Experimental Brain Research
https://doi.org/10.1007/s00221-018-5368-2

RESEARCH ARTICLE

Adaptation to visual feedback delays on touchscreens with hand vision

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Received: 30 May 2017 / Accepted: 25 August 2018

Abstract

Direct touch finger interaction on a smartphone or a tablet is now ubiquitous. However, the latency inherent in digital computation produces an average feedback delay of ~75 ms between the action of the hand and its visible effect on digital content. This delay has been shown to affect users' performance, but it is unclear whether users adapt to this delay and whether it influences skill learning. Previous work studied adaptation to feedback delays but only for longer delays, with hidden hand or indirect devices. This paper addresses adaptation to touchscreen delay in two empirical studies involving the tracking of a target moving along an elliptical path. Participants were trained for the task either at the minimal delay the system allows (~9 ms) or at a longer delay equivalent to commercialized touch devices latencies (75 ms). After 10 training sessions over a minimum of 2 weeks (Experiment 1), participants adapt to the delay. They also display long-term retention 7 weeks after the last training session. This adaptation generalizes to a similar tracking path (e.g., infinity symbol). We also observed generalization of learning from the longer delay to the minimal-delay condition (Experiment 2). The delay thus does not prevent the learning of tracking skill, which suggests that delay adaptation and tracking skill could be two separate components of learning.

Keywords Motor adaptation · Motor learning · Visual feedback delay · Tracking · Direct touch interaction

Introduction

While previous research has proved that humans are able to adapt to spatial distortions (e.g., von Helmholtz 1867; Krakauer and Mazzoni 2011), adaptation to temporal distortions such as visual feedback delay is more controversial.

Adaptation to delayed visual feedback has mainly been investigated in experimental setups involving indirect interactions, where participants manually control a device (button, mouse, joystick, pen, etc.) and get a feedback of their action on a screen. Under these conditions adaptation to visual feedback delay was observed in tapping tasks (Stetson et al. 2006; Sugano et al. 2012) or in reaching movements (Botzer and Karniel 2013). Partial adaptation was also found in indirect interception tasks (Cámara et al. 2018) or tracking tasks, after several training sessions (Foulkes and Miall 2000; Miall and Jackson 2006). This last result suggests that adaptation to visual feedback delay is relatively slow compared to adaptation to spatial distortion (Shadmehr et al. 2010). Furthermore, adaptation seems to be possible only if the tracking trajectory is predictable (Rohde et al. 2014) and might use an approximation for delay by assimilating it to the consequences of inertia in a mechanical system (Rohde and Ernst 2016; Leib et al. 2017). Other studies suggest that adaptation to visual feedback delay could be generalized to different versions of a same task (e.g., driving in different streets in a simulator, Cunningham et al. 2001b), but not across different tasks (e.g., from a target interception task to a task which involves passing through a moving gap, de la Malla et al. 2014).

Indirect interaction is ubiquitous in usual computer devices, and is useful in motor control and learning research to question visuomotor recalibration. It is yet to disappear on many devices such as smartphones or tablets, on which the finger is in direct touch with the screen displaying the consequence of the action. These touchscreens have a latency of around 75 ms as a result of the computation time between

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Published online: 06 September 2018

the touch and the feedback display on screen (Ng et al. 2012). Digital objects thus move with a delay causing them to lag behind the finger. Since the hand is visible in this situation the mismatch is mainly between the sight of the finger and the visual feedback of its action on the digital object.

The effect of the delay on users' actions achieved with direct touch interaction has been studied largely in relation to technical or ergonomic challenges in human–computer interaction (HCI) research. Even at very low magnitudes delay has proved to be a hindrance. Users can on average perceive delays as low as 6 ms (Ng et al. 2012) and their performances in pointing tasks are affected even for delays shorter than 25 ms (Cattan et al. 2015; Jota et al. 2013). However although people use touch devices for long periods of time, their ability to compensate for or to adapt to delays with direct touch interaction has never been studied. This could be due to the focus of HCI research on user performance rather than on the sensorimotor mechanisms that underlie the performance. The investigation of the way users of touch technologies deal with feedback delay provides a new framework for improving our knowledge of visuomotor learning mechanisms. In particular it raises new questions: Are people able to develop compensation strategies to this new type of visuomotor alteration? Are these compensation strategies achieved on an online feedback correction basis or are they learnt with practice? Can these strategies be generalized to task variations? Does feedback delay affect the learning of a motor skill?

As a first step toward a better understanding of sensorimotor adaptation to feedback delay in direct interaction, we ran two empirical studies involving a tracking task. The first study evaluates participant's abilities to adapt to the delay as well as generalization and long-term retention from this adaptation. We assessed the progress of two groups of participants, one group trained with the minimal delay permitted by our system (~ 9 ms) and one group trained with a delay comparable to that of current commercial touch devices (75 ms). The training involved 10 sessions, performed over more than 2 weeks. This dataset was first analyzed in a publication for an HCI conference (Cattan et al. 2017). In the current paper, we provide further analyses to better address the progression over days and the generalization of learning. These analyses also include an additional control group that performed only two sessions, 2 weeks apart. The results suggest that delayed visual feedback during training induces two processes that progress differently over time, adaptation to delay and improvement of tracking skills. These results are consistent with the idea that skill learning and adaptation could be independent processes (Krakauer and Mazzoni 2011). In a second study, we provide further evidence of the possible separation between these two components of learning. This was done by assessing how a tracking skill learnt with a 75 ms delay generalizes to the same skill achieved with the minimal delay permitted by our system. The results are discussed with reference to previous work on skill learning and to fundamental issues raised by the use of touch technologies on people's visuomotor competences.

