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# Making Interaction Gestural: Expressivity and Memorability of Gestures

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# 1 Introduction

1968 saw the release of *2001, A Space Odyssey,* a movie that stirred the audiences' imagination with the character of HAL, an intelligent computer, who was able to converse freely with humans. Considering the tremendous progress in speech interaction and the rise of personal assistants, does this vision foreshadow the reality of tomorrow and, as a journalist recently asked me, "Will this kill the mouse?" Despite the merits of current graphical interfaces and the *analogical*[1] model they are based on, still they involve drawbacks that are highlighted by the success of speech interaction, especially for small devices and large environments. The thesis defended below is that *gestural interaction* could provide an efficient means for solving some of these drawbacks, but only if certain conditions are met.

Current graphical user interfaces (GUIs) rely on the idea that using metaphors from the real world makes user interfaces sufficiently 'intuitive' to make them usable by non-experts. As stated by Jef Raskin, "intuitive equals familiar" [Raskin94] and, because GUIs resemble something the user has already learned, they can leverage "readily transferred, existing skills". Indeed, this idea was tremendously successful and allowed billions of people to use computing devices.

However, while *analogical* interfaces and *direct manipulation* [Shneiderman83, Hutchins85] provide many advantages, they also involve various drawbacks that were pointed out by the same authors (e.g. reduced generality and flexibility, insufficient support for repetitive operations, potentially misleading representations, excessive space occupancy, etc.). In particular, analogical interfaces are not very well suited for repetitive tasks, and thus for expert users. Moreover, because of limited screen space, most UI objects cannot be continuously displayed. Thus, such interfaces rely on many transient objects such as menus, tab bars, dialog boxes, or items in file or web browsers. Accessing these items requires a substantial number of additional interactions, not mentioning that the user must remember where these items are located. Thus, not only is it impossible, in current interfaces, to provide a continuous representation of all objects of interest and mediator objects that manipulate them, but transient objects also decrease the degree of indirection [Beaudouin-Lafon00].

**Leveraging users' knowledge**

While *analogical* interfaces are efficient for discovering commands and data, they are not very efficient in taking user expertise into account. Users of a specific piece of software typically perform the same actions hundreds or thousands of times, meaning that any user eventually becomes an *expert* in performing certain actions. But still, users will have to interact in the same way as novice users, although they already know the commands or data items they need to interact with. In that sense, analogical interfaces fail to efficiently employ the knowledge that users gained by using their favorite applications.

This problem comes from the fact that, due to their nature, analogical interfaces rely on *recognition*. As stated by Hutchins at al. [Hutchins85], manipulating representations of objects that behave like the objects themselves provides the feeling of directness of manipulation. But this implies that, in order to interact with these objects, the user must at least 1) search for them, 2) *recognize* them, 3) point at them. Performing these actions involves a non-negligible cost, especially when objects are transient.

In contrast, a major advantage of speech-based interfaces is that they rely on the *recall* of prior knowledge. Ideally, they should be capable of understanding whatever the user says, i.e., leveraging already existing skills. But even if this is not the case and the user must first learn keywords or specific

[1] (Analogy) 1.1 A correspondence or partial similarity. 1.2 A thing which is comparable to something else in significant respects. 'works of art were seen as an analogy for works of nature' (https://en.oxforddictionaries.com/definition/analogy)

sentences, at least the user will then have direct access to data and commands. The same advantage applies to command-line interfaces [Scarr11] and other techniques leveraging the lexical (and possibly syntactical) richness of language.

**Keyboard shortcuts**

Current GUIs also provide a mechanism based on recall, namely *keyboard shortcuts* or *hotkeys*. But this mechanism has various drawbacks:

- Hotkeys are disconnected from the logic of the analogical model because a different input modality is used. As a consequence, *explicit* learning is required [Grossman07], meaning that a voluntary action of the user is needed to learn the *expert* mode.
- Hotkeys offer limited expressivity because the Roman alphabet contains only 26 letters. This small size not only limits the number of possible hotkeys but leads to name collision as many commands are likely to start with the same letter. Using other letters or modifier key combinations involves limited semantic relationship and/or manipulation difficulties, as multiple keys must be pressed simultaneously.
- Customizing hotkeys is not an easy task for users. It generally requires system knowledge, and this task is error-prone because new hotkeys often conflict with already existing ones (which is a direct consequence of the previous drawback). This means that most users will not attempt to customize their environment to their own personal needs because of the extra effort this involves [Mackay11].

Therefore, keyboard shortcuts do not comply with at least two of the rules stated by Scarr et al. [Scarr11]: they do not maximize the likelihood that users switch to using them and they do not minimize the cost of doing so. This may explain why, as shown by previous research [Lane05], hotkeys are largely underused although they provide better efficiency. Moreover, hotkeys are unavailable on small and large devices because such devices usually have no keyboard (or using one is inconvenient). This is especially unfortunate as these devices present a wider range of interaction problems than PCs.

**Small and large devices**

The limitations of analogical interfaces are amplified on small mobile devices and large displays both for common (the lack of a keyboard, thus of a shortcut mechanism) and different reasons:

On small (or very small) mobile devices, reduced screen real estate not only limits the number of UI objects that can be simultaneously displayed (thus increasing the number of transient objects), but presents occlusion and accuracy problems [Vogel07, Vogel09, Wang09]. These constraints strongly limit applications, which usually only provide a very limited subset of the features they offer on their desktop version (for instance, Adobe Photoshop offers 648 menu commands on a PC and only 35 on a tablet [Wagner14]). Considering that tablets are almost as large as extra small laptops, this may explain why the tablet market has been decreasing for several years[2]. These limitations are emphasized on smartwatches, both because of their particularly small size and because interactions techniques tend to be directly adapted from those used on smartphones [Singh2018].

Conversely, the size of large (or very large) displays, such as interactive whiteboards or wall-sized displays, requires users to constantly walk and/or perform large arm movements to reach UI objects. In fact, some of them (e.g. top-located menu bar items) may be quite hard or even impossible to reach. Smart TVs or smart home environments are another interesting case. In the first case, the user may

[2] https://www.statista.com/statistics/272070/global-tablet-shipments-by-quarter/

have to point at UI objects displayed on the TV using a gyroscopic remote control or a vision-based system such as a Kinect, but mid-air interaction may be tiring [Hincapié-Ramos14, Jan17]. In the second case the system may not even have its own display.

**Gestural interaction**

Gestural interaction offers a valuable solution to provide recall-based shortcuts. First, compared to speech interaction, gestures are generally faster to perform and do not present privacy problems. They can be performed *discreetly* (e.g. in a meeting) and, possibly, *eyes-free*, for instance when the user is walking, driving, etc. As mentioned above, they are especially useful for small and large devices because they provide a shortcut mechanism. They also offer a way to save screen space on small devices (by displaying fewer UI objects) and to improve accuracy, as they are less error prone than pointing, especially when objects are small [Yatani08, Roudaut09]. For the same reason (pointing accuracy), gestures may be easier to use when interacting with a remote control or moving the arm in the air. They can also serve as an alternative or a complement to hotkeys on the PC. Gesture expressivity not only has fewer limitations than hotkeys but gestures also offer a large space for *customization*, as they are scarcely used on current systems.

However, gestures (and gesture/command associations) need to be learned. It is thus of critical importance to make it easy for users to *discover*, *learn* and *remember* gestures. Unfortunately, in HCI these last two aspects may have not yet received the attention they deserve. While numerous studies have proposed novel gestural techniques in the last decades, only a limited number of them have focused on the aspects of *learning* and *remembering*, which in our opinion is unfortunate.

First, psychology research has shown that human capabilities in this area are remarkable. Some researchers even believe that they are (almost) unlimited [Baddeley13]. These capabilities result in a large part from evolution: without them, no mammal could find its way back to its burrow, birds would be unable to fly thousands of kilometers to migrate, etc. Such strong capabilities provide a powerful reservoir of resources that could be utilized to create better user interfaces.

Second, there are large differences in 'gesture memorability' (by this term, we refer to the memorization of gestures as well as command/gesture associations). Gesture memorability depends on various factors such as structure, visual and semantic hints, spatial memory, the way they were learnt, etc. [Bower69, Nacenta13, Scarr13b]. More research is certainly needed to better understand these factors and their impact on performance.

Third, gestural interaction will actually only become useful, and gain popularity if it provides efficient ways of *learning* and *memorizing* gestures and gesture/command associations. Despite its promises, gestural interaction is only implemented in limited ways in current interfaces and there is no hope this will change if these aspects are not better taken into account. As stated by Norman [Norman10], "Most gestures are neither natural nor easy to learn or remember. Few are innate or readily predisposed to rapid and easy learning". Studies about 'user-defined gestures' [Wobbrock09] usually show that few commands elicit gestural agreement, especially if they are of an abstract nature.

To summarize, our argument is twofold. First, it is important to develop and study gestural techniques to increase the expressivity of gestures in order to provide a large reservoir of possibilities. These gestures should be quick and easy to perform, and should not conflict with usual operations (pointing, dragging) whenever possible. Second, providing mechanisms for better ways of discovering, learning and memorizing gestures is of primary importance, otherwise gestural interaction will remain mostly limited to zooming and rotating images in commercial systems.

### Reinventing interaction

Because gestural interfaces rely on an alternate means of interacting, they offer an almost blank space for creating new ways of interacting with applications and data. In current user interfaces, applications, commands and data are dealt with in very different ways [Fruchard17]. For instance, keyboard shortcuts can activate application commands, but on most systems they can neither activate applications nor open files or web pages[3]. The Apple Dock (or the Windows equivalent), desktop icons and their equivalent on mobile devices involve other yet similar constraints. Why should the user care whether he wants to activate an application, trigger an application command, open a file or a Web page, etc.?

For instance, users are likely to use their computer to work on different projects simultaneously, but may also use it to plan their vacations, work on their hobbies, buy personal goods, manage photos, videos, music, etc. This involves performing various actions (that often provide no shortcut mechanism) for triggering or opening applications, commands, data or combinations of them. We propose enabling the user to perform *any* type of action through gestural shortcuts and to let the user *organize* them depending on their needs. In an attempt to reduce the traditional distinction between applications, commands and data items, we define an *action* as whatever operation the user can perform, or a combination of them.

This idea was experimented in the *MarkPad* project [Fruchard17, MarkPad]. MarkPad is a gestural technique that provides a large number of simple gestures that can trigger various actions. MarkPad also implements a 'gluing mechanism' that allows interacting with applications and data in various ways. The gestural actions can be freely organized in groups or subgroups by means of an integrated direct manipulation tool. A preliminary longitudinal user study showed this idea was well appreciated. Interestingly, users used the system in a wide variety of ways, and used groups for either different activities and/or other purposes.

This system has also been using for about two years by two of the authors. Interestingly, some unexpected needs and usages emerged. For instance, the system was adapted for switching applications, organizing windows, copying and pasting text without style, storing text and keywords (notes, emails, telephone numbers, passwords, etc.). Even though gestural shortcuts are generally considered appropriate for frequent commands, some of these actions are not very often performed. This is because MarkPad provides a means to retrieve actions that the user needs occasionally and thus tends to forget. Since actions are grouped in a way that is meaningful to the user (and both leverages semantic and gestural similitude), he can quickly find a related action he often uses, which then leads to the more rarely used action. This example highlights that, because of the freedom they provide, gestural interfaces can provide new ways of interacting, and that benefits are not only about making interaction faster.

### Organization of the document

Although I have been working on various subjects with my PhD students and my colleagues, this document will mainly focus on gestural interaction. Apart from the next section, the first sections describe studies (or parts of studies) that were dedicated to the development of new gestural interaction techniques. Section 7. is focused on the learning and the memorization of gestures and gesture/command associations. Studies related to both topics appear in two sections but describe different aspects. For the sake of brevity, the studies I was involved in are summarized, leaving out some aspects which are covered in the corresponding papers. Finally, Section 8 concludes this document by summarizing these contributions and discussing directions for future work.

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[3] This may be achieved through hacking or by using custom applications but this is not targeted to the average user.

# 2 Gestures and gestural interaction

The terms *gesture* and *gestural interaction* are commonly used, but given various meanings. In the HCI domain, the word *interaction* refers to the interaction between a human and a computing system. If this interaction is *intentional*, meaning that the user is aware that he is controlling a system by making gestures, this de facto excludes gestures that only relate to communication between people, e.g., the movements of the hands and arms when people talk. However, such gestures, and body signals of various natures, might be taken into account in domains such as affective computing, embodied interaction or whole-body interaction, which attempt to analyze human activity and generate appropriate feedback. In this document, we only consider the case of *intentional* gestures for selecting commands and, in some cases, their parameters.

As noted by Wobbrock et al. [Wobbrock09], most existing gesture classifications are either dedicated to specific subdomains (e.g. pen gestures [Long99], cooperative gestures [Morris06], gesture in virtual environments [Vatavu05], etc.), or have been developed for human discursive gesture (e.g. [Efron41, Kendon88, McNeill92, Cadoz94]). Karam et al. [Karam05] attempted to propose a taxonomy better adapted to the field of human-computer interaction. Their work, which is based on previous research in the field, categorizes gesture-based interactions according to four major elements: the gesture *style*, the *application* domain, the *input* and *output* technologies. Gesture *styles* include: deictic gestures (pointing), manipulative gestures (which control some entity), semaphoric gestures (communicative gestures based on a stylized dictionary), gesticulation (typically used in combination with speech), language gestures (linguistically based as in sign languages).

Wobbrock et al. [Wobbrock09] followed a different approach. Their taxonomy, which is devoted to surface gestures, is based on an elicitation study. The authors were concerned with the fact that gestures created by system designers were not necessarily reflective of user behavior. Their approach consisted in using a guessability study methodology presenting the *effects* of gestures to non-technical users and then asking users to perform the gestures *causing* these effects. They classified the resulting gestures according to four dimensions: *form, nature, binding* and *flow*, which are described in Figure 1.

| TAXONOMY OF SURFACE GESTURES | | |
|---|---|---|
| ***Form*** | *static pose* | Hand pose is held in one location. |
| | *dynamic pose* | Hand pose changes in one location. |
| | *static pose and path* | Hand pose is held as hand moves. |
| | *dynamic pose and path* | Hand pose changes as hand moves. |
| | *one-point touch* | Static pose with one finger. |
| | *one-point path* | Static pose & path with one finger. |
| ***Nature*** | *symbolic* | Gesture visually depicts a symbol. |
| | *physical* | Gesture acts physically on objects. |
| | *metaphorical* | Gesture indicates a metaphor. |
| | *abstract* | Gesture-referent mapping is arbitrary. |
| ***Binding*** | *object-centric* | Location defined w.r.t. object features. |
| | *world-dependent* | Location defined w.r.t. world features. |
| | *world-independent* | Location can ignore world features. |
| | *mixed dependencies* | World-independent plus another. |
| ***Flow*** | *discrete* | Response occurs *after* the user acts. |
| | *continuous* | Response occurs *while* the user acts. |

**Figure 1: Taxonomy of Wobbrock et al. (from [Wobbrock09])**

Compared to previous studies, the *form* dimension of this taxonomy puts more emphasis on how the gesture is performed and the *binding* dimension adds the notion of a frame of reference. It also attempts to qualify the *nature* of gestures depending on their level of analogy with the physical world.

Ruiz et al. [Ruiz10] used a similar methodology for proposing taxonomy of motion gestures for mobile interaction. Among other differences, this classification takes into account some physical characteristics of 3D gestures (related to kinematics, DoFs, etc.). At about the same period, Baglioni et al. proposed a design space on the same topic [Baglioni09] and Scoditti et al. taxonomy for gestural techniques using accelerometers [Scoditti11] that covers the semantic, syntactic, lexical, and pragmatic issues of interaction. Cockburn et al. also proposed a design space for air pointing interactions that we will briefly describe in Section 6 [Cockburn11]. Some studies also considered the difficulty or perceived difficulty in performing gestures [Cao09, Vatavu11, Rekik14].

Finally, Zhai et al. [Zhai12] provided a state-of-the-art review on *stroke gestures*. Their design space relies on five dimensions: analogue vs. abstract, commands vs. symbols, order of complexity, visual-spatial dependency, aspects related to the implementation and sensor type.

**Nature vs. analogue-abstract**

Interestingly, in this article, the *nature* dimension of Wobbrock et al. is replaced by an *analogue-abstract* dimension, which the authors consider as a spectrum. *Analogue* is defined as "analogous to what a stroke gesture would do in the physical world or according to a *cultural convention*" and *abstract* is the opposite in their classification. While the dimensions *nature* and *analogue-abstract* are supposed to capture similar characteristics, this may not be completely true.

To start with, the fundamental problem with the *nature* dimension is that it is not an intrinsic property of gestures because it depends on the prior knowledge of the user. A Chinese character or a mathematical symbol may be *abstract* for one user and *symbolic* for another. Similarly, is the "X" gesture (Reject/Delete) *symbolic* (Windows-like) or *metaphorical* (cutting with scissors)? Moreover, sliding gestures that scroll the window content (an object that has "no real existence") *physical* or *metaphorical* [4]*?*

As stated by Zhai et al. "The more analogous gestures are to the user's prior experience, the easier they are to learn". But "physicality" is only one aspect among others of prior experience. The *nature* dimension is related to the degree of analogy with the real world, but the *analogue-abstract* dimension is more general as it considers the analogy with previous knowledge. These two notions thus refer to different concepts, so that the word *analogue* may be somewhat misleading in the second case. The *analogue-abstract* dimension seems in fact related to what Raskin would call *familiarity* [Raskin94], a term that might be more appropriate because it does not convey the (false) idea that 'naturalness' is an intrinsic, user-independent, property of gestures.

Moreover, while the level of familiarity is a key aspect for defining a common set of gestures for a specific population of users, this does not mean that *abstract/arbitrary* gestures are necessarily less useful. On the contrary, they provide freedom for users and application designers to define gesture/command associations that will not conflict with prior experience. Over time, users will have performed certain commands such a large number of times that these gestures may become just as overlearned [Shiffrin77], thus 'natural', as the words, symbols and other knowledge that people acquire in school and throughout their whole life.

[4] not having real existence but representing some truth about a situation or other subject (https://dictionary.cambridge.org/dictionary/english//metaphorical)

**Guessability studies and the fallacy of 'natural" gestures**

Whatever the merits (or problematic assumptions [Tsandislas18]) of guessability studies, a common problem of such studies is that only a few commands achieve a high level of gestural agreement (for instance only 7 actions had higher than 40% agreement scores in [Wobbrock09]). Moreover, as noted by Zhai et al., the actions that received "high" agreement were similar to their physical effects, i.e., these were *analogue* (aka *familiar*) gestures. In real applications, users have to deal with tens or hundreds of *abstract* commands that do not necessarily evoke any particular gesture (or will evoke different gestures for each user).

Another important point is that, in many cases, users do no need to trigger a 'command' but an application *and/or* a command *and/or* one or several data item(s). For instance, one of the most frequent actions that people perform is opening *certain* (user-specific) web pages. They may also need to open *certain* applications (calendar, contacts, tasks, etc.) or *certain* files or directories, or send emails to *certain* persons, or retrieve *certain* phone numbers, passwords, codes, memos, etc. On a mobile device, they may want to control their *own* home environment (e.g. switch on a certain light or TV or Web channel), which requires specifying a *specific* application, command and data item.

In other words, gestures and other alternate interaction techniques are only useful for actions that users cannot easily perform with current interfaces, and these actions tend to be *user-specific*. Why would anyone need new interaction means for actions that are already well supported (e.g. 'move-a-little', 'zoom-in', 'next') or that they seldom perform ('close', 'reject')? New interaction means must provide net added value to have a chance to be adopted [Mckay91]. For instance, speech-based interfaces are mostly used in cases where analogical interfaces provide insufficient efficiency or comfort (e.g. personal assistants for interacting with the home environment). While gestural interfaces cannot leverage the richness of language, they can enable performing more complex actions than just simple common 'commands'.

However, this requires changing the current paradigm that gestures should be 'natural', hence easily discoverable by a large number of people. In many cases, gestures are in fact useful for performing *specific* user- or application-dependent tasks. As stated in the introduction, this requires developing techniques that help to discover, learn and memorize gestures and command/gesture associations.

**Discovering gestures**

One important advantage of pointing-activated menus is that they are easy to understand and to use, notably because direct manipulation ensures an excellent level of stimulus-response compatibility [Fitts53]: the 'response' to the display does not require the user to perform any arbitrary encoding operation. However, they present various drawbacks that are described in the introduction, especially when using small and large devices.

*Marking menus* (Figure 2) [Kurtenbach91, Kurtenbach93a], which are themselves an improvement over *Pie menus* [Hopkins91], provide a remarkably straightforward solution for discovering and learning gestures: 1) In novice mode they work almost the same way as standard menus, and thus have the same advantages; 2) Expert mode relies on performing (almost) the same gestures as in novice mode, so that gestures are learned *implicitly* through the force of repetition. This combination of factors makes gestures both easy to discover and to learn.

Moreover, Marking menus (MM) rely on a simple but clever mechanism to differentiate between the *novice* and *expert* modes. While the expert mode is immediately available (which makes it faster to use), the novice mode is triggered after a small delay. Using the novice mode thus involves a cost. This cost is small and therefore acceptable to users. But still, this feature is likely to encourage users to learn the expert mode [Grossman07]. Furthermore, once users remember which menu item they want to trigger, they 'naturally' point to it faster, which has the magical effect of performing the action in expert mode. In other words, the user "seamlessly switches between novice and expert behavior" [Kurtenbach94].

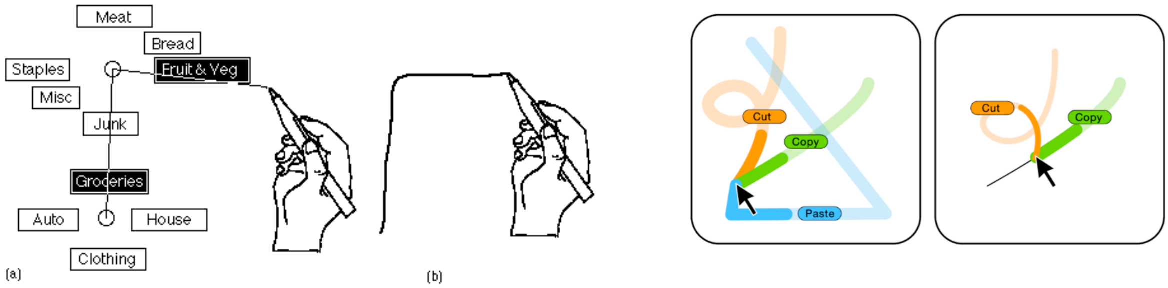



**Figure 2: Hierarchical Marking menus and Octopocus (from [Kurtenbach93a] and [Bau08])**

As mentioned by Bau & Mackay [Bau08], this approach, which takes advantage of novice users' hesitation when they are unsure of a gesture or command, offers an excellent compromise between learning and efficient use. The same authors proposed *OctoPocus* [Bau08], which extends this approach for any type of single-stroke gesture. As Marking menus, OctoPocus provides a dynamic guide that combines feedforward (to show the available gestures) and feedback (to indicate if the gesture was properly recognized). However, OctoPocus is not limited to stroke gestures and provides more sophisticated feedforward by rendering the gesture path using translucent colors (for the remaining part) or variable thickness (for indicating the state of the recognition process). This approach has also been adapted to multi-touch [Freeman09, Ghomi13] and 3D gestures [Delamare16] and a design space of guiding gestures has been proposed by Delamare et al. [Delamare15].

### Memorisation and performance impact of hierarchical structures

Marking menus rely on straight radial gestures starting from the activation point, which make them similar to the pointing gestures used in novice mode. Usually, only the *direction* of these gestures is taken into account. A consequence of this design is that a single Marking menu can hardly contain more than eight commands (12 at the price of decreased performance [Kurtenbach93]). As shown in [Bailly08], menus of current applications tend to contain more elements, with an average breadth of more than 12 items and about 45% (resp. 25%) containing more than 14 (at least 16) items.

*Hierarchical (Compound) Marking menus* [Kurtenbach93a] offer a solution to provide more items (Figure 2). But compensating limited breadth by a greater depth entails several disadvantages. First, for reasonably large breadths (e.g. about 8 items), this makes the resulting gestures (which are a spatial combination of elemental gestures) less accurate and longer to perform, as can be seen in Figure 3 [Kurtenbach93, Zhao04]. Moreover, some gestures (among which, unfortunately, are some of the simplest ones) are ambiguous and are therefore not available for N-level menus if N > 2 (e.g., a submenu located on the main menu's right side cannot have a right directed gesture).

Second, in many cases breadth is preferable to depth [Kiger84, Norman91, Jacko96, Cockburn09]. Deep menus may make it harder to discover commands, find them again, and thus learn them. Moreover, the limited breadth of each submenu does not allow for organizing commands in an optimal way [Zhao06]. Groups of related commands may have to be split into several submenus. Conversely, unrelated commands may have to be placed in the same submenus to save space and avoid increased menu depth. While the effects of menu organization may disappear with practice [Card85], these constraints are likely to impair learning because the structure does not properly reflect the semantic relationships [Mandler67, Bower69, Wagner14].

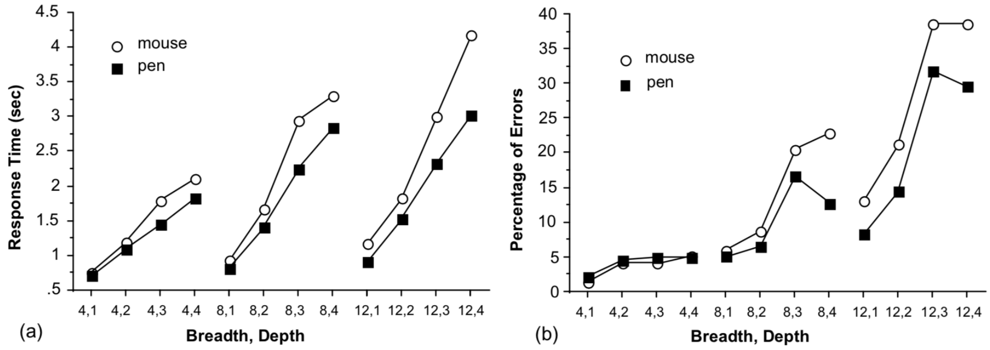



**Figure 3: Response time and percentage of errors (from [Kurtenbach93a])**

*Multi-stroke (aka Simple) menus* [Zhao04] were proposed as a solution to improve the performance of hierarchical Marking menus. They consist in breaking down the compound gestures into elementary parts that are drawn independently (the mouse is released after each mark). However, this may conflict with the idea that *chunking* [Buxton86] should help performing and memorizing commands. This remains an open question, as the memory performance of both variants of hierarchical Marking menus has not been formally compared. Moreover, *Multi-stroke menus* do not provide a solution for increasing the breadth and thus do not solve the other above-mentioned problems.

A possible solution to increase the breath consists in using symbols [Li10, Lu11, Roy13] or more complex gestures [Appert09], but this makes it difficult to design multi-level menus. In the next section we propose several approaches that rely on simple gestures and address this problem, as well as other limitations of Marking menus.

# 3 Stroke gestures

This section presents several techniques that have been developed to augment Marking menus or to solve some of their limitations: *Flower menus* allow increasing the menu breadth, *MicroRolls* provide an alternative to sliding gestures that do not conflict with standard interactions on a touch screen, *Control menus* enable selecting a command and controlling its parameters in a single gesture. In addition, *CycloStar* leverages geometrical attributes and kinematic analysis for panning and zooming a view in a continuous manner.

## 3.1 Curved gestures: Flower and Leaf menus

*Flower menus* [Bailly08a] (which were developed by Gilles Bailly, whose PhD thesis was co-directed by Laurence Nigay) provide a solution to the limited breadth of Marking menus by using a broader vocabulary of shapes (Figure 4). Flower menus rely on simple curved shapes to make them easy to perform (and, possibly, to memorize): Aside from using the *direction*, this technique also takes the *curvature* of the gesture into account. More precisely, it uses both the *curvature* and the *curvature direction* relative to the direction of the gesture. These two attributes can be seen as a single one with the convention that curvatures can have a negative value. This new resource significantly increases the expressiveness of Marking menus, and therefore the total number of possible commands. For instance, 56 commands were available in [Bailly08]: 8 directions x 7 curvatures (one = 0, three ≤ 0, three ≥ 0; see Figure 4, right).

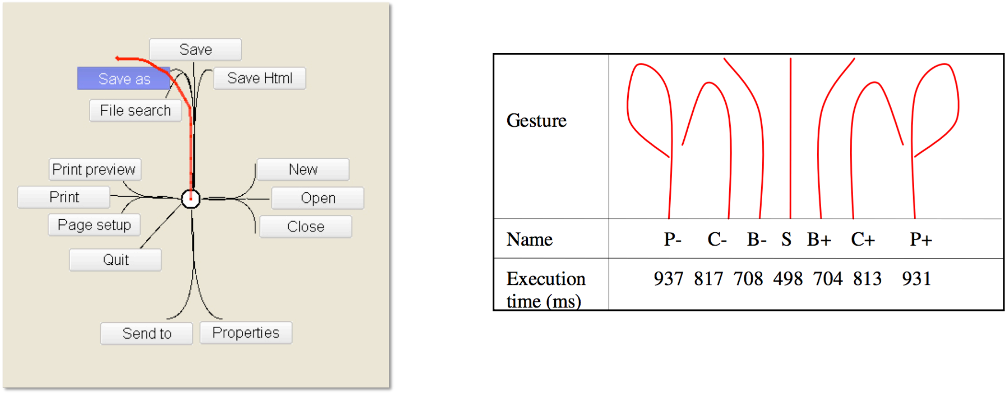



Figure 4: Flower Menus

The performance and the accuracy of Flower gestures was evaluated in an experiment were 14 right-handed participants performed all possible gestures. In theory, performance in expert mode should be the same for straight gestures for both Flower and Marking menus, but it should increase with curvature, as stated by Viviani's two-thirds power law [Viviani82]. In practice, total time was about 500ms for straight gestures and (respectively) 40%, 65% and 85% longer for curved gestures. The success rate, which was obtained by using a K-nearest-neighbors classifier [KNN] with a separate training and testing set of gestures, was high enough to ensure sufficient performance: 99% of correct gestures for the first 24 commands (curvature 0 and ±1), 96.5% for the first 40 commands (curvature 0, ±1, ±2) and 93% for all gestures.

The completion time was a bit longer than in some other experiments. However participants were not asked to draw similar gestures in sequence but to alternate gestures with different curvatures. While this procedure may lower performance, it also provides a more realistic estimate, as users are unlikely to perform long sequences of similar gestures in real-life situations. Considering that curved gestures require an increased amount of time, and that only a small number of commands are very frequently used, frequent commands should be associated with gestures with null or small curvature, as in Figure 4 (left), which shows an adaptation of the *File* menu of Microsoft Word 2003 for Windows. "Dangerous" commands can be associated with the most curved gestures to prevent involuntary activation.

