Haptic Learning of Freehand Semaphoric Gesture Shortcuts

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ABSTRACT
Haptic learning of gesture shortcuts has never been explored. In this paper, we investigate haptic learning of a freehand semaphoric finger tap gesture shortcut set using haptic rings. We conduct a two-day study of 30 participants where we couple haptic stimuli with visual and audio stimuli, and compare their learning performance with wholly visual learning. The results indicate that with <30 minutes of learning, haptic learning of finger tap semaphoric gestures is comparable to visual learning and maintains its recall on the second day.

Author Keywords
Haptics; Tactile; Mid-air; Gestures; Learning; Rings

ACM Classification Keywords
H.5.2. Information interfaces and presentation

INTRODUCTION
With the concurrent rise of wearables and sensors, there is a renewed interest in freehand gestures that can be used in stationary or mobile contexts (*e.g.,* while sitting on a desk, and while walking on the street). They can be used to interact with large screen displays using Kinect, desktops using Leap Motion, smartwatches and smartphones using motion or muscle sensing, and even with devices without a visual display using novel technologies such as smartrings. This diversity of user contexts demands not just freehand gestures that can be used across contexts, but also freehand gestural learning methods that can be integrated across contexts. Existing methods that support the learning of gestures typically rely on visual learning. However, constant engagement with visual displays is not always feasible or desired. We propose and evaluate haptic learning as a possible solution. Despite its potential benefits for eyes-free learning, haptic learning has never been explored for freehand gestural learning.

In terms of perceptual accuracy, the haptic modality has long been considered inferior to vision [8, 9, 25]. However, learning also depends on phenomena different from perception. Haptic feedback has been extensively used in motor training because 1) haptic training occurs in a body-centered manner through motor coordinates as opposed to visuospatial coordinates, 2) certain complex motor movement information like 3D movements are difficult to explain visually or verbally and haptics removes the need for complex sensorimotor transformations [9]. The promising haptic explorations for motor learning suggest the potential applicability of haptics for gestural learning. Gestural learning is fundamentally different from motor learning in that it is associative where the user learns an association between two stimuli, one corresponding to the command and the other to its gesture. The most pervasive example is the keyboard shortcut where one stimulus corresponds to the keyboard shortcut and the other, to the command action. The value of haptics for gestural learning has several open sub-questions—*a)* Can haptic stimulus be used for associative learning of gestures? *b)* Is it better or worse than visual learning? *c)* Does it support immediate recall, or longer-term recall, or both?

To answer the questions about haptic learning for freehand gesture shortcuts, we conduct a two-day study with 30 participants comparing the learning of haptic stimuli for gestures coupled with visual and audio command stimuli against visual-only learning. Although most freehand gestural interactions in the current literature are manipulative gestures [24] (which *"control an entity [on the screen] by applying a tight relationship between the actual movements of the gesturing hand or arm with the object being manipulated"*), we focus our study on a second class of gestures, called semaphoric gestures [24] (which *"employ a stylized dictionary of static or dynamic hand or arm gestures [...that...] serve as a universe of symbols to be communicated to the machine"*). Keyboard shortcuts for commands are semaphoric gestures which involve a fixed pattern of finger movement on the keyboard. Semaphoric gesture sets hold similar potential to be used as freehand gestures to rapidly invoke command shortcuts in a diversity of contexts through carefully designed actions that would be less prone to heavy hand

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and arm fatigue, known as the gorilla arm effect [14]. Learning of freehand semaphoric gesture sets, however, is an open question. The most popular gestural learning techniques rely on self-revelation of the gesture while the user is using the interface with manipulative gestures. This, however, is not possible for situations where the freehand gestures are designed for non-visual scenarios. Freehand semaphoric gestures are therefore, perfect for our investigation of haptic learning of gesture shortcuts. Our study shows that with <30 minutes of learning, haptic learning of semaphoric finger tap gestures is comparable to visual learning and maintains its recall on the second day.

RELATED WORK

Haptics for Learning

Haptics has commonly been used as feedback or notifications. Haptic feedback can help to guide users' movements for medical rehab purposes [30], and computer-based interactions, such as target acquisition [22] and visual search tasks [20]. With respect to training, it has been used for posture [21] or trajectory training [3] mostly consisting of repetitive motor movements. Yang *et al.* found the effectiveness of visual-haptic and visual training were comparable for helping people develop motor skills [32]. Passive haptic learning allows acquisition of motor skills (like piano tune) while the user is engaged in a distraction task [29]. All these works focus on non-associative learning of a movement through repeated exposure to the haptic stimulus. Seim et al.'s work on braille training [28] using passive haptic learning is the only instance of haptics in associative learning. While haptics have been used as feedback to assist or guide freehand manipulative gestures [7, 20, 23, 27, 31], active haptic learning has never been used for associative learning of semaphoric gesture sets.