Setup and general information about the procedure

Because to the best of our knowledge no regular-sized touch display achieves the necessary low level of end-to-end delay we use a custom-built apparatus (Fig. 1).

The setup is composed of a 24″ screen placed on a desk and of 3 OptiTrack infra-red cameras that track a hemispherical marker (4 mm diameter) attached to the nail of the participant's index finger. 3D positions of the marker are streamed to the main PC. A program computes whether or not the finger is touching the screen and displays the corresponding visual feedback with the chosen delay. This requires a spatial calibration procedure that is run before the experiment consisting of: (1) the computation of a 3D geometrical description of the screen surface, which is actually not strictly plane but slightly curved. This was done by moving a marker to the four corners of the screen and then over the whole surface of the screen; (2) the determination of a threshold height below which the participant's index is considered to be in contact with the screen. This threshold was computed for each participant by asking to move her index with the marker over the whole surface of the screen.

With the 120 Hz sampling rate of the cameras and low level synchronization with screen refresh, the setup achieves a delay of 25 ms. The delay has been accurately measured thanks to the method proposed by Bérard and Blanch (2013). In this method, a camera takes pictures

Fig. 1 The setup. The laptop computer is used to control the cameras and sends finger tracking data to the main PC (bottom right), which renders the graphical feedback on the main screen placed on the desk

of the moving finger while the screen records the touch positions. An analysis of the recording enables to compute the time difference between the moment when the finger reaches a given point and the moment when the corresponding touch is registered by the system. Several measures have been done, and they all confirm the 25 ms duration.

This baseline delay is compensated for by a short window prediction. The prediction makes a linear extrapolation of the final two data points received at time t to predict the future finger position at $t+25$ ms. The trajectories followed by the target and the finger being clearly curved, we could have expected more complex trajectory predictions involving more data points and nonlinear functions to be more accurate. In Cattan et al. (2015), we investigated the influence of different types of prediction on the participants' performances. We stated that the first-order polynomial prediction is the best in spite of its simplicity, essentially because of two characteristics: (1) it is very reactive, as it only requires two data points to operate; (2) it involves the computation of the first-order derivative only, which limits the amplification of high-frequency variations due to sensor noise. In addition, with a 25 ms delay combined with a linear prediction compensation using only two samples, motion trajectories were preserved, while with parabolic and/or longer windows, the predicted trajectories became jerky. Displaying the feedback at the predicted position partially counteracts the delay. Using this setup for target acquisition tasks with the prediction has been shown to be equivalent to using a device with 9 ms of latency. Further details of the setup, the prediction and its effect on users' performance can be found in Cattan et al. (2015).

The protocol, experimental design and methods for the tracking task used in the experiments are detailed in Cattan et al. (2017) and summarized hereafter. Full consent was obtained from all the participants who were free to stop the experiment at any time. The participants' anonymity was respected. The authors confirm that the procedure and processing of data follow the principles of the Declaration of Helsinki.

Experiment 1: Touch delay adaptation, generalization and retention

The first experiment aimed to answer three questions:

1. Do people adapt to the touch delay with practice?
2. If there is adaptation does it generalize to a task variation?
3. Is there long-term retention of what was learned during adaptation?

Methods

Participants

15 men and 5 women (aged 23–37 and all right-handed) were divided into two groups of 10. The groups were balanced according to the participants' average performance in ten trials of the tracking test on the ellipse (described below) with a delay of 75 ms. Performance was measured as the spatial tracking error (see section "data processing and measurement" here after). The test group was trained with a delay of 75 ms. The control group was trained at the minimal delay (25 ms + prediction).

Procedure

The tracking task consisted of a pursuit around an ellipse (398 mm major axis, 149 mm minor axis, Fig. 2a, cyan curve). In a trial over three laps (~20 s in total), participants tracked the target white disc (17.8 mm radius) with a controllable red disc of the same size. The first lap allowed the participant to catch up with the target and get into the rhythm of the target motion. Tracking performances were measured on the two subsequent laps. Participants were

