use PocketNavigator than HaptiGo. HaptiGo tactile signals provide users an intuitive and direct mapping to turn direction while the PocketNavigator uses an encoding that is non intuitive. The difference in resources required to process tactile signals and map them to directions is reflected in the form of temporal load, mental load and effort. In case of usability of direction signals, users rated HaptiGo direction signals significantly higher than PocketNavigator signals. The straight signal in HaptiGo was reported the most unusable of the direction signals. The usability concerns raised by users were due to loss of contact between tactors for straight signals and center back of users. The physiology — ridge in the center back — of users makes it difficult for a generic placement of tactors that stays firmly in contact with users' back.

8.2 Evaluating the Effect of Obstacle Detection Feature on Users' Navigation Experience

We evaluated HaptiGo with obstacle detection both enabled and disabled to measure the obstacle detection performance using routes similar to those used in study one.

8.2.1 Procedure

We followed the procedure described in our previous HaptiGo study. We collected users' demographics information, familiarity of the location, sense of direction (SBSOD survey), and familiarity with Gyro mobile app. After the surveys, we familiarized the participants with Gyro if they were not already so. The Gyro app acted as a distractor for users while navigating. In order to further limit navigational awareness, we donned the participants with sunglasses, a hooded sweatshirt, and headphones in order to a simulate situational impairment that diminishes their auditory and visual perception of the environment. Furthermore, we conducted the study in evenings to decrease their visual perception of the environment. This environment was chosen to increase the requirement of users to maintain awareness and test the obstacle detection feature of HaptiGo.

Participants were assigned one of the two navigation systems (HaptiGo with obstacle detection or HaptiGo sans obstacle detection) at random for the first round of the study. For the second round, they repeated the study with the second navigation system. Participants were instructed to follow the given navigation directions while playing Gyro. During the study, an experimenter accompanied the participants to ensure safety and to answer any questions or concerns. The experimenter also recorded the participants' scores from Gyro and observed their behavior to emphasize the importance of a high score in the game and ensure its value as a distractor. The time taken for a user to complete a route during the study was automatically gathered from the smartphones assigned to the participants.

After each navigation activity, participants filled a *NASA Task Load Index (NASA TLX)* survey. We collected subjective feedback from the participants about the system used and then asked them to repeat the procedure on the second system on a different route. The independent variable of the study was the system selected for the first study's navigation guidance activity, while the control variables were the paths taken during the study. The dependent variables recorded during the study included the elapsed time required to complete the navigation guidance activity, subjective feedback from the participant on the usability of the evaluated system and participants' cognitive load acquired from the NASA TLX survey.

8.2.2 Results

Table 8.3: Usability ratings for direction signals used in HaptiGo with and without obstacle detection. H - HaptiGo and HO - HaptiGo with obstacle detection

Direction Rating	**H**	**HO**	**F Test F(1,11)**	**T Test** ($T > t$, $\alpha < 0.05$)	**Wilcoxon Test (H)**	**Wilcoxon Test (HO)**
All Directions	4.83± 1.72	4.67± 1.75	0.8713	0.5643	41	37
Left	6.50± 0.55	5.50± 2.26	0.3196	0.8417	43.5	34.5
Right	6.33± 0.52	5.50± 1.87	0.3177	0.8412	43	35
Straight	2.50± 1.05	3.00± 2.37	0.6463	0.3281	40	38
Obstacle Detection		5.33± 1.75				

There were six participants in this study between the ages of 20 – 30 years. Participants reported a mean of 3.75 ± 2.22 for "sense of direction" on a Likert scale of 7, where 7 indicated a great sense of direction; and a mean greater than

Table 8.4: NASA TLX load data collected from participants in user study II. H - HaptiGo and HO - HaptiGo with obstacle detection

Load Type	**H**	**HO**	**F Test F(1,11)**	**T Test ($T > t$, $\alpha < 0.05$)**	**Wilcoxon Test (H)**	**Wilcoxon Test (HO)**
Mental Demand	5.00± 1.14	5.00± 1.67	1	0.5	39	39
Physical Demand	3.00± 1.67	2.67± 1.37	0.7134	0.6432	40.5	37.5
Temporal Demand	4.00± 1.90	3.83± 1.72	0.8766	0.5617	40	38
Perfor-mance	5.17± 1.33	5.83± 0.98	0.3466	0.1733	34	44
Effort	5.67± 1.03	4.17± 1.47	0.0683	0.9659	50	28
Frustration	4.17± 1.72	3.67± 1.75	0.6288	0.6856	41.5	36.5
Load Score	4.37± 1.31	3.99± 1.23	0.618	0.691	43.5	34.5

5 for good familiarity with mobile navigation apps on a Likert scale of 7, where 7 indicated great familiarity. Table E.1 lists the demography and familiarity data collected from participants and Tables E.2, E.3, and E.4 list users' sense of direction data. All six participants successfully anticipated all the obstacles that we introduced in their paths when the obstacle sensors were enabled while they were playing Gyro. Our initial hypothesis for this study was that enabling the obstacle tactors in HaptiGo would increase cognitive load, but that it would not change the mean course completion time. The mean value calculated for HaptiGo's cognitive load with

obstacle detection disabled was 4.63 ± 1.10 out of a maximum score of 7, while the mean value calculated for HaptiGo's cognitive load with obstacle detection enabled was 5.01 ± 1.09 out of a maximum score of 7. The mean course completion time was 524 ± 275 seconds with obstacle detection disabled and 450 ± 101 seconds with obstacle detection enabled. Table E.7, Table E.6, and Table E.5 show course completion time, cognitive load, and usability data collected from each user. Table 8.3 and Table 8.4 show the usability and the load data collected from the participants after user study respectively. The cognitive load and course completion time results for the obstacle detection activity are shown in Figures 8.4 and 8.5 respectively.

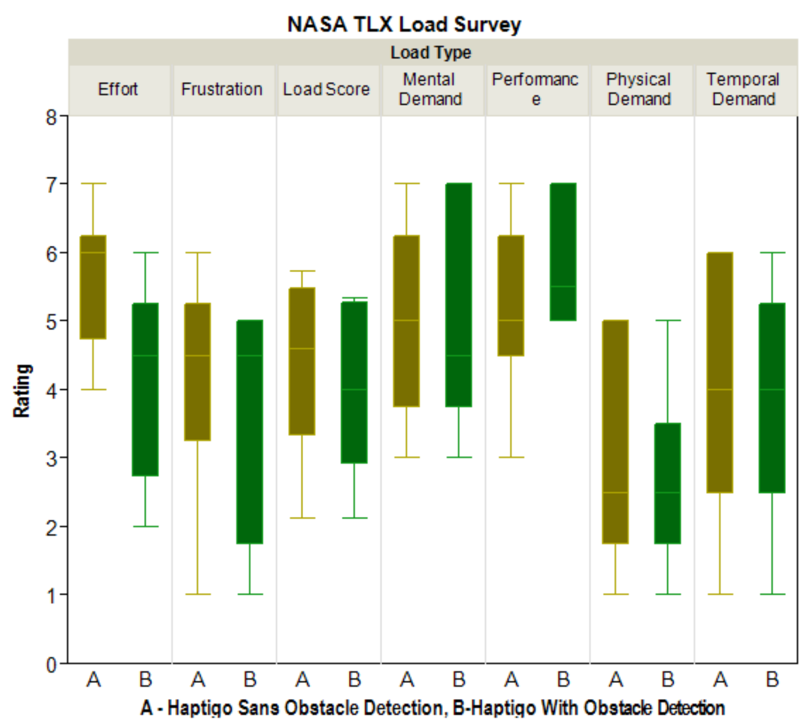


Figure 8.4: Comparison of NASA TLX indices for obstacle detection-enabled and -disabled HaptiGo.

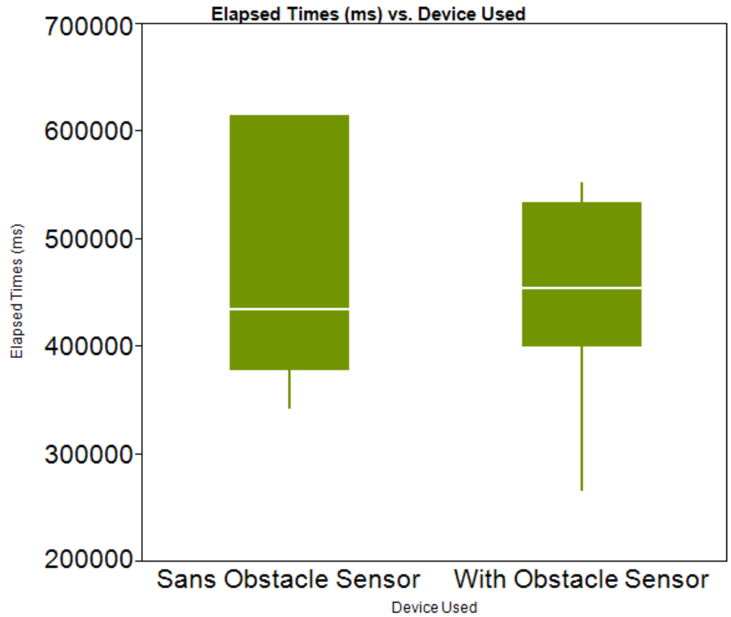


Figure 8.5: Comparison of course completion times for obstacle detection-enabled and -disabled HaptiGo.

8.2.3 Discussion

We observed that all users successfully anticipated approaching obstacles in their path. Users noted that when tactile feedback from the navigation guidance and obstacle detection were conveyed simultaneously, they found it difficult to determine the direction conveyed by the navigation tactors. To address this issue, users responded by first avoiding the obstacle and then waiting for subsequent navigational guidance. We anticipated this behavior for HaptiGo, since the system was designed to prioritize obstacle detection cues over navigational guidance cues. In other words, when there are simultaneous cues from both obstacle detection and navigational guidance, we designed the haptic cues so that users focus more on avoiding obstacles than on maintaining direction for those scenarios. Table 8.4 and Table 8.3 show a detailed comparison of cognitive load data and usability data for HaptiGo with and without obstacle detection repsectively. We conducted a Wilcoxon signed-rank test on the means obtained from the course completion time and cognitive load's non-normally distributed data. The Wilcoxon test confirmed our initial hypotheses that there is no significant difference in time taken by a user while using HaptiGo or HaptiGo sans obstacle detection (*h3*) and HaptiGo with obstacle detection functionality enabled caused significantly higher cognitive load for participants versus the same functionality disabled (*h4*). Analyzing the component load data shows that except for mental demand, other components are not significantly different. The mental load for users using HaptiGo with obstacle detection is higher than mental load for users using HaptiGo without obstacle detection.This is due to the fact that the users who require to process both direction signals and obstacle signals require more mental load when compared to users required to process just the direction signals.

8.3 Design Principles Learned

In this section, we have enumerated the design principles learned from the user studies with HaptiGo. These principles are applicable, in general, to develop any tactile vest that requires stimulating users' torso.

The first design principle that we learned was that duration of the tactor singals is a crucial factor in determining what direction a user turns. In our pilot studies, tactor signals with durations lasting longer than 1.0 second would evoke an analogous "push back" response and cause them to turn in the direction opposite to that of the source signal. However, tactor signals with durations lasting shorter than 0.8 seconds evoked an analogous "push forward" response and caused them to turn in the direction towards the source signal. We tested this with five users and found the same automatic response with all of them. In HaptiGo, short-duration signals were employed to convey navigation directions, while long-duration signals were employed to convey obstacle detection.

The second lesson that we learned was that gender plays an important consideration for optimal tactor placement. The first iteration of HaptiGo involved placing obstacle tactors right above the abdomen. While male participants were comfortable with this placement, female participants were less comfortable due to the sensitivity to the vibro-tactile feedback. We suspect that tactors placed just below the collarbone may be a better alternative since the location appears to be gender neutral.

The third lesson that we learned was that shared wearable systems integrated into form-fitting clothing are not appropriate. The first iteration of HaptiGo was designed as a compression shirt, in order to ensure that the tactor signals that participants received were apparent and perceptible, but we observed that participants were not comfortable sharing a common compression garment. Our redesign replaces the compression shirt with a vest harness with adjustable straps that is worn over users' clothing.

The fourth lesson that we learned was that a combination of conductive thread, electrical wire, and conductive fabric is one optimal approach for wearable interface fabrication. Our initial experiments with the LilyPad and conductive threads revealed that connections and wires consistently receiving signals (e.g., power/ground connections) quickly burned the conductive threads. In order to address this issue, we used a combination of conductive thread and electrical wire for control signals and power, respectively.

