The Transfer of Learning as HCI Similarity: Towards an Objective Assessment of the Sensory-Motor Basis of Naturalness

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ABSTRACT
Human-computer interaction should be *natural*. However, the notion of natural is questioned due to a lack of theoretical background and methods to objectively measure the *naturalness* of a HCI. A frequently cited aspect of natural HCIs is their ability to benefit from knowledge and skills that users develop in their interaction with the real (non-digital) world. Among these skills, sensory-motor abilities are essential to operate many HCIs. This suggests that the transfer of these abilities between physical and digital interactions could be used as an experimental tool to assess the sensory-motor similarity between interactions, and could be considered as an objective measurement of the sensory-motor grounding of naturalness.

In this framework, we introduce a new experimental paradigm inspired by motor learning research to assess sensory-motor similarity, as revealed by the transfer of learning. We tested this paradigm in an empirical study to question the naturalness of three HCIs: direct-touch, mouse pointing and absolute indirect-touch. The study revealed how skill learning transfers from these three digital interactions towards an equivalent physical interaction. We observed strong transfer of skill between direct-touch and physical interaction, but no transfer from the other two interactions. This work provides a first objective assessment of the sensory-motor basis of direct-touch naturalness, and a new empirical path to question HCI similarity and naturalness.

Author Keywords
transfer of learning; sensory-motor skill; interaction similarity; NUI; naturalness; empirical methods; motor learning

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INTRODUCTION
Human computer interaction creates sensory-motor experiences that can be more or less *natural* for the user. While often cited as a good quality of Human Computer Interactions (HCIs), naturalness is a blurred notion subject to questioning [16, 22, 23]. The term *natural* could refer to the user's expertise with a given HCI. For example, mouse interaction, can be considered as natural for many people who have been using it daily for many years. In this paper, we consider another commonly accepted aspect of natural: the ability to benefit from users' pre-existing knowledge and skills of the *physical* world (e.g. the *non-digital* world) [14]. In particular, we propose to assess the sensory-motor grounding of naturalness through an empirical measure of similarity between physical and digital interaction: the *transfer* of sensory-motor skills.

With respect to this aspect of naturalness, mouse interaction appears as less natural than direct-touch interaction. The mouse requires users to adapt to a visuomotor transformation: the mapping of the hand movement in the motor space to the displacement of the cursor in the visual space, with a dynamic gain [3]. By contrast, touch interaction on a tactile surface corresponds to a direct interaction between the user's body and the digital object. This direct interaction is supposed to benefit from the pre-existing skill of manual interaction with physical objects, which renders direct-touch pointing more natural than mouse pointing. The argument of naturalness is often used to explain the widespread success of touch-devices such as smartphone and tablet computers.

As ubiquitous computing moves the focus of HCI from designing tools that maximize *user performance* for a specific task towards the design of "*good user experiences*" [7], naturalness is becoming a central challenge of HCIs design [31]. A good user experience includes dynamical aspects such as learning cost or in situ use. These aspects are not captured by classical approaches of motor skills based on performances such as the Fitts' law [8]. New methods and investigations of human experiences are required to characterize and anticipate the experience that the user will perceive as good or natural. In particular, despite the frequent mention of skill transfer in the definition of naturalness, to our knowledge, there is no method in HCI to objectively assess the transfer of sensory-motor skills between the interaction with physical objects and the interaction with digital objects.

This work is a first effort towards an objective assessment of skills transfer between different forms of interaction, inspired from the motor learning research. This research has extensively studied the transfer of sensory-motor skills for both speech and limb movements as a “behavioral window” [25] towards the brain mechanisms that underlie human movement [2, 20, 28]. Transfer of skills is also a core question for sport and rehabilitation therapies, in particular to assess virtual reality training as a tool to enhance motor learning [12].

We propose a novel experimental paradigm as a first step towards an objective assessment of the sensory-motor grounding of naturalness. The aim is to measure the amplitude of transfer of a given skill between several interactions with digital objects and an equivalent interaction with physical objects. According to previous works in motor learning (e.g. [9, 21]), the amplitude of transfer (e.g. performance improvement) might be a function of the sensory-motor similarity between the digital and physical interactions. In other words, *gradients of transfer* should be observed as correlates of degree of sensory-motor similarity between the different interactions.

As a first implementation of this rational, we questionned the sensory-motor similarity of an interaction on a planar surface with a physical object (a small plastic token, “physical interaction”), and three equivalent interactions with a digital object (a disc the size of the plastic token, “digital interactions”): (1) direct touch pointing, (2) indirect touch (trackpad) pointing with an absolute positioning, and (3) mouse pointing with a dynamic gain. These interactions are chosen to vary the degree of sensory-motor similarity of the digital interaction with the physical interaction and thus, potentially generate a gradient of transfer. Participants are trained to a serial target acquisition task with one of the digital interactions. After a clear improvement in performances (learning effect), they are asked to do the same task with the physical interaction. The improvement of performances in the physical interaction due to the training with the digital interaction is considered as transfer effect. The amplitude of transfer is taken as an objective quantification of the sensory-motor similarity of the digital interaction with physical interaction.

