



# Understanding and designing tactile feedback interaction for secondary tasks

Adnane Guettaf

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# Thèse de doctorat

Pour l'obtention du grade de Docteur de

l'Université Polytechnique Hauts-de-France et l'INSA

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Présentée et soutenue par :

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Laboratoire : Laboratoire d'Automatique, de Mécanique et d'Informatique  
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COMPRENDRE ET CONCEVOIR L'INTERACTION À RETOUR TACTILE  
POUR LES TÂCHES SECONDAIRES.

---

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## UNDERSTANDING AND DESIGNING TACTILE FEEDBACK INTERACTION FOR SECONDARY TASKS.

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## Abstract

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The growth of mobile applications used in all aspects of life and the easiness of interaction they provide through tactile input had allowed users to interact with touchscreen in many different ways and in different contexts, including situations where the interaction complements or challenges another, a *primary* task, that either needs full attention or is cognitively demanding. Meanwhile, in the last few decades, touch interaction has been enhanced with a tactile feedback that provides stimulation when touching the surface. Especially, we are interested here by ultrasonic technologies that permit users to perceive different textures when moving their finger on the surface. In this context, we seek, here, to understand how to use tactile textures to successfully complete the secondary tasks without disturbing the primary one.

First, we started by determining the effectiveness of tactile textures in a real-world scenario. We conducted three studies. From the first study, we found that users are perfectly able to use and recognize tactile textures when performing a physical activity like walking, or taking a public transport. In the next studies, we considered an attention saturating and a cognitively demanding primary tasks to challenge the secondary one. Our finding also proved that users were perfectly able to recognize textures in such contexts. Through an in-depth analysis, we reveal new findings about how people perceive tactile textures when performing another primary task.

An important result of our work was that users were able for some situations to perceive tactile textures eyes-free when performing another primary task. In the same time, as tactile feedback is only felt when users' finger is moving over the surface following rectilinear gestures trajectories, we run a forth study, seeking to better understand the characteristics of stroke gestures and how these latter are be produced *eyes-free*. Our results indicate that gestures made eyes-free were geometrically different from gestures produced in the presence or absence of a visual feedback, and with a lower recognition rate of (95.53%), which it self was quite good.

Finally, we introduce a new interaction technique that features the use of tactile textures to deliver information eyes-free, relying so on the sens of touch to provide information to fingertips depending on user's finger speed and the perceived texture. When evaluating this latter technique, our findings indicated that users can learn and be accommodate to the dynamics of eyes-free tactile channel selection, and can reliable discriminate between different tactile patterns during multi-channel selection with an accuracy up to 90% when using two finger speed levels.

**Keys words:** primary task, secondary task, tactile textures, eyes-free interaction, user studies, interaction technique.





## Résumé

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L'utilisation des dispositifs mobiles est en forte croissance grâce à l'interaction tactile, ce qui permet aux utilisateurs d'interagir différemment et dans divers contextes y compris quand l'utilisateur est en train de faire une autre tâche principale. En même temps, ces dernières années, l'interaction tactile a été enrichie par le retour tactile qui fournit l'utilisateur une information tactile au bout des doigts. Dans ce cadre, dans cette thèse, nous nous intéressons aux technologies ultrasoniques permettant aux utilisateurs de percevoir différentes textures et étudierons leur utilisation dans la réalisation des tâches secondaires sans impacter la tâche principale.

D'abord, nous avons mis en place trois études utilisateur pour déterminer l'efficacité des textures tactiles dans des scénarios réels. Nous avons constaté que les utilisateurs sont capables d'utiliser et de reconnaître les textures tactiles en effectuant une activité physique. Ensuite, nous avons étudié l'impact d'une tâche principale qui sature l'attention ou qui est cognitivement exigeante sur la reconnaissance des textures tactiles. Nos résultats ont prouvé que les utilisateurs reconnaissent les textures dans de tels contextes. Aussi, l'analyse détaillée de l'ensemble de données a révélé qu'il existe différentes manières dont les gens perçoivent les textures tactiles lors de l'exécution d'une tâche principale.

En particulier, nos résultats ont montré que, dans certaines situations, les utilisateurs sont capables de percevoir les textures tactiles sans regarder l'écran lorsqu'ils effectuaient une tâche principale. En même temps, comme le retour tactile n'est ressenti que lorsque le doigt de l'utilisateur se déplace sur la surface suivant des trajectoires gestuelles, nous avons mené une quatrième étude utilisateur pour comprendre les caractéristiques des gestes produits sans visuel. Nos résultats indiquent que ces gestes sont géométriquement différents de ceux produits en présence ou en l'absence d'un retour visuel.

Enfin, une nouvelle technique d'interaction employant des textures tactiles pour fournir des informations sans nécessité d'un retour visuel est introduite. Cette technique s'appuie sur la texture perçue et la vitesse du doigt de l'utilisateur pour fournir l'utilisateur avec différents canaux d'information. Les résultats d'évaluation ont montré que les utilisateurs peuvent s'adapter à la dynamique de la sélection des canaux tactiles, et peuvent différencier de manière fiable entre différents retour tactiles avec une précision de 90% lors de l'utilisation de deux niveaux de vitesse.

**Mots clés:** tâche principale, tâche secondaire, textures tactiles, interaction sans regard, étude utilisateur, technique d'interaction.



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Part I

# INTRODUCTION



# CHAPTER 1

## Introduction

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In an “*age of accelerations*”, technology is constantly changing the world and the way we interact and live in it. For example, in *Elon Musk* perspective, everybody is already a super-human with much more capabilities than any human being thirty years ago. This is due to what he called “a machine extension of ourselves”. It represents all the computing devices available to users nowadays, including mobile devices and the applications they provide. They are currently used in almost every aspect of life (*e.g.*, walking in the street [88], dynamic/field environment [35], driving [68], social environment [108]). Consequently, mobile devices are taking more and more space and importance, challenging users in their everyday tasks and constraining them to be efficient in **multitasking** [107].

Speaking of tasks performed simultaneously by humans, the latter term “*human multitasking*” was driven from the word multitasking used by IBM [138] in 1965. It describes the computer ability to do several programs at one time. Regarding humans, it describes the person’s ability to do more than one task at a time [1], and this, by splitting the attention between the various tasks performed simultaneously. In the literature review, it is still unclear how human brain process input information from different sources. For instance, multitasking leads to either processing all information at once [85], or ordering tasks by priority [111]. In all cases, multitasking induces more errors with longer interaction [133]. Therefore, it results in a less suitable execution and time performances for each task. Additionally, although many research suggest that human brain can be trained to multitasking [37, 82], it is still constraining, cumbersome or even dangerous to share brain resources for situations involving daily activities such as driving while using phone or cooking while reading. Consequently, dependently on the performed tasks, it is important to study how users handle the different tasks and their effect on the user performance and behaviour.

In the same time, the proliferation of touch-enabled devices, such as mobile devices, have contributed to the popularity of touch input devices. For instance, mobile devices are one of the most pervasive touch-enabled devices in the world today. Mobile devices offer users different services and informa-



tion through a multitude of applications. Those applications were designed principally to assist users in their daily tasks, offer well-being, and overcome social distances and day-to-day difficulties (*e.g.*, communication, social media, GPS, banking, entertainment, etc.). Touch interaction allows also a direct input [44, 56, 89] and control of information through simple [77, 109] or multi-touch gestures [98, 104] with different kinds of displays and interactions in one same input/output space [50]. Also, thanks to the advancements made in hardware technologies and their continually shrinking size following Moore’s law [86], mobile devices form factors are becoming smaller. They allow diverse interactions using both hands [17, 39, 91] or a single handed grip [23, 39]. Consequently, it makes them sufficiently **portative** to be used in different contexts and situations (*e.g.*, checking emails while walking, or even using GPS while driving). However, unlike the traditional physical control or buttons [89, 135] on mobile devices, that have a distinct feel, and have a unique proprioceptive location [30] with limited interaction capabilities, mobile tactile devices can be visually cumbersome. The **flat** touch panel [30, 143] lacks physicality and tactile sensations. Besides, it can quickly be overloaded due to its support for multiple widgets on a same location. Therefore, it constraints users to rely only on visual feedback to guide their finger on the correct target [30], which increases the demand for visual attention to the display. Furthermore, touch-screen devices may cause some distraction or cognitive load, especially when users are already involved in another task [20, 30, 48], which is often a higher priority task involving users daily activities or occupations.

Recently, mobile devices were enhanced with tactile feedback that provides users stimulation when touching the surface [4, 15, 21, 25, 62, 130]. While, at present, with the exception of vibration, rich patterns of tactile feedback have been largely relegated to research systems, it is clear that the overall aim of tactile feedback research is eventual integration with mobile and multi-touch devices. With this in mind, two main technologies have emerged to support mobile device-based tactile feedback: (1) electrovibration technologies [15, 95] which enhance the friction between the finger and the interaction surface and (2) ultrasonic technologies which reduce the friction through the “squeeze film effect” [4, 25, 76, 106, 130]. By modulating the friction according to finger’s displacement, users are able to perceive different textures rendering when moving their finger on the surface. In this thesis, we leverage the latter type of tactile feedback, ultrasonic-based tactile feedback.

We are interested in an interaction context where a user is facing simultaneously a **primary task** and a **secondary task**. The primary task is the task that the user does not wish to be disturbed from an attention point of view and/or a cognitive point of view. The secondary task, however, is the task that the user wishes nevertheless to carry out during the time of the primary

task. For example, a driver may want to change the air condition level or adjust the music volume while driving [30, 112]. We seek, **to understand how to use tactile feedback to successfully complete the secondary task with low visual and cognitive resource.**

In this dissertation, we present the results of our investigations on tactile feedback for the support of secondary tasks on mobile devices. Our contribution lies in the fact that we investigated tactile textures usability for realistic primary tasks (real-world scenarios). We were able to prove that tactile textures could be effectively recognized and used in different life aspects. Furthermore, we designed a new interaction technique that benefits from tactile feedback to deliver a discreet and eyes-free interaction for secondary tasks.

## 1.1 CHARACTERIZING THE CHALLENGES

To be able to respond to the question raised in the previous section, we chose a road-map centred around exploiting the benefits of using tactile feedback for secondary tasks. We had then to establish and overcome some challenges that we list here after:

- Will users be able to use and correctly distinguish between tactile textures when performing at the same time another primary task? Indeed, before investigating the benefits of using tactile feedback to reduce visual load, we had to be sure that users will effectively be able to use this latter when facing simultaneously two tasks.
- Will using tactile textures allows users to rely less on visual feedback when interacting with the tactile device? More specifically, are users able to perceive and recognize tactile textures eyes-free? Being able to reduce the visual dependence over the secondary device surface may offer a considerable advantage for completing the primary task.
- If so, how stroke gestures are produced eyes-free. Indeed, as tactile textures are only perceived when user finger is moving on the surface and so stroke gestures movement are made, it is important to determine stroke gesture production when performed eyes-free.
- In the case where the eyes-free nature of tactile sensing can be preserved, how can we increase the bandwidth of tactile output to permit users to select between different tactile signals to deliver different information to the users. Designing a technique that increases the bandwidth of tactile feedback will be of a big benefit for using tactile feedback for secondary tasks with low visual feedback.

## 1.2 RESEARCH APPROACH & ORGANIZATION

This thesis is organized in three tightly related parts. In the first part, we are mainly concerned with users' capabilities to use tactile feedback when the user is performing another primary task. In particular, we consider situations where users are involved in different primary tasks. The goal of these investigations was to better understand how tactile textures can co-exist with users on-going primary tasks. For example, our findings indicate that tactile textures were accurately recognized and –for some primary tasks–, users were able to interact with the tactile device eyes-free. Then, as textures-based tactile feedback is only felt when user finger is moving on the surface, we investigate eyes-free *stroke-based gestures* production from a pure user-centric perspective. This investigation is presented in the second part of the thesis. Finally, in the third part, a tactile texture based technique was proposed to increase the bandwidth of tactile output for secondary tasks. This latter permits to deliver information to fingertips depending on user's finger speed and the perceived texture, and thus, can be perfectly suitable for multitasking situations.

In order to allow the reader to better appreciate our different contributions, we started first, in **chapter 2** – “Background”, by a literature overview where we address in a brief but systematic manner the different existing studies that relate directly or indirectly to the work presented all along this dissertation. In particular, we give an overview of mobile touchscreen interaction and especially, gesture based interaction. Then, we review tactile feedback interaction, and discuss techniques and rendering strategies for ultrasonic based tactile feedback. After this, we present previous results on mobile touchscreen interaction when a primary task is involved, and then review both the tactile feedback based techniques and gestures based ones to deal with multitasking context.

In the following, we present a resume of each contribution.

### Part I - “Tactile Textures Usability”

#### Chapter 3: Tactile Feedback For Physically Challenging Tasks

People ability to use and recognize tactile textures rendered using ultrasonic technologies on mobile surface had been widely investigated and proved during the last decades. However, the experiments were run in a lab setting where users were stationary, and their attention was dedicated solely to the task being performed. This rise a concern about more realistic scenarios which remains unclear on users capabilities to truly distinguish and recognize tactile texture in a real-world environment. In this chapter, we conducted an experiment with five conditions (1) seated in an office, (2) standing in an office, (3) seated in

the tramway, (4) standing in the tramway and (5) walking in the street. The goal of the experiment was to understand the effect of a physical activity on tactile textures perception. The results of the conducted experiment indicate that out of the five evaluated physical activities, walking did deteriorate users performance comparing to the remaining conditions by 8.45%. However, we can notice that the accuracy is still higher than 82%, thus suggesting that tactile textures could be effectively recognized and used in different physical activities including walking.

**PUBLICATION:**

*Adnane Guettaf, Yosra Rekik and Laurent Grisoni.  
Effect of Physical Challenging Activity on Tactile Texture  
Recognition for Mobile Surface In Proceedings of PACMHCI  
volume 4, Issue ISS, Article No: 190. Novembre (2020)  
DOI: [10.1145/3427318](https://doi.org/10.1145/3427318)*

#### **Chapter 4: Tactile Feedback for Attention Saturating or Cognitively demanding Tasks**

Always in the same perspective of evaluating tactile textures usability on mobile surface for situations involving user's implication in another primary task. This time, the focus was put on primary tasks that either saturate the attention or are cognitively demanding. For the primary task that saturate the attention, a highly visually demanding task was used. The task consisted in controlling a pseudo-randomly perturbed moving ball, in a manner similar to the approach used in [134]. The results gathered for this experiment regarding the tactile recognition secondary task show a decrease in performance by 6.98% accompanied with an increase in frustration, mental demand and physical effort. Also, an eyes-free recognition of textures was observed while performing at the same time the primary task. For the cognitively demanding task, however, a text typing exercise [28] was used. The results observed showed a trend toward a sequentiality while performing both tasks with gaze attention directed toward the current performed task. The primary task demands more time to switch to the texture recognition task but decreases the time needed to recognize the texture without compromising the accuracy. For both primary tasks evaluated in this chapter, the texture recognition stays higher than 82%, thus it suggests that tactile textures could be effectively recognized and used by users when performing a primary task that either saturates the attention, or is cognitively demanding.

**PUBLICATION:**

*Adnane Guettaf, Yosra Rekik and Laurent Grisoni.*  
*Effect of Attention Saturating and Cognitive Load on Tactile*  
*Texture Recognition for Mobile Surface In Proceeding of IN-*  
*TERACT 2021. Lecture Notes in Computer Science vol 12935*  
 DOI: [10.1007/978-3-030-85610-6\\_31](https://doi.org/10.1007/978-3-030-85610-6_31)

**Part II - “Stroke Gesture Production”****Chapter 5: Eyes-free Stroke Gestures Production**

In this chapter, we were interested in understanding eyes-free stroke gestures characteristics. From the literature part, we were able to notice that many interaction techniques and design guidelines based on touch gestures were proposed. In particular, they were addressed for situations where users visual attention is constrained, including situations where users are engaged in another more cognitively demanding primary task. However, more information about how these gestures are drawn, their potential effect on user interaction or satisfaction, and how are they different from gestures made eyes-on remains unclear. In this chapter, we present results of an investigation concerning eyes-free stroke gestures production for a single-handed mobile device interaction. We consider three visual feedback conditions: (1) with visual feedback, (2) without visual feedback and (3) eyes-free. Our findings indicate that gestures made eyes-free were geometrically different from gestures generated in the presence or absence of a visual feedback. In addition, they generated more directional movements around the y-axis and had a lower recognition rate which itself was quite good (95.53%).

*Visual feedback* covers three conditions: (1) *with visual feedback* (Figure 5.1a), which means that participants can see the phone and have a visual trace of the gesture being articulated; (2) *without visual feedback*, for this case, participants had the possibility to see the phone but no visual trace of the gesture being articulated was shown (Figure 5.1b), and (3) an *eyes-free* condition

**PUBLICATION:**

*Adnane Guettaf, Yosra Rekik, Laurent Grisoni and Kathia*  
*M. Oliviera. Understanding One-Handed Eyes-free Gesture*  
*Articulation on Mobile Surface This paper is under revision in*  
*MobileHCI conference*

### Part III - “Interaction Technique for secondary task”

#### Chapter 6: Multi-channel Tactile Feedback Technique

We introduce in this chapter, a new eyes-free interaction technique that takes advantage from tactile sensation to deliver information and so, free the user from the constraint of having a visual contact to perceive a feedback. We rely on the tactile sensory channel by increasing the feedback bandwidth. We allow the user to dynamically perceive several tactile signals by selecting between different channels of tactile feedback using variations in finger speed. Our experimental study revealed that users can learn and be accommodate to the dynamics of eyes-free tactile channel selection and can reliable discriminate between different tactile patterns during multi-channel selection with an accuracy up to 90% when using two finger speed levels.

##### PUBLICATION:

*Yosra Rekik, Edward Lank, Adnane Guettaf and Laurent Grisoni. Multi-channel Tactile Feedback Based on User Finger Speed In Proceedings of PACMHCI volume 5, Issue ISS, Article No: 504. Novembre (2021)*  
DOI: [10.1145/3488549](https://doi.org/10.1145/3488549)

Finally, in **chapter 7**, a summary of all the contributions made in this thesis is presented, with more insights about important findings and future work.



Part II

# BACKGROUND





## CHAPTER 2

### *Background*

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This chapter begins with an overview about mobile touchscreen device interaction. We highlight how the use of gestures and especially haptic feedback were proven in the literature to be relevant for mobile interaction contexts. After that, we discuss existing work about mobile touchscreen interaction as secondary task. Especially, we consider situations when another primary task is already involved and challenged by the secondary one. Finally, we present benefits of using either tactile feedback or gestures based interaction for mobile devices to improve both or one of the primary/secondary tasks efficiency.

#### **2.1 MOBILE TOUCHSCREEN INTERACTION**

Mobile devices started first as an information output for basic static displays or simply a manner to deliver additional information to the user. Nevertheless, it has surely become more dynamic and essential. For example, Fitzmaurice et al. [42] were among the first who proposed an application in which a mobile device is involved in order to interact with information displays. After which, many interaction techniques were introduced over the years. The majority and more relevant ones benefit from the adoption of touchscreen as an input interface. Touchscreen interaction benefits from a direct and absolute interaction style [44, 56, 89] in a two-dimensional input space with a continuous visual feedback [49]. Moreover, it uses a relatively new finger-based concept, in which users rely on their fingers to interact with a mobile device through a bigger space of exchange (no more space taken for physical keyboard). Besides, it provides a better display of users' ongoing interactions, and with more control over the interface reconfiguration when required (*e.g.*, rotating the screen from portrait to landscape or overlaying an application over another). Mobile tactile devices had become so more and more popular and important in everybody's life. The need for a physical keyboard to enter data and navigate on mobile devices has slowly but surely been replaced by the use of gestures [10, 20, 108] as a set of command invocation. As a conclusion, a "glowing enthusiasm" was observed and reported by Shneiderman [118] in 1983 after users interaction

with a graphical users interface that supports a direct input manipulation of objects. The success of the iPhone was also a big testament for the engagement and enjoyment due to the new way of interaction that touchscreen-based devices offer.

In the following, we give a short review of previous works on mobile touchscreen interaction in terms of interaction techniques, gestures recognition, gestures analysis and hand grip.

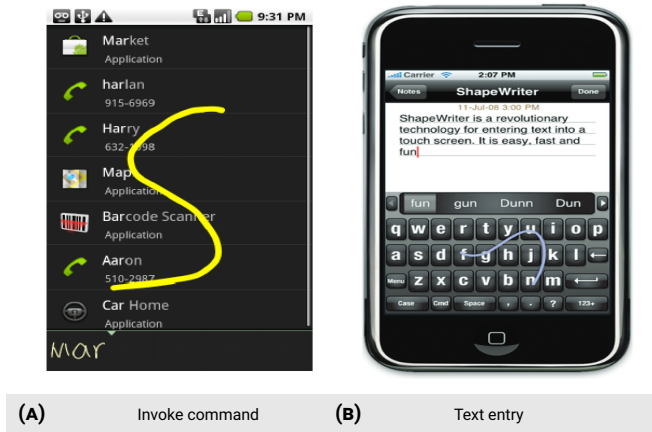
### 2.1.1 *Gesture-based Interaction techniques*

Gestures-based interaction have proven to be an efficient way to interact with touchscreen-based mobile devices. Particularly, through the use of one-finger for tapping [97], dragging [91], swiping [20], entering text quickly [70, 103] (Figure 2.1b), responding calls directly [10, 109, 142] or initiating stroke commands [77, 81], as well as the use of multiple-fingers for pinching or rotating [91]. Gestures had also been proven to be of big benefits for interactions where the visual attention is limited [20], or when users' gaze may be directed away from the mobile device [88, 96, 113]. Especially, stroke gestures were widely documented and used in the literature. They enable a variety of tasks with a confidential and quick manner such as invoking input commands [77] (Figure 2.1a), initiating search operations or navigating through menus [43, 71, 72, 145, 145]. Many works were also conducted for stroke gestures effectiveness for people with disabilities. For example, Vatavu et al. [128] investigated stroke gestures articulation for people with upper body motor impairment using data from 70 participants. Moreover, in [124], authors proposed improvements for the recognition of stroke gestures produced by people with visual impairments with a 10% of increase.

### 2.1.2 *Gesture Recognition and Analysis*

During the last few years, gesture recognition had became an interesting topic for researchers and designers. Especially, thanks to the adaption of gestures interaction for touchscreen devices. Researchers have, consequently, proposed different gestures recognizer. In particular, the popular \$-family recognizers [7, 8, 125, 140] allow both single and multi-strokes gesture recognition and are designed for rapid prototyping. Consequently, it deliver robust recognition accuracy with a set of simple-to-use techniques, easy to convey, implemented and deployed on any platform. Moreover, it contrasts the complexity of standard recognizers, such as Hidden Markov Models [116] and statistical classifiers [110]. For example, Microsoft used the \$N recognizer for multistroke ges-

ture recognition on their PocketTouch device [113], a gesture-sensing through a pants pocket for quick and ambient interactions.



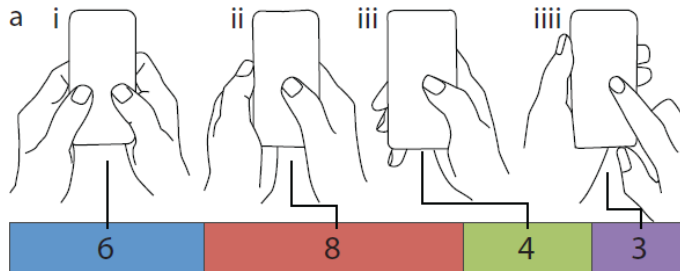
**FIGURE 2.1.** Examples of gesture use on touchscreen mobile devices. Images reproduced from [77, 103]

Researchers have also studied how gestures are produced and proposed a set of geometric and kinematic features to characterise gestures [19, 110]. Perceived difficulty [104, 129] and perceived scale of gestures [127] have also been examined. In addition, researchers have employed a variety of measures to characterize users' performance with gesture input. Anthony et al. introduced "Gesture Clustering Toolkit" to examine users' consistency of gesture articulation [6]. Vatavu et al. proposed "Gesture Heatmaps Toolkit" to highlight the variation in articulation localized on the gesture path [126], and they proposed "GATO", a human performance analysis technique that predicts production time of stroke gestures [74]. These tools have been used to evaluate gestures articulated by children [117], people with low vision [126], blind people [24], people with upper body motor impairments [74] and to validate gesture synthesis approaches [123].

### 2.1.3 Mobile Touchscreen's Hand Grip

Researchers have investigated how hand usage is affected by mobile device form factors. For example, Eardley et al. [38] explored how users will interact with different types of mobile phones (touchscreen, physical keyboard and stylus), and how this latter may affect their hands grip. For this study, three mobile phones were used. Each one with a different interaction style, but in average with approximately the same size. For the touchscreen device, 4 of

the 18 participants that took part into the experiment used only one hand to interact with the mobile touchscreen device (Figure 2.2).



**FIGURE 2.2.** Number of participants who used each grip with a touchscreen mobile device. Image reproduced from [38]

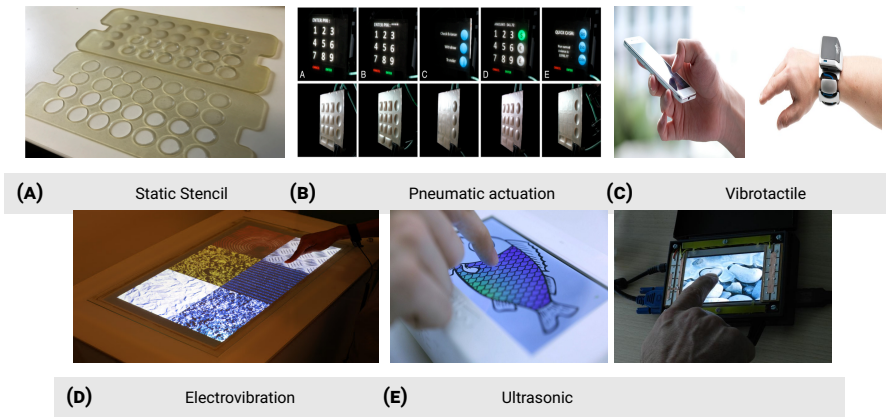
However, considering the context of interaction, all participants were seated and focused only on their interaction (a lab context). This finding was also supported by a survey conducted by Karlson et al. [65], in which authors revealed that the majority of users found that touchscreens are not designed to support a single handed use. However, single-handed touch interaction has been widely documented and reviewed in the literature. It's a common observed hand grip for situations like standing [39], walking [17, 91], holding items or being encumbered [23]. As well as situations where users are under some distractions [88] or when the physical and visual attention is hosted by the other hand [20]. Thumb reachability may be also an important factor to consider when interacting with large screen devices which depends mostly on user's thumb and palm size [27]. Consequently, newly released large smartphone tends to facilitate phone usage with one hand. For example, the *reachability* option on iPhone12 [2] and the *one-handed operation mode* on Samsung S10 [3]. Also, several interaction techniques were introduced to ease targeting mechanisms using a single-handed interaction. In particular, with the use of several mechanisms like Screen Transform [67], Proxy Region [64], Cursors mechanisms [55, 102] and phones tilt using built-in sensors [27].

## 2.2 TACTILE FEEDBACK FOR MOBILE INTERACTION

Touch interaction is the primary input modality of many modern mobile devices [76]. When enhanced with tactile feedback, it allows to deliver information about touched elements, and permit somehow to perceive touched objects through tactile feedback. Tactile feedback can also be of big help when interacting with mobile devices. It permits to guide user's finger to the correct

target, and free somehow the user from the constraint of having a constant visual contact toward the device screen. Many technologies were proposed in the literature. We highlight some of them hereafter. We also, review previous works on tactile feedback rendering, tactile feedback perception and tactile feedback based techniques.

### 2.2.1 Tactile Feedback Technologies

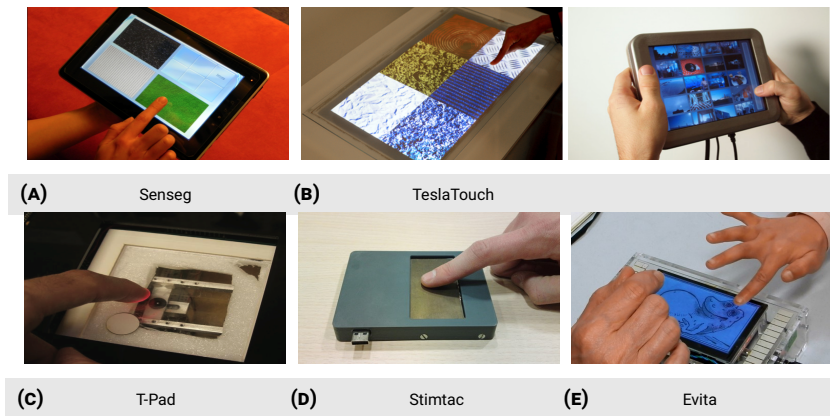


**FIGURE 2.3.** Examples of tactile feedback technologies. Image reproduced from [30, 50]

Nowadays, a range of technologies have emerged (Figure 2.3) that provide user with haptic feedback when interacting with computing devices. Among them, we present two main technologies that support mobile device-based tactile feedback and enable a wide variety of interactions augmented with tactile sensations. They use friction modulation by varying the friction between the user's finger and the instrumented touch surface. In one hand, we have: (1) electrovibration [15, 95, 141], a technology that enhance the friction between the finger and the interaction surface and in the other hand (2) ultrasonic technologies which reduce the friction through the “squeeze film effect” [4, 25, 76, 131]. In the remainder of this section, we present each of these two technologies.