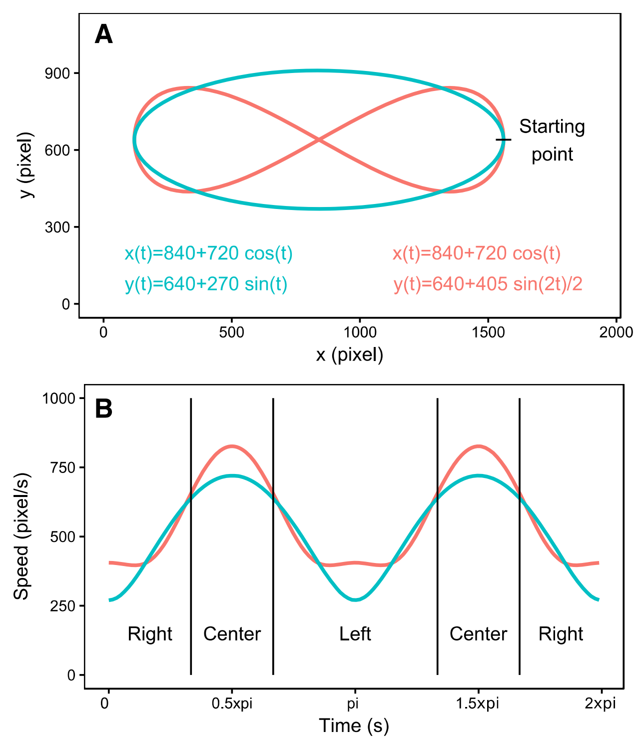

Fig. 2 **a** Shapes and equations of the two tracking trajectories used in the experiments (t is the time in seconds). Coordinates are given in pixels with 1 pixel = 0.2767 mm. **b** Speed profiles for the two trajectories and the three time sections in which we analyzed the generalization data separately

asked to “bring the center of the red disc as close as possible to the center of the target” and to try and “cover as much of the target as possible with the red disc”.

In accordance with the power law that links speed and curvature in human hand movements (Viviani and Terzuolo 1982) the speed of the target varied around the ellipse (see Fig. 2b, cyan curve). At constant speed the delay would have been associated with a constant spatial offset in the direction of the motion, whereas variable speed clearly associates the delay with a temporal disturbance that should stimulate adaptation (Rohde and Ernst 2016). The ellipse path was displayed on the screen to aid adaptation to the feedback delay (predictability of the trajectory, Rohde et al. 2014).

After each trial, to encourage participants to reduce their error from trial to trial, a bar chart showing the tracking error averaged over the last two laps of the trial was displayed, so that the participants could see the evolution of their performance across trials. Since adaptation might occur only after a significant period of time (Miall and Jackson 2006), ten half-hour training sessions were spread over at least 2 weeks. Participants performed 60 trials at each session.

Generalization of learning was investigated using a path having the shape of an infinity symbol (∞). This shape was chosen due to its properties when trisected. The right and left parts are spatially similar to those of the ellipse, but with different variations in curvature (Fig. 2a, red curve) and hence in speed, because of the power of law (Fig. 2b, red curve). The center part is spatially different from the ellipse but have similar variations in curvature and hence in speed. In this way the influence of trajectory location on generalization effects can be dissociated from that of velocity. Ten trials on the infinity shape were performed on day 1 before the ellipse training (pre-test) and again after the training on day 10 (post-test) under the same delay condition as the training itself.

To study long-term retention, 12 participants (6 control–6 test) were recorded again 7–9 weeks after their last training session on the ellipse. The task was to perform 30 trials of the tracking task on the ellipse in the same delay condition as during training. Not all the participants were able to come back for this long-term re-test but having six participants in each group still provides an insight into long-term retention.

Data processing and measurement

Performance on the tracking task was evaluated by the spatial tracking error calculated as the Euclidian distance between the center of the dragged object and the target center. This measure was chosen as it is the parameter participants were explicitly asked to minimize, and as it was standardly used in previous studies about tracking skills (Viviani et al. 1987; Foulkes and Miall 2000; Miall and Jackson 2006; Leib et al. 2017).

For each trial, the tracking error was the average of the error measured at each 120 Hz data sample of the last two laps. This resulted in a total of 12,360 data points: (60 trials × 10 sessions × 20 participants) + (30 trials × 1 long-term-session × 12 participants). The trials with a tracking error of over 1.5 times the interquartile range above the upper quartile or below the lower, for a given participant and session, were withdrawn. This corresponds to 317 trials, leaving 12,043 points for the analysis.

Analysis of the adaptation process

The delay was expected to significantly increase tracking errors in the early stages of training (i.e., larger errors for the test group than for the control group). If adaptation to the delay occurs, the performance for the test group should progressively catch up with the performance for the control group. To assess these hypotheses, we evaluated the global evolution of the performance across sessions, as well as the dynamic of the progression within each session, and memory decay and retention between sessions.

To describe the evolution of the tracking error across trials within each session, we tested exponential fitting but the model with three degrees of freedom was underconstrained giving misleading parameters. Assuming a linear progression within the sessions was a more reliable approximation. Linear mixed models (LMM) were thus built from the 12,043 data points (R software, v 3.3.2, R Development Core Team 2016; *lme* function; Pinheiro et al. 2007), with the tracking error as dependent variable and the trial (numerical factor), the session and the group as fixed effects. The participant was considered as a random factor.