After reviewing the literature on the topic of natural HCIs, we expose the main notions and methods from the motor learning literature that underlie our work. We then detail our experimental paradigm and report on an empirical study based on this paradigm. This study provides a first objective assessment of the similarity between the three tested digital interactions and the physical interaction, which is interpreted as an indication of their relative sensory-motor naturalness. We finally discuss the outcomes of the experiment and conclude.

PREVIOUS WORKS

What is a natural human-computer interaction?

With the development of ubiquitous computers and Post-WIMP interactions, the notion of *natural* is now commonly used in HCI. The notion is however broad and not well defined. Van Dam, for example, relates the naturalness of future “ideal” interactions to the naturalness of the interaction between humans, and to the ability of the interaction to become “invisible to the user” [29]. Jacob et al. extend the “Reality-Based” aspects of post-WIMP interaction to other natural human knowledge and skills (e.g. naïve physics, body, environment and social awareness and skills) [14].

Efforts of definitions and design guidelines have been made in order to better characterize and anticipate interactions that users would feel as natural [31]. *Naturalness* is however also criticized [22], in particular due to its subjective meaning and the lack of objective methods and theoretical background to understand and evaluate how and why an interaction can be felt as natural. The main issue is that “HCI researchers still do not understand why some post-WIMP designs are perceived as natural or intuitive, while others are not because there is no theory, model, or framework about the cognitive processes that let us perceive UIs this way or the other” [16] (See also [23]).

Natural HCIs commonly appear as: gestural interactions (1) that create good user experiences (2), in particular by benefitting from users’ pre-existing skills (3).

A natural interaction should allow users to manipulate digital objects or communicate with digital entities through their natural interactive skills: speech and manual gestures [24]. This idea has been criticized as both speech and gestures are learned through intensive daily uses and are culturally defined [22]. Involving direct gestures in HCIs also raised a number of issues. For example, a direct transfer from a sensory-motor skill with a physical object towards an action on digital objects could end in domestic drama (e.g. the Nintendo Wii thrown on TV screens while playing bowling [22]).

HCIs were first conceived as tools to optimize a specific task. By contrast, natural interactions are based on users’ feelings and experiences: the user should feel the interaction as a natural sensory-motor experience [31]. This is not the technology itself that is natural but the way users interact with it [23]. Hence, evaluation criteria progressively shift from usability and performance towards a more complex “new good”, that considers the user experience [7]. This creates new interests for sensory-motor in-situ phenomena [3], embodied and situated cognition in general [11, 17] and learning and adaptation in particular [4]. However, few works have studied motor learning in HCI [4], and the way it influences the user’s experience [15]. We are not aware of any work that specifically studied the transfer of sensory-motor learning from one interaction to another one.

Benefitting from user pre-existing skills. Wobbrock et al. introduced various methods to exploit users pre-existing knowledge and skills in the definition of gesture sets [32, 33], but their work was focused on finding easily *guessable* gestures rather than measuring a skill transfer. In their Reality-Based Interactions (RBI) framework, Jacob et al. expose the benefit of taking advantage of users pre-existing skills to reduce the cognitive load and the learning cost of the interaction [14]. This idea also appears in one of Wigdor et al.’s design guidelines for natural user interfaces, which is to "leverage innate talents and previously learned skills" [31].

The rational of our study is that an objective way to evaluate the *sensory-motor naturalness* of an interaction with digital objects is to measure how the sensory-motor skills involved in this interaction are influenced by similar skills in the physical world. This approach is inspired from the literature on motor learning and transfer.

Motor learning and transfer

Despite very successful application of motor control results in HCI [5, 8], uses of motor *learning* results are sparse [4]. Our study focuses on the *transfer* of *learning* of *motor skills*. Considering the broad literature on motor learning, the references below should be considered as illustrative.

The term *skill* covers a large range of phenomena from mathematical abilities to driving or running [2]. Here, we focus on interaction with real or digital objects through direct or indirect body actions: learned abilities that involved a specific control of the body via sensory-motor loops to achieve a specific task. Tennis playing and mouse pointing are classic illustrations of sensory-motor skills found in the literature on motor learning [6, 20, 34]. Pointing and reaching tasks have been extensively studies as experimental models of the upper-limb motor control and learning (e.g. [6, 19, 20, 21, 34]).

Learning of a motor skill is an "improvement, through practice, in the performance of sensory-guided motor behavior" [19].

Transfer of motor learning corresponds to a positive effect of past experiences on new ones, while negative effects are called *interferences* [20]. For example, previous expertise in typing on a QWERTY keyboard has negative effect or *interferes* with the use of an AZERTY keyboard, while learning to type with a large QWERTY keyboard may help, or *transfer*, to typing on a smaller QWERTY keyboard. Transfer and interference are extensively investigated in motor learning. These investigations not only aim at evaluating if a given training could improve the performance in another task or situation, but also at assessing the fundamental question of the nature of the representations that underlie motor control (e.g. [2, 20, 25, 28, 34]).