### 2.2.2 Electro-vibration based technology

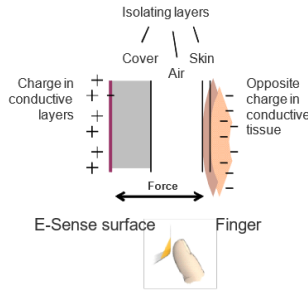
The electro-vibration based technology was first discovered accidentally by Mallinckrodt et al. [84] in 1953. The phenomenon accrued when moving a dry finger gently over a metal surface (conductive surface) covered with a thin



**FIGURE 2.4.** Tactile feedback devices

insulating layer and exited with a 110V signal. It induced a rubbery sensation between the surface and the finger moving over it (Figure 2.5). This technology was later exploited by Senseg [80, 136] (Figure 2.4a). For instance, in [80], authors presented the E-Sense feel screen technology. A touchscreen mounted with a external PC display with a Capacitive Electrosensory Interface (CEI). A novel sensing (electro-sense) which somehow permit to humans also to be sensitive for electric fields. The CIE creates an electrostatic pressure on the surface of human skin. By modulating this force in a range where the vibration perception is the most sensitive, the human skin vibrates, and this vibration will be interpreted by the vibration nerve as touch sensation. The feedback sensation can be perceived even without an effective screen contact for very small distance, and does not require from users to slide over the screen to perceive the sensation. Moreover, for the sake of the same company, Wijekoon et al. [136] investigated a way to increase the perceived intensity of the electrovibration stimuli based on pure sine waves by tuning both frequency and amplitude. Their findings show that electrovibration stimuli with a frequency of 80Hz provides the most intense touch perception.

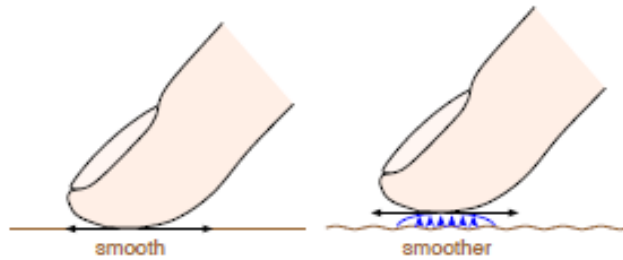
Another technology that rely on the electrovibration feedback was Tesla-Touch [15] (Figure 2.4b). A 3M Microtouch panel composed of a transparent electrode sheet applied over a glass plate and covered with an insulator and exited with a periodic electrical signal. The touch panel was combined with an interactive display and a multitouch input. It permits to exploit the electrovibration technology on a wide range and variety of interfaces. Users of this technology were instrumented with a return ground path to increase the touch sensation when interacting with the device.



**FIGURE 2.5.** Electro-vibration based technology principle. Image reproduced from [80]

### 2.2.3 Ultrasonic based technology

Most of the Ultrasonic-based haptic displays are based on the friction reduction by means of ultrasonic vibrations. It rely on a phenomenon called the “*Squeeze film effect*” technique. It consists on creating an over pressure between the user’s finger and the vibration surface at an ultrasonic frequency [45] (Figure 2.3e).



**FIGURE 2.6.** The squeeze film effect. Image reproduced from [25]

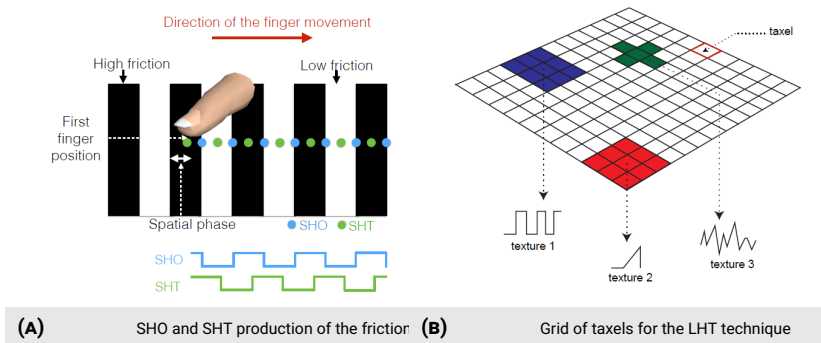
T-Pad [137] (Figure 2.4c) was one of the haptic devices supporting texture rendering through variations in the surface friction with low amplitude vibrations. It creates a squeeze film effect air between the surface and the finger and results in a friction reduction. Their device supported the variation of the coefficient of friction which enabled the implementation a big variety of haptic patterns. Therefore, it showed also that the spatial frequency of force modulation was the most important factor in a one dimensional shear force pattern. In [4], Amberg et al. presented Stimtac (Figure 2.4d), a hardware design where a touchpad was enhanced with ultrasonic feedback using friction reduction. In the other hand, we have also the E-vita [131] device (Figure 2.4e). A tactile feedback tablet that support friction reduction using ultrasonic vibrations. This air bearing resulting from the pressure between the finger and the vibrating



surface alter the device's coefficient of friction so that a user can feel different textures thanks to this variation in friction. The E-vita includes both visual and tactile feedback, alongside the tactile display. For the remaining of this section, we will more focus on this latter device for texture rendering and perception.

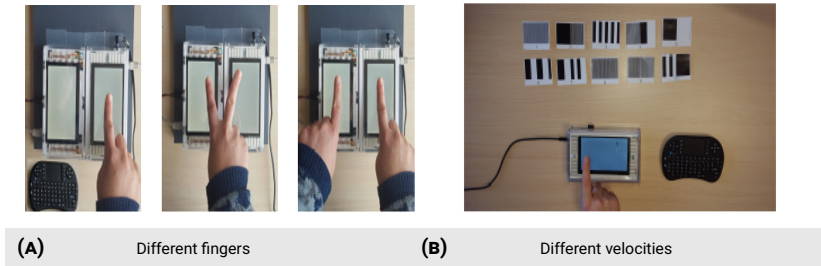
#### 2.2.4 Tactile Feedback Rendering Techniques

Three main rendering techniques for ultrasonic haptic devices have been proposed in the literature (Figure 2.7): Surface Haptic Object *SHO*, Surface Haptic Texture *SHT* and Localized Haptic Texture *LHT*. *SHO* is based on mapping a given texture with a discrete sampling of position and have been used by most existing surface devices (e.g., [4, 15, 69, 76, 95]). *SHT*, on the other hand, have been introduced by Vezzoli et al. [106, 131] recently. It relies on real time finger speed. Rekik et al. [106] compared the *SHO* and *SHT* techniques. Their findings indicate that *SHT* leads to the highest level of quality of tactile rendering for dense textures with either fast or moderate velocity. Whereas, *SHO* is still more accurate for sparser textures with moderate velocity due to positional shift. Considering these results, Rekik et al. [106] introduced the *LHT*, a new rendering technique [106]. *LHT* separates the tactile rendering into two different processes: first, the finger position is retrieved from the hardware, and then, the corresponding texture is selected through a search in a grid of taxels (Figure 2.7b). The taxel texture is then rendered locally by defining only one period of the texture and then repeated in a loop at a rate that depends on the finger's speed. *LHT* was shown to provide a high-fidelity between the tactile texture and its visual representation. In our work, we use the *LHT* technique to render the tactile textures.



**FIGURE 2.7.** Tactile Feedback Rendering Techniques. Images reproduced from [106]

### 2.2.5 Tactile Textures Perception



**FIGURE 2.8.** Experimental set-up for both [105] and [106] studies.

Previous work has examined user's perception of tactile textures on touchscreens devices. In [106], Rekik et al. investigated the user ability to perceive textures on a touchscreen when using different finger speeds (Figure 2.8b). Their findings showed that when using the LHT rendering technique, users were able to accurately recognize textures even when moving their finger at three different velocities. In [59], the authors determined the smallest tactile texture size that user can accurately perceive, which depends on the texture signal waveform. Their results showed that the square signal is more suitable for rendering small textures, with a perceivable size of 6.5 mm in most cases. Dariosecq et al. [34] provided the semantic perceptual space of tactile textures. The study conducted using an ultrasonic device showed that with tactile textures, users were able to perceive smooth and roughness by tuning three parameters: waveform, amplitude and spatial period.

In [105], researchers have investigated the users' ability to perceive simultaneous but different textures (Figure 2.8a). Their finding showed that when using two fingers, users are able to identify the number of textures composing a pair of textures. However, without being able to identify the perceived textures. Also, authors highlighted that a sequential exploration of tactile textures with one finger is clearly more accurate than a multi-finger synchronous exploration, and that only one texture at a time should be perceived by the user's hand. In another paper, Kalantari et al. [60] investigated the sensitivity in perception of differences in tactile texture according to different human finger for both single and multi-finger exploration. Their result showed that the index and thumb fingers are better for a one-finger exploration. Furthermore, their finding showed also that in a multi-finger exploration, the dominant hand was significantly more sensitive than the non-dominant hand while being as accurate as a index exploration.

### 2.2.6 Tactile Feedback Based Techniques



**FIGURE 2.9.** The design space for the scrolling technique. Image reproduced from [75].

Researchers have looked at the benefits of tactile feedback to enhance physicality while interacting with touchscreen devices, and also improve and strengthen the interaction techniques. In Levesque et al.'s work [75] for example, authors investigated the use of programmable friction to improve scrolling interactions. Five scrolling scenarios that sample the design space were taken into account (Figure 2.9). Based on these observations, authors ran a set of experiments in order to design haptically augmented scrolling interactions. Several studies also were conducted to improve pointing techniques using tactile feedback [61, 76, 144]. Authors in [76] proved that when using programmable friction based haptic feedback for dragging interactions, the design proposed showed a better subjective results with a lower dependence on visual feedback. In Zhang et al. [144] work, authors run a study exploring three haptic modality using different haptic designs. The purpose of the study was to improve targeting performance on touchscreens using dynamic electrostatic friction. Their results showed that electrostatic tactile feedback can improve targeting with 7.5%. In another study run after [61], in which authors repeated the same experiment, but with an ultrasonic haptic feedback using the E-vita device [131]. Although the results were different, findings showed that friction reduction using squeeze-film effect improved speed, accuracy and user satisfaction. Recently, Bernard et al. [18] found that, after training with visual and auditory feedback, the use of continuous, gradual feedback permits users to reduce their attention to the touchscreen. Tactile feedback can also prove to help visually impaired people to interact with objects [57] and enhance musical interaction [58].

## POSITION

*These studies highlight the usability of tactile textures for mobile touchscreen interaction and how eyes-free stroke gestures are produced. However, all these studies were conducted in a lab setting, where participants had to focus only on the evaluated task. Consequently, although of valuable contribution, the effectiveness of these findings remains unclear in a real-world scenario where users are making simultaneously another primary task. These primary tasks can be visually or cognitively demanding (e.g., walking in the street, driving or writing an email).*

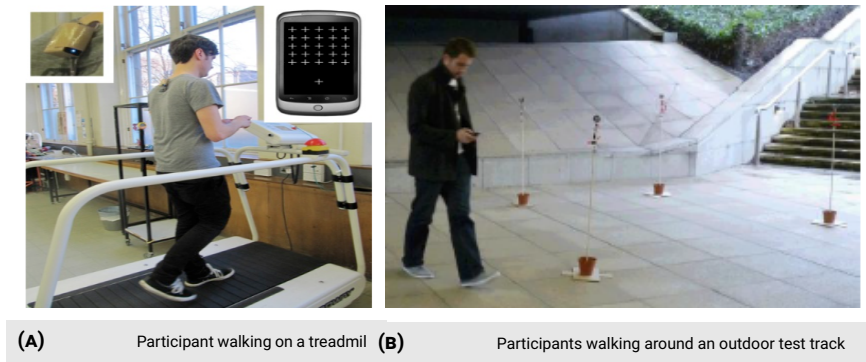
*In the next sections, we first review previous works where the user is engaged simultaneously with two tasks: a primary task, and a secondary task performed on a mobile touchscreen device. Then, we review previous works about interaction techniques and technologies for reducing visual attention and cognitive demand for secondary tasks. In particular, we dig deeper on the effect of tactile feedback when someone is already engaged on another primary task. However, as gesture based interaction techniques were highly used in many works as a way to reduce visual reliance toward the mobile devices, we also review previous works on gesture interaction for secondary tasks.*

## 2.3 MOBILE TOUCHSCREEN INTERACTION AS A SECONDARY TASK

Touchscreen interfaces offer benefits in terms of ease and richness of use. This is mainly due to their flexibility of interaction and their small form factors. Consequently, they have been sorely mounted and used in a variety of devices, from mobile phones to in-car technologies. However, mobile interaction can be so negatively impacted by contextual factors, depending on users' environment [20, 41, 94], mobile state [17, 114] and their implication for the accomplishment of other tasks [28, 50]. We highlight here below interaction contexts where users usually are facing simultaneously two tasks: a principal or primary task for which user attention and cognitive load must mostly be allocated for it, and for which user does not wish to be disturbed or at least, the least possible from a cognitive point of view. Secondly, a secondary task performed on a mobile computing device that the user wishes nevertheless to carry out during the time of the primary task. Although it's probably exhaustive

or impossible to list every single context of use in which a secondary mobile touchscreen interaction may be simultaneously involved, we tried to highlight common situations in which users are commonly observed interacting with their mobile devices.

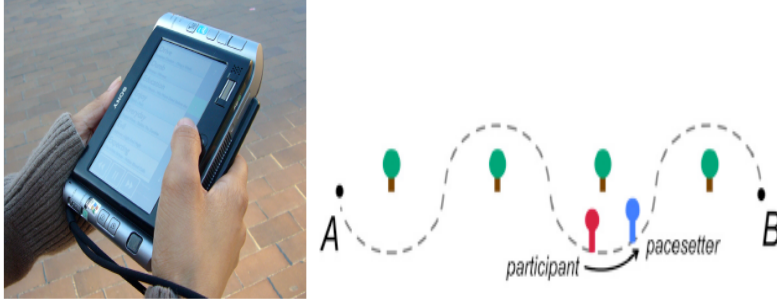
### 2.3.1 *With a Primary Physical Activity Task*



**FIGURE 2.10.** Experimental setup of the effect of walking on user performance taking into account user's preferred walking speed. Images reproduced from [17, 114]

Walking, standing or even running are a common activities that may affect users' interaction and performances on mobile devices. They also can be subject to some distraction caused by the user's attention to the secondary task performed on the touchscreen device. Several studies were conducted to investigate the impact of user's movement on handheld interactions. Bergstrom-Lehtovirta et al. [17] (Figure 2.10a) investigated the relationship or trade-off between walking speed and user performance. Authors used a treadmill to vary users walking speed and observe this latter's effect of users' targeting on a mobile touchscreen device. Their finding showed that users are able to maintain a good level of performance when walking at 40-80% of their PWS (Preferred Walking Speed). Moreover, they noticed that performances decreases by 11% compared to a standing position when walking only at 20-40% of their PWS. Another interesting result was that, when interacting with a touchscreen device, users walking speed was reduced at 76% of their PWS. This result was correlated with Schildbach et al. [114] work, where authors demonstrated the negative effect of walking when performing a target selection task or when reading on a mobile device with a one-handed interaction (Figure 2.10b). Their results showed also that users decreased their walking speed at approximately 75% of their PWS when interacting with a mobile phone, and that performing a walking activity yielded to an increase of 31% for the selection time and 23%

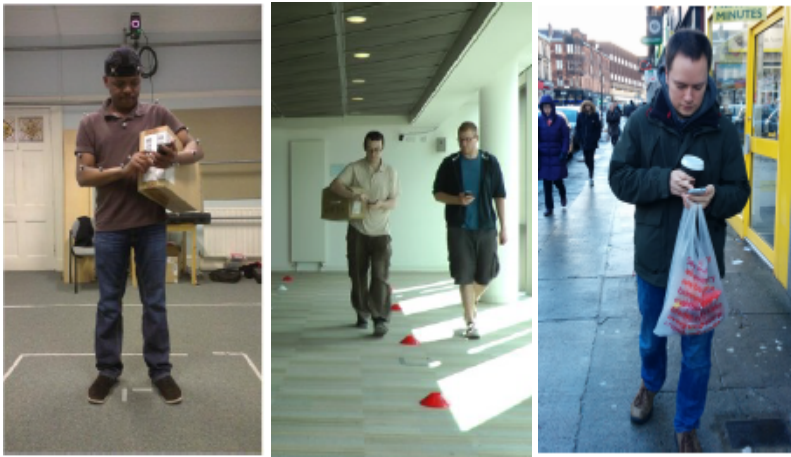
for error rate for the target selection. In addition, Schildbach et al. found that the negative effect of walking can be compensated with an increase of 40% for the target size.



**FIGURE 2.11.** Evaluation of the feasibility of an adaptive walking user interface in an outdoor walking course following a pacesetter. Image reproduced from [63]

In [31], authors investigated the optimal touch button size for an unhampered interaction with a mobile touchscreen device for two physical conditions: standing and walking. Their findings showed that both button size and walking had an impact on typing errors and interaction time. In particular, they found that using large buttons when walking resulted in less to none difference in errors than standing. Also, in Kan et al. [63] work, authors investigated the feasibility of walking user interfaces (WUIs) that adapt their layout when the user is moving (Figure 2.11). They conducted two experiments. In the first one, authors studied the effect of walking in an indoor public area on users' performance when interacting with a tactile music player with different button size. Their finding suggests that target size may have a positive impact on performance when providing adequate interface size depending on the user's walking speed. Based on those findings, authors ran a second experiment in an outdoor area testing a prototype that adjusts target size according to the user's movement. During the study, to monitor participants walking pace, participants had to follow a human pacesetter.

For situations where users are encumbered (Figure 2.12), Ng et al. [90–92] investigated the effects of mobility and encumbrance (holding objects such as bags) on users interaction with a mobile touchscreen device. In [90], with a targeting exercise, authors found that holding objects had a negative impact on accuracy especially if the hampered hand was the dominant hand. However, holding thinner box under the non-dominant hand may result on a quicker and more accurate interaction than unencumbered. Furthermore, when being encumbered, results showed a decrease on the user's PWS (Preferred walking speed) with a lower input precision compared to a stationary position. Since walking speed and input performance can be traded, in order to control the



**FIGURE 2.12.** Typical encumbrance scenarios during stationary and mobile usage. Image reproduced from [90–92]

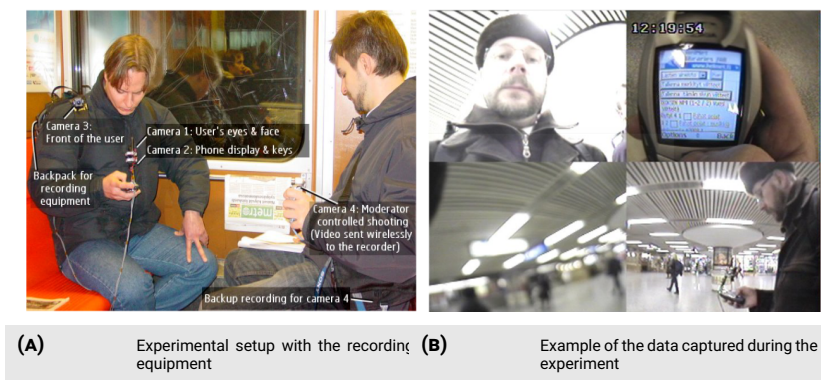
user's PWS, Ng et al. [92] evaluated targeting performance on a touchscreen while being unencumbered for two walking conditions: using a treadmill and walking on the ground. Moreover, in [91], when evaluating standard gestures commonly performed on touchscreens, their findings indicate that encumbrance and walking had a negative impact on each gesture in terms of accuracy. However, this deterioration was not observed for rotational actions which were performed well.

### 2.3.2 *When Being in a Mobile Environment*

As mobile devices became more and more affordable and present in everybody's life, it is not surprising to notice that users are becoming familiar with using them in various innovative and surprisingly ways while being on the move. Public transport like metro, bus or tramway are noticeably a hotspot of mobile device users. The main time killing activity is to use the mobile device in order to surf on the internet and navigate between the multitude of applications available nowadays on the majority of commercial smartphones or tablets. In Oulasvirta et al. [94] work, authors investigated users' fragmented attention when interacting with mobile devices in a real world scenario (Figure 2.13). They used the Resource Competition Framework (RCF) predictions to measure users attention when performing a secondary mobile task while being in urban situations like: railway station, metro platform, bus or a busy streets. The RCF leverage mobile secondary tasks competition for cognitive resources and their impact on resources depletion and a broken interaction.



In this study, participants had to perform a web search task on a mobile web browser. The surrounding environment was captured using two cameras on both the participant and the experimenter. User's visual gaze and phone display were also recorded. The rationale behind using a web search is that users' visual attention may vary between on-task and off-task depending on the time that a page takes to load, which vary considerably and can not be controllable (users can not anticipate when a page is loaded and so can not make strategies to adjust their attention). Their finding prove the difference between lab and field findings, and the resource competition that constrains mobile interaction when being in a real world environment.



**FIGURE 2.13.** Experimental setup and video output in urban fields. Images reproduced from [94]

In [36], authors investigated how usability testing may differ between a laboratory context and a real life environment. With 20 participants divided into two groups (10 participants within a laboratory and 10 other participants in the metro), users taking part into the experiments had to perform a set of tasks depending on whether they are on a dynamic environment or in the laboratory using a Nokia mobile device. In both contexts, users phone display and facial expression were captured, and participants had to fill a post-test questionnaire for subjective appreciation. The findings of this study showed clearly a potential increase in usability problems when being in dynamic environment. Those problems may be phone related or user's behaviour related. Furthermore, interacting with a secondary mobile task induce more time to perform some tasks, with a lower subjective appreciation.

### 2.3.3 *With a Primary Attention Saturating Or Cognitively Demanding Task*

Traditional touchscreen devices, from mobile phones to in-car interaction systems, impose without doubt some visual attention and cognitive load that



may interfere with users' safety, especially for a driving context.

In Victor et al. [132] work, authors investigated the relationship between eye-movements and the visual and auditory demands from in-vehicle information systems as well as driving demands. The study was run in three experimental sites for four context: a motorway in real traffic with an instrumented vehicle, a motorway in a fixed base simulator, and rural roads in two different fixed base simulators. For the visual task, participants were presented with an exercise with three different levels (from one to three) on a touchscreen mounted on the right of the steering wheel (Figure 2.14). The driving environments were implemented to be as similar as possible. They imply each three level of cognitive demand and driving efforts: from level one which consisted in a straight road to the third level which impose some speed regulation. Their findings showed that when interacting with tactile in-car systems, participants tended to have more gaze-away from the road ahead with longer periods for more varied duration. Furthermore, when looking back to the road after a gaze on the touchscreen surface, an increase in the gaze concentration toward the road center area was observed where eye movements were adapted to the driving complexity (e.g., difference between a motorway and rural road, or between a curved or straight section). Also, depending on the secondary task complexity, eye glances away from the road may vary. Authors observed result, even if it may be intuitive, that the more the secondary task on the touchscreen became difficult, the less participants looked at the road ahead and instead looked more toward the display. Eye movement were also sensitive to the driving environment complexity, as more concentration or gaze toward the road center was observed when the difficulty on driving increased.



**FIGURE 2.14.** The touch screen used for the secondary task mounted in the instrumented vehicle in both [41, 132] studies. Image reproduced from [41]

In Engstrom et al. [41] work, authors studied the effects of visual and cognitive demand of in-vehicle interaction systems on driving performance. Moreover, they were also concerned by driver safety, and the drawbacks that may result from such as a poorest event detection performances, or potential

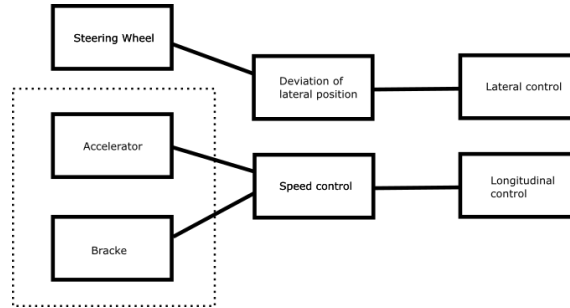
physiological changes. Three experimental setups were used during the study: a fixed base simulator, a moving base simulator and an instrumented vehicle in a field test. All the experimental setups were conducted following the same methodology and evaluated the same dependent variable (lateral control which consisted in the lane keeping variations, the longitudinal control or the vehicle speed (Figure 2.16), driver physiology, visual behaviour (Figure 2.15), subjective performance ratings and performance on touchscreen device). For the visual task –as the previous study [132]–, participants were presented with an exercise with three different levels (from one to three). The exercise was conducted on a touchscreen device mounted on the right of the steering wheel with a forth condition serving as a baseline. Their finding showed an effect of the visual secondary task on each of the driving performance and driver state, as well as driver speed and the steering wheel control (lateral control). This latter was more observed in the simulator setup. Furthermore, the secondary task had a physiological impact, strongly observed in the field test with effects on skin conductance and heart inter-beat interval.



**FIGURE 2.15.** Face LAB cameras mounted behind the steering wheel in order to record eye movements. Image reproduced from [41]

Many researchers in the past have also looked at the effects of visual load while interacting with a secondary task when simultaneously performing a driving activity. This results in a time sharing between the primary and the secondary task. Godthelp et al. [46] went in more details about the effects of sharing driving time with another secondary task. They showed that when users' gaze is directed away from the road, drivers had a fixed lateral control (a fixed steering wheel angle) which may lead, with longer glance duration, to a lane exits. Those findings were supported by many other studies like [47, 146]. Authors in this latter study demonstrated a strong relationship between visual demand and car lateral control. The same behaviour was also observed for the longitudinal control. Many studies [9, 33] have found that visual load had an effect on driving speed which cause this latter to decrease. Thus, when being visually load by a secondary task, users are less likely to be aware of road traffic

events [47, 93]



**FIGURE 2.16.** Lateral and longitudinal control

The display position is also an important factor when evaluating attention demands and driving performances. Summala et al. [121] showed that drivers' lateral control dropped by 30% when the angle deviation of the display from drivers' eye position at a vanishing point on the horizon changed from 23° to 38°. However, longitudinal control also can be subject to variation due to display position and especially vertical display eccentricities [120]. Wittmann et al. [139] showed that the best display positions are the nearer to the line of sight to the primary task. In particular, the horizontal eccentricity had minor detrimental effect than the vertical one.

## 2.4 ENHANCED MOBILE INTERACTION TECHNIQUES FOR A SECONDARY TASK CONTEXT

User interaction with mobile devices as a secondary task can be negatively affected by many factors. These factors includes user's activity and body posture, hands availability or even situational impairments such as the environment surrounding the user or the design of technology used to accomplish the task [115]. However, this same negative effect can also be spread and observed on the primary tasks being simultaneously carried out by the user. In particular, we observe many drawbacks such as a decrease in the walking speed when interacting while moving, or even affecting user's performance on much critical activities. To address this issue, many works were conducted exploring multiple design technologies for secondary tasks, and their benefits or drawbacks for contexts where a primary task with maybe a higher level of priority is involved. Those technologies were evaluated considering their impacts on users' performance and time improvement comparing to a standard touchscreen device. As well as their capability to better handle a fragmented interaction, and the possibility to require less cognitive load or visual attention by approximating an

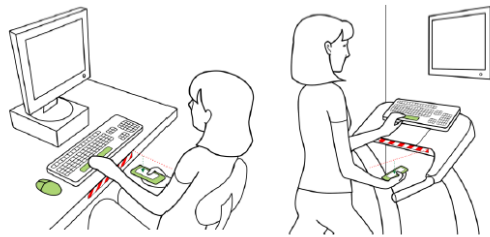
eyes-free interaction. Going through the literature, we were able to identify two main approaches used by researchers to propose novel interaction techniques or contributions that rely on either “*gestural interaction*” or “*haptic feedback*”. Hereafter, we review previous works on both gesture based interaction and haptic feedback interaction for secondary tasks.

### 2.4.1 *Gesture Based Interaction for Secondary Tasks*

In this section, we start by reviewing related works about gesture based interaction for contexts where users are engaged in another primary task.

#### **For a Primary Physical Activity Task**

Bragdon et al. [20] investigated the effects of mobility and environment distractions on soft buttons and gestures interaction. Two gesture types were evaluated during the study. They were chosen based on path-based gestures frequent in the literature, which were mark-based gestures and free-form gestures. They found that in the presence of environmental distractions (Figure 2.17), gestures can offer significant performance gains and reduce attentional load, while performing as well as soft buttons when the user’s attention is focused on the phone. Their findings also indicate that, in such context, some gestures could even be articulated eyes-free, with one hand. Negulescu et al. [88] investigated how gestures are produced for a distracted interaction with limited visual attention. Their findings indicate that motion gestures result in less time looking at the smartphone during walking than does tapping on the screen, even when using eyes-free input.

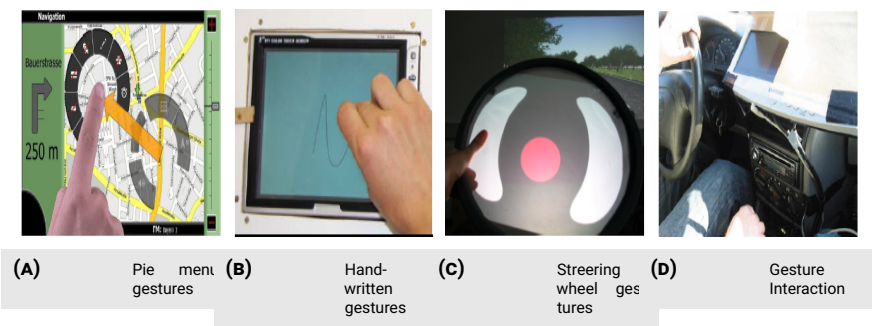


**FIGURE 2.17.** An evaluation of touch-screen Gesture Designs in Mobile Environments. Image reproduced from [20]

Tang et al. [122] investigated users’ preferences and performance for three interaction techniques (tap, swipe and tilt). Three physical activities and body postures were evaluated during their study like walking, running or laying on the bed. For a more realistic measure of usability, the visual attention during the

interaction was limited with more streamlined commands for common tasks. Based on that, four interfaces were implemented: one testing application of each interaction technique plus a game testing application that support the three input ways. For a more objective measure of user’s interaction and preferences, different experiments mode were tested including: standing, sitting, walking in a treadmill, running and lying. Their results showed that in relatively stable environment, users tend more for a tap or swipe input interaction, contrary to more dynamic environments like running were tilt is preferred. In [91] work, when evaluating standard gestures commonly performed on touchscreens when users are walking, authors showed that performing a dragging interaction on a touchscreen device when being on a walk was significantly slower in term of accuracy than typing. However, there was an exception for targets with large distance width. Furthermore, for gestures made with two fingers, pinching was significantly faster than spreading, although both of the interactions were evenly matched in term of accuracy. For rotating gestures, rotating in an anticlockwise direction was quicker than clockwise. These results were different from [29] work, where the interaction was made on a tablet PC and where users were stationary.