The best LMM was selected using likelihood-ratio tests and a backward deletion approach (Mundry and Nunn 2009). Autocorrelograms were plotted to check the absence of autocorrelation in residuals within a session. Post hoc tests were performed to compare:

- intercepts and slopes between groups with the *glht* function (*multcomp* package for R, Hothorn et al. 2008), with default parameters for multiple comparisons adjustment;
- the end point of the model in a session (final state of a session, i.e., at trial 60) with the intercept of the next session (initial state of the next session). This was done for each session and group. Bonferroni correction was used to compensate for multiple comparisons. These comparisons allow detecting discontinuities between sessions, which can be attributed to offline learning or memory decay.

Analysis of the generalization effect

Generalization of learning was analyzed separately by comparing performances on the infinity shape before and after learning on the ellipse. Only the last five trials of the pre-test and the post-test were considered to remove strong outliers resulting from an abrupt change in condition. Since we wanted a single indicator of performance for the pre-test and the post-test, these last five trials were averaged. Data were also analyzed separately for the three sections of the infinity shape (Fig. 2b):

right section: time $\in \left[0;\frac{\pi}{3}\right] \cup \left[\frac{5\pi}{3};2\pi\right]$,

center section: time $\in \left[\frac{\pi}{3};\frac{2\pi}{3}\right] \cup \left[\frac{4\pi}{3};\frac{5\pi}{3}\right]$,

left section: time $\in \left[\frac{2\pi}{3};\frac{4\pi}{3}\right]$.

The effect of session, section of the tracking path and group on tracking error were assessed using mixed ANOVA, with session and section as within-subject factors and group as between-subjects factor. For the control group, this comparison assessed the generalization of the tracking skill alone while in the test group it assessed the generalization of both the tracking skill and the adaptation to the delay. Our rationale is that a stronger generalization for the test group compared to the control group would show that not only is the tracking skill generalized but so is the adaptation to the delay.

All the effects were considered significant for $p < 0.05$.

Analysis of the long-term effect

To evaluate the retention effect after 7–9 weeks, we considered the average tracking error on the last 10 trials of the “long-term” session (i.e., after a short re-familiarization of 20 trials). This performance was compared to the averaged performance on the 10th session using an ANOVA, with session as within-subject factor and group as between-subjects factor.

Results

Adaptation effects

The selected LMM includes effects of group, trial and session on the tracking error as well as a triple interaction between the factors (nested models test without the interaction, $p < 0.025$) showing:

- a negative impact of the delay on participants’ performance;
- an improvement through practice across trials and over sessions;
- a different evolution of the tracking error across trials for different sessions depending on the group.

Multiple comparisons suggest that intercepts of the test group are significantly greater than intercepts of the control group in sessions 1–4 and 6 (Fig. 3). The magnitude of the difference decreases from 0.76 mm in session 1 (test–control: $z = 4.2$, $p < 0.001$) to 0.35 mm in session 10 ($z = 2.0$, $p > 0.4$). With training, the performance of the test group

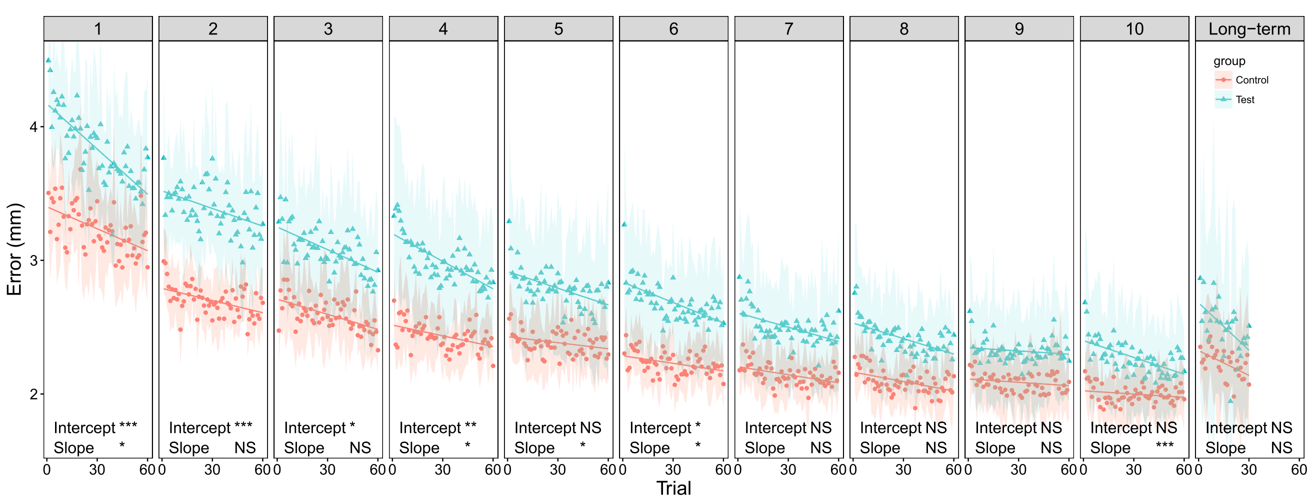

Fig. 3 Tracking error averaged across participants for each trial, each session, for the control group and the test group. Colored surfaces indicate 95% confident intervals. Linear fits are shown for each session and group. Note that for clarity, the vertical axis does not start at 0. Comparisons of intercepts and slopes of the linear mixed model between the two groups for each session are indicated at the bottom of the graph. Asterisks indicate the significance level of the p value: $0 < *** < 0.001 < ** < 0.01 < * < 0.05 < \mathrm{NS} < 1$

approaches the performance of the control group. The comparison of slopes between the two groups across sessions gives more variable results. The slope of the test group is always steeper than that of the control group but the difference is significant only in sessions 1, 4, 5, 6 and 10 ($z > 3.0$, $p < 0.04$).