As shown in Figure 4, another advantage of this technique is that it highlights the relationship between items. Each direction corresponds to a group of related items, which makes it possible to reintroduce inner groupings of items, a well-known feature of linear menus that was lost in the original Marking menu design. Such groupings help structure the menu by placing semantically related commands close to each other. This feature should help novice users to find and retrieve commands [Norman91] and to learn gesture/command associations, since related commands usually correspond to related gestures [Bower69, Wagner14]. This feature also inspired the name for this technique because the arborescent structure evokes plants or flowers.

In a second part, we compared the memorization performance of Flower menus vs. standard linear menus and Polygon menus [Zhao06] in a study that will be described in Section 7.

**Adaptation to small screens: Leaf menus**

Flower menus have been adapted to mobile devices (smartphones) under the name of *Leaf menus* (Figure 5) [Roudaut09]. Marking menus pose specific problems on mobile devices. One of them is that they may (partly) lie outside the screen limit when used as context menus because of the two following reasons. First, they are more than twice as large as linear menus. Second, linear menus incorporate a mechanism that places them to the left or the top of the activation point (or shifts them vertically) when there is not enough space to display them entirely. Such a mechanism is not easily adaptable for use with Marking menus because they need to be centered around the activation point to make gestures unambiguous.

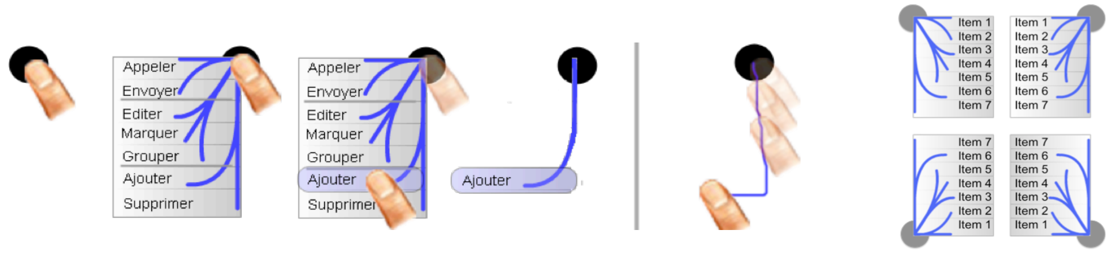



Figure 5: Leaf menus

For these reasons, and also to stay close to user habits, Leaf menus are linear menus. However, they integrate an expert mode based on Flower menus (Figure 5, left). While Leaf menus do not rely on performing the same gestures in novice and expert modes, the same input modality is used in both cases. Moreover, expert mode gestures and the menu items to which they correspond are made clearly visible in novice mode.

To ensure compatibility with linear menus, Leaf menus provide only one quadrant of a Flower menu. This quadrant is *mirrored* (its X or Y axes are inverted; Figure 5, right) when the linear menu is placed on the left or the top of the activation point (the linear menu is not shifted to allow performing Flower gestures properly).

A preliminary study showed that this unusual property did not seem to disturb users. Participants were quickly able to use the expert mode (both modes could be activated at the user's choice), especially when using straight gestures (25% during the first block = 4 repetitions). More surprisingly, they were also able to draw gestures that they had only seen in a mirrored representation. Combined with user comments, this observation suggests that mirrored gestures can provide an efficient way of solving the lack of space problem on mobile devices. Finally, as already observed in [Yatani08], the error rate was almost 5% lower when making gestures than when pointing at (Window Mobile-like) menu items.

To summarize, the added dimension provided by curvature offers a simple and reasonably efficient means of enriching the vocabulary of commands. In particular, it allows to overcome a limitation of Marking menus that makes them difficult to adapt to current applications.

**Related study: Wave menus**

*Wave menus* [Bailly07a] were developed to provide a novice mode to *Multi-stroke menus* [Zhao04]. Because Multi-stroke menus are based on a temporal (rather than spatial) combination of straight strokes they require less space than hierarchical (Compound) Marking menus [Kurtenbach93]. This property makes them especially interesting for mobile devices. Wave menus work the same way as Multi-stroke menus in expert mode. Their novice mode relies on an original layout (Figure 6, left) where menus are represented as circular rings that expand to reveal submenus within their parent. This layout is compatible with the expert mode as stroke gestures always correspond to the submenu that is currently displayed in the center. Another advantage is that parent menus may go out of the screen, but the most important submenu for interacting remains visible, as it is located in the center.

However, this unusual 'inverted' representation was a bit puzzling to some users. Therefore, we proposed an improved version, named *Wavelet menus* [Francone10], which rely on a stacking metaphor (Figure 6, center and right). An animation technique gives the feeling to the user that the submenus are stacked, which is in fact an illusion as the current submenu depends on the parent menu item that was selected. A qualitative evaluation showed that this simple illusion reinforces the perception of the hierarchy and helps the user to understand how the technique works. Another experiment showed that participants could use Wavelet menus eyes-free while walking.


Figure 6: Wave and Wavelet menus

**Survey and design space**

A design space of menu techniques was also developed during this study [Bailly07b]. This design space is organized according to usability criteria (speed & accuracy, learnability and memorization, satisfaction) and applicability criteria (adequation with the application, with the platform, with the task), which are inspired from [Shneiderman86a]. An interactive web version was also made available [MenUA].

This eventually led to the publication of a literature review paper that was published in ACM Computer Surveys [Bailly16]. This article presents a taxonomy of menu properties, which is organized along three dimensions: Menu System, Menu, and Item. Each menu property is illustrated by various menu techniques of the literature. This survey also focuses on menu performance through a list of criteria and discusses under-researched areas and some open research questions.

## 3.2 No-friction rolling gestures: MicroRolls

*Rolling gestures* [Benko06, Bonnet13] can provide an interesting alternative to *sliding* gestures such as those used in Marking menus. Under certain conditions, these two kinds of gestures can be differentiated, which can be advantageous for touch screens. One of the major problems of such devices is their reduced number of interaction states compared to computers. A computer mouse (or an equivalent device) enables at least three states [Buxton90] depending on whether 1) no button is pressed (tracking state, for pointing and mouse hovering), 2) the left button is pressed (for selecting and dragging), 3) the right button is pressed (for menuing). In fact there is also a fourth state, i.e., when the mouse is in the air (for clutching and when no interaction is performed).

With a touch screen, the first and third states do not exist which leads to several limitations. Pointing is then essentially performed in the air (4$^{th}$ state). It is thus less accurate and necessarily ends with a selection (2$^{nd}$ state). Moreover, mouse hovering is not supported (no 1$^{st}$ state), and neither is menu activation (no 3$^{rd}$ state).

On touch screen devices, menu must thus be opened using more or less convenient alternatives, such as a delay or a double click. This makes common operations (e.g. cut and paste), longer and more tedious to perform than on a PC. Moreover, user interfaces for touch screens generally rely on drag gestures to scroll pages. As they use the same type of gestures, Marking menus thus conflict with standard interactions. The absence of a 3$^{rd}$ state, which could be used to distinguish Marking menu gestures, complicates this problem. This makes it problematic to use Marking menus on touch screens, thus on mobile devices (a delay is already used for activating the novice mode; a double click would complicate and slow down the interaction).

Because *rolling* gestures do not involve friction, they can be physically distinguished from sliding/dragging gestures[5]. While dedicated hardware can be used, a simpler solution consists in detecting the very specific *form* of these gestures, or, more precisely the form of the signal that is captured by the touch screen.

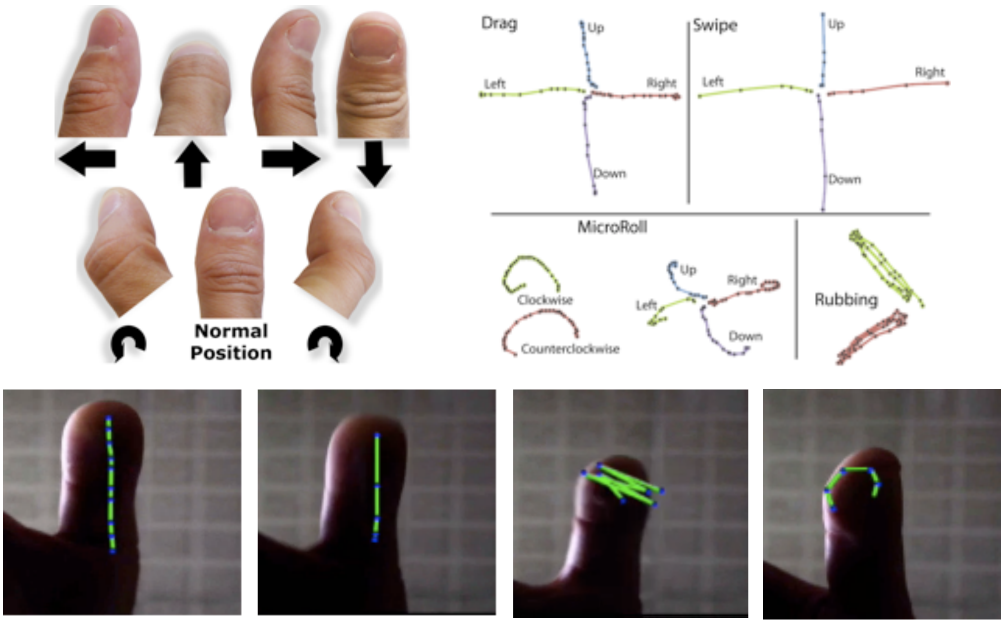



**Figure 7: MicroRolls (and other tested gestures)**

This idea was presented and evaluated as part of Anne Roudaut's thesis, in collaboration with Yves Guiard [Roudaut09a]. Specifically, we assessed the ability to differentiate between 16 types of gestures, which were performed by 10 participants during the same experiment. We thus tested:

- Six *MicroRoll* gestures (the proposed technique): 4 straight gestures in all cardinal directions and 2 circular gestures (clockwise and counterclockwise);
- Four *Drag* gestures
- Four *Swipe* (aka Flick) gestures [Geißler98]
- Two *Rubbing* gestures (diagonal to-and-fro movements of the finger proposed in [Olwal08]).

Each of the 16 gestures was performed four times, using the thumb, at nine screen locations covering the screen real estate. They were recognized using a KNN recognizer [KNN] and a set of 10 features adapted from Rubine's algorithm [Rubine91]. The overall recognition rate was more than 95%.

MicroRolls performance was compared with two common interaction techniques, tool bars and context menus, using buttons of two different heights (either sized as Windows Mobile items or iPhone-like icons) in a copy and paste task. Tool bars, which involve the drawback of occupying permanent space, were used as a baseline. MicroRolls were significantly faster than tool bars and menus containing items (resp. 5.8s, 8.1s, 10.1s) and not slower than tool bars and menus containing (rather large) icons.

The MicroRolls technique provides a novice mode (*RollMark menus*) inspired by Marking menus and it was also combined with a zooming technique called *TapTap* [Roudaut08] for selecting small targets.

[5] More details are provided in [Roudaut09]

This combined technique, named *TapZoom*, was about twice as fast as tool bars (containing items for zooming in and out) in a copy and paste task.

## 3.3 Command selection and control in a single gesture: Control menus

Gestures can serve not only to select commands but also to control discrete or continuous parameters of these commands. We investigated this idea in an interaction technique called *Control menus* [Pook00a, Pook00b, Lecolinet02a] developed in the context of the PhD thesis of Stuart Pook.

A *Control menu* (Figure 8) works like a Marking menu except that, as soon as the pointer (or the finger) has been moved a given distance from the center of the menu, the selected command enters a mode that enables controlling its parameters by moving the pointer. The operation ends when the user releases the mouse button (or lifts his finger). This design allows users to proceed directly from command selection to direct manipulation without interruption. As with Marking menus, a user that has learnt the position of the desired command does not have to wait to see the menu and can move the pointer immediately. In all other respects, the gesture is the same.

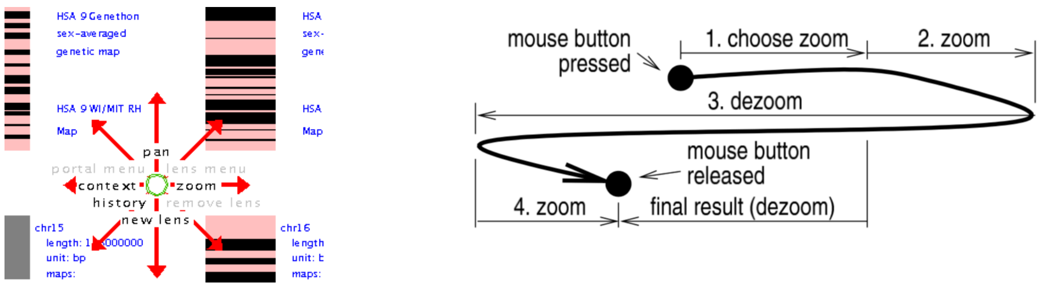



**Figure 8: Control menu (left), zooming operation (right)**

Controls menus have first been introduced as a mechanism for zooming and panning Zoomable User Interfaces (ZUI) [Pook00b]. Figure 8 (right) shows the mouse movements to choose the *Zoom* command and to then control the zoom level. Once the *Zoom* command (right menu item) is selected, the cursor changes on the screen (and the menu is closed in novice mode). From this moment until the mouse button is released, mouse movements to the right (movements 2 and 4) zoom in and movements to the left (movement 3) zoom out.

The feedback is immediate: the view changes as the user moves the mouse. The user releases the mouse button once the desired scale has been obtained. During the zoom operation, the user can undo the zoom by moving the mouse up or down a large distance, and then release the mouse. Undo operations are only possible for commands that have only *one parameter*, i.e. when only one of the X or Y directions is used.

Similarly, a Control menu can select and control commands with *two parameters*, e.g. a two-dimensional *Pan* (top menu item). During the operation the view is scrolled according to mouse movement. This type of interaction is appropriate when the two parameters are integral [Jacob92], i.e. when these attributes are combined to form a single composite attribute in the user's mind. A diagonal mouse movement has a simple meaning in this situation (e.g. panning the view diagonally). Finally, Control menus can also support commands with *discrete* parameters. In this case, a linear (or tabular) menu is displayed as soon as the command is triggered.

Control menus can also serve to provide additional commands on touch screen interfaces while (to some extent) preserving standard interactions. For instance, if the *Pan* operation is triggered as described above, seven other commands are still available. A drawback of this solution is that users must perform a small movement (towards the top the screen in our example) before the pan operation is started, which may be disturbing for novice users (however the pan operation then works as usual). By replacing the *Zoom* command with a *Text Selection* command, text selection could be done in the same way. For this, the user would place his finger before the first letter to be selected and then perform a gesture along the X and Y directions to select the text. Copying and pasting could then be done using other gestures instead of depending on delays and popup menus.

Because Control menus rely on an *activation distance* (a small distance that is empirically chosen) to delimit the selection of the command and the control of its parameters, they are conceptually related to *crossing interfaces* [Accot02, Appiz04]: The second step of the operation (parameter control) is started as soon as an (invisible) line is crossed. This feature enables merging both steps (selection and control) in a single operation but may make this technique inconvenient for introspection or fine tuning [McGuffin02] as the parameter value changes as soon as the line is crossed. Additional feedback (e.g. displaying the value) or using a dedicated widget as in [McGuffin02] would then be helpful.

This technique was evaluated by Guimbretières et al. [Guimbretière05] in a study that compared a standard tool palette, a *Toolglass* [Bier93], a *Control menu* and a *Flow menu* [Guimbretière00]. *Flow menus* are another type of radial menus that share some similarities with Control menus and were introduced almost simultaneously. The main difference is that Flow menus require leaving and reentering the central rest area in specific directions to select menus, which enables more complex interactions but also makes this technique more difficult to learn [McGuffin02].

With all these techniques, except tool palettes, selection and direct manipulation can be merged. And all of them are one handed, except *Toolglasses*. With *Toolglasses*, users use their non-dominant hand to manipulate a translucent tool palette and their dominant hand to select commands and perform direct manipulation tasks.

Participants were asked to perform a sequence of operations that consisted in selecting a color and defining the endpoints of a line. Results show that Control and Flow menus are faster [6] than Toolglasses, which are faster than tool palettes. Control menus are faster than Flow menus in the selection of commands (no difference for the entire task) and Toolglasses are less error prone than the other techniques.

These results highlight the appeal of techniques that can fluidly mix command selection and direct manipulation. For instance, the Toolglass technique was 22% faster than the tool palette for the tested task. However, differences in performance and preferences across interaction techniques may depend on the task, as pointed out by Mackay [Mackay02]. This study also shows that two-handed techniques are not necessarily faster for all tasks. This result has some practical implications as two-handed techniques 1) may be difficult to use on small devices (lack of space, one hand holds the device), 2) require additional hardware when using a PC and, in this latter case, 3) require users to switch both hands between the keyboard and the pointing devices.

## 3.4 Gestures as trajectories in space-time: CycloStar

With kinematic analysis, which does not only consider geometrical paths but space-time trajectories, yet more information can be extracted from the input flow. For any particular path traced by the finger on a tactile surface, the user may have produced an infinite number of different velocity profiles. Kinematic analysis thus exploits a larger proportion of the information conveyed by gestures than does geometric analysis [Williamson04].

[6] In this paragraph and the following one "faster" means significantly faster, "less" significantly less.

A well-known instance of a kinematics-based technique is *flicking* (or swiping), a scrolling technique now widely available in commercial systems. A *flick* and a *drag* are easy to distinguish kinematically: at release, finger velocity (and acceleration) are typically positive for a *flick* and close to zero for a *drag* [Aliakseyeu08]. Another example is Rub-Pointing [Olwal08], which relies on diagonal to-and-fro movements of the finger (see section 3.2). This technique allows a zooming progression to be controlled in closed loop by a modulation of the oscillation frequency, each reversal of the rubbing gesture resulting in a doubling of viewing scale. Depending on the amplitude of the gesture, the movement is either interpreted as a *rubbing* or a *dragging* gesture.

Oscillatory gestures are of special interest because it is quite easy for humans to perform oscillations and keep them stable, in particular with the hand [Kugler87]. The parameters of the oscillatory motion, which the user can modulate at every single instant, can be used as controls. This idea was generalized within the context of the PhD thesis of Sylvain Malacria, in a study conducted in collaboration with Yves Guiard. This approach, named *CycloStar* [Malacria10], focuses on elliptic oscillatory gestures and, more specifically, on straight and circular periodic gestures (i.e. ellipses with an eccentricity of 0 and 1, respectively).

Such gestures have several interesting properties. First, they make it theoretically possible to control up to *seven* mathematically independent variables. An ellipse has five geometrical degrees of freedom (DoFs) in the plane, which may be described as: (1) major axis orientation relative to the X axis, (2) amplitude along its major axis, (3) eccentricity (the minor/major axis amplitude ratio), (4) and (5) X/Y ellipse location. Provided the approach is kinematic, we have another two DoFs, (6) frequency and (7) drawing direction (clockwise or counterclockwise). Indeed, it would be unreasonable to expect users to be able to vary all these variables orthogonally (some preferred couplings are known to exist, e.g., between amplitude and frequency in walking [Danion03]). Nevertheless, elliptic control offers an abundant set of DoFs for designing novel techniques for interaction on sensitive surfaces.

We derived two techniques from this principle. *CycloPan* was designed for panning large documents. Like Rub-Pointing-Click [Olwal08] it relies on to-and-fro oscillatory gestures but exploits more DoFs. *CycloPan* exploits stroke orientation φ (panning direction), stroke amplitude A and frequency F (F = 1/ 2*(T2-T1) where T*i* stands for time as shown in Figure 9). F controls the *gain*, in a similar fashion as mouse pointer 'acceleration', which enables panning faster when long distances must be covered (details in [Malacria10]).


Figure 9: CycloPan

Finger motion during the first stroke of a CycloPan oscillation has the same effect as a standard drag gesture, but the view continues to be panned in the initial direction after the first direction reversal. Then direction correspondence is restored after the second reversal, and so on. Contrary to standard drag, which requires *clutching*, no movement in motor space is wasted as both back and forth strokes contribute to the pan. Panning can thus be performed for large distances without releasing the finger. Moreover, the panning speed can be increased by controlling the frequency (thus the gain). These two properties make CycloPan well adapted for long displacements without requiring specific hardware (as for instance RubberEdge [Casiez07], which also avoids clutching but requires extra equipment).

Importantly, CycloPan is compatible with standard interaction techniques like drag and flick. A drag is just a degenerate case of a CycloPan gesture where no reversal occurs and a flick gesture can be detected in the usual way. To avoid triggering CycloPan involuntarily, it is activated only if the mean speed of the first stroke exceeds 50 pixels/sec (and if a direction reversal occurs), and deactivated if the finger stops moving for a 300ms delay (or if it is lifted).

*CycloZoom* combines zoom and pan. It is also compatible with standard interactions, and with CycloPan. CycloZoom is triggered when the user performs approximately circular gestures. This means that the eccentricity of the elliptic movement is used to trigger either CycloPan or CycloZoom. Once triggered, five DoFs are then used to control CycloZoom (Figure 10):

- The drawing direction (clockwise or counterclockwise) controls zooming (resp. in and out),
- The frequency (i.e., the velocity) controls the gain: the faster the angular velocity of the finger, the faster the zoom progression,
- The circling radius indirectly controls the level of accuracy because it affects the velocity (so-called Vernier effect). When zooming too fast or too slow, users can use the radius as an adjustable gain parameter. This parameter may be easier to control for small adjustments than the velocity (or both can be controlled simultaneously),
- The center of the circular gesture (X, Y position) corresponds to the expansion or contraction focus. This enables panning and zooming simultaneously, and thus makes it possible to always keep the region of interest visible when zooming.

In summary, CycloZoom makes it possible to zoom and pan simultaneously, while controlling the scale with a dynamically adjustable level of resolution.

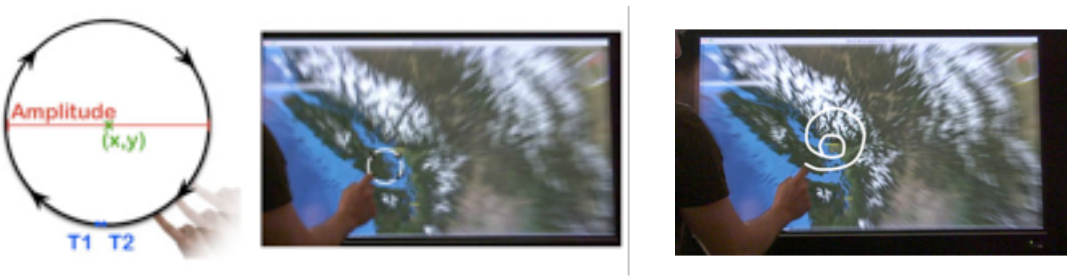



**Figure 10: CycloZoom**

CycloPan was compared with Drag and Flicking in a path-following task (see [Malacria10] for details). Performance was fastest with CycloPan and slowest with the Drag technique (about 30% slower). Differences were significant between CycloPan and Drag, but not between CycloPan and Flick. However, contrary to Flick, CycloPan offer continuous control over panning speed, which can be advantageous for certain tasks (but not for the tested task).

CycloZoom was compared with Rubbing and Drag for navigating on a map. We resorted to the multi-scale pointing paradigm proposed in [Guiard04], using a fairly high index of difficulty (ID = 15). For example, on Google Earth such an ID would correspond to the task of reaching a 500m target (say, a stadium) on the opposite side of the planet. CycloZoom was significantly faster for zooming out (33.5% time saving) and fell short of significance for zooming-in (11.3% time saving) but non-parametric tests were significant. This difference may be due to the fact that the gain factor was higher for zooming-out than for zooming-in, because pilot tests showed that this last operation was harder to control. Finally, both techniques were well appreciated by users, especially CycloZoom.

As a conclusion, this study shows that it is possible to derive a rather large number of variables (seven) from gestures (including kinematic dependent variables) and that users are able to perform gestures appropriately to control these parameters. CycloPan and CycloZoom are not meant to replace well-known and well-tried techniques such as flicking or basic drag (with which they are compatible) but rather to enrich the users' resources for input expression.

## 3.5 Interacting with small devices: WatchIt

Because the small screen of smartwatches suffers from visual occlusion and the fat finger problem, we investigated the use of the wristband as an available interaction resource (PhD of Simon Perrault, co-supervised by Yves Guiard). *WatchIt* [Perrault13] is a prototype device that extends interaction beyond the watch surface to the wristband (Figure 11). It can also be used as a simple input device, on a bracelet without any screen, or on a watch with a non-tactile screen.

WatchIt consists of a 2-cm wide (0.79") wristband that is composed of four resistive potentiometers, two for each band. These potentiometers are attached to a cloth wristband with a circular-shaped piece of plastic in the middle to simulate the watch bezel. The potentiometers (position sensors) consist of thin bands with enough flexibility to be used around the wrist. Not only does WatchIt use a cheap, energy efficient and invisible technology, but it also involves simple, basic gestures that allow good performance after little training.

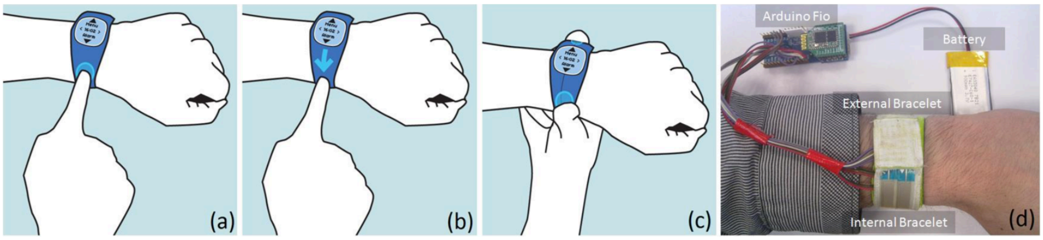



**Figure 11: WatchIt: (a) pointing, (b) sliding, (c) with two fingers, (d) experimental prototype**

WatchIt can be used in two different ways. First, it can serve to perform *analog* continuous gestures, for instance for scrolling a list (Figure 12, left). This considerably increases the input surface by extending it from the touch screen to the wristband. This not only avoids the drawback of screen occlusion by the finger, it also evokes the metaphor of a moving band whose content is revealed when it reaches the screen. Second, this device can be used for interacting *eyes-free*.

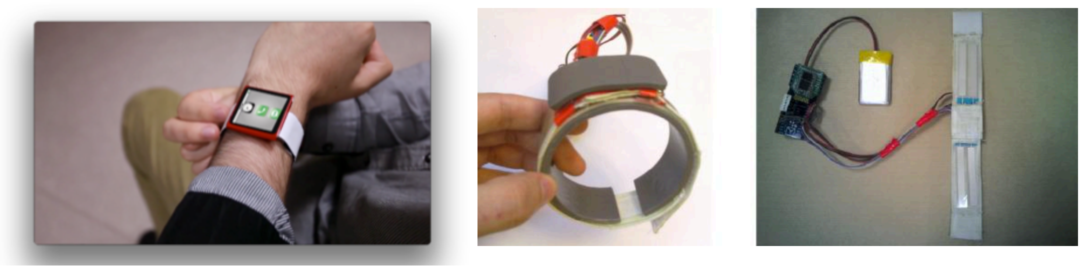


**Figure 12: Mockup, First and final prototypes (with Arduino Fio, BlueeTooth shield and battery)**

WatchIt offers a total of 15 gestures: five gestures on each of the two bands of the wristband and five double-band gestures with one finger touching the inner band and another finger touching the outer band. These five gestures consist of two *sliding* gestures (either towards the bezel or towards the clasp), and three *pointing* gestures (a brief press of the fingertip on the band, which is divided into three areas). For double-band gestures, the presence of a second finger on the external band is seen as an all-or-nothing modifier (the reverse combination was not considered to avoid ambiguities).

These 15 gestures were tested in two experiments (12 and 8 participants). The first experiment evaluated their performance in eyes-free interaction. The success rate was particularly high for one-band pointing gestures (> 97%), and a bit lower for the other gestures (above or close to 90%). The second experiment compared these gestures with an audio menu technique [Zhao, Asbrook11]. The audio menu was slightly more accurate than the gesture technique (93.83% vs. 91.25%) but it was substantially slower (3.19s vs. 2.69s).

In a last experiment (12 participants) we compared *sliding* gestures and absolute *pointing* on the wristband with *pan* and *flick* on the tactile screen for list scrolling. We considered different list sizes (15, 60 and 240 items) and asked participants to reach one particular item located at various distances in these lists. Participants were allowed to interact on the tactile screen at any time in all conditions (e.g. for fine tuning). Absolute *pointing* was the fastest technique (4.82 vs 7.50s vs 5.47s), especially for small lists (15 items) where it was nearly twice as fast as *pan* and *flick* on the tactile screen. *Sliding* gestures on the wristband was the slowest technique because it was hampered by the fact that the sensors we used (resistive potentiometers) could not support *flick* gestures, a limitation that could be solved with more advanced technology.

Finally, it is interesting to note that, although participants could use the tactile screen at any time, they tended to stick with scrolling on the bracelet. They all agreed that absolute *pointing* was the best technique, but half of them explained that they liked *scrolling* on the bracelet, despite its lower overall performance.

## 3.6 Interacting collaboratively with large devices: CoReach

Multi-touch wall-sized displays afford collaborative exploration of large datasets and re-organization of digital content. However, standard touch-based interactions, such as dragging to move content, do not scale well to large surfaces and were not designed to support collaboration, such as passing an object around. This study introduced *CoReach* [Liu17], a set of collaborative gestures that combine input from multiple users in order to manipulate content, facilitate data exchange and support communication (Figure 13). This study was conducted by Can Liu during her PhD, which was co-supervised by Michel Beaudouin-Lafon, Olivier Chapuis and myself.

Figure 13: CoReach: Cooperative gestures on wall-sized displays

To draw inspiration for the design of cooperative gestures in this context, we first conducted a study to observe how people collaboratively manipulate physical objects and understand the dynamic exchanges among users within their workflow. Based on the findings in this study, we then designed a set of cooperative gestures to facilitate data-centric collaborative tasks on large interactive surfaces. This set of gesture involves multi-touch *"Hand"* gestures that are performed using at least three fingers. Other gestures are performed using one or two fingers:

- *Throw and Catch*: The action initiator throws an item towards the action follower with a *Hand Swipe* gesture. The item flies in that direction with a friction effect. The action follower can then catch the item with a *DoubleTap* gesture anywhere. The item then flies over to this position.
- *Preview*: The action initiator performs a *Hand Dwell* gesture (more than 600ms) on an item. A temporary copy of the item appears under the hand of the action follower if she performs the same gesture. She can then get the real item by performing a *DoubleTap* on the copy before the action initiator releases her hand.
- *Shared Clipboard*: A *Hand Tap* on an item adds it to a virtual clipboard. Such items are high-lighted with a thick green border. A *Hand DoubleTap* collects all selected items. A second *Hand DoubleTap* moves them to this new location. A Finger Zigzag gesture cancels the selection.