Motor learning and transfer of arm-movements are studied in laboratory mainly using two types of tasks: (1) common pointing/reaching tasks or speech tasks under unusual but systematic perturbation of movement or feedbacks (e.g. [13, 20, 21, 28]); (2) novel tasks, such as tracking more or less predictable trajectories [35] or pointing at targets in more or less predictable orders [10]. Our experimental task is based on the latter.

The motor learning literature indicates that skill learning is globally *specific*: in other words, to observe a transfer, the training and test situations must be very similar. However, *gradients of transfer* can be observed as correlates of the *similarity* between the training and testing experiences (e.g. [9, 21]). In our study, we attempt to observe a gradient of transfer as a correlate of the sensory-motor similarity between a physical interaction and various digital interactions. This similarity could be used as an objective evaluation of the naturalness of the digital interactions at the sensory-motor level.

AN EXPERIMENTAL PARADIGM TO STUDY THE TRANSFER OF LEARNING IN HCI

Learning and transfer of learning are assessed in controlled situations based on a paradigm that includes three mains steps [10]: (1) A *baseline phase* that allows to assess participants' performance before learning (e.g. pointing at targets in a given order A for a short period); (2) A *training phase* during which participants repeat the task (pointing in order A) for a given duration. This phase could be achieved on a single session on one day or several sessions over several days; (3) A *test phase* for transfer during which participants achieve a more or less similar task (e.g. pointing to the same targets in a new order B). Learning is assessed through the analysis of the progression of performance from the baseline to the last training period. Transfer is assessed by comparing performances in the test phase to that in the baseline.

We adapted this paradigm to the purpose of studying transfer of learning in the execution of an identical task achieved with different forms of interaction. In the remainder of this paper, we will use the expression "physical interaction" for "interaction with physical objects"; the expression "a HCI" to denote a common form of human-computer interactions such as direct touch, or mouse-pointer interaction; and the expression "a digital interaction" to denote an interaction with digital objects using a particular HCI.

Our first idea was to observe a transfer from physical interaction towards digital interaction. However, training all subjects in one condition (physical) and testing the transfer towards other conditions (the tested HCIs) present two main issues well known in the motor learning literature [10, 18, 20, 21, 28, 30]: (1) it provides no indication of the potential improvement effect for each condition. Some HCIs offer large performance improvement from training, others don't. As a result, (2) it leads to compare apples to oranges: i.e. the percentage of improvement for a given HCI-A is not equivalent to the percentage of improvement for another HCI-B. Problem (1) can be solved by introducing one control group per HCI (which makes the design more complex) but this does not solve problem (2). Therefore, the standard approach in the motor learning literature is to compare the amount of tranfer from different conditions towards a single condition. We use this "reversed" approach because it allows the indisputable *comparison* of the amount of transfer from various digital interactions towards a single physical interaction.

By reversing the experimental design, we are now observing how sensory-motor skills acquired using a particular HCI with digital objects transfer to the interaction with physical objects. This may appear as moving away from the concept of naturalness as the ability to use pre-existing skills from physical interaction. This raises the question of the *symmetry* of the transfer: if a skill acquired with a digital interaction transfers well in physical interaction, does this mean that the

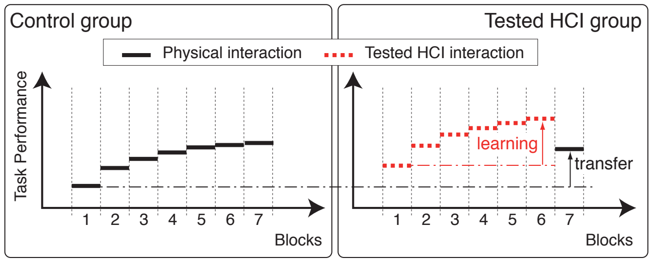

Figure 1. Observing a transfer of learning. A "Control" group of participants is trained for a novel task executed with physical interaction. The performance of another "Tested HCI" group of participants is measured after prior training on several blocks of trials on a similar task executed with the tested HCI. Transfer is observed if the performance of the tested HCI group with physical interaction is better than the initial performance of the control group.

opposite is true? While there are no obvious rational to suggest a strong asymmetry, this remains an open question that we will discuss at the end of this article. However, in our study the transfer of learning is not seen as an end but rather as a means to study the *similarity* between various forms of interaction. In this regard, observing a strong transfer of skills from a digital interaction towards physical interaction is as much an indication of the similarity of the two interactions than the opposite.

The following steps summarize our experimental paradigm:

- A *control* group of participants is trained to a novel task with a physical interaction. The initial performance of this group (i.e. block #1 of the control group in Figure 1, left) serves as the baseline;
- For each HCI, a *test* group of participants is trained to a similar task, but with digital objects moved using the tested HCI. Sensory-motor *learning* of the task is observed through performance increase over the training session (i.e. the red arrow in Figure 1);
- After a number of training blocks made of several repetition of the same task, the tested HCI group executes the task again but this time with physical interaction (i.e. block #7 on Figure 1). *Transfer* is assessed by comparing the performance in this last block with the baseline performance (black arrow on Figure 1).
- A *gradient* of transfer is observed by comparing the transfer effects from the different tested HCI to the physical interaction.