Semaphoric Gestural Commands Learning

Aside from cheat-sheets and video instruction, the common approaches to semaphoric gestural command learning are: self-revelation of gestures while performing manipulative gestures [16, 17], dedicated or active learning of gestures [2, 11, 12, 15], and a combination of the two (*i.e.,* revelation while actively learning gestures, also called dynamic guides [1, 4, 10]). Most use only visual learning, except a few [11, 13] where audio cues are investigated for gesture presentation and have been found to be similar in performance to visual cues. Some active learning works include gesture cues in the visual interface [2, 13] similar to keyboard shortcuts being displayed next to the menu item. However, unless the user actively engages in learning, observational learning does not help [5, 18]. Our research investigates whether active haptic learning can support the learning of semaphoric gestures without the use of visual stimuli used in the learning process. Haptic cues are arguably easier to integrate in the interfaces because they do not take up any visual space.

DESIGN OF A FREEHAND SEMAPHORIC GESTURE SET

We design a simple set of freehand semaphoric gestures that are amenable to simple haptic learning. The set consists of 14 gestures, which is the standard number used in earlier shortcut gesture set learning investigations [2, 11, 13]. Each gesture is composed of a sequence of exactly three finger tap movements in air using the index (I), middle (M), and ring (R) fingers. For instance, the IMR gesture involves the index air-tap, followed by the middle air-tap, followed by the ring air-tap. Any finger can repeat and therefore we have a potential set of 27 gestures in total.

We selected 14 gestures from these 27 based on i) the ease of performing them, and ii) on minimizing the confusion between them. We conducted a pilot with four users to test the ease of performance for the 27 gestures. Although the users performed most gestures with ease, they were most uncomfortable in performing gestures that involved using the ring finger twice, consecutively or alternately. Thus, we removed all gesture sequences which involved a repetition of the ring finger, except RRR which would have high memorability. For every gesture sequence, there are six other gesture sequences that only differ by a single finger tap. For instance, IMR has IMI, IMM, IIR, IRR, MMR, and RMR. To minimize confusion, we next removed gestures such that for every gesture there is a maximum of three other gestures that differ by a single finger tap. The final gesture set is as follows – III, IIM, IMR, IRI, IRM, MIM, MIR, MMM, MMR, MRI, RII, RMI, RMM, and RRR.

HARDWARE IMPLEMENTATION OF HAPTIC RINGS

We designed the haptic setup such that i) the fingers are actuated directly, b) the system can be made compact, cost-effective, and practical across diverse contexts, c) the gesture is presented in a duration no longer than an optimal visual presentation, and d) there is zero confusion over which fingers were actuated. We built a set of three vibrotactile rings, one for each finger. Each ring contained a mini coin Dura Vibe™ motor that is 8*mm* diameter and 2.5*mm* height. The motor is housed within elastic straps to ensure firm positioning of motors across finger sizes. The motor is controlled by pulses from an Arduino Pro Mini and driven through the ULN2003 chip to minimize load on the microcontroller. For any gesture, the rings on the respective fingers vibrated one by one in order. Because a finger can repeat in some patterns (*e.g.,* IIM), we included a time gap between two vibrations to keep the patterns distinct. The ON duration of a single vibration ring was fixed at 100*ms* and the OFF duration at 350*ms,* resulting in a total gesture presentation time of 1000*ms*. The circuit assembly is mounted on an arm band as shown in Figure 2.

Psychophysics has established that vibrations are best perceived in the ventral regions (like the palm) because they have less hair and more Pacinian corpuscles that are responsible for detecting vibrations on skin. However, motors placed in the ventral region of one finger can produce vibrations incorrectly perceived by the adjacent

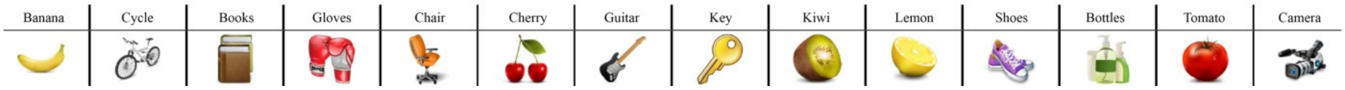

Figure 1: Object images and names.

fingers. We conducted a small pilot with three participants to test whether the ventral and dorsal regions was the better position on a finger to place the vibration motors. Testing with all 14 gestures, we found that participants incorrectly perceived the gesture in 7.9% of the cases with the ventral placement as opposed to 0.8% with the dorsal placement.