These multi-touch gestures depend on temporal and spatial criteria and require different levels of synchronization between users (respectively, modest, strong or no synchronization).

A first experiment compared CoReach gestures with standard gestures. All the participants preferred performing the task with CoReach gestures. This study shows that CoReach gestures reduced physical fatigue and facilitated collaboration. A second experiment compared using CoReach gestures on the wall-sized display only vs. on the wall-sized display and on tablets (with minor adjustments to the gestures to accommodate the tablet). This experiment showed that users were able to blend direct and indirect interaction on different surfaces, using a variety of strategies.

# 4 Multi-finger gestures

By taking advantage of the rich dexterity of our hands, we can obtain large sets of postures and gestures [Olafsdottir14]. Multi-finger or two-handed gestures thus provide many possibilities for increasing the interaction bandwidth. However, current technology (e.g. capacitive input sensors) provides limited information about the user's hand posture, i.e., mostly the number and position of finger touches, but not the finger's identity. In this section we present several techniques that leverage the multitouch capabilities of touch screens, which either consider the relative positions of fingers or just how many of them touch the surface. In addition, we also investigated whether finger identification might help users invoke commands on touch screens.

## 4.1 Finger-Count shortcuts

A simple solution to activate commands consists in using zero-order gestures (i.e. postures) and just count the number of fingers touching the sensitive surface. This idea, which relies on the human ability to code numbers with fingers, was proposed in a study conducted with Gilles Bailly [Bailly10, Bailly12]. The *Finger-Count* technique was initially developed to provide gestural shortcuts for interacting with a standard menu bar displayed on a multitouch table. It makes use of both hands: the non-dominant hand selects the $N^{th}$ menu (where N is the number of fingers of this hand touching the surface) and the dominant hand selects the $M^{th}$ item in this menu. Each hand can select up to five menus or items, for a total of 25 items.

*Finger-Count* is thus compatible with a standard menu bar system, except that the number of fingers needed for activating a certain menu or item are displayed on the right side of this element (instead of the associated keyboard shortcut), as shown on Figure 14. Not all menus or items are required to be associated with a finger-counting shortcut, so that the menu bar system can contain an arbitrary number of menus and items. A short study, showed the feasibility of the technique, with a success rate of 91.4% (versus 93.8% when pointing on menu items in the usual way).

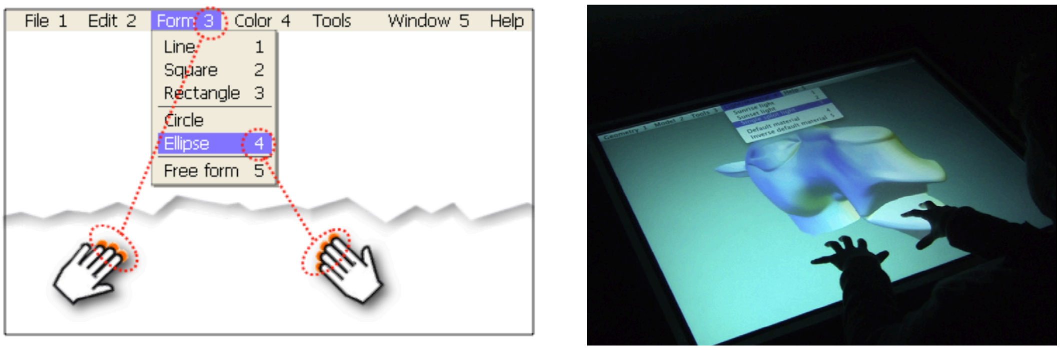



**Figure 14: Finger-Count menus**

This technique has several advantages: 1) it provides a simple substitute to keyboard shortcuts, 2) contrary to Marking menus, it does not conflict with standard interactions (as previously said, on touch screens dragging gestures are often used for scrolling content), 3) it does not require identifying fingers, a non-trivial problem as explained below. However, using more than one finger increases the perceived difficulty, but this effect decreases with familiarity [Rekik14]. Moreover, this technique requires differentiating the dominant and non-dominant hand. In this study this was just done by splitting the sensitive area of the multitouch table in two vertical parts (one for each hand) but this simple solution is not appropriate in all contexts (e.g. multi-user interaction). This technique was later adapted to mid-air interaction, as will be explained in Section 6.

## 4.2 Multi-finger chords

Considering chords provides an additional means to extend input expressivity. However, not only might it be difficult for the average user to produce chords (and also, to distinguish them without ambiguity and to remember them), but they also require the identification of fingers. Existing solutions have resorted to clumsy external hardware such as gloves or cameras [Ramakers12] or built-in table cameras. Another solution, which is compatible with standard capacitive touch screens and does not require additional hardware, consists of using registration gestures [Au10, Lepinski10]. However, as explained in [Wagner14] these solutions require additional time and may require visual attention (e.g. [Au10]) or be challenging to perform (e.g. Lepinski10]).

Arpège [Ghomi13] also focuses on static chording gestures. This technique, which relies on geometrical features based on an initial calibration of the user's hand, guides the user step by step by extending the Octopocus technique [Bau08]. Arpège also proposes guidelines based on studies of the motor abilities and biomechanical constraints of the human hand. Results suggest that users prefer relaxed to tense chords, chords with fewer fingers and chords with fewer tense fingers.

In a study conducted with Julie Wagner and Ted Selker [Wagner14], we proposed a method for recognizing a set of *Multi-Finger Chords* that relies on generic hand-shape characteristics. This technique can thus be used on standard capacitive tablets and does not require a calibration procedure. Users do not have to spread or flex their fingers, thus to perform tense chords, and only perform three-fingers chords. Similar to playing piano-chords, some fingers touch the surface while some are lifted up, so that fingers remain extended in a relaxed position.

*Multi-Finger Chords* rely on three families of simple postures based on the observations of human hand-shape characteristics [Missile84] and provide simple ways of measuring them. These measurements are based on relative measurements, which make them insensitive to variations in the size of users' hand. These three families (detailed in [Wagner14]) rely on:

1. The relative distance between neighboring fingers (ratio D1/D2 on Figure 15)
2. The relative length of fingers (angle $\alpha$)
3. The order of the fingers (relative position P)

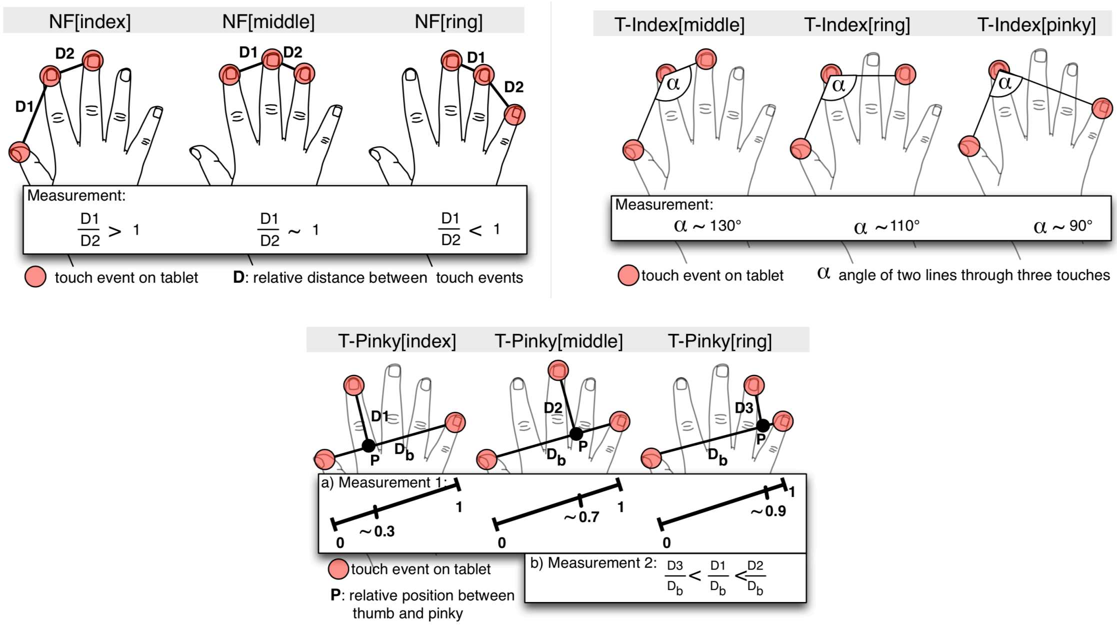



**Figure 15: Multi-finger chords** (neighboring finger, thumb-index base & thumb-pinky basis families)

Each family provides three different gestures. The nine resulting gestures can be unambiguously distinguished using two-step postures. Steps are rapidly performed in sequence (≈ 150ms apart); contrary to [Lepinski10], the second step requires holding down only one finger.

An experiment with 20 users (9 gestures x 5 replications) with different hand sizes showed the feasibility of the approach. A KNN classifier was used for recognizing the postures in a way simulating three different usage cases: (1) private use, (2) a device shared by a small group of users, (3) a public setup. Depending on these cases, recognition was trained and tested: (1) with trained gestures (TG) of the test user (for all users, then results were averaged), (2) with TG of *all* users *including* those of the test user, (3) with TG of all users *excluding* those of the test user. An m-fold cross validation procedure was used so that a tested gesture was never part of TG (e.g., in case (1) different gestures of the same user were used for testing and training). The overall recognition rates were, respectively, 98.5%, 95.2% and 91.5%. These results suggest that this technique provides sufficient efficiency in the first two cases, which are also the most common usage scenarios for tablets. Recognition rates could probably be improved in the third case by using a more sophisticated recognizer, and/or complementary attributes. In a second part, this study investigated memorization performance depending on random vs. categorized gesture-command mappings. These results will be described in Section 7.1.

## 4.3 MTM menus

*MTM menus* (Gilles Bailly) [Bailly08b] is a one-handed multitouch technique that combines Marking menus and finger postures. The palm heel is used to trigger this technique, which avoids relying on delays, etc. (as touch screens do not offer a *menuing* state as already explained). Because of its specific shape, a touch with the palm heel can be easily distinguished from a touch with a finger if the device provides basic information about the contact surface (e.g. the size of its two main axes).

Touching the screen with the palm heel also makes it possible to display and orient the menu (Figure 16) according to the position of the palm. The thumb can then control a Marking menu that selects a submenu. This submenu consists of a double range of buttons that appear close to the expected positions of the four other fingers, taking into account the position of the thumb and the (previous) orientation of the hand heel. This technique makes it possible to select a relatively large number of items (8 menus x 2 x 4 buttons = 64 items) using one hand. Even more commands (64 x 8 = 768) can be made available if each item controls a circular menu. While MTM is more complex and involves more steps than the previously described techniques, it suggests that quite a large number of gestures can be performed with only one hand.

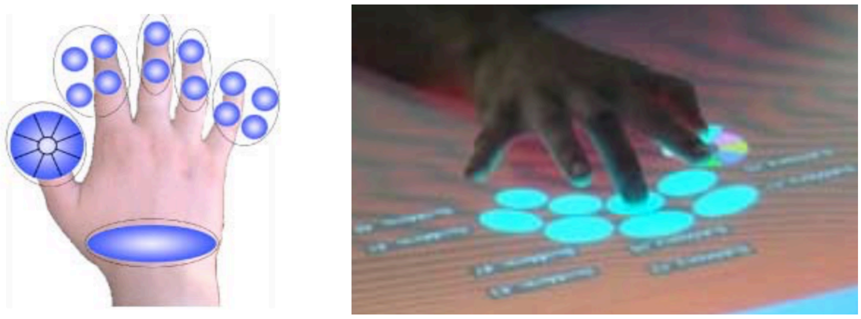


Figure 16: MTM menus

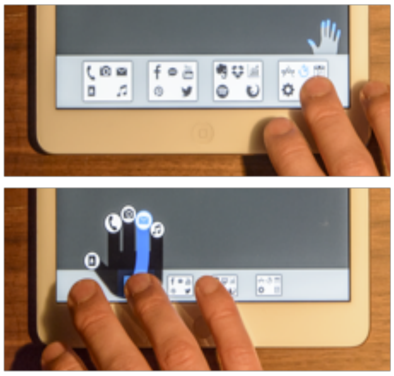
## 4.4 Finger-dependent buttons

In the *Glass+Skin* study [Roy15] (PhD thesis of Quentin Roy, who was codirected by Yves Guiard), we tried to better understand how interaction techniques relying on finger identification might help users invoke commands on touch screens, especially on mobile devices where the screen real estate is limited. For this purpose, we conducted a user study (14 participants) comparing the performance of finger-dependent buttons (*Glass+Skin* condition) with traditional buttons (*Glass* condition) for various sizes of the command vocabulary (Figure 17, left).

The target area was displayed as a horizontal layout extending over the complete width of a representation of an iPhone screen (59 mm) simulating the common toolbars/docks of smartphones. Button height was a constant 0.90mm (as on an iPhone) and button width depended on the number of buttons. Finger-dependent buttons triggered different command depending on which finger was used (one of the five fingers of the dominant hand of the participants). They were five times larger than traditional buttons so that the total number of commands was the same in both cases. In other words, finger-dependent buttons involved the added difficulty of choosing the proper finger, but this was compensated by the fact that they were larger. The goal of the study was thus to learn when it becomes beneficial to use finger identification, provided that this allows using larger buttons without consuming more space.

**Table 1.** Number of commands, number of buttons, and horizontal button size

| *Number of Commands* | *Number of Buttons GLASS* | *Number of Buttons GLASS+SKIN* | *Button Width GLASS* | *Button Width GLASS+SKIN* |
|---|---|---|---|---|
| 5 | 5 | 1 | 12mm / 0.46in | 58mm / 2.3in |
| 10 | 10 | 2 | 5.8mm / 0.23in | 29mm / 1.2in |
| 15 | 15 | | 3.9mm / 0.15in | |
| 20 | 20 | 4 | 2.9mm / 0.11in | 15mm / 0.58in |
| 30 | 30 | 6 | 1.9mm / 0.077in | 9.7mm / 0.38in |
| 40 | 40 | 8 | 1.4mm / 0.058in | 7.3mm / 0.29in |
| 50 | | 10 | | 5.8mm / 0.23in |
| 70 | | 14 | | 4.2mm / 0.16in |



(c )

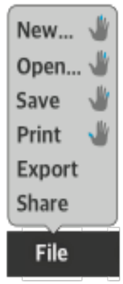



Figure 17: Sizes of the command vocabulary and visual cues

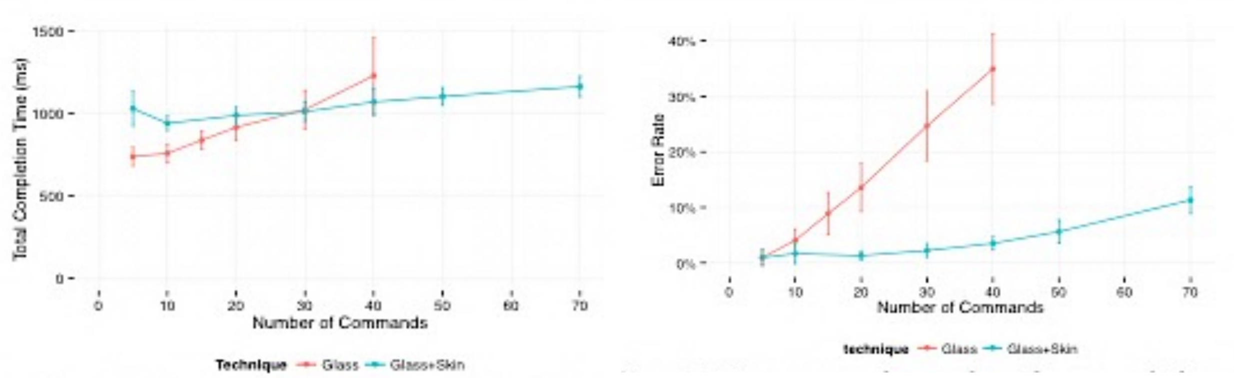



Figure 18: Total time and error rate vs. the number of commands

The results show that time, and more particularly errors, increased at a slower pace with finger-dependent buttons as vocabulary size was raised (Figure 18), so that, the larger the input vocabulary, the more promising the identification of individual fingers. We also analyzed the data in terms of a throughput measurement, which enables combining speed and accuracy information into a single quantity. As shown on Figure 19, the maximum is reached for a larger size of the vocabulary (higher entropy) with *Glass+Skin* (green curve) than with *Glass* (red curve). In addition, we proposed visual cues to communicate this novel modality to novice users (Figure 17, right)

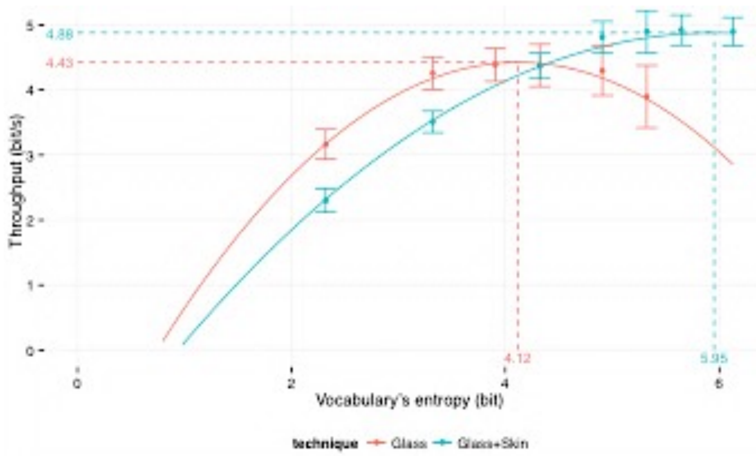



Figure 19: Throughput for *Glass* (red) and *Glass+Skin* (*green*)

# 5 Combining attributes and modalities

As shown in the previous sections, various information can be extracted from the input flow: for instance, up to seven attributes were used in the *CycloStar* technique. Taking into account multiple attributes provides a powerful means to increase the expressivity of gestures, not only for controlling the parameters of a command, as in *CycloStar* or *Control menus*, but also for increasing the number of commands a gesture menu can support. This idea was already used in the *Flower menu* technique, which relies on using both the *direction* and the *curvature* of gestures. In a similar fashion, Zhao proposed the *ZoneMenu* technique [Zhao06], which relies on using both the *position* (for detecting a zone in the screen), then the *direction* of a straight gesture that depends on this position.

In this section we describe two techniques that leverage combinations of gesture attributes and another modality. *BezelTap* combines bump and taps detection, or bumps, taps and straight gestures. *MarkPark* leverage the *position*, the *direction* and the *length* of straight gestures and also makes use of a supplemental modality (tactile feedback). In addition, both techniques rely on bezel gestures and do not conflict with standard interactions.

## 5.1 BezelTap menus

This study (developed by Marcos Serrano with the help of Yves Guiard) introduced a new type of hybrid gestures, called *BezelTap* gestures [Serrano13], which allows performing micro-interactions[7] [Ashbrook09, Ashbrook11] on mobile devices. As noted above, a limitation of mobile devices is that they provide little support for quick commands because they lack keyboard shortcuts. This problem is exacerbated when they are used to control other devices (TV and multimedia devices, home equipment, etc.) because mobile devices constantly switch to sleep mode to save energy. Interaction is thus hampered by the need to reactivate them whenever they have gone to sleep, typically by pressing a physical button and sliding a widget on the screen. In addition, the user must then select the proper application and the proper command.

While gestural shortcuts can offer a solution to the first problem (activating an application and a command), they provide no help for solving the second problem (reactivating the device quickly). This technique provides a way of triggering all necessary actions by performing a single gesture. Instead of relying on gestures only, it uses a combination of input modalities. Hence, *BezelTap gestures* consist of two input events in close succession: a tap on the bezel of the device (i.e. a bump), which is detected by the accelerometer, and a tap (or two taps or a sliding gesture, as explained later) on the touch screen. This technique requires little visual attention and can even be operated eyes-free.

While the idea of using the bezel was proposed in previous studies for activating commands [Hinckley10, Bragdon11] and opening menus [Hinckley11, Jain12], BezelTap gestures offer several additional advantages. First, they do not interfere with common interaction techniques (including Bezel gestures), because they rely on a supplementary input resource (a tap on the bezel). Second, this tap enables waking up the device just in time to make it possible to detect the gesture on the touch screen. The accelerometer must thus be running constantly, which is not a problem as such devices consume low energy (or very low energy, e.g. accelerometers used in biofeedback devices such as the *Fitbit* wristband).

[7] “interactions with a device that take less than four seconds to initiate and complete” [Ashbrook09]

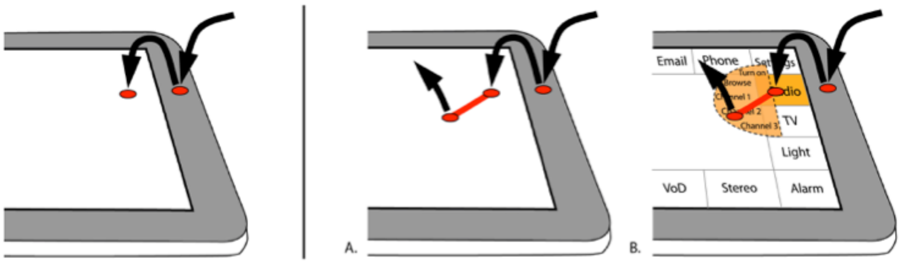



Figure 20: BezelTap gestures

A first study showed that there was very little risk of an accidental activation of the technique, a problem that would have impaired its usability. A second study (12 participants) evaluated the performance of basic BezelTap gestures (one tap on the bezel, one tap on the screen) in terms of speed and precision. The second tap had to take place on an item of a menu bar adjacent to the bezel. The menu bar either contained 4, 5, 6 or 7 items and was located either on the top, bottom, left or right side of the device.

The *position* of the second tap (on the screen) is used to determine which item is selected. The first tap (on the bezel) is generally performed close to the first tap, as this reduces distance, but its position is (mostly) unknown because it is detected by the accelerometers (two accelerometers are used to ensure perfect tap detection on all sides). The technique was tested in expert mode, meaning that the menu bar was not displayed (the screen of the tablet was completely black). A Samsung Galaxy Tab 10.1 tablet was used for the experiment.

Selection time is reasonably short (about 1.5s), which makes this technique appropriate for micro-interactions. The number of items has little or no influence on selection time but impacts accuracy (about 96.5% for 4 or 5 items and 90.5% for 6 or 7 items, see Figure 21). There is no consistent effect of the location (although left and right menu bars are smaller due to the aspect ratio of the tablet) and no consistent interaction between the number of items and the location. This experiment suggests that an odd number of items is preferable and that 5 items seems to be an optimal size on a tablet.

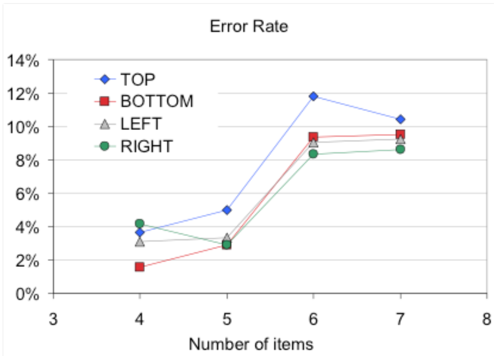



Figure 21: Error rates for 4, 5, 6 and 7 items

A last study (12 participants) evaluated two variants of the technique relying on menus for increasing the number of available commands (Figure 22). The first variant, BezelTap3 (BT3) involves three taps: one tap on the bezel and two taps on the screen. The second tap selects a semi-circular menu containing 5 items and the third tap an item in this menu (except for items located in the corners, which directly trigger a command to make the technique easier). The second variant, BezelTap Slide (BTSlide), is similar except that the two last taps are replaced by a sliding gesture. The starting *position* and the *direction* of the gesture are used simultaneously to select the menu and the item in this menu respectively.

Both variants can support up to 64 items (Figure 22): 4 items in the corners + 60 menu items (4 sides x 5-2=3 menus x 5 items). They were compared with an extension of *Bezel Gestures* [Bragdon11] that allowed selecting the same number of items. While all techniques support a novice mode (using a delay as with Marking menus) they were tested in expert mode (black screen). BezelTap gestures (BT3 and BTSlide) are more accurate than Bezel Gestures (resp. error rates: 5.2%, 4.5% and 8.7%) but slower (about 1.6s vs. 1.12s for Bezel Gestures). However, as mentioned above, BezelTap gestures do not require additional interactions to reactivate the device.

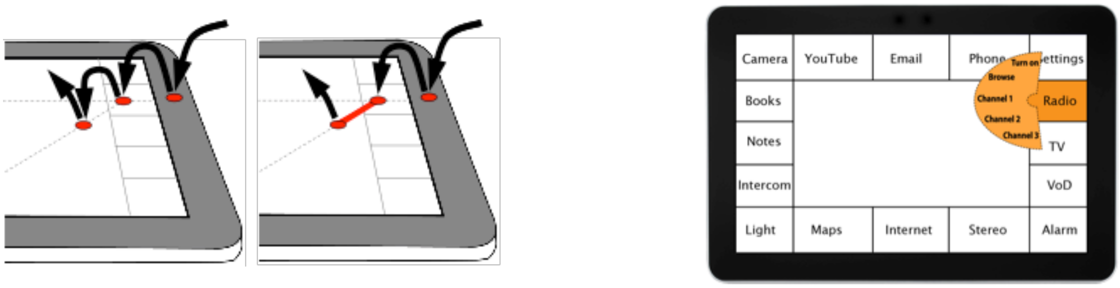



**Figure 22: BezelTap menus (BezelTap3 and BTSlide)**

Considering Ashbrook's definition of micro-interactions [Ashbrook09], this technique thus seems appropriate for this usage, especially in cases where a mobile device serves to control other equipment, as for instance a multimedia or a smart home system.

## 5.2 MarkPad

*MarkPad* [Fruchard17] was developed by Bruno Fruchard during his PhD thesis (co-directed by Olivier Chapuis). As noted in the introduction, MarkPad allows creating a very large number of gestural shortcuts that the user can spatially organize as desired. Our initial goal was twofold: (1) explore the limit of gestural techniques using straight gestures, (2) offer a maximum of flexibility to the user for organizing gestures (and commands) in his personal workspace. The touchpad[8] of a laptop was used in this study but the technique has also been adapted, with some modifications, to mobile device touchscreens.

As noted above, straight gestures offer the double advantage of being especially fast and easy to perform. Curvature or complex shapes reduce speed [Bailly08, Cao09] and may also involve making more errors. However, the expressivity of straight gestures is limited if just using their *direction*. A first solution consists in taking into account both their *position* and their *direction* as in ZoneMenus, Bezel menus or BezelTap [Zhao06, Bragdon11, Serrano13]. Using bezels provides two advantages compared to ZoneMenus: 1) the number of zones that can safely be used is larger because the bezel (and its corners) provides visual and tactile feedback (e.g. at least 4 sides x 5 zones on a tablet with no indications on the screen [Serrano13]); 2) bezel-gestures do not conflict with ordinary pointing or dragging operations which are started outside the border area.

**Straight gesture expressivity, visual and tactile marks**

Nonetheless, the number of possible gestures remains relatively limited (e.g. 64 in BezelTap). More radical solutions are thus needed to significantly increase expressivity. We therefore explored the last attribute that characterizes a straight-line stroke, its *length*. As explained below, this solution considerably increases the number of possible gestures (680 in our experiments). However, as stated by Kurtenbach and other authors [Kurtenbach93, Zhao06, Nancel08], length is difficult for people to

[8] We also considered using the touchpad for performing commands in a previous study [Berthellemy15]

precisely control, especially without visual feedback, and this is why Marking menus are *scale-independent*.

We investigated a simple solution that consists in using *visual* or (passive) *tactile* marks for guiding the user (Figure 23, left and center). Such marks only involve small modifications that do not require specific skills and cheap materials can be used (e.g. plastic sheets, paper stickers, adhesive tape, marker paint). Visual marks can consist of small unobtrusive landmarks. Tactile marks can be almost invisible, for example by using transparent adhesive tape directly stuck onto the touchpad. Moreover, tactile marks enable "eyes-free" interaction, in the sense that the user may not need to look at the touchpad for performing gestures. Previous studies have shown that physical buttons, the bezel or the device border could help users to interact with a smartphone [Bragdon11] or with the back of a mobile device [Corsten 14].

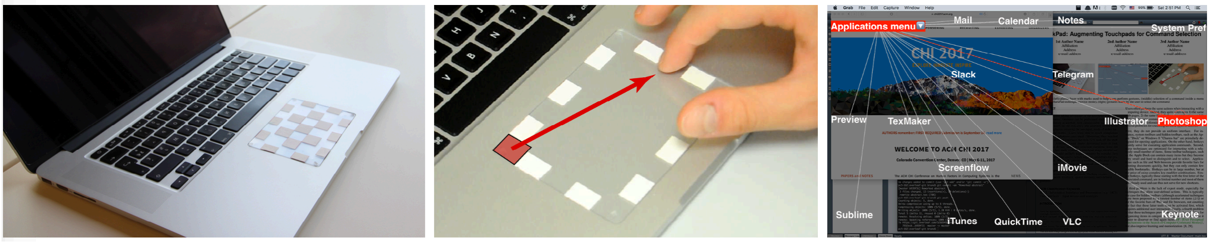



**Figure 23: Two examples of tactile marks and MarkPad novice mode**

### MarkPad gestures and menus

A MarkPad gesture consists in a straight line starting from a (rectangular) zone located in the touchpad border and ending in any other (rectangular) zone, including a zone in the border. A gesture is thus defined by two X,Y *positions* (and a X,Y tolerance), or, roughly equivalently, by a *position*, a *direction* and a *length*. All zones can be predefined or customized by the user according to his preferences (an integrated editing tool is provided for this purpose). A zone typically corresponds to the presence (or the absence) of a tactile or visual mark, but the user can choose not to put marks in certain areas (Figure 23, center). A starting zone corresponds to a menu that includes all the gestures starting from this zone. The technique also supports 2-level menus (thus, compound gestures), in which case the starting zones of the submenus can be located anywhere on the touchpad.

The novice mode is triggered by touching a menu zone (i.e. its starting zone) with a certain delay (e.g. 0.5s). The corresponding menu appears in transparency over the current applications on the computer screen (Figure 23, right). Pressing a predefined key combination (e.g. Fn-Ctrl) displays all menu zones, but does not open the menus. Touching/releasing a menu zone then opens/closes this menu. This feature allows quickly previsualizing menus. Once a menu is displayed on the screen, the user can switch to the editing mode and change its content by pressing another predefined key (e.g. Shift).