**For a Primary Attention Saturating Task or Cognitively Demanding Task**



**FIGURE 2.18.** Different interaction techniques using gestures for the in-car systems. Image reproduced from [12, 40, 68, 98]

Several studies examined the use of an alternative input modality for in-car display for driving situations. Ecker et al. [40] found that their combined design of direct manipulation with gestures using a pie menu for an alternative interaction with in-vehicle information systems (IVIS) (Figure Figure 2.17) can lead to an eyes-free interaction after some training. In their work, authors compared the use of a pie menu serving as a visualisation of gestures with a generic touchscreen interface. A LCT (Lane Changing Task) driving simulation

was used as an evaluation for the drivers' distraction from the driving task when interaction with the secondary device. Their results showed that using pie menu for in-car interactions, especially with short menus, yielded to a faster user's interaction and a more important and higher learning effect. Kern et al. [68] investigated text input using hand writing on a touchscreen mounted on the steering wheel or the central console (Figure 2.18b). Their finding showed that using the steering wheel as a handwritten interface using fingers was more appreciated by users. In addition, it yielded to fewer errors when interacting, and so, more concentration can be conducted toward the driving task. Pfeiffer et al. [98] investigated advantages of gesture based input on multi-touch steering wheel using thumb-based gesture (Figure 2.18c). Their first results showed that participants enjoyed interacting with the steering wheel. They noticed also that they were often using gestures associated with well known symbols or accumulated through their experience with phone interaction. For Bach et al. [12] work however, authors compared the use of gestural interaction for controlling a radio with haptic and touch on a touchscreen mounted on the vertical center stack (Figure 2.18d). The aim of their study was to measure the impact and effects of three different interaction techniques on driving performances and eyes-gaze toward the secondary device screen. Their results showed that gestures helped to considerably reduce eye glances, especially for longer eye-gaze toward the secondary task. However, despite the fact that touch interaction had been the faster interaction technique, it leads to longer eye glances with more than 2 seconds of duration.

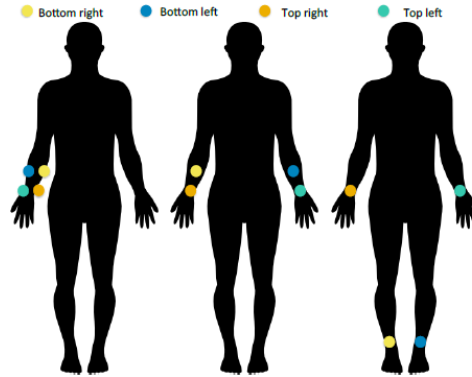
#### 2.4.2 *Tactile Feedback Based Interaction for Secondary Tasks*

In this section, we review related works on the use of tactile feedback as potential way for reducing visual or cognitive reliance toward the touch screen device for contexts including users engagement with another primary task.

##### **For a Primary Physical Activity Task**

In Pielot et al. [99] work, authors used vibrotactile feedback on a touchscreen device for an optimized eyes-free menu for in-pocket interaction. In order to test their prototype, they implemented a simple MP3 player resembling the iPhone's VoiceOver. The prototype was equipped with the required basic functions as: Start/Pause or volume control. Their results showed that, while walking, the improved menu with tactile feedback surpassed a replica of the iPhone's VoiceOver. In addition to that, when using the PocketMenu, participants managed to keep a higher walking speed comparing to when using the VoiceOver menu, which was a manner to approximate the cognitive workload,

as users are more likely to reduce their walking speed when the cognitive load is more important.



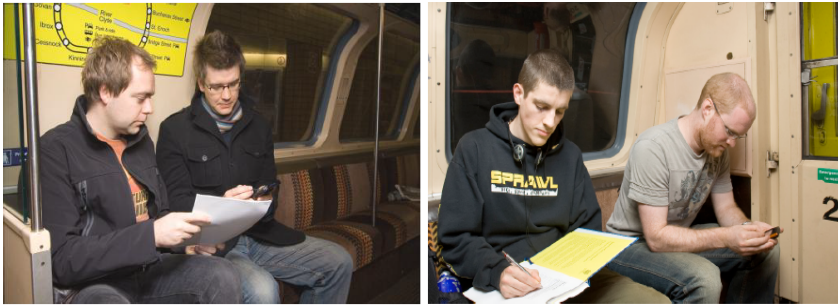
**FIGURE 2.19.** The three combinations of the vibration motors across users' forearms and ankles for the SVP. Image reproduced from [28]

Also, for real-world scenario using Cross-device Spatiotemporal Vibrotactile Patterns (SVP) (not touch surface) (Figure 2.19), Chen et al. [28] investigated how running may affect temporal pattern recognition across body parts. Three combinations of set of devices were used during the study on a  $2 \times 2$  grid layout. They were distributed in the user's forearms, and also ankles for some combinations. As a primary task, participants had to either stay, stand or run on a treadmill in an indoor environment at a speed of 7km/h. At the same time, users had to recognize the correct pattern which was composed in a sequence of three vibrations administered to users using two temporalities (simultaneously or sequentially). Results showed that, even when performing a physical activity (running in this context), participants did achieve good performances with no significant difference from the standing position for both time and accuracy measure. In another interesting paper [26], authors used a smartwatch to deliver discreet feedback using vibrotactile patterns. A set of vibrotactile patterns encoded using duration and rhythm and ranging from 1 to 10 were designed to represent progress (from 10% to 100%). Two user studies were conducted in a laboratory context to evaluate the ability to recognize and match vibrotactile icons with the visual representations. After that, another outdoor third study was run for a period of 28 days. Results showed that users were able to recognize and match to eyes-free vibrotactile patterns with an accuracy average of 88.7% in wild environment. Furthermore, for a manner to help people when walking, Azenkot et al. [11] proposed a three non-visual feedback methods for wayfinding for people with visual impairments using vibration of the smartphone. In particular, in Heuten et al. work [52], authors proposed a non-visual vibration-based tactile display support for walking orientation.



Their prototype was tested in an indoor then an outdoor environment. Their findings showed promising results to accurately guide users or travelers within an unfamiliar environment without any landmarks.

### When Being in a Mobile Environment



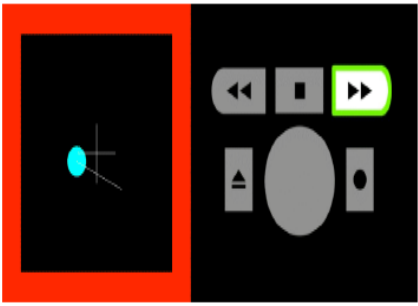
**FIGURE 2.20.** Tactile displays on the move. Image reproduced from [21]

Brewster et al. [21] (Figure 2.20) examined the effect of augmented tactile buttons with vibrotactile feedback for text input task on PDAs when being seated in an office or in a train. Their findings indicate that tactile feedback provides significant benefits for keyboard interactions, both in static situations and mobile ones. Meanwhile, they found that tactile feedback based technique has a key role in improving the touch interaction experience. Also, it is the same perspective of evaluating feedback consistency in public transports. In another similar study, Hoggan et al. [54] evaluated to potential benefits of tactile feedback for finger-based text entry for mobile devices. They compared an enhanced soft keyboard with tactile feedback with a standard touchscreen and a physical keyboard in both static and mobile environment(subway train). Their results proved that with tactile feedback, user's can type text with a precision close to the level of a physical keyboard. Also, in the same perspective of evaluating feedback consistency in public transport. Pohl et al. [101] investigated reliability of notifications delivered using compression feedback through pneumatic actuation compared to a vibrotactile feedback on user attention when walking and taking a public transport.

### For a Primary Attention Saturating Task Or Cognitively Demanding Task

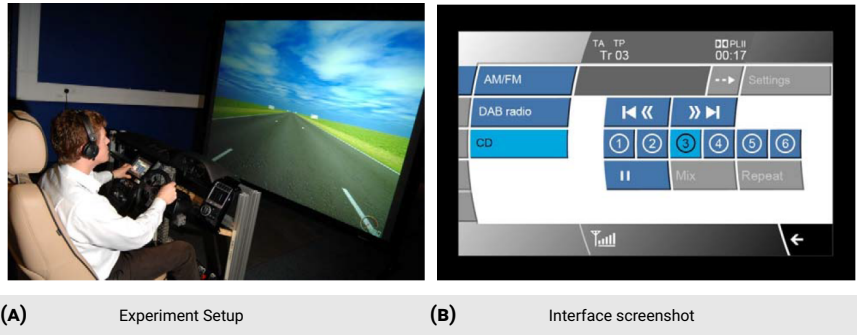
Harrison et al. [50] investigated the relevance of dynamic buttons displays based on pneumatic actuation when the user is performing simultaneously an attention saturating primary task. They employed the same attention saturating dual task framework than in [20, 32]. It consists on performing an





**FIGURE 2.21.** Experiment interface for the evaluation of dynamic buttons displays based on pneumatic actuation when performing an Attention Saturating Primary Task. Image reproduced from [50]

attention-saturating task while simultaneously performing additional tasks on the pneumatic display. As in [20, 32], the goal of the attention saturating task was to keep a moving circle centered on a fixed crosshair (Figure 2.21). The attention needed to perform actions in the secondary task was measured as a drop in performance in the primary one. Results showed that pneumatic displays performs as well as physical buttons with fewer glances towards the surface when performing the primary task. Chen et al. [28] studied the effect of a cognitively demanding primary task, through a typing text, on recognizing spatiotemporal vibrotactile patterns which constitute the secondary task. They found a strong effect of the primary task on recognition rate.



**FIGURE 2.22.** Haptic Feedback for automotive touchscreens. Image reproduced from [100]

For driving situations, where the users' attention is constantly solicited, several studies had been conducted to investigate whether haptic feedback would improve users' interaction with in-car display with less cognitive efforts. Cockburn et al. [30] investigated users' performances when interacting with a touchscreen covered with a static stencil overlay while driving in a 2D emulator. Their results showed that with tactile feedback, users selected a target quickly.

In particular, they found that stencil significantly reduced the visual attention demands on normal touchscreens with shorter eye-glances directed away from the primary task. In [89], authors compared input performances and visual distraction of three types of input controls: physical dial, pressure-based input and touch input. A haptic feedback condition was also considered for both the physical dial and the pressure-based input. Results showed a high target accuracy across all methods with the touch interaction being faster. Nevertheless, although pressure-based input being the slowest interaction implying also the largest number of glances towards the touchscreen, this latter resulted on a shorter glances compared to directly tapping on the surface. However, in Rydström et al. [112] work, authors used a driving simulator as a primary task while asking participants to interact with a secondary one through a haptic ridges rotary device. Their goal was to investigate whether haptic ridges can facilitate the interaction with the rotary device while driving. Their findings showed that driving performance did not significantly vary between haptic-only and haptic/visual conditions. Also, adding haptic ridges to the visual information did not necessarily reduce the gaze-away time from the road. Others studies highlighted tactile importance over other modalities when interacting with in-car switches [22]. Barón and Green [14] stated that performances when using speech recognition for in-car interactions are not constant and can vary from one situation to another. Lee and Spence [73] showed that drivers were quicker in performing a virtual car avoidance task when multimodal feedback was given, and Pitts et al. [100] found a subjective preference for drivers towards touchscreen enhanced with haptic feedback over visual feedback only [Figure 2.22](#).

## POSITION

*In this thesis, we are interested in the use of haptic feedback for secondary task interactions when another primary task is simultaneously involved. In particular, to the best of our knowledge, although there are many works in the literature studying the use of tactile feedback for laboratory contexts, and also for more realistic scenarios, none have investigated the effect of tactile texture for secondary tasks. We thus, investigated the use of tactile textures, as a way to reduce visual reliance for secondary task interaction. Then, we explore tactile textures effectiveness for situations that include users' engagement in simultaneously two tasks. Despite our interest for tactile feedback interaction, and especially in the use of textures to provide stimulus for users, we did explore, however, also gestures interaction. The primary reason being that it represents the main mechanism to explore rendered textures on device surface, requiring usually finger movement through the surface to perceive the tactile texture. In particular, in our review of related works, we do not find insights about eyes-free gestures production. Consequently, as tactile texture perception depends on finger movement, this concern was also considered in this thesis.*

## 2.5 SUMMARY

In this chapter, a review about tactile feedback and also gesture based interaction is presented. These two interaction designs have proven in the literature to be of big benefits when users interaction with the mobile device (secondary task) is negatively affected by another primary task which may include user's activity, situational impairments or performing another task simultaneously. In particular, for tactile texture which is perceived locally on the fingertip, we highlighted that current existing work were all conducted in a lab setting and have so dealt with the use of tactile texture when the users only had to focus on a single primary task. As a result, despite of valuable findings, the findings there-in are not available when the users are performing some other primary tasks.

We seek so in this thesis, to fill a gap in the literature about tactile textures efficiency for real-world interactions, and also explore gestures production for eyes-free interaction as they represent the main mechanism to explore textures.

In the rest of this thesis, we shall describe in more details the different results that we were able to find during our research investigations. In particular, we organize the rest of this dissertation into three parts which are directly motivated by the different aspects discussed in this chapter. In the first part, we will start by understanding textures-based tactile feedback efficiency for situations involving user's implication in others primary tasks. Then, in the next part, we will determine how eyes-free gestures are produced. Finally, in the last part, we will introduce a new interaction technique that provides the users with multi-channel tactile feedback based on the use of the perceived texture and the user finger speed.



Part III

# TACTILE TEXTURES USABILITY



## CHAPTER 3

### *Tactile Feedback For Physically Challenging Tasks*

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A solid background was already established and addressed for tactile texture recognition on mobile surfaces. Researchers have, for example, provided more insights about users' ability to accurately recognize textures in different challenging situations including when using different finger speeds [106], or when the size of the rendered texture is small [59, 119], or even when perceiving simultaneous but different textures [105]. In addition, tactile feedback have been proved to be beneficial for users' interaction with mobile devices, as it can be used to strengthen the interaction [61, 76] (e.g., dragging an object above a target), enhancing the expressiveness of touched objects [76, 141], or by offering accessible design for people with impairments [57].

Taking a step to a more realistic environment, however, may question the previous findings, and thus, the consistency of textures recognition when users are already performing another primary task that is physically challenging, like, walking in the street [28, 63, 91, 99], being in a public transport either standing [36] or seated [21], etc. These primary tasks makes environmental demands, visual loads and mental resources another parameters to take into account when designing touch devices. In the same time, tactile textures only require from user finger exploration on the screen. Consequently, tactile texture based interaction can potentially free user from the constraint to get visual feedback, which constitute an interesting way to reduce the visual attention to the touchscreen, in the case where the user is doing a physically challenging activity.

In this chapter, we went more in depth about such primary tasks, *i.e.*, physical activities. In particular, we were more concerned about the consistency and effectiveness of users perception of textures when the user is performing a primary physical activity. More specifically, the main research issues that we are addressing in this chapter are:

- Does walking deteriorate performances compared to other activities in which users are seated or standing?
- Does being in a dynamic environment like public transports affect textures recognition compared to more stable environments?



- Is there any difference between being seated or standing when interacting with textures based mobile device?

To be able to answer these questions, an experiment was conducted considering the following five physical activities: (1) seated in an office, (2) standing in an office, (3) seated in the tramway, (4) standing in the tramway and (5) walking in the street. The physical activities were chosen with respect to common situations where users are often observed using their smartphones at the same time. Considerable quantitative but also qualitative results are reported in the sections below, in which we present effects of performing a primary physical activity on tactile textures recognition for secondary task. In particular, our findings indicate that the textures recognition performances deteriorated only in the walking in the street condition. However, the recognition rate stay higher than 82% suggesting that tactile textures could be effectively recognized and used by users in different physical activities including walking. The chapter concludes with a detailed discussion on the implications of our results for tactile textures recognition when performing one of our five evaluated physical activities.

### 3.1 EXPERIMENT

An experiment was conducted in order to evaluate users' capabilities to use tactile feedback for mobile surfaces in situations where users are physically active. Thereby five physical activities that represent common situations where users often use their smartphones were considered: (1) seated in an office [20], (2) standing in an office [39], (3) seated in the tramway [21], (4) standing in the tramway [36] and (5) walking in the street [91, 99].

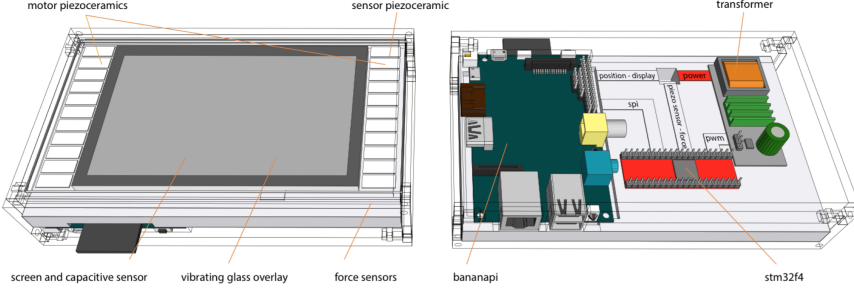
#### 3.1.1 Participants

12 participants (three females) volunteered to take part in our experiment. Participants ages were between 24 and 35 years (mean=26.9, sd=2.78). One participant was left handed, and all participants had a smartphone for at least 5 years with a daily use in different contexts situations.

#### 3.1.2 Method

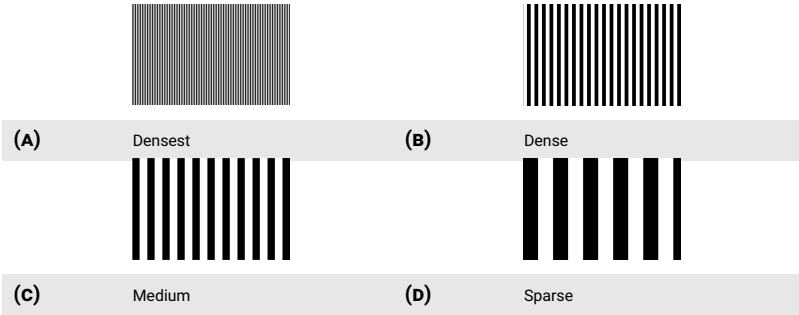
We used *E-vita* a tactile feedback tablet that supports friction modulation by mean of ultrasonic vibrations [131], where the squeeze film effect generates an ultra-thin film of air between the finger and the surface when an ultrasound

frequency is applied to a display overlay (Figure 2.6). *E-vita* includes both visual and tactile feedback; alongside the tactile display, the *E-vita* device [131] is equipped with a 5-inch LCD display including a capacitive sensor which allows a sampling frequency of 50 Hz, similar to the capabilities of commercial mobile devices.



**FIGURE 3.1.** The Evita device used in the experiment

During the experiment, we consider four different tactile textures (see Figure 3.2) following previous studies of Rekik et al. [106] for which users have been able to distinguish them (e.g., [59, 105, 131]). We encode the different textures with respect to different texture densities by considering the following spatial periodicity: *densest* – 1.2 mm; *dense* – 5.1 mm; *medium* – 25.5 mm and *sparse* – 51 mm. In Figure 3.1, the tactile textures are shown by alternating black and white bars; high friction is associated with the black color and low friction with the white color. Given that, we use the Evita, which, when vibrating, reduces friction, this maps black to off and white to on to create tactile patterns. The set of textures is also limited to one-dimensional textures in order to simplify the task. To render a given texture we used the Localized Haptic Texture (LHT) rendering technique [106] (Please refer to section 2.2.4 about tactile feedback rendering techniques).



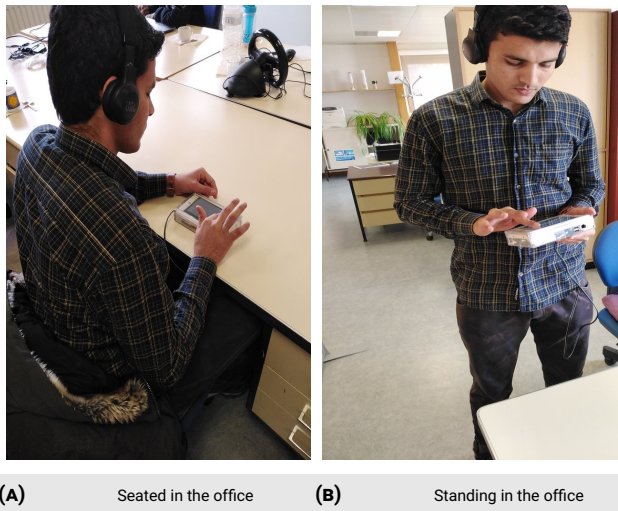
**FIGURE 3.2.** The visual representations of the four tactile textures used in the experiment.

### 3.1.3 Design

The experiment used a  $5 \times 4$  within-subjects design for the two independent variables: *physical activity* (seated in an office, standing in an office, walking in the street, seated in the tramway and standing in the tramway) and *texture* (densest, dense, medium and sparse).

### 3.1.4 Task

For each of the five conditions, participants had to be in a specific physical activity while interacting at the same time with the tactile feedback. For the *seated in the office* condition, participants were asked to seat comfortably in front of a desk on which the tablet was placed, and had to use their dominant hand to interact with the haptic tablet (Figure 3.3a).



**FIGURE 3.3.** Physical activities for the office environment

For the four other physical activities, users were instructed to use a two handed input posture. The non dominant hand was used to hold the tablet while ensuring a firm grasp. Participants had the time to explore which grasp they feel comfortable with and could best stabilize the tablet with it. Once this latter was chosen, participants had to maintain it during the whole activity while performing the task with their dominant hand. For the *standing in the office* condition, participants were asked to stand on a free space in front of a desk (Figure 3.3b). For more dynamic environments, when *seated in the tramway* participants were told to seat on a chair (Figure 3.4a), and when *standing in the*

*tramway*, participants were asked to stay standing while having the possibility to lean on the places reserved for people standing (Figure 3.4b), this setup permits us to replicate a real-world scenario of use while being in public transports, and also ensure users safety which is primordial.



**FIGURE 3.4.** Physical activities for the tramway environment

Finally, for the *walking in the street* condition (Figure 3.5), the experiment took place in an ambient outdoor environment at the university campus (Figure 3.7), the area was frequently filled with people walking both ways, and the walking course consisted of route with approximately 400m from point A to point B marked by two places known to the participants. However, when reaching point B before finishing the task, participants had the possibility to come back on the same road after a small turning. During this condition, and following Ng et al. [90], participants were instructed at the beginning of the experiment to use their preferred walking speed (PSW) while interacting at the same time with the haptic device, and were advised to maintain it during the whole task. An experimenter (Figure 3.6) serving as a human pacesetter had to walk beside the participants and help to ensure that participants keep approximately the same pace if a sudden change is noticed.

For the secondary task performed on the tablet while being on one of the five physical activities, participants were instructed to use their dominant hand and move their finger on the surface from left to right, and from right to left in order to perceive the texture, without a starting finger position or time restrictions or limited number of clutches or swipes. Participants were free to choose how to browse the texture Eyes & Noise free relying only on tactile feedback. No visual feedback was provided about the rendered textures when sensing



**FIGURE 3.5.** The walking in the street activity

this latter. Also, as the Evita device makes noise when alternating high and low frictions, participants were equipped with noise reduction headphones to avoid any bias. After pressing on the "confirm" button after each trial, participants were presented with the visual of the four evaluated textures on the screen, and had then to select the perceived one during the trial before moving to the next one.



**FIGURE 3.6.** The walking course

### 3.1.5 Procedure

Before starting the experiment, participants were asked to answer a demographic questionnaire, after which, the experiment task was explained along with the additional requirements for each activity. The experiment then began, the five conditions or *physical activities* were randomly presented to the

participants. The experimenter was able to regenerate another order if the activities generated were more or less similar to the previous ones. Thus, it helped to make sure to keep a certain balance during the experiment. Inside each activity, participants completed three *blocks*. The first block was later discarded from analyses and served as a training block as we were concerned with user performance after familiarization. Inside each block, the four *textures*  $\times$  three repetitions were randomly presented to the participants, which make a total of 180 trials per participant ( $=5 \text{ activities} \times 3 \text{ blocks} \times 4 \text{ textures} \times 3 \text{ repetitions}$ ). After each activity, participants were asked to complete a NASA-TLX questionnaire worksheets plus a 5-point Likert-scale questionnaire (strongly disagree to strongly agree) for measuring enjoyment while interacting with the device. Participants were also encouraged to take a break after each activity and also when needed to avoid fatigue and keep data consistency. Also, during the whole experiment, one author accompanied the participants all along the different activities while observing users' behaviour and taking detailed notes, particularly concerning the think-aloud data, and after each experiment, participants were asked to describe the strategy used in order to identify the perceived textures, and also to give subjective feedback about the experiment, and if there is, about each of the five physical conditions. The experiment took around 90 minutes to complete.



**FIGURE 3.7.** A preview of the outdoor walking course in the university campus

## 3.2 RESULTS

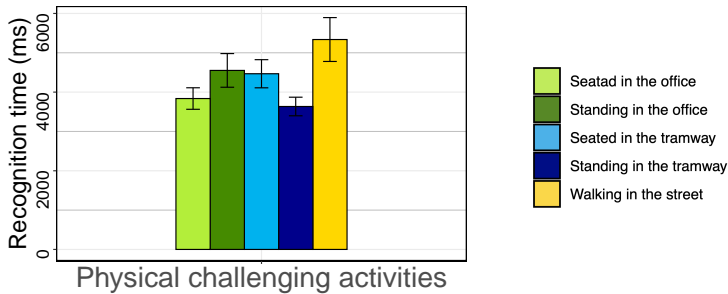
Four dependent variables were evaluated: recognition time, accuracy, number of swipes and number of clutches. We present here after the results obtained



during the experiment for each one of them. All analysis are using multi-way ANOVA. Tukey tests are used post-hoc when significant effects are found. We also present the analysis of subjective results concerning the NASA-TLX and the 5-point Likert-scale questionnaires, and also users comments, mental modal and behaviour. Due to a technical issue, the data of three participants were not completely logged. Consequently, we excluded these three participants from the analyzes, and thereby, we report results for each of the dependent variables for our nine remaining participants.

### 3.2.1 Recognition Time

Recognition time represents the time taken by the participant to sense and recognize the texture, from the first touch, until pressing the “confirm” button. It also include the time user’s finger is not touching the surface, like when performing a clutch for example. We excluded error trials were participants did not recognize correctly the perceived texture from analyses, and only considered timing data from correct trials to better account for user performance [83].



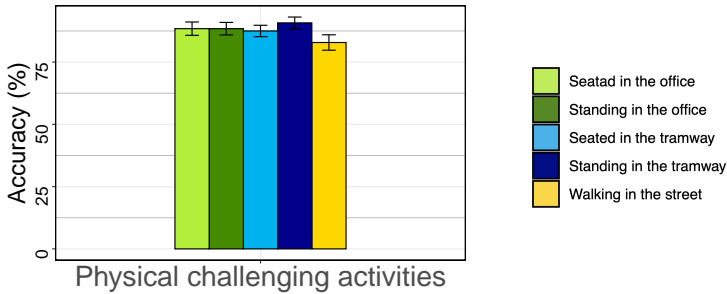
**FIGURE 3.8.** Recognition time for each of the five physical activities

There were significant main effect of *activity* ( $F_{4,31.36} = 2.58, p = .05$ ) and *texture* ( $F_{3,23.78} = 17.04, p < .0001$ ) on *recognition time*. Post-hoc tests revealed that walking (mean=5337 ms, sd=1115 ms) is significantly slower than both seated in the office (mean=3836 ms, sd=547 ms) and standing in the tramway (mean=3634 ms, sd=472 ms) with no significant difference with standing in the office (mean=4551 ms, sd=856 ms) or seated in the tramway (mean=4467 ms, sd=715 ms) (see Figure 3.8). We also found that the densest texture (mean=1817 ms, sd=186 ms) is recognized significantly faster than all remainder textures (dense: mean=4545 ms, sd=793 ms, medium: mean=6096 ms, sd=786 ms, sparse: mean=5044 ms, sd=508 ms). There was no significant activity×texture interaction ( $p=.06$ ), suggesting that the drawback of walking are consistent across

textures and the benefits of densest texture are consistent across different activities.

### 3.2.2 Accuracy

Accuracy (%) is defined as the proportion of correct identification of the perceived textures. There were a significant main effect of activity ( $F_{4,32} = 1.30$ ,  $p = .0289$ ) and texture ( $F_{3,24} = 7.13$ ,  $p = .0014$ ) on accuracy. Post-hoc tests revealed that walking in the street (mean=82.87%, s.d.=6.19%) deteriorated significantly the performance compared to the remainder activities (seated in an office : mean=88.42%, sd= 5.35%, standing in an office: mean= 88.42%, sd= 5.03%, seated in a tramway:mean= 87.5%, sd= 4.55%, standing in a tramway:mean= 90.74%, sd= 4.69%) (see Figure 3.9). We also found that the densest texture (mean= 98.51%, sd= 1.42%) is significantly better recognized than the remainder textures. There was no significant activity×texture interaction ( $p=.658$ ), suggesting that the drawback of walking are consistent across textures and the benefits of densest texture are consistent across different activities.