STUDY OF ACTIVE HAPTIC LEARNING OF GESTURES

To investigate the possibility of haptic learning with no visual engagement, we conducted a study comparing three conditions: Sound-Haptic (SH), where the command stimulus is given via sound and the associated gesture is presented haptically; Visual-Haptic (VH), where the command stimulus is visual; and Visual-Visual (VV), which is the baseline condition where both the command stimulus and the associated gesture are presented visually. The SH and VH conditions will inform our understanding of the performance of haptic learning with different command stimuli modalities. Because visual stimuli may lead to higher engagement, we hypothesize that the users will perform best in VV, followed by VH and then SH.

Experiment Design

We conducted a *between-subjects* study for the three conditions. The experiment followed closely the study design used by Ghomi *et al.* [11], which itself followed earlier studies by Appert *et al.* [2] and Grossman *et al.* [13]. In total, there were 30 (9 female) participants who were randomly assigned a condition (10 per condition). The participants were all right-handed and aged between 18 and 29 (μ = 23.3). Each participant took part in the study for two-days. The experiment consisted of one *learning* block and two *testing* blocks on day 1 to test immediate learning, and a third testing block on day 2 to test mid-term recall. In the learning block, depending on the condition, the image or the audio stimulus for an object (representing a command) was presented to the participant, and then the associated gesture was presented visually or haptically. We asked the participant to perform the gesture after the presentation of each object and gesture pair. We repeated these steps with another object-gesture pair until all pairs have been presented. Then, in the testing blocks, the participant was presented with the object stimulus only and then asked to perform the associated gesture. If the participant does not remember the gesture, she may request a hint which showed the associated gesture to the participant. If the participant performed the gesture wrong, the correct gesture was presented and then she was asked to perform the gesture again.

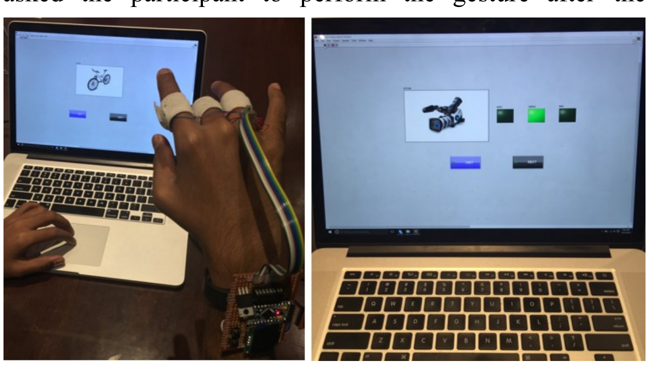

Figure 2: (left) A participant wearing the haptic rings setup for the Visual-Haptic condition. (right) The screen for the Visual-Visual condition.

We defined a set of 14 common objects to act as commands that can be associated with the gestures (see Figure 1). Because the finger tap gestures vary in difficulty, both in terms of required motor control and memorability, we generated 10 random associations between the 14 gestures and the 14 objects; *i.e.,* a different association was used for each of the 10 participants in a condition. To simulate a more realistic setup where some commands may appear more frequently than others, an appearance frequency is randomly assigned to each of the 14 objects following a Zipf distribution [X]. For the learning block, we use the frequencies (6, 6, 3, 3, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1) and for the testing blocks (12, 12, 6, 6, 4, 4, 3, 3, 2, 2, 2, 2, 1, 1). Therefore, there were 30 trials in total in the learning block, and 60 trials in a testing block. The presentation of trials was randomized.

Apparatus

During the experiment, participants sat in front of a laptop which displayed the study interface using the LabVIEW software. During the learning block of the VV condition, participants saw an interface with the object image on the left and the three visual indicators that highlight in sequence according to the associated gesture (see Figure 2, right). For VH and SH, visual indicators were not shown on the interface. Instead, the participants wore the haptic rings along with the armband in their right hands. For SH, audio of the object name was played, instead of the object image. LabVIEW connects serially with the Arduino Pro Mini and administers the haptic pattern for gesture presentation without delay. We asked all participants to use the laptop's trackpad with their left hand to press the Hint/Next button, and to perform the gestures with their right hand which rested vertically on an armrest.