So far, we have discussed the design of Haptigo, its implemention, and evaluation. Next we will move onto the extension of HaptiGo—HaptiMoto, a haptic navigational system for motorcyclists.

9. HAPTIMOTO DESIGN AND IMPLEMENTATION

The third part of the dissertation is extending HaptiGo, a tactile vest for pedestrian navigation, to a vest for motorcyclist navigation. Motorcyclists are under high cognitive load while riding a motorcycle and are prone to fatal accidents. It is critical for motorcyclists to have their visual and auditory attention on the road. It is also critical for any navigation system design to not introduce any additional load on the visual or auditory medium. In this chapter, we discuss the design of a navigation system called HaptiMoto. HaptiMoto is designed for navigating motorcyclists and is an extension of HaptiGo. This chapter illustrates the differences in pedestrian and motorcyclist navigation guidance, the design of HaptiMoto navigation system, and the difference between HaptiGo and HaptiMoto.

HaptiMoto consists of a tactile vest and an Android application. The vest is adjustable to fit different user sizes (figure 9.1(a)). The vest is fitted with a LilyPad Arduino [82], BlueSmirf bluetooth module [81], and three LilyPad Vibe Boards (vibrational tactors) [83]. The three tactors are placed at back of left shoulder, back of right shoulder and center lower back (figure 9.1(a)). The Android application provides location updates (GPS), the alignment of the user, and a processing unit for calculating directional cues. Direction cues are communicated to the Arduino through the Bluesmirf bluetooth communication module. The Arduino activates vibrational tactors to provide directional cues and serves as the navigation system. The microcontroller platform is used in the implementation because of its cheap cost, lightweight nature, and its capability to be integrated into fabric with conductive thread. The schematic diagram of the vest is shown in figure 9.1(c).

We implemented tactile feedback on the HaptiMoto vest's upper back area for navigational guidance. Since the upper back area of motorcyclist is the least prone to vibrational disturbances. the motorcycle vibration and the air turbulance while riding are the most common sources of vibrational disturbances for riders. Arms, front of the body, hips and legs are the parts of the riders body which absorb the vibrational disturbances. Change blindness is higher for tactile stimulus when it is applied to these parts of riders body [24, 80].

(a) User wearing HaptiMoto vest (b) Location of Vibe-boards. (c) Schematic diagram

Figure 9.1: HaptiMoto. A - Lilypad Arduino, B - 9V Battery, BT - Bluesmirf, L, R, S - Vibe-boards

9.1 Selecting Directional Cues

The tactile signals for direction were presented to the user's back and shoulders (figure 9.1(b)). These location were selected as they have been found to be effective and intuitive regions to communicate navigation signals without directional training when walking [6]. Participants naturally turn in the same direction given a signal with no prior instruction, describing it akin to "a tap on the shoulder". The tactile signal on the shoulder is inspired from the human behavior to turn in the direction of where our shoulder is tapped (e.g., to gain someone's attention). The system was inspired by HaptiGo [6] and modified to meet the needs of motorcyclists.

There are four primary direction signals—left, right, straight and U-turn. The turn signals are defined as

Left turn signal is provided by activating the vibe-board on the left shoulder. This signal mimicks the tap on the shoulder and primes the user to turn in the direction of tap.

Right turn signal is provided by activating the vibe-board on the right shoulder. This signal also mimicks the tap on the shoulder and primes the user to turn in the direction of tap.

Straight turn signal is presented by activating the vibe-board on the lower back. This signal mimicks a gentle nudge on the lower back of the user and primes the user to go forward.

U-turn signal is presented by activating vibe-boards on both the shoulders. This signal provides a sense of pulling from the back by holding both shoulders of user. This signal primes the user to move backwards.

We modified the direction cue timing to suit motorcycle route guidance. The tactile signal dictionary (in figure 9.2) shows the possible number of pulses in each direction signal. The meaning for the number of pulses and the timing of the pulses are discussed further below in this chapter. The direction tactile cues (except U-turn which is continuous) are provided every three seconds or every 15m travelled. The results from pilot study conducted with HaptiGo showed that pulsed vibrational signals of no greater than 0.7 seconds on one shoulder were interpreted as cues "tapping" users towards the side of the same shoulder (e.g., the "tapped" signal on

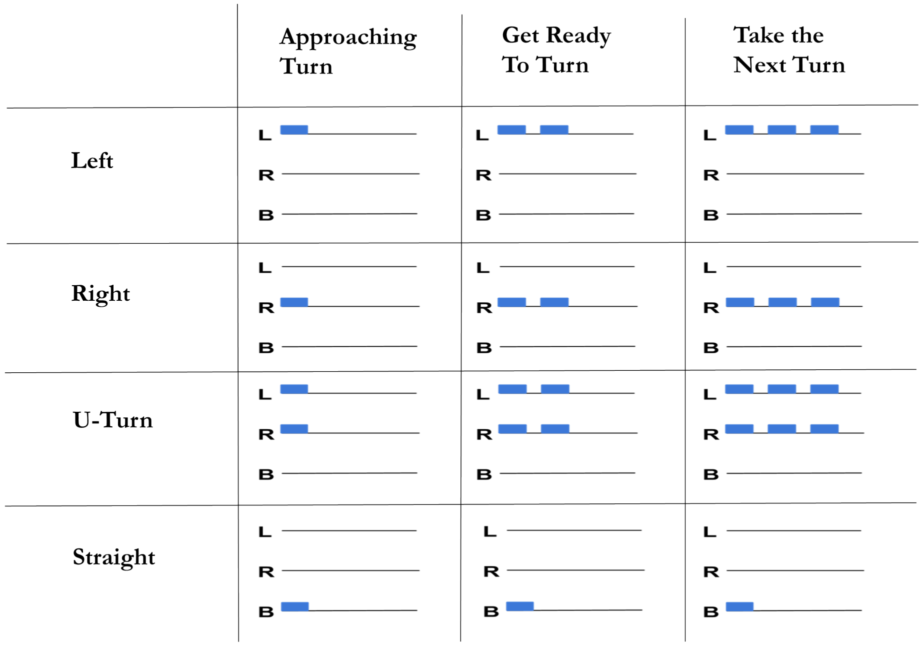


Figure 9.2: The dictionary of the tactile signals used in HaptiMoto.

the right shoulder would cue the user to turn clockwise to the right). In HaptiMoto, we have used directional pulses of duration 0.5 seconds to provide the sense of tapping on the shoulder.

9.2 Differences in Pedestrian Navigation Guidance and Motorcycle Navigation Guidance

Our work in HaptiMoto is an adaption of HaptiGo, a pedestrian navigation system. HaptiGo provides pedestrians navigation signals every five seconds based on the orientation of the user and the location of the user. The users are guided towards a waypoint in the route and the direction to the next waypoint is provided only after reaching the current waypoint. Initially, we applied the navigation guidance logic in HaptiGo for motorcycle navigation. Applying this logic to HaptiMoto, a motorcyclist received information about a turn only after reaching the turn. We conducted a pilot study with two users. The participants had to navigate through two turns using HaptiGo vest. This study provided us with insights about key differences between pedestrian navigation and motorcycle navigation.

Our evaluations show key differences between pedestrian navigation and motorcycle navigation:

1. Walking is slower and less attention is needed than while driving a motorcycle. So, the timing of directional signals presented to users is not as critical for pedestrians as motorcyclists.

2. The lead distance to convey directions for walking is smaller than the lead distance for riding a motorcycle due to higher traveling speed of motorcycles. In otherwords, motorcyclists should be warned about an approaching turn well before they reach the turn. The distance before which they should be warned of an approaching turn is called lead distance.

3. While walking, pedestrians can change orientation in any of the four directions. The motorcyclists are restricted by the orientation of the road while driving. So the orientation of the driver is not used to calculate the direction cue for the next turn.

9.3 Determining Lead Distance for Directional Cues

The number of pulses in a vibrotactile cue encode the distance to a turn. We accept that the rationale behind this is not explained in the paper well. Duration between pulses and number of pulses are dimension that are used to encode a sense of urgency or nearness to target [36, 96, 97]. We choose to increase the number of pulses from 1 – 3 as a rider approaches a turn keeping the duration between start of tactile signals (ISI) constant. As ISI is constant, the duration of OFF time between signal decreases as the number of pulses increase. Decrease in duration of OFF time and increase in number of pulses provide users a sense of nearness to target turn.

HaptiMoto uses the lead distance approach but must also take into account GPS delay. The direction of the approaching turn is encoded by the location of vibro-tactile stimulus and the distance to the approaching turn by the number of pulses. The tactile signals for turns are provided at 4X, 2X and X distances before the turn, where X is the ideal lead distance in meters proposed by Department of Transportation design guidelines [8]. When the vehicle is beyond 4X from location of the turn, the user is provided with a straight signal. When the vehicle is located between 4X and 2X, the user is provided with a single pulse on the shoulder every three seconds denoting the user of approaching turn. When the vehicle is between 2X and X, the user is provided with two pulses on the shoulder for every three seconds telling the user to get ready to make the turn. When the vehicle is within X distance from the turn, the user is provided with three pulses on the appropriate shoulder denoting the user to make the next possible turn.

1. Minimum lead distance *(in meters)* = (speed *(in m/s)* * 1.637) + 14.799
2. Ideal lead distance, X *(in meters)* = (speed *(in m/s)* * 1.1973) + 21.307
3. Maximum lead distance *(in meters)* = (speed *(in m/s)** 2.22) + 37.144

Figure 9.3 illustrates the timing of tactile signals while the user is driving. Each pulse of tactile signal is ON for a 300 ms duration. For more than one pulse in the tactile signal, the time between pulses is 150 ms.

Thus far, we have discussed the design of HaptiMoto navigation system—the choice of location and duration of tactile pulses to encode direction, the number of tactile pulses to encode distance, and the time interval between two direction cues. We have also discussed the differences in pedestrian and motorcyclists navigation,

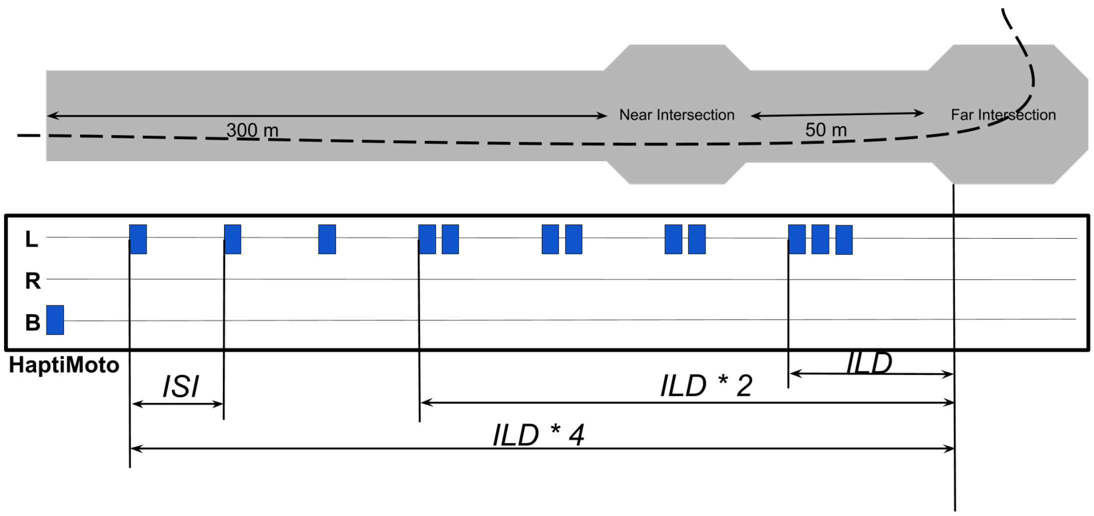


Figure 9.3: An example of the tactile signals presented to users before an approaching left turn. Note: ILD – Ideal Lead Distance (X), ISI – Inter Stimulus Interval—three seconds or time taken to travel 15 meters.

and how the differences are accommodated in HaptiMoto. The next chapter will discuss in detail the usability tests performed on HaptiMoto.

10. HAPTIMOTO USER EVALUATIONS

We evaluated HaptiMoto in three user studies. The purpose of the evaluation is to test the following hypotheses while driving a motorcycle:

1. The users can perceive and understand the tactile direction cues (*h1*).

2. The users can react appropriately to tactile direction cues (*h2*).

3. The users can understand a tactile direction cue well enough before approaching a turn and make the turn comfortably (*h3*).