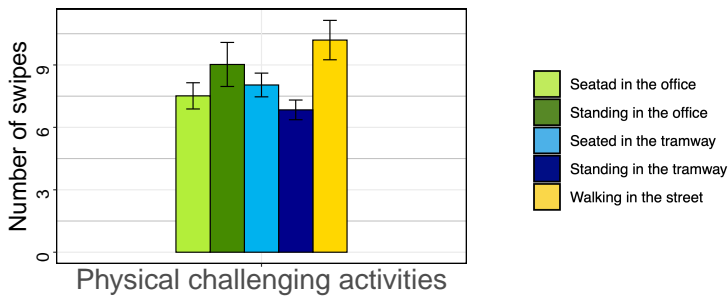
**FIGURE 3.9.** Accuracy for each of the five physical activities

### 3.2.3 Number of Swipes

Directional swipes are defined as being user's finger movement on the haptic surface from left to right, or right to left. Thereby, during the experiment, we recorded users' generated number of swipes as we think it may be a good metric to capture textures identification difficulty. We hypothesize, that the more the texture perception is difficult, the more the user needs time to recognise it and the more he makes swipe gestures to perceive the evaluated texture.

There were significant main effects of activity ( $F_{4,32.28} = 3.76$ ,  $p = .0128$ ) and texture ( $F_{3,23.95} = 11.82$ ,  $p < .0001$ ) on number of swipes. Post-hoc tests re-





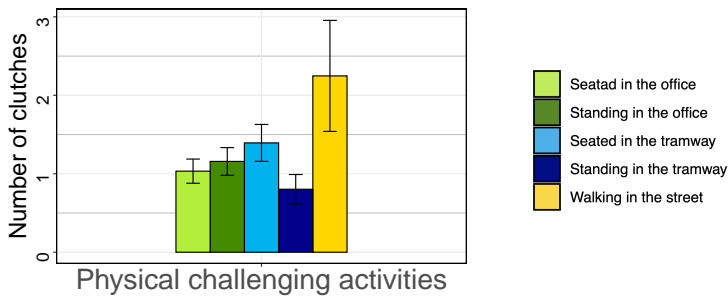
**FIGURE 3.10.** Number of swipes for each of the five physical activities

vealed that walking in the street (mean=10.19, sd=1.89) produced significantly more swipe gestures than when standing in the tramway (mean= 6.84, sd= .94) with no significant difference with when being seated in the office (mean=7.514, sd=1.26) or standing in the office (mean= 9.02, sd= 2.11) or seated in the tramway (mean= 8.03, sd= 1.13) (see [Figure 3.10](#)). We also found that the densest texture (mean= 4.02, sd=.50) produced significantly less swipe gestures than the remainder textures (dense:mean=8.93, sd=1.38, medium:mean=11.08, sd= 1.71 and sparse:mean= 9.31, sd= 1.2). There was no significant activity×texture interaction ( $p=.06$ ), suggesting that the increase (respectively, the decrease) of number of swipes when walking (respectively, when using densest texture) is consistent across textures (respectively, activities).

### 3.2.4 Number of Clutches

We consider a clutch as the action of removing the finger from the haptic surface then putting it again. We recorded during the experiment the number of clutches made by our participants from the first touch on the beginning of each trial. Computing the number of clutches helps to indicate if the interaction can be fragmented and so can be more adequate for multitask situations.

There was a significant effect of textures ( $F_{3,23.41} = 5.34$ ,  $p = .0059$ ) on *number of clutches*. Post-hoc tests revealed that the medium texture (mean= 1.99, sd=.76) produced significantly more clutches than the densest texture (mean=.31, sd=.15) with no significant difference with the dense (mean= 1.42, sd=.91) and the sparse texture (mean= 1.57, sd=.38). There was no significant activity×texture interaction ( $p=.27$ ), suggesting that the increase of number of clutches when using the medium texture is consistent across different activities ([Figure 3.11](#)). There was no significant effect of activity on the number of clutches.



**FIGURE 3.11.** Number of clutches for each of the five physical activities

### 3.2.5 Subjective Results and Observations

**Walking Activity Appreciation.** We recall that our participants were asked to rate the task after each activity using NASA-TLX questionnaire plus a 5-point Likert-scale for enjoyment. Overall, questionnaire responses (Table 3.1) show that the mean ratings for the walking condition were mostly less appreciative than seated in the office or in the tramway, but only significantly for mental demand, physical demand and effort.

	<b>Seated (office)</b>		<b>Standing (office)</b>		<b>Seated (tramway)</b>		<b>Standing (tramway)</b>		<b>Walking (street)</b>		<b>Friedman <math>\chi^2(4)</math></b>
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d	
Mental demand	1.77	.43	2.77	.54	2.11	.60	2.55	.57	3.33	.46	17.44
Physical demand	1.11	.217	2.22	.63	1.66	.56	2.44	.47	2.66	.73	17.73
Temporal demand	3	.97	2.66	.56	2.33	.65	2.44	.66	2.77	.54	16.59
Performance	3.88	.51	3.77	.54	3.88	.60	3.77	.63	3.33	.46	4.75
Frustration	1.44	.47	2	.65	2	.65	2.33	.80	2.33	0.86	6.18
Effort	1.88	.39	2.66	.65	2.33	.80	2.77	.71	3.44	.66	15.73
Enjoyment	4	.86	3.66	.86	3.77	.85	3.77	.91	3.33	.92	6.77

Note: Friedman tests are reported at  $p=.05$  (\*) significance levels. The significant tests are highlighted.

**TABLE 3.1.** Mean and s.d questionnaire responses, with 1=very low, and 5 = very high.

These findings were correlated to our participants' comments. The majority of our participants felt that when walking in the street, identifying textures at the same time was harder and more mentally challenging than the four other activities. Some quotes: "walking in the the street demands more concentration and more finger gestures (swipes), caused principally by the body movements", "it was more

*difficult for me to manage two tasks in the same time (walking and performing the experiment),” “when walking, I had difficulties sometimes to differentiate between the four textures due to the physical activity”.* Also, being in an outdoor context requires from users a constant vigilance and awareness of the surrounding environment, and thus, it logically will demand more attention and cognitive resources, like for example avoiding obstacles like trees by constantly keeping an eye on the road, and also to stay alert for people passing or even bikers by keeping an ear for a possible bicycle bell. One participant reported that he noticed that the environmental attention needed for avoiding obstacles like stones and the trees shadow on the road may also affect the concentration and respond time.

**Textures recognition for a calm environment.** When being in the office -which was a quiet environment-, despite being seated or standing, participants expressed their satisfaction for identifying textures, and felt that recognizing the textures is easier and that they are more confident. For instance, while seated, one participant said *“it is very easy to me to identify the textures in this posture”.* One participant stated that *“when being in the office, I am more sure about my touch sense and choices ... and I can easily distinguish the different textures”.* Another participant had correlated his ability to easily spot the textures in the sitting position compared to the other activities with the fact that he felt comfortable and in a calm environment while using the tablet.

**Textures recognition for a dynamic environment.** For the two activities (setting and standing in the tramway) -which were a more dynamic environment-, participants stated that they felt also confident in their choices, mainly because they were already trained and used to use their smartphone when they are in the tramway during their daily needs. One participant said *“As I use always my phone in the tramway, I feel confident about my responses”.* Two participants described the sensations felt at their fingertips as being fairly perceived and comparable to the use in the office situations. In addition, for the standing condition, participants felt that they are still *“confident in their identifications, even if they had sometimes to regain their balance when they leaned because of tramway movements”.*

### 3.2.6 Methodologies for Identifying Textures

After the experiment, thanks to the follow-up interview, we were able to collect the feedback of five participants on the strategies used in order to identify the perceived textures. We report here-after the three main strategies reported by our participants:

- Visualizing the texture image in the user mind when perceiving the

texture. This strategy was used by *P4*.

- Counting the number of all tactile feedback and then matched its position with the visual texture (*P6*).
- Using the densest and the sparse textures as a reference *P1*, *P2*, *P8*.

These findings are correlate to the findings of Rekik et al., [105, 106]. Interestingly, many participants were able to know that they had made a mistake during the task for a particular texture when they were feeling the next one. With full practice, one may conjecture that the accuracy and the speed in the different activities should eventually increase. Importantly, our participants used these three main strategies independently of the activity.

### 3.3 DISCUSSIONS

Our key findings indicate that the walking in the street condition deteriorated both the accuracy and time measures, increases the number of swipes, the mental demand, physical demand and effort over the office and the tramway conditions. These findings were also consistent across different *textures*. In the following we discuss our findings according to three angles:

**Body posture.** For both the office (which is a quite environment) and in the tramway (which is a more dynamic environment that requires user's attention and physical effort for ensuring balance for example), users' body posture for the two evaluated stances (seated and standing) did not impact the performances, which suggests that the two postures could and should be equally used and exploited.

**Textures viability in dynamic environments.** For the dynamic environment evaluated in this experiment -which was being in the tramway-, no negative impact was observed on users' performances for either recognition accuracy or time measure, and this, even when being standing. Consequently, this suggests that tactile textures could be effectively recognized and used by users on touchscreens when being in the tramway. However, researchers interested in other vehicles contexts, in which another speed traveling can be used, and thus, produce more or fewer jitters, may first study how other vehicles contexts can affect user recognition of tactile textures.

**The walking activity.** We observed a performance drop up to 8.45% for the walking in the street activity, with a significant impact on recognition rate. We try to explain this deterioration with the potential impact of the environmental demands and the visual load needed when walking, as users stay alert to the surrounding environment by avoiding obstacles like stones, trees or people walking on the same road, as reported by our participants. Additionally,

the disturbances in the finger swipes caused by the body movements can also consequently disturb the exploration of the texture. Thus, researchers may want to take the walking in the street into consideration when designing experiments on texture recognition, even if there was a drop in accuracy, as this latter did achieve indeed an exploitable and usable rate of 82.87%. Consequently, this suggests that tactile texture could be effectively recognized and used by users when walking in the street.

### 3.4 CHAPTER SUMMARY

In this chapter, we conducted an investigation on the effect of physical activities on users' perception of tactile textures on ultrasonic haptic tablet. We showed that such primary tasks including different body posture (seated and standing) and the environment mobility (here the tramway) do not affect the texture recognition performance. However, the physical activity (walking in the street) decreases the performances compared to being in a static environment (the office) or in a dynamic one (the tramway). However, despite this deterioration, the recognition rate did achieve good rate suggesting that tactile texture could be effectively recognized and used by users in different physical activities including walking in the street.

With these findings, we laid the first brick for textures recognition when users are performing at the same time another primary task. However, users are brought to face many others interaction contexts, including divers challenging primary tasks (*e.g.*, tasks that saturates the attention like driving [46, 132], or tasks that are cognitively demanding like working [28]) that may be performed while simultaneously using their mobile device. Thus, in the next chapter, we will investigate tactile textures effectiveness when performing two other kinds of primary tasks (an attention saturating task, and a cognitively demanding one).

## CHAPTER 4

### *Tactile Feedback for Attention Saturating or Cognitively demanding Tasks*

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In the previous chapter, we showed that users' perception of tactile textures on mobile tablet was reliable independently of the physical activity, achieving so a very acceptable recognition rate of more than 82%. These promising results drove us to investigate other challenging primary tasks that are more likely to be faced by users when interacting with a mobile device. In particular, we investigated two types of primary tasks, one that continuously saturates the attention and another one that is cognitively demanding. More specifically, the main research issues that we are addressing in this chapter are:

- Will users be able to use and distinguish between tactile textures when performing at the same time an attention saturating or a cognitively demanding primary task?
- Will all users behave the same in order to perform both the primary and the secondary task?
- Will users use the same strategies in order to handle the primary and the secondary tasks?
- Does the perception of tactile textures can be made eyes-free when performing at the same time another primary task?
- Would different primary tasks result in different findings and behaviours?

For that purpose, we conducted two experiments to examine users' perception of tactile textures rendered on a mobile touchscreen when performing another primary task on a laptop. In the first experiment, we study the effect of the attention saturating task on textures recognition: the primary task in this experiment is a highly visually demanding task which feature the control of a pseudo-randomly perturbed moving ball, in a manner similar to the approach used in [32]. In the second experiment, we study the effect of the cognitively demanding task on textures recognition, considering as a primary task a text typing exercise [28]. We also varied the secondary task position (on the left,

right and forward) relatively to the primary display, and explored its effects on users interaction and behaviour. For both experiments we refer to a control situation, in which none cognitively nor visually constraining primary task is involved, serving so as a basis for comparison and allowing to measure the potential drop in performance.

Considerable quantitative but also qualitative results are reported in the sections below, in which we present effects of performing an attention saturating or cognitively demanding primary task on tactile textures recognition for secondary task. In particular, for both primary tasks, the recognition rate stays higher than 82% and the total time does not decrease, suggesting that tactile texture could be effectively recognized and used by users when performing a primary task that either saturate the attention, or is cognitively demanding. The chapter concludes with a detailed discussion on the implications of our results for tactile textures recognition when performing an attention saturating primary task or a cognitively demanding one.

## 4.1 EXPERIMENT

We conducted two experiments to investigate the effect of a primary task on tactile textures recognition on a touchscreen. We consider two primary tasks, the first saturates the attention while the second is cognitively demanding. The two primary tasks are described in the corresponding experiment section. The two experiments share many similarities that we describe in this section.

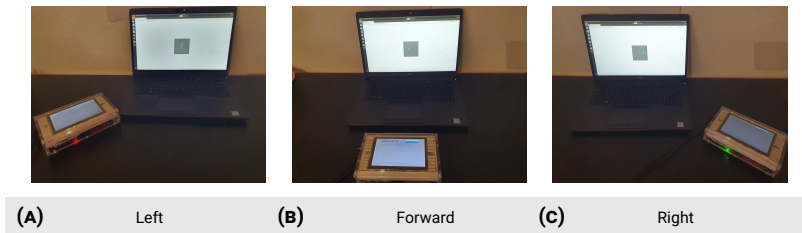
### 4.1.1 Method

As for the previous chapter, we used the E-vita device [131](Figure 3.1) as the main device holding the secondary task consisting of a series of texture recognition. These later were considering following previous studies [59, 105, 106, 131], and encoded the same way as in the previous chapter (please refer to section 3.1.2 for more details).

The primary task was implemented in JavaScript framework using the Node.js runtime and ran on a Dell laptop machine with a 13-inch LCD display screen with a desktop resolution of 1920×1080. Participants' faces were also videotaped. In addition, one author observed each session and took detailed notes, particularly concerning think-aloud data, hand postures, and mental model.

### 4.1.2 Design

The experiment used  $2 \times 3 \times 4 \times 3$  within-subject design for the factors: *activity*, *position*, *texture* and *block*. Activity presents if the participant is doing a primary task or just waiting for the notification that we named here the *control condition*. Consequently, in the first experiment, the activity is either *centering the ball* (i.e., the attention saturating task) on the laptop or the *control condition* and in the second experiment, activity is either the *text-typing* (i.e., cognitively demanding task) or the *control condition*. Position is the position of the surface compared to the laptop and covers three values: right, left and forward (see Figure 4.1). The tactile surface was oriented horizontally (i.e., parallel to the ground). For the right position, the surface was placed 5cm away diagonally from the bottom-right of the laptop with an orientation of  $45^\circ$ . For the left position, the surface was placed 5cm away diagonally from the bottom left of the laptop with an orientation of  $-45^\circ$ . And for the forward position, the surface was centered and placed 5cm below the laptop keyboard which in turn was centered in front of participants. *Texture* covers the four presented textures in the previous section. *Block* covers 3 value (1-3), with the first block serving as a training phase.



**FIGURE 4.1.** Experiment setup according to the three positions of the haptic table.

### 4.1.3 Procedure

Before starting the experiment, our participants were asked to seat comfortably in front of a desk in face to the laptop, after which they had to answer a demographic questionnaire followed by an explanation about the experiment task along with the additional requirements for both the primary and the secondary tasks.

The experimental trials were administered as blocks of 12 trials (4 textures  $\times$  3 repetitions). For each activity, and for each tablet position, participants had to perform three blocks of textures identification. The three blocks were administered consecutively for each position before moving to the next one to



minimize physical device displacement; then grouped by primary activity to allow questionnaire assessment. The two primary *activities* were counterbalanced. Inside each *activity*, the three tablet *positions* were also counterbalanced. Inside each *block*, the four *textures*  $\times$  three repetitions were randomly presented to the participants – a total of 216 ( $=2 \text{ activities} \times 3 \text{ positions} \times 3 \text{ blocks} \times 4 \text{ textures} \times 3 \text{ repetitions}$ ) trials per participant. After each block of trials, participants were encouraged to take a break. After each activity, participants completed a NASA-TLX worksheets.

#### 4.1.4 Task

Both experiments required from participants to interact with a primary task on the laptop and to recognize textures on the tablet (secondary task) each time they receive a notification. Participants were asked to prioritize the primary task over the secondary one, and were told that their performance was being measured for both tasks.

For each experiment, we consider two primary tasks : (1) the attention saturating task (experiment 1) or the cognitively demanding task (experiment 2) and (2) a control task. In the control condition, participants had only to react to the notifications displayed on the laptop screen to perform the texture recognition task. The rationale of adding the control condition, is to better understand the effect of the attention saturating/cognitively demanding primary task on user perception of tactile textures.

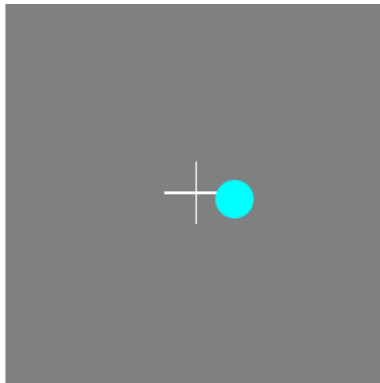
For the secondary task, participants were asked to move their index finger on the surface from right to left and inversely to perceive the texture, without a predefined hand or a starting finger position or time restrictions or limited number of clutches or swipes. Participants had the total liberty in choosing how to proceed to explore the whole texture. No visual feedback of the rendered texture was shown on the surface, only tactile feedback was sent to the participants while sensing the texture. In addition, as the Evita device makes noise when alternating high and low frictions, the participants were equipped with noise reduction headphones to avoid any bias. Once the participant recognized the perceived texture, he pressed on the “confirm” button that is positioned on the top of the tactile surface. This location was chosen to be sure to not disturb the texture perception task. A new screen is then displayed, and participants had to select the visual representation of the perceived texture from the four visual representations of the four evaluated textures on the tablet surface and then confirm their choice by pressing again the “confirm” button.

At the experiment phase, participants started interacting with the primary task. And after a random period of time between 2 and 14 seconds (following

Harrison et al. [50]), a notification was shown up in the computer screen and a texture was rendered in the tablet surface. The rationale behind choosing a duration that varies each time is to avoid that a rhythm settles in the procedure and that the participants become familiar with it and put in place strategies to anticipate the secondary task. The notification display indicate to the participants that they can start recognizing the rendered texture on the tablet surface. Participants were free to choose the appropriate strategy to handle the primary task and the secondary one while keeping in mind that the primary task should be prioritized. Participants had the total liberty to interact with both tasks at the same time or sequentially by switching from one to another etc. After ending a trial by selecting the visual representation of the perceived texture, our software presented the next notification after a random period of time between 2 and 14 seconds. Each experiment took around 90 minutes to complete. To reduce fatigue, sufficient resting periods were given between conditions and as required by the participants.

#### 4.2 EXPERIMENT 1: WITH AN ATTENTION SATURATING PRIMARY TASK

In this experiment, we investigated the effect of an attention saturating primary task on the recognition of textures. We followed [20, 32, 50] and used the same primary task that saturates the attention. Our primary attention saturating task featured a circle moving pseudo-randomly according to a two-dimensional Perlin noise function (Figure 4.2).



**FIGURE 4.2.** The primary saturating task that features a moving circle

Participants were asked to keep the circle centered over a cross-hairs displayed in the center of the square as the best they could, and this by contracting its movement using the arrow keys of the laptop keyboard. Participants were also asked to use one hand to perform the primary task while having the total

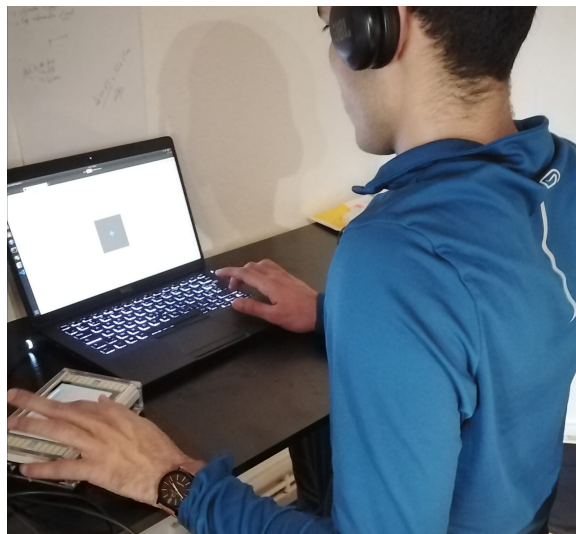
liberty in choosing which hand to use. Participants were free to use the same hand to interact with the secondary task or to use their second hand (Figure 4.3). Participants were told that keeping the circle centered on the crosshair was the most important task and that their performance was being measured for both the primary and the secondary task. The procedure and task as well as common apparatus are presented in the Experiments section 4.1.

#### 4.2.1 Participants

13 participants (five females) volunteered to take part into the experiment. Participants ages were between 24 and 36 years (mean=30.23 years, sd=4.45years). All participants were right handed.

#### 4.2.2 Quantitative Results

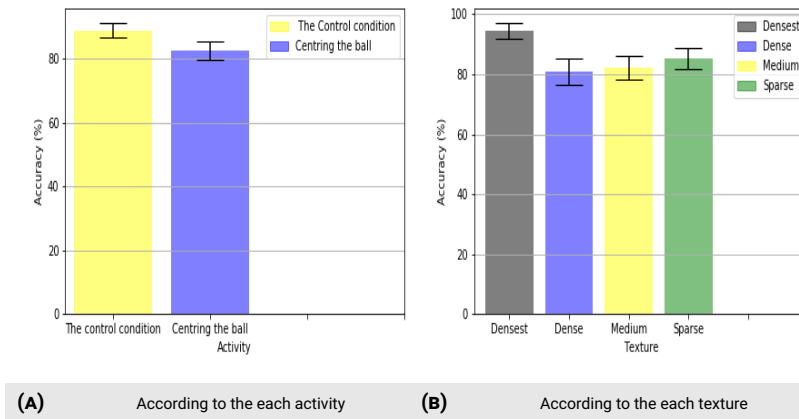
Results for each of the dependent variables (*reaction time, movement time, total time, accuracy, number of swipes and number of clutches*) are presented below. All analyses are using multi-way ANOVA considering the following independent variable: activity, tablet position, texture and block. Tukey tests are used post-hoc when significant effects are found. We also analyzed subjective responses.



**FIGURE 4.3.** The primary saturating task that features a moving circle

## Accuracy

Accuracy is defined as the proportion of correct identifications of textures. There were significant main effects of *activity* ( $F_{1,12} = 3.86, p = .008$ ) and *texture* ( $F_{3,36} = 3.17, p = .0357$ ) on *accuracy*. Post-hoc tests revealed that the control condition (mean=88.78%, sd=2.25%) is significantly more accurate than centering the ball (mean= 82.58%,sd= 2.50%) (see Figure 4.4a). We also, found that the densest texture (mean= 94.44%, sd= 1.42%) is significantly better recognized than the remainder textures (see Figure 4.4b). There was no significant interaction ( $p > .1951$ ), suggesting that the drawback of centering the ball activity are consistent across textures and surface positions and the benefits of the densest texture are consistent across different activities and tablet positions.



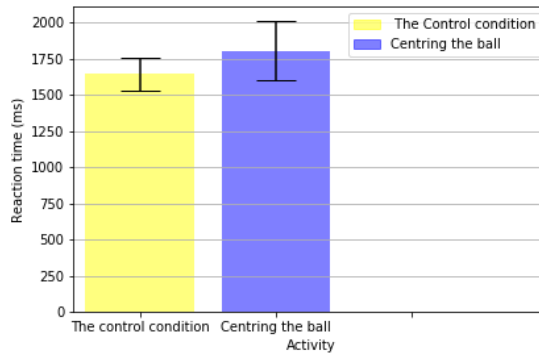
**FIGURE 4.4.** Users accuracy for textures recognition when performing an attention saturating primary task

## Time Performance

We measured *reaction time*, *movement time* and *total time*. *Reaction time* was the interval time between the appearance of a notification on the laptop screen and the first touch on the surface device. It represents the time taken by the participant to react and switch to the secondary task. *Movement time* represents the time taken by the participant to sense and recognize the texture, from the first touch, until pressing the “confirm” button for the first time. *Total time* represents the time taken by a participant all along a trial, from the moment the notification is shown up, until pressing the “confirm” button. It is the sum of reaction and movement times. For time measures, we only considered timing data from correct trials to better account for user performance.

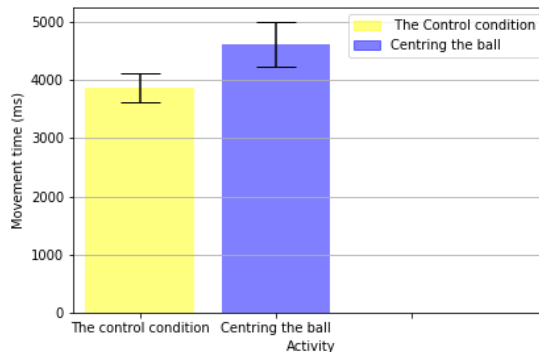
**Reaction time.** There were no significant effects of activity ( $p=.58$ ), posi-

tion ( $p=.36$ ) and texture ( $p=.82$ ) on reaction time nor interaction ( $p>.13$ ), with similar means of 1644 ms ( $sd= 115$  ms) with the control condition, and 1803 ms ( $sd= 203$  ms) when centering the ball (see Figure 4.5)



**FIGURE 4.5.** Users reaction time according to the each activity.

**Movement time.** There was a significant effect of textures ( $F_{3,36.23} = 18.26$ ,  $p < .0001$ ) on movement time. Post-hoc tests revealed that the densest texture (mean= 2619 ms,  $sd=376$  ms) is recognized faster than the remainder textures (dense: mean=4513 ms,  $sd=445$  ms, medium: 5117 ms,  $sd=472$  ms, sparse: mean=4684 ms,  $sd=411$  ms) (see Figure 4.6).



**FIGURE 4.6.** Users movement time according to the each texture.

**Total time.** Repeated-measures ANOVA revealed a significant main effect of block ( $F_{2,24} = 13.70$ ,  $p < .0001$ ) on total time. Post-hoc tests showed a significant decrease in the time between the first block and the two remaining ( $p < .05$ ; block1: mean=6924 ms,  $s.d=445$  ms, block2: mean=6174 ms,  $s.d=402$  ms and block3: 5744 ms,  $s.d=383$  ms) due to a learning during the first block. As we are concerned with user performance after familiarization, the

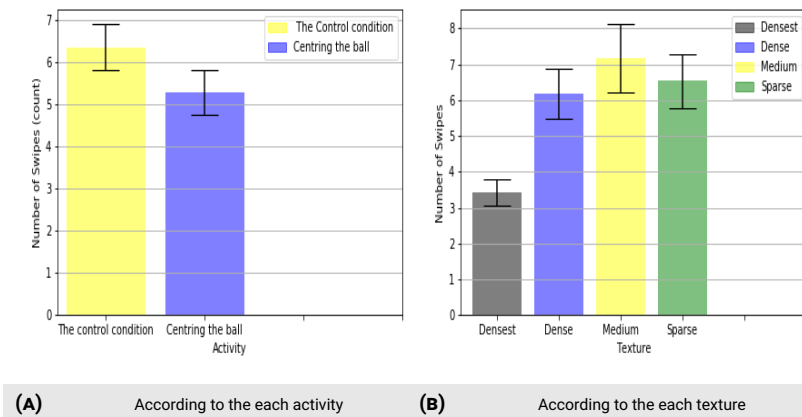
remaining analysis discards the first block.

There was a significant main effect of *texture* ( $F_{3,36} = 15.37, p < .0001$ ) on *total time* with a significant *activity*×*position*×*texture* ( $F_{6,71.83} = 2.23, p = .0498$ ) interaction. Post-hoc tests revealed that when centering the ball, and having the tablet on the right (respectively, forward), the densest texture is significantly better recognized than both the dense and the medium (respectively, medium) textures ( $p < .05$ ).

### Number of swipes

Directional swipes represent the number of times user's finger moves on the surface from left to right and inversely during the movement time. As explained in the previous chapter 3.2.3, this metric makes it possible, among other things, to capture the difficulty of identifying textures. We excluded error trials from analyses.

Analysis of number of swipes shows no significant effect of activity ( $F_{1,11.98} = .99, p = .33$ ), with similar means of 6.35 (sd=.53) for the control situation and 5.26 (sd=.52) for centering the ball (see Figure 4.7a). There was, however, a significant effect of *texture* ( $F_{3,36.12} = 10.67, p < .0001$ ) on *number of swipes*. Posthoc tests revealed that the densest texture (mean= 3.42, sd=.37) produced significantly less swipe gestures than the remainder textures (dense:mean=6.16, sd=.70, medium:mean=7.16, sd=.94 and sparse:mean= 6.52, sd=.76)( 4.7b).

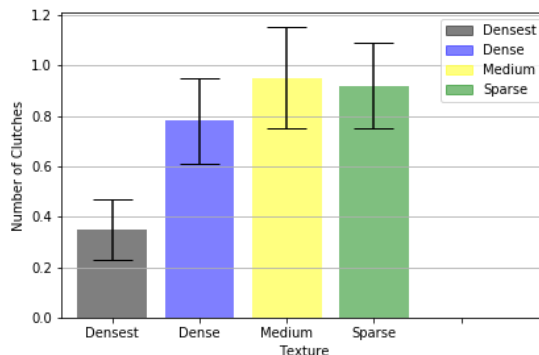


**FIGURE 4.7.** Directional swipes for textures recognition when performing an attention saturating primary task

### Number of clutches

*Number of clutches* is defined as the number of times the user released his finger from the surface and then put it again on the surface from the first touch and only during the movement time. We excluded error trials from analyses.