### Performance experiments

The goal of these experiments was to assess the feasibility of the technique when using *visual* or *tactile* marks. We considered an extreme case (680 possible gestures) in order to test the limits of the technique. Because, marks (especially *tactile* marks) may make the interaction less pleasant for pointing or dragging tasks, we considered also cases where marks were only present on the border area of the touchpad. We thus considered six different cases:

1. No marks (Exp. 2)
2. Visual marks everywhere (Exp. 1)
3. Tactile marks everywhere (Exp. 1 and 2)
4. Tactile marks on the borders, visual marks elsewhere (Exp. 1)

5. Tactile marks on the borders, no marks elsewhere (Exp. 2)
6. Visual marks on the borders, no marks elsewhere (Exp. 2)

Because not all conditions could be performed in a single experiment, we conducted two experiments (Exp.1 and Exp. 2) with different participants. Condition 3 (Tactile marks everywhere) was performed in both experiments. As all 680 gestures could not be tested, we chose a representative subset of 42 gestures (Figure 24, left; details in [Fruchard17]). A grid of 7 × 5 = 35 zones was used for both experiments. Twenty of them were in the border area (7 x 2 + 5 x 2 - 4) and used as starting zones. Therefore, the total possible number of MarkPad gestures was 20 × (35-1) = 680. Compound gestures (2-level menus) were not tested in this experiment. Results show that accuracy is:

- Insufficient (less than 72%) without marks (Condition 1).
- Sufficient (about 95%) with marks everywhere, whatever their type (Conditions 2, 3 and 4).
- Acceptable (about 90%) with marks only on the borders (Conditions 5 and 6).

Contrary to our expectations, the type of marks had very little or no impact on accuracy (no significant difference between Conditions 2, 3, 4 and between Conditions 5, 6). However participants seemed to slightly prefer *tactile* marks and they spend slightly more time looking at the touchpad with *visual* marks (but this did not affected the total task duration). In fact, *tactile* marks may require longer training time (thus more user confidence) to demonstrate their potential.

Task duration, which is approximately 2s in all cases (execution time about 1s), is in line with other techniques supporting a large (although lower) number of commands (e.g. 3 × 8 hierarchical Marking menus, 6 × 16 Zones or Polygons menus). Note however that time performance is likely to depend on the number of gestures. For instance, Bezel menus, which can roughly be seen as a special case of MarkPad menus with large areas, provide an execution time of 382ms for trained users [Jain12].

These experiments show that quite a large (and in fact unrealistic) number of gestures can be performed with sufficient accuracy when using either *tactile* or *visual* marks. They also suggest that the technique can work properly with marks only on the border provided that larger zones are used elsewhere. Another possibility would be to use dynamic *tactile* marks that are activated after the user initiates a gesture from the borders, by using technologies that provide tactile feedback in real time [Bau10, Casier11]. Finally, *visual* marks could be displayed on computers equipped with a "screenpad" as the Asus Zenbook 15 Pro (Figure 24, right). This could also enable making marks more informative, thus helping the interaction.

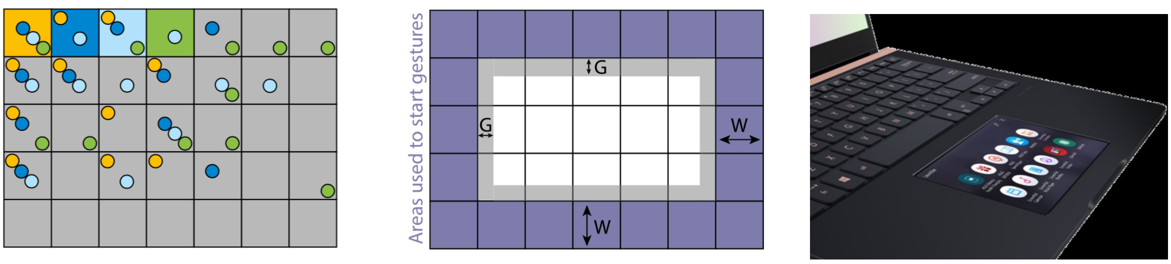



Figure 24: Evaluated gestures (left), Gesture detection (center), Screenpad (right)

**Unintentional activations**

Because MarkPad relies on gestures starting from the touchpad border, it uses the touchpad as an *absolute* pointing device (using its internal API). The touchpad is thus both used as an absolute device (for MarkPad) and a relative device (for other interactions). Hence, MarkPad does not conflict with interaction techniques such as active borders or hidden toolbars (or methods improving them

[Schramm16]) that trigger commands or display menus when the mouse cursor reaches the corners or the borders of the screen.

However, MarkPad gestures would conflict with ordinary gestures starting from the border area of the touchpad. Our assumption is twofold: 1) users will avoid willingly touching this area when using the technique, 2) they rarely touch the border area involuntarily [Malacria16], especially on now common large touchpads. We conducted a study to verify this hypothesis. We logged the gestures of 12 Macbook participants (unaware of the MarkPad technique) using their own computer during one week. A "gesture" consisted of any sequence of events between a touch and a lift event.

We then analyzed this data by considering a combination of constraints. A gesture was identified as a MarkPad gesture (Figure 24, center) if it 1) started in the border area ($W$ constraint), 2) was longer than $L$, 3) ended sufficiently far from the border area ($G$ constraint). Results are provided for various values of these constraints in [Fruchard17]. For instance, the detection rates were, respectively, 0.22%, 0.61%, 1.54% for $W = \{1, 5, 10\text{mm}\}$, with $L = 5$mm and $G = 10$mm.

In practice, $W$ can be as small as 3mm without causing possible misdetections because of a too small border size. Moreover, a valid MarkPad gesture must end in a given zone, not just somewhere outside the border as in this study. This means that, with a reasonable number of zones that are properly located (as explained below), the number of involuntary activations can be quite low.

**Actual use**

The MarkPad prototype, which runs on MacOSX, has been used for about two years by two of the authors (here called "expert users"). A preliminary longitudinal study of 1 to 2 months has also been performed with six participants (3 students in ergonomics, 2 students in HCI, 1 researcher in HCI). The two expert users used tactile marks only on the border of the touchpad. The six participants used a simplified version without marks and had regular meetings with an ergonomics researcher about every two weeks to understand how they used the system, and to help them if needed. They were provided with an initial configuration with 5 menus that they then modified according to their needs.

At the end of the study, four participants used 5 menus (except one, 4 menus) and between 12 to 36 gestures (mean 23). Unfortunately, the last two participants experienced problems because of an erroneous initial menu configuration, and thus used only 11 and 6 gestures. All participants customized their menu configurations, both for changing the menu layout and for specifying their own favorite actions. They used an average of 17.8 different gestures and were able to perform 88% of them in expert mode, meaning that they could easily learn and remember gestures.

In comparison, the two expert users use up to 10 menus and more than 100 gestures. One of them uses about half of them in expert mode. However these results cannot be directly compared because, contrary to the expert users, the participants did not use the technique with marks. The technique can thus efficiently work without marks, but at the cost of a much smaller number of gestures, as already suggested by the previous experiments.

Most of the actions were used by the participants for opening user-defined Web pages (33%), favorite applications (27%), or for zooming in and out the current application window (18.5%). One user connected MarkPad with another application that allows performing complex combinations of commands. Thus, in most cases, participants did not use MarkPad for performing application commands but actions that have no hotkey equivalent (except for zooming but this command requires a three key combination).

Most participants liked the fact that they could group arbitrary actions according to their needs. For instance one participant created a "PhD" menu. Another participant organized his gestures as if they belonged to cascaded menu (although 2-level menus were not yet available). The two expert users also created groups that were either related to their different activities or other sorts of thematic relationships. While both used a large number of gestures, the associated actions and the way they grouped them were quite different and user-specific.

Unintentional activations were the main problem faced by the participants when they started using the technique (especially the two already mentioned participants). This is because, the menu (i.e. starting) zones must be located according to the hand movement of the user. Thus, for right-handed users, the left side of the touchpad is "safe", but the right side is not. Similarly, the bottom side is "safe" for most users but not the top side because they may involuntary touch it when using the keyboard. The pattern is opposite for some other users because their palm heel tends to touch the bottom of the touchpad. These interesting differences would merit a dedicated study to understand how users place their hands and their fingers when interacting with a laptop. Anyway, for all of our 8 users, two sides of the touchpad were safe while the two others needed to be used with care (e.g. only for gestures parallel to the bezel side or ending sufficiently far from it). Provided that these rules are followed, involuntary activations then become negligible.

In summary, MarkPad can be used in various ways: with marks it can provide a large number of gestures for expert users, without marks if can still be used efficiently for activating a smaller set of actions. Participants used most gestures in expert mode, which suggests that the technique helps learning and remembering them, presumably because it flattens the hierarchy of commands and leverages spatial memory [Scarr12, Gutwin14]. By enabling users to group arbitrary actions according to their own needs, it provides an alternate way for interacting with computing devices, which leverage semantic relationships instead of forcing users to rely on functional categories. Finally, it is worth noticing that *PageFlip*, a technique that relies on corner-command mappings has been recently proposed for interacting with a smartwatch [Han18]. *PageFlip* gestures also take into account the angle and the distance, which shows that this approach can be effective even with very small surfaces.

# 6 Three dimensional and body gestures

Taking advantage of the popularization of gyroscopic sensors and vision-based technologies such as the Kinect, I contributed to several studies devoted to the use of 3D gestures. These studies took place in the context of Gilles Bailly's postdoctoral fellowship and of the theses of Dong Bach Vo and Mathias Baglioni (which were both co-supervised by Yves Guiard). These studies focused on two different application frameworks: mobile device augmentation and remote interaction with an interactive display. Before describing them, I present some general considerations about the types of 3D gestures, input delimiters, 2D interaction and body-relative gestures.

*Different types of 3D gestures* can be considered depending on their interaction dimensions. Cockburn et al. [Cockburn11] proposed a framework for air pointing interactions with five dimensions: the reference frame for the air pointing technique, the scale of input control, the input degrees of freedom, the feedback modality, and the feedback content. Considering the reference frame, this framework distinguished between spatial locations that are absolute (i.e. relative to the *world*), relative to an external *object*, relative to the *body*, relative to the *device*, or hybrid combinations.

This classification can also be applied to non-pointing gestures. For instance, when performing directional gestures with a gyroscopic device (e.g. a smartphone or a remote control), these gestures are relative to the *world*. However, when performing the same kind of gestures with a Wii Remote or a

Kinect to control a TV set, they are rather relative to this external *object* as the device (or the arm) may have to point towards the vision sensor to ensure proper detection.

It is important to remark that *gestures with a device* (i.e., by rotating or translating it) are not relative to the *device*, but to the *world* or to an external *object*. Gesture that are actually *relative to the device* can be performed *on* the device (2D interaction) or *around* the device (3D interaction). In the first case, the interaction can take place on the touch screen, on the back of the device [Baudisch09], on its sides, etc. In the context of on-body interaction, body parts such as the arm can play the role of a "*device*" that serves as a sensitive surface [Harrison10, Xiao18] for the other arm.

*3D gestures and delimiters.* A major obstacle with 3D gestures is that they are generally indistinguishable from everyday motions [Ruiz11a]. An input *delimiter* is thus needed to avoid false positives. This delimiter can be a specific gesture such as, for instance, tense positions of the hand [Baudel93], opening or closing the hand [Bailly12] or a *DoubleFlip* gesture [Ruiz11a]. In this context, we developed *JerkTilts*, a technique that provides *self-delimited gestures*, which is presented below.

*2D gestures is not 2-dimensional*. In contrast, 2D gestures do not (necessarily) require delimiters because the third, "unused" dimension serves to detect whether the user wants to interact. In fact, 2D devices such as a mouse or a touch screen leverage all three possible translations, the one perpendicular to the surface being used to activate the device (by touching the screen or pressing the mouse button). Strictly speaking, there is thus no such thing as a '2D interaction': while 2 DoF devices capture a 2D signal, they require 3D movement. Hence, following a terminology used in the graphics domain, *2D½ interaction* may be a more appropriate name.

*Body-relative gestures* can involve some subtle problems, as will be illustrated below in a study that investigates gestures on the belly. Such gestures are susceptible to ambiguity and symmetry problems may arise since the user can interpret the information in a mirrored way.

## 6.1 JerkTilt self-delimited gestures

*JerkTilt* gestures [Baglioni11] were developed by Mathias Baglioni during his PhD thesis. The purpose of this study was to provide fast gestural 3D shortcuts for the smartphone. As explained above, a major problem of such gestures is that they require a delimiter because they are often indistinguishable from everyday motions. But using delimiters complicates interactions and slows them down. In an attempt to solve this problem, we investigated whether certain gestures could have a signature that would allow to distinguish them from ordinary movements. This study on *self-delimited gestures* led to the development of the JerkTilt technique.

JerkTilt gestures are quick back-and-forth tilting gestures that combine device pitch and roll. Because these gestures consist of abrupt back-and-forth movements they have a very specific kinematic signature so that inadvertent activations are unlikely. Using rotations also has practical advantages when using a mobile device such as a smartphone. Device translations are often impractical in public situations, but a rotation of the device about itself requires minimal space. Moreover, provided that angular amplitudes are moderate, the screen of a rotating device may remain visible for users, enabling them to receive output information. Using tilt gestures also has the advantage that they can be performed one-handedly. This is an important factor in the context of mobility since the second hand is often reserved for an alternate use (carrying a bag, holding the subway handrail, etc.) Finally, JerkTilt gestures can be performed eyes-free.


**Figure 25: JerkTilt back-and-forth tilting gestures**

One important characteristic of a JerkTilt gesture is that it consists of one complete cycle of to-and-fro movement (Figure 25, right): the device is tilted in a certain direction and immediately brought back to its initial rest position thanks to the natural elasticity of the wrist. The return phase of such movements is quite automatic, the mechanical energy stored as elastic potential energy in the antagonist muscles of the forearm during the initial tilt being converted back into kinetic energy during the return to rest [Guiard93]. Hence, the execution of this sort of movement should take little time and cost little effort.

As eight-item angular selections were shown to be easily differentiated in Marking menus, we chose the same number of different directions. A first experiment (12 participants) asked about the discriminability of tilting directions. A KNN recognizer [KNN] was used for this purpose. The kinematics attributes used by the recognizer are detailed in [Baglioni11]. The accuracy was sufficiently high (95% or more, depending on conditions).

In a second experiment (12 participants) we compared, on an eyes-free task, the performance of JerkTilt and Marking menus. In both cases, participants were interacting using only one hand (and the thumb in the latter case). Performance accuracy was similar (91.0% vs. 92.6%). JerkTilt gestures required about 30% more time, but unlike Marking gestures they do not conflict with standard pointing gestures.

Finally, a last experiment evaluated the workability of JerkTilt in the context of real-life mobility. For this purpose, we developed a logging system for evaluating whether accidental accelerations of the device could lead to false identifications of JerkTilt gestures. On average we found less than one false detection a day per user (14 participants), which suggests that JerkTilt gestures are suitable for everyday use. Several applications were developed (copy and paste, music control, application switcher, etc.) to illustrate the utility of the technique (Figure 25, left).


**Figure 26: TimeTilt lenticular metaphor**

In addition, we also investigated the use of smooth gestures for switching between multiple windows on a mobile device. This technique, called *TimeTilt* [Roudaut09c], relies on a lenticular metaphor that enables the user to see different images depending on the orientation (as with certain gift postcards, see Figure 26).

## 6.2 Controlling a remote display

We conducted two studies on this topic, in the context of smart TV control. Because remote controls with many buttons tend to be confusing, we investigated whether gestures could make this task easier. The first study considered how a basic gyroscopic remote control could be used for this purpose. The second study relied on "in the air" gestures inspired by the *FingerCount* technique.

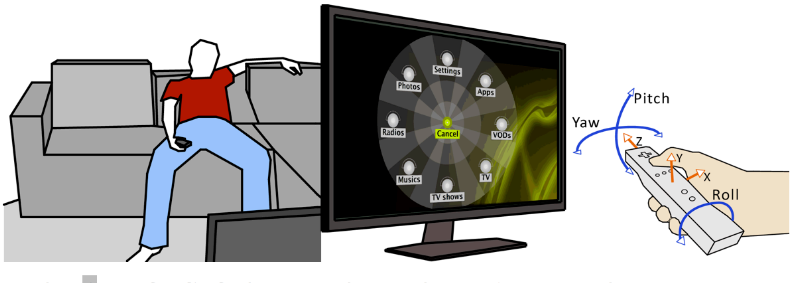



Figure 27: Controlling a TV set with a gyroscopic remote control

In the first study [Bailly11a], we considered the case of a remote control with a very limited number of buttons (a Wii Remote). The goal of this study was to investigate which gestures users would prefer to perform and if this would allow sufficient expressivity for controlling a complex system. A first experiment showed that users favored rotational gestures in this context.

A second experiment showed that participants could accurately select (more than 95%) up to 5 items with eyes-free rolling gestures. This result contrasts with the study of Rahman et al. [Rahman09] where users were able to select 16 items by rolling a smartphone. But a major difference was that in their study, visual feedback was provided, whereas in our experiment, this was not the case. We chose this setup based on our assumption that when users are interacting with a remote display, they would probably prefer not to continuously have to switch between their main focus of interest, the remote display, and the tool for controlling it.

Finally, this study evaluated the combination of two input techniques among (four) directional buttons, pitch+yaw and rolling gestures. Button/button and button/pitch+yaw gestures where slightly faster and more accurate than button/roll and pitch+yaw/pitch+yaw gestures.

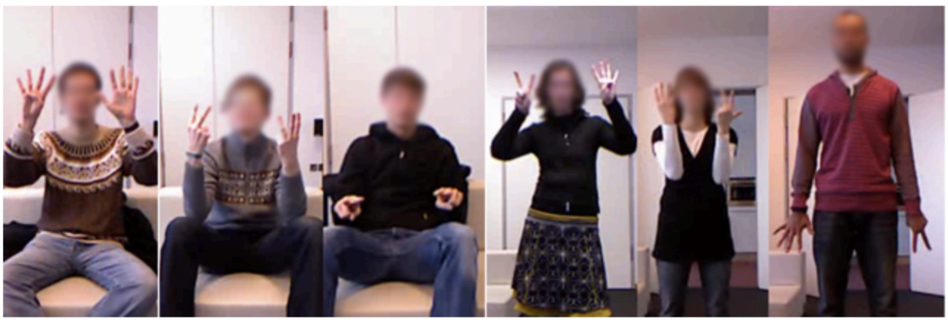


Figure 28: In-the-air FingerCount gestures

In the second study [Bailly11b, Bailly12], the *FingerCount* technique (see Section 3.1) was adapted to free-hand interaction. A Kinect device was used and the user performed selections by exhibiting the appropriate number of fingers of the non-dominant hand to select a menu and of the other hand to select an item in this menu. This technique was compared with linear menus and Marking menus. Results showed that in-the-air FingerCount was as fast and accurate as the other two techniques.

Interestingly, while FingerCount and its in-the-air counterpart share the same concept, in practice, users did not use the same fingers in both cases [Bailly12]. Moreover, they were not aware of which fingers they used. Unsurprisingly, in-the-air FingerCount gestures involved more physiological and cognitive limitations than when touching a screen, which makes them appropriate for the considered use case (smart TV control), but not for intensive tasks.

## 6.3 On-body gestures

On-body interaction has several advantages: (1) body parts are by essence always available, (2) they offer a convenient surface for gestural interaction, and (3) they provide tactile feedback, not only from the body part acting as an interactive surface but also from the limb which is interacting with it [Serino10]. Moreover, because of proprioception, users can sense the position and the orientation of their limbs without looking at them, meaning that they can interact eyes-free [Lin11].

On-body gestures can thus ease interaction in usage contexts where users are engaged in activities that would suffer from interruptions. For example, users devote a large part of their attention to avoid obstacles when they are walking or running. Such situations make it difficult to interact with mobile devices, especially if the user must look at them, and thus lead to undesired interruptions.

Various efforts have been devoted to exploring new ways to capture on-body touch (e.g. [Harrisson10, Nakatsuma11, Zhang16, Xiao18]). The forearm is generally considered as particularly appropriate [Lin11] as it is easy to access, but some studies investigated using other body parts as an input surface to trigger actions [Angeslevä03, Guerreiro08, Wagner13] or to store information [Chen12]. In particular, interactions on the shoulders, ribs, and hips were evaluated positively [Karrer11, Wagner13]. In addition, natural (e.g. knuckles or birthmarks [Bergstrom17]) or artificial [Weigel15, Weigel17] landmarks can be exploited to enhance the recall of items.

In a study conducted during the PhD thesis of Dong-Bach Vo, we investigated how belly interaction can serve to facilitate interaction [Vo14]. While [Wagner13] reported that the abdomen should be suitable for interacting, no exploratory study had been conducted so far. The abdomen surface has several interesting advantages in comparison to other body areas: it offers a large and relatively stable area (even when walking and running), enables easy access from both hands and does not require tiring movements because hands do no need to be moved far from their rest position. The abdomen seems especially appropriate for interacting while moving because its surface is remarkably stable. As noticed in [Karrer11], with a range of motion between 2 to 17.5° across all planes during gait, this part of the body is particularly well suited for interacting while walking or running. It should also be less prone to interpersonal or accidental touch compared to other body parts such as the arms.

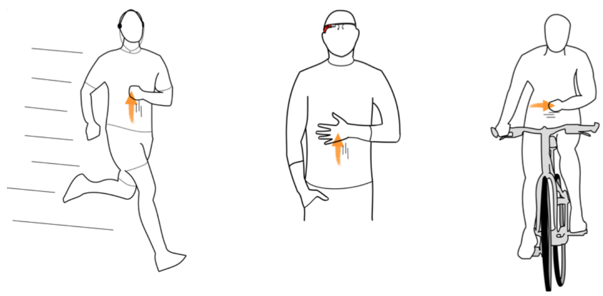


Figure 29: Belly gestures

Contrary to usual vertical interactive surfaces the belly is not located in the user's field of view but in the body mid-coronal plane. Because of this spatial configuration, proprioceptive information from the hands, arms and their contacts with the abdomen are essential to interact with the belly. However, as noticed in [Cockburn11], gestures relative to body locations are susceptible to ambiguity and it is unclear to which extent the abdomen's spatial configuration might influence the users' spatial mental representation, especially when interacting eyes-free.

We thus conducted an experiment to investigate how users perceive their belly as an interactive surface. The nature of the stimulus was either a *directional stroke* or a *digit* in the (0-9) interval, which was displayed on a screen in front of the participant. Moreover, the stimulus was shown either as a *graphical* representation (with a starting point and a direction to draw) or as a *textual* representation (without hints relative to the orientation).

Inversions relative to the *horizontal* axis gathered 17.5% of all samples across all conditions. Inversions were more frequent for *digits* (resp. 19% and 24.5% for *graphical* and *textual* presentations) than for *directional strokes* (about 13%). This result somewhat contrasts with previous results in psychology literature that suggest that spatial representation of up/down direction is relative to the perception of gravity and through sight [Mergner98]. In fact, some participants reported performing gestures while picturing themselves watching their abdomen.

There were fewer inversions relative to the vertical axis (13.5%), and almost all of them occurred when *digits* were shown *textually* (42.9%). Some participants emphasized the difficulty to select a unique representation and changed their spatial mental representation during the experiment. Unsurprisingly, reaction time was significantly longer for *digits* than for *strokes* (about 27%).

This study highlights that simple gestures should be preferred, as mental representations are more likely to change with more complex gestures such as digits. Moreover, performing digit gestures was cognitively more demanding. We also analyzed directional gesture traces and found that they were fast and efficiently done.

Finally, this study addresses the question of social acceptance [Rico10, Ahlström14]. The appearance of gestures are influencing social acceptance in public spaces and familiar gestures should thus be more socially acceptable in this context. Belly gestures fall into two categories. Digits require space and relatively large movements of the arm, which are noticeable in public spaces. These gestures are thus more suited for private spaces such as the living room. Conversely, directional gestures only require simple and small movements and should hence be usable in public spaces. They are as fast as scratching the belly since only a direction has to be determined. This makes them hardly noticeable especially when used as command shortcuts.

In addition, in a more recent study [Fruchard18], we compared an on-body interaction technique named *BodyLoci* to mid-air Marking menus in a Virtual Reality context. As this study focuses on command memorization, we will present it in Section 7.5.

## 6.4 Head gestures

In the physical world, humans use head and eyes movements to control what they see, and limbs movements to manipulate objects. In contrast, interactive systems generally require using the mouse or the keyboard to manipulate the viewpoint. The same modality (hand gestures) is thus used to both control what users see and to manipulate it. As a result, when a task requires frequent changes of the point of view, the user must continuously switch between his main task, which is his actual focus of interest, and the manipulation of the viewpoint.

In a study [Jacob16] performed during the PhD of Thibaut Jacob (co-supervised by Gilles Bailly) in cooperation with Gery Casiez, we investigated the use of head movements as an additional input channel to control the viewpoint. This study took place in the context of the development of a 3D sound editor. In such a situation the user must draw a large number of overlapping curves in the 3D space, so that the representation can quickly become confusing. In many cases, quickly and temporarily changing the viewpoint permits to disambiguate the view. But this comes at the cost of many manipulations, which made the proposed solution especially appropriate.

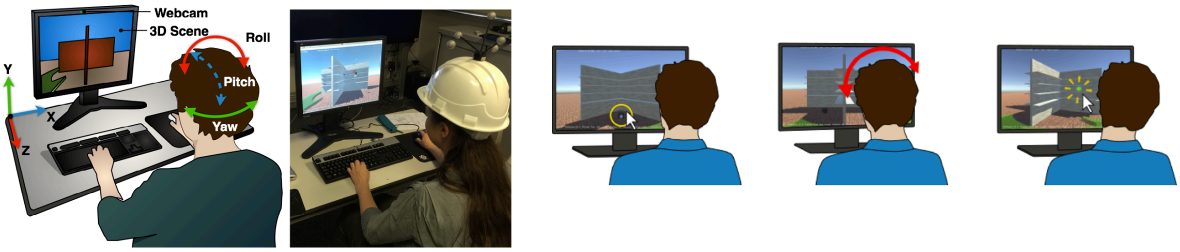



Figure 30: Head yaw/roll rotations (left) and experimental task (right)

In several studies, head movement has been used to improve the feeling of immersion in Virtual Reality environments [Cruz-Neira93, Qi06]. But this approach has seldom been investigated for desktop workstations [Harrison08], although such an approach can be implemented at little cost as many computers have an integrated webcam. In this study, we investigated how to best define head-camera couplings to favor both comfort and efficiency [Bowman04]. We focused on orbital control because this type of camera motion is frequently used in 3D software (Blender, SketchUp), especially in 3D room-planning applications (e.g. IKEA Home Planner). We focused on screen desktop environments because they are still the most used for 3D editing.

We first investigated the widest angles at which users can rotate the head on *yaw* and *roll* axes while maintaining a high level of physical and visual comfort. Results show that, when taking into account both criteria (using a desktop workstation), larger head angles can be performed for *roll* ($35^{\circ}$) than for *yaw* ($26^{\circ}$). A second study showed a useful resolution (the smallest movements that can be intentionally executed by users [Aceituno13]) of $1^{\circ}$ could be achieved at a 95% success rate for both head *yaw* and *roll*. We then designed a transfer function for controlling orbital camera motion with the head, either using *roll* or *yaw* rotations. An evaluation showed that participants performed better using *roll* and preferred it to *yaw*.

Finally, an experiment (10 participants; Figure 30, right) comparing head *roll* rotations with a well-known standard technique (using the *mouse* and the *keyboard* as in the Blender application) showed that *roll* rotations were (significantly) 14.5% faster. In a post-experiment where participants were free to use either technique or a combination of them. Most participants (8 out of 10) chose to combine *roll* rotations with either the *mouse* (2/10) or the *keyboard* (6/10) and the total time was lower than in the previous *roll* vs. *mouse/keyboard* experiment.

In summary, head roll is an efficient input modality for head-camera coupling and participants are faster and more accurate with roll head movements and prefer them when interacting with a screen. Moreover, users liked combining different techniques because they offer complementary advantages. For instance some participants used the keyboard for performing large imprecise rotations and the head for precise adjustments, while others used both simultaneously to perform even faster.

# 7 Gesture memorization

As advocated in the introduction, providing mechanisms for better ways of learning and memorizing gesture/command associations is needed for allowing a large spectrum of useful interactions. The next subsections present several studies considering this topic. These studies focus on the following aspects: the efficiency of directional radial gestures, the automaticity of overlearned gestures, the categorization of gestures and commands, mnemonic devices and the combined use of memory components, and the efficiency of body gestures. Some of these studies suggest that a large number of gestures can be learnt and recalled with little difficulty, provided that certain conditions are met.

## 7.1 Directional radial gestures

Rather than inciting users to invent new gestures that evoke their associated functions, as in the user-defined gestures approach, *Marking menus* are based on the opposite hypothesis: the vocabulary of gestures is simple, "abstract", and defined a priori. When these menus are hierarchical, the gestures can be composed to provide a larger set of gesture/command associations. With expertise, low-level details are performed automatically [Card83] and users develop an ability to perform larger *chunks* [Miller56, Buxton86], which should make compound Marking gestures memory efficient. This can be seen as a syntactic approach where a simple syntax enables creating gesture sequences that are eventually considered as a single entity by the user.

Since their introduction by Kurtenbach, Marking menus have been presented as a technique that "helps users make a smooth transition from novice to expert" [Kurtenbach91]. While this statement makes sense, other factors affect the learning of gestures and gesture/command associations. For instance, user-defined gestures are believed to be easier to memorize [Nacenta13] and techniques that increase the mental effort of interaction tend to increase retention [Ehret02, Cockburn07, Anderson13, Scarr13b, Scarr14] because this effort aids memorization. Moreover, it encourages users to transition to expert mode [Grossman07]. In this section we consider another aspect, which is whether some techniques make it *inherently* easier to learn gesture/command associations. Moreover, we investigate whether using direction (as in Marking menus) or position affects gesture learning.

**Marking and Flower menus**

In the *Flower menu* study [Bailly08a], which was partly presented in Section 3.1, we compared the memory performance of the expert mode of linear menus (i.e. hotkeys) and of the *Flower* and *Polygon menus* techniques. As Flower menus are an extension of Marking menus (Flower gestures with a null curvature are identical to 8-item Marking menu gestures; Figure 4), their performance provides a rough estimate (i.e., a lower baseline) of the performance of Marking menus.

Polygon menus [Zhao06] are a variant of Marking menus that was designed to increase the number of available commands (Figure 31, center). Unlike Marking menu, they do not rely on radial gestures. Instead, users must draw strokes corresponding to edges of an N-sided polygon and the command depends on the direction in which the stroke is drawn. Thus, the breadth of an N-sided Polygon menu is 2N.

We chose these three techniques because 1) linear menus are widely used and thus serve as a baseline, 2) all these techniques support a sufficient number of commands without resorting to multi-level menus. While comparing 2-level Marking menus could be an interesting option, this adds an additional factor, as not all items are simultaneously visible in this case, which might decrease memorization. Moreover, as said above, we found it interesting to compare menus with different designs.