Figure 1 illustrates a case where user performance with the digital interaction is generally better than with the physical interaction. But even in the opposite case, a transfer of learning would still be demonstrated as long as the performance with the physical interaction is significantly higher in the test group than in the control group. This underscores the independence between transfer of learning and user performance.

We chose a between-subjects design because any experimental session provides some training that potentially influences participants' behavior in the following sessions. The difficulty is then to dissociate, in subjects' performances, how much is due to transfer and how much is due to repeated sessions. This is not an issue in Fitts paradigms [26] which focus on the *trained performance* (i.e. discarding the training) and mitigate transfer effects by balancing the order of presentation. This is a major problem in paradigms that measure learning and transfer. However, as the general performance of participants is variable, groups must be balanced, so that the initial performance difference between groups cannot explain the performance difference between the control group and the test groups.

THE EXPERIMENT

We conducted an empirical study based on this paradigm in order to evaluate the similarity of various HCIs with an equivalent physical interaction.

Experimental task

The task was chosen to meet the following requirements:

- the task can be performed both with a physical and digital objects, and with the different HCIs of interest;
- the task is novel to the participants, so that all participants are supposed to be similar in regard to their knowledge and practice of the task at the beginning of the experiment;
- the task is difficult enough that learning can be observed as a performance increase through training.

We chose a serial target acquisition task as previous work showed that it was appropriate to study motor learning [10]. With this kind of task, improvement in participant performance can be the result of sensory-motor learning, which depends on the interaction, but also the result of learning the sequence of targets, which is independent of the interaction. As we wanted to contrast the sensory-motor learning from various interactions, we aimed at reducing the effect of the learning of the sequence. We thus chose a very simple constant order for the target positions so that it was quickly learned in few trials. Our objective was that performance improvement would result mostly from the learning of two new *sensory-motor skills*: acquiring targets repeatedly at well known positions (e.g. by developing a proprioception of the target positions), and anticipation (e.g. using the best trajectory in the approach of a target in preparation of the acquisition of the next target).

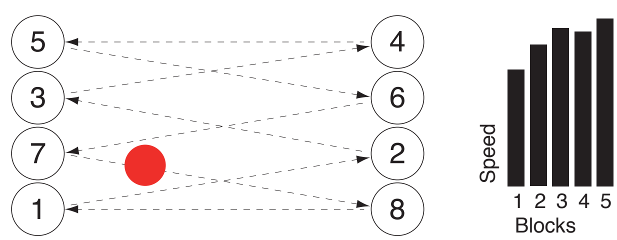

Figure 2. Left: the sequence of targets. The numbered white discs represent targets, the red disc represents the object controlled by participants. Disc size, target size and positions are represented to scale. Dashed arrows and numbers are illustrations of the order, they were not shown to the participants. Right: representation of the speed of target acquisition during pauses.

Participants had to move a red disc object (either physical or digital) on the top of a circular target which could take 8 different positions on display, as illustrated in Figure 2, left. The display was set horizontally on a desk. The outermost target centers defined a $430\,\mathrm{mm} \times 200\,\mathrm{mm}$ rectangle. Target diameter was $64\,\mathrm{mm}$, object diameter was $50\,\mathrm{mm}$. The targets were acquired when the object was entirely within the boundaries of the target, which translates in terms of Fitts' law [26] to a target size of $64 - 50 = 14\,\mathrm{mm}$. Inter-target distance was either $430\,\mathrm{mm}$ (horizontal) or $438\,\mathrm{mm}$ (diagonal). Hence, every object placement had a Fitts index of difficulty of $\approx 5\,\mathrm{bits}$.

In a block of trials, participants executed a sequence of 64 target acquisitions made of 8 repetitions of the sequence presented in Figure 2, left. They initiated a block by moving the object on top of a "start area" located at position #8. Then, after a short delay, the first target appeared at position #1. The targets disappeared as soon as they were acquired, and the next target was displayed. Target acquisition was thus a *goal crossing* task [1] rather than a pointing task. In particular, target acquisition did not require the object to stop on top of the target, which fostered anticipated motion towards the next target. We also indicated the position of the next target as a hollow circle to foster anticipation and reduce the effect of learning the sequence. Participants were instructed to acquire the targets as fast as possible. They were explicitly asked to find the right speed-accuracy trade-off in order to go through each block of 64 targets as fast as possible.

After each block of trials, participants were asked to relax for 30 s. During this pause, an indication of their speed was displayed in the form of a bar chart. This is illustrated in Figure 2, right, in the case of the pause coming after the 5th block. The bar for the first block had a fixed size, the height of the other bars indicated the average speed of target selection during each block relative to the first block. The goal of this chart was to encourage participants to maintain their effort and to stay at their maximal performance across the 10 training blocks.