Similar to number of swipes, when analyzing number of clutches, we found no significant effect of activity ( $F_{1,11.98} = 3.27, p = .09$ ) with similar means of .55 (sd=.09) for the control condition and .94 (sd=.14) for centering the ball ( $F_{1,11.98} = 3.27, p = .09$ ). There was a significant effect of *texture* ( $F_{3,35.86} = 6.83, p = .0009$ ) on *number of clutches* (Figure 4.8). Post-hoc tests revealed that the densest texture (mean=.35, sd=.12) produced significantly less clutches than the remainder textures (dense:mean=.78, sd=.17, medium:mean=.95, sd=.20 and sparse:mean=.92, sd=.17).



**FIGURE 4.8.** Number of clutches for texture recognition according to each texture.

### 4.2.3 Subjective Results and Observations

Our quantitative data were accompanied by considerable qualitative data that capture users' mental models as they handle and perform the primary task and the secondary one.

#### NASA TLX results

We recall that our participants were asked to rate the overall task after each activity condition. Overall, questionnaire responses (see Table 4.1) showed that recognizing textures when centering the ball was significantly more demanding mentally and physically while having significantly higher perceived effort and being more frustrated than in the control condition.

<i>Experiment 1</i>					
	<i>Control</i>		<i>Centring the ball</i>		<i>Wilcoxon</i>
	mean	s.d	mean	s.d	Z
Mental demand	2.38	.41	3.84	.43	-3.20
Physical demand	1.84	.66	3.30	.56	-2.75
Temporal demand	2.76	.63	3.76	.32	-1.96
Performance	4.07	.34	3.92	.34	.70
Frustration	1.84	.53	3.23	.55	-2.91
Effort	2.15	.53	4	.44	-3.23

Note: Wilcoxon-Signed-Rank tests are reported at  $p=.005$  (\*) significance levels.

**TABLE 4.1.** Mean and s.d questionnaire responses, with 1=very low, and 5 = very high for experiment 1. The significant tests are highlighted

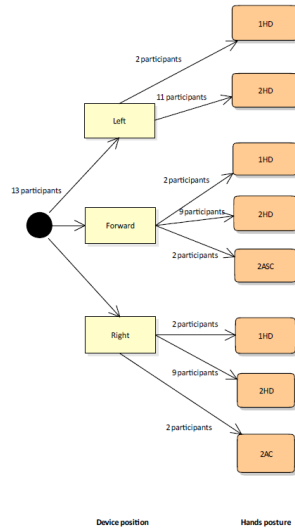
We correlate these findings with comments from participants that felt that managing the ball while performing a texture recognition is more difficult than when they had just to identify the texture after receiving a notification. Some quotes: “for me, doing both tasks simultaneously was difficult”, “it is stressful to center the ball and recognize the texture at the same time”. In addition, one participant felt that “the overall task demands a lot of effort and is highly frustrating ... I try to quickly identify the texture to not loose time or getting the ball not centred but I felt confident in recognizing the textures”.

### Hands input posture

We instructed participants to prioritize the primary task (centering the ball) over the secondary one (recognizing the textures) while giving them the total liberty on the number of hands to use and which hand to use to handle and perform the primary and the secondary task. Interestingly, for a given surface position, we observed that once the participant starts the task with a given hands posture, he continues with that posture until finishing all the trials in that position. In the following, and as described in [Figure 4.9](#), we present the different hands postures used to perform the primary and the secondary task once the notification has shown-up:

- **One-handed (dominant hand) – 1H.** Two participants used their dominant hand (here right hand) to perform sequentially the primary and the secondary task during all the experiment and independently on the position of the touch surface (see [Figure 4.10a](#)).
- **Two-handed directional posture – 2HD.** This hands posture is strongly correlated to the position of the tactile surface and consists of using the





**FIGURE 4.9.** Participants hands posture according to each device position

hand closed to the tactile surface to perform the secondary task and the other hand to perform the primary one (see Figure 4.10b). For the forward position, as to interact with the primary task, participants have to press on the arrow keys which are localized at the extreme right of the keyboard and so the laptop, we then considered the primary task as being more on the right than the secondary one. For 2HD posture, when performing the secondary task, the hand used for the primary task remains on the keyboard arrow keys. While when the secondary task finished (*i.e.*, participants have to only perform the primary task), we were able to observe three postures performed by the hand used for the secondary task: (1) **fingers-above**: the hand fingers are kept above the surface by placing the wrist in a stable position just below the surface (see Figure 4.10c), (2) **fingers-closed**: the participants' wrist was placed just below the surface, but the hand was a little bit moved back with a closed fingers (see Figure 4.10d), and (3) **hand-moves**: the hand used for the secondary task was put on the office and maintained in a perimeter around the surface (see Figure 4.10e). In addition, we observed two participants using the *finger-above* posture often touching the screen of the surface before a notification shows up to anticipate the appearance of this latter. Overall, this hand posture is used by nine participants for the right, eleven for the left and nine for the forward surface position.

- **Two Arms Crossed – 2AC.** This hand posture is strongly correlated to the task priority and consists of using always the dominant (here right)

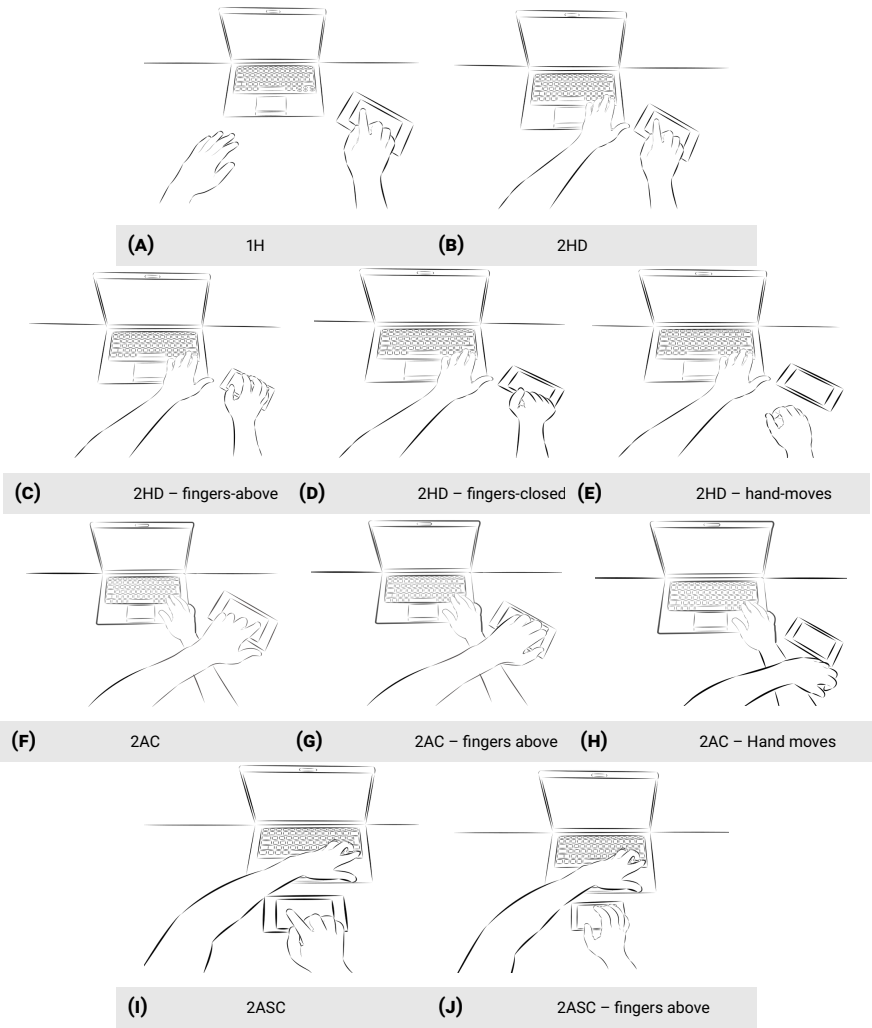
hand for the primary task and the non-dominant (here left) hand for the secondary task despite the surface is on the right position. Consequently, the participants arms were crossed (see Figure 4.10f). Participants kept their dominant hand on the keyboard array keys when performing the secondary task, and when this latter is finished, they used either the *fingers-above* (see Figure 4.10g) or the *hand-moves* (see Figure 4.10h) for the hand used to interact with the secondary task while keeping the hands crossed. Overall, two participants used this posture for the right surface position.

- **Two Arms Semi-Crossed – 2ASC.** This posture occurred essentially in the *forward* position, when users used their non-dominant (left) hand to interact with the primary task, and their dominant (right) hand for the secondary task crossing a little their arms to perform both tasks (see Figure 4.10i). Here, participants kept their dominant hand on the keyboard array keys when performing the secondary task, and when this latter is finished, they used the *fingers-above* for the hand used for the secondary task while keeping the hands semi-crossed (see Figure 4.10j). Two participants used this posture.

### Strategies used to handle the primary and the secondary task

We noticed different methods or behaviours adopted by our participants to prioritize the primary task (centring the ball) over the secondary task (recognizing the textures), which we grouped into three main strategies that we highlight here-after. Interestingly, we observed that once the participant starts the task with a given strategy, he continues with that strategy until finishing all the trials of the activity independently of the surface position or the hand posture used. We highlight the different strategies and the hand postures used hereafter:

- **Competitive interaction with Exclusive attention to Primary task (CEP).** Five of the thirteen participants kept interacting strongly with the primary task when they were interacting with the secondary one while their gaze attention was mostly conducted toward the laptop screen (*i.e.*, the primary task) with a nearly eyes-free interaction with the tactile surface (*i.e.*, the secondary task). In addition, all of them used to put more visual attention for the tactile surface only when they have to select the texture after perception, as it needs three button selections (confirm the end of perception, selecting a texture and then confirming the selection) with generally glances toward the primary task screen between those three actions. They also, rarely look at the tactile surface before starting



**FIGURE 4.10.** The different hand postures used during the experiment.

perceiving the texture or for locating this latter during the experiment. Two participants using this strategy found that the activity is similar to “driving” while “checking the GPS on the phone” or “manipulating their multimedia car radio”.

Four of the five participants interacted with the primary task in the same way and with almost the same rhythm during all the experiment *i.e.*, even when they have additionally to identify a texture. While we observed a different behavior for the remaining participant which used to move sequentially the ball from left to right, and from right to left by continuously alternating pressing on the left and the right arrow buttons to “insure keeping the ball centered” while performing the texture

identification.

Three hands posture were associated to this strategy. *2-HD* was used by respectively three, five and four participants for the *right*, *left* and *forward* surface positions. Two participants used *2AC* for the *right* position and one participant with a *2ASC* for the *forward* position.

- **Reactive Interaction with Shared Attention to Both tasks (RSB)**

Three of the thirteen participants interacted principally with the secondary task and reacted to the primary task only when necessary *i.e.*, the ball moves away from the center, while keeping their hand over the arrow keys. Their gaze attention was shared almost equally between the primary and the secondary task when identifying textures, with certain cases where the primary task got more gaze attention than the secondary one. This strategy was used with a *2HD* by three participants for both the *right* and *left* surface positions. Two of them continue using this hand posture for the *forward* position while the latter used a *2ASC*.

- **Divided interaction with Exclusive attention to Secondary task (DES)**

Five of the thirteen participants stopped interacting with the primary task and switched to the secondary one until they select a texture. In addition, to insure that the ball will not deviate from the box center, participants perform quick identifications of the rendered textures. And sometimes, when the notification showed up, participants start by making sure to center well the ball before switching to the secondary task. Most of the gaze attention was conducted toward the secondary task with only few glances toward the primary one. Two participants used a *1H* and the three latter used a *2HD* for the three surface positions.

### Methodologies for identifying textures

As for the previous chapter, to better understand how participants performed during the textures recognition when being at the same time under a constant attention solicitation, participants' elaborated strategies were collected in order to identify the perceived *textures*. Three of the four collected strategies were already reported in the previous chapter: visualizing the texture in the mind, counting and matching the number of felt feedback, and using some textures as references (please refer to the section 3.2.6 of the methodologies used to identify textures when performing a primary physical activity). Plus a new strategy that was stated by one of our participants:

- Comparing the distance between two successive feedback and compare it to the user' finger width to determine if the texture is sparse or medium.

One participant said: *“for the medium and sparse textures... I had to look to my finger to make the correspondence between the distance between two successive signals and my finger width to determine which texture I am feeling.”*

**Summary.** The main findings during this first experiment in which users are challenged with an attention saturating primary task while performing a texture identification is that, performing a primary task had an impact on recognition rate without compromising the speed. We observed an average decrease of performance of 6.98% (from 88.78% to 82.58%) with an additional mental and physical demands, frustration and effort. These findings are consistent across different surface positions. We also observed different hands postures (one one-handed and three two-handed) and strategies to handle the primary and the secondary task with some participants performing the secondary task *Eyes-free*, which mean without the need to see the surface device. Additionally, for the two-handed postures, the hand used for the primary task remains on the keyboard even when performing the secondary task to be ready to react to the primary task. However, interestingly, the hand used for the secondary stays in the surrounding area of the tablet even when the two hands are crossed or semi-crossed.

### 4.3 EXPERIMENT 2: WITH A COGNITIVELY DEMANDING PRIMARY TASK

In this experiment, we followed [28] and used the same text-typing<sup>1</sup> exercise as our cognitively demanding primary task (Figure 4.11). Participants had to type the text displayed in front of them in the computer screen (see Figure 4.12), with a cursor showing with the red color the next character to type. Typing the wrong character was considered as an error and was not taken into account, and thus, it was impossible also to delete a character. Participants were free to choose how to interact with the primary task, and the same logic was also applicable with the secondary task when receiving a notification. We asked our participants to prioritize typing over texture recognition, and told them that their performance was being measured for both the primary and the secondary task. The procedure and task as well as common apparatus are presented in the Experiments section 4.1.

#### 4.3.1 Participants

Twelve new participants (3 females) volunteered (not paid) to take part into this experiment. Participant ages ranged between 22 and 41 years (mean=30.41 years,

<sup>1</sup> <https://www.goodtyping.com/test.php>

Sudoku is a logic-based number placement puzzle. The goal is to fill a 9x9 grid so that each column, each row, and each of the nine 3x3 boxes (also called blocks or regions) contains the digits from 1 to 9 only one time each. The puzzle setter provides a partially completed grid. The modern puzzle was invented by an American architect, Howard Garns, in 1979 and published by Dell Magazines under the name "Number Place". It became popular in Japan in 1986, after it was published by Nikoli and given the name Sudoku, meaning single number. The numerals in Sudoku puzzles are used for convenience; arithmetic relationships between numerals are irrelevant.

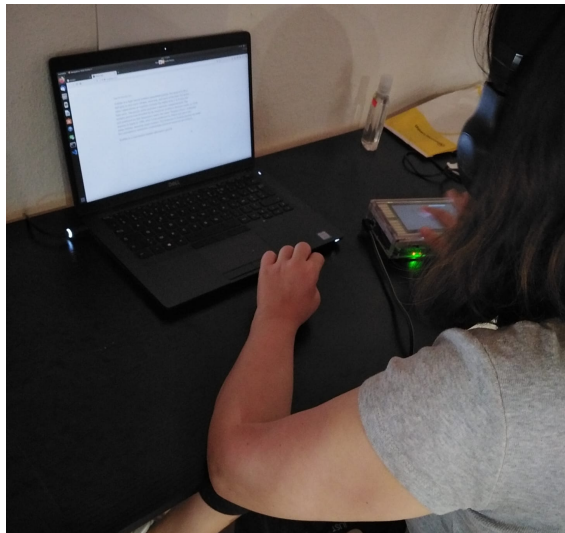
Sudoku is a logic-base

**FIGURE 4.11.** The text-typing exercise serving as a cognitively demanding primary task for the second experiment.

sd=6.05 years). All participants were right handed.

#### 4.3.2 Quantitative Results

We consider the same dependent variables than in experiment 1.

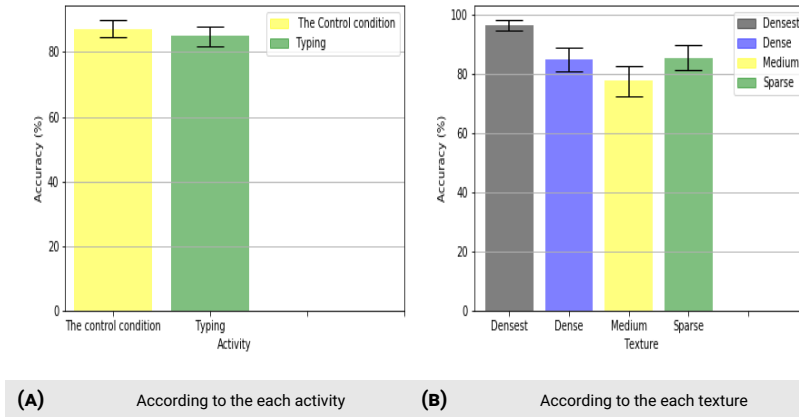


**FIGURE 4.12.** The primary cognitively demanding task that features a text typing exercise.

#### Accuracy

Analysis of count of trials containing an error shows no significant effect of activity ( $F_{1,11} = 1.66, p = .2236$ ) on accuracy, with similar means of 87.15% with the control condition, and 84.95% for typing (Figure 4.13a). There was

a significant effect of texture ( $F_{3,33.47} = 5.13, p = .0051$ ) with the densest texture (mean= 96.30%, sd= 1.72%) being more accurate than the remainder textures (dense:mean= 96.29%, sd=1.71%, medium:mean= 77.54%, sd=4.98%, sparse:mean=85.41%, sd= 4.15%) (see Figure 4.13b).



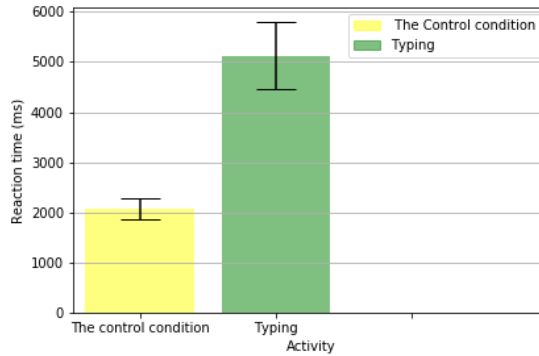
**FIGURE 4.13.** Users accuracy for textures recognition when performing the cognitively demanding primary task

## Time Performance

As for the precedent experiment, reaction time, movement time and total time were all measured and analysed.

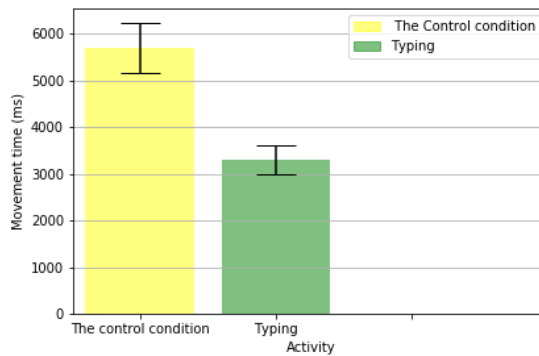
**Reaction time.** There was a significant effect of activity ( $F_{1,11.02} = 7.95, p = .0166$ ) on *reaction time*, with the control condition faster (mean=2065 ms, sd=208 ms) than typing (mean=5124.839ms, sd=661ms) (see Figure 4.14). Post-hoc comparison confirms differences between the control condition and typing ( $p < .05$ ). We correlate this result with user behavior. For instance, contrarily to the control condition where participants started the texture recognition when receiving the notification, in the typing activity, participants continued writing their word/sentence before switching to the recognition task. There was no significant interaction ( $p > .35$ ), suggesting that the drawbacks of typing are consistent across different textures and surface positions.

**Movement time.** There was a significant effect of activity ( $F_{1,11.02} = 7.47, p = .0194$ ) and texture ( $F_{3,33.47} = 9.86, p < .0001$ ) on *movement time*. Posthoc test revealed that typing (mean=3296 ms, sd=300 ms) is significantly faster than the control condition (mean= 5695 ms, sd=524 ms) ( $p < .05$ ) (see Figure 4.15). We also found that the densest texture (mean=2719 ms, sd=415 ms) is recognized significantly faster than all remainder textures (dense: mean=4968 ms, sd=732 ms, medium: mean=5458 ms, sd=689 ms, sparse: mean=5014 ms,



**FIGURE 4.14.** Users reaction time according to the each activity for the second experiment.

sd=595 ms). There were no significant interactions ( $p > .05$ ), suggesting that the benefits of typing are consistent across textures and surface position.



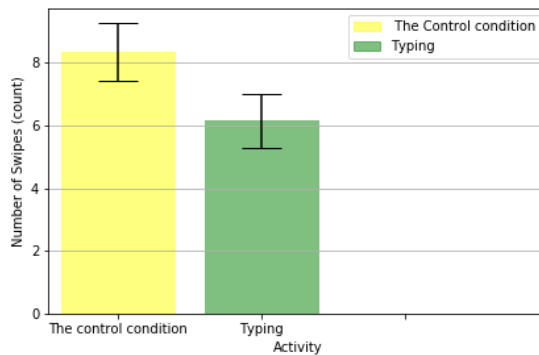
**FIGURE 4.15.** Users movement time according to the each activity for the second experiment.

**Total time.** Analysis of total time shows no significant effect of activity ( $F_{1,11.03} = 0.43$ ,  $p < .5251$ ), with similar means of total time between the control condition (mean= 7761.085 ms, sd= 608.148 ms), and typing (mean= 8421 ms, sd= 726 ms). There was a significant effect of *texture* ( $F_{3,33.47} = 9.72$ ,  $p < .0001$ ) with the densest texture (mean=6237 ms, sd=785 ms) being recognized significantly faster than all remainder textures (dense: mean=8821 ms, sd=1080 ms, medium: mean=9163 ms, sd=1012 ms, sparse: mean=8210 ms, sd=814 ms). Importantly, there was no significant interaction ( $p > .30$ ) suggesting that these results are consistent.



### Number of Swipes

There was a significant main effect of activity ( $F_{1,11.02} = 4.57, p = .05$ ) on *number of swipes*. Post-hoc tests revealed that the control condition (mean= 8.33, sd= .91) produced significantly more swipe gestures than when typing (mean= 6.15, sd= .85) ( $p < .05$ ) (see Figure 4.16). This result is correlated to the movement time that decreases with the typing activity. There was no significant interaction ( $p > .12$ ), suggesting that this finding is consistent across different tablet positions and textures.



**FIGURE 4.16.** Directional swipes according to the each activity for the second experiment.

### Number of Clutches

We found no significant effect on number of clutch nor interaction ( $p > .05$ ) (mean= .81, sd=.15).

#### 4.3.3 Subjective Results and Observations

Nasa-TLX responses (see Table 4.2) showed that *typing* was significantly more demanding physically and temporally than the control condition. However, contrarily to experiment 1, in this experiment, only the *DES strategy* is used to prioritise the handle of both tasks. When participants received a notification, they first finish the word or the sentence they were writing then switch completely to the secondary task. Then-after, they make quick textures identification. The gaze attention was exclusively conducted toward the secondary task *i.e.*, identifying the textures on the tactile surface when interacting with the secondary task, with some rarely glances toward the primary task for the *forward position*.

Experiment 2					
	Control		Typing		Wilcoxon
	mean	s.d	mean	s.d	Z
Mental demand	2.75	.68	3.41	.65	-1.90
Physical demand	1.75	.42	2.75	.64	-2.89
Temporal demand	2.25	.42	3.08	.61	-2.77
Performance	3.91	.44	3.58	.56	1.63
Frustration	1.83	.58	2	.53	-1.15
Effort	2.33	.60	2.91	.61	-1.86

Note: Wilcoxon-Signed-Rank tests are reported at  $p=.005$  (\*) significance levels.

**TABLE 4.2.** Mean and s.d questionnaire responses, with 1=very low, and 5 = very high for experiment 2. The significant tests are highlighted

The switch from the primary task to the secondary one was accompanied with a switch in the number of used hands: from two hands to one hand. For instance, ten participants used exclusively their dominant hand when interacting with the secondary task, while the two remainder used the closest hand to the tactile surface to identify the texture (*i.e.*, their right hand for *right* and *forward* positions and their left hand for the *left* position). Finally, all our participants used one same methodology among the methodologies observed in experiment 1 for identifying textures.

**Summary.** The main findings of this second experiment is that user’s primary task (typing text) had an impact on recognition time and number of swipes and was mentally more demanding than the control condition. an increase in reaction time of 148% (from 2065ms to 5124ms) can be observed accompanied with a decrease in movement time and number of swipes by respectively 42% (from 5695ms to 3296ms) and 26.17% without compromising total time and accuracy. These findings are consistent across different surface positions. These findings are also correlated to user strategy to handle the two simultaneous tasks while prioritizing the typing task over the texture recognition task. Our participants, first, finished writing the current word or sentence before moving to the textures recognition task. And then-after, our participants made quick interactions with the secondary task, before resuming the primary one.

4.4 DISCUSSION & IMPLICATION

In this section, we discuss the implications of the results obtained for the attention saturating and cognitively demanding primary task, posture, tactile

texture design and eyes-free interaction.

#### 4.4.1 *Attention saturating primary task*

The first experiment highlights an effect of the attention saturating primary task on textures recognition rate: we observed an accuracy drop from 88.78% to 82.58% when participants have to keep the ball centred. However, the recognition accuracy did achieve good rate of 82.58%. Consequently, this suggests that tactile textures could be effectively recognized and used by users on touch-screens when making such primary task. However, researchers interested in validating lab results in more realistic conditions may want to include tasks that saturate the attention as a factor for their experiment. We believe that more attention saturating tasks, in particular when considering a realistic scenario, *e.g.*, driving, would see a higher drop of accuracy.

#### 4.4.2 *Cognitively demanding primary task*

The second experiment highlights an effect of the cognitively demanding task (typing) on recognition time: we observed an increase in reaction time from 2065ms to 5124ms and a decrease in movement time from 5695ms to 3296ms without compromising the recognition rate or the total time needed for the recognition. However, in the real world, what matters is the total time to convey information, which is why we included the total time to present the stimulus. The differences between the different activities is not significant. Consequently, this suggests that tactile texture could be effectively recognized and used by users when typing-text on laptop. Additionally, we believe that with practice users can cognitively chunk the simultaneous two tasks and greatly reduce their reaction time. The typing activity was as accurate as the control condition, but with shorter movement time to recognize the texture, which requires more concentration. Thus, one may conjecture that the accuracy should eventually increase with practice.

#### 4.4.3 *Eyes-free interaction design*

Our findings indicate that the perception of tactile textures can be made *eyes-free* when performing at the same time an attention saturating primary task. This suggests that interacting with the tactile surface through textures can permit a user to sense the regions without diverting the eyes from the primary display during visually demanding tasks. Thus, designers should consider tactile

texture to create *eyes-free* dialog between the surface and the user especially when the user have to interact with another primary task that needs a visual attention.

#### 4.4.4 *Hands posture during two simultaneous tasks*

Different hand postures have been used to handle and perform the primary and the secondary task. In particular, For an attention saturating primary task, our findings indicate that the 2HD posture is the most used posture. This posture is strongly correlated to the position of the surface device (used for the secondary task): the closed hand to the secondary task will perform it. This finding may help designers to choose the appropriate position for the secondary task device dependently on their preferred hand for the primary task.

#### 4.4.5 *Users mental model*

We observed during both experiments, that the surface position had an affect only on users' behaviour without harming performances. In particular, with hands posture as we were able to observe for example two users switching from the 2HD posture used for the left position to the 2HC posture for the right position, and one user switching from a 2HD posture to the 2HSC when the surface was placed in the forward position. For the strategies adopted to prioritize the primary task, however, each one of those latter was used and maintained by users across the whole activity independently of the hands posture or the surface positions. These observations lead us to think that the strategy chosen depends more on user's mental and aptitude than the context of interaction contrary to the postures.

#### 4.4.6 *Tactile texture design*

Our results showed that the *densest* texture was the easiest and quickest one to identify among the four evaluated textures, and as most participants reported: "*it's easy to guess the densest texture*". It also required less effort then the other textures with significantly less swipes and clutches when users had to perform an attention saturating task simultaneously. Those findings suggest that the *densest* texture may be a good choice when designing tactile texture based interactions. Designers can also consider combining the densest texture with the sparse texture to create a large set of textures as our participants felt that "*it's easy to determine the difference*" between those two textures.

## 4.5 CHAPTER SUMMARY

With these two experiments, we laid another important brick to measure tactile textures effectiveness for situations where users are already engaged in another primary task. We conducted an investigation of textures recognition usability on an ultrasonic haptic tablet when performing an attention saturating primary task and a cognitively demanding primary one. Our findings indicate that for both primary tasks, the recognition rates for tactile textures stays higher than 82% without compromising the total time. However, contrarily to the cognitively demanding task, the attention saturating task increases frustration and mental demand compared to the control condition. We were also able to gain insight into users behaviour, hands posture and mental model when the texture recognition is performed simultaneously with another more prioritized task.

Another important finding was the ability of users to perceive tactile textures *eyes-free* when performing at the same time an attention saturating primary task. This result drove us to think about the possibility to design and propose textures based interaction techniques for secondary tasks, that will allow a less visually constraining interaction, and permit so users to focus on the primary task while interacting with a mobile secondary one. In the same time, as tactile feedback is only felt when user finger is moving on the surface and so stroke gestures movement are made, before digging deeper in this interaction technique in the sixth chapter (see chapter 6), we will now consider for the next chapter, stroke gesture production when performed eyes-free.