4. The use of HaptiMoto does not increase the workload of riders when compared to workload of riders without HaptiMoto (*h4*).

5. HaptiMoto is more usable than the Google Maps audio guidance system (*h5*).

6. The directional signals from HaptiMoto can be followed by users over long periods of time/long routes. (*h6*).

We identified driving circuits and routes to assess the ability of riders to navigate through circuits and routes with the help of HaptiMoto. We used the number of turns made in the correct direction, the number of turns made at the correct intersection, the number of turns that were nearly missed, the number of turns that were missed and the time taken to complete the routes as quantitative representatives of the usability of HaptiMoto. We also measured the workload of riding motorcycle with NASA TLX load survey [28].

NASA TLX Survey – There are six dimensions to work load—effort, frustration, mental demand, performance, physical demand and temporal demand. Each of these dimensions is rated by the user on a scale of 1 – 7. A single NASA load score is then calculated from the weighted average of the six dimensions of load scores. Weights of each of the dimensions is assigned by making pairwise comparison of dimensions. The experimenter makes 15 pairwise comparison of dimensions and selects the most important dimension in the pair. Each dimension is compared to other dimensions five times. The weight assigned to the dimension is the number of instances when a dimension is chosen important in pairwise comparisons with each of the other dimensions [28]. Table 10.1 shows the weights assigned to each of the dimensions. The mental demand is assigned the highest weight of 5 followed by temporal demand, effort, frustration, performance and physical demand. HaptiMoto is designed to maintain a subjects attention on the road while simultaneously providing direction signals. Both the driving events and the HaptiMoto direction signal require mental processing time. Since our primary focus is measuring the mental workload, we have assigned the highest weights to mental and temporal demand. The effort and frustration is given the next highest weights since these dimensions reflect the usability of a system being rated.

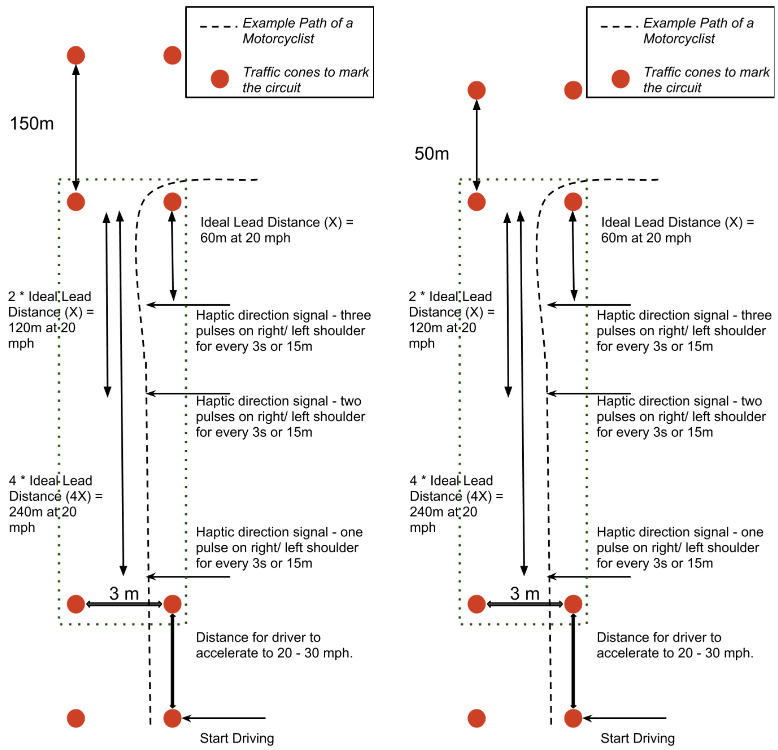
10.1 Usability of Tactile Cues

In order to evaluate the ability of users to perceive and understand tactile cues for direction and their ability to react to them (*h1* & *h2*), the vest-wearing users drove a motorcycle in an open parking lot and performed the commands as intuited by the vest. This study was also used to test if there is an increase in workload of riders while using HaptiMoto (*h4*).

10.1.1 Procedure

Before driving, users were introduced to the HaptiMoto vest by adorning the vest and ensuring the tactors fit snuggly against the shoulders and the center back. The user was required to wear a safety helmet, gloves, shoes, and a jacket. Each tactile signal was presented to ensure that it was perceived by the user, but no explanation of the meaning of any signals was given to the user. The tactile directional signals were presented in order to show the users the complete set of signals that will be used during the user study. The signals were not explained because we wanted to test the ability of users to understand the directions from the signals and determine the intuitiveness of the signals.

The first task for a subject in the user study was to drive the motorcycle in the open parking lot without the HaptiMoto vest. The subjects were requested to ride the motorcycle for a distance of 500m around the parking lot. They then completed a NASA TLX survey that quantified the workload of riding the motorcycle. The subjects were then asked to perform a series of four riding tasks with HaptiMoto. In the first task, the vest-wearing motorist, starting at the pre-specified start point, was asked to accelerate to a speed of $20 - 30$ mph before reaching a second point on the circuit marked by red traffic cones. S/he was expected to respond to the directional instruction which was provided once the user reached the specified speed, a single pulse (chosen randomly) specified one of the four possible directions—straight, left, right or back. The subjects were asked to perform twelve iterations of this driving task. In the twelve iterations, each direction was tested three times in a random sequence. The experimenter noted the correct/wrong turns made during each task. The overall turn accuracy is used as a metric to evaluate hypotheses *h1* & *h2*. This part of the study evaluates the perceivability of a tactile signal and intuitiveness in mapping the tactile signal to a turn direction.

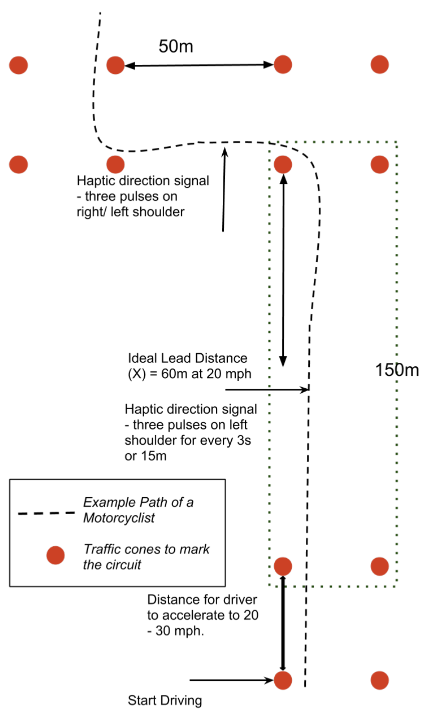


(a) Intersection separated by 150m (Circuit I).

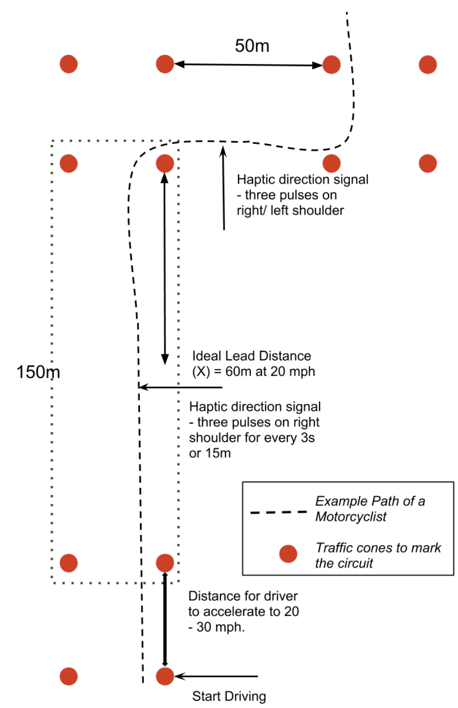
(b) Intersection separated by 50m (Circuit II).

Figure 10.1: Circuits I & II used in User Study.

The usability of HaptiMoto depends on the users ability to understand the tactile signals, that is, map the tactile signals to appropriate turns, identify the turns that the user has to turn into, and demonstrate ability to follow the tactile turn signals while driving. We conducted a user study to evaluate HaptiMoto usability. We identified four common driving scenarios a motorcyclist encounters while riding. The task involved riding the motorcycle through these four scnearios. The scenarios included double turns, single turns, straightaways, turns after 50 meters, and turns after 150 meters. The distance of 150 meters and 50 meters between the intersection was chosen from road and highway guidelines [1, 50]. According to road geometric design guidelines, the minimum distance between intersections should be 150 meters for roads with 20 mph speed limit. 50 meters is the recommended minimum distance between intersection for roads with 10 – 20 mph speed limit [1, 50]. The number of turns made in correct direction, the number of turns made in correct intersection, the number of turns that were nearly missed, and the number of turns that were missed were noted.



(a) Circuit with two turns in quick succession (Circuit III).



(b) Circuit with two turns in quick succession (Circuit IV).

Figure 10.2: Circuits III & IV used in User Study.

Figure 10.1(a) shows a circuit with two intersections separated by 150 meters (Circuit I). A user drove 150 meters before reaching the first intersection. The user had to make a decision on which direction to turn (or not turn) and the intersection into which s/he has to turn (order or turn sequence selected at random). Figure 10.1(b) shows Circuit II where there are two intersections are separated by only 50 meters. The first two circuits help us evaluate the ability of a user to follow the signals and perform a turn correctly while driving on a straightaway. Figure 9.3 shows examples of the turn signals instructed.

Circuits III and IV reflect a scenario where turns are made in quick succession. The turns made on street Y and immediately onto Z (Figures 10.2(a) & 10.2(b)). The circuit contains 150 meters of straight driving up to the first intersection (gaining sometimes significant speed), and then a turn to the left or right folllowed by a second turn at a distance of only 50 meters. Instructions for turns were given to the subjects via HaptiMoto. This scenario tested the ability of the users to make turns in quick succession with HaptiMoto guidance.

Users were asked to drive the four circuits shown in Figure 10.1 and Figure 10.2 at random using the directional HaptiMoto vest. The test was performed in a parking lot with real and distractor turn cones. The subjects were asked to accelerate to at least 20 – 30 mph. The ideal lead distance (X) at 20 mph is 60 meters and 30 mph is 110 meters. For the second task, the three, two, and single pulse notifications were given to the user at 4X, 2X and X distance from the turn respectively (as explained in the implementation). After the completion of the two tasks, the subjects completed a NASA TLX survey that quantified the workload of riding a motorcycle with HaptiMoto. The overall turn accuracy was used as metric to evaluate hypotheses *h1* & *h2* and the workload data from NASA TLX survey was used to evaluate hypothesis *h4*.

10.1.2 Results

Sixteen users participated in the first user study. The users were male and their age between 25 – 30. The users had at least two years of experience riding a motorcycle. In the first part of the user study, the user had to perform a total of 48 turns in each of the following directions—left, right, straight and back. There was a 100% accuracy in performing the intended turn during Evaluation 1. Figure 10.3 illustrated the total number of correct turns made in the first part of the study.

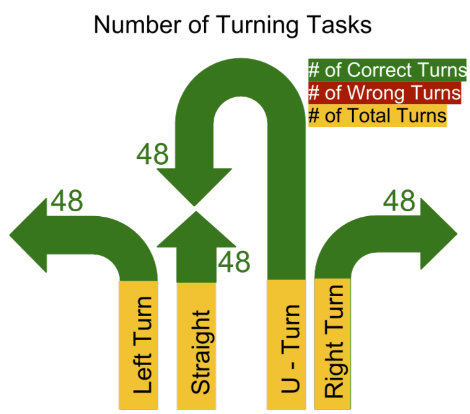
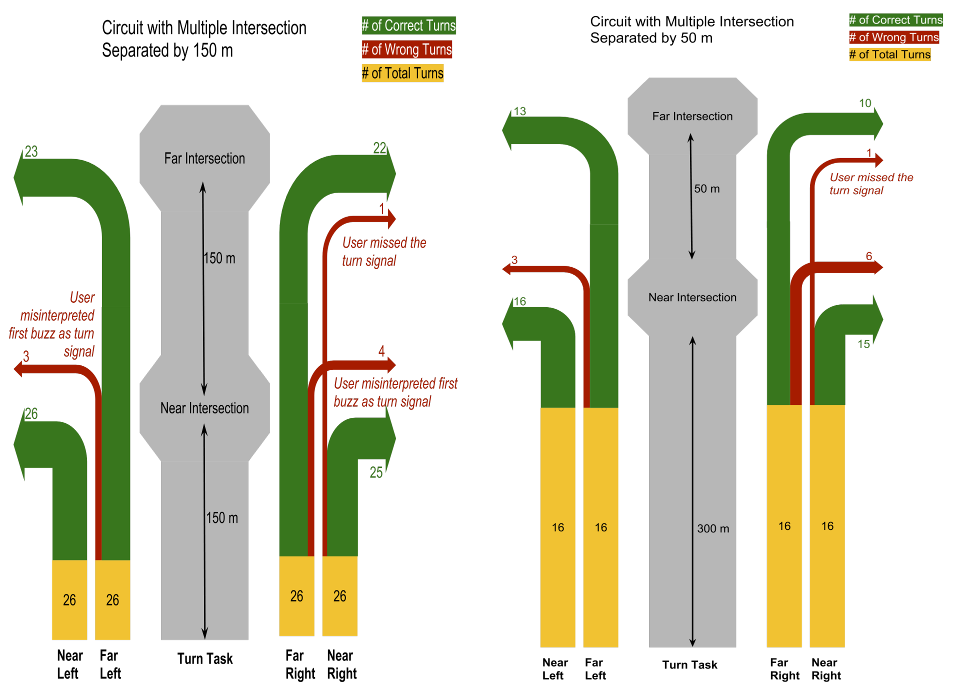


Figure 10.3: Illustration of the number of turning task performed in the user study and number of correct turns made.