The experiment was performed with 16-item menus, both because the breadth of a Polygon menu is a multiple of 2 and because this size should be sufficient for most applications. An informal analysis of six popular applications [Bailly08] showed that, on average, their first-level menus contained 12.4 items, and that this number was between 10.6 and 14.2 for half of these applications and equal to18 for one of them (Photoshop).

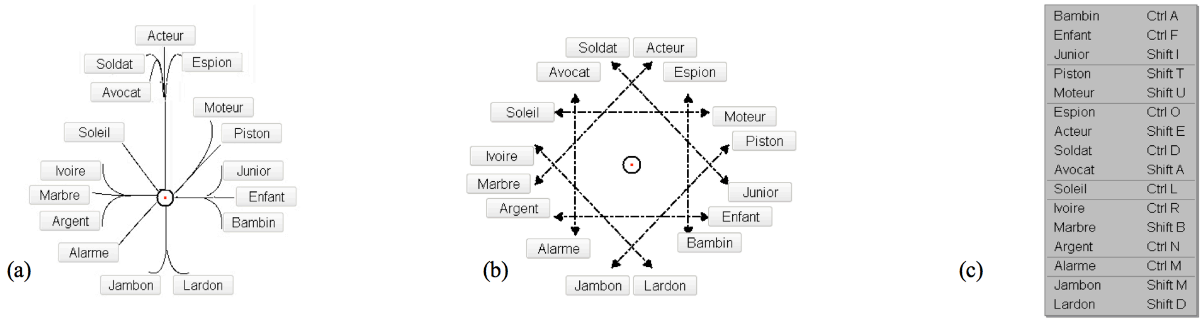



**Figure 31: Flower menus, Polygon menus and Linear menus with hotkeys.**

Contrary to some studies, we did not use a Zipfian distribution, but a uniform target frequency. The first reason is that memorization may depend on various factors, such as the ordering of items in linear menus or their orientation in Marking menus. Results may thus depend on where the most frequent items are laid out in the menu, a factor which is difficult to control. A second reason is that the number of repetitions is considerably smaller in a controlled experiment than in real life. Thus, some items might not be presented sufficiently often to make it possible for the participants to learn them, especially for large vocabularies (conversely, some other items might be presented unnecessarily often). This may "flatten" results compared to what would be obtained in a real situation, or require performing very long experiments. Finally, time experiments are generally performed using a uniform distribution, thus implicitly considering real life situations where the user has been practicing for a long time. It seems reasonable to make the same hypothesis for memory experiments.

The experiment was performed with 18 participants (using a within-subjects design) in a single session with a typical menu configuration (Figure 31, details in [Bailly08a]). The participants were asked to learn as many commands as possible. As expected, this experiment showed that Flower menus provide much better recall performance than linear menus (81% vs. 35% memorized items), but also, more surprisingly, than Polygon menus (40%). Completion time was also significantly shorter for Flower menus than both linear menus and Polygon menus (2.4s vs. 3.5s. vs. 3.8s.). As they do not require performing gestures, we expected hotkeys to be the fastest technique, but reaction time was much longer than for Flower menus (almost twice as long). Flower menus were also the most appreciated technique by all participants except one.

**Conclusions**

The first conclusion of this study is that Flower menus, and consequently Marking menus, are actually efficient for memorizing gesture-command associations. To the best of our knowledge, we are not aware of previous studies that formally compared their memory performance with linear menus.

Another interesting conclusion is that differences in design can lead to large differences in performance. In addition to the fact that the 'learning by repetition' principle may not be sufficient to make a technique memory efficient, it is reasonable to think that there are specific reasons why Marking (and Flower) menus are efficient.

First, radial directional gestures may be especially efficient because of human directional abilities, which may even be innate [Wills10]. Such gestures could be treated as egocentric gestures [Klatzky98], as if the user were moving in space. Moreover, in most cultures, the eight cardinal and intermediate directions (and the clock layout) are learned since childhood. In one of their experiments, Kurtenbach et al. [Kurtenbach93b] already observed that response time and accuracy do not only depend on the menu size, but that certain menu sizes (4, 8 and 12 items) facilitate performance when no menu is displayed, presumably because some layouts are more familiar than others. This phenomenon is likely to also affect memorization.

Incidentally, this also raises the question of whether Marking menus follow the law of the 'Magical Number Seven' of George A. Miller [Miller56]. In this famous article, Miller observed that most of us can identify about seven different values plus or minus two for (most) given dimensions when performing an absolute judgment. Considering that Marking menu items depend on one dimension (their angle), performance should be significantly better with 8 items rather than 12. While this seems to be true for multi-level menus (Figure 3 in Section 2), the difference in performance is more modest for 1-level menus, presumably because of the familiarity of the clock layout.

In the same article, Miller also stated that, for multidimensional judgments, the addition of independently variable attributes increases the channel capacity. This may explain the efficiency of Flower menus as they use a combination of dimensions (direction, curvature, curvature direction relative to the direction of the gesture) that have a small number of values. While this statement is about absolute judgment, not memorization, the ability to recognize values of on one or several dimensions is likely to affect memorization.

More research is needed to confirm these hypotheses. First, it would be interesting to compare Marking and Flower gestures with other types of gestures, as for instance those proposed in [Appert09], for memorizing gesture/command associations. Similarly, Flower menus could be compared with hierarchical Marking menus to investigate the respective advantages of a flat vs. a hierarchical representation. Finally, it would also be worth testing long-time retention, which was not evaluated in this experiment.

**Directions vs. positions**

Fast command selection can indeed rely on gestures, but also on touching/clicking positions when spatially stable arrangements of items are used [Gutwin14, Scarr12]. When items are laid out around a central point, pointing "gestures" are then somewhat similar to directional Marking gestures. We were interested in finding out if and how these techniques affect learning.

In a recent study [Fruchard18b] conducted by Bruno Fruchard (whose PhD thesis is co-supervised by Olivier Chapuis) we compared the effect of using *positions* vs. *directions* on command memorization and studied the strategies that users elaborate. In both cases, participants had to memorize a set of 16 items (out of a total of 32 possible commands), placed hierarchically in menus containing 8 items, for each of these two modalities. The study took place over three sessions. The first and second sessions were composed of learning phases and recall phases (Figure 32). The second session was performed one day later and the third session, which consisted of a single recall phase, one to two weeks later. A within-subject design was used and 16 participants took part in the experiment.

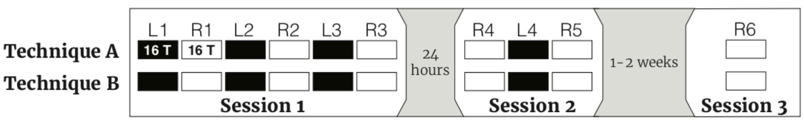



Figure 32: Learning (L) and recall (R) phases in the three sessions

The two techniques both rely on a two-step selection mechanism. The *direction* technique is similar to MultiStroke (aka "Simple") Marking menus [Zhao04] (Figure 33, right). The *position* technique associates each command with a unique position in space as in FastTap [Gutwin14] or in current user interfaces that do not involve transient objects (or that are "flattened" to make them spatially stable as in [Scarr12]). A menu is represented by a rectangular area (Figure 33, left) containing the commands, which are placed close to spatial/graphical cues (the corners and edges of the menu) in order to help memorization [Scarr13b, Uddin17]. To select a command, the participant first selects a menu by clicking within its interaction area, then on the desired item. In both cases, learning phase trials start in expert mode and the user must touch the surface for one second to enter the novice mode and see the labels of the commands. A Samsung Galaxy tablet (13.6×21.8cm) was used.

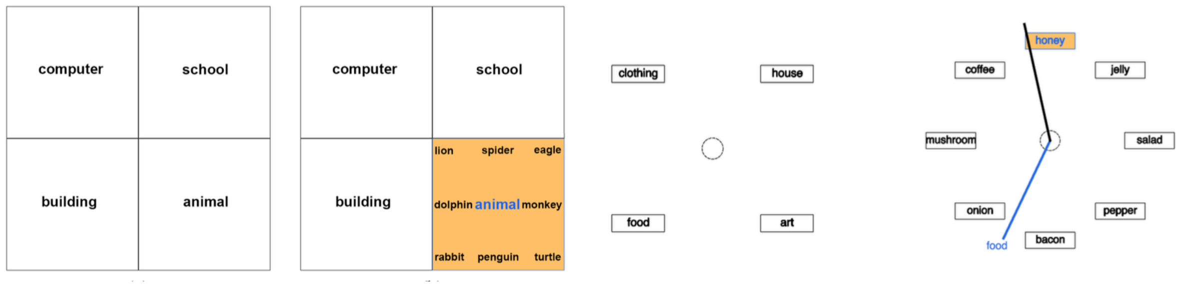



Figure 33: *Positions* and *directions* techniques

The mean values of the recall rates were higher for *positions* (Figure 34, left) but the differences were not significant (p's > 0.1). For instance, at the end of the first session the recall rate was 77.5% for *directions* and 83.3% for *positions*. As expected, recall rates were lower after 24 hours (56.2% vs. 62.1%), but not much lower (53.6% vs. 57.1%) after a period of one to two weeks. These mean values may suggest a possible advantage of *positions*, but this would need to be confirmed with a larger number of participants.

There were also some interesting differences. First, in the learning phases, the participants used the novice mode less often with *positions* than with *directions*. The difference was consistent and significant (L2: 72.5% vs. 83.8% activations; L3: 53.3% vs. 64.2%; L4: 55.8% vs. 66.7%). Moreover, when the participants used the novice mode, this was for a shorter amount of time with *positions* (Figure 34, right). The difference ranged from 1.70s to 1.25s depending on the phase (p's < 0.001). Subjective opinions, gathered in a questionnaire based on the NASA TLX model, also pointed to the same direction for cognitive (p = 0.014) and physical (p = 0.014) loads. Finally, nine out of 16 participants preferred using *positions*.

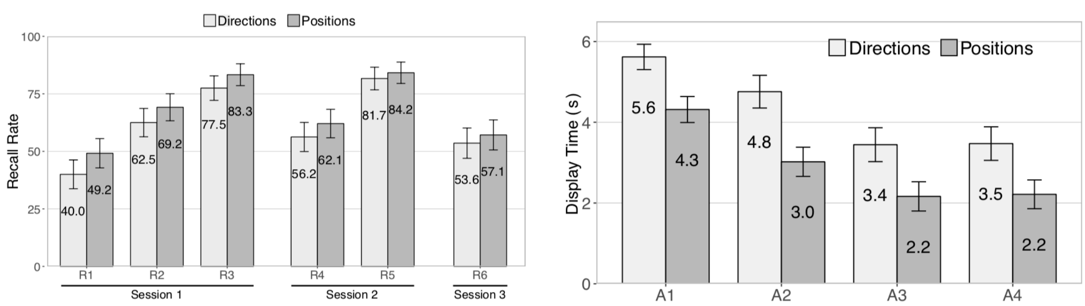



Figure 34: Left: recall rates; Right: display time in learning phases

While these results need to be confirmed by further research, they seem to indicate that *positions* requires less training to encode information in memory. Moreover, recall rates are not lower (in fact they are not significantly higher) for *positions* although shorter training time usually involves lower retention. These differences are intriguing and may have several explanations.

First, *directions* (MultiStroke menus) may require more attention from the user, for instance because he must continuously touch the surface. Second, *positions* may leverage spatial memory more efficiently than *directions* because rectangular menus provide more spatial and graphical cues [Scarr13b]. This would mean that the layout of Marking menu is not optimal and that other graphical representations (for instance using a rectangular or orthogonal layout [Ahlström10]) may be preferable. A last possible reason may be that directions and locations are not exactly encoded in the same way in memory. Navigating through environments and remembering object locations are different classes of tasks with only partial correlations in spatial ability [Scarr13b]. If directions are associated with egocentric movement, as hypothesized above, they may be related to the first class. However, we are not aware of studies addressing this specific aspect.

Finally it is interesting to observe that participants developed various strategies in both conditions, such as forming (mental) groups of commands to facilitate memorization. Categorization has been shown to improve memorization [Bower69] and similar strategies have been observed in other studies (e.g., [Bergstrom-Lehtovirta17]). Participants formed groups of items according to their position (spatial patterns) or their meaning. For instance, many of them created sentences such as "the eagle is *up* because it flies" or "the bacon goes *down* into the belly" to remember gesture/command associations, a strategy which was also observed in other studies [Appert09, Ghomi12, Perrault15]. These observations highlight the importance of the positioning of commands in an interface, including their relative positions. We will come back to these aspects in the next sections, with some experiments showing that such strategies can be surprisingly efficient.

## 7.2 Overlearning: Augmented letters

While the previous section showed the efficiency of Marking menus (and derived techniques such as Flower menus) for learning gesture/command associations, the user must still learn them. A solution for avoiding this learning stage (or making it easier) consists of using symbolic gestures that have a direct non-ambiguous relationship with the desired command. However, as already seen in Section 2, few gestures have an obvious meaning for all users. One exception is letters, numbers, and ideograms (in Asian cultures), because they have been learned since childhood.

The simplest way to create a straightforward semantic mapping between gestures and commands consists in using their first letter as a gesture. Unfortunately, this is generally not possible because of name collisions (multiple commands can start with the same letter). One solution then consists of writing the next starting letters (or even the entire command name), as proposed for instance by Lü and Li [Lü11]. However, because they contain curves and corners, letters take more time to write than straight gestures [Viviani82, Cao07]. Moreover, the number of starting letters that need to be drawn to avoid ambiguities may depend on commands, or be relatively large. For example, distinguishing the commands *"Save"* and *"Save As"* may require writing five letters, not mentioning that the latter contains a space, which may be another source of confusion.

*Augmented Letters*, which were developed by Quentin Roy during his PhD (co-supervised by Yves Guiard), propose a hybrid strategy to solve this problem. This technique combines a unistroke letter with a Marking menu (Figure 35). The letter is the initial letter of the corresponding command, which simplifies command memorization and should reduce cognitive load. This letter is augmented with a *tail* that can be oriented in up to eight directions, so as to handle conflicts amongst commands that share the same initial. The tail is spatially combined with the unistroke letter so that that the entire stroke can be drawn in a single gesture. This can be seen as a syntactic approach, as with hierarchical

Marking menus, except that the first level of the menu is not an abstract but a symbolic gesture, which has a direct relationship with the command.

In theory, this design makes it possible to define up to 26 x 8 = 208 different commands. In fact there are a few conflicts, e.g. a left tailed *C* is similar to a left tailed *G* (tail length does not matter). We counted about six of them depending on the recognizer, leaving 208 - 6 = 202 different commands.

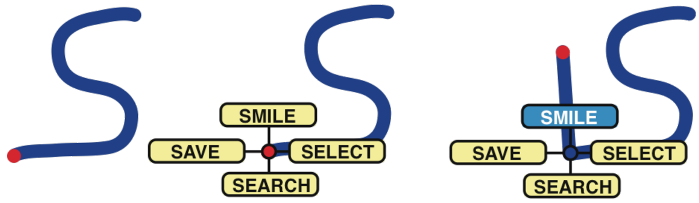



Figure 35: Augmented Letters

This technique supports a novice mode. If the user does not know the tail, he can write the letter and then wait for a delay (500ms) while touching the screen. The corresponding Marking menu is then displayed so that the user can see all existing tails for this letter. As with Marking menus, the same gestures invoke the same commands in either mode, so that this technique also allows a fluid transition from novice to expert mode.

However, the user may not know the names of the available commands and whether they have an associated shortcut. A solution consists of using cheat sheets, or linear menus. Menu items then show the corresponding tail instead of a keyboard shortcut, as with the *FingerCount* menus described in Section 4.1.

**Overlearning and gesture automaticity**

This technique capitalizes on the fact that the various skills that constitute the human language are considerably overlearned [Saussure16]. In the literate adult, owing to a considerable amount of sustained practice, naming, reading, typing, and handwriting are remarkably automatic, despite the arbitrariness of the linguistic signs.

As expressed by the Hicks-Hyman law [Hyman53], choice reaction time increases linearly with the logarithm of the number N of alternatives. But the slope of that linear dependency strongly depends on training. For instance, Fitts and his colleagues [Brainard62] have shown that the slope of the Hicks-Hyman law virtually zeroes out if the task is to utter the name of visually presented characters: the duration of such a reading reaction is not just short, it is hardly affected by the size of the stimulus set. Considering the design of gestural input vocabularies, in general, the larger the set of possible commands, the more difficult the choice. Yet if the memory link has been trained to the point of becoming automatic, the number of alternatives no longer matters.

This point also illustrates that the *nature* dimension of Wobbrock et al. [Wobbrock09] and even the *analogue-abstract* spectrum of Zhai et al. [Zhai12] are relative concepts (cf. Section 2 and Figure 1). For instance, a digit is *abstract* in the sense that there is an arbitrary relationship between its graphical representation and its meaning (i.e., its corresponding value). But it is also *symbolic*, because the meaning of this graphical representation has been overlearned by billions of people, and *analogue*, because it refers to cultural conventions. Finally, the mapping between a digit gesture and its meaning is so well known that it may be more obvious to users, and thus involve less cognitive load, than *physical* or *metaphorical* gestures.

Hence, again we claim that the *degree of familiarity* [Raskin94] is the most pertinent dimension because it can take into account all cases without considering low-level considerations that can lead to possible ambiguities. Moreover, and very importantly, familiarity is evolving and contextual. Not only does it depend on users' culture but also on which tools they use, as humoristically depicted in the "Modern Times" movie by Charlie Chaplin where the character cannot help performing some gestures automatically.

**Experiment**

We evaluated the performance of Augmented Letters with respect to Marking menus. The commands had 5 different starting letters and up to 4 tails. A two-level Marking menu was used, with 8 items at the first level and one of them opening a submenu also containing 8 items. This design, which enables selecting 15 commands, was chosen in order to avoid complex menus. The experiment had 3 learning blocks (with 3 repetitions for all tested items) alternating with 3 testing blocks for each technique. Twelve participants participated in the experiment. They could use either the novice or the expert mode in the learning blocks.

The recall rate was significantly higher with Augmented Letters than with Marking menus and reached 85.4% vs. 63.2% in the last testing block (Figure 36). The completion time was similar with both techniques (about 3.8s). Interestingly, the execution time was higher for Augmented Letters (as expected, because gestures are more complex), but the reaction time was lower. This finding is consistent with the view that Augmented Letter benefits from familiarity. Moreover, in the learning blocks, the spontaneous use of the expert mode was more frequent with Augmented Letters (66.0%) than with Marking menus (43.8%).

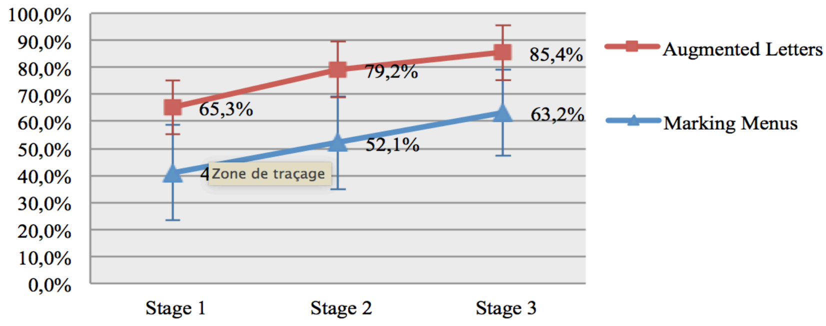



Figure 36: Recall rate of Augmented Letters vs. Marking Menus

This study suggests that language (and syntax), which tends to be an under-exploited resource in graphical user interfaces, can provide a way to make interaction more efficient for expert users: The larger the set of commands, the greater the benefit that can be expected from the over-learned skills of language such as drawing letters.

## 7.3 Structure and memorability: Multi-finger chords

Structure has been shown to improve memorability [Mandler67]. Previous findings in psychology have demonstrated that people can recall more items if those items are grouped by category [Bower69, Gollin88]. Indeed, participants spontaneously used such strategies in the *Directions vs. Positions* study (Section 7.1).

Inspired by this finding, we investigated whether a categorical structure can facilitate learning and long-term retention of gestures. This work was performed in the context of the *Multi-Finger Chord* study [Wagner14], conducted by Julie Wagner, Ted Selker and myself, which was presented in Section 4.2. As a reminder, this technique allows recognizing a set of nine multi-finger chords by taking into account hand-shape characteristics. It relies on three families of simple postures, each providing three different gestures (Figure 37).

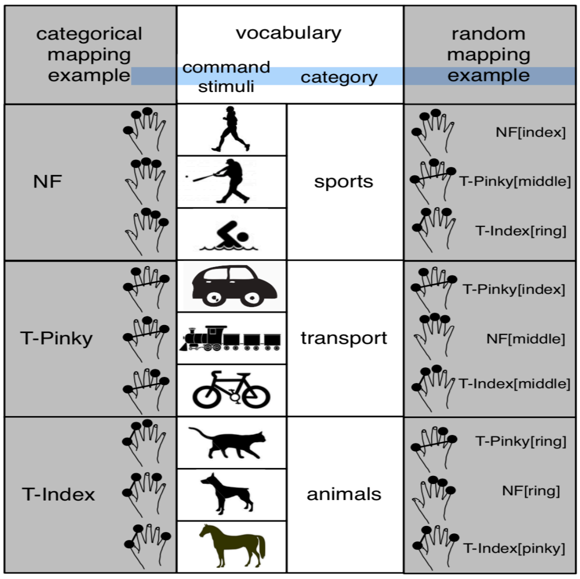



**Figure 37: Examples of gesture/command associations**

Our goal was thus to investigate whether users would 1) learn the gesture-command mappings faster and 2) remember those mappings more accurately in mind over a long period of time, if the gestural language was structured in a way that reflects the menu-structure of commands. For this purpose, we performed an experiment with 18 right-handed participants who were randomly assigned to two groups, which were taught *categorical* or *random* associations respectively. We used a between-subject design to avoid a carryover effect from one condition to another. All participants were instructed to learn nine commands organized in three categories (Figure 37).

The experiment was divided into two sessions (Figure 38). The calibration phase consisted in training the recognizer (*private tablet* setup in section 4.2). The command and the corresponding gesture were shown to the participants in the training phase (2 blocks of 9 trials). Only the gesture, and feedback about errors, was shown in the memorization phase. This phase ended when the participants could (*criterion A*) successfully reproduce all gestures twice in sequence *and* (*criterion B*) decided that they were trained enough. Then they watched a 10-minute cartoon and *short-term retention* was tested (phase 5). Finally, *long-term retention* (phase 6) was tested 6 or 7 days later (details in [Wagner14]).

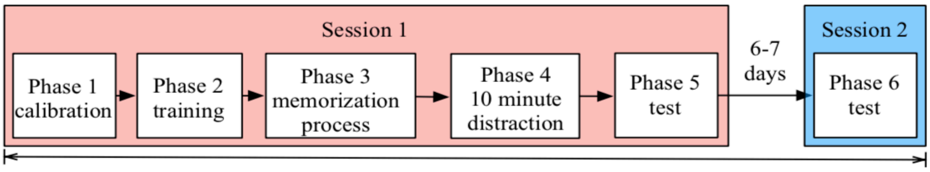



Figure 38: The different phases of the experiment in two sessions

**Results**

Participants learned the mappings significantly faster in the *categorical* group according to *criterion A* (7 vs. 11.5 blocks), but no significant difference was observed for *criterion B* (10.3 vs. 12.7 blocks). There was no significant difference[9] for *short-term retention* (0.11 vs. 0.22 errors) but a significant difference in favor of the *categorical* group for *long-term retention* (0.56 vs. 3.4 errors). Moreover, the same pattern was observed for completion time.

These results confirm that a structured mapping leads to less error-prone long-term memorization. This is also supported by the fact that participants in the *categorical* group did not mix up mappings between gesture families and menu categories and did not perform completely wrong gestures. They also highlight that participants can efficiently learn *abstract* gestures and their corresponding commands provided that they are organized in a meaningful way. Finally, they show the importance of long-time retention tests since some effects on memorization might first show up after some time has passed [Anderson13, Nacenta13].

## 7.4 Memory devices and multiple memory components: Physical loci

While handling a few shortcuts may be easy for most people, as suggested by the *Multi-Finger Chords* study, increasing the number of shortcuts makes the recall harder, therefore limiting the applicability and effectiveness of gestural shortcuts.

In this study [Perrault15] (mainly performed by Simon Perrault during his PhD thesis, who was co-supervised by Yves Guiard) we introduced a novel way of memorizing gestural shortcuts inspired by the method of loci [Yates92, Higbee01]. This method is an ancient memory technique that dates back to the time of Aristotle and offers impressive learning capabilities. We proposed a practical implementation of this method, called *Physical Loci*, for interacting with a smart home environment, a context of use that is well suited to this technique.

**Method of Loci**

The method of loci is a method of memory enhancement that uses images and spatial learning to organize and recall information. "Loci" refers to locations. The user of this classic technique first memorizes the layout of certain spatial structures that have a number of discrete locations, such as a building, or shops on a street, and then the user mentally 'walks' through these loci and assigns an item to each of them by forming an image of the item and any distinguishing feature of that locus. The retrieval of items is achieved by 'walking' again through the loci, which activates the desired items.

The efficacy of this technique has been well established in psychology [Briggs70, Crovitz69, Higbee01]. Most of these studies, which were generally conducted with students, were designed for remembering lists of 20, 40 or 50 words. The method of loci has also been used by memory contest champions to recall large amounts of faces, digits and lists of words. Some people have been known to achieve amazing performance, such as remembering thousands of digits [Maguire03, Raz09].

[9] A non-parametric Mann-Whitney test on the number of errors was used in this case because of non-normality.

In the classic technique, creating loci involves two steps. First, users must memorize *mental* images of familiar *locations* in some natural or logical order. Next they will associate a *visual image* of each item to be remembered with a *location* in the series. The first step is by far the most demanding but it needs to be performed only once since the same series of locations can be used for different lists of items with little interference [Bower70]. However, this constraint makes it difficult to apply the technique to HCI in its original form. A technique requiring too much initial effort is unlikely to be adopted by users.

Another constraint is that this method relies on a spatial configuration and positioning of loci that is specific to the user. This can be problematic in the context of HCI as several people may need to interact with the same system and use the same set of shortcuts. Moreover, this mental representation is not supposed to change, which means that loci are not meant to move.

**Memory components**

Human memory has been extensively studied in the field of psychology (i.e., Baddeley's survey [Baddeley13]). In their Working Memory model Baddeley and Hitch illustrate the distinction between verbal and visuospatial information. Further, neuropsychological and neuroimaging studies place a distinction between visual object and visual spatial information. We examine this distinction below.

***Object/image memory*** involves processing features of an object or material such as texture, color, size, and orientation. In the case of the method of loci, object memory plays a role in remembering precise details of the room. Yates [Yates92] and Briggs et al. [Briggs70] showed the importance of *imagery* in such memory techniques because the more stunning, disturbing, or noticeable the mental images are, the better items will be memorized. More generally, landmarks have been shown to be especially important for the development of spatial memory [Allen78, Scar13b].

***Spatial memory*** is another key component of the loci method, as users must mentally "place" the items they want to remember in different locations. This aspect is specific to the loci technique, as opposed to other mnemonic devices. Spatial memory has garnered much attention in psychology (e.g., [Jones86, Andrade93, Maguire03]) and, to a lesser extent, in HCI (e.g., [Ark98, Robertson98, Scarr13b]). Partly because spatial learning occurs automatically, even without focused attention [Mandler77, Andrade93], spatial memory can help users remember large numbers of items [Baddeley13]. Maguire et al. [Maguire03] found that most of the champion memorizers they observed used a spatial learning strategy. Using functional neuroimaging they also noted this strategy engaged specific brain regions such as the hippocampus, which are critical for memory (and spatial memory in particular).

The utility of spatial metaphors has been shown since the development of HCI [Bolt80]. An interesting example is Data Mountain, which used a spatial 3D representation and thumbnails to help users organize, store, and retrieve 100 Web bookmarks [Robertson98, Czerwinski99]. This technique was shown to be faster than Internet Explorer's bookmark tree and remained effective after several months. However, this technique did not require users to recall the exact locations of bookmarks (whose names were visible on demand) but rather helped them find their location faster. Command selection was considered in ListMaps [Gutwin06], which illustrated the efficiency of grid interfaces for experts. Spatial memory was used in CommandMaps [Scarr12], in combination with hierarchy flattening, to improve GUI performance and in FastTap [Gutwin14] to allow faster command selection on tablets. Finally, Virtual Shelves [Li09] relies on spatial awareness and kinesthetic memory, but has only been studied in terms of pointing accuracy, not for the memorization of commands.

***Verbal/semantic encoding*** also occurs in the method of loci. First, items were clustered into categories in our experiments, as in most actual user interfaces. As explained in the previous section, structure is known to improve memorability [Bower69]. Not only do people recall more items if they are grouped by category [Mandler67, Baddeley13] but long-term retention increases when the structure of a set of gestural shortcuts reflects the structure of the corresponding command set, as seen in the previous subsection. Moreover, mental images used with the loci method can involve stories [Yates92] such as a painting, a place related to an historical event, etc.

***Combinations*** and complementary processes: Combining spatial memory with other cues has been shown to improve performance in terms of memorization [Jones86]. According to Pavio's Dual Coding Theory [Paivio71] one can expand on learned material through verbal associations and visual imagery. Visual and verbal information are processed differently, along distinct channels, which increases the chance of remembering a given item compared to when the stimulus is coded in a single way. Moreover, imagery potentiates recall of verbal material and vice-versa, so that both channels should reinforce each other. Finally, elaborative encoding [Anderson79], which is the process of actively relating new information to knowledge that is already in memory, may also improve long-term retention.

In conclusion, embedding memory in a detailed surrounding or context should help remembering it later and the combination of different memory channels is likely to improve memorization.

**Physical Loci**

The *Physical Loci* technique is a practical implementation of the loci method for gestural invocation in the context of a smart home environment. The significant difference is that this technique uses *physical objects* for recall (e.g. the familiar objects in the living room) and does *not* require the creation and memorization of an imaginary place, which is a tedious operation. In other words, users do not have to memorize a virtual place; instead they use the *physical space that is surrounding them*.

