Effect of Temporality, Physical Activity and Cognitive Load on Spatiotemporal Vibrotactile Pattern Recognition

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ABSTRACT

Previous research demonstrated the ability for users to accurately recognize Spatiotemporal Vibrotactile Patterns (SVP): sequences of vibrations on different motors occurring either sequentially or simultaneously. However, the experiments were only run in a lab setting and the ability for users to recognize SVP in a real-world environment remains unclear. In this paper, we investigate how several factors may affect recognition: (1) physical activity (running), (2) cognitive task (i.e. primary task, typing), (3) distribution of the vibration motors across body parts and (4) temporality of the patterns. Our results suggest that physical activity has very little impact, specifically compared to cognitive task, location of the vibrations or temporality. We discuss these results and propose a set of guidelines for the design of SVPs.

KEYWORDS

Tactile feedback; spatiotemporal vibrotactile pattern; wearable computing; physical activity; cognitive load.

CCS CONCEPTS

Human-centered computing → Haptic devices.

1 INTRODUCTION

Vibration motors are commonly used to convey information, such as notifications [1,27], in a discreet, eyes-free and private manner. This modality is especially suitable for wearable devices, as they usually are in contact with the skin. By adding multiple vibration motors to a device, we can generate Spatiotemporal Vibrotactile Patterns (SVP): succession of vibrations, happening on different motors arranged in different locations on the body. Such patterns are usually richer than non-spatial temporal patterns, as they can convey more information (e.g. direction [28], or draw meaningful symbols).

Researchers have previously investigated the design of rich SVP, specifically with phone-sized devices held in the palm of the hand [1,27,29,30]. Most relevant to the present work, Alvina et al. [1] investigated different body parts, i.e. palm, arm, thigh and waist, and proposed a set of SVP that achieved around 80% recognition accuracy. However, these works were all conducted in a lab setting, where participants only had to focus on the recognition task. As a result, the effectiveness of SVPs remains unclear in a real-world scenario where participants are likely to have their attention focused on some other primary tasks (e.g. walking in the street or writing a text).

Possible primary tasks usually combine two types of activities: (1) physical activity, e.g. walking or running; (2) cognitively demanding task, e.g. reading a map or checking their surroundings. To design easily recognizable SVP, one must understand how both may have an impact on pattern recognition.

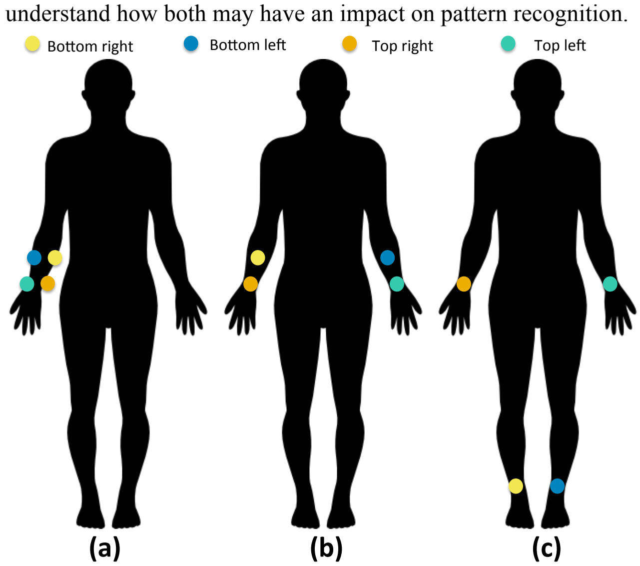

Figure 1. We investigated multiple distributions of our four vibration motors across body parts. Vibration motors layout for the (a) 1-Device, (b) 2-Devices and (c) 4-Devices conditions. Note: the 1-Device silhouette shows horizontal mirrored positions, as the arm is shown with palm facing the viewer and not in resting position.

While previous work focused on single device vibration patterns, in this paper, we investigate SVPs leveraging several devices worn on different locations on the body. The recent releases of many affordable wearable devices on the market open new perspectives for cross-device vibration patterns; happening on multiple body parts, potentially simultaneously. To explore different possible distributions across body parts, we designed three sets of devices

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(see Figure 1): a phone-sized device with a 2×2 grid of vibration motors, two wrist-worn devices with 2 vibration motors on each, and four smaller devices worn on both wrists and ankles, with one motor on each device. We explored the recognition accuracy of our SVPs in the context of physical activity and cognitively demanding tasks. As an additional factor, we considered the temporality of the patterns, i.e. whether vibration happens simultaneously or sequentially on the different motors.

In our first experiment, we show that the distribution of the vibration motors across body parts and temporality of the patterns (sequential or simultaneous) have a significant main effect on recognition. However, we did not observe any effect of the physical activity (standing vs. running). In our second experiment, we consider a cognitively demanding task (sitting vs. typing) and find out that pattern recognition is strongly affected by all our three independent variables.