Figure 10.4 shows the results from Circuits I and II. In Circuit I (150 meters), the tasks for each turn and intersection were performed twice in random order. Out of the 16 users and a total of 128 turns, the users performed 52 correct left turns, 52 correct right turns, 12 missed left and 12 missed right turns. Six missed turns were due to a mis-fitting of the vest and the user not being able to feel the vest, at which point the vest was re-fit for users who had trouble feeling the signals. Figure 10.4(a) shows the results from the data points where the users could perceive the tactile signals. All users chose the correct turn direction to turn. There were seven different users who chose the near intersection to turn while the HaptiMoto was guiding them to the far intersection from the starting point of the circuit. There was one user who missed the first intersection and made the turn at the far intersection.

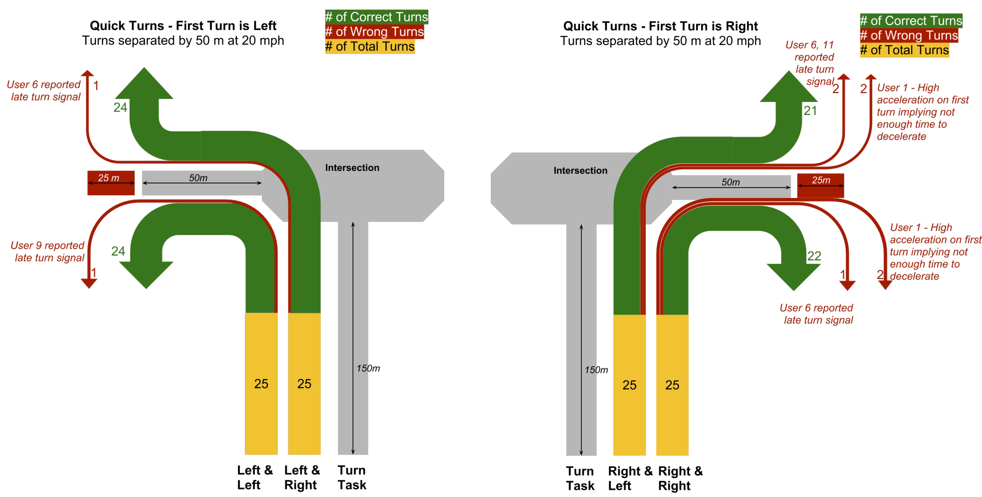


(a) Circuit with intersection separated by 150m.

(b) Circuit with intersection separated by 50m.

Figure 10.4: Illustration of the number of turning task performed and number of correct turns made in the Circuit I (a) and Circuit II (b) with two intersections.

In Circuit II (50 meters), each turn task was performed once. There were a total of 16 data points for each turn and each intersection. The users had to perform 32 turns each for left and right directions. They chose the correct turn direction in each turn task. Figure 10.4(b) shows the number of correct turns and intersections made. Of a total of 32*4 = 128 turns, there were nine instances when a user chose to turn at the near intersection when the HaptiMoto was guiding the user to the far intersection. There was one instance where a user did not make the turn at the near intersection and instead made the turn at the far intersection.



(a) (b)

Figure 10.5: Illustration of the number of turning task performed in the user study and number of correct turns made in the Circuit III (a) and Circuit IV (b) with two turns in quick succession.

Figure 10.5 shows the performance of users in Circuits III & IV. There were seven data points dropped due to inability of the users to perceive the tactile signals due to vest fit. The 16 users had to perform a total of 128 turns. They chose the correct direction in 100 instances and could not perceive the signal in 28 instances for left and right turns. Of the total of 50 instances in which a user makes a left turn at the first intersection, there were two instances when the user missed making the second turn at the appropriate intersection. In the two instances, the users made the turn 25 meters after the intended intersection. Figure 10.5(a) shows the illustration of the number of correct turns and wrong turns made by the users in the Circuit III. Of the total of 50 instances in which a user makes a right turn at the first intersection, there were seven instances when the user missed making the second turn in the appropriate intersection. In the seven instances, the users made the turn 25 meters after the intended intersection. Figure 10.5(b) shows the illustration of the number of correct turns and the seven wrong instances in the Circuit IV.

Table 10.1: Table listing the workload ratings for six components of the NASA TLX survey, corresponding weights and the NASA TLX workload score for driving a motorcycle with and without HaptiMoto.

Load Component	Driving without HaptiMoto	Driving with HaptiMoto	Weight of the component
Effort	3.06 ± 1.75	3.2 ± 1.65	2
Frustration	1.93 ± 1.39	2.53 ± 1.45	2
Mental Demand	3.2 ± 1.78	3.6 ± 1.68	5
Performance	5.73 ± 1.57	5.46 ± 1.45	1
Physical Demand	2.86 ± 1.68	2.66 ± 1.49	1
Temporal Demand	2.60 ± 1.54	2.66 ± 1.44	4
NASA Load Score	2.68 ± 1.37	2.93 ± 1.22	15

The users were asked to ride the motorcycle for about 500 meters in the open parking lot and asked to rate the workload of riding the motorcycle. The users were asked to rate the load of driving the motorcycle with HaptiMoto at the end of the study. The results of the survey are shown in figure 10.6. Table 10.1 lists the mean and standard deviation of each of the six components calculated from the load survey and the NASA load score. The table also provides the weights used to represent each of the six components in calculating the NASA load score.

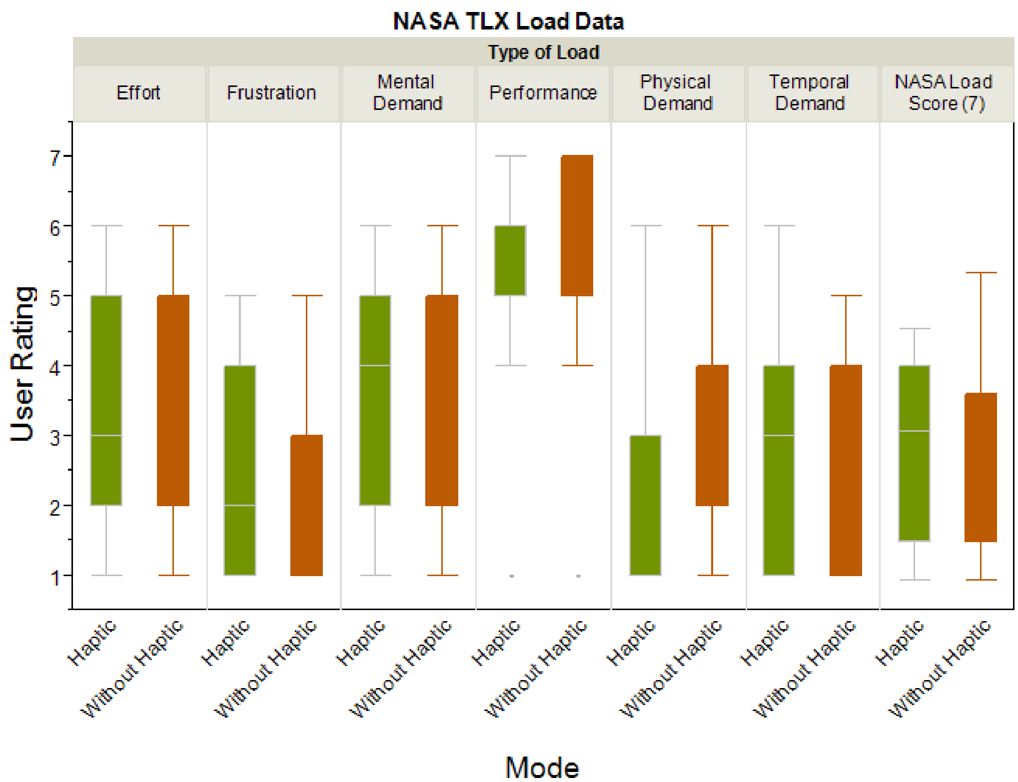


Figure 10.6: Chart depicting the NASA TLX load survey data with HaptiMoto (shown in red) and without HaptiMoto (shown in green).

10.1.3 Discussion

This evaluation showed that users could perceive and understand haptic cues (*h1*) and understand the intent of haptic cues (*h2*). Some of the users reported they would interpret the tactile signal for U-Turn as straight and vice versa. The confusion did not seem to affect the accuracy in performing the turns. In this evaluation, there were 40 instances where the users did not perceive the tactile signal, which they attributed to the looseness of the HaptiMoto vest. The results show that the users did not have problems perceiving or understanding the haptic cues when HaptiMoto vest was fit appropriately.

The evaluation of users driving through four circuits showed that the users could use the haptic cues to choose appropriate turns (*h3*) and also showed the errors while choosing a turn. The users chose correct turns with 91% accuracy in Circuit I, 84.4% in circuit II and 92.3% in circuit III & IV. 7 out of 8 errors were caused by users choosing to turn in near intersection while the users were guided to far intersection. These were errors due to misinterpretation of tactile signals by users. The users reported that they made the turn after receiving two pulses for turning rather than three pulses (for which they were given no initial instruction). The three pulses were explained after the first mistake, and the users performed the turn task accurately in following turns. While some adapting to the system is required, we are excited that the users needed almost no instruction for the direction nor distance feedback provided by the system. This emphasizes the intuitiveness of the system.

In case of the Circuits I & II, there was one instance in each of the circuits when a user missed the near intersection turn and made the far intersection turn. The user reported that he had missed noticing the tactile signal for turning and noticed it late to make the turn, so he continued to next possible intersection and made the turn. This shows that the tactile signals are strong enough to pressure the users into making turns that are uncomfortable to make due to agressive driving. Though this was not considered during designing the HaptiMoto, we would like to keep the tactile signal intensity at levels that could be ignored while driving.

Circuit II also had nine instances where the users turned into the near intersection when the HaptiMoto was navigating them to turn at the farther intersection. These errors were due to a bug in latency of android GPS updating. HaptiMoto is reliant on the frequency and accuracy of the GPS updates provided by the Android platform. The GPS update from the Android platform created instances where two GPS update events were raised sequentially. The Android platform allows developers to set a minimum distance travelled or time elapsed between two location update events but there were some instances where these conditions were not met. This bug caused two haptic signals to be clubbed into a single signal. For example: When a driver is at 150 meters from the intended turn travelling at 20 mph, HaptiMoto sends out a haptic signal to the user's left shoulder. The signal is shown in figure 10.7. The next haptic signal should not be sent to user until s/he reaches within 135m to the intended turn or travelled for three seconds. But in our case, there were instances where such conditions were not met between GPS updates. The location updates were sent sequentially which resulted in two turn signals being sent simulataneously. This is shown in figure 10.7 on the right side of the route. The number of pulses in a signal determines the turn to be taken by the user. When two turn signals are sent simultaneously, two 2-pulse signals are perceived as one 4-pulse signal and the users perceived any signal which had more than three pulses as the turn that has to be taken. This bug was later fixed by adding an additional time-elapsed check during the location update event.