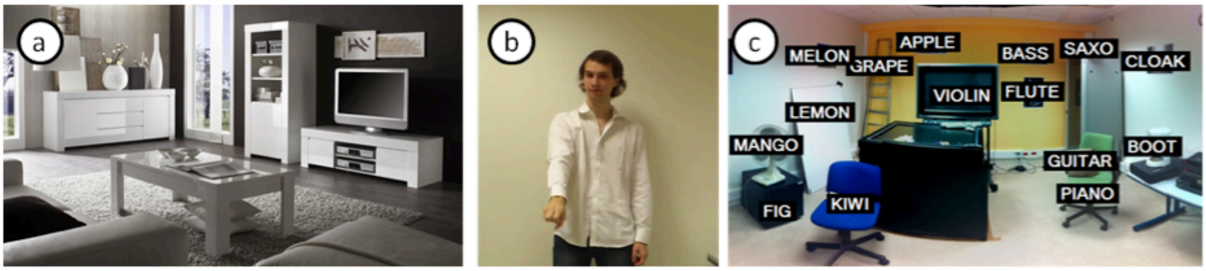



Figure 39: Physical Loci

The user must first set up a mapping between a set of desired commands and loci in the room (Figure 39, left). For each command, he must point to the corresponding locus with his arm and validate to store this mapping. Commands can then be activated just by pointing to the corresponding loci and performing a validating action (Figure 39, center). Depending on the available technology, the pointing action can be done through free-hand interaction or by using a gesture- and location-aware remote control [Wilson03]. There is little constraint on the choice of loci except that they should be reasonably distant from one another to avoid confusion and easily identifiable by the system when the user points to them. As novice-to-expert transition is of particular importance in gestural interfaces, we also provided a visual help, which is displayed on demand. This visual representation, which is typically displayed on a living room TV screen, shows the locations of the loci and the corresponding commands (Figure 39, right).

**First experiment**

In a first experiment (within-subjects design, 12 participants), Physical Loci was compared with a mid-air version of MultiStroke Marking menus [Zhao04] with a vocabulary of 25 items divided into five categories of five items. The experiment consisted of three training blocks (in expert mode by default, but the user could trigger the novice mode) and one recall block. The experiment was conducted in a room emulating a home environment (with a sofa, a table, two cupboards and posters on the walls). In an initial "mapping" phase, the participants were asked to associate the 25 items with the Marking gestures or physical objects of their choice. A Kinect was used for detecting gestures. Participants significantly recalled more items with Physical Loci than with mid-air Marking menus (88% - 22.1 items vs. 65% - 16.4 items).

**Main experiment**

Considering the relatively large number of items that participants could recall, we performed a second experiment with 48 items (16 participants, only the loci technique was tested). Items were also divided into categories, but of different sizes (6 categories with 6, 8 or 10 items). We added a recall test on the following day and one week later to evaluate memory retention. Moreover, 11 of the (still available) 16 participants performed an additional recall test about two months later.

To avoid constraints and accuracy problems, we used a laser pointer and a Wizard-of-Oz approach. This made it possible to place several loci on smaller objects and/or at different locations of the same physical object, which was not possible in the previous experiment because of insufficient precision of the recognizing system. Another difference is that names were used instead of icons to identify the loci, to save space and avoid possible ambiguities. The novice mode was also slightly improved (Figure 38, right). It was displayed on a large TV when requested by participants in the learning phases.

While the original loci method was developed for personal use, we wanted to see whether participants could efficiently use a mapping somebody else created. This also allows estimating to which extent using predefined mapping degrades performance (or, requires added effort) compared to user-defined gestures. We thus performed a between-subjects experiment with two groups: the *active* mapping group created their own mapping while the *passive* group used someone else's.

**Results**

The results were surprisingly high, not only for the *active* group but also for the *passive* group: *active* participants could remember almost *all* items (M=47.5) already in the *first* recall block, and *passive* participants could achieve similar performance (M=47) in the second recall block (Figure 40 and Figure 41, on the left).

Retention over time was also quite impressive as participants of both groups could remember almost all items after one day, and even after one week (Figure 40, left). Even more impressive, the 11 remaining participants could still remember most of them after two months (45.5 items for the 4 *active* users and 43 for the 7 *passive* users).

As memorization depends on time, we compared the overall time required to achieve a nearly perfect recall rate of 47 items or more in the first session. While participants of the *passive* group needed an additional training block to achieve this rate, they also spent less time in the initial phase, which only consisted of familiarizing themselves with the technique, as they had no mapping to perform. The overall time was similar for both groups (24.9 vs. 25.6 min for *active* vs. *passive* groups). Hence, contrary to our expectations and some previous results [Nacenta13], using user-defined gestures showed no or limited benefit for this technique.

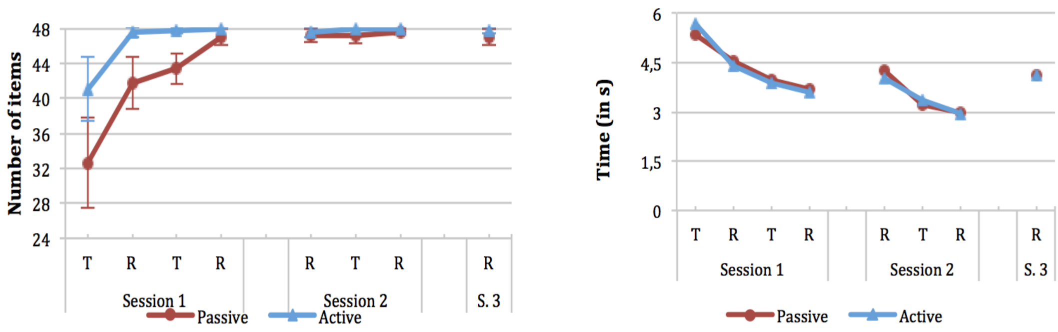



**Figure 40: Recall rates and completion time**
**(blue = *active* vs. red = *passive* group; T = training vs. R = recall block)**

**Moving objects**

As mentioned above, the method of loci is likely to rely on several memory components and, in particular, spatial memory. We were thus curious to see to which extent moving the objects would affect recall. We thus performed a last experiment with 9 participants were objects were moved in different ways. This experiment was divided into two sessions, with the spatial configuration of the room changing between sessions. The first session was as in the previous study. The second session consisted of a recall, training and recall block and it was performed the next day.

Spatial memory may be involved either *globally* (absolute loci positions in the room help remembering the items) or *locally* (relative loci positions in a group help remembering the items). We thus used five groups of five items, each group being moved in a different way between sessions:

- *Baseline* group: unchanged
- *Global* group: the set of loci is moved to another side of the room
- *Local* group: only the positions of the loci within the set are changed (they are changed randomly, not using specific transformations as for instance in [Scarr14]).
- *Global+local* group: both operations are performed
- *Scattered* group: the loci are scattered and relocated haphazardly in the room.

For the sake of brevity, we focus on the results of the second session (next day). There was no significant effect of loci reconfiguration on recall rate (p=.67) with a *nearly perfect* recall rate of 99.3% (Figure 41, right). However, there was a significant main effect on recall time (about 26.3% slower than in the first session), with *baseline* being significantly faster than all other conditions except *local*.

Hence, participants were able to find the correct locus in most cases, but this took them more time, except, as expected, in the baseline condition. Participants were somewhat puzzled when they discovered the new configuration, but they could gradually adapt as shown by the difference in time between the first and the second recall blocks (Figure 41, right).

| Mapping Condition | Session 1 | | | | Session 2 | | | Ses. 3 |
|---|---|---|---|---|---|---|---|---|
| | T | R | T | R | R | T | R | R |
| Active | 41 (0) | 47.5 (5) | 47.8 (6) | 48 (8) | 47.5 (5) | 48 (8) | 47.9 (7) | 47.8 (6) |
| Passive | 32.6 (0) | 41.8 (0) | 43.4 (1) | 47 (4) | 47.1 (4) | 47.3 (6) | 47.6 (5) | 47 (4) |

| Condition | Recall rates (in %) | | | Mean recall time (in s) | | |
|---|---|---|---|---|---|---|
| | B1 | B2 | Session | B1 | B2 | Session |
| Baseline | 100 | 100 | 100 | 3.67 | 2.47 | 3.07 |
| All but baseline | 98.9 | 99.4 | 99.2 | 4.66 | 3.09 | 3.88 |
| Global | 100 | 100 | 100 | 4.7 | 3.34 | 4.02 |
| Local | 100 | 97.7 | 98.9 | 4.41 | 2.9 | 3.66 |
| Global+Local | 97.7 | 100 | 98.9 | 4.51 | 3.19 | 3.85 |
| Scattered | 97.7 | 100 | 98.9 | 5.04 | 2.93 | 3.99 |

**Figure 41: Recall rates (Left: main experiment; Right: when moving objects)**

**Users' feedback and strategies**

Participants were surprised by their own results, especially those who had not previously heard about mnemonic devices and memory contests. This is not a surprising result as users tend to underestimate their memory capabilities [Baddeley13, Scarr13b].

Although we did not give them specific cues, *active* participants used similar strategies in the initial mapping phase, such as placing related items in the same spatial areas or imagining semantic links between the items and the loci by *making stories* such as "the dog barks at the cat from the floor" or "the peach goes with the red door". *Passive* participants used similar strategies and had no problem in reinterpreting the existing mappings by inventing completely different stories. These strategies are very similar to the ones observed in Section 7.1 for the *Directions vs. positions* study.

Indeed, the participants' ability in creating stories, whatever the mapping, was quite stunning. Some of them were remarkably inventive and used complex associations of ideas, e.g., "the waiter goes with the coffee machine because waiters deal with coffee machines in real life, the professor with books, etc.". Although simpler, these strategies are reminiscent of the mnemonic techniques used by the Russian mnemonist Shrereshveskskii, who had an amazing memory (he could virtually remember anything in any order) and was studied by the Russian psychologist A. R. Luria. For instance, Figure 42 shows how he would remember a complex equation.

$$\sqrt{N.d^2 \cdot x \frac{85.}{vx}} \qquad \sqrt{\frac{276^2.86x.n^2b}{\pi^2 v.\pi 264}}$$

Neiman (N) came out and poked with his stick (.). He looked at a dried-up tree which reminded him of a root (√) and he thought: 'It is no wonder that this tree withered and that its roots were lain bare, seeing that it was already standing when I built these houses, these two here ($d^2$)', and again he poked with his stick (.). He said 'The houses are old, a cross (x) should be placed on them.' This gives a great return on his original capital, heinvested 85,000 roubles in building them. The roof finishes off the building (___), and down below a man is standing and playing a harmonica (x). He is standing near the Post Office and at the corner is a large stone (.) to stop carts bashing the corner of the house …

Figure 42: Shrereshveskskii's way of remembering equations (from [Baddeley13])

**Conclusions**

While mnemonic devices such as the method of loci has been use to achieve amazing performance in memory contexts, we were impressed by the results we obtained as our participants were not trained in using such techniques (in fact most participants had never heard about them). However, this is not so surprising because, as said above, previous experiments with non-expert users (e.g. students) have shown comparable results for learning lists of words.

While the conditions of this experiment were particularly favorable (a room containing various objects and remarkable landmarks that were always visible) it shows that users can efficiently remember a rather large number of items provided that certain conditions are met. Considering that they could achieve nearly perfect recall of 48 items, it would be interesting to replicate this experiment with a larger number of items to see when performance starts to drop.

Another outcome is the importance of *semantic relationships* and the ability of users to make stories for remembering command/gestures associations. We initially expected spatial memory to be the most important component involved in the loci technique but this may not be the case. As shown by our last experiment, participants were surprisingly efficient in retrieving items although they were not at the same locations. This took them more time, which shows the impact of spatial memory, but still they could find them, which shows that they also used other memory components.

Also, it is important to observe that, in many cases, users made use of several memory components simultaneously. For instance, stories almost always refer to a spatial cue, to one or several objects, or to both types of information. In further research, it would be interesting to investigate the individual and combined effects of these memory components.

Finally, an interesting question is how to apply this type of technique to more conventional interfaces on PCs and mobile computers. Somehow, this is already partly the case with the *MarkPad* technique [Fruchard17] (with was presented in Section 5.2) as it relies on spatial, tactile and visual cues and on grouping strategies. However, it does not specifically encourage users to create stories and does not leverage object memory. Mobile devices touchscreens and computers equipped with a "screenpad" (as in Figure 23, right) could provide interesting opportunities.

## 7.5 Interacting with the body: Body loci

Several studies have investigated the body as an input surface by pointing on body areas to trigger actions [Angeslevä03, Guerreiro08, Wagner13, Vo14] or store information [Chen12]. The body provides natural landmarks that should support spatial memory and provide semantic information that might help memorize commands (e.g. knuckles or birthmarks) [Weigel17, Bergstrom-Lehtovirta17]. Moreover, by leveraging proprioception, body-centric interfaces can allow eyes-free interaction, which is particularly interesting in contexts such as mobile interaction or virtual reality environments where the users do not see their own body. However, despite their possible benefits, few studies have investigated the use of on-body interaction to leverage command memorization and, to our knowledge, none have compared their memory performance to a conventional interaction technique.

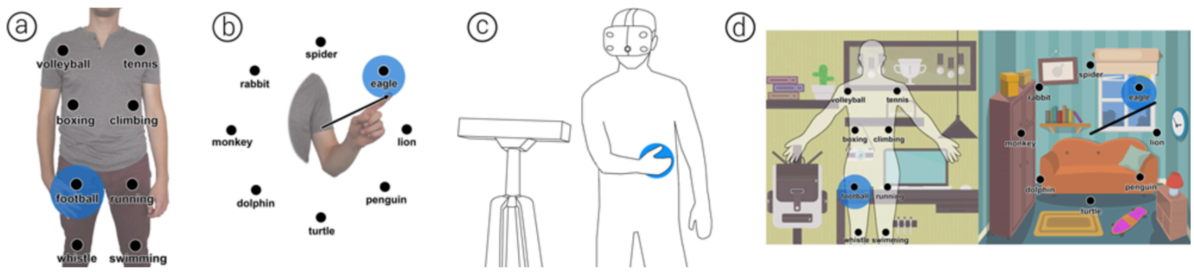



**Figure 43: BodyLoci vs. Marking menus**
**(a) BodyLoci; b) Marking menus; c) Setup; d) Background images for both techniques)**

This study, which was inspired by the work described in the previous subsection (Physical Loci), investigated whether the body could serve as a support for associating gestures to commands. It was conducted by Bruno Fruchard during his PhD (co-supervised by Olivier Chapuis). We first developed an on-body interaction technique, named *BodyLoci* (Figure 43-a), and then compared it to a mid-air variation of MultiStroke Marking menus (Figure 43-b), which was acting as a baseline. This study was performed in a Virtual Reality environment (Figure 43-c) in an attempt to support expert techniques in this context. Both techniques are well adapted to such environments because they do not require the user to see their hands when performing gestures in expert mode.

As MultiStroke menus, the BodyLoci technique relies on hierarchical menus to provide a sufficient number of gestural shortcuts. Based on previous studies [Karrer11, Wagner13], we selected 12 areas of the body (Figure 44, left). An area is selected by moving the hand close to the desired body location and activating a trigger (a dedicated device was attached to the user forearm and a Kinect was used for detecting gestures). A command is triggered when two areas are selected in sequence (to select a menu, then an item in this menu), as with Marking menus. Overall, a maximum of 12×12=144 commands can be performed. Novice mode (Figure 44-right) is triggered if the user keeps hovering over a body location for at least one second.

The mid-air MultiStroke menu technique works as expected, except that the user presses the dedicated trigger instead of a button of the mouse. We used successive straight marks rather than "zigzag" marks because the latter was shown to be less accurate in 2D [Zhao04] and may be even harder to perform accurately "in the air".

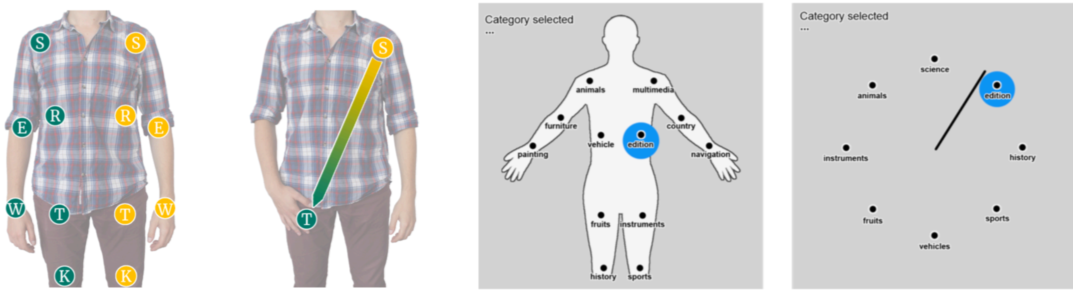



Figure 44 Left: Locations of the areas on the body; Right: Novice mode

**First experiment: BodyLoci vs. Marking menus**

In a first experiment (24 participants, within-group design), we compared learning and retention for both techniques. We used two sessions separated by 24 hours (Figure 45). Trials started in expert mode in the learning blocks but participants could trigger the novice mode if needed. The first level of the hierarchy consisted of 8 menus/categories (4 that were actually used and 4 distractors). Each category contained 8 items semantically related to this category. The first session lasted approximately 1 hour and the second session 30 minutes.

Since the body provides spatial landmarks and associated semantics, we expected BodyLoci to provide better memorization performance than Marking menus, but rates were quite similar, with no significant difference except for the first recall block (Figure 45, left). Moreover, the average time of a trial in the learning phases was significantly higher for BodyLoci than Marking menus, except for the first learning phase (Figure 45, right). Marking menus were preferred by the participants (58.3% vs. 20.8%), who also found them significantly better for comfort, fatigue, and perceived recall rate (a trend was also observed for mental demand ($p = 0.06$)).

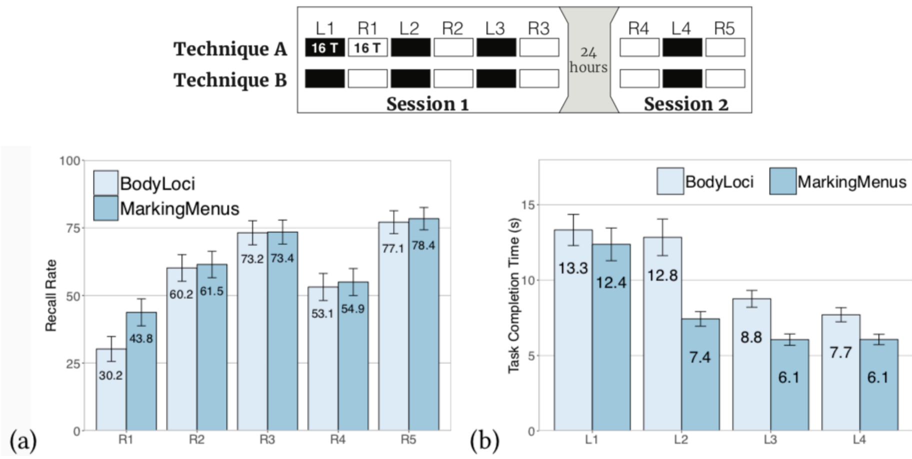



Figure 45: Top: learning (L) and recall (R) blocks
Bottom: recall rate (left) and completion time in learning phase (right)

**Second experiment: semantic aids**

The method of loci does not only rely on spatial memory but also on remembering mental images and on making stories to enhance memorization. Thus, in a second experiment (24 other participants), we augmented both techniques with semantic aids. We used two different kinds of aids: *Story making* and *Story making+Background images*. In the first case, we instructed participants to create stories about the command/position pairs that they had to remember. In the second case, we gave them the same instructions but also added a background image to the graphical representations of the menus in novice mode (Figure 43-d) in order to provide more materials for users to create mnemonics. In other words, we re-run the first experiment, but with a between-group design, with half of the participants using the *Story* aids, and the other half using the *Story+Images* aids.

Both conditions lead to very similar results, with not significant difference between conditions for recall rate or completion time. Hence, background images (used in addition to stories) did not significantly improve memorization.

We thus merged both conditions and compared the resulting data set with the first experiment, then seen as a *baseline* of the second experiment. Completion time was similar but the overall recall rate was significantly higher for the second experiment (Figure 46), except for the first recall phase. Moreover there was an interaction effect with the technique, and the improvement was higher for Marking menus. These differences are large, e.g., an improvement of 18.3% for R3 (end of first session) and of 28.5% for R4 (retention). Thus, inciting users to create stories substantially improves memorization with Marking menus, and a (non significant) trend suggests that BodyLoci also benefits from this mnemonic aid. In accordance with this result, Marking menus performed better than BodyLoci in this second experiment (17.3% better retention).

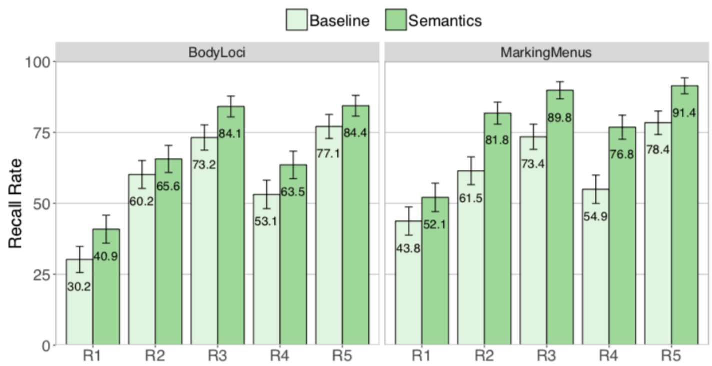



**Figure 46: Recall rates for first (Baseline) and second (Semantics) experiments for each technique**

**Conclusions**

The most compelling result of this study is that a simple instruction inviting users to create stories substantially improved memorization: up to 13.1% for BodyLoci and 28.5% for Marking menus. This confirms the effectiveness of verbal/semantic encoding, which we already suspected to play an important role in the previous study. Such methods do not require hard effort and they can even be seen as a sort of game. This suggests that encouraging users to leverage memorization strategies can have an important impact on user interfaces. For instance, providing hints or examples while using a graphical interface could help users master gestural techniques, and thus popularize such techniques.

The memory performance of the BodyLoci technique did not meet our expectations and was somewhat disappointing. A likely reason, grounded in the subjective results and the participants' comments, is that the cognitive load was higher because they were not used to this kind of interaction.

Remembering loci on the body may not be as easy as expected. People do not see their own body, except when looking in a mirror, so that they may not have such a vivid visual mental representation of it. Moreover then can encounter symmetry problems (15% of our participants in this study), as already seen in Section 6.3. In contrast, spatial and iconic cues were always visible in the Physical Loci study. However, performance may improve with time, when the user acquires a better mental representation and when motor learning develops. As mentioned in [Cockburn07], automaticity only develops after extensive learning and it is unlikely to play a major role in short controlled experiments.

Adding background images did not yield noticeable improvements. Uddin at al. [Uddin17] made a similar observation in a recent study and observed that some participants may not have been aware of the presence of images. In our study, over the 12 participants who performed under this condition, 7 of them said that they used images with the Marking menus, but only 2 of them with BodyLoci. Participants may have been overloaded with information in this latter case (see Figure 43-d).

The smaller impact of *Story* (or *Story+Images*) aids on BodyLoci may be due to the fact that body parts involve semantic information that people use spontaneously, contrary to Marking menus that rely on abstract gestures. Moreover, the directional radial gestures of Marking menus provide a different type of information, and thus an additional way of memorizing. In other words, combining different types of cues is all the more efficient when these cues are of different natures [Miller56, Jones86, Pavio71]. This suggests that semantic aids are especially helpful for techniques that rely on *"abstract"* gestures, such as Marking menus.

# 8 Conclusions and perspectives

In this document we addressed two different questions: 1) Can gestural interaction provide sufficient *expressivity* for performing a large number of tasks; 2) Can gesture be efficiently *learned and memorized* for making these techniques actually useful. Below, we consider these two aspects by summarizing the outcome of the presented studies.

## 8.1 Gesture expressivity

We first showed, in the *Flower* menu study, that using additional dimensions such as curvature could efficiently solve a major drawback of Marking menus, their limited breadth. Marking menus, and related techniques, are of special importance, because they provide a simple and 'natural' means for users to *discover* commands. By ‘natural’ we mean that their novice mode is similar to what users are accustomed to, which means that little effort is needed to learn using these techniques. Moreover, because gestures are similar in novice and expert modes, these techniques help users make a smooth transition from novice to expert.

In both cases, ***familiarity***, i.e., similarity with well-known techniques and similarity between the novice and expert modes, is a key aspect because users are not eager to adopt new techniques that involve learning new skills or lead to a decrease in performance. Contrary to the premises of classical economics, users are not "rational" [Goodwin18]. They tend to favor short-term solutions that optimize their immediate gains rather than make efforts that would be more beneficial in the long term. While this observation leads to a revisitation of mainstream economics theories (not to mention political implications), it also has practical implications in HCI, where it is known as the *Paradox of the Active User* [Carroll87]. As summarized by [Krisler08]: "once a user acquires a basic understanding of the operations required, she repeats those successful operations even when she knows that more efficient execution methods probably exist". Moreover, as stated by Newell and Rosenbloom's law of practice [Newell93, Scar11], changing modalities actually results in a performance drop, with the risk that users will reject using technologies that require such a change. Marking menus brilliantly solve this problem, as users do not even notice that they use a different modality.

***Additional dimensions*** are the second key aspect that we want to emphasize. Many of the studies that we presented above rely on the idea of using several different perceptual dimensions or different types of information. Besides *Flower* and *Leaf* menus, *BezelTap*, *MarkPad*, *Augmented Letters, Physical Loci* and *BodyLoci* rely on this idea by using, respectively, bumps, visual/tactile marks, symbolic information, and different memory components. The same is true of *CycloRoll* gestures (speed and location), *MTM* (locations and directions) and *Multi-Finger Chords* (families of gestures). Many of these techniques allow performing a large number of gestures, especially *MarkPad* and *Physical Loci,* which can support tens or even hundreds of gestures. In accordance with Miller's statement on multidimensional judgments [Miller56], all these studies show that large numbers of gestures can be efficiently performed provided that several dimensions are used.

In Sections 3.3 and 3.4, we have also shown that gestures cannot only be used for selecting commands by also for ***controlling their parameters***. *Control* menus provide a simple way to control one or two continuous or discrete parameters. *CycloRoll* goes a step further by taking into account up to five degrees of freedom. *FingerCount,* which relies on the number of fingers, was also used in combination with scrolling gestures for controlling parameters in [Bailly12].

We also showed that gestures provide efficient ways of ***interacting with small and large devices***. By using alternate dimensions, or gestures with a *specific signature*, these techniques avoid confusion with ordinary gestures. *MicroRolls* and *JerkTilts* respectively rely on rolling or self-delimiting 3D gestures, which can be distinguished from other gesture because of their specific shape or kinematic properties. *BezelTap* and *FingerCount* leverage an additional physical dimension, bumps or the number of fingers, for the same purpose. *WatchIt* and *MarkPad* rely on using an input surface (or a part of it) that is ordinarily not (or seldom) used for interacting: the border of the trackpad or the wristband. *WatchIt* avoids occlusion, enables performing gestures eyes-free, and depends on an accessory that is needed anyway to wear a watch.

All these techniques were evaluated in controlled experiments and demonstrated good to high performance. Considering the many other studies that have been performed on this topic, we can thus safely conclude that gestural interaction does provide a large reservoir of possibilities and that well-designed gestures can be efficiently used in various contexts with various devices (laptops, mobile devices, small and large displays, 3D interfaces, on-body interaction).

## 8.2 Learning and memorization

As stated in the introduction, gestural interaction will actually only become useful and gain popularity if it provides efficient ways of *learning* and *memorizing* gestures and gesture/command associations. As seen in Section 2, few commands elicit agreement about the associated gestures, especially if they are of an abstract nature, so that most gesture/command associations must be learned.

***When are gestures useful?*** Gestures are especially useful for performing operations that cannot be easily done otherwise. Except on small or large devices, because they do not provide hotkeys and make pointing uneasy in some situations, useful tasks tend to be more diverse and more complex than just triggering a predefined command. As mentioned in Section 2, tasks can involve performing an operation using 1) an application, 2) a command, 3) a document, 4) other elements such as a keyword, a string to search for, etc., or various combinations of these elements. They can also involve chaining several operations so that the output of the first operation serves as input for the second operation, and so on.

In other words, gestures are especially useful in the cases where current 'analogical' interfaces provide insufficient efficiency or comfort. Many of these cases involve some sort of *syntax* to allow combining different elements in a meaningful way. This point is likely to explain the recent popularity of speech-based interface and suggests that gestural interfaces should be targeted at performing more sophisticated operations than just triggering simple commands. However, such operations are generally *user-* or *application-dependent*, which again highlights the fact that most gesture/command pairs need to be learned. Moreover, this diversity of tasks also suggests that some users may need to use a relatively large number of gestures, as pointed out in the *MarkPad* study.

***Directional radial gestures and overlearning***. In Section 7.1, we first focused on directional radial gestures and on the fact that such gestures may be especially efficient because of prior learning and human directional abilities. As observed in this section, the memory performance of *Marking menus* has rarely been evaluated, and it would be interesting to compare them with other gestures, such as those proposed by Appert and Zhai [Appert09] (who compared their gestures with traditional hotkeys, but not with Marking menus).

However, however efficient they may be, abstract directional gestures will necessarily require more learning than gestures that already convey a well-known meaning. Letters and digits are overlearned, which makes them especially useful for activating commands that have a straightforward semantic relationship with them, as shown in Section 7.2 (*Augmented Letters*). However, because they contain curves and corners, letters take more time to draw than straight gestures. While, in our experiment, longer execution time was compensated by shorter reaction time, this is unlikely to be true in the long term. Thus, although they require more learning, straight directional gestures should be favored for commands that are performed very frequently.

*Curved gestures* offer another interesting alternative. While longer to draw than straight gestures, they still require less time than letters and most other symbols. Moreover, they can easily coexist with straight gestures in a menu system, as shown in the *Flower menu* technique. They were also shown to be efficient for memorization in Section 7.1. This may be an indirect consequence of Miller's law on multidimensional judgments [Miller56]. Because they rely on a combination of dimensions that each have a small number of values, *Flower* gestures are easy to distinguish, which is likely to help memorization. Moreover these dimensions (curves vs. directions) may be related to different memory components, which is another factor that enhances memorization, as will be discussed later. Finally, their layout emphasizes the semantic relationships between related commands. *Grouping* into categories also facilitates learning, as explained below.

***Positions vs. directions.*** We also compared the effect of using positions vs. directions on command memorization and observed intriguing differences. While these results need to be confirmed by further research, they seem to show an advantage in learning positions rather than directions, or, more exactly, in using pointing/clicking menu interactions rather than *Marking menus*. The most likely explanation is that *Marking menus* make the interaction slightly more difficult and that they do not provide as many graphical/spatial cues (corners, borders) as traditional menus. Alternate graphical representations may thus be more efficient, which is an interesting idea to investigate.

However, the differences we observed may be caused by more fundamental reasons, i.e., that directions (which may be related to egocentric movement) and positions may not be encoded in the same way in memory. While navigating through environments and remembering object locations are different classes of tasks involving different properties, it is not clear to which class directional gestures are related. Again, this is an interesting topic for future work.