As a between-subjects design, any difference in groups' performances after the training session could be related either to the training, or to unbalanced average abilities between groups. In order to avoid the second possibility, the groups of participant were built according to the participants' performance in a first *group balancing* task. The group balancing task was chosen to be representative of participants' ability to quickly move the *physical* disc on top of targets. This task was also chosen so as to avoid any training to the main experiment's training task: the targets were positioned differently than in the training task (in a five arms star configuration) and anticipation was prevented by requiring the participants to move the physical disc to a start area after each target acquisition, and by displaying the next target after a varying delay (in the range 200 ms to 800 ms). The group balancing task was made of 64 target acquisitions.

Interactions

In the physical interaction, participants had to slide a plastic disc of diameter $50\,\mathrm{mm}$ and height $4\,\mathrm{mm}$. The disc had soft fabric at the bottom in order to provide smooth sliding on the surface. Soft fabric was also taped on its top side it order to improve the finger grip on the disc, as compared to bare plastic.

In this study, we focused on the two most common forms of HCI, mouse pointing and direct-touch, and on a more specific form of HCI: indirect-touch in absolute mode. We introduced the latter as an intermediate between the two formers in terms of similarity with the physical interaction. All the three HCIs were used to control the position of a red digital disc of diameter $50\,\mathrm{mm}$.

As it can be expected, the digital disc was controlled by landing a finger on its surface with *direct-touch*, and by pressing on the mouse button while the pointer was on its surface with *mouse pointing*. For the mouse interaction, participants were told that it was not necessary to maintain the mouse button depressed: once acquired, the digital disc remained under control of the mouse for the entire block. Doing so, we focused on participant's control of the mouse position and eliminated the effect of pressing on the button. Mouse pointing was used with the standard control-display transfer function of Mac OS X with "Tracking speed" set to level 3 on the 10-level scale of the control panel. Control of the digital disc with *indirect-touch* on a trackpad was more specific: we did not use a common transfer function with relative control and dynamic gain as used on most laptop computers. Instead, the trackpad was used in an *absolute* mode, similar to digitizing tablets: when a finger landed on the trackpad, the digital disc teleported to the corresponding position on the display. However, teleportation very rarely occurred during the experiment as the task was best performed with the finger remaining in contact with the trackpad during the entire block of trials. For the two *indirect* HCIs, the mouse or trackpad were placed to the left or to the right of the display surface, depending on the participant's handedness.

The rational of these choices was to create gradients of similarity between the physical interaction and the digital interactions. The tested interactions could be ordered according to their respective sensory-motor overlapping with the physical interaction as followed:

- direct-touch was the closest to the physical interaction as it involved similar visuomotor associations and arms configuration. Differences with the physical interaction included a delay in the visual feedback, the absence of somatosensorial (tactile) feedback to perceive the texture, and a difference in friction forces
- indirect-touch (trackpad) was considered as intermediate as it introduced a spatial transformation between the finger and the object motion. However, used in absolute mode, the simple linear transformation was less radical than with mouse pointing. It also involved a similar configuration of the finger;
- mouse pointing was considered the furthest to physical interaction due to the speed-dependent transformation between mouse and object motion and different finger configuration.

Figure 3. Implementing direct-touch with optical tracking. An optical marker is taped on the nail. A piece of soft fabric is taped underneath the finger to improve sliding.

Participants and procedure

28 volunteers (9 females, 19 males) participated in the experiment, split into the following four groups of 7 participants according to the training device:

- The control group (CTR) was trained with the physical disc, the mean age was 31.9 (range [25-41]), all participants were male,
- The touch group (TOU) was trained with direct touch, the mean age was 29.0 (range [22-39]), it included 3 females,
- The trackpad group (PAD) was trained with the trackpad, the mean age was 32.0 (range [23-43]), it included 3 females,
- The mouse group (MOU) was trained with the mouse, the mean age was 30.6 (range [21-42]), it included 3 females.

The participants were not informed about the expectations of the experiment prior the completion of the experiment. They were all graduated students or university staff used to computer, mouse or touch interactions.

Participants were instructed that the experiment was anonymous, and that it included three sessions separated with breaks:

- Group balancing session. Participants performed the 64 target acquisitions of the group balancing task. Their performance was immediately computed and they were assigned to a group so as to balance the average performance of each group.
- Training session. Participants performed 10 blocks of the training task using one of the four interactions depending on their group.
- Test (or transfer) session. After training, all participants performed 4 blocks of the training task by moving the physical disc.

Overall, participants finished the tree sessions in about half an hour.

Apparatus

The experimental tasks were performed on a 1920×1080 pixel 120 Hz LCD monitor which foot was removed so that it could be taped horizontally on a desk. The monitor was driven by custom developed software running on a 3.4 GHz workstation.

The physical disc was equipped with 3 spherical optical markers captured by 2 Flex 13 120 Hz Optitrack cameras. The outputs of the cameras were processed by the tracking software running on a dedicated 2.6 GHz workstation, the computed position was then sent over the network to the main workstation. The same optical tracking system was used to implement the direct-touch interaction on the non-touch sensitive monitor: an optical marker was attached to the pointing finger of the participant, as shown in Figure 3. In addition, a small patch of soft fabric was taped at the bottom of the finger to improve the sliding of the finger on the surface and to prevent burning sensations during the high speed dragging of the digital disc.