We use manual detection to decide if the participants performed the gestures correctly or incorrectly. To achieve this without making the participants overly conscious of the experimenter's gaze, the setup was such that their fingers were visible in the laptop webcam which was live streamed to the experimenter in another area of the room. When the participants performed a gesture, the experimenter sees the

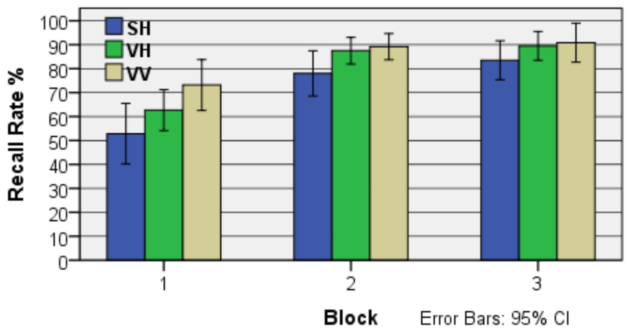

Figure 3: Recall Rate % for all techniques by blocks.

live stream and sends a Correct/Incorrect signal to LabVIEW which displays a popup window informing participants if their response was correct or not. LabVIEW keeps a log of all the events.

Procedure

When a participant arrives, she is introduced to the task and its interface using a sample object image or audio of its name and an associated gesture outside the sets of 14. The experiment starts after the introduction, with 2 minute breaks after every 15 trials. After the learning block, we inform the participant that the testing block will begin and instruct the participant to seek a hint whenever she is unsure of the response. We ask the participant to complete a questionnaire at the end on Day 1 and interview the participant about her approach at the end of the experiment on Day 2. The experiment takes about 50 minutes on Day 1 and 20 mins on Day 2. Each participant completes in total 30 learning block trials and 60 testing block 1 trials + 60 testing block 2 trials +60 testing block 3 trials. Thus, there were (30+180) × 30 participants = 6,300 trials.

RESULTS

The primary measures of the study are *recall rate*, the percentage of correct answers in a testing block without hint; *hint rate*, the percentage of trials where participants used hint. We examine these two measures by their learning technique for each block.

Quantitative Results

We found a significant effect of learning technique on the recall rate in Block 1 ($F(2, 27) = 4.590$, $p<0.05$) and Block 2 ($F(2, 27) = 3.703$, $p<0.05$). Post hoc Tukey tests revealed that the recall rate for Sound-Haptic was significantly lower than Visual-Visual in both blocks 1 ($p<0.05$) and 2 ($p<0.05$). Figure 3 shows the mean recall rate % for each technique by block. The recall rate for SH is 52.8% compared to 62.7% and 73.2% for VH and VV respectively in Block 1. In Block 2, SH closes its gap with VH and VV with a recall rate of 78%, compared to 87.5% and 89.2% for VH and VV. However, it is still significantly lower than VV. By Block 3 on Day 2, there is no significant difference between the techniques. Further, there is a significant effect of Block on the recall rates for all techniques (VV: $F_{Greenhouse\text{-}Geisser}(1.172, 10.547) = 12.964$, $p<0.01$; VH: $F_{Greenhouse\text{-}Geisser}(1.260, 11.339) = 76.830$, $p<0.001$; SH: $F(2, 18) = 46.594$, $p<0.001$). The post hoc tests with Bonferroni correction revealed that the difference was between blocks 1 and 2, and blocks 1 and 3 ($p<0.01$ for all pairs). There was no significant difference between blocks 2 and 3 for any technique (see Figure 3).

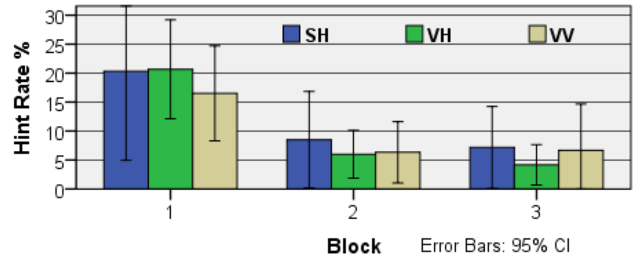

Figure 4: Hint Rate % for all techniques by blocks.