Based on the results from both experiments, we designed guidelines useful both for researchers willing to investigate realistic environments, and for the design of cross-device SVP.

The contribution of this paper is thus three-fold:

1. Empirical results on the effect of physical activity and cognitive load on pattern recognition gathered through two user experiments,
2. Empirical results on the relative impact of body location and temporality for SVPs,
3. A set of guidelines both for researchers willing to investigate realistic environments (i.e. for everyday life), and about the design of cross-device SVP.

2 RELATED WORK

2.1 Temporal Vibrotactile Patterns

The literature on non-spatial temporal vibrotactile pattern—i.e. patterns involving a single point of vibration—showed an effect of the intensity and the frequency of vibrations on perception [5,6,10,15]. The duration of each vibration has also been extensively studied. Specifically by Saket et al. [23] who suggested the use of 600 ms vibrations separated by 200 ms. Such a 200 ms gap was then reused by Cauchard et al. [7] and Qian et al. [20].

2.2 Spatiotemporal Vibrotactile Patterns

SVPs have been suggested for many different contexts, such as phone notifications [1,27,30], or for directing visual attention [13]. Wang et al. [26] proposed a meta-study that compared the efficiency of tactile signal perception for detection, discrimination and identification tasks. They suggested that accuracy would drop if users had to detect precise locations or directions of SVPs.

SemFeel [30] is one of the earliest work about SVPs on phones, with users keeping the phone in the palm of their hand. This work led to several other projects, e.g. T-Mobile [27], with phone kept in the palm. Yatani et al. [28] used a 3×3 grid on the back of a smartphone to deliver spatial information, and map 8 cardinal points with vibration. In a subsequent work, they [29] used a similar setup to provided vibrotactile feedback in addition to visual feedback. Alvina et al. used a similar layout in OmniVib [1] before reducing the number of motors to a 2×2 layout. Results from OmniVib suggests that spatial representation is not consistent across different body locations, and suggested to use SVPs where the precise localization of each motor would not be an important factor of the patterns.

While all these projects did achieve satisfying levels of accuracy, they were all performed in a lab setting with users focusing on the task. For the case of OmniVib, an informal follow up study was done in which participants recognized a subset of the patterns while watching a movie.

2.3 Tactile Perception across Body Parts

Each body part has a different sensitivity to haptic stimuli. Previous work has provided estimations of the required distance between two motors to be accurately distinguished from each other. Gibson and Craig [11] measured gap detection on finger pad, finger base and palm, then on arm. Their results indicate important differences between body parts, with a minimal required gap 4.2 times higher on the arm than on the finger pad. The ratio of palm spacing to forearm spacing was 1:1.45. Alvina et al. [1] also considered four locations: palm, arm, thigh and waist and found recognition to be significantly easier to perform on arm and palm.

The wrist is also a good candidate for SVP, as explored by [6,12,16,17,19]. However, precise localization of more than three points around the wrist is hard as suggested by Carcedo et al. [6]. Other locations, such as the waist [1,25] have been explored as well. In this work we decided to focus on a grid layout, which excluded circular layouts that work well on the wrist and waist. Vibration thresholds on ankle were tested by Bikah et al. [3], showing that the area is generally less sensitive than the others considered.

2.4 SVP for Physical Activity

Wearable devices are in close contact with the skin. Designing patterns for physical activity is therefore a logical step forward. Cauchard et al. [7] designed ActiVibe, a set of temporal vibrotactile patterns to show progress during exercise. Their set of patterns achieved 96% accuracy in a lab setting and over 88.7% in a longitudinal field study. Spelmezan et al. [24] demonstrated the usage of a simple SVP to help users correct their posture while snowboarding.

Blum et al. [4] developed a system based on acceleration measurements to improve vibration perception while performing physical activity. This work was based on earlier work from Andersen et al. [2] which showed a correlation between detection of haptic stimuli and activity. Note that detection of such stimuli also greatly depends on the intensity of the vibration, as Blum et al. [4] pointed that their system was mostly helpful at low levels of stimulation.

Roumen et al. [22] investigated the effect of physical activity on different modalities, including vibration and suggested that running or walking did not impair the users' ability to detect a long temporal pattern (20 seconds) at maximal intensity. Chapman et al. [9] investigated factors influencing the perception of tactile stimuli during movement, and suggest that a higher intensity improves detection.

Pakkanen et al. [18] showed that users were less accurate and slower at perceiving low-amplitude vibrotactile stimuli on the wrist, leg, chest and back while biking than while resting.