Figure 3 indicates that the test group tends to begin each session with an error greater than that observed at the end of the previous session. However, discontinuity tests between sessions were of no significance.

Generalization effects

Generalization effects on the infinity shape are detailed in Fig. 4. The control group performs better than the test group (effect of group: $F(1,18) = 25$, $p < 0.001$). The performance is also better in post-rather than pre-test (effect of session: $F(1,18) = 123$, $p < 0.001$). Between the pre- and post-tests the improvement of the test group is greater than that of the control group (group × session: $F(1,18) = 6.9$, $p < 0.02$) which varies with the section of the trajectory (group × session × section: $F(2,36) = 5.1$, $p < 0.02$). The generalization effect appears similar in the three sections for the control group but not for the test group. This is supported by two post hoc ANOVAs, with Bonferroni corrections. They show a strong interaction between session and section for the test group ($F(2,18) = 12$, $p < 0.001$) but not for the control group ($F(2,18) = 4.5$, $p = 0.052$).

To ensure that the improvement in performances on the infinity shape was not only related to a test–retest effect, we ran a post hoc control experiment with a third cohort of participants. In a first session, participants performed the tracking on the infinity shape without delay, as in the control group. 9 participants (4 females, age 22–38, right-handed) were selected to have average error performances comparable with those of the control group in the first session (4.3 mm (mean) ± 0.51 (se)). These participants came back 12.5 (± 1.6) days later to perform again the tracking on the infinity shape. They significantly reduced their tracking error (to 3.9 mm ± 0.36, $t(8) = 4.2$, $p < 0.01$). However, this ~ 0.4 ± 0.33 mm reduction was about three times smaller than the reduction observed initially in the control group (~ 1.2 ± 0.6 mm). A post hoc ANOVA was limited to the control group and this new group shows a significant (group × session) interaction effect ($F(1,17) = 13.7$, $p < 0.005$). This suggests that the improvement of performances observed for the control and the *test* group could not be entirely explain by a test–retest effect but rather by the training experience on the ellipse trajectory.

Retention effects

Participants tested 7–9 weeks after the last training session seem to show fast re-learning (see "Long-term" session, Fig. 3, last panel on the right) and good retention. Performances averaged over the last ten trials of the long-term session are lower than the average error at session 10 ($F(1,10) = 6.39$, $p = 0.03$) but with a small effect size (+ 0.2 mm) compared to the global decrease in the tracking error between sessions 1 and 10 (− 1.39 mm); and without any influence of the group ($F(1,10) = 0.46$, $p > 0.5$) nor interaction group × session ($F(1,10) = 0.16$, $p > 0.69$).

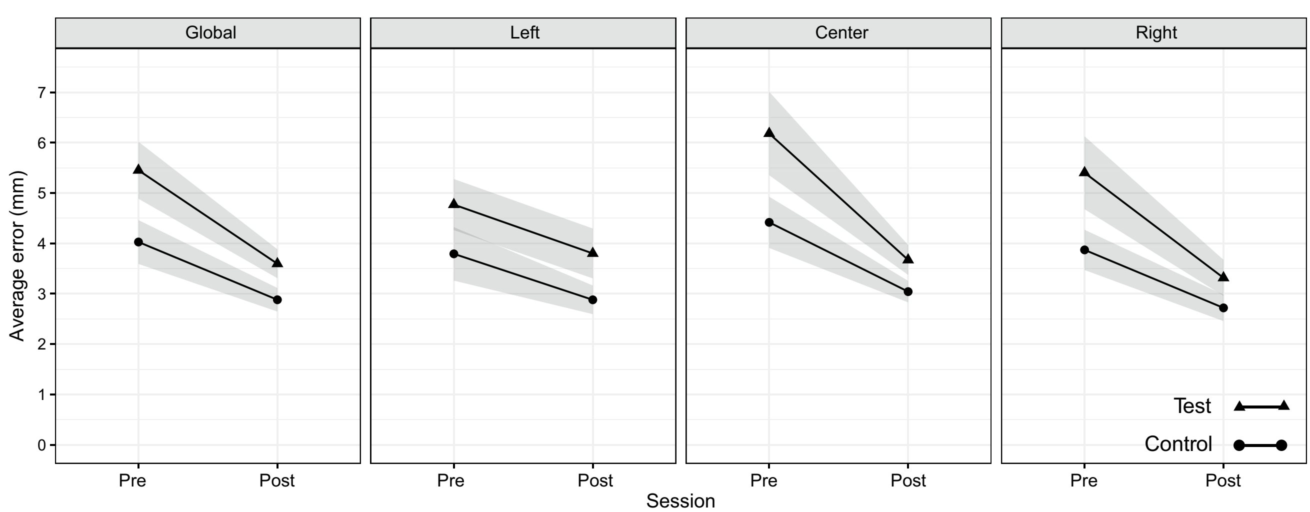

Fig. 4 Tracking performances on the infinity shape before and after the training on the ellipse for the control group and the test group. Grayed surfaces indicate 95% confident intervals. The graph on the left shows the global progress while the three other graphs illustrate separately the results for the three sections of the ellipse