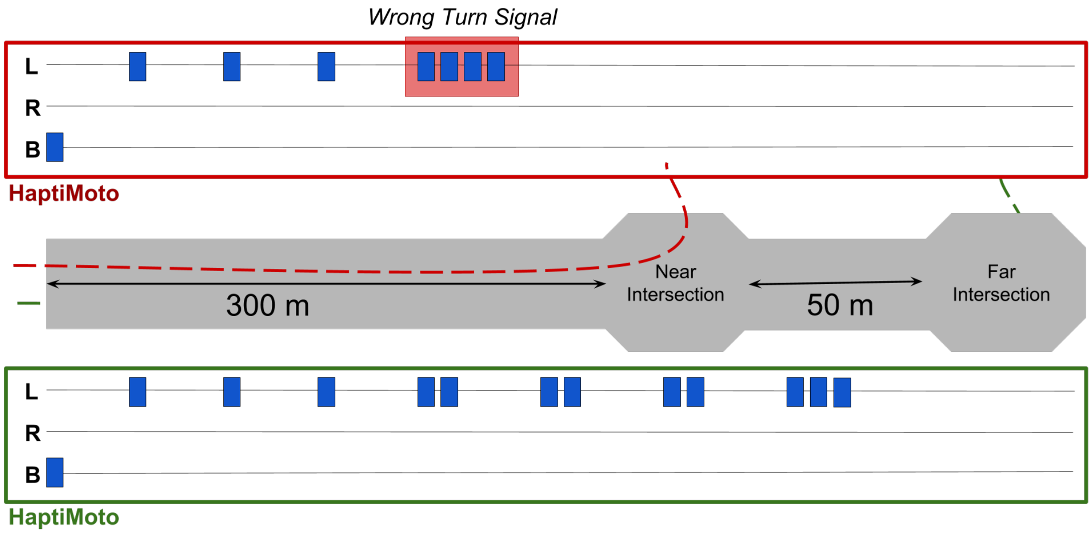


Figure 10.7: An example scenario where two sequential GPS updates causes error in HaptiMoto navigation.

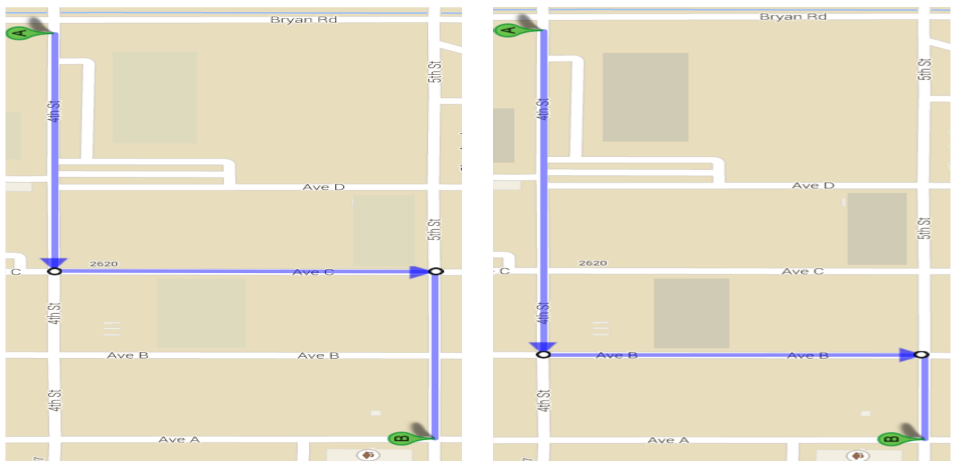
When the users performed two turns in quick succession with HaptiMoto, there were nine instances when the users missed making the second turn (shown in figure 10.7). Four users accounted for the nine error instances. The users reported two reasons for their inability to make the second turn. Firstly, when leaving the first turn, if the user drives with higher acceleration, it makes it difficult for the users to decelerate in time to make the second turn. Secondly, the users reported instances where the HaptiMoto tactile signal for turns were too late to make the turn. Our system is limited by the speed of GPS updates from the Android platform and thereby limited in providing the tactile signal for turns. All four users performed the turn comfortably at 25 meters after the second turn. It is safe to assume that, the HaptiMoto could support navigation of quick turns in succession when the turns are separated by more than 75 meters.

Comparison of NASA TLX load score for driving the motorcycle with and without HaptiMoto shows that there is not a significant change in workload while using the HaptiMoto. There is no significant difference in any of the six load components identified by the NASA TLX work load survey. The mean load score for riding the motorcycle was 2.68 out of 7. The mean load score for riding a motorcycle with HaptiMoto was slightly higher at 2.93 out of 7. The standard deviation of load score was higher for riding the motorcycle (1.37) than the load score for riding the motorcycle with HaptiMoto (1.22). The F-test performed on the data showed that the difference in variance is significant. The F score is $F(1,31) = 0.6$. The T-test performed on the data showed that the increase in workload while riding a motorcycle with HaptiMoto is not significant. At 95% confidence interval, the $T(\alpha < 0.05) = 0.7$. The mental demand and temporal demand were not significantly different for subjects driving with and without HaptiMoto. The data supports our hypothesis that the HaptiMoto does not increase the mental workload of motorcyclists (*h4*). This implies that mental processing demands for driving events and the HaptiMoto tactile guidance can be performed in tandem. The users reported increased level of frustration while using HaptiMoto when compared to riding without HaptiMoto. The frustrations were caused when the HaptiMoto vest loosens and makes the tactile direction signals imperceptible.

10.2 Comparing HaptiMoto with Google Maps Audio Navigation Interface

In the second user study, we compared the usability of Google maps audio guidance interface against HaptiMoto route guidance on a 0.5 mile circuit (*h5*). The routes used in this evaluation are shown in figure 10.8. The user study was performed in a campus with restricted traffic. The performance of users was measured with time taken to complete riding through the circuit and the workload was measured with the NASA-TLX survey.

10.2.1 Procedure



(a) Circuit A has one left and one right turn, and the length of the circuit is 0.5 miles.

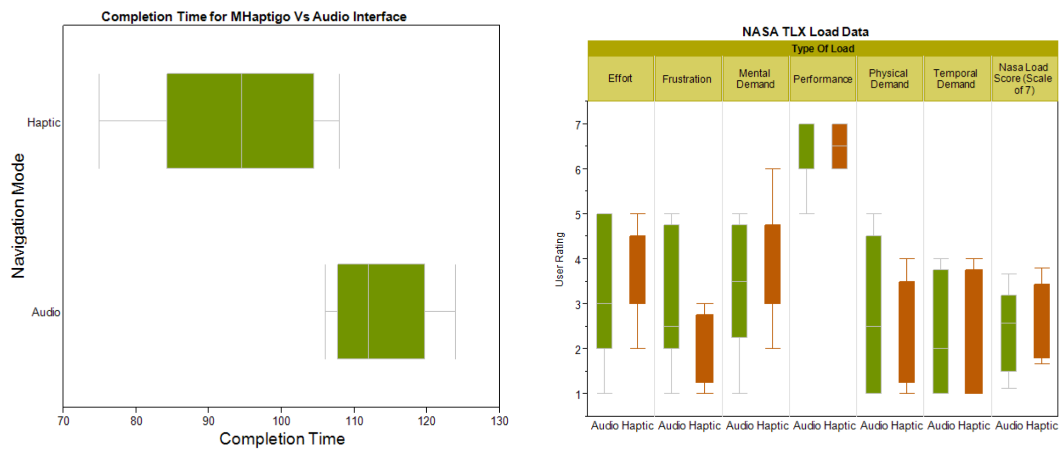
(b) Circuit B, similar to Circuit A, has one left and one right turn, and the length of the circuit is 0.5 miles.

Figure 10.8: Circuits used in the study to compare HaptiMoto with Google Maps audio interface.

The experimenter introduced the HaptiMoto and the vest to the user. The introduction included having the user wear the vest such that the tactors fit snuggly against the shoulders and the center back. The user was also required to wear a safety helmet, gloves, shoes and a jacket. The experimenter introduced the set of tactile signals that would be used in the HaptiMoto for route guidance. The experimenter asked the user to drive through one of the figure 10.8 with Google Maps audio interface. The user was provided with earphones to use the audio interface while driving. The experimenter noted the time taken to complete the circuit by the user.

The user was then asked to fill in NASA TLX load survey. The user was then asked to drive through the 0.5 mile circuit that was not used in the first task with HaptiMoto route guidance. The experimenter noted the time taken to complete driving through the circuit by the user. The user filled in a NASA TLX load survey after the driving task.

10.2.2 Results



(a) Comparing the completion time for driving with Google Maps audio interface and HaptiMoto.

(b) NASA TLX load survey for motorcycle driving with Google Maps audio interface (shown in green) and HaptiMoto (shown in red).

Figure 10.9: Results from User Study II – Charts comparing the completion time to drive a 0.5 mile circuit and the NASA TLX load survey data while using Google Maps audio interface and HaptiMoto for route guidance.

The user studies II and III were conducted together with eight users. The users were male and their ages were between 25 – 30. The users had atleast two years of experience riding motorcycles. All the users successfully completed driving through 0.5 mile circuit. The mean and standard deviation in completion time for driving with audio routing interface and the HaptiMoto interface are 113.25 seconds ± 6.52 and 93.625 seconds ± 11.84 respectively.

Table 10.2: Table listing the workload ratings for six components of the NASA TLX survey, corresponding weights and the NASA TLX workload score for driving a motorcycle with Google maps audio interface and HaptoMoto system.

Load Component	Driving with Google Maps	Driving with HaptiMoto	Weight of the component
Effort	3.25 ± 1.58	3.37 ± 1.06	2
Frustration	3.00 ± 1.51	2.00 ± 0.75	2
Mental Demand	6.5 ± 0.75	3.62 ± 1.30	5
Performance	2.62 ± 1.68	6.5 ± 0.53	1
Physical Demand	2.62 ± 1.68	2.25 ± 1.16	1
Temporal Demand	2.25 ± 1.28	2.50 ± 1.30	4
NASA Load Score	2.40 ± 0.91	2.54 ± 0.83	15

Figure 10.9(a) shows the comparison of completion time for driving 0.5 mile circuit with the audio interface and the HaptiMoto interface. Table 10.2 shows the workload rating for the audio and HaptiMoto interface and the NASA load score

for each of the interface. Figure 10.9(b) shows the comparison of the load scores for audio and HaptiMoto interfaces. The mean and standard deviation of the NASA TLX load score is 2.4 ± 0.91 for audio interface and 2.54 ± 0.83 for HaptiMoto.

10.2.3 Discussion

The comparison of the completion time for driving a motorcycle on a 0.5 mile circuit (shown in figure 10.8) shows that the completion time while using Google Maps audio interface is significantly higher than driving with HaptiMoto. Wilcoxon Rank Sum score for Google Maps completion time is 98 which is higher than 38, the sum score for HaptiMoto completion time. Users reported the conscious effort they had to make to hear the directions and the effort reduced the speed at which they could drive their motorcycle. Users also reported discomfort driving with earphones and helmet on. Two users removed the helmet while riding motorcycle with Google Maps audio guidance due to discomfort caused by having earphones while the helmet pressed against their ears. Users reported greater comfort while riding with HaptiMoto than when compared to Google Maps Audio Interface. This opinion was not reflected in the overall NASA TLX load score. Wilcoxon Rank Sum test showed that the NASA TLX load survey did not show any significant change in the work load for using audio interface (Sum Score – 67) or HaptiMoto (Sum Score – 69). Analyzing the individual dimensions showed that the users reported higher mental demand required to use HaptiMoto when compared to Google Maps. The ratings for temporal demand and effort were not significantly different for the two systems. The users also reported higher level of frustrations while using Google Maps when compared to HaptiMoto. The users slowed down the vehicle to have Google Maps guidance be audible. Driving at slow speeds reduced the amount of attention (mental demand) required for driving. The higher level of frustration reported for

Google Maps is due to the guidance being inaudible at high speeds. Riding at lower speeds is the cause of lower mental demand for Google Maps in comparison to HaptiMoto. The tactile perceptibility was not affected while driving at speeds between 20 – 30mph. So the users did not require to slow down the motorcycle to perceive the HaptiMoto directional signals. The results show that HaptiMoto is more usable when compared to the Google Maps audio interface.

10.3 Assessing Usability of HaptiMoto for Long Routes

The third user study was to drive through the two-mile circuit from point A to point H on the map shown in the figure 10.10. This user study evaluated the ability of users to follow HaptiMoto instructions over long routes (*h6*). The circuit has a total of six turns—three left turns at points B, C & D and three right turns at points E, F & G. This user study was conducted along with the study comparing HaptiMoto with Google Maps audio interface.