2.5 Pattern Recognition during Cognitively Demanding Task

Chan et al. [8] investigated the effect of a few primary tasks, such as solving a puzzle, listening to specific keywords, all while trying to recognize temporal patterns. Their results suggest a longer reaction time, without a drop in accuracy. In this work, we focus on more complex patterns, as we consider SVPs that are more complex, and we also consider the temporality of the pattern. Our results suggest that the primary task also affects accuracy.

To the best of our knowledge, this work is the first to investigate the effect of physical activity, cognitively demanding tasks, and temporality with SVPs using multiple distributions of the motors on the body.

3 HARDWARE

In our experiments, we consider three different possible distributions of the motors across body parts. Many previous works investigated the feasibility of such patterns on phone-sized devices [1,27,29,30]. However, with the emergence of affordable wearable devices, the option of having multiple small devices embedding vibration motors is a viable option. We thus decided to design three different sets of devices, each of them representing a specific distribution of the motors.

3.1 Body Locations

In this paper, we want to investigate the potential for rich SVPs on 2×2 grid layouts. We investigated body locations in term of (a) sensitivity to tactile stimuli to increase accuracy, and (b) available real estate to maximize the gap between the vibration motors. For the 1-Device and 2-Devices distributions, we selected forearms as they offer the best compromise in terms of available real estate and tactile sensitivity. Palms were tempting candidates due to their unrivaled tactile sensitivity. However, wearing a device on the palm is cumbersome during virtually all daily activities. We also investigated wrists—in particular with circular layouts [6,12,17] and grid layouts [14,16]—but discarded them due to poor performances during our pre-tests. For the 4-Devices condition we added ankles to maximize the distance between devices.

3.2 Common Parts

Each of the devices we used embeds a DF Bluno Beetle, an Arduino clone with an ATmega 328 (16 MHz) controller, working at 5V, with Bluetooth Low Energy Transmission. The DF Bluno draws power from a 3.7V LiPo Battery, with a DC Voltage Converter 3.3 to 5V between the battery and the controller. We connected between one and four vibration motors (coin-type Precision Microdrives 310-103, 1.2 cm diameter) to each microcontroller. For each set of devices, the device worn on the right hand would embed a small push button, used to measure reaction time. The motors were taped to the body to ensure unbroken skin contact. The phone-sized device with the RF Bluno is shown in Figure 2.

3.3 Phone-sized Device (1 device, 4 motors)

For our phone-sized device, we connected four vibration motors to the DF Bluno. The motors are set up in a 2×2 grid, with a 10 cm gap on the vertical axis, and a 5 cm on the horizontal axis (see Figure 3-b). The top motors were located exactly 2 cm below the palm, close to the joint, on the back of the wrist. This specific layout for the phone sized device could thus be adapted on most existing smartphones, e.g. iPhone 7 (138.3×67.1 mm) or iPhone 7+ (158.2×77.9mm).

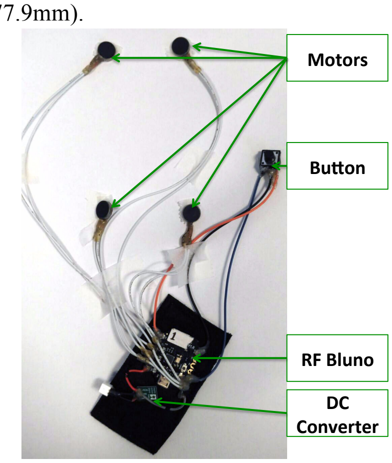

Figure 2. Apparatus for the 1-Device condition.

3.4 Wrist-worn Devices (2 devices, 2 motors)

For these two devices, we vertically aligned two motors with a gap of 10 cm. The top motor was located 2 cm below the palm, close to the joint, on the back of the wrist (see Figure 3-c). The button was located on the device worn on the right wrist.

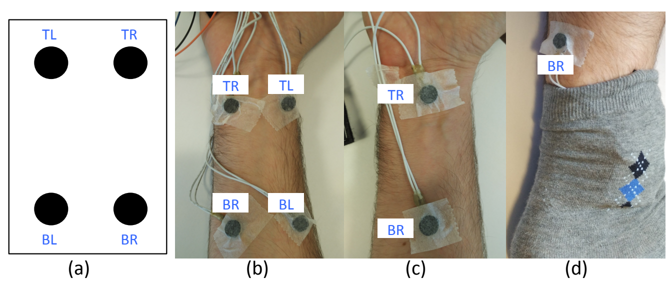

Figure 3. We rely on (a) a general 2×2 grid layout. (b) Precise location of all motors for the 1-Device condition [mirrored], (c) TR, BR on the left wrist for the 2-Devices condition and (d) BR on the left ankle for the 4-Devices condition. Note: the TL/BL motors for the 2-Devices condition are similarly located. For TL and TR in 4-Devices condition, the precise location is as TR in (c).