We used a standard wired optical mouse for the mouse pointing interaction. For indirect-touch, we used a wireless 130×110 mm Apple magic trackpad. The raw touch position on the trackpad was used to implement an absolute position mapping to the display. Only a subpart of the height of the trackpad was used in order to provide an isomorphic $x - y$ mapping on the $16/9$ display.

Results

We based our analyses on the duration of the target acquisition (in_time) measured as the time span between the appearance of a target and the first time when the disc (either physical or digital) is entirely within the target boundaries. For each subject and trial block, we withdraw trials with in_time values higher than 1.5 the interquartile range from the mean of the block. This effectively removes *failed* trials where a participant fails to acquire the target, anticipates the acquisition of the next target, and then realizes the failure and comes back to the current target.

The third block of the test session (block 13, Figure 4) of one participant in *TOU* was removed due to outlier behavior of the participant during this specific block.

The Figure 4 displays the average *in_time* values for each group and block over the whole experiment. We can observe that:

- The ability to interact with the physical object before training is equivalent for the four groups;
- The performances for MOU and PAD are worst than TOU and CTR, at the onset but also at the offset of training;
- The performances improve over the training phase for the four groups, with variable degree of improvement according to the HCIs;
- The performances are better at the onset of the transfer phase for CTR and TOU than PAD and MOU. Moreover, the progression of performances over the four blocks of the post-phase for PAD and MOU are similar to that observed over the four first blocks of training of CTR.

We will now analyze in more details these different points and their statistical reliability.

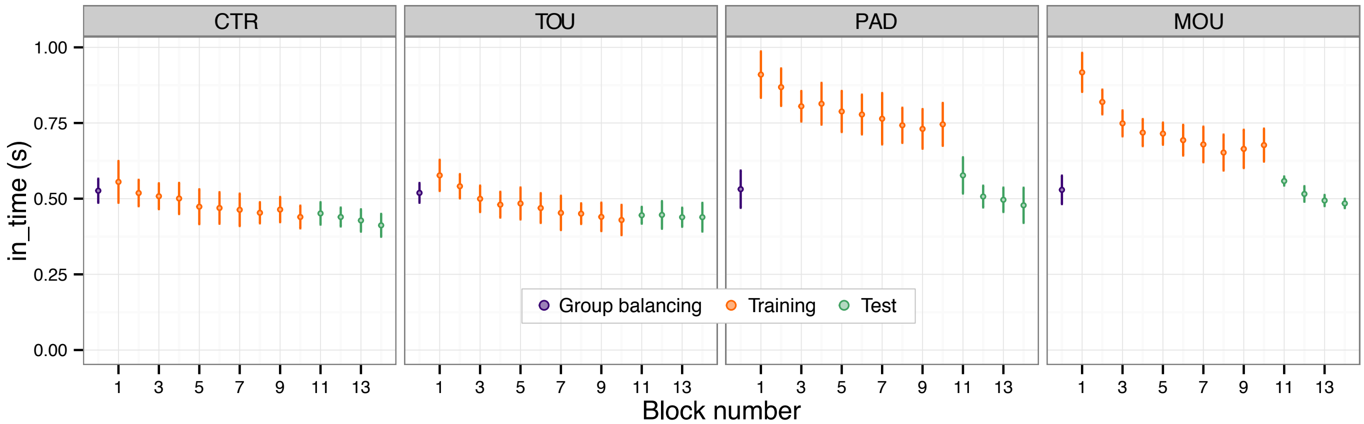

Figure 4. Mean target acquisition time, with 95% confidence intervals, for each group and each block of trials and for the three sessions.

Equivalent abilities in the physical interaction

As a result of the method used to constitute the groups, subjects' performances during the group balancing task was similar for the four groups with average in_time in the range 0.52 s to 0.53 s. A between subjects ANOVA shows no significant effect of the group on the group balancing task performances ($F(3, 24) = 0.25, p > .86$).

Training session

In order to investigate the effect of HCIs on global performances and on learning, we focused on the first and last blocks of the training session. We ran a mixed ANOVA with the group as a between subject factor and the block (1 vs. 10) as a within subject factor. It showed a significant effect of the group ($F(3, 24) = 39, p < .0001$), the block ($F(1, 24) = 221, p < .0001$) and an interaction between the two factors ($F(3, 24) = 5.5, p < .01$). We then ran post-hoc tests to evaluate differences in performance according to the HCIs and to the block (Tukey's HSD for the group factor and paired sample t.test with a Bonferroni correction for the block factor).

Different performances according to the HCI. The task required large motions of the controlled object on the display surface. As MOU and PAD both use a control-display gain to amplify the motions in motor-space, we expected smaller in_time compared to direct interactions (CTL and TOU). We actually observed the reverse: during the first block of training, the average in_time was 0.92 s for MOU, 0.91 s for PAD, 0.58 s for TOU, and 0.56 s for CTR. Even at the end of the training, in_time was still more than 0.24 s longer for PAD (0.75 s) and MOU (0.68 s) than CTR (0.44 s) and TOU (0.43 s). Comparisons between groups' performances during the first and the last block separately showed no significant differences between PAD and MOU ($p = 0.9$, for the first block and $p = .06$ for the last block). Similarly, TOU and CTR were not different in the first and last block ($p > .9$). By contrast, in_time for both TOU and CTR was significantly smaller than for MOU and PAD in all block comparisons ($p < .0001$).