Part IV

# EYES-FREE STROKE GESTURE PRODUCTION



## CHAPTER 5

### *Eyes-free stroke gestures production*

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As discussed in the previous chapters, touchscreen devices are used in almost every aspect of life and in different contexts, including situations where users are already engaged in another primary task. As a result, it has become important to many designers to support eyes-free interaction (*i.e.*, without the need to see the phone) to permit user to freely interact with the mobile device when eyes-on input may be constraining, limited (*e.g.*, answering a text message while being in a meeting) or even dangerous (*e.g.*, adjusting the GPS or the air conditioning while driving).

In the previous chapter, when perceiving tactile textures while simultaneously performing another primary task, some users were able to perceive tactile feedback *eyes-free*. In the same time, as tactile feedback is only felt when users' finger is moving over the surface following a certain trajectory (*e.g.* horizontally from left to right and from right to left as observed in previous chapters, or also by drawing curved and mark-based stroke gesture [108]). It's thus important to understand the characteristics of stroke gestures and how these latter may be produced *eyes-free*.

For instance, even though many studies were conducted enlightening benefits of stroke-gesture interaction on user's performance, especially for contexts requiring less cognitive load and visual attention, from empirical examinations of their use when performing a primary task [20] to designing eyes-free interaction techniques [108]. No previous works had already focus on stroke-gesture characteristics when these latter are drawn eyes-free, or how and why they can be different from gestures drawn eyes-one or without a visual feedback. More specifically, the main research issues that we are addressing in this chapter are:

- How well are produced stroke gestures when users have not the possibility to see the phone?
- Are these gestures different from gestures produced in the presence or absence of visual feedback?
- Is there a difference in articulating directional strokes and curved stroke?



- Is there a difference between initiating the gesture from the edge of the phone or from a freely chosen position?
- Does eyes-free interaction affect consistency of the gestures made or users hand movement?

For that purpose, we investigate in this chapter how eyes-free strokes gestures were produced. We conducted an experiment to examine the difference in stroke-gesture production under three visual feedback conditions: (1) with visual feedback, (2) without visual feedback and (3) eyes-free, when using single-handed mobile interaction.

Besides allowing us to answer the previously mentioned questions, the results obtained for this experiment constitutes a comprehensive and in-depth quantitative and qualitative analysis of eyes-free stroke gestures production. Results gathered during the experiment indicate that gestures made eyes-free were geometrically different from gestures generated in the presence or absence of a visual feedback, and had a lower recognition rate but with an average accuracy of (95.53%). We then discuss our findings and present new insights that we hope will come of considerable help when designing mobile applications that supports stroke gestures input for an eyes-free single-handed mobile interaction.

## 5.1 EXPERIMENT

We conducted an experiment comparing eyes-free stroke gestures articulation for one-handed mobile device interaction to gestures made in the presence and the absence of visual feedback. We evaluated also eyes-free gestures characteristics from a geometric point of view, gesture recognition and phone movements. In the following, we describe the performed tasks by the participants and how visual feedback varied.

### 5.1.1 Participants

21 participants (8 females) volunteered to take part into the experiment. Participants ages were between 23 and 36 years (mean=29.33 years, sd=4.09). All participants were right handed, and all were daily users of smartphones devices.

### 5.1.2 Design

The experiment used a  $3 \times 2 \times 2$  within-subject design for the following factors: *visual feedback*, *gestures set* and *gesture beginning*. *Visual feedback* covers three con-

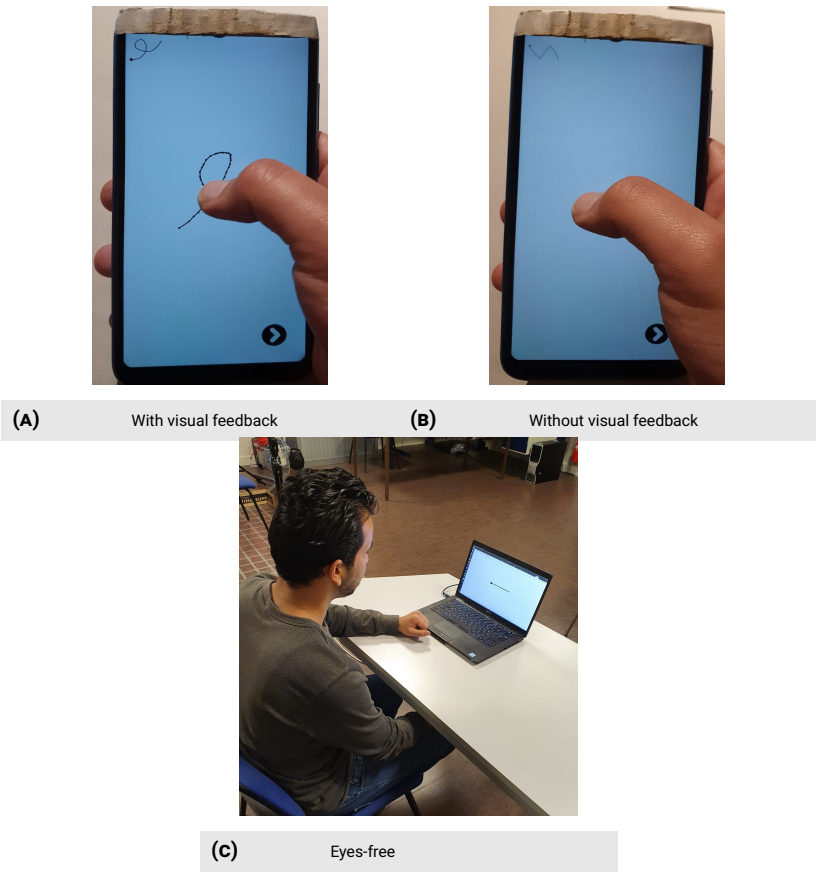
ditions: (1) *with visual feedback* (Figure 5.1a), which means that participants can see the phone and have a visual trace of the gesture being articulated; (2) *without visual feedback*, for this case, participants had the possibility to see the phone but no visual trace of the gesture being articulated was shown (Figure 5.1b), and (3) an *eyes-free* condition, where participants can not see the phone and no trace of the gesture input was shown (Figure 5.1c). *Gesture set* and *gesture beginning* are similar to the work of Bragdon et al. [20]. The rationale behind considering the *Gesture set* factor which covers two conditions: *freeform* path gestures and *mark-based* gesture, is Bragdon et al. finding which states that gestures made with directional strokes were more accurate than curved ones (please refer to the next section for more details about the gesture set). *Gesture beginning* covers two conditions: (1) *free*, where gesture can start from anywhere on the screen, and (2) *bezel*, where gesture should start from one of the four screen edges. This interest was also supported by Bragdon et al. [20] work in which authors found that, in addition to the fact that gestures did increase performance, bezel gestures offered a more faster interaction.

### 5.1.3 *Gesture set*

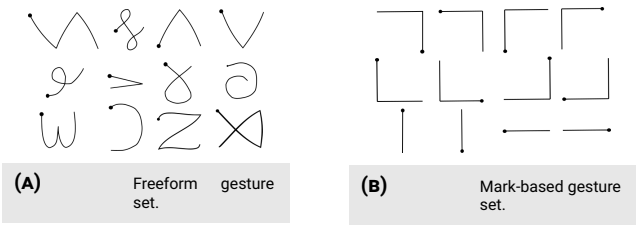
We consider the same gesture sets used in [20]: mark-based gestures and free-form path gestures. Each set is composed of 12 unistroke gestures carefully selected from the authors [20] and are frequently used in the literature *e.g.*, [10, 53, 78, 87, 140]. The free-form gestures were composed of operands, reasonably invariant and mnemonic gestures and were simple to perform, do not include any on-axis mark, distinct enough and can be drawn imprecisely [20] (see Figure 5.2a). Similar to marking menus, mark-based gestures consist of on-axis rectilinear mark segments like those in the primary compass directions (N, S, E, W or up, down, left, right) and off-axis marks of 45° angles (NE, SE, SW, NW), which can form compound path, *e.g.*, “down” followed by “left” [20] (see Figure 5.2b), for mark-based gestures used during this study, we just considered compounded path gestures of on-axis rectilinear mark segments. These two sets were shown to be articulable without looking at the phone [20]. For example, in [20], authors found that on average, when users were performing those gestural interactions while being distracted with another primary task, had gaze toward the phone of only 3.5% of the time.

### 5.1.4 *Apparatus*

We used a Huawei Y7 Pro running an Android operating system with a 8.1.0 version. The phones' dimension were 6.23"× 3.02"×0.32", with a diagonal size



**FIGURE 5.1.** The three visual feedback conditions evaluated during the experiment



**FIGURE 5.2.** Gesture sets used during the experiment.

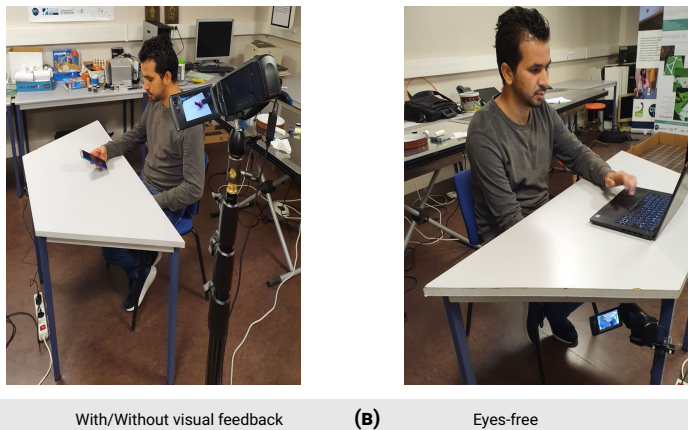
of 6.26", and weighted 168 grams. Display resolution was 720×1520 pixels with a pixel density of 269 ppi (pixels per inch). The choice of the phone was made taking into account modern phones size and the most sold smartphones of the year 2020 such iphone 11 or Samsung Galaxy A51 which have a screen size of about 6.2" diagonally. We developed our main application using JavaScript on the React Native framework, with some modules made natively using Java like

for the interface module responsible for drawing gestures and computing data, to avoid any additional latency. The application was designed to support the three visual conditions and permit us to log all input event generated by our participants in an embedded database

For the *eyes-Free* condition, in order to display the required gesture to draw, we implemented another application in JavaScript using the Node.js runtime, which was ran on a Dell laptop machine with a 13-inch LCD display screen with a desktop resolution of 1920×1080 pixels. Both applications communicated through a TCP protocol. The laptop application was only responsible to display gestures, and all the computing was still made in the phone side, avoiding any latency that may be induced due to the communication protocol.

In addition, as participants were asked to perform bezel gestures (gestures that start from one of the screen edges), we added a small piece of cardboard at the top of the screen to permit users to perform bezel gestures from the top of the screen without engaging the Android status bar. The cardboard dimensions were 1cm of height and 0.2cm of thickness covering 0.35cm of the screen which represents approximately the height of the Status Bar (see [Figure 5.1](#)).

Users' hands were videotaped using two Sony HDR Camcorders, the first one was placed on a tripod high enough to capture well hand movement, and was used for the two conditions: *with/without visual feedback* (see [Figure 5.3a](#)). The second one was hung on one of the desk legs (under the desk) and was used to record the hand interacting with the phone for the *eyes-free condition* (see [Figure 5.3b](#)).



**FIGURE 5.3.** The experimental setup for each of the three visual feedback conditions.

### 5.1.5 Task & Procedure

Before starting the experiment, our participants were asked to seat comfortably in front of a desk in face to the laptop, after which they had to answer a demographic questionnaire followed by an explanation about the experiment task along with the additional requirements.

During the study, a single-handed grip was used, participants were instructed to hold the phone with their dominant hand, and use the thumb of their dominant hand to draw gestures onscreen. We asked our participants to use this grip among the four commonly used grips [38] to ensure a proper simulation of a realistic scenario where users are often interacting with their mobile devices while being engaged in multiple context such as walking [17, 91], driving [12, 40], being under some distractions [88], or when their physical and visual attention is hosted by the other hand [20]. Also, the use of such a grip permit to represent more closely an eyes-free interaction context. For the *with/without visual feedback* conditions (see Figure 5.1 and 5.1b), participants interacted only with the phone, their arm was putted above the desk, and participants articulated the gestures onscreen. A preview of the gesture to be drawn was shown at the top left of the screen. After drawing the gesture, participants could click on the “next” button represented with an arrow-right icon which was placed at the bottom right of the screen to draw the next gesture. In order to be sure that the locations of the preview of the current gesture and the “next” button will not disturb the gesture articulation, we followed Eardley et al. [38] work and placed them in a non-functional area of the thumb for a single-handed grips. Finally, for the *eyes-free* condition, participants hand was put under the desk to ensure that participants can not see the screen and so how their thumb finger is drawing the gesture (see Figure 5.1c). A preview of the current gesture to draw was shown on the laptop in front of them. After entering the gesture, participants clicked on the space button of the laptop keyboard using their non-dominant hand to move on to the next gesture.

In the experiment phase, the three *visual feedback* conditions were counterbalanced among our 21 participants, and inside each *visual feedback*, the two gesture *beginning* conditions were counterbalanced. Inside each gesture *beginning*, the two gesture *set* were also counterbalanced. Participants performed five repetition for each of the twelve gesture type with a total of 60 gestures randomly administered For each bloc (*feedback*, *beginning*, *set*) – a total of 720 ( $=3 \text{ visual feedback} \times 2 \text{ gesture beginning} \times 2 \text{ gesture set} \times 12 \text{ gesture types} \times 5 \text{ repetitions}$ ) gestures were articulated per participant, which make a total of 15120 gestures collected during the experiment. The experiment took one hour on average to complete, and participants were encouraged to take breaks between blocs if needed. Additionally, one experimenter accompanied the par-

ticipants during the experiment, observed their interaction and took detailed notes, particularly concerning the think-aloud data.

## 5.2 RESULTS

The dependent variables evaluated during the experiment include gesture features, gesture recognition and mobile directional movements. Results of each of the dependent variables are presented below. All analyses are using multi-way ANOVA. Tukey tests are used post-hoc when significant effects are found. Only significant effects and significant interaction are reported. Qualitative data were also analyzed.

### 5.2.1 Gesture Features

In order to evaluate potential differences in articulating the two sets of gestures under the three visual conditions and with the two gesture beginning possibilities, we used a list of six gesture geometric features based on previous works [5, 19, 104, 110, 129]. These features are likely to be representative of how the stroke gestures were input by our participants, and why they may look different for a recognizer [5]. Table 5.1 shows how they were computed.

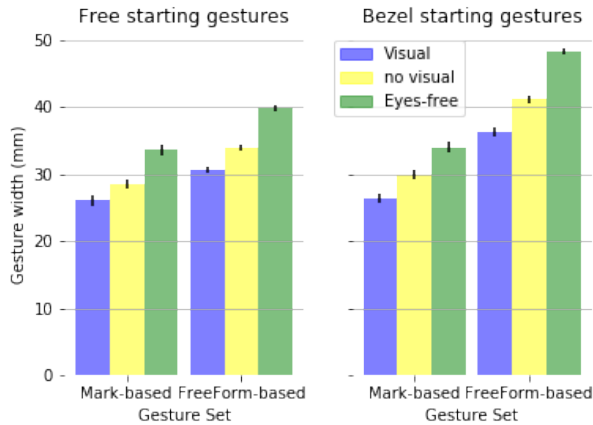
Gesture feature	Definition
Gesture width	Width of the smallest bounding box that contains the gesture ( $max_x - min_x$ )
Gesture height	Height of the smallest bounding box that contains the gesture ( $max_y - min_y$ )
Gesture length	Cumulative path distance from the first touch event registered for the gesture to the last.
Gesture area	The surface area of the smallest bounding box containing the gesture (height $\times$ width)
Gesture speed	Average speed registered over all the touch events belonging to a gesture (duration / length)
Gesture duration	Time elapsed while drawing the gesture, i.e., time of the last touch event registered for the gesture minus time of the first touch event.

**TABLE 5.1.** The geometric gesture features evaluated during the experiment.

We analyzed each feature for the two gesture sets (mark and freeform) with different beginning (bezel and free) drawn eyes free and in the presence and absence of visual feedback. We conducted a series of multi-way ANOVA tests to determine where differences may lie for each feature.

#### Gesture width

There were significant main effects of *feedback* ( $F_{2,40} = 67.42, p < .0001$ ), *gesture set* ( $F_{1,20} = 205.08, p < .0001$ ) and *gesture beginning* ( $F_{1,20} = 30.61, p < .0001$ )



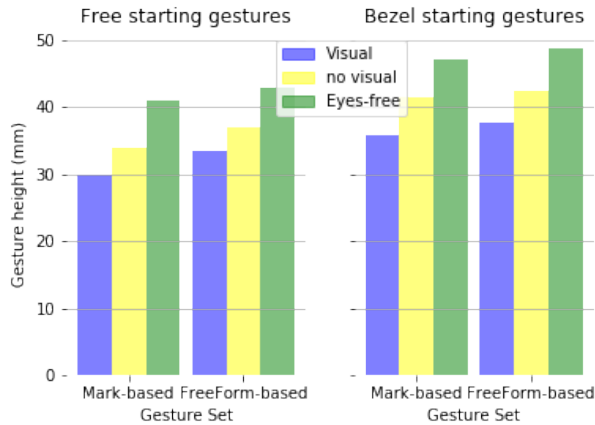
**FIGURE 5.4.** Gesture width grouped by Gesture beginning and by visual feedback.

on *gesture width* with significant *feedback*×*gesture set* ( $F_{2,40} = 13.37$ ,  $p < .0001$ ), *gesture set*×*gesture beginning* ( $F_{1,20} = 89.36$ ,  $p < .0001$ ) and *feedback*×*gesture set*×*gesture beginning* ( $F_{2,40} = 6.63$ ,  $p = .0032$ ) interactions.

Post-hoc comparison showed that mark-based gestures were significantly narrower than freeform gestures for all feedback and beginning conditions ( $p < .05$ ). In addition, for mark-based gestures, eyes-free gestures were significantly wider than both gestures produced in the presence and absence of visual feedback ( $p < .05$ ). In contrast, for freeForm gestures, for each feedback condition, bezel gestures were articulated with significantly larger width than those started on a free space ( $p < .05$ ). Additionally, when starting from the edge, in the presence of visual feedback, articulated gestures were significantly narrower than those articulated on the absence of feedback or eyes-free ( $p < .05$ ) with a significant difference between no-visual and eyes-free conditions ( $p < .05$ ). Besides, for freeForm gestures, when starting on a free position, eyes-free gestures were produced with significantly larger width than gestures produced in the presence or absence of visual feedback ( $p < .05$ ) with no significant differences between the presence and the absence of visual feedback (see [Figure 5.4](#)).

### Gesture height

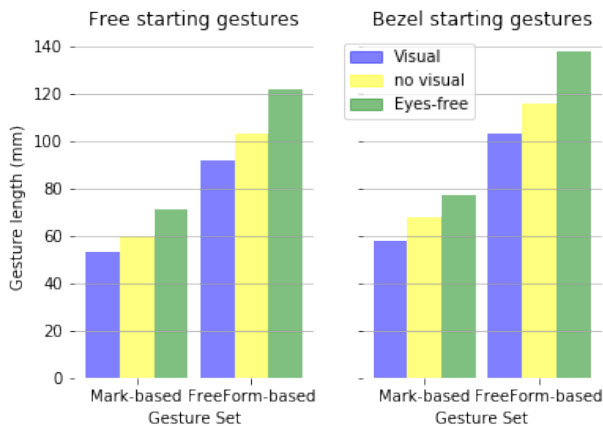
There were significant main effects of *feedback* ( $F_{2,40} = 38.10$ ,  $p < .0001$ ), *gesture set* ( $F_{1,20} = 8.78$ ,  $p = .0077$ ) and *gesture beginning* ( $F_{1,20} = 26.75$ ,  $p < .0001$ ) on *gesture height*. Posthoc comparisons revealed that eyes-free gestures (mean 44.98cm,  $sd=.51$ cm) are significantly higher than gestures produced in the absence of visual feedback (mean 3.87cm,  $sd=.04$ cm) or in the presence of visual



**FIGURE 5.5.** Gesture height grouped by Gesture beginning and by visual feedback.

feedback (mean=3.41cm, sd=.04cm) ( $p < .05$ ). Freeform gestures (mean=4.03cm, sd=.03cm) were significantly higher than mark-based gestures (mean=3.82cm, sd=.04cm) ( $p < .05$ ). And bezel gestures (mean 4.22cm, sd=.04cm) were significantly higher than free gestures (mean=3.63cm, sd=.03cm) ( $p < .05$ ) (see [Figure 5.5](#)).

### Gesture length



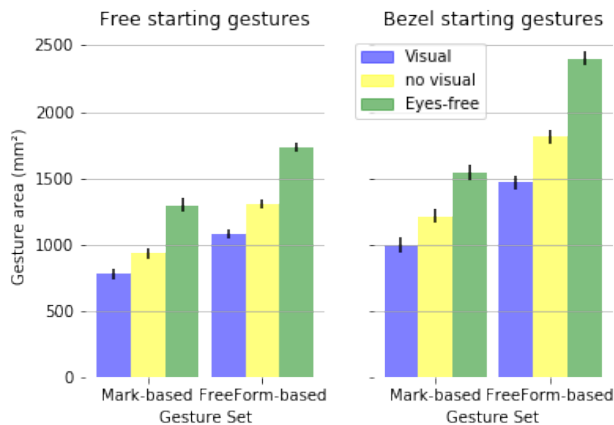
**FIGURE 5.6.** Gesture length grouped by Gesture beginning and by visual feedback.

There were significant main effects of *feedback* ( $F_{2,40} = 53.49$ ,  $p < .0001$ ), *gesture set* ( $F_{1,20} = 360.15$ ,  $p < .0001$ ) and *gesture beginning* ( $F_{1,20} = 18.00$ ,  $p = .0004$ )



on *gesture length* with significant *set* × *beginning* ( $F_{1,20} = 14.20, p = .0012$ ) interaction. Post-hoc tests showed that the three feedback conditions were significantly different with gestures produced in the presence of visual feedback (mean=7.66cm, sd=.105) were the shortest followed by the gestures produced in the absence of visual feedback (mean=8.68cm, sd=.105) and then gestures the eyes-free (mean=10.21cm, sd=.12cm) condition ( $p < .05$ ). We also found, that either when the gesture started from the edge or was free, freeform gestures (bezel: mean=11.89cm, sd=.14cm, free: mean=10.58cm, sd=.11cm) were longer than mark-based gestures (bezel: mean=6.77cm, sd=.08cm, free: mean=6.16cm, sd=.07cm) ( $p < .05$ ). In addition, freeform gestures produced significantly longer gesture length when they started from the edge than when they started on a free space ( $p < .05$ ) (see Figure 5.6).

### Gesture area

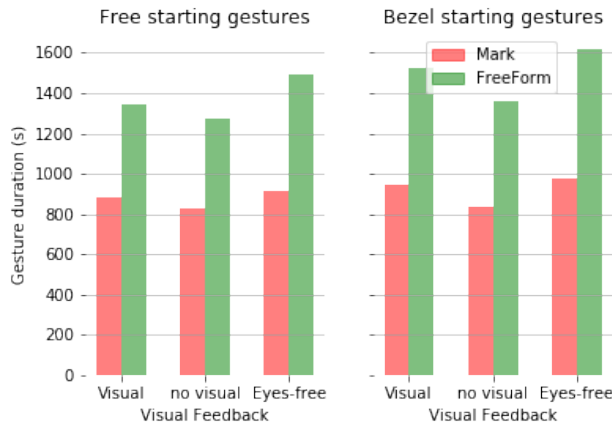


**FIGURE 5.7.** Gesture area grouped by Gesture beginning and by visual feedback.

There were significant main effects of *feedback* ( $F_{2,40} = 52.90, p < .0001$ ), *gesture set* ( $F_{1,20} = 95.67, p < .0001$ ) and *gesture beginning* ( $F_{1,20} = 29.45, p < .0001$ ) on *gesture area* with significant *feedback* × *set* ( $F_{2,40} = 14.65, p < .0001$ ), *set* × *beginning* ( $F_{1,20} = 30.25, p < .0001$ ) and *feedback* × *gesture set* × *gesture beginning* ( $F_{2,40} = 9.53, p = .0004$ ) interactions. Post-hoc comparison showed that mark-based gestures were articulated with significantly smaller area than free-form gestures for all feedback and beginning conditions ( $p < .05$ ). In addition, for mark-based gestures, eyes-free gestures were articulated with significantly bigger area than both gestures produced in the presence and absence of visual feedback ( $p < .05$ ). For free-form gestures, when starting the gesture from the edge, eyes-free gestures were articulated with significantly bigger area than

both gestures produced in the presence and absence of visual feedback with gestures with no visual being significantly bigger than those produced in the presence of visual feedback ( $p < .05$ ). In contrast, when the beginning of the gesture is freely chosen, eyes-free gestures were produced with significantly bigger surface than both gestures produced in the presence and the absence of visual feedback ( $p < .05$ ) with no significant difference between visual and no visual conditions (see Figure 5.7).

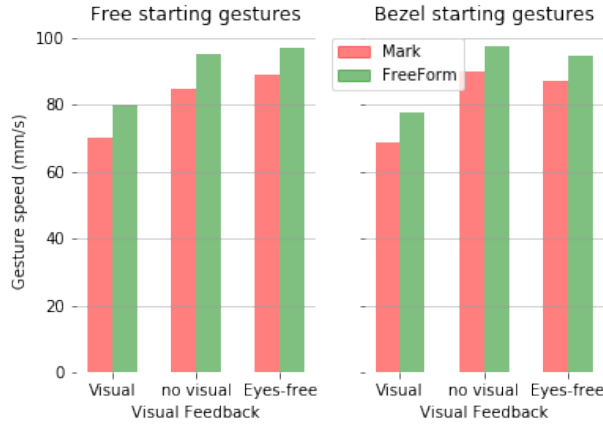
### Gesture duration



**FIGURE 5.8.** Gesture duration grouped by Gesture beginning and Gesture Set.

There were significant main effects of *feedback* ( $F_{2,40} = 8.0, p = .0011$ ), *gesture set* ( $F_{1,20} = 71.95, p < .0001$ ) and *gesture beginning* ( $F_{1,20} = 5.31, p = .0319$ ) on *gesture duration* with significant *feedback*  $\times$  *gesture set* ( $F_{2,40} = 6.63, p = .0032$ ) and *gesture set*  $\times$  *gesture beginning* ( $F_{1,20} = 4.91, p = .0383$ ) interactions. Post-hoc comparison showed that for each feedback and beginning conditions, freeForm gestures imply significantly more time to be drawn than mark gestures ( $p < .05$ ). For freeForm gestures, the amount of time taken to draw a gesture in eyes-free condition (mean=1558ms, sd=34ms) was significantly bigger than no-visual feedback (mean=1317ms, sd=27ms) with no significant difference with the visual one (mean=1431ms, sd=30ms). For that gesture set, starting the gesture from the edge (mean=1500ms, sd=25ms) tended to take significantly more time than when being free (mean=1371ms, sd=24ms) ( $p < .05$ ). Interestingly, for mark-based gestures there were no significant differences between the different feedback and beginning conditions ( $p > .05$ ) (see Figure 5.8).

## Gesture speed



**FIGURE 5.9.** Gesture speed grouped by Gesture beginning and Gesture Set.

There were significant main effects of *feedback* ( $F_{2,40} = 21, p < .0001$ ) and *set* ( $F_{1,20} = 15.79, p = .0007$ ) on *gesture speed*. Post-hoc comparison showed that gestures produced in the presence of visual feedback (mean=7.89cm/s, sd=.15) were significantly slower than both gestures produced in the absence of visual feedback (mean=9.62cm/s, sd=.15) or eyes-free (mean=9.58cm/s, sd=.14) ( $p < .05$ ). We also found that freeform gestures (mean=9.03cm/s, sd=.08) were significantly faster than mark gestures (mean=8.16cm/s, sd=.07) (see [Figure 5.9](#)).

### 5.2.2 Gesture Recognition

For the gesture recognition, we used the \$N-protractor [8] recognizer for both sets, a multistroke gesture recognizer based on template-matching. Since both gesture sets use only unistroke gestures, \$1 recognizer [140] may seem more adequate for such a data set, however, the latter was found inadequate with 1-D gestures that are present in our Mark-based gesture set, contrary to \$N which supports recognition of one-dimensional gestures. Also, as \$N generates for each multistroke gesture all unistroke permutations [7] in order to be independent from gesture order or direction, we removed this feature as we are concerned with stroke direction especially for mark gestures where two different gestures may share the same stroke shape but with different directions, e.g., “up” and “down” gestures. We then, conducted user dependent training, in which recognition rates were computed individually for each participant

with the same methodology as in [7, 8, 125, 140]: for each user, we first trained the gesture recognizer on a small set (we select four candidate for each gesture type) and then tested the recognizer on the remainder of that user's samples. We repeat this process 100 times. Note that we conducted separate tests for each gestures set generated in different feedback and beginning condition.

There was a significant main effect of feedback ( $F_{2,40} = 7.03, p = .0024$ ) and *gesture beginning* ( $F_{1,20} = 14.69, p = .001$ ) on gesture recognition. Post-hoc comparison showed that gestures produced eyes-free (mean=95.53%, sd=.14%) were significantly less accurate than both gestures produced in the presence (mean=96.88%, sd=.12%) or absence of visual feedback (mean=97.27%, sd=.11%) ( $p < .05$ ) with no significant difference between gestures produced in the presence and absence of visual feedback ( $p > .05$ ). We also found that free gestures (mean=97.68%, sd=.11%) were significantly more accurate than bezel gestures (mean=95.44%, sd=.11%) ( $p < .05$ ). Interestingly, there were no interaction ( $p > .09$ ) suggesting that the the benefits of the presence/absence of visual feedback over eyes-free are consistent across different gesture sets and beginnings. The benefits also of free gestures over bezel gestures are consistent across the different gesture sets and feedback conditions.