3.5 Single Motor Devices (4 devices, 1 motor)

The four devices were worn on both wrists and ankles. Each only embedded one motor that was located at the back of the wrist or ankle (see Figure 3-d). The different layouts are summarized in Figure 1 and Figure 3.

4 SET OF PATTERNS

In this paper, we focus on a 2×2 grid. Previous works suggests that a 2×2 grid layout exposes a good tradeoff between expressivity and accuracy [1].

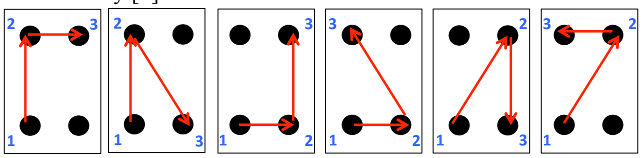

Figure 4. Set of SVPs used in both experiments for the "sequential" temporality condition. Numbers shows the order in which the motors were activated.

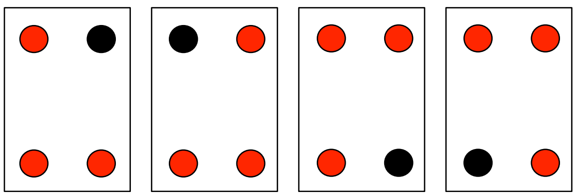

Figure 5. Set of SVPs used in our experiment for the "simultaneous" temporality condition. Dots in red indicate that the corresponding motor is activated.

We defined the following rules to design our patterns:

1. Each pattern is a sequence of three vibrations, played simultaneously or sequentially.
2. All the vibrations in a pattern happen on different motors.

Additionally, since we include the temporality as a factor—i.e. whether the vibrations are happening simultaneously or sequentially—we included additional rules for both levels of the factor. For sequential patterns, we always start the patterns from the same motor, as starting from different motors would make the pattern easier to distinguish, and therefore to ultimately identify. By convention, we start from the bottom-left motor, which is thus located either on:

- The bottom left motor on the right wrist, for our device with a 2×2 grid.
- The bottom motor on the left wrist, for our configuration with two devices with 2 motors disposed on the vertical axis.
- The motor on the left ankle device for our configuration with four devices.

By following these rules, we generated six different patterns, shown in Figure 4.

For simultaneous patterns, we decided to activate three motors at the same time, therefore we use all the four possible combinations as seen in Figure 5.

5 EXPERIMENTS

We conducted two experiments: one to investigate the effect of physical activity of perception, and one to find out how cognitively demanding tasks affect perception. In both experiments, participants had to recognize SVPs. The experiments share many similarities that we describe in this section.

5.1 Common Apparatus

The experiments were performed with specially designed wearable devices described in the Hardware section. After each stimulus, participants had to select the pattern they thought corresponded to the stimulus by using our experimental interface on an iPad mini. We used an iPhone to run our experimental software, which would send the stimuli to the wearable devices using Bluetooth Low Energy (BLE).

5.2 Common Procedure

At the beginning of both experiments, participants filled a pre-experimental questionnaire, including demographics data. The experiment was then divided in three sections, one for each set of devices (i.e. distribution of the motors). The experimenter would assist the participant in putting the devices on the corresponding body parts. The participants would then be trained with each of the patterns of our two sets (10 patterns). They would then perform both physical activities. Both sets of patterns were tested in one block, with two repetitions of each pattern per block. There were two blocks for each set of devices × activity.

5.3 Common Task and Stimuli

In both experiments, our participants had to recognize the correct pattern from our set of patterns (see Figure 4 and Figure 5). After the stimulus was presented, participants would first click on the button located on the device worn on the right wrist as soon as they identified the pattern, then would input their selection using our interface on the iPad Mini. No feedback was provided after selection. For each pattern, vibration motors were activated for 600 ms, followed by a 200 ms gap for the sequential condition as recommended by Saket et al. [23].The playback duration of a stimulus is thus 600ms for the simultaneous condition, and 2200 ms for the sequential condition. There was a pause of a randomized duration between 15-25 seconds between trials.

6 EXPERIMENT 1: PHYSICAL ACTIVITY

In this first experiment, we investigated how physical activity impacts perception of spatiotemporal patterns across different motors distributions and temporality. The previous section summarizes part of the apparatus, the procedure, task and stimuli. We applied Greenhouse-Geisser sphericity correction when needed, which corrects both p-values and the reported degrees of freedom.

6.1 Primary Task

The primary task was to run on a treadmill at a speed of 7 km/h. The speed was selected to ensure that all participants needed to run but would not get too fatigued. We included a control condition during which participants stood.