Participants associated object-gesture pairs easiest when the object commands were presented visually (VV & VH). No statistical differences could be found in the recall rates of VH and VV. This suggests that in less than 20 minutes of active haptic learning with visual command stimuli, users can learn gestures with similar recall rates as wholly visual learning. However, even though the difference in VH and VV is not significant after Block 1, VH seems to trail VV in magnitude which might be worth looking into in larger studies. On the other hand, SH had the lowest recall rate. However, the improvement in SH recall rate from block 1 to block 2 is 47.7% which indicates the learning with SH may start slowly but can briskly catch up with the other two techniques; by block 3, no statistical difference could be found in the recall rates of the 3 conditions ($\eta_{adj}^2 = .026$). This suggests that in less than 30 minutes, the learning of gesture shortcuts with haptic gesture presentation and audio command stimuli without any visual engagement is comparable to wholly visual learning.

The mid-term recall rate from Block 3 is unaffected by a day's gap for all three techniques. This is interesting because a majority of the studies in prior haptic literature for motor training have reported that participants get overly dependent on haptic feedback during training, thus harming performance later [19, 26]. Although prior work had already shown that visual learning is retained by the participants in medium-term, this has proven to be the case for haptic learning as well. The participants across all techniques invariably mentioned that after Day 1, they expected to forget most gestures by Day 2. In the words of one participant: *"I just sat for the experiment on Day 2 thinking I don't remember anything, but then when the objects appeared, the gesture just automatically came to my fingers."* This suggests that the techniques result in muscle memory of the gestures in at least the mid-term.

Figure 4 shows the hint rate for each technique by block. There is a significant effect of Block on hint rate for all techniques (VV: $F_{Greenhouse\text{-}Geisser}(1.223, 11.003) = 6.774$, $p<0.01$; VH: $F_{Greenhouse\text{-}Geisser}(1.094, 9.845) = 29.920$,

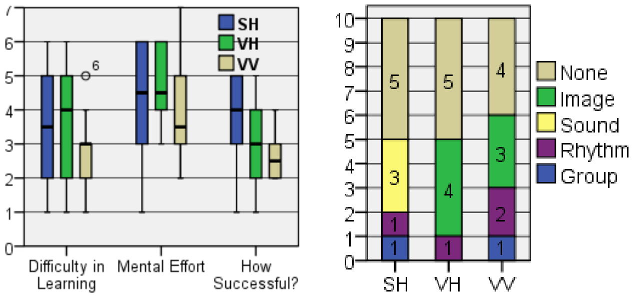

Figure 5: (left) Questionnaire Results, (right) Mnemonics used by participants by learning technique

$p<0.001$; $F_{Greenhouse\text{-}Geisser}$ $(1.015, 9.132) = 7.739$, $p<0.05$.) The post hoc tests revealed the significant difference to be between blocks 1 & 2 and 1 & 3 for all techniques ($p < 0.05$ for all pairs). There is no significant effect of technique on hint rate in any block. Essentially, participants took a lot of hints uniformly across all techniques in block 1, after which they did not need as many. 43% of the hints in block1 were for objects that appeared only once or twice per block even when they were only 10% of the total trials. Participants reported that remembering the gestures for objects that rarely appeared was the most difficult.

Although the lower recall rate for SH was much lower than for VV and VH, the hint rate for SH is same for VV and VH. This suggests that the participants in SH did not seek hints when they were unsure and gave more incorrect responses. Participants reported they got confused between similar sounding words such as Chair and Cherry, Gloves and Guitar, and Key and Kiwi. To a lesser extent, there were also confusions because of similar images, such as Banana and Lemon being both yellow-colored confused some participants. Consequently, the performance of SH could potentially have been closer to VV and VH if there were similar number of confusing elements in the images.

Subjective Feedback

The results from the questionnaire are illustrated in Figure 5 (left). A Kruskal-Wallis test revealed no effect of the technique on the participant's perception of task difficulty, mental effort, and how successfully they thought they performed in the task.

Participants reported confusion with gestures in which only two fingers were involved, for instance IIM and MIM. Participants found the gestures with three distinct fingers to be easier, probably because it enabled the fingers to move in a smooth wave, for instance IMR, MIR, *etc.* Participants found patterns with one distinct finger (*i.e.,* III, MMM, RRR) the easiest to remember.