Discussion

In answer to the three main questions posed by the study the results of Experiment 1 show that:

1. Participants adapt to touch delay but the adaptation takes time. The test group performed significantly worse than the control group in the first session. In the 10th session, differences between the two groups are not statistically significant. Both groups improved their performances over time but the amount of improvement depended on the group. We assume that the control group essentially learnt the tracking task while the learning in the test group concerned a combination of tracking task learning and delay adaptation.
2. After 10 sessions of training with the ellipse trajectory, both groups show a generalization effect on the infinity shape that still depends on the section of the shape for the test group only.
3. When re-tested 7–9 weeks after the last training session, participants from both groups show long-term retention effect.

Analyses by session also suggest that the test group shows greater progress within a session than the control group: the absolute slope within each session is systematically greater for the test group than the control group, even if the difference between groups is not always reliable. Although no significant discontinuity is found between sessions, Fig. 3 indicates that the test group tends to begin each session with greater error than at the end of the previous session. Motor memory is known to decay with the passage of time but it can be re-activated (Criscimagna-Hemminger and Shadmehr 2008). The delay may increase this decay and the delay adaptation might require some trials to be carried out again.

Altogether Experiment 1 suggests that learning in the test group may involve two processes at the same time:

- a slow process of learning the tracking skill (this also holds for the control group) with good retention
- a fast process of adaptation to the delay, with weak retention but fast re-learning in each session.

Experiment 2 was designed to further investigate this hypothesis and to better understand the interaction between the two processes. The rationale was that if the delay does not interfere with the learning of tracking skills, then, learning the tracking task in a long-delay condition should generalize to performing the same task in minimal-delay condition.

Experiment 2: Generalization of learning from delayed to non-delayed feedback

Methods

Design and procedure

The design of Experiment 2 is similar to that of Experiment 1 but limited to a single session. 26 new participants (age range 21–40, 11 females, right-handed) had to perform the tracking task around the ellipse trajectory using direct touch interaction, the hand being visible. Participants were divided into two balanced groups based on their tracking abilities evaluated during the first ten trials of the experiment (see Fig. 5, "Pre"). The data of two participants (one female) were discarded, as their performances on these first trials were larger than two standard deviations from the average performance of all the participants. In total, the control group (four females) performed 80 trials in the minimal-delay condition. The test group (four females) performed 10 trials in the minimal-delay condition (baseline), then 60 trials in the long-delay condition (training) and finally 10 trials in the minimal-delay condition (generalization of learned tracking skills).

Data analyses

The comparison between the first and the last block of the test group enabled us to assess the generalization of learning from long-delay condition to minimal-delay condition. The

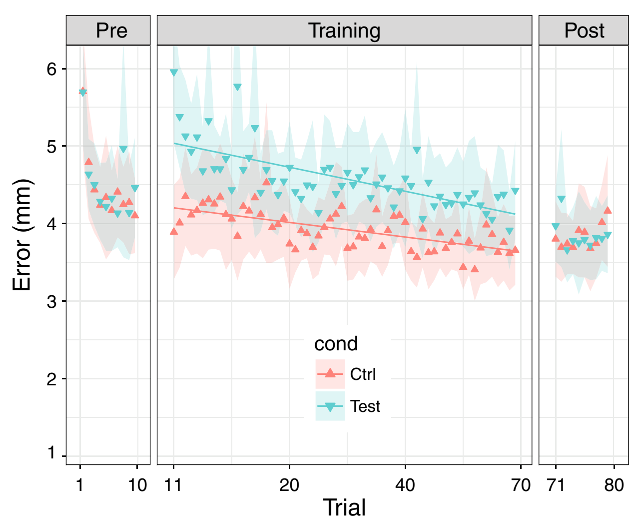

Fig. 5 Tracking error on the ellipse for Experiment 2 averaged across participants for the control and test groups. Each dot represents a trial and colored surfaces indicate 95% confident intervals. During training, the control group is trained without latency while the test group is trained with latency

comparison with the control group evaluated the quality of the generalization. A complete generalization would indicate that the tracking skills are learned separately from the delay without interference. No generalization would suggest that learning tracking skills with a given delay is a specific global process that does not generalize to the other delay condition. Partial generalization would be compatible with the two alternatives: as the product of interference between two independent processes or as the product of a similarity between two specific global processes.