6.2 Apparatus

During the running condition, participants run on a FreeMotion Reflex T 11.8 Treadmill. The experiment was conducted in the gym of the local university. Air-conditioning ensured a stable 25°C temperature.

6.3 Participants

Twelve participants (3 female), aged 20 to 31 (*M*=24.6 SD=3.17) were recruited from the university community. All participants were right handed.

6.4 Design

A 3×2×2 within-subject was used with three independent variables: *motors distribution { 1 device with 4 motors, 2 devices with 2 motors, 4 devices with 1 motor }*, *temporality { simultaneous, sequential }* and *physical activity { standing, running }*. The *motors distribution* was counterbalanced with Latin Square, the physical activity was fully counterbalanced and the temporality was randomized within blocks. We measured recognition time, which is the sum of the time taken to present the stimulus (2200 ms for sequential and 600 ms for simultaneous) and of the time it took participants to press the small button. Participants were instructed to only press the button when they were certain they correctly identified the pattern. We did not count the time to select their answer on the iPad as part of the recognition time. We also measure recognition rate (referred to as accuracy). A trial was considered as successful if the participant could correctly identify the presented stimulus.

Each participant performed the experiment in around 1 hour and 40 minutes, with breaks between blocks if needed. Our overall design is as follows: 12 participants × 3 motors distributions × 2 physical activities × [6+4 (stimuli)] × 2 blocks × 2 repetitions per block = 2880 trials (240 trials per participant).

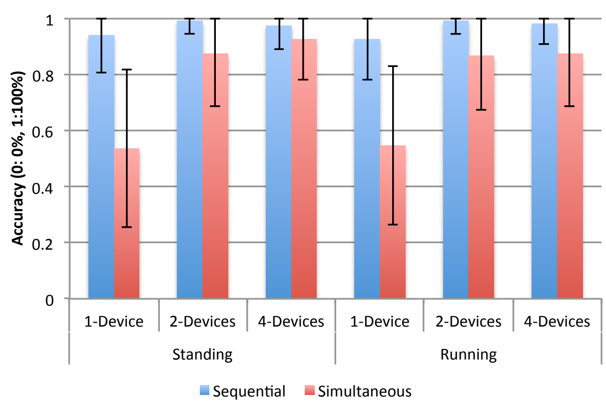

Figure 6. Average recognition rate across different conditions in Experiment 1. Error bars show .95 confidence intervals.

6.5 Results

We used three-way ANOVA with repeated measures on all factors to get our main effects. For post-hoc comparisons, we used pairwise t-tests with Bonferroni correction.

6.5.1 Recognition Rate (Accuracy). The average accuracy for the experiment was 88.9%. We observed a significant main effect of Motors Distribution on Accuracy ($F_{2,22}$=127.2, *p*<.0001). Pairwise comparison showed that both 2-Devices (*M*=94.4%) and 4-Devices (*M*=94.8%) conditions were more accurate than 1-Device (*M*=77.7%, both *p*<.001). Temporality also had a significant main effect ($F_{1,11}$=59.9, *p*<0.0001), with the Sequential condition (*M*=96.8%) performing better than Simultaneous (*M*=77.1%).

We also observed a Motors Distribution × Temporality interaction ($F_{2,22}$=45.7, *p*<.0001). The individual performance of each condition is summarized in Figure 6.

Note that we did not observe any main effect of Activity or any interaction involving interaction.

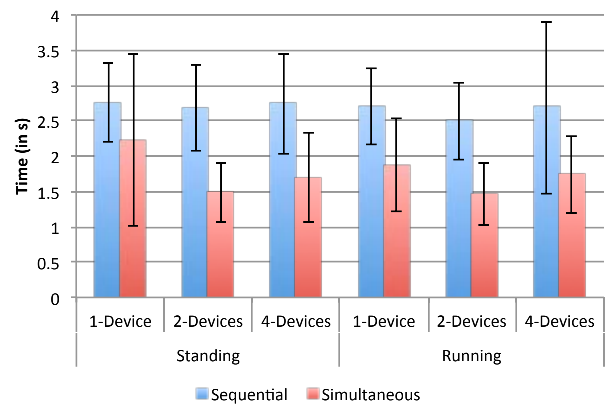

Figure 7. Average recognition time across all conditions in Experiment 1. Error bars show .95 confidence intervals.

6.5.2 Recognition Time. A three-way ANOVA found a significant main effect of Motors Distribution on recognition time ($F_{2,22}$=5.83, *p*<.001). The 2-Devices configuration offers the best recognition time (*M*=2.17s), which is significantly faster than both 4-Devices (*M*=2.33s, *p*<.001) and 1-Device (*M*=2.54s, *p*<.001).