Half of the participants reported using mnemonics of some kind while the other half did not use any memory techniques. We classified their approaches into the following five categories:

- **No technique.**
- **Image mnemonics.** Participants developed tricks from how the object images looked and associated them with the gesture labels; for example, *"Cycle has rims. And the gesture was MIR, so I remembered opposite of rim is mir."*
- **Sound mnemonics.** Similar to above, SH participants also developed tricks from the way object names sound; for example, *"Chair ends with IR, so MIR"* and *"Ba- -na- -na, so it is 1 2 2".*
- **Rhythm mnemonics.** Some participants were music enthusiasts and used rhythm techniques to help them remember; for example, *"I associated the patterns with piano playing and imagined every image in front of the piano playing the gesture."*
- **Grouping of mnemonics.** Participants created associations with similar objects or similar gestures; for example, *"123 for Tomato, so 321 for Cherry."*

Figure 5 (right) shows the distribution of these by participant count for each learning technique. Although group mnemonics were used by many participants, only two participants reported it as their dominant memorization technique. As we can see, mnemonics based on image or sound were the most popular. However, almost half of the participants reported using no technique to remember the associations. We performed an ANOVA test to see if there was a difference between participants who used mnemonics *vs.* who used no memorization techniques, across all three learning techniques. We found that the recall rate was significantly higher for participants who used mnemonics for all three blocks (B1: $F(1, 28)=5.347$, $p<0.05$, B2: $F(1, 28)=9.579$, $p<0.01$, B3: $F(1, 28)=7.326$, $p<0.05$). Although the differences are significant, with the first block having a recall rate of 69% for participants using mnemonics compared to 56% for no technique ones, by the second block, the recall rate of participants with no technique was 80% compared to 90% for participants using mnemonics. This suggests that even without mnemonics, participants would be able to achieve fairly good recall rates with less than 20 minutes of active learning.

DISCUSSION, RESEARCH & DESIGN CONSIDERATIONS

Active *vs.* Passive Haptic Learning Approach

Passive Haptic Learning (PHL) allows acquisition of motor skills via haptic stimulation while no perceived attention is given to learning [29]. If users would be able to learn gestures passively in this way, it removes the need for active or self-revelation learning.

Before we investigated active haptic learning, we conducted a short pilot study with four participants to investigate PHL's potential for gestural learning. We randomly selected 8 gestures from the set and associated them with 8 object names randomly selected from the set shown in Figure 1. We employed a testing procedure similar to the design used in earlier PHL studies [29]. First, in the introductory phase, we played the audio of an object name and the haptic sequence for the associated gesture. We then asked participants to perform the gesture once. This was done once for all 8 object-gesture pairs. Then in the PHL phase, we asked participants to play the Candy Crush game [6] on a smartphone and score as much as they can. At the same time, we played the audio cue followed by the associated haptic sequence for all 8 pairs in random order repeatedly. The PHL phase lasted 40 minutes within which each audio-haptic pair was played exactly 20 times. At the end of the PHL phase, we asked participants to reproduce the associated gesture to the different audio cues. Participants could only reproduce an average of 2 gestures correctly out of 8. We concluded that associative learning tasks where the user has to learn multiple command-gesture associations are not conducive for passive learning. As a result, we did not use PHL in our study.

Active Haptic Learning Strategies

Given our results show that haptic learning can be learned, an open research question that needs to be investigated next is how to naturally integrate haptic learning of gestures into actual systems. One possibility, for instance, is that whenever a user selects an icon (*e.g.,* by dwelling on it), the associated shortcut gesture's haptic cue can be played.

Mnemonic associations depended heavily on the object-gesture pairings that participants randomly received. However, even when there were no natural associations, participants found creative ways to make associations. We believe these associations have been uniquely bolstered by the type of gestures we used. The I, M, R finger patterns are amenable to different strategies that participants may use to connect them to images, sounds, and rhythms. Such connections are arguably not as easy to other types of gestures (*e.g.,* drawing gestures), thus making finger tap gestures more compelling in practice. However, participants performed well even without mnemonics and participants in haptic conditions reported that the vibrations helped them build muscle memory without much conscious effort. An interesting question to explore would be the extent of active engagement that is elicited by each technique.

Freehand Finger Tap Gestures

Our results show that haptic learning of gestures can work comparably to visual learning. However, the extent of learning will depend on the kind of gestures that are involved; this is, of course, true for visual learning as well.

Although we designed the finger tap gestures to explore haptic learning of gestures, we note that there have been no semaphoric finger gesture sets previously proposed in the literature. The finger tap gestures are uniquely positioned to fill this gap because they satisfy multiple requirements for practical gesture sets—*i)* they are easy to remember and associate, *ii)* they form a gesture vocabulary that uses the same style of invocation, *iii)* finger air-taps cause minimal fatigue, *iv)* their subtlety allows them to be performed across diverse contexts, and *v)* they are potentially less prone to variations in scale and user drawings of the gesture, allowing consistent detection by the computer.