10.3.1 Procedure

This study was performed as a continuation of the previous study. After finishing the tasks in the previous study, the experimenter asked the user to follow the HaptiMoto route guidance signals along the two-mile route (Figure 10.10). The experimenter followed the user while driving to note the number of correct turns made and number of missed turns. The experimenter also noted the total time taken by the user to complete driving through the circuit. This task evaluated the ability of users to follow HaptiMoto route guidance signals for long routes with more than one turn.

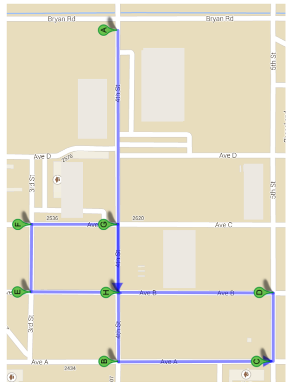


Figure 10.10: Circuit used in User Study II (2 miles).

10.3.2 Results and Discussion

The mean and standard deviation of completion time for driving the two-mile circuit was found to be 280.5 seconds ± 43.17. This showed the ability of the users to follow HaptiMoto instruction over long routes (*h6*). The users did not perform any errors in taking turns along the two-mile circuit shown in 10.10. Users suggested a change in signal for immediate turn haptic signal. Two users proposed that the immediate turn haptic signal be changed from 3 haptic pulses to a continuous haptic signal that turns on at about 20 – 30m before the turn and stops just after the user makes the turn. The users proposed this suggestions since they felt using a long continuous pulse as a signal could help them differentiate from other signals than change in number of pulses. Though a single long continuous pulse for immediate turn is good to attract the attention of the user to turning, it can be disruptive and divert the attention of the user from driving, the primary task, to listening to directions which is a secondary task. We want the haptic signals to be strong enough to be identified by the user while keeping their attention on driving and not be disruptive. So, we did not implement the suggested change into the HaptiMoto.

11. CONCLUSION

We have proved the feasibility of using tactile medium for communicating verb phrases and the usability of tactile directional interface, HaptiGo, in pedestrian navigation, and HaptiMoto, in navigating motorcycle.

11.1 Communicating Verb Phrases with Tactile Code

We have proposed the following step by step procedure to select distinguishable tactile codes and map these to verbal phrases with design rationale:

1. Identify the tactile code space, measure the average time to distinguish tactile codes in the space, and find the average number of errors committed by users in distinguishing the tactile code.

2. Use the data to construct a graph model of the tactile code space. The edge weight between any two nodes is a weighted combination of the average response time and the number of errors committed.

3. Use the proposed clustering algorithm to identify a cluster of tactile codes which are easy to distinguish. Use the codes from one cluster to encode messages in the interface.

4. Map the selected shapes to the object part of the verb phrase and the rendering methods to the verb/adverb part of the verb phrase.

We have proved the validity of the model by conducting a user study where the users were asked to recognize haptic ringtones. The results show that the tactile codes from the model perform better than those from the experimenter's list in terms of the number of correct recognitions. We have also used the ringtone scenario and proved the ability of users to perceive verb phrases from tactile codes. Comparing the performance of users in recognizing the audio and haptic ringtones shows that users perceive information faster and more accurately from an audio channel as compared to a haptic channel. This could be due to the familiarity of an audio channel over a haptic channel of perceiving information. While performing the visual task and the ringtone identification task simultaneously, the haptic ringtone identification task causes greater drop in visual task performance of users than the audio ringtone identification task. When the user is involved in the visual task, there is no increase in time taken or accuracy drop in haptic ringtone identification.

11.2 HaptiGo — A Navigational "Tap on the Shoulder"

We have designed a wearable computing device which can act as a navigational aid for pedestrians while maintaining users' awareness about their environment by detecting approaching obstacles. We evaluated this device against PocketNavigator, a mobile tactile navigation aid and found that participants of our study were able to navigate to the intended destination even with diminished visual and auditory perception of their environment using both navigation systems. Furthermore, we found that while participants were able to reach the destination, the cognitive load required to get there using the PocketNavigator system was significantly greater than the cognitive load required by HaptiGo. Also, HaptiGo provided the added benefit of increasing awareness of the participant's surrounding environment, due to its obstacle detection capability.

11.3 HaptiMoto — Tactile Navigation Interface

We have successfully designed an adjustable vest with Lilypad vibe-boards to assist motorcyclists with navigation. Two vibe-boards are located at back of each of the shoulders and one at the center back of the user in this vest. We have identified and implemented the minimum required information for route guidance—next turn direction, distance to the approaching turn, and the street into which the turn should be made. The tactile signals for HaptiMoto have been designed to accommodate the information for route guidance. Specifically, we have tested the following hypotheses: 1) that tactile cues can be understood (felt) by motorcycle drivers; 2) that motorcycle drivers can understand the intent of the haptic cues; 3) that haptic cues can be used to perform routine motorcycle tasks; 4) that the presence of HaptiMoto does not increase the mental workload as compared to its absence; 5) that HaptiMoto is more usable when compared to Google Maps audio guidance interface; and 6) that the users can follow HaptiMoto directions over long routes. The results from user study I, conducted with 16 subjects, and user studies II & III, conducted with 8 subjects, support our hypotheses.

12. FUTURE WORK

12.1 Communicating Verb Phrases with Tactile Code

From an information theory perspective,we have showed an example of selecting shapes from a space of 512 shapes. We have not showed how to calculate the entropy of shapes in space, the upper bound on the number of codes that could be generated and a measure of quality of the codes. Given a designer requires n codes in an interface, this paper does not provide a method to calculate the minimum number of codes N that should be analyzed in the model to choose n. Our future work will focus on formulating the information theoretical framework of the model developed in this dissertation.

The vocabulary of verb phrases that can be represented with haptic codes can be increased in two ways—increasing the number of dimensions to represent haptic codes and/or combining existing codes sequentially. Our future work will focus on the ability of users to perceive information from haptic codes when multiple codes are presented sequentially. For example, a simple English sentence can be formed using a noun phrase and a verb phrase. Further research will focus on mapping noun phrases to two dimensions of haptic code and using sequential presentation of haptic codes to transmit simple sentences.

12.2 HaptiGo

In the user studies conducted with HaptiGo, the subjects participating in the user studies noted the weakness of the tactile signal for the straight direction. We used two tactors in place of one to increase the strength of the signal but this solution did not solve the weak signal problem. We believe the position of the tactors on the vest is critical to being perceived by the users. We would like to modify the position of the tactors on the vest to make the tactile signal stronger.

Another area of further work would include testing the effectiveness of the HaptiGo system in assisting visually impaired users navigate.

12.3 HaptiMoto

In the three user studies conducted on HaptiMoto, the perceptibility of the tactile signals was tested at a maximum speed of 30 mph. The tactile perceptibility did not affect the usability or the workload of the users. The perceptibility of tactile signals and thereby the work load to listen to navigation signals increases with speed at which the users travel. The future work involves usability studies of HaptiMoto on higher speed limits. In order for the HaptiMoto to be usable in real life, the system needs to be test on higher speed limits (30 – 80 mph).

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APPENDIX A

DATA COLLECTED FROM A/B DISTINGUISHABILITY TESTS

Table A.1: Performance of Users in Recognizing Tactile Shapes with Tactor II.

Number of Tactors	**User**	**Accuracy**	**Response Time**	
			Mean	**SD**
1	1	1.00	14.23	11.17
1	2	0.97	7.77	7.26
1	3	1.00	16.71	10.48
1	4	0.97	9.73	13.03
1	5	0.94	7.55	3.93
1	6	0.92	5.14	3.44
1	7	0.97	4.96	2.32
1	8	0.97	22.76	106.81
2	1	0.99	12.87	5.58
2	2	0.96	7.69	6.99
2	3	0.90	19.39	17.14
2	4	0.97	10.23	11.89
2	5	0.99	10.69	5.85
2	6	0.95	7.02	4.41
2	7	0.89	5.85	4.12
2	8	0.96	6.66	6.80

Table A.2: Performance of Users in Recognizing Tactile Shapes with Tactor II. (Continuation of Table A.1)

Number of Tactors	User	Accuracy	Response Time	
			Mean	SD
3	1	0.98	13.29	6.11
3	2	0.96	7.64	6.61
3	3	0.82	16.54	17.10
3	4	0.97	10.77	10.40
3	5	0.97	11.2	6.47
3	6	0.85	6.68	5.43
3	7	0.90	7.6	5.57
3	8	0.96	7.98	6.39
4	1	0.97	15.06	9.68
4	2	0.92	7.68	8.15
4	3	0.75	15.11	15.47
4	4	0.95	10.88	11.24
4	5	0.96	12.28	7.60
4	6	0.88	6.92	4.25
4	7	0.82	7.67	5.86
4	8	0.93	8.63	6.04
5	1	0.96	16.66	20.35
5	2	0.92	8.31	11.49
5	3	0.72	12.43	12.31
5	4	0.95	10.99	10.01
5	5	0.95	12.64	8.04
5	6	0.86	6.92	5.04
5	7	0.85	8.06	5.59
5	8	0.92	9.48	7.67
6	1	0.96	17.23	22.21
6	2	0.94	8.09	7.93
6	3	0.74	12.47	10.94
6	4	0.94	11.6	10.83
6	5	0.96	12.42	7.29
6	6	0.89	7.31	4.90
6	7	0.85	7.98	4.79
6	8	0.94	9.71	6.32

Table A.3: Performance of Users in Recognizing Tactile Shapes with Tactor II. (Continuation of Table A.1)

Number of Tactors	User	Accuracy	Response Time	
			Mean	**SD**
7	1	0.97	16.13	7.40
7	2	0.96	8.05	7.38
7	3	0.73	11.92	13.11
7	4	0.97	11.37	10.89
7	5	0.98	13.97	10.24
7	6	0.89	7.21	4.30
7	7	0.91	8.08	4.45
7	8	0.92	9.23	5.55
8	1	1.00	14.07	3.88
8	2	0.97	8.82	8.47
8	3	0.75	11.85	12.04
8	4	0.94	10.25	8.09
8	5	0.97	13.25	6.61
8	6	0.89	6.76	3.79
8	7	0.97	7.78	3.36
8	8	0.97	7.94	2.99
9	1	1.00	13.35	1.75
9	2	1.00	14.65	21.68
9	3	1.00	13.28	2.64
9	4	1.00	11.73	12.30
9	5	1.00	12.87	7.00
9	6	1.00	8.02	2.63
9	7	1.00	7.67	2.59
9	8	1.00	6.2	2.17

Table A.4: Table listing the T-test probabilities comparing response accuracy for each pair of number of tactors in a shape. We check if the recognition accuracy for a shape with number of tactors listed in first column is higher than the recognition accuracy for a shape with number of tactors listed in second column of table.

Number of Tactors	**Number of Tactors**	**T > t**
5	2	0.0035
6	2	0.0086
5	8	0.6449
4	2	0.0208
6	8	0.6817
5	9	0.9995
6	9	0.9995
7	2	0.2501
4	8	0.8131
4	9	0.9998
7	8	0.9283
7	9	0.9999
5	3	0.0468
6	3	0.116
5	1	0.9754
6	1	0.9807
1	2	0.9898
4	3	0.2501
3	2	0.8717
7	3	0.8784
4	1	0.9962
1	8	0.9998
1	9	1
7	1	0.9996
3	8	0.9997
3	9	1
5	7	0.9969
6	7	0.9986
9	2	1
5	4	0.9982
8	2	1
6	4	0.9996
1	3	1
4	7	1

Table A.5: Table listing the T-test probabilities comparing response time for each pair of number of tactors in a shape. We check if the recognition time for a shape with number of tactors listed in first column is higher than the recognition time for a shape with number of tactors listed in second column of table.

Number of Tactors	**Number of Tactors**	$T > t$
9	5	0.0015
9	4	0.0025
9	6	0.0035
9	7	0.0109
1	5	0.022
9	3	0.0244
1	4	0.0331
1	6	0.0435
9	8	0.0448
2	5	0.0769
1	7	0.1035
2	4	0.1084
9	2	0.1334
2	6	0.1361
1	3	0.1863
8	5	0.2083
8	4	0.2748
2	7	0.2749
1	8	0.2853
3	5	0.315
8	6	0.3295
9	1	0.3358
3	4	0.4023
2	3	0.4351
3	6	0.4716
7	5	0.4884
8	7	0.5678
1	2	0.5838
7	4	0.5999
2	8	0.6001
7	6	0.6845
3	7	0.7531
6	5	0.7738
8	3	0.7969
4	5	0.8658
6	4	0.9057

Table A.6: Performance of Users in Recognizing a Tactile Shape of Particular Rendering Method with Tactor II. M - Mean, SD - Standard Deviation.