Temporality also had a significant main effect ($F_{1,11}$=132.4, *p*<.0001), with Simultaneous condition (*M*=1. 70s) being faster than Sequential (*M*=2.68s). Motors Distribution × Temporality interaction ($F_{1.28,14.08}$=4.56, *p*=.04). Similarly to accuracy, we did not find any main effect or interaction involve Activity on recognition time. The recognition times for each condition are shown in Figure 7.

6.6 Discussion

While the accuracy of pattern recognition for the standing activity and sequential temporality was high, with 1-Device achieving 93.4% on average, 2-Devices 99.3% and 4-Devices 97.9%, the accuracy for simultaneous condition shows that our participants were not able to recognize patterns for the 1-Device distribution (i.e. phone-sized configuration), with an average recognition rate of only 54.2%. 2-Devices (87.1%) and 4-Devices (90.1%) did perform better. These performances explain the interaction Motors Distribution × Temporality we observed.

The time performance of simultaneous patterns shows a generally better recognition time of these patterns over sequential ones. However, as we consider the whole stimulus playback time + reaction time, simultaneous temporality has a strong advantage here. If we only consider reaction time, the average reaction time (not including playback time) for sequential patterns is lower than simultaneous (0.47 s vs. 1.10s). We argue that in the real world, what matters is the total time to convey information, which is why we included the time to present the stimulus. The differences between different motors distributions, while significant, are not so important: there is only a 370 ms difference between 1-Device (slowest) and 2-Devices (fastest) configurations.

Our results show that simultaneous SVP could be recognized at high accuracy (~90%) using the 2-Devices (87.1%) and 4-Devices (90.1%) configuration, and would convey information faster than traditional sequential patterns. By comparing with 1-Device, we note that 1-Device is the condition with the lowest gaps between two motors, i.e. 10cm between two horizontal motors, which is likely the source of the low accuracy.

Surprisingly, our results do not show any effect of the physical activity on the performance of our participants that is both in terms of time and accuracy. Roumen et al. [22] suggested a similar trend through a perception-only task (i.e. was the stimulus sensed or not). Our results show that it remains valid even with complex recognition tasks. Some previous work did highlight differences, but for low levels of stimulation [18]. We believe that since the vibration motors were strongly taped to the skin, prevented loss of contact, and therefore, variability of perceived vibrations, which could have impaired the recognition of SVPs. To design SVPs for daily activities, one may consider other primary factors than physical activity, at least on low to moderate levels.

7 EXPERIMENT 2: COGNITIVELY DEMANDING ACTIVITY

In this second experiment, we investigated the effect of a cognitively demanding task on identification of SVP across our motors distribution and temporality. The procedure, task and stimuli as well as common apparatus are presented in the Experiments section.

7.1 Primary Task

We selected a text-typing task[1] because it is cognitively demanding. We asked our participants to prioritize typing over SVP recognition, and told them that their performances were being measured. We included a control condition where the participants were sitting on a chair.

7.2 Apparatus

Participants would perform the typing task on a MacBook Pro laptop (13", Early 2015, OS X 10.10.5). The experiment was conducted in a room with a desk and a chair, with air-conditioning ensuring a stable temperature of 25°C.

[1] https://www.goodtyping.com/test.php

7.3 Participants

Thirteen participants (6 females), aged 20 to 32 (*M*=26, *SD*=4.39) were recruited from the university community. All of them were right handed. They were all students and all declared to use a laptop computer daily.

7.4 Design

A 3×2×2 within-subject was used with three independent variables: *motors distribution { 1 device with 4 motors, 2 devices with 2 motors, 4 devices with 1 motor }*, *temporality { simultaneous, sequential }* and *activity { sitting, typing }*. The motors distribution was counterbalanced with Latin Square, the activity was fully counterbalanced and the temporality was randomized within blocks. We measured both recognition time and recognition rate (referred to as accuracy).

Each participant performed the experiment in around 1 hour and 40 minutes, with breaks between blocks if needed. Our overall design was as follows: 13 participants × 3 configurations × 2 activities × [6+4 (stimuli)] × 2 blocks × 2 repetitions per block = 3120 trials (240 trials per participant).

7.5 Results

We used the same statistical tests, post-hoc and corrections as in Experiment 1.

7.5.1 Recognition Rate (Accuracy). Our three-way ANOVA showed a significant main effect of all the three factors on accuracy. We found a significant main effect of motors distribution ($F_{2,24}$=82.7, *p*<.0001). Overall, participants were significantly less accurate with the 1-Device distribution (*M*=67.8%), than with 2-Devices (*M*=86.6%, *p*<.001) and 4-Devices (*M*=88.8%, *p*<.001). We also found a significant main effect of Activity ($F_{1,12}$=73.3, *p*<.0001), with participants performing better while sitting (*M*=89.7%) than typing (*M*=72.4%), and of Temporality ($F_{1,12}$=133.5, *p*<.0001), where it was easier for participants to recognize sequential patterns (*M*=88.1%) compared to simultaneous ones (*M*=70.4%).