***Structure and categories***. Structure has been shown to improve memorability and participants intuitively used such strategies in several of our studies (*Directions vs. Positions, Physical Loci, BodyLoci*). The results of the *Multi-Finger Chords* study confirm that a structured mapping leads to less error-prone long-term memorization. Moreover, participants did not perform completely wrong gestures when a structured mapping was used, which may reduce the cost of errors (confusing related commands generally involves less serious consequences than confusing unrelated commands). Interestingly, in this study, the difference in memorization increased with time: recall rates were different from the first recall test but this difference became significant only after one week. This highlights the fact that long-time retention tests are needed to detect effects that are not immediately visible.

***Hierarchical menus.*** Another question is whether and to which extent hierarchical *Marking menus* degrade memory performance compared to a one-level representation (such as *Flower menus*). This is not an easy question because it involves various factors, such as the number of items to memorize, whether they appear on cardinal or intermediate directions, whether submenus correspond to obvious *categories* and what is the degree of semantic relationship between the items and these categories. Moreover, memorization may depend on the degree of abstraction of the commands. For instance, 29% of the participants of the *BodyLoci* study reported having more trouble memorizing abstract items (e.g. items in the "Edit" menu), compared to more concrete items (e.g., items in the "Animals" menu). However, we did not observe noticeable differences in the results.

Because of different settings, the results of different experiments are difficult to compare. We can however observe that, in the studies reported in Section 7, *hierarchical Marking menus* performed better when four submenus were used (no other item being used in the first level), and they were located on the cardinal directions, and the item/submenu relationships were obvious (i.e., in the *Positions vs. Directions* and *BodyLoci* studies). While this is not a surprising result, such an optimal configuration is unlikely to occur in real use. In real applications, more than four submenus are generally needed, they may not correspond to obvious well-separated categories, and related items may be spread in several menus because of limited menu breadth. Incidentally, this also suggests that the differences between *positions* and *directions* may be stronger in more realistic settings, and that the memory performance with *BodyLoci* and *Marking menus* might be different in such a case.

***Loci and multiple memory components.*** While we knew that the method of loci had been used to achieve amazing performance, we were impressed by the results we obtained. This study clearly shows that users can learn a relatively large number of items (48 in this experiment) in a short amount of time when proper conditions are met. They were able to remember them almost perfectly after one week, and could still remember most of them after three months.

The ability to remember locations for a long period of time was already observed in the *Data Mountain* study [Czerwinski99]. In a different context (word-gesture keyboard), Zhai and Kristensson observed that participants could master 50 to 60 gestures in four test sessions [Zhai03, Zhai12]. Considering these results, we suspect that there is a tendency to underestimate the potential of human memorization in HCI studies, and that abstract gestures could be used in a much larger variety of cases than generally expected.

Because the power of ***spatial memory*** has been demonstrated in various studies in psychology and in HCI, we started the *Physical Loci* study with the idea that location would play the most important role in making this method efficient. While this study cannot precisely account for the respective role of the different memory components, it clearly shows that spatial memory is not the only factor. As shown by our last experiment, participants were able to retrieve almost all items although their locations had changed. This took them more time, but they could still find them.

This study, as well as the *Positions vs. Directions* and the *BodyLoci* studies, clearly shows the role of ***semantic encoding***. Participants were very creative in creating stories, they found it fun and they could easily remember these stories. The *BodyLoci* study also showed that just suggesting users to create stories can substantially improve memorization performance (up to 28.5% for Marking menus). This suggests that gestural techniques should provide ways of encouraging users to leverage such strategies. This is another interesting topic for future research.

While ***object/image memory*** is also likely to play an important role, our results are mixed. Background images provided no discernible benefit in the *BodyLoci* study and a similar observation was made in [Uddin17]. Their impact is unknown in *Physical Loci* as this aspect was not specifically tested. As mentioned above, the presence of graphical cues (corners, borders; which are also spatial cues), may explain the differences that we observed in the *Positions vs. Directions* study. However, some participants may not have been aware of such cues, especially background images, because of selective attention or because they were overloaded with information. Maybe background images should be more "bizarre", as in the original loci method [Briggs70] in order to retain the user's attention.

Finally, participants often make use of ***several memory components*** simultaneously, and their stories generally refer to spatial cues, objects or images. This is in accordance with Paivio's Dual Coding Theory [Paivio71], which states that verbal representations and mental images rely on different memory systems, so that associations between them improves memorization. In other words, "the chances that a memory will be retained and retrieved are much greater if it is stored in two distinct functional locations rather than in just one" [Plato-Stanford]. This idea is also present in the *Working Memory model* of Baddeley [Baddeley13] where visuospatial and verbal information rely on two different subsystems, the visuospatial sketchpad and the phonological loop.

Leveraging appropriate ***combinations of memory components***, and getting users to employ strategies that favor verbal/semantic encoding may thus be the key idea for making interaction techniques more efficient for learning and memorizing gestures, which opens various perspectives for future research.

## 8.3 Perspectives

My research perspectives are in line with my recent work, with a more specific focus on learning and memorization. Considering the outcome of the studies performed in the fields of psychology and HCI, and those I performed with my students and colleagues, I believe that interactive systems could be improved by exploiting human cognitive abilities more effectively. Who would not dream to be able to almost instantly trigger or access frequent commands and data items? This objective is not totally unrealistic but requires 1) to acquire a better understanding of the phenomena involved in the learning and memorization of gestures, and 2) to propose new interaction techniques that take these results into account. I already mentioned several directions for future research in the previous sections that I briefly summarize below.

First, it would be interesting to investigate more precisely the ***individual and combined effects*** of the different memory components involved in gesture memorization and when and whether performance starts to drop. In the Physical Loci study, participants were in fact able to remember all items and did very few errors. Similarly, in an experiment conducted by Zhai and Kristensson, the participants' capacity to memorize gestures seemed to be only limited by their speed of learning [Zhai03].

One particular aspect is the use of ***images and other graphical cues***, as they seemed to be less efficient than expected in some experiments. The effect of different types of images or graphical representations, or of their positioning in the user interface could be investigated, as well as the idea of using pictograms, animations or graphical effects [Baudisch06, Giannisakis17]. They could also be used in combination with graphical representations that inform the user about the benefits of using expert techniques, which appear to favor their use [Malacria13b]. As such cues may distract or disturb users, they could be represented on demand or differently according to user expertise.

A similar problem occurs for getting users to ***leverage verbal/semantic encoding***. As seen above, such strategies seem especially efficient but interaction techniques should not be intrusive or disturb users while they are focusing on a task. Again, the user interface could be adapted depending on user expertise or activity, or provide discreet hints such as interactive tooltips or small help widgets that users could trigger when they have idle time. As most users are skilled at creating stories, and enjoy doing so, this could also be presented to them as a game that will eventually enable them to improve their performance by playing.

Another interesting subject is the difference between ***positions and directions***. From a theoretical point of view, it would be interesting to know the actual reason of these differences. From a practical point of view, this could lead to a better graphical representation of Marking menus. It would also be worth knowing whether directional radial gestures actually have specific advantages compared to other categories of gestures, besides the fact that they are particularly fast to draw. Similarly, it would be useful to have better knowledge of the advantage and drawbacks of flat vs. ***hierarchical*** representations.

We already mentioned that gestures are more useful for performing more ***complex tasks*** than just triggering simple commands. This raises the question of how to make it easy for users to create such gesture/complex command associations and of whether some sort of *syntax* for combining gestures could be useful. *MarkPad*, *Augmented Letters* or *Control menus* are first steps in these directions. These techniques could be expanded to take into account textual parameters, as for instance *CommandBoard* [Alvina17], which allows selecting an object by entering text, and a command that is applied to this object. Moreover, more work is needed to understand what kind of operations are actually useful and enable users to customize their working environment easily.

***Small and large devices*** raise specific problems that gestures can help address. Interacting with smartwatches and smaller objects (e.g. digital jewelry) still remains challenging while enabling many interesting application use cases, especially, but not only, for performing eyes-free interactions when the user is mobile. They provide interesting opportunities for developing new gestural techniques as well as *wall-sized displays* and *AR and VR environments*.

***Wall-sized displays*** require users to constantly walk and to perform large arm movements. They are particularly useful for collaborative interaction, which requires specific tools as seen in the *CoReach* study. ***AR devices*** present the same problems as small mobile devices except that they can display more information. How can the user easily and efficiently access all this data? ***VR environments*** allow displaying even more data but the users cannot see their hands. Gestural interaction is then especially appropriate for accessing data and triggering commands as it avoids manipulating long menus and performing tiring 3D gestures, as seen in the *BodyLoci* study.

***On-body or wearable interaction*** seems especially interesting in these three contexts. While on-body gestures were shown to provide good memorization performance in the *BodyLoci* study, many questions remain open. For instance, other types of gestures or graphical representations may be more appropriate in this context. Smaller gestures than the ones we used in the *BodyLoci* study could be tested with a more accurate sensing technology. This would also make it possible to estimate the accuracy of on-body eyes-free gestures more precisely. Other questions such as confusion between directions because of the symmetry of the body (as observed in the *Belly Gestures* and *BodyLoci* studies) would also be worth investigating.

***Tactile feedback*** could also improve accuracy of memory performance. In the context of wearable interaction, the different parts of a garment could serve as tactile landmarks, and they could also be augmented to provide active tactile feedback. Visual feedback could serve the same purpose, by projecting data on the parts of the body (or of the garment) that are visible, such as the arms [Xiao18]. AR glasses could be used to provide permanent information to help novice users. Finally, new handheld devices could be developed to make interaction easier and more effective, especially when interacting with a VR environment or a wall-sized display.

Gestural interaction is thus particularly promising in all these use cases, and we plan to continue working on them in the future.

**Other research topics**

This document only focuses on my work on gestural interaction. However, I have also worked on other topics such as *cursive script recognition* [Lecolinet90,91,93, Plessis93, Cote95,98, Ruiz-Pinales00,04,08], *graphical toolkits and software architectures* [Lecolinet96,98,99,02a,02b,03], *information visualization* [Robert98,01, Pook00b, Plenacoste01, Huot06,07, Blanch07, Cohé16], *tangible interaction* [Muhammad07,08a,08b, Teyssier17a], *interactive paper* [Malacria09,11], *tactile feedback* [Lecolinet05, Ziat07,14], *augmented reality* [Gacem15,16], *target acquisition on small device*s [Roudaut08], and on the advantages and drawbacks of *wall-sized displays*, in comparison with desktop monitors [Liu14] and for performing shared tasks [Liu16].

I was also involved in the writing of several survey papers. The two most well-known are related to my former research area ([Casey98] on *character segmentation*, which has been widely cited, and [Lecolinet94] on *handwriting recognition*). I also participated in a survey on *Visual menu techniques* [Bailly16], and in several other French-speaking papers dedicated to literature reviews or design spaces [Bailly07b, Roudaut07, Malacria08, Baglioni09, Vo11, Gacem14, Jacob14, Teyssier17b].

I still plan to work on some of these topics, for instance interaction techniques for ***wall-sized displays or virtual environments***. Interacting with such systems still poses challenging problems and provides opportunities for adapting some of the techniques and ideas that were presented in this document. For instance, they could provide interesting solutions for data visualization in virtual reality.

***Graphical toolkits and software architectures*** is another domain that I am still interested in. Common graphical toolkits are amazingly cumbersome and using them is extremely time-consuming. I believe that most graphical user interfaces should be almost as easy to write as a standard Web page, at least for what concerns their presentation aspect. The specification of their interactions could also be greatly enhanced by using efficient tools (e.g., state machines [Appert08] or StateCharts) in combination with appropriate formalisms.

Mathematical notation has a long story [Wolfram00] and considerably helps in understanding complex demonstrations, compared to long paragraphs written in natural language. As mentioned by Ben Shneiderman in [Shneiderman95], "Leibniz sought to make the form of a symbol reflect its content. 'In signs,' he wrote, 'one sees an advantage for discovery that is greatest when they express the exact nature of a thing briefly and, as it were, picture it; then, indeed, the labor of thought is sonderfully diminished.'" Similarly, I believe that a large part of the complexity of GUI programming comes from the verbosity of programming languages and graphical toolkits APIs. I am thus interested in developing a dedicated language that, ideally, would be to GUIs what equations are to mathematics.

Another key idea is to develop a generic model enabling a GUI toolkit to rely on small number of actually different widget classes. This idea is inspired by the HTML/DOM model, where all tags rely on the same DOM class, or the car industry where the same car platform can serve to produce many different models. This results in a great homogeneity as most objects rely the same actual classes and are thus programmed in the same way. A preliminary version of a toolkit experimenting these ideas has been implemented, using OpenGL, SDL and the C++11 language.

Finally, I recently started working on a new research topic, ***Social touch***. The goal is to examine how the sense of touch can be integrated into interactive systems to leverage communicative and emotional channels between humans and machines or between humans via machines. The sense of touch has been shown to increase trust, worthiness, warmth, politeness, and the sense of social presence and to trigger emotional attachment. However, this modality has been much less studied than vision or verbal communication and little research has been devoted to technologies that are specifically aimed at transmitting emotion. I thus plan to work on the design of novel techniques and devices for simulating human touch.

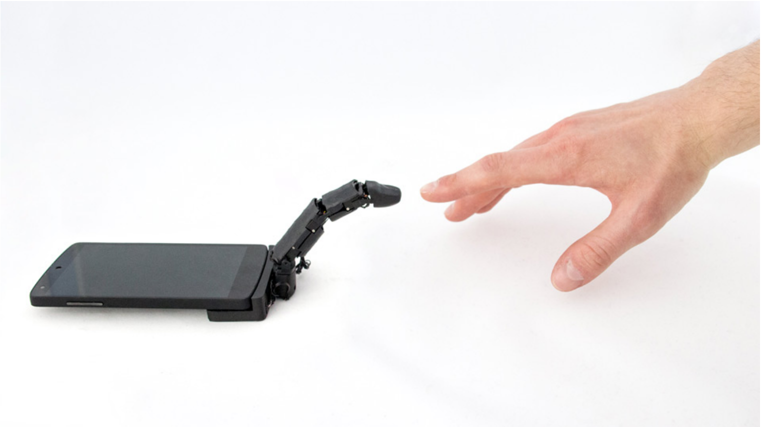
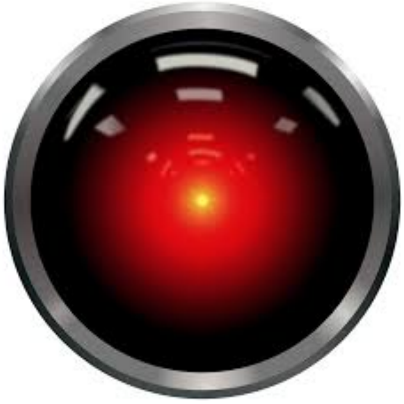


**Figure 47: MobiLimb**

As a first example, *MobiLimb* (Figure 47), an innovative and intriguing device developed by Marc Teyssier (whose PhD is co-supervised by Catherine Pelachaud, Gilles Bailly and myself) was recently presented at the UIST 2018 conference [Teyssier18, MobiLimb]. This project, which is related to the fields of shape changing interfaces [Robinson16, Kim18] and micro-robots [Le Goc19], relies on the idea of augmenting mobile devices with a robotic device, *instead* of augmenting humans with robotics.

*MobiLimb* is thus also related to gestures, except that these gestures are not performed by the user but by the robotic device. These gestures are not semaphoric, but deictic or manipulative [Karam05] or intend to convey emotion. This radically changes the nature of such a familiar object as a smartphone, which is supposed to be an inert object. Such a 'creature' does not even attempts to look human, as humanoid robots, which raises interesting questions about how humain see 'machines' and how 'machines' could look like in the future. Hence, in 20*1, HAL may not be just a talking eye, but an even stranger creature...



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B. Plessis, A. Sicsu, L. Heute, E. Lecolinet, O. Debon, J.V. Moreau. **A MultiClassifier Strategy for the Recognition of Handwritten Cursive Words**. In *IAPR International Conference on Document Analysis and Recognition (ICDAR'93)*, IEEE (1993). 642-645.

E. Lecolinet. **A New Model for ContextDriven Word Recognition**. In *Annual Symposium on Document Analysis and Information Retrieval (SDAIR'93)* (1993). 135-145.

E. Lecolinet, J.P. Crettez. **A GraphemeBased Segmentation Technique for Cursive Script Recognition**. In *IAPR International Conference on Document Analysis and Recognition (ICDAR'91)*, AFCET (1991). 740-748.

E. Lecolinet, J.V. Moreau. **OffLine Recognition of Handwritten Cursive Script for the Automatic Reading of City Names on Real Mail**. In *IAPR International Conference on Pattern Recognition (ICPR'90)*, IEEE (1990).

E. Lecolinet, J.-V. Moreau. **A New Sytem for Automatic Segmentation & Recognition of Unconstrained Handwritten Zip Codes**. In *IAPR Scandinavian Conference on Image Analysis (SCIA'89)*. IEEE (1989). 585-592.

E. Lecolinet, J.-V. Moreau. **Automatic Segmentation & Recognition of Zip Codes on Handwritten Real Mail**. In *International Conference on Image Processing and its Applications*. IET (1989). 217-221.

## 2.2 French-speaking conferences

B. Fruchard, E. Lecolinet, O. Chapuis. **Mémorisation de Commandes : Positions Spatiales versus Gestes Directionnels**. *In* Conférence francophone sur l'Interaction Homme Machine (IHM'18), ACM (2018). To appear (Oct. 2018).

M. Teyssier, G. Bailly, E. Lecolinet, C. Pelachaud. **Revue et Perspectives du Toucher Social en IHM**. *In* Conférence francophone sur l'Interaction Homme Machine (IHM'17), ACM (2017).

Th. Jacob, G. Bailly, E. Lecolinet. **Etude du controle du point de vue 3D à partir de la tête et des épaules**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'15)*, ACM (2015) 4-*

M. Berthellemy, E. Cayez, M. Ajem, G. Bailly, S. Malacria, E. Lecolinet. **SpotPad, LociPad, ChordPad & InOutPad : Exploration de l'interaction gestuelle sur pavé tactile**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'15)*, ACM (2015), 6 pages.

Th. Jacob, G. Bailly, E. Lecolinet, R. Foulon, E. Corteel. **A Design Space for Threedimensional Curve Edition**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'14)*, ACM (2014) 105-112.

S. Gosh, G. Bailly, R. Despouys, E. Lecolinet, R. Sharrock. **SuperVision : controler spatialement les objets connectés dans une maison intelligente**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'14)*, ACM (2014). 201-206.

H. Gacem, G. Bailly, J. Eagan, E. Lecolinet. **A design space of guidance techniques for large and dense physical environments**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'14)*, ACM (2014). 9-17.

S. T. Perrault, G. Bailly, Y. Guiard, E. Lecolinet. **Promesses et contraintes de la joaillerie numérique interactive : Un aperccu de l'état de l'art**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'11)*, ACM (2011). 14-*.

D.B. Vo, G. Bailly, E. Lecolinet, Y. Guiard. **Un espace de caractérisation de la télécommande dans le contexte de la télévision interactive**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'11)*, ACM (2011). 17-*.

K. Adjanor, E. Lecolinet, Y. Guiard, M. Ribière. **Visualisation interactive de données temporelles: un aperçu de l'état de l'art**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'10)*, ACM Press (2010). 97-104.

M. Baglioni, E. Lecolinet, Y. Guiard. **Espace de Caractérisation des Interactions Gestuelles Physiques sur Dispositifs Mobiles**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'09)*, ACM Press (2009). 203-2012.

S. Malacria, E. Lecolinet. **UNote : Classe augmentée et Stylo numérique**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'09)*, ACM (2009). 255-258.

J. Francone, G. Bailly, L. Nigay, E. Lecolinet. **Wavelet menu: une adaptation des marking menus pour les dispositifs mobiles**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'09)*, ACM (2009). 367-370.

G. Bailly, A. Roudaut, E. Lecolinet, L. Nigay. **Menus Leaf : Enrichir les menus linéaires par des gestes**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'08)*, ACM (2008). 169-172.

G. Bailly, A. Demeure, E. Lecolinet, L. Nigay. **MultiTouch Menu (MTM)**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'08)*, ACM (2008).

S. Malacria, E. Lecolinet, Y. Guiard. **Espace de Caractérisation du Stylo Numérique**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'08)*, ACM (2008). 255-258.

R. Blanch, E. Lecolinet. **Treemaps Zoomables: Techniques d'Interaction Multi'Echelles pour les Treemaps**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'07)*, ACM (2007). 131-139.

S. Huot, E. Lecolinet. **ArchMenu et ThumbMenu : Controler son dispositif mobile "sur le pouce"**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'07)*, ACM (2007). 107-110.

A. Roudaut, E. Lecolinet. **Un espace de classification pour l'interaction sur dispositifs mobiles**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'07)*, ACM (2007). 99-106.

G. Bailly, E. Lecolinet, L. Nigay. **Quinze Ans de Recherche sur les Menus : Critères et Propriétés des Techniques de Menus**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'07)*, ACM (2007). 119-126.

E. Lecolinet, G. Mouret. **TACTIBALL,TACTIPEN,TACTITAB, ou comment `` toucher du doigt '' les données de son ordinateur**. In *Conférence francophone sur l'Interaction Homme Machine (IHM'05)*, ACM (2005).

C. Faure, P. Benci, A. Danzart, E. Lecolinet. **Conception de services mobiles pour étudiants**. In *Journées francophones Mobilité et Ubiquité*, ACM (2006).

E. Lecolinet, D. Nguyen. **Représentation focus+contexte de listes hierarchiques zoomables**. In *Conférence francophone sur l'Interaction HommeMachine (IHM'06)*, ACM (2006).

E. Lecolinet, C. Faure, I. Demeure, J. C. Moissinac, S. Pook. **Augmentation de cours et de réunion dans un Campus**. In *Conférence Mobilité et Ubiquité (Ubimob'05)*, ACM (2005).

E. Lecolinet, M. Nottale. **Immersion d'interfaces 2D dans un espace 3D**. In *Conférence Francophone sur l'Interaction HommeMachine (IHM'04)*, ACM (2004).

E. Lecolinet. **Pointeurs multiples: étude et implémentation**. In *Conférence Francophones sur l'Interaction HommeMachine (IHM'03)*, ACM (2003). 134-141.

A. Goye, G. Chollet, E. Lecolinet, S.S. Lin, X. Ding, C. Pelachaud, Y. Ni. **Interfaces multimodales pour un assistant au voyage**. In *Conférence Francophones sur l'Interaction HommeMachine (IHM'03)*, ACM Press (2003). 244-247.

P. Plenacoste, E. Lecolinet, S. Pook, C. Dumas, J.D. Fekete. **Zoomable and 3D Representations for Digital Libraries**. In *Conférence francobritannique IHMHCI (Interaction HommeMachine / Human Computer Interaction),* IOS Press (2001).

S. Pook, E. Lecolinet, G. Vaysseix, E. Barillot. **Des aides transparentes de navigation et un nouveau type de menu pour les interfaces zoomables**. In *Conférence Ergonomie et Interaction HommeMachine (ErgoIHM)*, Europia (2000). 170-177.

L. Robert, E. Lecolinet. **Techniques d'interaction et de visualisation pour l'accès à des documents numérisés**. In *Conférence Ergonomie et Interaction HommeMachine (ErgoIHM)*, Europia (2000). 178-185.

E. Lecolinet. **Réification et duplication dans les interfaces graphiques**. In *Journées Francophones sur l'Interaction HommeMachine (IHM'99)*, Europia (1999).

L. Robert, E. Lecolinet. **Couplage de représentations globales et locales pour l'exploration d'hyperdocuments**. In *Journées Francophones sur l'Interaction HommeMachine (IHM'98)*, Europia (1998).

L. LikformanSulem, L. Robert, E. Lecolinet, J.L. Lebrave. **Edition hypertextuelle et consultation de manuscrits : le projet Philectre**. In *Conférence Internationale Hypertextes et Hypermédias, Réalisation, Outils et Méthodes* (1997).

E. Lecolinet. **Une approche biunivoque pour la construction d'interfaces graphiques**. In *Journées Francophones sur l'Interaction HommeMachine (IHM'96)*, Europia (1996).

E. Lecolinet. **Création incrémentale d'interface graphiques par programmation visuelle avec équivalence textuelle**. In *Actes Conf. Interface des mondes réels et virtuels* (1995). 479-488.

Eric Lecolinet, Jean-Vincent Moreau. **Lecture Automatique des Codes Postaux et des Noms de Villes Majuscules sur Courrier Manuscrit**. In Conférence Reconnaissance des Formes et Intelligence Artificielle (RFIA'98). (1989). 975-988.

## 3. Books chapters and editing

E. Lecolinet, B. Defude (Eds.). **Proceedings Ubimob'06**. *Journées francophones Mobilité et Ubiquité (Ubimob'06)*, ACM (2006).

J.M. Robert, M. Desmarais, E. Lecolinet, B. David (Eds.). **Proceedings IHM'06 : Nouveaux espaces d'interaction**. *Conférence Francophone sur l'Interaction HommeMachine (IHM'06)*, ACM (2006).

J.D. Fekete, E. Lecolinet (Eds.) **Coordination du numéro spécial "Visualisation pour les bibliothèques numériques"**. *Document Numérique*, *9*, 2, Hermès (2006).

P. Girard, T. Baudel, E. Lecolinet, D. Scapin (Eds) **Proceedings IHM'02**. *Conférence francophone sur l'Interaction Homme Machine (IHM'02)*, ACM (2002).

E. Lecolinet. **A Visual+Textual Environment for Building Graphical User Interfaces**. In *Computer-Aided Design of User Interfaces*, Kluwer Academics (1999) 115126.

C. Faure, E. Lecolinet. **OCR Handwriting**. In *Joint ECUS Survey on the State of the Art in Human Language Techology. Chapter 3: written language recognition*, Cambridge University Press & Giardini Editori (1997).

M. Cote, E. Lecolinet, M. Cheriet, Y.C. Suen. **Using Reading Models for Cursive Script Recognition**. In *Handwriting and Drawing Research: Basic and applied issues, M. Simner, C. Leedham, A. Thomassen (Eds.)*, IOS Press (1996). 299-314.

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E. Lecolinet, O. Baret. **Cursive Word Recognition: Methods and Strategies**. In *Fundamentals in Handwriting Recognition*, Springer Verlag (1994). 235-263.

## 4. Workshops, demos, misc.

E. Lecolinet. **Bientôt de nouvelles façons d'interagir avec les machines.** Interview IMT Tech (2018). https://blogrecherche.wp.imt.fr/2018/02/05/interactions-homme-machine

B. Fruchard, E. Lecolinet, O. Chapuis. **Démonstration de MarkPad : Augmentation du pavé tactile pour la sélection de commandes**. *In* Conférence francophone sur l'Interaction Homme Machine (IHM'17), ACM (2017).

M. Teyssier, G. Bailly, E. Lecolinet. **VersaPen: Exploring Multimodal Interactions with a Programmable Modular Pen**. In CHI'17 Extended Abstracts (demonstration): ACM SIGCHI Conference on Human Factors in Computing Systems, ACM (2017). 377-380.

E. Lecolinet. **Interaction and command memorization for body-centric interfaces.** *Winter workshop on Embodied Interaction*. Saarland University, Saarbrücken, Germany. January 2014.

D. J.C. Matthies, S. T. Perrault, E. Lecolinet, S. Zhao. **Peripheral Microinteraction For Wearable Computing**. In *CHI'14 Workshop on Peripheral Interaction: Shaping the Research and Design Space*. May 2014.

L. Sun, S. T. Perrault, E. Lecolinet. **The Ring Ring: Drawing Attention through Light**. *Chinese CHI 2014 Poster Session*. May 2014. 1516.

J. Eagan, C. Klokmose, E. Lecolinet. **What are Applications in Multisurface Environments?** In *CHI'13 Workshop on Powerwall international workshop on interactive ultrahighresolution displays,* May 2013. 6-*.

E. Lecolinet. **Interaction miniature mobile / incarnée**. Workshop ISN INTERCO. Paris. Mars 2013.

S. T. Perrault, G. Hind, E. Lecolinet, Y. Guiard. **Augmenting digital jewelry with advanced display capacities**. In *CHI'13 Workshop "Display take new Shapes".* May 2013. 4-*.

E. Lecolinet. **L'interaction gestuelle, un gisement de ressources pour l'interaction mobile**. *Forum sur l'Interaction Tactile et Gestuelle (FITG'12*). Lille. November 2012.

S. T. Perrault, S. Malacria, Y. Guiard, E. Lecolinet. **WatchIt: Simple Gestures for Interacting with a Watchstrap**. In *CHI Extended Abstracts: ACM Conference on Human Factors in Computing Systems*, ACM. May 2012, 14671468.

Th. Pietrzak, S. Malacria, A. Tabard, E. Lecolinet. **What do UNote? An Augmented Note Taking System for the Classroom**. In Ubicomp'10 workshop : *PaperComp: International Workshop on Paper Computing*. October 2010.

T. Muhammad, G. Bailly, E. Lecolinet, G. Mouret. **Categorization, Analysis and Properties of Tactile Patterns**. In *Conference Chi NL'09.* Leiden, The Netherlands. June 2009.

T. Muhammad, G. Bailly, Y. Guiard, E. Lecolinet. **Tactile Assistance for Selecting List Favorites with a Bifocal Absolute and Relative Representation**. In *Conference Chi NL'09.* Leiden, The Netherlands. June 2009.

R. Blanch, E. Lecolinet. **Navigation Techniques for Zoomable Treemaps**. In *Adj. Proc.: Demos of ACM UIST'06.* Montreux, Switzerland (2006).

E. Lecolinet. **Nouvelles techniques de visualisation et d'interaction**. Course at *Ecole Franco-Vietnamienne de Recherche Do Son, Multimédia 2005*, CNRS/MICA. Vietnam. Nov. 2005.

E. Lecolinet. **Techniques de visualisation**. Course at *Ecole Jeune Chercheur Interaction et Visualisation de l'Information*. Cap Ferret, France, Septembre 2004.

E. Lecolinet. **Contexte et interaction dans les interfaces zoomables**. *Séminaire de la revue I3*, Universite Pierre & Marie Curie, Paris. Mars 2004.

E. Lecolinet. **Context in Zoomables interfaces**. *Workshop on the Visualization of Relational Data (WVDR'2002)*, Université de Montpellier, France. January 2002.

E. Lecolinet. **The Ubit graphical toolkit: An atomic architecture for GUIs**. IFIP WG 2.7/13.4 workshop. Paris. October 2002.

E. Lecolinet, S. Pook. **Zoomable interfaces: the Zomit toolkit**. IFIP WG 2.7/13.4 workshop. Paris. October 2002.

E. Lecolinet, J.D. Fekete, S. Pook. **Bibliothèques : comparaisons entre le réel et le virtuel en 3D,**

**2D zoomable et 2D arborescent**. In *Conférence ASTI 2001, Cité des Sciences et de l'Industrie*, (2001), 2425.

J.L. Lebrave, B. Cerquiglini, E. Lecolinet. **Digitizing Medieval Manuscripts: Creating a Scholarly Resource**. *Invitational Colloquium of The Johns Hopkins University*. Baltimore, Maryland. November 1998.