Waveform	**User**	**Accuracy**	**Response Time**	
			M	**SD**
Pattern Mask	1	0.98	15.26	18.08
Pattern Mask	2	0.91	6.45	9.67
Pattern Mask	3	0.77	15.86	11.38
Pattern Mask	4	0.92	9.75	4.28
Pattern Mask	6	0.93	20.53	11.46
Pattern Mask	7	0.85	11.80	4.87
Pattern Mask	8	0.74	13.40	6.46
Pattern Mask	9	0.85	17.55	7.93
Constant	1	0.95	18.94	8.12
Constant	2	0.93	4.62	1.60
Constant	3	0.94	11.40	6.80
Constant	4	0.97	5.56	1.97
Constant	6	0.99	9.58	2.22
Constant	7	0.89	4.93	1.90
Constant	8	0.89	6.91	3.19
Constant	9	0.95	7.09	28.42
Pulsed	1	0.96	19.52	18.35
Pulsed	2	0.93	8.15	7.35
Pulsed	3	0.69	30.32	15.65
Pulsed	4	0.97	4.61	2.83
Pulsed	6	0.99	10.13	1.75
Pulsed	7	0.92	6.27	3.19
Pulsed	8	0.85	10.06	5.31
Pulsed	9	0.96	8.21	4.23
Sketch	1	0.99	10.29	10.57
Sketch	2	0.98	14.72	9.94
Sketch	3	0.68	18.64	14.12
Sketch	4	0.96	25.96	11.69
Sketch	6	0.95	10.33	2.80
Sketch	7	0.86	9.45	4.97
Sketch	8	0.96	7.24	2.90
Sketch	9	0.99	7.23	1.83

Table A.7: Table listing the T-test probabilities comparing response time for each pair of rendering method used in a shape. T-test is used to check if the response time for waveform in first column is higher than the response time for waveform in second column of table.

Waveform	**Waveform**	**T >t**
Pattern Mask	Constant	.0001
Sketch	Constant	.0001
Pulsed	Constant	.0001
Pattern Mask	Pulsed	.0001
Pattern Mask	Sketch	0.0004
Sketch	Pulsed	0.0006

Table A.8: Table listing the T-test probabilities comparing response accuracy for each pair of rendering method used in a shape. T-test is used to check if the recognition accuracy for waveform in first column is higher than the recognition accuracy for waveform in second column of table.

Waveform	**Waveform**	**T >t**
Constant	Pattern Mask	0.1024
Sketch	Pattern Mask	0.232
Pulsed	Pattern Mask	0.3763
Constant	Pulsed	0.4364
Constant	Sketch	0.6443
Sketch	Pulsed	0.7493

APPENDIX B

DATA COLLECTED FROM THE USER STUDY COMPARING SHAPES FROM

Table B.1: Performance of ten users in recognizing haptic ringtones where the shapes are chosen from experimenter's list (EL) and model. The table contains the accuracy, precision, recall and mean reaction time of each user. M - Mean, SD - Standard Deviation.

Set of Codes	**User**	**Number of Calls**	**Correct Responses**	**Response Time**		**Errors**	**Accuracy (%)**
				M	**SD**		
EL	1	40	4	25.75	16.57	36	10
EL	2	40	28	17.46	10.18	12	70
EL	4	40	37	23.91	14.43	3	92.5
EL	5	40	18	34.75	16.70	22	45
EL	6	40	33	23.08	14.81	7	82.5
EL	7	40	31	18.71	13.69	9	77.5
EL	8	40	38	16.59	5.77	2	95
EL	9	40	39	15.93	7.14	1	97.5
EL	10	40	26	21.52	12.84	14	65
Model	1	40	25	21.78	14.99	15	62.5
Model	2	40	34	14.96	6.76	6	85
Model	4	40	33	29.30	22.23	7	82.5
Model	5	40	19	44.69	21.08	21	47.5
Model	6	40	32	24.44	11.15	8	80
Model	7	40	35	12.06	13.63	5	87.5
Model	8	40	33	23.31	12.41	7	82.5
Model	9	40	36	21.56	13.30	4	90
Model	10	40	34	22.51	10.20	6	85

APPENDIX C

DATA COLLECTED IN MULTI-TASK STUDY

Table C.1: Performance of nine users while performing visual object tracking task and recognizing audio ringtone. The table contains the accuracy, precision, recall and mean reaction time of each user.

Task	**User**	**True Positive**	**False Positive**	**False Negative**	**Accuracy**	**Precision**	**Recall**	**Reaction Time**
Visual + Audio	1	54	3	38	0.57	0.95	0.59	1.07
Visual + Audio	2	56	0	45	0.55	1.00	0.55	1.06
Visual + Audio	3	103	16	56	0.59	0.87	0.65	1.26
Visual + Audio	4	56	8	13	0.73	0.88	0.81	1.10
Visual + Audio	5	52	1	14	0.78	0.98	0.79	0.71
Visual + Audio	6	71	0	27	0.72	1.00	0.72	1.13
Visual + Audio	7	98	0	31	0.76	1.00	0.76	0.92
Visual + Audio	8	65	0	18	0.78	1.00	0.78	0.96
Visual + Audio	9	50	2	14	0.76	0.96	0.78	1.19

Table C.2: Performance of nine users while performing visual object tracking task and recognizing haptic ringtone. The table contains the accuracy, precision, recall and mean reaction time of each user.

Task	**User**	**True Positive**	**False Positive**	**False Negative**	**Accuracy**	**Precision**	**Recall**	**Reaction Time**
Visual + Haptic	1	109	5	94	0.52	0.96	0.54	1.36
Visual + Haptic	2	48	0	75	0.39	1.00	0.39	1.08
Visual + Haptic	3	135	28	53	0.63	0.83	0.72	1.35
Visual + Haptic	4	83	13	45	0.59	0.86	0.65	1.22
Visual + Haptic	5	126	3	71	0.63	0.98	0.64	1.00
Visual + Haptic	6	48	0	60	0.44	1.00	0.44	0.92
Visual + Haptic	7	77	2	24	0.75	0.97	0.76	1.16
Visual + Haptic	8	82	0	64	0.56	1.00	0.56	1.15
Visual + Haptic	9	52	4	53	0.48	0.93	0.50	1.18

Table C.3: Performance of nine users while performing visual object tracking task. The table contains the accuracy, precision, recall and mean reaction time of each user.

Task	**ID**	**True Positive**	**False Positive**	**False Negative**	**Accuracy**	**Precision**	**Recall**	**Reaction Time**
Visual	1	31	0	4	0.89	1.00	0.89	0.79
Visual	2	23	0	23	0.50	1.00	0.50	0.71
Visual	3	52	1	4	0.91	0.98	0.93	0.74
Visual	4	41	0	6	0.87	1.00	0.87	0.58
Visual	5	56	2	11	0.81	0.97	0.84	0.64
Visual	6	20	0	8	0.71	1.00	0.71	0.73
Visual	7	40	0	2	0.95	1.00	0.95	0.74
Visual	8	28	0	8	0.78	1.00	0.78	0.99
Visual	9	40	2	9	0.78	0.95	0.82	1.26

Table C.4: Table describes the performance of users while recognizing the audio/haptic ringtone while tracking objects. The performance is measures in terms of response time (mean and standard deviation), number of correct responses and the accuracy of the responses.

Task	**ID**	**Number of Calls**	**Response Time**		**Correct Responses**	**Errors**	**Accuracy**
			Mean	**Std Dev**			
Audio	1	40	6.82	3.37	40	0	1
Audio	2	40	7.55	5.56	32	8	0.8
Audio	3	40	9.36	9.54	35	5	0.875
Audio	4	40	5.08	2.63	33	7	0.825
Audio	5	40	4.80	2.98	39	1	0.975
Audio	6	40	7.34	4.86	34	6	0.85
Audio	7	40	9.38	4.54	17	23	0.425
Audio	8	40	6.36	5.16	40	0	1
Audio	9	40	4.82	2.88	32	8	0.8
Haptic	1	40	15.11	9.72	29	11	0.725
Haptic	2	40	9.18	6.76	14	26	0.35
Haptic	3	40	13.94	12.21	37	3	0.925
Haptic	4	40	9.61	3.91	38	2	0.95
Haptic	5	40	13.94	8.40	21	19	0.525
Haptic	6	40	8.03	4.43	28	12	0.7
Haptic	7	40	7.51	5.85	32	8	0.8
Haptic	8	40	10.90	12.59	38	2	0.95
Haptic	9	40	7.82	4.64	30	10	0.75

Table C.5: Mean and standard deviation of change in accuracy, precision, recall and reaction time for tracking objects at different configurations.

Task	**Visual + Audio**		**Visual + Haptic**		**Visual**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Accuracy	0.693303	0.094496	0.554296	0.109076	0.801188	0.135377
Precision	0.958954	0.053788	0.94766	0.062648	0.988781	0.018303
Recall	0.71525	0.095161	0.577445	0.124631	0.809246	0.137364
Reaction Time	1.05455	0.645533	1.1827	0.732729	0.78943	0.41799

APPENDIX D

PRE-SURVEY, SBSOD, WORKLOAD, AND USABILITY DATA COLLECTED FOR FIRST USER STUDY PERFORMED TO COMPARE HAPTIGO AND POCKETNAVIGATOR

Table D.1: Demography and mobile navigation familiarity data collected from participants before user study I.

User	**Gender:**	**Age Range**	**Mobile Navigation Familiarity**	**Gyro Game Familiarity**
1	Male	21 and Under	1	1
2	Female	22 to 34	6	4
3	Male	22 to 34	7	7
4	Male	22 to 34	4	2
5	Male	22 to 34	6	1
6	Male	21 and Under	7	5
7	Male	22 to 34	7	5
8	Male	22 to 34	5	1
9	Female	21 and Under	3	1
10	Male	22 to 34	6	1
11	Male	22 to 34	7	1
12	Male	22 to 34	4	1

Table D.2: Self reported sense of direction ratings collected from participants before user study I.

User	Giving Directions	Poor Memory	Judging Distances	Good Sense of Direction	Cardinal Direction
1	6	1	5	3	2
2	2	1	4	1	5
3	3	7	3	4	1
4	5	2	5	4	5
5	5	5	5	7	6
6	6	3	2	6	7
7	7	7	4	7	7
8	5	5	4	5	2
9	4	4	1	3	4
10	4	3	6	2	5
11	7	3	5	6	2
12	5	5	5	4	6

Table D.3: Self reported sense of direction ratings collected from participants before user study I.

User	Enjoy Reading Maps	Lost in a City	Trouble Understanding Directions	Good at Reading Maps	Good Navigator in a Car
1	6	1	1	1	6
2	4	1	3	5	7
3	1	3	5	7	7
4	4	5	3	4	2
5	5	6	6	6	1
6	5	7	5	5	6
7	1	5	7	7	1
8	3	3	3	5	5
9	4	5	5	5	6
10	7	2	5	6	6
11	4	2	6	5	6
12	5	2	3	4	5

Table D.4: Self reported sense of direction ratings collected from participants before user study I.

User	Don't Enjoy giving Directions	Should Know Where I am	Poor Navigation Planner	Good Memory of Places Travelled	Bad Mental Map	SB-SOD Score
1	6	3	2	7	4	3.60
2	7	2	3	1	2	3.20
3	1	7	1	1	7	3.87
4	4	5	4	4	5	4.07
5	5	6	7	6	6	5.47
6	6	6	3	5	7	5.27
7	4	7	7	7	7	5.67
8	5	4	3	3	3	3.87
9	4	3	3	3	4	3.87
10	5	6	3	3	3	4.40
11	5	6	6	5	5	4.87
12	4	6	4	4	4	4.40

Table D.5: Usability ratings for HaptiGo and PocketNavigator collected from participants for user study I.