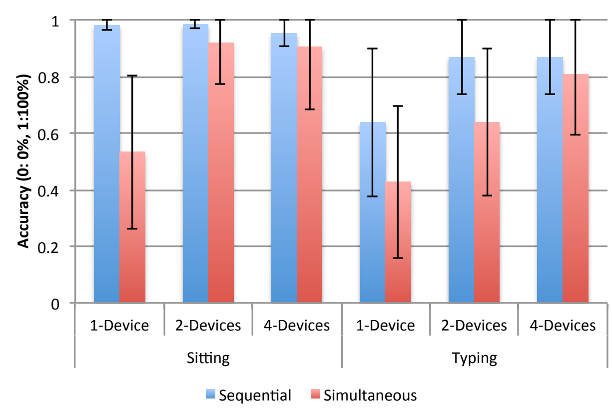

Figure 8. Average recognition rate across conditions in Experiment 2. Error bars show .95 confidence intervals.

We also observed a Motors Distribution × Activity interaction ($F_{2,24}$=4.38, p=.023), and a Motors Distribution × Temporality interaction ($F_{2,24}$=19.51, p<.0001). The individual performance of each condition is shown in Figure 8.

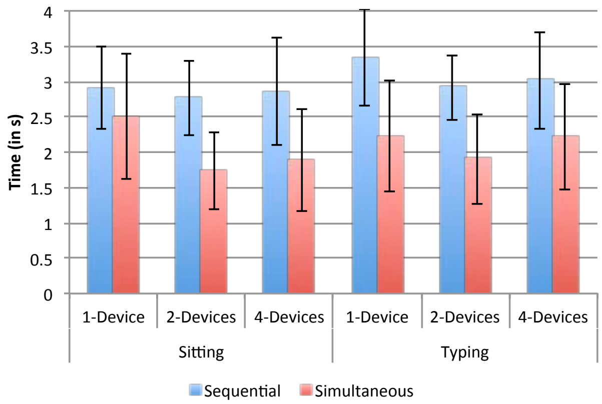

Figure 9. Average recognition time across conditions in Experiment 2. Error bars show .95 confidence intervals.

7.5.2 Recognition Time. A three-way ANOVA showed a significant main effect of Motors Distribution on recognition time ($F_{2,24}$=5.28, p=.012). A post-hoc comparison showed significant differences between all conditions (all p<.05): our participants were faster at recognizing patterns with the 2-Devices condition (M=2.43s) than with 4-Devices (M=2.59s) and 1-Device (M=2.88s). Temporality also had a main effect ($F_{1,12}$=19.3, p<.001): our participants had a smaller recognition time with simultaneous patterns (M=2.03s) compared to sequential ones (M=2.95s). We did not find any other interaction or any effect of Activity. Figure 9 shows the individual performance of each condition.

7.6 Discussion

Our results show that user's primary task had an impact on recognition rate. We observe an average decrease of performance of 17.3 percentage points (from 89.7% to 72.4%) with the additional cognitive load. As a consequence, researchers may want to take a cognitively demanding task into consideration when designing experiments on pattern recognition.

At first glance, it may look like the recognition accuracy of SVPs for the simultaneous level of Temporality (70.4% accuracy). However, some specific sets of conditions did achieve good accuracy: for the 2-Devices configuration, recognition rate of simultaneous patterns was 77.5%, while it reaches 84.4% with the 4-Devices configuration.

The overall acceptable accuracy of the 4-Devices distribution can likely be explained by the fact that users can quickly process the vibration just by identifying the body part upon which the vibration is happening, instead of having to decide from which specific motor it came from.

During the experiment, 4/13 participants also reported that they needed to focus on the vibration to be able to correctly recognize the pattern and that they may not be that attentive in a real-world scenario. This suggests that the loss of accuracy might be even worse than what we observed.

8 DISCUSSION AND GUIDELINES

Our experiments allow us to get a clear idea of the role of posture, cognitive demand of the primary task, motors distribution, and temporality, in the design of SVPs. In this section, we will discuss guidelines and suggestions on how to apply these results.

8.1 SVP for everyday life

Our results show that low to moderate physical activity does not impact recognition of SVPs in general, as it does not have an effect either on recognition accuracy or time. We believe that these results are valid for general everyday life activities, during which people are likely to walk or brisk walk. The results are similar to the ones obtained by Roumen et al. [22]. Many previous works [7,24] considered more intense levels of activity. Our results suggest that designers and researchers interested in validating SVPs designed for everyday life may not necessarily need to focus on physical activity, but should consider the cognitive demand of a potential primary task.