Learning effect. The learning effect was significant for each group ($t(6) > 4.5$, $p < 0.05$, for all the within-subject comparisons between the first and the last block of each group after a Bonferroni correction). Over the training phase, in_time significantly decreased on average by: -0.12 s for CTR (a 21% improvement), -0.15 s for TOU (a 25% improvement), -0.16 s for PAD (a 18% improvement) and -0.24 s for MOU (a 26% improvement).

Transfer

We tested if the training with each HCI influenced participants' performances when they switched to the physical interaction. For this, we specifically focused on the first block of the training session of the control group, which indicates the *baseline* performance with the physical interaction with no training at all, and on the first block of the test session for all groups, which still indicates the performance with the physical interaction, but this time after training with various interactions depending on the group. This focus is illustrated on Figure 5. Between-subjects ANOVAs revealed a significant effect of the group, both when comparing the baseline performance ($F(3, 24) = 6.0, p < 0.01$) and the trained performance ($F(3, 24) = 12.7, p < 0.001$) of the control group with the performance after training of the test groups. Performance improved by 20% from the baseline when trained with

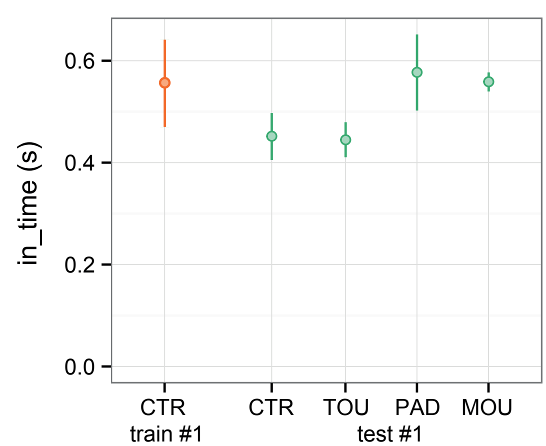

Figure 5. Close-up on Figure 4 for the first block of the training session of the control group (train #1), and the first block of the test session of all groups (test #1).

TOU ($p < 0.05$). On the contrary, no significant variation from the baseline performance was observed when training with PAD or MOU ($p > 0.9$): the initial test performance was 4% lower and less than 1% higher than the baseline for PAD and MOU, respectively. Performance after training for the CTL or the TOU groups was very similar, differing by only 1%.

DISCUSSION

The aim of this work was to propose an experimental paradigm to objectively assess the sensory-motor grounding of the naturalness of various HCIs. We use this paradigm to empirically questionned the sensory-motor naturalness of three HCIs. This paradigm rests on the rational that the naturalness of an HCI is anchored in the similarity of the sensory motor-skills involved in the HCI and those involved in the interaction with the physical world. In our paradigm, the sensory-motor similarity is operationalized in a well-known and extensively investigated phenomenon in the motor control literature: the transfer of sensory-motor learning. Using a serial target crossing task, we observe that the skills learned through training with direct-touch transfer fully to the physical interaction while no skill transfer is observed when training with indirect-touch or mouse pointing. According to our rational, this means that direct-touch is more similar to the physical interaction at a sensory-motor level, which provide an empirical and objective correlate of the widely circulated belief that direct-touch is a more natural form of interaction than mouse pointing. Taken together, the results of the experiment are not trivial: they include a number of unexpected aspects that we will now discuss and interpret.

Interpretation of the observed transfer profiles

The study was designed to observe a gradient of transfer by manipulating the sensory-motor similarity between the three tested HCIs and the physical interaction. In particular, considering the sensory-motor couplings involved in the HCIs, we were expecting the following trend in the first block of the test-session: $CTR > TOU > PAD > MOU > 0$. What we observed, however, was a binary profile of transfer with a full transfer for direct-touch and no transfer for the two other interactions: $CTR = TOU > PAD = MOU = 0$.

$CTR = TOU$

The first unexpected result concerning the transfer effect is the absence of difference between the control and the direct-touch groups. Despite substantial differences in sensory-motor associations for the two interactions (e.g. delay in visual feedback, absence of inertial mass, different tactile feedback between the display and the physical disc, different frictions), shifting from direct-touch to the physical interaction seems *transparent*: participant trained with direct-touch performed similarly than participants trained with the physical interaction. This may be explained in the current study by the limited delay of the visual feedback thanks to the high frequency/low latency tracking, and the limited friction forces of the physical token in the physical interaction. It would be interesting to study the effect of various characteristics of the direct-touch interaction, such as feedback latency or friction, to observe how they affect transfer.