To obtain a pre-training and post-training indicator of minimal-delay performance the error of the 10 trials in the pre-test and post-test (see Fig. 5, left and right panels respectively) were averaged for each participant. The effects of block and group on tracking error were assessed using a mixed ANOVA, with block as within-subject factor and group as between-subjects factor.

Using the same method as in Experiment 1, the training phase was analyzed with linear mixed models, with post hoc comparisons between groups when required.

Results

The tracking error for the first and last block together with the training trials performance can be seen in Fig. 5. As a consequence of group balancing, the performances of the two groups are comparable in the pre-training block. Differences between groups then appear in the training phase. The selected LMM includes the effects of group and trial but not the group × trial interaction ($p > 0.26$). It shows a negative impact of the delay on participants' performance, with the intercept in the test group being greater than in the control group (test–control: $z = 2.3$, $p < 0.05$), and a significant improvement across trials (slope significantly different from 0, $z = -4.3$, $p < 0.0001$). A supplementary ANOVA was run to compare the five first and five last trials of the training phase according to the group (mixed group × phase ANOVA). It confirms the general progression during the training phase ($F(1,22) = 24.4$, $p < 0.0001$) and the worst performances of the test group ($F(1, 22) = 5.9$, $p < 0.05$). However, it also suggests a larger progression in the test group as compared with the control one ($F(1,22) = 5.2$, $p < 0.05$).

After training, both groups displayed a clear progression in the post-training block as compared with the pre-training one (effect of block: $F(1,22) = 23.7$, $p < 0.001$), that is yet comparable for the two groups (block × group: $F(1,18) = 0.03$, $p > 0.86$). Therefore, there is no indication of any global effect of the group in the pre- and post-training blocks ($F(1,18) = 0.04$, $p > 0.85$).

The performance of the two groups in the post-training block thus appears similar regardless of the training condition. This suggests that the progression observed in the test group in the course of the training phase might involve an adaptation to the delay as well as a delay-independent learning of tracking skills (i.e., the ability to track a target moving with predictable trajectory and velocity).

General discussion

Experiment 1 shows that participants were able to adapt to delayed feedback in direct touch interaction on a tracking task. This adaptation took time but enabled generalization to a tracking task with a different trajectory and a good retention 7–9 weeks after the last training session. Experiment 2 suggests that learning to perform a tracking task with delay may not prevent the learning of the tracking skill per se.

The evolution of learning across sessions in Experiment 1 and the results of Experiment 2, suggest that two separated learning processes might be involved: one for the tracking skill and one for adaptation to the delayed feedback. These results will now be discussed with reference to previous studies on skill learning, and on the interplay between visuomotor competences acquired in digital and physical interactions.

Tracking skills learning without delay

In this section, we consider only the behavior of the control group in Experiment 1, which enables us to understand how tracking skills are acquired when delay is negligible.

Although the task was repeated over days, the generalization effects toward the infinity shape in the last training session suggest that participants in the control group did not only learn a specific motor skill to track on the ellipse at the appropriate rate but rather that they have developed more general tracking skills. This is also suggested by the fact that generalization does not appear to depend on the section of the infinity shape (e.g., trajectory location or velocity similarity with the ellipse).

In their experiment, Miall and Jackson (2006) did not observe much improvement in tracking performance for the control group over 5 days. In our study 5 days were sufficient to decrease the tracking error by over 25% (from an average of 3.28 mm in session 1 to 2.39 mm in session 5). In comparison with Miall and Jackson we found that at least two factors might have accelerated learning:

1. The performance feedback provided to the participant after each trial;
2. The fact that direct touch interaction could reactivate everyday skills and benefit from them (Bérard and Rochet-Capellan 2015) while indirect tracking with a joystick as in Miall and Jackson might not.

Further investigation is needed to determine whether direct interaction accelerates skill learning compared to indirect interaction.

The comparison of the control groups between the first session in Experiment 1 and the unique session in Experiment 2 suggests that participants in Experiment 2 performed worse than those of Experiment 1 (Fig. 3 vs. Fig. 5, the difference was ~0.5 mm in average between the two groups). This could be related to two major differences in the procedures of the two experiments. (1) In Experiment 1, participants performed an additional balancing task with delay before being trained that may have improved their initial performance in tracking the ellipse without delay. (2) They also knew that they would perform the task over several days, which may have induced a greater implication in the task than the single session in Experiment 2. Supplementary work is required to address directly the effect of long-term implication on initial performance.

Dealing with feedback delay on a tracking task

Previous studies have demonstrated that feedback delay alters performances for manual tracking tasks in indirect interaction, as participants have to adapt to the delay (Foulkes and Miall 2000; Miall and Jackson 2006; Sarlegna et al. 2010). This is supported here for direct touch by the results of the two experiments as in both experiments, the delay reduces performance.

To the best of our knowledge, only Miall and Jackson (2006) have investigated the adaptation to feedback delay on a tracking task over more than 3 days. This was done using indirect joystick interaction. The authors reported clear evidence of adaptation with a decrease in the mean error scores and the performance of the test group (300 ms delay) gradually approaching that of the control group (no delay). Experiment 1 shows that slow progression across training sessions is also characteristic of delay adaptation in direct touch interaction for shorter delay.