8.2 Posture (Sitting vs. Standing)

In Experiment 1, our control condition is having our participants standing, while in Experiment 2, our participants are sitting. Since the protocol of both experiments is similar, we run a t-test to find potential differences. In Experiment1-Standing condition, our participants achieved 89.4% with a time of 2.38s, vs. 89.7% and 2.53s for Experiment2-Sitting. T-tests on independent samples did not show any significant differences for both accuracy (p=.45) and time (p=.58).

8.3 Cognitively Demanding Task

Our second experiment highlights the strong effect of primary task on recognition. Therefore, researchers interested in validating lab results in more realistic conditions may want to include cognitively demanding tasks as a factor for their experiment: we observed an accuracy drop from 89.7% to 72.4% when participants were typing text. The recognition time only increased from 2.53s to 2.74s. We believe that more demanding tasks would see a higher drop of accuracy. Under cognitively demanding task, the interaction between Devices and Activity suggests that using multiple devices may mitigate this drop. In the 4-Devices case specifically, users did not need to discriminate different locations on the same device, which led to a higher accuracy of 84.4% while typing.

8.4 Generalizability to other body parts

Recognition greatly varies between body parts. In this paper, we focus on the part near the wrists (and ankles to a lesser degree). Results from Alvina et al. [1] showed that Palm and Arm may have comparable sensibility to SVPs, suggesting some potential for generalizability. However, it is likely that recognition would be harder on body parts such as trunk, waist, thigh and legs.

8.5 Temporality

Delivering multiple vibrations at the same time allows conveying information faster, but at the cost of fewer possible patterns and lower recognition rate. Therefore, simultaneous patterns might be worth considering on a limited set of patterns (in our case we had 4 patterns). Given our results, we would advocate not using simultaneous SVPs with the 1-Device - 4 motors condition, and generally not as long as a cognitively demanding task is being performed. On the other hand, the 4-Devices distribution achieved an acceptable level of accuracy even during the typing task (80.7%), proving that simultaneous SVPs may be used. The gap on recognition accuracy was also documented by Carcedo et al. [6] with a wristband.

8.6 Motors Distribution across Body Parts

We considered three different motors distributions across body parts, ranging from a single phone-sized region with four motors to four small wearable devices on each wrist and ankle. Our results show that recognition was greatly impacted by the motors distribution on the body.

8.6.1 Phone-sized Single Area (1-Device). Overall, we noticed that the phone-sized distribution usually achieves lower accuracy. This is likely due to the small horizontal gap between two devices that makes it hard for users to precisely locate the motor at a given time. This is especially true in Experiment 2-Typing condition. Our results would suggest that some previous research on SVPs may not be applicable in real-life scenarios where the users are performing a primary task. However, this specific form factor still offers good performance across physical activity and if sequential SVPs are used. There are still a lot of everyday life scenarios in which this specific configuration would perform well.

8.6.2 Wrist-worn Devices (2-Devices). The 2-Devices distribution achieves good accuracy for most of the conditions, except one: Typing-Simultaneous. In any other condition, the average accuracy is always above 86.7%, up to 98.3%. Therefore, it is a form factor to consider. Likely, simultaneous SVPs may be limited by the difficulty of detecting whether two motors are vibrating on the same side.

8.6.3 Wrist/ankle-worn Devices (4-Devices). Our 4-Devices condition is the only one to perform well (above 80%) under all the values of our other independent variables. 4-Devices is therefore the most robust motor distribution to convey information. The fact that each motor is located on the extremity of different limbs, i.e. that the distance between motors is maximized, can explain the good performance. More experiments would need to be done to determine whether a similar condition with other body locations would give similar results. Our current results do show that leveraging multiple small wearable devices to produce richer SVPs is a promising approach.

9 LIMITATIONS

For both experiments, we only considered low levels for both physical activity and cognitively demanding task. While this is generally representative of the kind of tasks performed during an average day, it does not provide insights for athletes [7,24] and more active users. Additionally, we did not consider any potential interaction between physical activity and cognitively demanding task. Activities like dance [21] usually combine both physical and cognitive load.

10 CONCLUSION

We presented two experiments investigating the effect of physical activity, a cognitively demanding task and temporality on recognition of spatiotemporal vibrotactile patterns. We found that all factors have an effect on recognition (time and/or accuracy), except for physical activity. We also considered three different distributions of our vibration motors: either a phone-sized device with a 2×2 grid, two wrist-worn devices with 2 motors, or four individual devices worn on wrists/ankles with one motor. The phone-sized condition was the most affected by task and temporality, while the four devices condition was the one performing well with every possible condition. As future work, we would like to evaluate more levels of activities and tasks, as well as consider different configuration for the multiple devices conditions.

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