We observed that while some users performed the gestures in a wavy rhythmic form, others performed it in a jerky motion. The gesture detection algorithm needs to handle these different input scenarios. Additionally, gestures that are very similar to each should be avoided. Particularly, if possible, the number of gestures with exactly two distinct fingers should be minimized to reduce initial confusion in learning the gesture set. Gestures with a single distinct finger were the easiest to remember, followed by the ones with three distinct fingers, and then the ones with two. Because the gestures are of varying difficulty, different assignment strategies can be developed and tested. For instance, frequent commands could be assigned to the easiest gestures so that the user can start using them immediately. On the other hand, if the application requires all commands to be learnt at the same rate, then perhaps the easiest gestures should be assigned to less frequent commands, and the hardest gestures assigned to the most frequent ones. Alternatively, perhaps the users can also be given the freedom to choose which gestures to associate with different commands.

CONCLUSION

Our work is the first exploration into haptic learning of semaphoric gestures. To this end, we have designed freehand finger tap gestures and haptic rings which can potentially be used across diverse user scenarios. Through a two-day study with 30 participants, we learn that haptic learning can be successfully used for associative learning of freehand finger tap gestures and command shortcuts. We show that when combined with visual command stimulus, haptic learning of freehand semaphoric gestures performs comparably to visual learning. Further, haptic learning with audio command stimulus and no visual engagement initially has a lower initial recall rate, but with less than 30 minutes of learning, it becomes comparable to visual learning. We also show that the mid-term recall rate for haptic learning stays constant, as has been reported earlier for visual learning. Our results suggest that gestural learning can be integrated into many contexts with minimal visual engagement. As the first work that investigates the active haptic learning of semaphoric gestures, our findings are highly encouraging for future explorations in this space.

REFERENCES

[1] Anderson, F. and Bischof, W.F. 2013. Learning and performance with gesture guides. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '13* (New York, New York, USA, Apr. 2013), 1109.

[2] Appert, C. and Zhai, S. 2009. Using strokes as command shortcuts. *Proceedings of the 27th international conference on Human factors in computing systems - CHI 09* (New York, New York, USA, Apr. 2009), 2289.

[3] Bark, K., Hyman, E., Tan, F., Cha, E., Jax, S.A., Buxbaum, L.J. and Kuchenbecker, K.J. 2015. Effects of vibrotactile feedback on human learning of arm motions. *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*. 23, 1 (Jan. 2015), 51–63.

[4] Bau, O. and Mackay, W.E. 2008. OctoPocus. *Proceedings of the 21st annual ACM symposium on User interface software and technology - UIST '08* (New York, New York, USA, Oct. 2008), 37.

[5] Blandin, Y., Lhuisset, L. and Proteau, L. 2010. Cognitive Processes Underlying Observational Learning of Motor Skills. *The Quarterly Journal of Experimental Psychology: Section A*. (Oct. 2010).

[6] Candy Crush Saga - King: *http://candycrushsaga.com/*. Accessed: 2016-04-11.

[7] Carter, T., Seah, S.A., Long, B., Drinkwater, B. and Subramanian, S. 2013. UltraHaptics. *Proceedings of the 26th annual ACM symposium on User interface software and technology - UIST '13* (New York, New York, USA, Oct. 2013), 505–514.

[8] CONNOLLY, K. and JONES, B. 1970. A DEVELOPMENTAL STUDY OF AFFERENT-REAFFERENT INTEGRATION. *British Journal of Psychology*. 61, 2 (May 1970), 259–266.

[9] Feygin, D., Keehner, M. and Tendick, R. 2002. Haptic guidance: experimental evaluation of a haptic training method for a perceptual motor skill. *Proceedings 10th Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems. HAPTICS 2002* (2002), 40–47.

[10] Freeman, D., Benko, H., Morris, M.R. and Wigdor, D. 2009. ShadowGuides. *Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces - ITS '09* (New York, New York, USA, Nov. 2009), 165.

[11] Ghomi, E., Faure, G., Huot, S., Chapuis, O. and Beaudouin-Lafon, M. 2012. Using rhythmic patterns as an input method. *Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems - CHI '12* (New York, New York, USA, May 2012), 1253.

[12] Ghomi, E., Huot, S., Bau, O., Beaudouin-Lafon, M. and Mackay, W.E. 2013. Arpège. *Proceedings of the 2013 ACM international conference on Interactive tabletops and surfaces - ITS '13* (New York, New York, USA, Oct. 2013), 209–218.