E. Lecolinet. **Nouvelles techniques de visualisation des espaces d'information**. Colloque « *Retour vers le futur : supports anciens et modernes de la connaissance à l'aube du XXIe siècle* », Fondation des Treilles, Tourtour, 2000.

S. Pook, E. Lecolinet, G. Vaysseix, E. Barillot. **Contexte et Interaction dans les Interfaces Zoomables**. In *RJC IHM 2000*. June 2000. 5760.

M. Cote, M. Cheriet, E. Lecolinet, C. Suen. **Détection des lignes de base de mots cursifs à l'aide de l'entropie**. *Congrès de l'association canadiennefranccaise pour l'avancement de la science (AFCAS'96)*. 1996.

M. Cote, E. Lecolinet, M. Cheriet, C. Suen. **Lecture automatique d'écriture cursive utilisant des concepts perceptuels**. *Congrès de l'association canadiennefranccaise pour l'avancement de la science (AFCAS'96)*. 1996.

C. Faure, E. Lecolinet. **Interactions hommemachine : trois études**. Rapport 96C005, ENST (1995).

L. Likforman, E. Lecolinet. **Handwriting Analysis: Segmentation and Recognition**. *IEE European Workshop on Handwriting Analysis and Recognition*. 1994. 17/117/8.

## 5. Dissemination

Public presentations and demonstrations at Télécom ParisTech for various events: inauguration of the Télécom Fab lab (2016), inauguration of the DIGISCOPE platform (2014), solemn reception of academic year 2013 (with the French minister of industry), « Futur et ruptures » day (2012), « Multimedia contents and services » day (2008 and 2004), etc.

Demonstrations at « Futur en Seine », a popular public event devoted to science and technology. Paris. June 2013.

Demonstrations at the Alcatel-Lucent Open Days in June 2009 and June 2011.

Public presentation of the UBIMEDIA common lab between Alcatel-Lucent Bell labs and Institut Mines-Télécom. Bibliothèque Nationale, Paris. December 2011.

Public demonstrations for the QUAERO (Rennes, 2010) and CONNEXION (Chatou, 2015) collaborative projects.

## 6. PhD thesis

E. Lecolinet. **Segmentation d'images de mots manuscrits : application à la lecture de chaînes de caractères majuscules alphanumériques et à la lecture de l'écriture cursive**. Université Pierre et Marie Curie (Paris VI). 1990.

## 7. Patents

M. Teyssier, G. Bailly, C. Pelachaud, E. Lecolinet. **MobiLimb - Actuated robotic arm for mobile device.** Patent pending FR 1858553, 09-20-2018.

J. Robinson, M. Ribière, M. Baglioni, E. Lecolinet, J. Daigremont. **Servers, display devices, scrolling methods and methods of generating heatmaps.** Patent number: 8994755. March 31, 2015.

M. Serrano, E. Lecolinet. **Génération perfectionnée de commandes dans un équipement à écran tactile**. Submission PCT/FR2013/050794.

## 8. Software

***https://perso.telecom-paristech.fr/elc/***

**MarkPad**: Augmenting Touchpads for Command Selection

**Bibtoweb**: A tool for generating HTML bibliographies in HTML from BibTex files.

**MacMote**: A tool for controlling multimedia software and devices using 2D and 3D interfaces.

**Ubit GUI Toolkit and Mouse server**: A Molecular Architecture for Building GUIs.

**XXL / XlBuild / XlSketch**: Visual+Textual Equivalence for Building GUIs and for Designing GUIs by Sketch Drawing.

# 11 Curriculum vitæ

## Eric Lecolinet

Télécom ParisTech / LTCI Laboratory
INFRES Department, DIVA Team (team leader).

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DIVA web site: https://diva.telecom-paristech.fr/
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### 1. Employment

- *Since May 2015:* Maître de conférences hors classe at Télécom ParisTech.
- *May 1994 - April 2015:* Maître de conférences (associate professor) at Télécom ParisTech.
- *February 1992 - April 1994:* Enseignant-chercheur (assistant professor) at Télécom ParisTech.
- *October 1990 - January 1992:* Post-Doc at IBM Almaden Research Center, San José, CA, USA.
- *April 1990 - September 1990:* Post-Doc at INRIA (SYNTIM project), Rocquencourt, France.
- *September 1986 - August 1987:* Military service.
- *September 1985 - August 1986:* Assistant professor at Institut National Agronomique Paris-Grignon (INAPG), Paris.

### 2. Education

- *September 1987 - March 1990:* PhD Thesis in computer science at University Pierre & Marie Curie (Paris VI), Paris and Matra MS2I, Velizy, France. Mention très honorable (high honors).
  Title : « *Segmentation d'images de mots manuscrits : application à la lecture de chaînes de caractères majuscules alphanumériques et à la lecture de l'écriture cursive* »
  Supervisor: J-C. Simon.
  Jury: J-P Crettez, G. Lorette, G. Stamon, M. Lucas, J-P. Haton, J-C Simon, G. Gaillat, C. Roche.
- *October 1984 - September 1985:* DEA (M. Sc.) in computer science at University Pierre & Marie Curie (Paris VI), Paris. Mention très bien (high honors).

### 3. Teaching

Since my recruitment at Télécom ParisTech I have been involved in the conception and the coordination of two study tracks in HCI and of various teaching units in computer science, in HCI and (formerly) in pattern recognition at Télécom ParisTech. I am also responsible of a teaching unit at University Pierre & Marie Curie (Paris VI) and at University Paris-Saclay and I act as a local coordinator for the corresponding Master's programs (ANDROIDE Computer Science Master at Paris VI, HCI Master at Paris-Saclay). My current responsibilities are detailed below:

- Co-supervisor (with Tamy Boubekeur) of the *IGR* study track (2 year track) on Human Computer Interaction and Computer Graphics at Telecom ParisTech.

- Advisor of the following teaching units at Telecom ParisTech:
  - *IGR201:* Interactive Application Development (48h, ~30 students)
  - *IGR203:* Human-Computer Interaction (48h, ~30 students)
  - *INF224:* Programming Paradigms: Theory and Practice (2x24h, ~150 students)

- *INF720:* C Language Programming (24h, ~30 students)

− Advisor of the following teaching units at universities Paris VI and Paris-Saclay:
  - *Human-Computer Interaction* (60h, ~30 students) - Master in Computer Science, ANDROIDE specialty - University Pierre et Marie Curie (Paris VI)
  - *Gestural and Mobile Interaction* (21h, ~15 students) - Human Computer Interaction (HCI) Master - University Paris-Saclay.

− Former responsibilities:
  - Co-supervisor of the *IWG* track (1 year study track) at Télécom ParisTech
  - HCI courses at ENSTA (2007-2010) and Paris VI (DEA IARFA then Master IAD, since 1998)
  - Courses in computer science at Télécom ParisTech (since 1992)
  - Courses in pattern recognition at Télécom ParisTech and Paris VI (before 2002)

− Summer schools:
  - HCI course at the Do Son summer school, Vietnam, 2005.
  - Course on interaction & information visualization, Cap Ferret summer school, France, 2005.

# 4. Research

Since my PhD, I have been working in two different research fields: first in Pattern Recognition (more precisely on handwriting recognition), then in Human-Computer Interaction (HCI). My current research interests focus on 1) gestural interaction for command selection, 2) the learning and the memorization of gestures, and 3) user interaction with small and large devices. I have also been working on haptic/tactile feedback, data visualization and user interface engineering.

From an institutional point of view, I have been involved in the coordination of several projects or teams aiming at developing HCI research at Télécom ParisTech and Institut Mines-Télécom (which is the academic institution Télécom ParisTech belongs to). I am now in charge of coordinating the DIVA team [10] of the Computer Science and Networks (INFRES) department of Télécom ParisTech, which is dedicated to human-computer interaction, interactive visualization and design.

I have also been involved in working towards the same goal at the national level, as a board member, then president of AFIHM, the French research association in HCI (and as a member of its steering committee). I have also been a member of the National Committee of CNRS (French National Center for Scientific Research), which is in charge of the recruitment and the evaluation of CNRS researchers nationwide.

## 4.1 Publications

Google Scholar (July 2018): 3596 citations, H-Index 28.

- International journals: 9
- French-speaking journals: 7
- ACM CHI, ACM UIST full papers: 15
- Other international conferences: 52
- French-speaking conferences: 38
- Book chapters: 5
- Editing: 4
- Workshops and demos: 20

[10] DIVA Web Site: https://diva.telecom-paristech.fr/

- Patents: 2

## 4.2 Student supervision

### PhD theses

I have been supervising 17 PhD theses (15 already defended) either as a director or a secondary advisor:

- Marc Teyssier (Since Jan. 2017)
  *Comprendre, concevoir et évaluer la modalité tactile dans les interactions homme-machine sociales.*
  Supervision: 35% (PhD director). Co-supervised by Gilles Bailly (ISIR) and Catherine Pelachaud (ISIR)
- Bruno Fruchard (Since October 2016 - defense in December 2018)
  *Techniques d'interaction exploitant la mémoire spatiale pour faciliter l'accès rapide aux commandes et aux données.*
  Supervision: 60% (PhD director). Co-supervised by Olivier Chapuis (CNRS/LRI)

Defended theses:

- Thibaut Jacob (September 2017)
  *Edition et visualisation de signaux spatiaux-temporels, application au son 3D.*
  Supervision: 40% (PhD director). Co-supervised by G. Bailly (CNRS/Télécom ParisTech).

- Hind Gacem (April 2016)
  *Intégration du numérique dans l'analogique : augmentation d'objets tangibles.*
  Supervision: 50% (PhD director). Co-supervised by James Eagan (Télécom ParisTech).
  Currently: HCI engineer at TechViz, Paris.

- Quentin Roy (December 2015)
  *Manipulation et analyse d'images médicales 3D via des interactions gestuelles sur surfaces tactiles*.
  Supervision: 60%. Co-supervised by Yves Guiard (PhD director, CNRS/Telecom ParisTech).
  Currently: Post-doc researcher at the University of Waterloo.

- Can Liu (December 2015)
  *Embodied Interaction for Data Manipulation Tasks on a Wall-Sized Display.*
  Supervision: 30%. Co-supervised by Michel Beaudouin-Lafon (PhD director, LRI) and Olivier Chapuis (CNRS/LRI).
  Currently: Faculty position in the School of Creative Media at City University in Hong Kong.

- Dong-Bach Vo (September 2013)
  Supervision: 60%. Co-supervised by Yves Guiard (PhD director, CNRS/Telecom ParisTech).
  *Conception et évaluation de nouvelles techniques d'interaction pour la télévision interactive.*
  Currently: Post-doct at Glasgow University, UK.

- Simon Perrault (April 2013).
  Supervision: 40%. Co-supervised by Yves Guiard (PhD director, CNRS/Telecom ParisTech).
  *Techniques d'interaction pour les dispositifs miniaturisés de l'informatique mobile.*
  Currently: Assistant Professor à Yale-NUS College, Singapore.

- Mathias Baglioni (April 2012)
  *Interactions Physiques sur Dispositifs Mobiles.*
  Supervision: 60%. Co-supervised Yves Guiard (PhD director, CNRS/Télécom ParisTech).
  Currently: Technical and development director at Acretion, France

- Sylvain Malacria (May 2011)
  *Conception et Evaluation de Techniques d'Interaction pour Surfaces Tactiles et Papier Interactif.*

Supervision: 100% (PhD director).
Currently: Researcher (CR2) at INRIA Lille Nord-Europe, France.

- Anne Roudaut (February 2010)
  *Conception et Evaluation de techniques d'interaction pour dispositifs mobiles.*
  Supervision: 100% (PhD director).
  Currently: Leverhulme Research Fellow, Interaction & Graphic group, University of Bristol, UK.

- Muhammad Tahir (September 2001)
  *Tangible and Tactile InteractionTechniques for Multimedia Systems.*
  Supervision: 100% (PhD director).
  Currently: Assistant Professor at FCIT, University of Jeddah, Saudi Arabia.

- Gilles Bailly (May 2009).
  *Techniques de menus : Caracterisation, Conception et Evaluation.*
  Supervision: 50% (PhD director). Co-supervised by Laurence Nigay (PhD director, Grenoble University 1).
  Currently: Researcher (CR2) at CNRS.

- José Pinalès (December 2001)
  *Reconnaissance hors-ligne de l'écriture cursive par l'utilisation de modèles perceptifs et neuronaux.*
  Supervision: 100% (PhD director).
  Currently at Universidad de Guanajuato, Mexico.

- Laurent Robert (June 2001)
  *Annotation et visualisation interactives de documents hypermédia.*
  Supervision: 100% (PhD director).
  Currently: Technical director at Orsys, Paris.

- Stuart Pook (June 2001)
  *Interaction and context in zoomables user interfaces.*
  Supervision: 100% (PhD director).
  Currently: Senior software engineer at Criteo, Paris.

- Myriam Côté (June 1997)
  *Utilisation d'un modèle d'accès lexical et de concepts perceptifs pour la reconnaissance d'images de mots cursifs.*
  Supervision: 50% (PhD director). Co-supervised by M. Cheriet (PhD director, ETS, Montréal).

### Post-docs and research engineers

I have supervised 11 post-docs and 3 research engineers:

- Bastien Liutkus (research engineer, 2014/15). Currently: software engineer at à Quematech, Paris.
- Aurélie Cohé (2014/2015). Currently: UX engineer at Renault Technocenter, Guyancourt.
- Minzhi Luo (research engineer, 2013). Currently: Software engineer at Soldata, Paris.
- Simon Perrault (2013). Currently: Assistant Professor à Yale-NUS College, Singapour.
- Julie Wagner (2012/2013). Universität München, then senior UX researcher à Fujitsu Enabling Software Technology GmbH, Munich.
- Marcos Serrano (2011/2012). Currently: Assistant professor at Université de Toulouse (IRIT), Toulouse.
- James Eagan (2011). Currently: Assistant professor at Télécom ParisTech (LTCI), Paris.
- Thomas Pietrzak (2010). Currently: Assistant professor at Université de Lille 1 (Cristal), Lille.

- Gilles Bailly (2009). Currently: Researcher (CR CNRS) à Télécom ParisTech (LTCI), Paris.
- Aurélien Tabard (2009). Currently: Assistant professor at Université Lyon 1 (LIRIS), Lyon.
- Karim-Pierre Maalej (research engineer, 2008). Currently: Software engineer at Kypselia.
- Stéphane Huot (2006). Currently: Senior researcher (DR INRIA) at Inria Lille Nord-Europe (Cristal), Lille.
- Renaud Blanch (2005). Currently: Assistant professor at Université Joseph-Fourier (LIG), Grenoble.
- Stuart Pook (2001-2002). Currently: Senior software engineer at Criteo, Paris.

#### Master and engineering internships

I have also supervised 17 Master (or equivalent) internships and about 50 engineering internships.

## 4.3 PhD defense committees

I have participated to 29 defense committees:

- Jessalyn Alvina (12/2017)
  *Increasing The Expressive Power of Gesture-based Interaction on Mobile Devices*
  Université Paris-Saclay
  Supervisor : Wendy E. Mackay
- Maxime Guillon (11/2017)
  *Expansion de cibles pour le pointage et la selection*
  Université de Grenoble
  Supervisors : Laurence Nigay and François Leitner
- Alix Goguey (10/2016)
  *Comprendre et concevoir l'interaction tactile avec identification des doigts*
  Université de Lille
  Supervisor: Géry Casiez
- Sébastien Pelurson (9/2016)
  *Navigation multimodale dans une vue bifocale sur dispositifs mobiles*
  Université de Grenoble
  Supervisor: Laurence Nigay
- Bin Yang (06/2015)
  *Memory Island: Visualizing Hierarchical Knowledge as Insightful Islands.*
  Université Pierre et Marie Curie (Paris 6), spécialité informatique.
  Supervisor: J-G. Ganascia.
- Yosra Rekik (12/2014)
  *Comprendre, Modéliser et Concevoir l'Interaction Gestuelle Tactile.*
  Université Lille 1, spécialité informatique.
  Supervisors: L. Grisoni et N. Roussel.
- Joey Scarr (06/2014)
  *Understanding and Exploiting Spatial Memory in the Design of Efficient Command Selection Interfaces.*
  University of Canterbury, New Zealand.
  Supervisor: A. Cockburn.
- Huiyuan Cao (11/2013)
  *Design of a Turn-Taking Control System Based on Tactile in Multi-user, Synchronous Remote Communication.*

Université de Technologie de Compiègne, specialité Sciences et Technologies Cognitives
Supervisor: O. Gapenne.

- Adriano Scoditti (09/2011)
  *Gestural interaction techniques for handheld devices combining accelerometers and multipoint touch screens.*
  Université de Grenoble, spécialité informatique.
  Supervisors: R. Blanch et J. Coutaz.

- Dimitri Voilmy (06/2011)
  *Les arrangements de l'attention conjointe : interactions en situations d'apprentissage équipées de tableaux augmentés.*
  Télécom ParisTech (Ecole doctorale EDITE), spécialité sociologie.
  Supervisors: C. Licoppe et B. Conein.

- Marcos Serrano (06/2010)
  *Interaction multimodale en entrée : conception et prototypage.*
  Université de Grenoble, specialité informatique.
  Supervisor: L. Nigay.

- Fabien Pfander (06/2009)
  *Spatialisation de l'information.*
  Université de Technologie de Compiègne, spécialités : Science de l'information et Informatique.
  Supervisors: C. Lenay et F. Ghitalla.

- Qing Pan (12/2008)
  *Isotonic elastic hybrid interaction for 2D and 3D navigation / manipulation.*
  Université de Lille, specialité informatique.
  Supervisors: C. Chaillou et G. Casiez.

- Sawsan Alshattnawi (11/2008)
  *Concurrence et Conscience de Groupe dans l'Édition Collaborative sur Réseaux Pair-à-Pair.*
  Université Henri Poincaré, Nancy 1, spécialité informatique.
  Supervisor: G. Canals.

- Nathalie Henry (07/2008)
  *Exploring large social networks with matrix-based representations.*
  Université Paris Sud - University of Sydney, spécialité informatique.
  Supervisors: J-D. Fekete et P. Eades.

- Alexandre Demeure (10/2007)
  *Modèles et outils pour la conception et l'exécution d'interfaces homme-machine plastiques.*
  Université Joseph Fourier - Grenoble 1, spécialité informatique.
  Supervisors: J. Coutaz et G. Calvary.

- Caroline Appert (03/2007)
  *Modélisation, évaluation et génération de techniques d'interaction.*
  Université Paris-Sud, spécialité informatique.
  Supervisor: M. Beaudouin-Lafon.

- Mounia Ziat (11/2006)
  *Conception et implémentation d'une fonction zoom haptique sur PDAs. Expérimentations et usages.*
  Université de Technologie de Compiègne.
  Supervisor: O. Gapenne.

- Maxime Collomb (12/2006)
  *Vers des systèmes de fenêtrage distribués : l'évolution du drag-and-drop.*

Université Montpellier II - Sciences et Techniques du Languedoc, spécialité informatique.
Supervisor: M. Hascoet.

- Jérome Darbon (10/2005)
  *Composants logiciels et algorithmes de minimisation exacte d'énergies dédiées au traitement des images.*
  Ecole Nationale Supérieure des Télécommunications, spécialité informatique et réseaux.
  Supervisors: P. Bellot et T. Geraud.

- Renaud Blanch (09/2005)
  *Architectures logicielles et outils pour les interfaces hommes-machines graphiques avancées.*
  Université Paris-Sud, spécialité informatique .
  Supervisor: M. Beaudouin-Lafon.

- Suzanne Kieffer (07/2005)
  *Assistance multimodale à l'exploration de visualisations 2D interactives.*
  Université Henri Poincaré - Nancy 1, spécialité informatique.
  Supervisor: N. Carbonell.

- Christophe Lachenal (2004)
  *Modèle et infrastructure logicielle pour l'interaction multi-instrument multisurface.*
  Université Joseph Fourier - Grenoble 1, spécialité informatique.
  Supervisor: J. Coutaz.

- Chaouki Daassi (07/2003)
  *Techniques d'interaction avec un espace de données temporelles.*
  Université Joseph Fourier, spécialité informatique.
  Supervisor: L. Nigay.

- Pierre Abel (06/2001)
  *Supervision d'informations dynamiques et distribuées à l'aide de mondes 3D interactifs : Application à la gestion de réseaux.*
  Ecole Polytechnique Fédérale de Lausanne.
  Supervisor: D. Thalmann.

- Frédéric Vernier (02/2001)
  *La multimodalité en sortie et son application à la visualisation de grandes quantités d'information.*
  Université Joseph Fourier, spécialité informatique.
  Supervisor: L. Nigay.

- Christophe Bruley (06/1999)
  *Analyse des représentations graphiques de l'information - extension aux représentations tridimensionnelles.*
  Université Joseph Fourier, spécialité informatique.
  Supervisors: J. Lemordant et P. Genoud.

- David Price (1996)
  *Classification probabiliste par réseaux de neurones ; application à la reconnaissance de l'écriture manuscrite.*
  Université Pierre et Marie Curie.
  Supervisor: G. Dreyfus.

- Romel Moradkhan (1993)
  *Détection des points critiques d'une forme : application à la reconnaissance de caractères manuscrits.*
  Université Paris Dauphine, spécialité : informatique des organisations.
  Supervisor: Alain Chécroun.

## 4.4 Contractual projects

I have been responsible or co-responsible for Télécom ParisTech (unless otherwise stated) of the following projects and have been involved in their conception:

- DIGISCOPE National Equipex (2011-2020) and DIGIPODS twin project (funded by Région Ile de France). DIGISCOPE is a network of high-performance platforms for interactive visualization of large datasets and complex computation.
- ANR SocialTouch (2017-2022). *Understanding, modeling and evaluating social touch in human-machine interaction*. Project leader.
- ANR Edison3D (2014-2017). *Editing and Rendering for next generation of 3D sound*. Also responsible of a subproject.
- FUI PresAge (2015-2017). *PRospEctives Statistiques liées à l'Age.*
- DIGITEO DigiZoom (2012-2015) and MemSpace (2015-2018) projects, funding the PhD theses of Can Liu and Bruno Fruchard.
- BGLE CONNEXION (2012-2016). *COntrôle Commande Nucléaire Numérique pour l'EXport et la rénovatION.* Local responsible of a subtask of this project.
- CIFRE contract with GE Heathcare funding the PhD thesis of Quentin Roy (2012-2015).
- ITEA TWIRL (2012-2014). *Twinning virtual World Information with Real world data sources.* Also responsible of a work package.
- FUI Quatro 2 (2010-2011). *Interaction pour tablettes à vocation domotique.* Also responsible of a work package.
- Bilateral NIU project (2009-2011) which was part of the UBIMEDIA Common Lab between Alcatel Lucent Bell Labs and Institut-Mines-Télécom.
- QUAERO PVAA (2009-2013). *Interaction pour la télévision interactive.* Local responsible of a subpart of this project.
- DGE/IDF ENEIDE project (2007-2010). *e-Education et Formation, classe numérique.* Also responsible of a work package.
- ANR XWiki Concerto project (2008-2009). *Travail collaboratif pair-à-pair en situation de mobilité.*
- Bilateral MOBA et MOBA2 projects with Alcatel Lucent Bell Labs (2005-2008). *Interaction mobile.*
- Responsible of a project funded by Région Ile de France (2006). V*isualisation et interaction pour l'accès aux masses d'information.*
- CNRS TCAN project (2004-2005). *Interfaces mobiles à retour tactile.*
- RNRT INFRADIO project (2003-2006). *Services et interfaces mobiles.* Responsible of a subtask.
- Action Innovante « Campus Mobile », an internal multi-site project funded by Institut Mines-Télécom (then named GET). (2002-2005). *Conception, réalisation, évaluation de services nomades pour un campus universitaire.*
- Bilateral INFOVISE project with France Télécom (1999-2001). *Interfaces zoomables.*

## 4.5 Collaborations

- Local collaborations with C. Faure, I. Demeure, R. Sharock, G. Mouret, J-C Moissinac, G. Chollet, C. Pelachaud, O. Rioul, F. Detienne, B. Cahour, A. Gentes, I. Guiard, G. Bailly, J Eagan. Various publications or common projects.
- Collaboration with M. Cheriet (ETS) and Y. Suen (Concordia University), Canada. PhD thesis of Myriam Côté. Several publications in 1995-1998.
- Collaboration with R. Casey, IBM Almaden Research Center, USA. Publication IEEE PAMI 1998.
- Collaboration with J.-L. Lebrave and F. Role, ITEM, CNRS. Publications in 1997 and 1998.
- Collaboration with G. Vaysseix and E. Barillot, Infobiogen. PhD thesis of of S. Pook. Several publications in 2000-2003.
- Collaboration with J-D. Fekete, INRIA Saclay. Publications in 2001 and 2006.
- Collaboration with O. Gapenne et C. Lenay, Université de Compiègne. Publications in 2007 and 2014.
- Collaboration with L. Nigay, LIG, Université de Grenoble. PhD thesis of Gilles Bailly. Several publications in 2007-2010.
- Collaboration with M. Ribière, Alcatel-Lucent Bell labs. Publication in 2010.
- Collaboration with T. Selker, UC Berkeley. Publication at ACM CHI 2014.
- Collaboration with S. Zhao, National University of Singapore. Publications in 2014 and at ACM CHI 2015.
- Collaboration with O. Chapuis and M. Beaudouin-Lafon, LRI. PhD thesis of Can Liu. Publications at ACM CHI 2014 (with W. Mackay) and ACM CHI 2016.

### 4.6 Administrative duties

- Leader of the DIVA team (Design, Interaction, Visualization & Applications) at LTCI - Télécom ParisTech.
- Former responsible of the « Campus Mobile » and « VIA » (Advanced Interaction and Visualisation) projects at Télécom -ParisTech and Institut Mines-Télécom (then called GET).
- Member of the section 7 of the CNRS National Commitee (2013-2016). This committee is in charge of the recruitment and the evaluation of CNRS researchers nationwide. Sections 6 and 7 are devoted to Computer Science.
- Vice-chair (2010-2012), then chair (2012-2014) of the ACM SIGCHI Paris Local chapter.
- Member of the LTCI council
- Member of the steering committee of the RT4 thematic network « Content, knowledge and Interaction » of Institut Mines-Télécom.
- Member of the steering committee of the DIGISCOPE Equipex.
- Scientific responsible of the Télécom ParisTech Fab lab.
- Member of the Research and Innovation Committee of Paris-Saclay DigiCosme Labex and of Interaction and Robotics working group of the STIC Department.
- Observer member of IFIP WG 2.7/13.4 group in 2002- 2005.
- Member of recruiting committees (LRI 2010, Télécom ParisTech 2008, 2011, LIG 2018).
- Project expertises (ANR, PACA Labs, Futur et Ruptures, etc.)

## 4.7 Organization and committees

- Current president of AFIHM (Association Française d'Interaction Homme-Machine) and board member in 1999-2003 and 2006-2010.
- Former member of AFIHM steering committee of (CPPMS) in 2007-2017.
- Regular member of the reading committees of the main medias in HCI (almost each year for the last ten years: ACM CHI, ACM UIST, INTERACT, IHM)
- Member of the program or scientific committees of INTERACT 2017, IHM 2016, IHM 2011, IHM 2010, IHM 2007, INTERACT 2007, IHM 2004, UIST 2003.
- Program co-chair of the IHM 2015, IHM 2006, IHM 2002, Ubimob 2006 conferences.
- Member of the scientific board of Annals of Telecommunications in 2002-2007.
- Co-editor of the special number « Visualisation pour les bibliothèques numériques » of the Document Numérique journal in December 2006.
- Local organization of the program committee of ACM CHI 2013 (+200 people), participation to the organization of ACM UIST 2002, local organization of the IFIP WG 2.7/13.4 meeting, October 2002.
- Member of the steering commitee of CNRS GDR I3 and responsible of the ALF working group in 2002-2006.
- Member of the board of GRCE (Groupe de Recheche en Communication Ecrite) in 1996-2002.

# 12 Selected papers

## Gestural interaction

Fruchard, B., Lecolinet, L., Chapuis, O. (2017). **MarkPad: Augmenting Touchpads for Command Selection**. *In* CHI'17. ACM. 5630-5642.

Perrault, S.T., Lecolinet, E., Guiard, Y., Bourse, Y., Zhao, S. (2015). **Physical Loci: Leveraging Spatial, Object and Semantic Memory for Command Selection**. *In* CHI'15, ACM. 299-308.

Wagner, J., Lecolinet, E., Selker, T. (2014). **Multi-finger Chords for Hand-held Tablets: Recognizable and Memorable.** *In* CHI'14. ACM. 2883-2892.

Bailly, B., Müller, J., Lecolinet, E. (2012). **Design and Evaluation of Finger-Count Interaction: Combining multitouch gestures and menus**. International Journal of Human-Computer Studies (IJHCS), 70 (10). Elsevier. 673-689.

Roudaut, A., Lecolinet, E., Guiard, Y. (2009). MicroRolls: **Expanding Touch-Screen Input Vocabulary by Distinguishing Rolls vs. Slides of the Thumb**. *In* CHI'09. ACM. 927-936.

## Other research topics

Liu, C., Chapuis, O., Beaudouin-Lafon, M., Lecolinet, E., Mackay, W. (2014). **Effects of Display Size and Navigation Type on a Classification Task**. *In* CHI'14. ACM. 4147-4156.

Roudaut, A, Huot, S., Lecolinet, E. (2008). **TapTap and MagStick: improving one-handed target acquisition on small touch-screens**. *In* AVI'08. ACM. 146-153.

Blanch, R., Lecolinet, E. (2007). **Browsing Zoomable Treemaps: Structure-Aware Multi-Scale Navigation Techniques**. IEEE Transactions on Visualization and Computer Graphics (TVCG), 13 (6). IEEE Computer. 1248-1253.

Lecolinet, E. (2003). **A molecular architecture for creating advanced interfaces**. *In* UIST'03. ACM. 134-144.

Côte, M., Cheriet, M., Lecolinet, E., Suen, Y. (1997). **Automatic reading of cursive scripts using a reading model and perceptual concepts**. International Journal on Document Analysis and Recognition (IJDAR), 1 (1). IAPR. 3-17.

## Surveys (not included in this document for size concern)

Bailly, G. Lecolinet, E., Nigay, L. (2016). **Visual Menu Techniques**. *ACM Computing Surveys, 49* (4). ACM. 41 pages.

Casey, R., Lecolinet, E. (1998). **A Survey of Methods and Strategies in Character Segmentation**. *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, *18* (7). IEEE. 690-706.

Lecolinet, E., Baret, O. (1994). **Cursive Word Recognition: Methods and Strategies**. In *Fundamentals in Handwriting Recognition*. Springer Verlag. 235-263.