### 5.2.3 Mobile Directional Movement

In order to characterise the phone's movement when articulating gestures for the three *visual feedback* condition according to each gesture *beginning* and gesture *set*, we considered the same dependent variables than in [38]. We then, captured the mobile phone's movements around the three directional axis: Alpha (z-axis), Beta (x-axis) and Gamma (y-axis) (see Figure 5.10) using the inbuilt accelerometer and gyroscope. For each of the directional axis, we captured the total deviation made around this axis computed as the difference between the largest and the smallest value. Data were captured during the gesture articulation, *i.e.*, from the first touch until the participant removes his finger for the last time. Movements made before the interaction or when clicking on the "next" button were not captured.

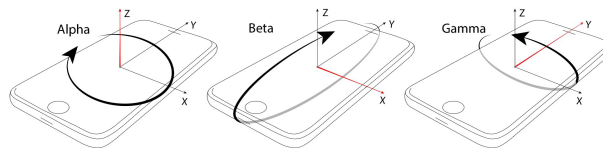


FIGURE 5.10. Phone directional movements

### Alpha deviation – deviation around z axis

There were significant main effects of *feedback* ( $F_{2,40} = 3.31, p = .0464$ ), *gesture set* ( $F_{1,20} = 21.11, p = .0002$ ) and *gesture beginning* ( $F_{1,20} = 18.81, p = .0003$ ) on *alpha deviation* with significant *feedback* × *gesture beginning* ( $F_{2,40} = 5.24, p = .0094$ ) interaction. Post-hoc comparisons showed that producing freeform gestures (mean=7.54°, sd=.21) imply significantly more phone movement around z axis than when producing mark-based gestures (mean=7.54°, sd=.21) ( $p < .05$ ). Additionally, we found that for eyes-free condition, starting the gesture from a free space (mean=6.04°, sd=.17) implies significantly less phone movement around z axis than when starting the gesture from the edge (mean=9.70°, sd=.65) ( $p < .05$ ). Besides, when starting the gesture on a free space, gestures produced eyes-free imply significantly less phone movement than gestures produced in the absence of visual feedback (mean=8.78°, sd=.19) ( $p < .05$ ).

### Beta deviation – deviation around x axis

There were significant main effects of *feedback* ( $F_{2,40} = 7.61, p = .0016$ ) and *gesture beginning* ( $F_{1,20} = 32.52, p < .0001$ ) on *beta deviation* with significant *feedback* × *gesture beginning* ( $F_{2,40} = 9.17, p = .0005$ ) interactions. Post-hoc comparisons showed that, for each feedback condition, gestures started from the edge implied significantly more phone movement on x axis than those which started on a free space (visual: (1) bezel: mean=7.15°, sd=.21; (2) free: mean=5.11°, sd=.13, no-visual (1) bezel: mean=8.58°, sd=.23; (2) free: mean=5.72°, sd=.15, eyes-free: (1) bezel: mean=9.38°, sd=.25; (2) free: mean=5.67°, sd=.14) ( $p < .05$ ). In addition, for bezel gestures, we found that the presence of feedback implies less phone movement on x axis than both in the absence of visual or eyes-free conditions ( $p < .05$ ).

### Gamma deviation – deviation around y axis

There were significant main effects of *feedback* ( $F_{2,40} = 23.21, p < .0001$ ), *gesture set* ( $F_{1,20} = 35.58, p < .0001$ ) and *gesture beginning* ( $F_{1,20} = 88.21, p < .0001$ ) on *gamma deviation*. Post-hoc comparisons showed that, eyes-free gestures (mean=10.46°, sd=.19) produced significantly more phone movement on the y axis than both gestures produced on the presence (mean=7.43°, sd=.15) or the absence (mean=8.22°, sd=.16) of visual feedback ( $p < .05$ ). We also found that freeform gestures (mean=9.67°, sd=.14) and bezel gestures (mean=10.81°, sd=.16) produced significantly more phone movement on the y axis than respectively mark-based gestures (mean=7.74°, sd=.14) and free gestures (mean=6.60°, sd=.10) ( $p < .05$ ).

### 5.2.4 Subjective Results and Observations

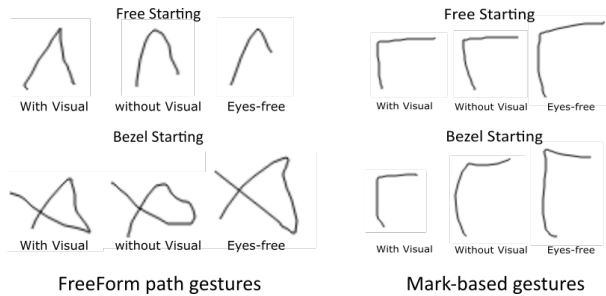
Our quantitative data were accompanied by considerable qualitative data that capture users' mental model as they perform gestures. We recall that during the experiment, one of the authors accompanied each of the participants, and took detailed notes of participants' feedback and comments. We try hereafter to summarize these results and to give an overview of participants' experience during the articulation of the two sets of gestures for the three different *visual feedback* conditions.

#### Participants comments and preferences

An overall confidence was observed within our participants when producing gestures in a eyes-free condition as well in the presence or the absence of visual feedback. Some quotes: *"producing gestures without looking to the phone is not more difficult to when having visual feedback"* and *"it is easy to draw gestures without looking to the phone"*. However, once they have visual feedback, they realize that there are some deformations and comment that *"finally, drawing gestures without visual feedback or without the possibility to look at the phone may give you a false impression about the difficulty of the task, or how good was the gesture drawing"*. These comments were especially common if the participants had done the eyes-free or the no visual feedback conditions first.

Additionally, six participants felt that drawing *freeForm* gestures is easier and more comfortable than *mark-based* gestures. In addition, for *mark-based gestures*, our participants felt that while this set looks undoubtedly simple at first glance, in the presence of visual feedback they realized that it is difficult to draw gestures perfectly. Some quotes: *"drawing lines seems simple, but afterwards we realize that it is not, especially when we have visual feedback"*, *"the straight lines are more difficult and I knew it when I saw what I am drawing... without visual feedback you think you are good"*. Additionally, in the presence of visual feedback, they felt that freeform gestures *"look better done"* than mark gestures. One participant who was drawing gestures from mark set added *"drawing these directional gestures is more difficult and looks uglier that is why when I draw curves I find it easier"*. However, but interestingly, our participants felt that the presence of visual feedback gave them the possibility to be more accurate as they *"can see what they are doing, and so they can correct it"*. This findings is correlate to the findings of Anthony et al. [5] who commented that their participants like to see what their finger draws to better draw the gesture.

Most of the participants felt that bezel gestures are more difficult and demand more efforts than free gestures. Some quotes: *"I feel much more comfortable when I start the gesture from where I want"*, *"it is complicated to make gestures from*



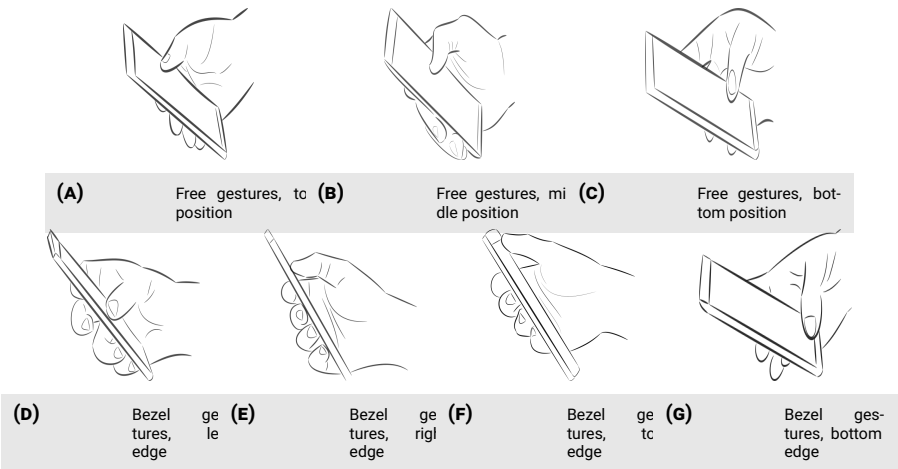
**FIGURE 5.11.** Examples of freeform gestures and mark-based gestures produced in the three visual feedback conditions when starting from the bezel or freely. For the freeForm gesture set, an example of the articulation for the 'caret' gesture is displayed for the Free Starting condition, and one of the 'X' gesture for the Bezel Starting condition. For the mark-based gesture set, an example of the articulation for the 'UpRight' gesture is displayed for the Free Starting condition, and one of the 'Left-Down' gesture for the Bezel Starting condition

*the screen edge*", or "*edge gestures are difficult since I have to move the phone to perform them*". However, but interestingly, when performing *bezel* gestures, some participants felt "*more comfortable*" starting the gesture from the right or the left edges than from the upper or the lower edges as they found them "*more simple to reach*". These results are correlated to the findings of Karlson et al. [66].

Figure 5.11 shows some visual comparative examples of freeform gestures and mark-based gestures produced eyes free and in the presence or in the absence of visual feedback. The preview shows clearly a difference on how gestures had been articulated between the three visual conditions, demonstrating the gesture feature differences we found (e.g., gesture length, height, width, etc.), as well as others (e.g., corner joining, line straightness).

## Handgrips

Based on the observations made during the experiment, and also the data gathered from analyzing the video tapes, we were able to notice that for gestures initiated *freely*, our participants tended to draw these latter approximately in three different positions of the touchscreen surface according to the y axis (bottom, in the middle and on the top). Therefore, to confirm our observations, we ran the k-means clustering algorithm, an unsupervised learning algorithm that groups data into different clusters according to a number "*k*" of predefined clusters. We made the assumption of *k* equal to three (*k*=3) based on the observations explained above, after which, we ran the algorithm for the whole gestures started *freely* of both data sets taking on consideration the two edges (bottom-left and top-right) of each gesture. The result obtained confirms our deduction with gestures drawn approximately in average between 2.6cm



**FIGURE 5.12.** Examples of handgrips for free gestures (a-c) and bezel gestures (d-g).

and 5cm of height for below position, between 4.1cm and 7.3cm of height for middle position and between 6cm and 9.2cm for top position. However, when running the k-means clustering algorithm for each feedback condition independently, we observed that For *eyes-free* condition, gestures were higher than the two remaining feedback conditions with, on average, gestures varying between 2.61 and 6.51cm for bottom, 4.47 and 8.47cm for middle and 6.47 and 10.08cm for top. In contrast, we found similar positions for gestures drawn in the presence or absence of the visual feedback which, on average, varied between 2.55 and 4.80cm for bottom, 3.86 and 6.82cm for middle and 5.36 and 8.62cm for top. Also, all those gestures were drawn approximately in the middle of the screen according to the x axis. For *eyes-free* condition however, we noticed that gestures tended to take more width and were closer to either the left or right screen side and, on average, varied between 1.85 and 5.55cm. For the gestures made in presence or absence of a visual feedback, gestures were drawn, on average, between the two positions 2.36cm and 5.28cm. Considering the work of Karlson et al. [66], these different locations were considered as not hard to reach with the thumb.

Also, when examining the video tapes to capture the different hand grip used, we noticed that our participants used the same hand grip (see Figures 5.12a to 5.12c) with some variations on the tilt of the phone and fingers movements in order to adapt their grip to easily reach their preferred region of interaction. We can notice for example that when participants interacted with the bottom region of the phone, they either supported the phone more with their fingers than the hand's palm raising the index finger and reducing the distance between this latter' tip and the right edge of the surface, enabling more space and motion



for the thumb to reach easily more surfaces at the bottom as found in [16] (see Figure 5.12c), or sometimes used their small finger in order to lift the phone to get a better access to this region as found in [38]. Accordingly to [16, 38], these variations influenced the “thumb agility” allowing it to better reach the different region of the touchscreen. We observed however, that using the small finger to lift the phone was also used by some participants as a usual grip to draw in other regions of the phone. For interacting with top region of the phone, however, we noticed for example that participants had sometimes a firmer grip than those used to interact with the bottom of the screen (especially when the small finger was not used to lift and stabilize the phone) with a more use of the index finger as a device support. Although all those observations, we can not provide a generalization about our findings for hand movements according to each region of interaction as we were able to notice that some of those grip adaptations were used in more than one region, and were more dependent on users behaviour and hand characteristics.

Contrary to gestures initiated *freely*, where no noticeable difference in how the device was hold have been observed. For bezel gestures, our participants used the same single-handed grip than for free gestures, but by adapting it depending on the starting edge of the current articulated gesture. In Figures 5.12d to 5.12g, we highlight some of the hand movements and how this grip is adapted during the experiment.

### Visual feedback usefulness

When articulating gestures without a visual feedback, we noticed -especially from participants comments- that some of our participants were relying on finger traces made on the screen as a substitute to the visual feedback. Some quotes: *“I cheat a bit by looking at my finger traces”*, *“I can see my finger traces on the screen”*. One participant even expressed his satisfaction with this substitute of visual feedback: *“Having traces allows us to see what we are drawing and since it’s thick, it looks softer”*, and another one stated that it’s almost the same as performing with a *visual feedback* as he comments: *“Whether it is with or without visual, there is not a big difference in drawing, knowing that in this condition (without visual feedback), we can see the movement of the finger or even the traces of what we have drawn thanks to the light”*.

## 5.3 DISCUSSION

We have found evidence that eyes-free gestures were different from gestures produced in the presence or absence of visual feedback. In particular, our findings indicate that eyes-free gestures were produced with significantly longer

length and height, implies more phone movement around y axis and were faster than gestures produced in the presence or absence (except finger speed) of visual feedback. Also, in terms of recognition, *eyes-free* gestures were less accurate than those made with or without visual feedback, although the recognition did achieve an average rate of 95.53%. These results are consistent across different gesture set and gestures beginnings. Our participants felt also confident while they were performing the gesture task. But then after, when having the visual feedback, anecdotally, our participants commented that their eyes-free gestures may be produced with less precision than in the presence of visual feedback.

In contrast, gestures made in the presence of a *visual feedback* were significantly shorter (length, height and width (only when started from the edge) and were slower than the ones made *without a visual feedback* or in an *eyes-free* conditions. Interestingly, our participants were also, more careful when drawing gestures when seeing the trace of their articulated gestures which implies slower movements with an amount of time not significantly different from gestures drawn in an *eyes-free* condition knowing that these latter were considerably bigger. Relying on the *visual feedback* helped participants to be more accurate and gave them the ability to check and correct continuously while articulating the gestures. However, in terms of gesture recognition, our findings indicate that there was no significant difference between gestures produced in the presence or absence of visual feedback. Those results were correlated with Anthony et al.'s [5] findings for adult participants, despite that the evaluated gesture sets were different, and that in Anthony et al.'s work, the participants had the liberty to chose how to hold and interact with the touch device.

When producing gestures in the *eyes-free* condition, bezel gestures were significantly higher, less accurate, implied more mobile directional movements around x, y and z axis than free gestures. The same results were also observed for the two other visual conditions except for the directional movements around the z axis, and were consistent across the different set conditions. Bezel gestures were also perceived as more difficult to articulate, and demand more efforts than free gestures.

*Mark-based* gestures took considerably less space to be drawn in an *eyes-free* interaction than *freeForm* gestures: they were shorter in height and length, they presented a smaller width and bounding box area. Consequently, they generated less directional movements to be performed than the *freeForm* set around both y and z axis. The same results were also observed for the two other visual conditions, and were consistent across the different set conditions. However, Despite these results, some participants expressed their preference for *freeForm* gestures over *mark* ones.

Concerning the used handgrips, our findings indicate that users used the

same single-handed grip with some variations in the way to hold the device and how to interact with it using their thumb finger and depending on the *feedback* condition, the gesture set and the starting position. In addition, our findings revealed that for gestures started freely, users can draw their gestures in the top of the screen but also on the middle and bottom.

## 5.4 CHAPTER SUMMARY

In this chapter, we presented the results of an investigation concerning *eyes-free* stroke gestures articulation for a single-handed mobile interaction. Our findings indicated that gestures articulated eyes-free were geometrically different from gestures generated in the presence or absence of a visual feedback, they implied more rotational movement around the y axis and were less well recognized than gestures made in others feedback conditions, but still with an accuracy of 95%.

Despite differences in eyes-free gestures production compared to gestures made in the presence or absence of a visual feedback, gestures made in an eyes-free context were generally efficient, well recognized, and felt easy to produce and to use by our participants. Thus, based on these results, but also on our findings for the previous chapters, we propose in the next chapter, a new tactile feedback interaction technique. We combine both tactile feedback and stroke gestures capabilities (in particular, the finger speed) to increase the expressiveness of tactile feedback interaction in order to provide the user with different information.

Part V

# INTERACTION TECHNIQUE FOR SECONDARY TASK



## CHAPTER 6

### *Multi-channel Tactile Feedback Technique*

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Our results presented earlier in this thesis, showed that the tactile texture can be perceived with precision during the execution of another primary task. Our results also indicate that, in some primary tasks, the tactile perception of texture can be made eyes-free. Besides, as the perception of texture is strongly linked to finger movement on the surface, in a second part, our work studied how eyes-free stroke gestures were produced, and showed that users are completely able to perform eyes-free gestures accurately. Especially, directional stroke gestures -which are the main gestures used when perceiving textures- were produced precisely and accurately. Therefore, in this chapter, we introduce a new interaction technique that features the use of tactile textures to deliver information eyes-free, relying on the sense of touch.

Most of the computing systems usually rely on tactile feedback as a complement or proxy to visual information, *e.g.*, sensing a vibration may indicate to the user that a notification had been received, however, still a visual contact with phone screen is necessary to get a feedback about the notification content. The same case can be noticed in the real world, where tactile information is usually accompanied with a visual input stream. However, in our work, we wanted to preserve the eyes-free nature of tactile sensing while increasing the bandwidth of tactile output by considering a multi-channel tactile feedback, where different haptic or tactile signals can be monitored selectively by the user, and this, by only relying on the sense of touch to deliver a consistent feedback.

The major challenge that we are tackling can hence be formulated as follows:

- How best to multiplex information across multiple channels?
- Will users be able to distinguish between different tactile feedback perceived at different channels?
- At which level the range of haptic output channel can be increased without harming performance?

For that purpose, in this chapter, we investigate increasing the expressiveness of tactile feedback by allowing users to dynamically choose between

multiple haptic feedback channels using changes in finger speed. In the remainder of this chapter, we introduce the concept of multi-channel tactile feedback. Then through a controlled experiment leveraging three levels of finger speed and three different textures, we show that a user can learn the dynamics of tactile channel selection and that, with training, users can perform accurate tactile channel selection using two levels of finger speed with up to 90% accuracy.

## 6.1 MULTI-CHANNEL TACTILE FEEDBACK VIA SPEED

In order to increase the tactile feedback bandwidth, we decided to rely on level of variations for user finger speed to multiplex output information. We describe hereafter the motivation behind proposing a multi-channel tactile feedback based on user finger speed

### 6.1.1 *Motivating Multi-Channel Feedback*

Haptic feedback—like touch in the real world—is primarily considered an output modality and a complement to visual information. However, in some real-world scenarios, touch perception is used without eyes gazes even visual information. For example, a user can quickly tap a coffee mug to check its temperature, stroke the surface of a woodworking project to spot defects, or rub Braille on a door to determine his or her location.

In modern multi-touch devices, haptic feedback can be viewed as both an input and output modality. A potential benefit of multi-channel haptic feedback is that it allows for richer output (in addition to the richness of multi-touch input), *i.e.*, a richer interactive experience. To illustrate the benefits of multiplexing haptic feedback across multiple channels, we consider the following example scenario:

- A user places his cellphone in do not disturb mode or a user puts his cellphone in his pocket during a meeting or a conversation with another person, but wishes to check for new mail, text messages, or calls on her cellphone [108]. Rather than looking at the display or turning on his phone, he can leverage multi-channel tactile feedback to determine whether he has new messages and which type of new messages they are. This would enable a less obtrusive way to check messages especially in social scenarios (*e.g.*, having a conversation with another person).
- Another more critical example if when a user is walking or driving and wishes to monitor various communication channels, but needs to visually

attend to his primary task, driving the car. Eyes-free haptic feedback can be performed without the need to visually attend to the screen while driving.

### 6.1.2 *Motivating Speed-Based Selection*

For systems based on haptic feedback, users must refer to their sense of touch to interact with the system. This task can be performed eyes-free. Therefore, the number and type of haptic textures used must be considered when designing haptic feedback-based systems, as these factors can significantly affect the user experience. In terms of interactive expression, we might wonder how to increase the range of haptic output without over saturating the user's sense of touch with too much texture. For example, should each texture represent different information, or are we free to mix and match depending on the application context? While designers must make these decisions based on the context of their application, they still benefit from guidelines that can systematically introduce new information about textures without unduly complicating interactions.

The question then arises, how best to multiplex information across the haptic channel. Since users only perceive texture when they move their finger across the surface, it makes sense to use finger movement to define different input channels. We considered other parameters, including movement direction (*e.g.*, east-west, north-south, northeast-southwest, northwest-southeast), the movement sense (*e.g.*, east-west vs. east, clockwise vs. counterclockwise, etc) and finger trajectories (*e.g.*, linear, circular, etc). Given that fingers must move to perceive tactile feedback, finger speed (*e.g.*, slow, medium, and fast) appears to be a relevant parameter for tactile channel selection, and previous work [106] has shown that users are able to correctly identify tactile textures when using slow, medium, and fast speeds.

In the next section, we study the potential of using two and three levels of finger speed combined with three textures to increase the expressiveness of tactile feedback based surfaces.

## 6.2 EXPERIMENT

We conducted an experiment with the goal of understanding whether participants will be able to reliably extract first, then distinguish after between different information assigned to different textures perceived at different finger speeds. While asking our participants to perform different tasks dedicated to different levels of finger speed and information multiplexing, we wanted also



to measure and determine the number of levels of finger speed that our participants will be able to use and the learnability of finger-speed-based channel selection in multi-channel tactile feedback, *i.e.*, in how accurately participants could leverage speed to select from the available channels, and with a large output bandwidth that does not saturate the user from a cognitive point of view

### 6.2.1 Participants

10 participants (two female) volunteered to take part in our experiment. Participants ages were between 22 and 36 years (mean=28, sd=4.53). All participants were right handed.

### 6.2.2 Method

For textures rendering, we used the same E-vita device [131](Figure 3.1) as for the previous chapters (chapter 3 and 4). A tactile feedback tablet that supports friction modulation by mean of ultrasonic vibrations [131].

We recall the definition of a tactile texture. A tactile texture (see Figure 3.2) refers to a sequence of periodic tactile feedback [105, 106, 131] such that the period to be reproduced inside the texture can be formed by some specific signal (periodic, structured noise, micro-geometry extracted, etc.). We then consider the same tactile textures used in the previous chapters, but limiting the number to only three textures: *Dense*, *Medium* and *Sparse*. We recall that for the set of considered textures, users have been able to distinguish them independently regardless of finger speed [106]. For finger speed thresholds, we follow Rekik et al. [106] and use the same thresholds: the slow speed is slower than 30 mm/s; the moderate speed is faster than 30 mm/s and slower than 180 mm/s; and, the fast speed is faster than 180 mm/s.

### 6.2.3 Tasks & Design

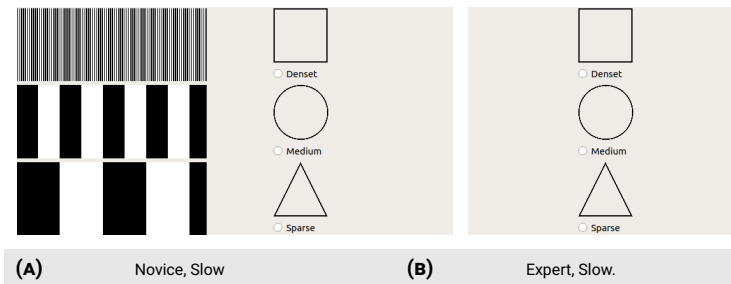
The experiment consisted of four consecutive tasks designed as following:

#### Task 1: One speed:

In the first task, participants were asked to identify the textures perceived each time at a specific finger's speed participant. In this task, each participant identified 54 textures = 3 finger speed (slow, moderate and fast)  $\times$  2 expertise levels (novice and expert)  $\times$  3 textures (D, M, S) (Figure 6.4a)  $\times$  3 repetitions. The experiment took on average 15 minutes to complete.

### Task 2: One finger speed channel:

In the second task, participants were asked to move their finger at a specific speed, identify the texture perceived at that speed, and further identify the corresponding association of information. The slow speed is associated with the form, moderate speed is associated with the color and fast speed is associated with the contour line. In this task, each participant identified 54 pieces of information = 3 finger speed  $\times$  2 expertise levels  $\times$  3 textures (D, M, S) (Figure 6.4a)  $\times$  3 repetitions. Figures 6.1a-6.1b show the interfaces used to represent the textures and map the textures with the associated information in, respectively, the novice and the expert expertise levels. The experiment took on average 15 minutes to complete.



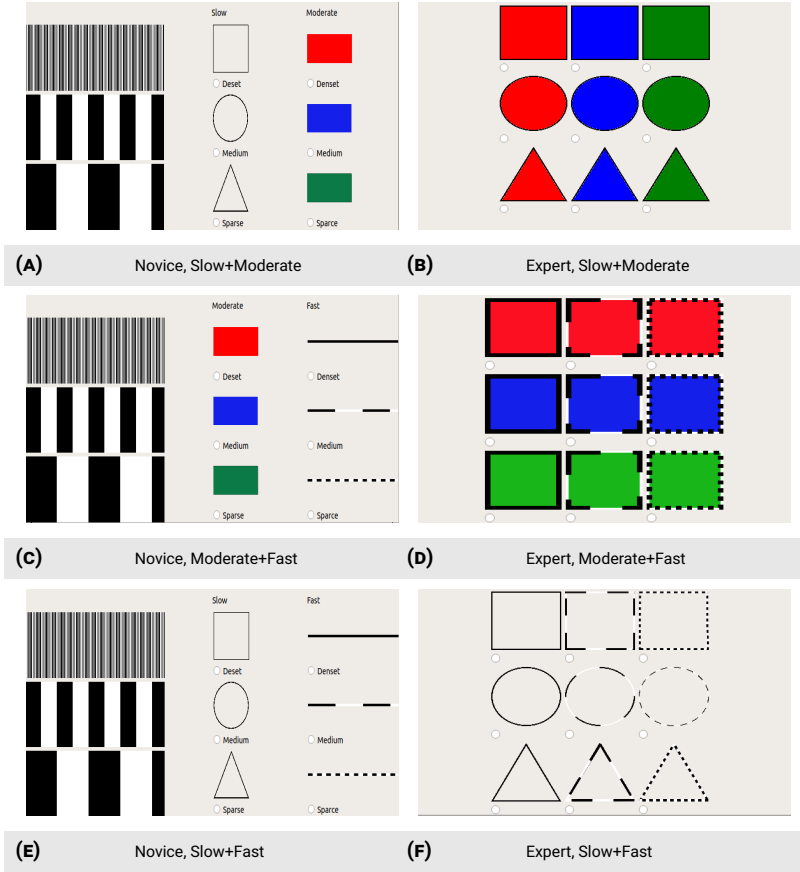
**FIGURE 6.1.** The interface for choosing the information for the one finger speed channel with the novice level (left) and the expert level (right).

### Task 3: Two finger speeds channels:

In the third task, participants were asked to move their finger at two different speeds, identify the texture that is perceived at each speed, and further identify the corresponding association of information. In this task, each participant identified 162 pieces of information = 3 sets of finger speeds (slow+moderate, slow+fast, moderate+fast)  $\times$  2 expertise levels  $\times$  9 sets of textures (DD,DM,DS, MD,MM, MS, SD, SM, SS) (Figure 6.4b)  $\times$  3 repetitions. Figures 6.2a-6.2f show the interfaces used to represent the textures and map the textures with the associated information in, respectively, the novice and the expert expertise levels. The experiment took on average 90 minutes to complete.

### Task 4: three finger speeds channels:

In the fourth task, participants were asked to move their finger at three different speeds, identify the texture that is perceived at each speed, and further identify the corresponding association of information. In this task, each participant identified 54 pieces of information = 1 set of finger speeds (slow+moderate+fast)

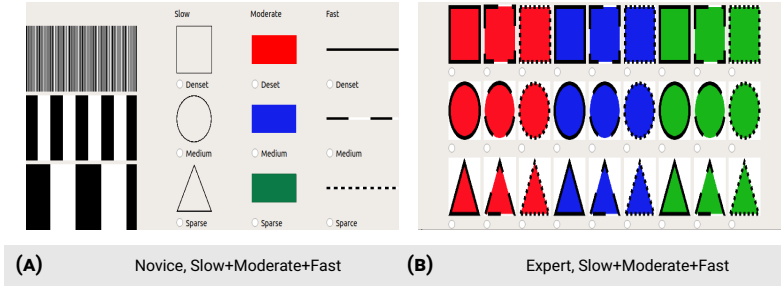


**FIGURE 6.2.** The interface for choosing the information for the two finger speeds channels with the novice level (left) and the expert level (right) for three speed combinations.

$\times 2$  expertise levels  $\times 9$  sets of textures  $\times 3$  repetitions. We decided to limit the set of textures to only 9 sets to minimize fatigue and preserve data consistency. The sets used were: DDS, DMM, DSD, MDM, MMD, MSS, SDD, SMM, SSS (Figure 6.4c). Figures 6.3a, 6.3b show the interfaces used to represent the textures and map the textures with the associated information in, respectively, the novice and the expert expertise levels. The experiment took on average 45 minutes to complete.