Navigation System	**User**	**Overall Direction Signals**	**Left**	**Right**	**Straight**
Haptigo	1	7	7	7	7
Haptigo	2	3	5	5	3
Haptigo	3	5	7	7	7
Haptigo	4	6	5	6	5
Haptigo	5	6	7	7	4
Haptigo	6	7	7	7	7
Haptigo	7	7	5	5	4
Haptigo	8	6	6	6	6
Haptigo	9	6	7	7	6
Haptigo	10	6	7	7	3
Haptigo	11	6	6	6	4
Haptigo	12	5	5	4	6
PocketNavigator	1	1	7	2	7
PocketNavigator	2	5	5	5	7
PocketNavigator	3	3	2	2	7
PocketNavigator	4	6	4	4	6
PocketNavigator	5	3	3	3	3
PocketNavigator	6	6	4	6	7
PocketNavigator	7	6	5	5	7
PocketNavigator	8	5	4	4	3
PocketNavigator	9	5	4	4	6
PocketNavigator	10	6	5	5	7
PocketNavigator	11	4	3	3	6
PocketNavigator	12	5	5	5	6

Table D.6: Nasa TLX load survey data collected from participants after user study I. MD - Mental Demand, PD - Physical Demand, TD - Temporal Demand, P - Performance, E - Effort, F - Frustration, LS - Load Score.

Navigation System	**User**	**MD**	**PD**	**TD**	**P**	**E**	**F**	**LS**	**LS (7)**
Haptigo	1	5	6	4	5	3	6	67	4.47
Haptigo	2	5	2	4	7	5	2	57	3.80
Haptigo	3	4	1	2	6	2	1	36	2.40
Haptigo	4	2	2	2	5	5	2	36	2.40
Haptigo	5	4	2	3	7	2	1	40	2.67
Haptigo	6	5	5	3	6	4	2	55	3.67
Haptigo	7	3	3	3	6	3	3	43	2.87
Haptigo	8	3	1	2	6	1	1	29	1.93
Haptigo	9	3	1	1	6	2	1	27	1.80
Haptigo	10	3	2	3	7	5	2	43	2.87
Haptigo	11	3	1	2	6	2	1	31	2.07
Haptigo	12	3	5	3	5	3	1	42	2.80
Pocket Navigator	1	7	5	7	3	5	7	96	6.40
Pocket Navigator	2	5	3	4	7	3	2	54	3.60
Pocket Navigator	3	5	3	4	6	3	1	53	3.53
Pocket Navigator	4	2	2	3	5	3	1	34	2.27
Pocket Navigator	5	6	2	3	3	4	3	62	4.13
Pocket Navigator	6	6	5	6	4	6	5	84	5.60
Pocket Navigator	7	3	1	2	7	2	2	32	2.13
Pocket Navigator	8	5	4	6	4	6	3	74	4.93
Pocket Navigator	9	6	2	4	5	3	2	60	4.00
Pocket Navigator	10	5	2	5	6	4	2	60	4.00
Pocket Navigator	11	5	1	3	6	5	4	57	3.80
Pocket Navigator	12	5	4	3	5	3	2	53	3.53

Table D.7: Elapsed time data collected from participants after user study I.

Navigation System	**User ID**	**Elapsed Time (ms)**
Haptigo	1	1120911
Haptigo	2	594540
Haptigo	3	459204
Haptigo	4	333312
Haptigo	5	378226
Haptigo	6	272887
Haptigo	7	378087
Haptigo	8	395693
Haptigo	9	464753
Haptigo	10	312068
Haptigo	11	275811
Haptigo	12	824162
Pocket Navigator	1	410661
Pocket Navigator	2	398684
Pocket Navigator	3	512473
Pocket Navigator	4	543040
Pocket Navigator	5	389772
Pocket Navigator	6	266763
Pocket Navigator	7	284732
Pocket Navigator	8	948519
Pocket Navigator	9	476689
Pocket Navigator	10	353695
Pocket Navigator	11	311936
Pocket Navigator	12	536371

APPENDIX E

PRE-SURVEY, SBSOD, WORKLOAD, AND USABILITY DATA COLLECTED FOR SECOND USER STUDY PERFORMED TO COMPARE HAPTIGO WITH AND WITHOUT OBSTACLE DETECTION

Table E.1: Demography and mobile navigation familiarity data collected from participants before user study II.

User	**Gender**	**Age**	**Mobile Navigation Familiarity**	**Gyro App Familiarity**
1	Male	22 to 34	6	5
2	Male	21 and Under	7	4
3	Male	22 to 34	7	1
4	Male	22 to 34	7	1

Table E.2: Self reported sense of direction ratings collected from participants before user study II.

User	**Giving Directions**	**Poor Memory**	**Judging Distances**	**Good Sense of Direction**	**Cardinal Direction**
1	6	7	4	5	1
2	6	4	4	6	1
3	5	5	3	5	2
4	2	3	6	1	3

Table E.3: Self reported sense of direction ratings collected from participants before user study II.

User	**Enjoy Reading Maps**	**Lost in a City**	**Trouble Understanding Directions**	**Good at Reading Maps**	**Good Navigator in a Car**
1	5	5	5	6	5
2	5	6	6	6	1
3	1	3	7	6	3
4	5	2	2	5	5

Table E.4: Self reported sense of direction ratings collected from participants before user study II.

User ID	**Don't Enjoy giving Directions**	**Should Know Where I am**	**Poor Navigation Planner**	**Good Memory of Places Travelled**	**Bad Mental Map**	**SBSOD Score**
1	4	5	6	5	5	4.93
2	4	6	6	6	6	4.87
3	4	5	4	5	7	4.33
4	2	1	1	2	7	3.13

Table E.5: Usability ratings for HaptiGo with and without obstacle detection collected from participants for user study II.

HaptiGo Vest Type	**User**	**Overall Direction Signals**	**Left**	**Right**	**Straight**	**Obstacle Detection**
With Obstacle Detection	1	6	7	7	2	6
With Obstacle Detection	2	5	6	6	1	7
With Obstacle Detection	3	6	6	6	1	6
With Obstacle Detection	4	3	6	5	2	6
With Obstacle Detection	5	2	1	2	6	2
With Obstacle Detection	6	6	7	7	6	5
Sans Obstacle Detection	1	6	7	6	2	N/A
Sans Obstacle Detection	2	4	7	7	2	N/A
Sans Obstacle Detection	3	6	7	7	1	N/A
Sans Obstacle Detection	4	3	6	6	4	N/A
Sans Obstacle Detection	5	7	6	6	3	N/A
Sans Obstacle Detection	6	3	6	6	3	N/A

Table E.6: Nasa TLX load survey data collected from participants after user study II. MD - Mental Demand, PD - Physical Demand, TD - Temporal Demand, P - Performance, E - Effort, F - Frustration, LS - Load Score.

Navigation System	**User**	**MD**	**PD**	**TD**	**P**	**E**	**F**	**LS**	**LS (7)**
With Obstacle Detection	1	4	3	4	6	5	4	58	3.87
With Obstacle Detection	2	3	1	1	5	3	2	32	2.13
With Obstacle Detection	3	7	2	6	7	4	5	79	5.27
With Obstacle Detection	4	7	5	4	5	6	5	80	5.33
With Obstacle Detection	5	4	2	5	7	2	1	48	3.20
With Obstacle Detection	6	5	3	3	5	5	5	62	4.13
Sans Obstacle Detection	1	5	3	4	5	6	4	66	4.40
Sans Obstacle Detection	2	3	1	1	5	4	1	32	2.13
Sans Obstacle Detection	3	7	2	6	7	6	4	81	5.40
Sans Obstacle Detection	4	6	5	6	6	7	6	86	5.73
Sans Obstacle Detection	5	5	5	4	3	6	5	72	4.80
Sans Obstacle Detection	6	4	2	3	5	5	5	56	3.73

Table E.7: Elapsed time data collected from participants after user study II.

HaptiGo Vest Type	**User**	**Elapsed Time (ms)**
With Obstacle Detection	1	529026
With Obstacle Detection	2	552593
With Obstacle Detection	3	457280
With Obstacle Detection	4	452731
With Obstacle Detection	5	444519
With Obstacle Detection	6	266009
Sans Obstacle Detection	1	341957
Sans Obstacle Detection	2	451000
Sans Obstacle Detection	3	460638
Sans Obstacle Detection	4	1079915
Sans Obstacle Detection	5	419910
Sans Obstacle Detection	6	390628

APPENDIX F

WORKLOAD AND USABILITY DATA COLLECTED FOR FIRST USER STUDY PERFORMED WITH HAPTIMOTO

Table F.1: HaptiMoto Usability Ratings of users in Study I

User ID	Directions	Left	Right	Straight	U-Turn
1	6	7	6	7	6
2	5	6	6	7	7
3	5	7	7	7	7
4	6	7	7	6	2
5	4	4	4	6	3
7	5	7	7	6	6
8	7	7	6	7	7
9	6	4	5	5	7
10	6	7	7	7	7
11	6	7	7	5	7
12	7	7	7	7	7
13	5	7	7	7	7
14	4	6	6	6	4
15	5	5	6	6	6
16	3	5	5	4	4

Table F.2: NASA TLX Load Survey data of users in Study I. MD - Mental Demand, PD - Physical Demand, TD - Temporal Demand, P - Performance, E - Effort, F - Frustration, LS - Load Score.

Survey Type	User	MD	PD	TD	P	E	F	LS	LS (7)
Pre	1	6	6	5	5	6	5	80	5.33
Pre	2	3	3	2	6	4	1	37	2.47
Pre	3	2	2	4	4	2	1	37	2.47
Pre	4	5	6	5	5	5	4	71	4.73
Pre	5	3	2	3	6	5	4	48	3.2
Pre	7	3	2	2	7	3	1	33	2.2
Pre	8	1	1	1	7	1	1	14	0.93
Pre	9	5	5	5	6	5	3	67	4.47
Pre	10	1	1	1	1	1	1	15	1
Pre	11	2	2	1	7	2	1	22	1.47
Pre	12	5	3	1	7	2	1	38	2.53
Pre	13	1	1	1	6	1	1	15	1
Pre	14	3	3	3	6	2	2	39	2.6
Pre	15	2	2	2	6	5	1	33	2.2
Pre	16	6	4	3	7	2	2	54	3.6
Post	1	6	5	4	6	4	4	68	4.53
Post	2	2	2	2	7	2	4	32	2.13
Post	3	1	1	2	5	1	1	20	1.33
Post	4	3	3	4	6	3	2	45	3
Post	5	5	3	2	6	5	5	57	3.8
Post	7	4	2	3	4	3	2	47	3.13
Post	8	1	1	1	7	1	1	14	0.93
Post	9	4	3	6	6	4	2	60	4
Post	10	5	4	1	6	4	2	46	3.07
Post	11	2	1	1	6	1	1	20	1.33
Post	12	2	1	1	1	2	1	22	1.47
Post	13	4	2	3	5	2	2	44	2.93
Post	14	4	3	4	6	6	5	62	4.13
Post	15	5	3	3	6	5	2	55	3.67
Post	16	6	6	3	5	5	4	68	4.53

APPENDIX G

WORKLOAD AND ROUTE COMPLETION TIME DATA COLLECTED FOR SECOND USER STUDY WITH HAPTIMOTO

Table G.1: Completion Time of users riding motorcycle on 0.5 circuit with Google Maps and Haptimoto, and 2-mile circuit.

User	**0.5 Mile Route**		**2-Mile Route with HaptiMoto**
	Google Maps	**HaptiMoto**	
1	106	84	205
2	107	99	346
3	124	90	282
4	110	108	321
5	112	75	277
6	112	85	244
7	113	103	280
8	122	105	289

Table G.2: NASA Load Survey data of users riding motorcycle on 0.5 circuit with Google Maps and Haptimoto. MD - Mental Demand, PD - Physical Demand, TD - Temporal Demand, P - Performance, E - Effort, F - Frustration, LS - Load Score.

Navigation System	**User**	**MD**	**PD**	**TD**	**P**	**E**	**F**	**LS**	**LS (7)**
Google Maps	1	1	1	2	7	2	2	22	1.47
Google Maps	2	3	3	3	6	5	5	41	2.73
Google Maps	3	5	3	4	6	5	4	55	3.67
Google Maps	4	5	5	1	7	5	5	44	2.93
Google Maps	5	4	5	4	5	3	3	49	3.27
Google Maps	6	3	1	1	7	2	2	24	1.6
Google Maps	7	2	1	1	7	1	2	17	1.13
Google Maps	8	4	2	2	7	3	1	36	2.4
Hapti-Moto	1	3	1	1	6	3	2	31	2.07
Hapti-Moto	2	3	2	3	6	3	2	36	2.4
Hapti-Moto	3	2	2	3	7	3	1	30	2
Hapti-Moto	4	3	2	1	7	2	1	25	1.67
Hapti-Moto	5	4	4	4	6	3	3	47	3.13
Hapti-Moto	6	3	1	1	7	3	2	26	1.73
Hapti-Moto	7	6	4	3	6	5	2	57	3.8
Hapti-Moto	8	5	2	4	7	5	3	53	3.53