[13] Grossman, T., Dragicevic, P. and Balakrishnan, R. 2007. Strategies for accelerating on-line learning of hotkeys. *Proceedings of the SIGCHI conference on Human factors in computing systems - CHI '07* (New York, New York, USA, Apr. 2007), 1591.

[14] Hincapié-Ramos, J.D., Guo, X., Moghadasian, P. and Irani, P. 2014. Consumed endurance. *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI '14* (New York, New York, USA, Apr. 2014), 1063–1072.

[15] Ismair, S., Wagner, J., Selker, T. and Butz, A. 2015. MIME. *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '15* (New York, New York, USA, Aug. 2015), 199–206.

[16] Jain, M. and Balakrishnan, R. 2012. User learning and performance with bezel menus. *Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems - CHI '12* (New York, New York, USA, May 2012), 2221.

[17] Kurtenbach, G.P. The Design and Evaluation of Marking Menus.

[18] Laguna, P.L. 2000. The effect of model observation versus physical practice during motor skill acquisition and performance. *Journal of Human Movement Studies*. 39, 3 (Jan. 2000), 171–191.

[19] Lee, J. 2010. Effects of haptic guidance and disturbance on motor learning: Potential advantage of haptic disturbance. *2010 IEEE Haptics Symposium* (Mar. 2010), 335–342.

[20] Lehtinen, V., Oulasvirta, A., Salovaara, A. and Nurmi, P. 2012. Dynamic tactile guidance for visual search tasks. *Proceedings of the 25th annual ACM symposium on User interface software and technology - UIST '12* (New York, New York, USA, Oct. 2012), 445.

[21] van der Linden, J., Schoonderwaldt, E., Bird, J. and Johnson, R. 2011. MusicJacket—Combining Motion Capture and Vibrotactile Feedback to Teach Violin Bowing. *IEEE Transactions on Instrumentation and Measurement*. 60, 1 (Jan. 2011), 104–113.

[22] Oron-Gilad, T., Downs, J.L., Gilson, R.D. and Hancock, P.A. 2007. Vibrotactile Guidance Cues for Target Acquisition. *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*. 37, 5 (Sep. 2007), 993–1004.

[23] Pfeiffer, M., Schneegass, S., Alt, F. and Rohs, M. 2014. Let me grab this. *Proceedings of the 5th Augmented Human International Conference on - AH '14* (New York, New York, USA, Mar. 2014), 1–8.

[24] Quek, F., McNeill, D., Bryll, R., Duncan, S., Ma, X.-F., Kirbas, C., McCullough, K.E. and Ansari, R. 2002. Multimodal human discourse: gesture and speech. *ACM Transactions on Computer-Human Interaction*. 9, 3 (Sep. 2002), 171–193.

[25] ROCK, I. and VICTOR, J. 1964. VISION AND TOUCH: AN EXPERIMENTALLY CREATED CONFLICT BETWEEN THE TWO SENSES. *Science (New York, N.Y.)*. 143, 3606 (Feb. 1964), 594–6.

[26] Schmidt, R.A. and Lee, T.D. *Motor control and learning: A behavioral emphasis (4th ed.).*

[27] Schönauer, C., Fukushi, K., Olwal, A., Kaufmann, H. and Raskar, R. 2012. Multimodal motion guidance. *Proceedings of the 14th ACM international conference on Multimodal interaction - ICMI '12* (New York, New York, USA, Oct. 2012), 133.

[28] Seim, C., Chandler, J., DesPortes, K., Dhingra, S., Park, M. and Starner, T. 2014. Passive haptic learning of Braille typing. *Proceedings of the 2014 ACM International Symposium on Wearable Computers - ISWC '14* (New York, New York, USA, Sep. 2014), 111–118.

[29] Seim, C., Estes, T. and Starner, T. 2015. Towards Passive Haptic Learning of piano songs. *2015 IEEE World Haptics Conference (WHC)* (Jun. 2015), 445–450.

[30] Shull, P.B. and Damian, D.D. 2015. Haptic wearables as sensory replacement, sensory augmentation and trainer – a review. *Journal of NeuroEngineering and Rehabilitation*. 12, 1 (Jul. 2015), 59.

[31] Sodhi, R., Poupyrev, I., Glisson, M. and Israr, A. 2013. AIREAL. *ACM Transactions on Graphics*. 32, 4 (Jul. 2013), 1.

[32] Yang, X.-D., Bischof, W.F. and Boulanger, P. 2008. Validating the Performance of Haptic Motor Skill Training. *2008 Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems* (Mar. 2008), 129–135.