#### 6.2.4 Procedure

During the experiment, the four tasks were administrated consecutively, starting with the first task, our simplest configuration, then allowed the complexity

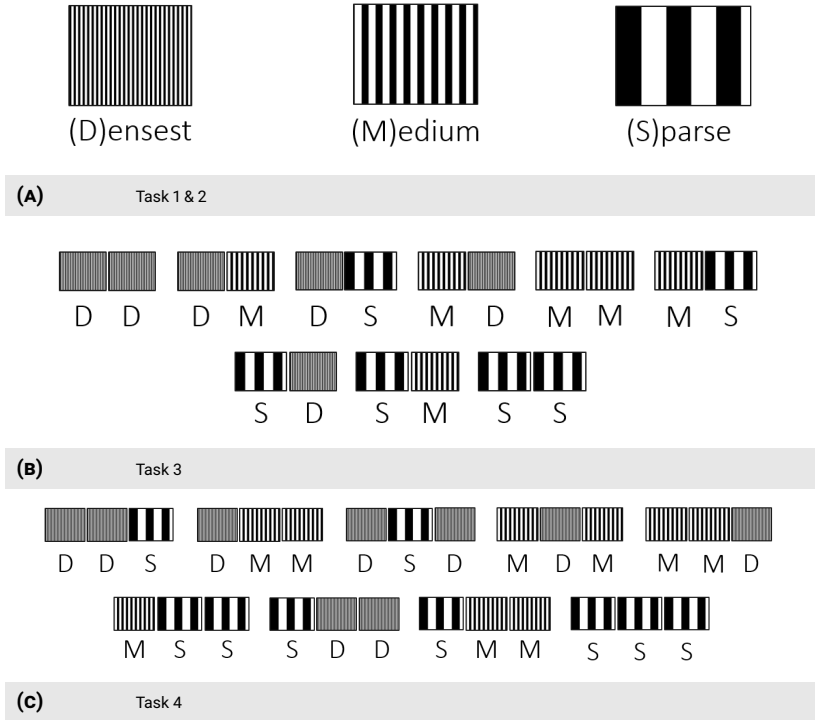


**FIGURE 6.3.** The interface for choosing the information for the three finger speeds channels with the novice level (left) and the expert level (right).

of the interface to gradually increase (*i.e.*, *task2*, then *task3* and finally *task4*). We did this so we could allow users to gradually learn finger speed (*task1*) and then to identify the associated information with each texture for each finger speed (*task2*), then with two associated pieces of information for two different finger speeds (*task3*) and finally three associated pieces of information for the three different finger speeds (*task4*). After each task and after each finger speed condition, participants were required to take a break to avoid fatigue.

In tasks 1, 2 and 3, the different finger speed conditions (*i.e.*, slow, moderate, fast in task 1 and 2 and slow+moderate, slow+fast, moderate+fast in task 3) were ordered randomly. For each task, inside each finger speed condition, we did not counterbalance condition (novice vs expert) between users. Instead, each user tested the novice condition first to learn the finger speeds (and the associated information for task 2, 3 and 4) with each perceived texture, and then tested the expert condition. This strategy was informed by our goal of evaluating user reproducibility of the finger speed and the information associated with the perceived texture in expert level given their experience in novice level. Inside each expertise level, the different texture sets (*times 3 repetitions*) were also ordered randomly. The user was also provided a tactile texture only if finger speed corresponded to the allowed speeds *i.e.*, no texture is provided to the user if the finger speed is greater than the finger speed thresholds allowed in the trial.

In the novice condition, to foster training, a message with the actual finger speed was displayed on the screen in a black color *i.e.*, slow, moderate or fast. If the finger speed corresponds to one of the speeds evaluated in that trial, the finger speed message is then displayed with a green color. For example, if the finger speed condition corresponds to *slow+moderate*, the user is shown the word “slow” or “moderate” in a green color if his finger is moving at that speed; otherwise, the finger speed is displayed in black (in this example, the word “fast” is shown with a black color for the *fast* condition). In the expert level, no information about finger speed is provided. In both levels, the order



**FIGURE 6.4.** The sets of textures used in the four tasks during the experiment.

of execution of the different finger speed conditions was counterbalanced

In addition, throughout the trial, the participant can reassess a previous speed. For example, in task 4, the participant can start with the moderate speed, then the fast speed, then the slow speed, and then finish by reassessing the moderate speed. The exploration time was not limited, and participants were free to move their index finger from the dominant hand from left to right and back to perceive the texture without any specified starting finger position or time restrictions or obligation to keep the finger on the surface during the trial.

In both levels, when perceiving the texture no visual feedback of the perceived texture was shown on the surface, only tactile feedback was sent to the participant, to preserve a simulated eyes-free input condition. In addition, as the Evita device makes noise when alternating high and low friction, the participants were equipped with noise reduction headphones to avoid any bias from multi-modal feedback. Tactile feedback was hence made both eyes and ears-free since the participants were not able to see any visual nor to hear any audio rendering on or by the surface.

A trial ended once the participant pressed on the “enter” button on the top of the surface and selected the identified information for the trial. That is, once

the “enter” button was pressed, tactile feedback stopped and the participant was asked to select the identified information according to the perceived texture(s) and the finger speed(s). Each finger speed defines the type of output channel, and, for a trial to be correct, the perceived texture must be matched to the output channel. For example, the moderate speed is associated with the object color. Sparse texture is, then, associated with green, medium texture is associated with blue, and dense texture is associated with red (please refer to [Figure 6.2](#) for the other speed conditions).

Given the above example, the information content of the multi-channel tactile effects corresponds exactly to the information in the trial. For example, for the *slow+moderate* speed, participants identified the object form (*i.e.*, the information associated with the slow speed) and the object color (*i.e.*, the information associated with the moderate speed).

In the novice condition, to select information after the experiment, the participant is provided with a table showing a visualization of the texture and the associated information according to each finger speed. The participant selects sequentially the associated information for each finger speed. For the expert level, the participant is shown all possible combinations of information at once. For example, for task 4 (*slow+moderate+fast*), while in the novice level, the participant had to select sequentially the geometrical form, its color, and the contour line; in the expert level, the participant selects only the information that corresponds to the final desired information *e.g.*, red circle with continuous line contour (see [Figure 6.3](#)).

For tasks 3 and 4, after each of the finger speed conditions, participants were asked to comment on the interface used and respond to both the NASA TLX and the SUS (System Usability Scale) questionnaires, plus a 5-point Likert-scale question (strongly disagree to strongly agree) measuring enjoyment while interacting with the haptic device. At the end of the experiment, we asked participants to describe their experience with multi-channel tactile feedback, including whether they would use this type of interaction, and what number of levels of finger speeds they prefer and why.

### 6.3 RESULTS

Results for each of the dependent variables (*accuracy* and *trial time*) are presented below. The *accuracy* is defined as the proportion of correct identifications of information which provides a measures of whether participants are able to perceive the different textures associated with different velocity-selected channel and to identify correctly the information provided. For example, for the *Slow+Moderate* condition of the third task (Two finger speeds channels),

the accuracy corresponds to a correct identification of the combination of information perceived at the two different speeds (the identification of the object form (*i.e.*, the information associated with the slow speed) and the object color (*i.e.*, the information associated with the moderate speed). The *trial time* is defined as the time that a user takes from starting moving his finger on the surface until pressing the “enter” button. Compared to the *accuracy*, it is more subjective and only provide an estimate of how difficult the identification task is for participants. All analyses are using multi-way ANOVA considering the following independent variable: *Speed* and *Expertise*, considering only *expertise* for task 4 as participants had only one combination of finger speeds. Due to a technical issue, the data of two participants were not completely logged. Consequently, we excluded these two participants from the analyses.

### 6.3.1 Task 1

#### Accuracy.

There was no significant main effect on accuracy nor interaction ( $p > .28$ ) (overall: mean 83.79%, s.d= 3.47).

#### Recognition time.

There was a significant main effect of speed ( $F_{2,14} = 28.51, p < .0001$ ) on recognition time. Post-hoc tests revealed that, unsurprisingly, the slow speed (mean 14.39s, s.d. 2.47s) takes significantly longer than both the moderate (mean 7.93s, s.d. .92s) and fast (mean 4.65s, s.d. .55s) speeds ( $p < .05$ ).

### 6.3.2 Task 2

#### Accuracy.

There was significant main effect of expertise ( $F_{1,7} = 7.46, p = .02$ ) on accuracy. Post-hoc tests revealed that the expert level (mean 94.44%, s.d. 3.06s) is significantly more accurate than the novice level (mean 87.03%, s.d. 4.48%) ( $p < .05$ ). There was no significant interaction ( $p > .05$ ) suggesting that the benefits of expert level are consistent across different speed conditions.

#### Recognition time.

There were significant main effects of speed ( $F_{2,14} = 8.03, p = .0004$ ) and expertise ( $F_{1,7} = 5.65, p = .04$ ) on recognition time. Post-hoc tests revealed that the slow speed (mean 7.78s, s.d. 1.34s) takes significantly longer than both

moderate (mean 5.65s, s.d. .94s) and fast (mean 4.22s, s.d. .63s) speeds ( $p < .05$ ). We also found that the expert level (mean 5.13s, s.d. .89s) takes significantly less time than the novice level (mean 6.64s, s.d. .79) ( $p < .05$ ).

### 6.3.3 Task 3

#### Accuracy.

There was a significant main effect of speed ( $F_{2,14} = 4.98$ ,  $p = .0231$ ) on accuracy. Post-hoc tests revealed that slow+moderate (mean. 90%, s.d. 2.85%) is significantly more accurate than both slow+fast (mean. 81.01%, s.d. 3.70%) and moderate+fast (mean. 78.70%, s.d. 3.86%) ( $p < .05$ ).

#### Recognition time.

There were no significant main effects on recognition time nor interaction ( $p > .24$ ) with a total mean of 15.37s (s.d=.541s).

### 6.3.4 Task 4

#### Accuracy.

A Wilcoxon Signed-rank test showed that the expert level (mean. 85.18%, s.d. 4.74%) is significantly less accurate than the novice level (mean. 70.83%, s.d. 6.07%) ( $Z = 3.57$ ,  $p < .0001$ ).

#### Recognition time.

A Wilcoxon Signed-rank test showed that there was no significant difference between the expert level (mean. 26.46 s, s.d. 1.71s) and the novice level (mean. 24.77s, s.d. 1.71s) ( $Z = -1.51$ ,  $p = .13$ ) for recognition time.

### 6.3.5 Subjective Results

We highlight hereafter the subjective results gathered during the experiment.

#### Perceived Workload

We recall that we asked our participants to rate each finger speed conditions for task 3 and 4 using a NASA-TLX questionnaire plus a 5-point Likert-scale for enjoyment. Overall, questionnaire responses (Table 6.1 show that mean



ratings for slow+moderate+fast were poorer for all six questions, followed by moderate+fast, but only significantly so for mental demand, physical demand, temporal demand and effort. Pairwise comparison using Bonferroni correction showed that slow+moderate+fast (respectively moderate+fast) is significantly more demanding mentally, physically and temporally and implies more effort than slow+moderate and slow+fast (respectively, slow+moderate) ( $p < .05$ ).

	<b>S+M</b>		<b>S+F</b>		<b>M+F</b>		<b>S+M+F</b>		<b>Friedman</b>
	Mean	s.d	Mean	s.d	Mean	s.d	Mean	s.d	$\chi^2(3)$
NASA TLX questionnaire									
1. Mental demand	2.5	.64	3.625	.51	3.87	.93	4.5	.52	13.01
2. Physical demand	1.87	.68	2.75	.32	3.12	.57	4.12	.44	14.25
3. Temporal demand	2.12	.57	2.5	.52	3.25	.80	3.37	.51	12.28
4. Performance	4.37	.35	4	.37	3.62	.73	3.37	.51	6.59
5.Frustration	1.62	.63	2.25	.71	2.62	.82	2.75	.80	7.10
6. Effort	2.12	.57	2.87	.68	3.75	.48	3.87	.68	17.73
7. Enjoyment	3.75	.48	3.37	.63	2.87	.78	3.25	.48	3.17

Note: Friedman tests are reported at  $p=.05$  (\*) significance levels. The significant tests are highlighted.

**TABLE 6.1.** Mean and s.d questionnaire responses for the two and three channels conditions (S+M: slow+moderate; S+F: slow+fast, M+F: moderate+fast and S+M+F: slow+moderate+fast) for the NASA TLX questionnaire, with 1=very low, and 5 = very high.

### The ease of use

In addition to the NASA-TLX questionnaire, we recall that participants were also asked to fill a SUS questionnaires (Table 6.2) for both the two finger speed channels and three finger speed channel. The analyses show that the average SUS score Table 6.3 for the slow+moderate channel is 82.81, suggesting that this speed channel has an excellent perceived usability. The slow+fast channel also has good perceived usability with an average SUS score of 73.44. In contrast, the SUS score for the moderate+fast and slow+moderate+fast channel were respectively 65.94 and 57.81, suggesting that these two speed channels have a poor perceived usability.

Also, based on the SUS questionnaire, we found that in term of complexity of the task, the three finger speed channel is perceived to be more complex (Q2) and less easy to use (Q3) than the two channels conditions but this was significant only for complexity. Pairwise comparisons using Bonferroni corrections revealed that slow+moderate+fast is significantly more complex than

slow+moderate ( $p<.05$ ). Similarly, in terms of learning, the three channels demand more support (Q4), a learning step (Q7), and to learn a lot of things before using it (Q10) but the difference was significant only for learning. Pairwise comparisons using Bonferroni corrections revealed that slow+moderate+fast demands significantly more learning than slow+moderate ( $p=.02$ ).

	<b>S+M</b>		<b>S+F</b>		<b>M+F</b>		<b>S+M+F</b>		<b>Friedman</b>
	mean	s.d	mean	s.d	mean	s.d	mean	s.d	$\chi^2(3)$
SUS questionnaire									
1. Frequency of use	3.75	.71	3.375	.82	3.12	.93	2.5	.52	6.68
2. Complexity	1.5	.37	2.25	.61	2.62	.82	3.25	.80	10.47
3. Easiness	4	.52	3.125	.86	2.87	.78	2.37	.63	7.37
4.Support demand	1.12	.245	1.375	.51	1.62	.97	1.87	.68	7.57
5. Functions integration	4	.52	4.5	.52	4.25	.71	4.12	.44	4.45
6. Inconsistency	1.62	.51	1.75	.71	1.62	.51	1.87	.68	.34
7. Learning	4.25	.32	3.875	.57	3.12	.78	2.75	.48	13.08
8. Cumbersome	1.62	.73	2.25	.48	2.62	.73	3	.74	6.80
9. Confidence	4.12	.78	3.62	.73	3.37	.73	3.375	.73	2.65
10. Leaning a lot of things	1.12	.24	1.5	.74	1.87	.93	2	.74	9.14

Note: Friedman tests are reported at  $p=.05$  (\*) significance levels. The significant tests are highlighted.

**TABLE 6.2.** Mean and s.d questionnaire responses for the two and three channels conditions (S+M: slow+moderate; S+F: slow+fast, M+F: moderate+fast and S+M+F: slow+moderate+fast) for the SUS questionnaire, with 1=very low, and 5 = very high.

	<b>S+M</b>	<b>S+F</b>	<b>M+F</b>	<b>S+M+F</b>
SUS Score	82.81	73.44	65.94	57.81
Grade	A	B	D	D
Adjective Rating	Excellent	Good	Poor	Poor

**TABLE 6.3.** SUS Score, grade and adjective rating for the two and three channels conditions (S+M: slow+moderate; S+F: slow+fast, M+F: moderate+fast and S+M+F: slow+moderate+fast)

### Participants comments

All participants found that giving the user different information according to different perceived textures at different finger speeds was effective and enjoyable (see last line of Table 6.1), noting: “providing different information to

*the same perceived texture depending on the finger speed is absolutely useful and enjoyable*” and *“it is (a) very enjoyable and smart way to get information”*.

Also, interestingly, we gathered some participants comments and appreciations that were correlated with the average SUS score for each of the finger speeds combinations Table 6.3. For instance, all of our participants preferred using two finger speed channels over three as it was perceived to be easier. In addition, two participants found *“the fast speed is very fast which demands more physical effort to perform the task”* and consequently they preferred slow+moderate. Two other participants commented that *“it is difficult to switch from the fast speed to the moderate one”*, as it was difficult to know if they have slowed down enough without the finger speed indicator, and so they preferred the slow+moderate channel. Two other participants found that slow+fast channel was best as they found *“the gap between the slow and fast finger speed easier to differentiate between the two speeds”*. One of them said: *“slow with fast was easier because I had a dip between the two speeds”*. On the other hand, another participant preferred to combine moderate speed with fast speed as he found *“the slow speed very slow”* for him. He added: *“moving my finger slowly demands naturally more time to identify the texture than when moving the finger moderately or fast. So the task can be annoying and so more concentration is needed to identify the texture”*. While there was a stated preference for two speeds, six of our participants noted that they would prefer three finger speeds if the system allowed them some penalization:

Some participants stated that personalizing the finger speed thresholds at the beginning of the task would have make it easier for them to use three finger speeds, nothing: *“I would appreciate using three finger speeds if there was more space between the defined velocities”*, *“three finger speeds would be more convenient if the slow and moderate velocity were more separated”*.

As for the finger speeds thresholds, some other participants noted that : *“in the novice level, I could adjust my speed along the way since it is displayed, but not in the expert level... I would prefer three speeds if the finger speed is always displayed”*.

Interestingly, three participants associated the finger speed used to specify the level of the detail of the output information. For example, the first participant noted that *“adjusting the speed was a manner to get information depending on its importance: slow for important information and the opposite for the fast speed”*. For the two remaining participants, the finger speed was associated with the precision of the information delivered by the tactile surface: slow speed can be associated with fined-grained information, while fast speed can be associated with coarse-grained information. The moderate speed can be associated with basic information. One participant said: *“the slow speed may be necessary to get more precise details about the information being delivered, however, the fast speed is just for checking the existence of this as it can be made quickly, especially for contexts that demands attention like driving”*. Meanwhile, the second participant declared

that “the slow speed is for precise information with enough available time, for example, getting the content of a text message, while the fast speed is when we need to get the information as fast as possible, for example, getting just the idea of the message”.

## 6.4 DISCUSSION

The results presented here demonstrate that participants can effectively use the velocity of the finger movement to differentiate tactile input channels. In particular, our results show that users are able to control the speed at which they move their fingers, identify the textures they perceive and identify the associated feedback, especially when using two finger speeds. Furthermore, our results show that the slow+moderate channel outperforms the slow+fast and medium+fast channels in terms of accuracy (90%), while having excellent ease of use with the lowest mental, physical and temporal demands and value by participants in terms of learnability and ease of use. Therefore, when using finger speed to select channels, we recommend to choose Slow+Medium as the two-stage channel output.

Our findings also show that slow+fast also has good perceived ease of use, with an average accuracy of 81%, suggesting that this two finger speed channel is also potentially exploitable. However, the moderate+fast channel scored worse in perceived usability, with an 78% score for usability, while being more mentally, physically and temporally demanding than the slow+moderate channel. These results can be explained by the fact that a fast finger speed is more physically demanding than other speeds. Especially when combined with a moderate speed, due to the limited difference between moderate and fast, discrimination between the speeds places participants under greater physical/-mental/temporal demand, a fact commented on by our participants. These results suggest that this two finger speed channel, moderate+fast, should be used with caution.

Looking at the three finger speed channel, the accuracy of the expert level dropped to an average of 70% compared to the novice level (85%). The three speed channel also scored poorly in perceived usability, being considered the most mentally, physically, and temporally demanding task, and least valued by participants in terms of learning, ease and preference. These results suggest that the three finger speed channel may be too difficult for users, so we do not recommend its use. However, as pointed out by our participants, the three finger speed channel can be exploited with longer learning steps to allow the user to discover the different finger velocities and information related to different textures before starting the expert level, or by allowing the user to personalize the finger speed threshold at the start of the task. Further research focusing on this transition could assess the training effort required and the potential benefits of adjusting the speed threshold.

One thing that surprised us about the results is that the time measurements showed that the expert level was generally statistically as fast or faster than the novice level. Our assumption is that expert users will be slower. In fact, we were more interested in how easy it was for participants to work with limited learning, but in our study, the transition from novice to expert appeared to be easy for users to overcome. Additionally, we found that trial times did not double or triple when switching from one speed state (7 seconds on average) to two or three speeds. Our results are consistent with those of Rekik et al. [106] where they found that slow (average 12.22 seconds) took more time to detect textures than medium (average 7.48 seconds) and fast (average 10.31 seconds) speed. Our results show that multi-channel sensing does not require additional time to identify different textures and the information associated with them.

Finally, it is interesting to note that our participants generated design ideas for the type of information they associated to each finger speed level: the importance of the information (slow for important information and the opposite for fast) or the precision of the information (slow for fine-grained information, moderate for basic information and fast for coarse-grained information). This feedback indicates that multi-channel tactile feedback based on user finger speed is perceived of, by our participants, as an intuitive way to differentiate information saliency.

## 6.5 CHAPTER SUMMARY

In this chapter, we introduced the concept of multi-channel tactile feedback, a new technique that takes advantage of the eyes-free nature of tactile sensing to deliver information, without the need to visually attend to the screen. Users have the possibility to monitor various communication channel only through haptic feedback, which can be of a big help when the visual attention is already solicited by users implication for other primary tasks such as driving or simply walking. To do so, we explored increasing the expressivity of tactile feedback based interaction by allowing the user to dynamically select between several channels of tactile feedback using variations in finger speed, and in a controlled experiment, we showed that the user can learn two different haptic channels using slow and moderate finger speed or slow and fast speed.

Part VI

# CONCLUSION



## CHAPTER 7

### *Conclusion And Perspectives*

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Over the past few years, touch-based mobile devices have become omnipresent in our daily lives. Their small size in addition to the richness of the proposed applications has made them sufficiently portable to be used in several aspects of life including situations where users are performing another primary task (*e.g.*, walking, driving, working, etc). However, the lack of physicality on these devices requires a high level of visual attention to perform the task. The challenges are exacerbated when the user is performing simultaneously another primary task. Recently, mobile devices have been enhanced with tactile feedback that provides users stimulation when touching the surface. In this context, we seek, in this thesis, to understand how the use of tactile feedback can help or contribute to complete the secondary task with low visual attention and cognitive efforts. We advocate for deeper user studies to better understand how users perceive tactile feedback when performing another primary task, identify users behaviour and take full benefit from tactile feedback when designing interaction techniques for secondary tasks. To this end, we used an ultrasonic device that provides the user with haptic feedback in the form of a tactile texture perceived at the tip of the finger when this latter is moving on the surface.

In our research methodology, we started first by exploring the effect of a primary task on user perception of tactile textures, from a user-centric perspective. We then conducted three user studies. In the first study, we investigate the effect of a physical activity on user perception of tactile textures. We considered five activities: seated in the office, standing in the office, seated in the tramway, standing in the tramway and walking in the street. Our findings indicate that only walking in the street decreases the performance. However, the accuracy still higher than 82%, suggesting that tactile textures could be effectively recognized and used by users in different primary physical activities including walking in the street. In the two next studies, we investigated textures recognition usability when performing an attention saturating primary task and a cognitively demanding primary one. The results obtained showed that for both primary tasks, the recognition rates for tactile textures stays higher than 82% without compromising the total time of interaction. We also provide a deeper analysis from which we characterize user behaviour when recognizing a



tactile texture and performing another primary task. In particular, our findings indicate that users were able for some situations to perceive tactile textures eyes-free when performing another primary task. Interestingly, as tactile texture is only felt when the finger is moving through a stroke gesture on the surface (*i.e.*, directional movement during our experiments), this motivated us to investigate how stroke gesture were produced eyes-free. To achieve this goal, we conducted a fourth user study, where users are asked to draw a set of stroke gestures eyes-free but also with visual feedback and without visual feedback. Our findings indicated that gestures articulated eyes-free were geometrically different from gestures generated in the presence or absence of a visual feedback. They implied, for example, more rotational movement around the y-axis and were less well recognized than gestures made in other feedback conditions, but still with an accuracy of 95%. Finally, we proposed a tactile feedback based interaction technique that increases the bandwidth of tactile output to permit users to select between different tactile signals to deliver different information to the users. The proposed technique takes advantage of the eyes-free nature of tactile sensing to deliver information, without the need to visually attend to the screen. Users have the possibility to dynamically select between several channels of tactile feedback using variations in finger speed. In a controlled experiment, we showed that user can learn two different haptic channels using slow and moderate finger speed or slow and fast speed.

It is our hope that the results presented in this thesis can serve as a starting point for future insightful research. Hopefully, many research issues remain open and deserve further investigations. In the following, we present some future works that we organized in three parts: the first one deals with tactile textures usability, the second one deals with eyes-free stroke gesture production, and the third one deals with the design of interaction techniques for secondary tasks:

**Tactile Textures Usability.** As reported in our findings, users' body postures for the two evaluated stances (seated and standing) did not impact tactile textures usability for secondary tasks. However, although these two postures represent the main kind of postures used when interacting with a mobile surface, it does not provide insights for other more challenging postures (*e.g.*, lying down while interacting with the mobile device [39]). Thus, further work is needed to study more challenging postures. Regarding the results gathered when users were in the tramway, no negative impact was observed. We hypothesize that our finding can not be generalized to other vehicles contexts, in which another speed traveling can be used, and thus, produce more or fewer jitters. As the jitters are likely the reason why tactile recognition increases in difficulty, the accuracy might change depending on the vehicle. Consequently, additional

work will be required to explore how best to recognize tactile textures while being in other vehicles contexts. In the street context, we only considered the walking activity. While this is generally representative of the kind of tasks performed when being in the street, it does not provide insights for other activities like walking at different speeds [17, 79, 90] or running [28]. More work is needed to fully investigate these challenging activities when recognizing textures.

We observed different strategies to handle and perform both of the attention saturating task and the texture recognition one, either accompanied with exclusive attention to one task or shared attention to both tasks. However, the current study, does not allow us to determine which strategy is better. Consequently, more work will be needed in order to compare these different strategies while fixing the gaze attention. The goal being to examine the effectiveness of tactile textures on touchscreen surfaces in each scenario and to determine its effectiveness when being able to see the tactile surface or not.

In addition, we do not found the same results nor the same behaviour (only one shared strategy to handle both tasks) when switching from the attention saturating task to the cognitively demanding one. We believe that the overall message of this finding is simply that different interaction contexts produce different performances and behaviours on the texture recognition for the end user. These differences limit the overall generalization of our findings for other different primary tasks. Many other scenarios exist where user can make a primary task while checking his mobile (*e.g.*, a person using his smartphone while being in a meeting or speaking with another person [108], making a reading comprehension task or a word search [13] or when the attention is fragmented [51]). Additional work will be required to explore how best to recognize textures on touchscreen while performing other primary tasks.

When performing the attention saturating task, or the cognitively demanding one, our participants were able to (at the same time) recognize and distinguish between different textures using the haptic tablet. The tactile surface was oriented horizontally (parallel to the ground) at three different positions. For the left and the right positions, the haptic surface was 5 cm away diagonally from the bottom left (respectively bottom right) of the laptop with an orientation of  $45^\circ$  (respectively  $-45^\circ$ ). For the forward position, the surface was centered and placed 5 cm below the laptop keyboard which in turn was centered in front of participants. However, the current findings may differ depending on other positions, and do not provide insights for other vertical or horizontal variations of the haptic tablet position [120, 121, 139].

Regarding our finding for tactile feedback usability when performing another primary task at the same time, previous works [61, 131] proved that

different haptic technologies produce different physical sensations for the end user. These differences in physical sensation limit the overall generalizability of our results to other technologies. Consequently, additional work will be required to explore how best to recognize tactile feedback on other technologies (e.g., vibrotactile devices) when performing another primary task.

Moreover, when conducting both experiments for tactile feedback usability when another primary task is simultaneously involved, only subjective results and observations were reported and used to evaluate the primary task. We did not measure users' performance for task completion, and thus, we did not measure the impact of the secondary task on users' currently performed primary task. Additional work will be required to explore effect of performing a tactile feedback secondary task on users' performed primary task.

**Eyes-free Stroke Gesture Production.** When investigating stroke gestures characteristics for eyes-free situations, our participants were instructed to use a single-handed grip. Gestures were generated on the touchscreen device while being to seat comfortably in front of a desk. Other interactions involving different hand grips [38] or body postures [39] may result on different findings. Furthermore, during the experiment, only one phone was used and tested for all the participants independently of their hand sizes or OS preferences. Maybe other phone sizes or form factors may produce different results or observations. We believe these issues are worthy of investigation, but don't limit the scope of our contribution.

When investigating eyes-free stroke gestures production, users did not have to interact with a primary task while producing the gestures. Therefore, additional work will be required to investigate how stroke gestures are produced when performing at the same time another primary task, and how both tasks can be handled simultaneously.

**Interaction Techniques for secondary tasks.** For the proposed eyes-free interaction technique, one aspect of this work that may prove a significant hurdle is the basic concept of multi-channel tactile feedback. Specifically, the idea of multi-channel tactile feedback is at odds with our experience with physical objects (where physical objects do not have different tactile characteristics to be chosen between). Thus, multi-channel tactile feedback may be both unintuitive and less discoverable for users. A learning step is important to inform users how to elicit information from the tactile surface. As a result, one important limitation of multi-channel tactile feedback, in general, is that it is primarily appropriate for application domains where learning is appropriate. However, there are a number of examples of these domains, including productivity applications and gaming, where, if appropriately incorporated, the burden of learning might be effectively off-set by the perceived advantages

of skilled performance yielded by eyes-free monitoring.

It is worth noting that further investigations could be conducted on how to take full benefit from tactile feedback to design new interaction techniques for secondary tasks. A good starting point could be to extend and to enhance the multi-channel application. Thus, to integrate them in a complete interaction system and to evaluate them while the user is performing another primary task. Besides, other techniques could be explored as well. One can for instance ask how to benefit from haptic feedback to accurately perform the secondary task while keeping full visual attention on the primary task. To give a concrete example, it can be interesting to design a set of techniques that take benefits from tactile textures to permit the driver to interact with the dashboard while staying completely concentrated on the driving primary task.







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