$PAD = MOU = 0$

Indirect-touch and mouse pointing showed no transfer, despite the observation of a learning effect in the training session with both interactions and despite offering quite different sensory-motor controls, with the absolute PAD control arguably closer to the physical interaction than the dynamic gain control of the mouse. These results support the idea that sensory-motor transfer is very specific, as previously shown in motor learning research [21, 28]. An important repercussion of the specificity of transfer is that, when attempting to create novel *natural* interactions, designers may not be able to depart very far from a faithful reproduction of a physical interaction. Here again, it will be interesting to study more systematically how different intermediates between TOU and PAD can exhibit a transfer of learning to physical interaction. Absolute indirect-touch, for example, could be "moved" closer to physical interaction by using a control-display gain of 1 (i.e. using a pad with the same size of the display). Such study may inform about the fundamental sensory-motor requirements of natural interactions.

Previous works also showed that mouse vs. touch navigation lead to different improvements of spatial memory and that kinesthesic cues involved in touch are important for spatial memory [15, 27]. In our case, MOU and PAD may lead to different memorization of the target trajectory than the CTR condition, while the exploration with TOU may be close to CTR. More studies are required to better understand the relationship between sensory-motor experience and the cognitive aspects of naturalness [15].

Limits and improvements of the paradigm

Transfer effect vs. performance effect

The experimental task that we used was performed more efficiently with the direct interaction techniques (physical and direct-touch) compared to the indirect ones (indirect-touch and mouse). One could argue that the absence of transfer from indirect-touch and mouse is related to the bad performances in these HCIs as compare with direct-touch. However, the learning curves in Figure 4 show that performances clearly increased for these two interactions and that the higher performance of the mouse, compared to indirect-touch, did not end up in a greater transfer. Even so, it would be interesting to create an experimental task that yields better performance with mouse pointing than with direct-touch to test the independence between task performance and transfer of learning.

From digital to physical

As explained above, we chose to reverse the experimental paradigm: we measured transfer from digital to physical rather than the more intuitive opposite. We assumed that a transfer in either directions was an indication of the similarity of the sensory-motor skills involved in the two interactions, and that if two interactions use similar sensory-motor skills, then newly learned skills should transfer either way. This points to further experimentations aimed at evaluating the *symmetry* of the transfer. This could be done by measuring a baseline performance of a control group interacting with direct-touch interaction, and measuring a transfer on another group trained with physical interaction.

Beyond naturalness, why are transfer effects important for HCI

As mentioned in the "previous work" section, ubiquitous computing orients HCI towards new methods that should help evaluating what is a good user experience [7, 31]. At the same time, future HCIs might be more and more non-representational and thus intrinsically more oriented towards sensory-motor skills [11]. The consequence is that HCI designers now need to better understand sensory-motor skills, their adaptation and plasticity, especially to anticipate if and how the modern human, used to many forms of digital interactions, will be able to extend her/his sensory-motor skills to integrate novel interaction designs. Transfer of learning should thus be studied not only to and from physical interaction, but also between digital interactions.

Study of sensory-motor learning and transfer is also important at a more fundamental level: new technologies come with more and more new sensory-motor skills. These skills may interact together but also influence real word behaviors. For example, Wei et al. recently compared visuomotor learning for computer and non-computer users [30]. Using a classic direct finger pointing task, they observed greater transfer of visuomotor training with computer users than with non-computer users. This suggests that computer use, and in particular the daily exposition to the mouse visuomotor transformation, changes our subsequent visuomotor abilities in the non-digital world. This study and similar ones in motor learning, neurosciences and psychology also emphasized the relevance of studies of learning and transfer in laboratory to assess more global phenomena. As a consequence, models of sensory-motor learning may be developed and used in HCI in order to simulate the consequences of the daily use of some forms of human-computer interaction on human sensory-motor abilities.

CONCLUSION

HCI designers need theories to better understand user experience and tools to anticipate what forms of interaction would create a good user experience [7, 11, 16, 23]: interactions that will be easily integrated to user sensory-motor competences in the real world, but also that will have no negative effects on these competences. Design guidelines have been presented towards the conception of natural user interfaces [31]. However, these guidelines do not include methods to objectively assess the different rules that designers should respect to create an interaction that could be natural to the user, that will respect her/his sensory-motor abilities and extend beyond.

Facing the lack of theoretical and empirical background with regard to naturalness in HCI, our contribution was to explore the literature of sensory-motor skills learning and exploit the advances in this field to propose a first step towards an objective measurement of the sensory-motor basis of HCI naturalness. We introduce a classic paradigm in motor learning research: the transfer of sensory-motor skills.

In an empirical experiment, we found that the learning of a novel task with direct-touch interaction transferred very well to physical interaction, a first objective indication of the sensory-motor similarity of the two interactions, and an indication of the naturalness of direct-touch. We also observed that the transfer of learning may be very specific and that the design space around physical interaction is not very large for the design of novel human-computer interactions that use natural sensory-motor skills.

As mentioned elsewhere, "HCI is at a crossroads" between the digital and physical world [17]. Our feeling is that many authors look for answers in psychology or cognitive sciences [3, 16, 17] but omit what is actually one of the building blocks of HCI: sensory-motor learning. The connection with embodied and situated cognition is certainly a necessity for HCI to progress towards more and more embodied and natural interactions, but the interest for motor learning theories, models and methods will certainly be a fruitful road towards naturalness.

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