It would be interesting in the future to ascertain whether this adaptation comes from instrumental or perceptual learning. Kennedy et al. (2009) have suggested that adaptation to a sensorimotor temporal misalignment is closely related to perceptual learning. In their study after effects persist for a time following adaptation without visual feedback. In our case feedback was always visible so no conclusion can be drawn.

Tracking skills learning and delay adaptation: two learning processes?

While the tracking skill improved progressively through practice, as observed in the control groups, the management of the delay might follow a different evolution (with a slight tendency to decay and faster re-learning, as suggested by Experiment 1). This could suggest that a different learning process may operate under this condition parallel to the learning of the tracking skills. This would be consistent with the findings of Smith et al. (2006) who studied adaptation to a force field imposed by a robot manipulandum. The authors showed that their experimental data fit on a multi-rate model of two learning processes: a slow one with good retention and a fast one with poor retention. While Smith et al. do not argue that the two processes are distinct, Krakauer and Mazzoni (2011) clearly separate the adaptation that involves the cerebellum and the skill learning that is associated with a motor cortical organization.

The separation of the two processes is consistent with the results of Experiment 2 where participants who learn the tracking task while adapting to the delay then perform the tracking task without delay in a similar way than participants who learn the tracking task without delay. This suggests that the former group may develop a control policy that is, at least to some extent, independent of the delay. In parallel, they may try to recalibrate this control policy to adapt to the inconsistent feedback. If this is the case observations of Experiment 1 (where there is a tendency to retention or offline gain for tracking skills and a tendency to decay for delay adaptation) would coincide with those of Telgen et al. (2014). They argue that automatization of a new control policy should show offline gains while recalibration of an existing control policy should show offline forgetting.

The test group's stronger generalization in Experiment 1 indicates that as well as tracking skills participants were able to generalize their ability to deal with the delay. This generalization is consistent with the work of Cunningham et al. (2001a) who showed that feedback delay adaptation can be transferred across task variations. Unlike the control group the test group's generalization differed according to the infinity section. This might be due to an influence of velocity or trajectory location on the generalization but another explanation can be that in the center and right section the participant's right hand was hiding the delayed object. This becomes less influential in the post-test after adaptation when control strategies rely less on visual feedback. To clarify the origins of this phenomenon further investigation is necessary.

Interaction of motor learning in the digital world with actions in the physical world

Human–computer interactions are increasingly "Reality-based". The gestures we make to interact with physical objects lead to the development of new gestural interactions with digital objects (Norman 2010), such as direct touch interactions (Wigdor and Wixon 2011). This raises an important challenge for movement sciences. How does the user brain transfer sensorimotor skills from physical to digital objects and vice versa (e.g., Bérard and Rochet-Capellan 2015)?

In the current study, a tendency to memory decay for participants dealing with delay would be consistent with the Bayesian hypothesis according to which people associate a prior assumption about the states of the world with evidence about the current state (Turnham et al. 2011). When people are learning from childhood in a physical world that does not suffer from delay, their prior assumption when moving an object does not include any delay. People may use this prior assumption to perform touchscreen tasks. However, when the feedback of the touched object does not match their expectation, they may recalibrate their motor commands to compensate for the delay. When people stop using their touch devices, they go back to the physical world and unlearn the recalibration.

According to Kitago et al. (2013), unlearning is "an active process where adapted behavior gradually reverts to baseline habits", which, in the physical world does not include any delay. Retention, however, indicates that the recalibration process may be re-activated very quickly. Results from Miall and Jackson (2006) study also indicate that this recalibration can be generalized between two levels of delay. On a tracking task, participants who adapted to a 300 ms delay performed much better on a post-test at 400 ms than participants who were trained with no delay. This ability to recalibrate fast and for different levels of delay could explain why users of new technologies can shift so easily from one device to another (the same task achieved on a smartphone, a tablet or a larger touch surface).

Wei et al. (2014) have shown that the use of computers can re-shape our sensorimotor behaviors: users of a mouse generalized more visuomotor learning than people who never use the mouse. When performing a task on a touchscreen, it seems that people use a control policy that does not include any delay disturbance. This certainly comes from previous knowledge of the physical world. The performances on the digital task, with delay are affected by this prior knowledge and it takes time to counteract the delay. By separating the processes of learning skill and adapting to the delay, learning skill is not really affected by the presence of delay. A task learned in a digital world impacted by delay can be generalized to a condition with or without negligible delay. Further studies on generalization are required to determine if this result is specific to our study and tracking task or if it also applies to other tasks.

Acknowledgements This work has been partially supported by the LabEx PERSYVAL-Lab (ANR-11-LABX-0025-01). This work is based on an earlier work: "Does Practice Make Perfect? Learning to Deal with Latency in Direct-Touch Interaction", in CHI 2017© ACM, https://doi.org/10.1145/3025453.3025585. The authors also thank Linda Sherwood for her careful proofreading of the manuscript.

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