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Highlights

- A new interaction technique based on contextual information using a multimodal system for force pattern learning is proposed.
- Using the contextual information approach, the trainees obtain information about the evolution of their performance along the time (helping to correct the errors).
- The findings suggest that the contextual information provides a better trainee’s performance than the punctual information.
- One drawback of the training strategies based on punctual feedback is the difficulty that users have in interpreting the information.
- The contextual approach could be used to extend the capabilities of haptic training procedures based on haptic guidance to provide information about the level of force to be applied during the execution of a specific task.

Learning Force Patterns With a Multimodal System Using Contextual Cues

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***Abstract* —Previous studies on learning force patterns (fine motor skills) have focused on providing "punctual information", which means users only receive information about their performance at the current time step. This work proposes a new approach based on "contextual information", in which users receive information not only about the current time step, but also about the past (how the target force has changed over time) and the future (how the target force will change). A test was run to compare the performance of the contextual approach in relation to the punctual information, in which each participant had to memorize and then reproduce a pattern of force after training with a multimodal system. The findings suggest that the contextual approach is a useful strategy for force pattern learning. The advantage of the contextual information approach over the punctual information approach is that users receive information about the evolution of their performance (helping to correct the errors), and they also receive information about the next forces to be exerted (providing them with a better understanding of the target force profile). Finally, the contextual approach could be implemented in medical training platforms or surgical robots to extend the capabilities of these systems.**

Keywords: force skill training, motor skill training, virtual training, multimodal training

1. Introduction

Most daily activities require motor skills. A motor skill is a learned sequence of movements that combine to produce an action with a high degree of precision and accuracy (Singer, 1980). Using a traditional method, we can learn a new skill by observing a model, watching a video, reading instructions, listening to a trainer's explanation and of course by practicing on our own. The best training method depends on the nature of the skill to be acquired. In general, motor skills are learned by doing and can be reinforced only through practice (Varela, Thompson and Rosch, 1991).

In recent years, virtual reality (VR) and multimodal systems have been used as training platforms in order to teach or improve human skills, and there are several studies that have demonstrated the efficiency of such platforms (Basdogan et al., 2004; Ruffaldi et al., 2009; Rodriguez et al., 2010, Williams and Carnahan; 2014). These multimodal systems allow trainees to have an active interaction with the virtual environment that represents the target task; it means they support the "learning by doing" paradigm

(Temmen, 2013). Additionally, multimodal platforms should provide clear, useful and sufficient information so the target knowledge can be efficiently transferred to users.

Regarding the learning of motor skills, multimodal systems based on VR and haptic feedback have been used to train gross motor skills by providing physical guidance in order to transfer expert movements in terms of positions and velocities (Avizzano et al., 2002; Feygin et al., 2002; Grindlay, 2008; Lewiston, 2009; Liu et al., 2005; Morris et al., 2007, Rodríguez, et al., 2010, Tao et al., 2002). Nevertheless, in medical operations such as blunt dissection, biopsy, palpation, needle insertion, etc. (Culbertson et al., 2016; Meli, Pacchierotti and Prattichizzo, 2016, Xiong et al., 2016), trainees must learn specific fine motor skills. For example, the training approach must transfer the knowledge of force exertion during the execution of the task. One advantage of multimodal systems that use force feedback is that learners can receive information that cannot be successfully described via traditional methods such as an expert's presentation or a demonstration video. Examples of this type of information are how much force clinicians have to apply to a subject during a palpation task or the force necessary to insert a needle into human tissue without causing any damage.

It is important to note that the term "force feedback" is sometimes used in the same way as "haptic feedback". For example, Hayward and Maclean (2007) related "haptic feedback" with the replication of the proprioceptive sensations of interacting with real objects in a virtual environment (friction, texture, stickiness, etc.); meanwhile Morris et al. (2007) defined it as the use of a haptic system to deliver other information via felt forces. More recently, Williams and Carnahan (2014) used the term feedback to refer to augmented movement-induced feedback. In this study, the term force feedback means the use of a multimodal system to provide information about the level of force that needs to be exerted during the execution of a specific task. Some previous works showed that in general motor skills retention is improved by using augmented feedback (Molier et al., 2010; Thorpe and Valvano, 2002; Vliet and Wulf, 2006), while other works postulated that learners come to depend on the augmented feedback and their performance suffers when it is removed (Salmoni, Schmidt and Walter, 1984; Schmidt and Bjork, 1992). Consequently, more studies are necessary in order to draw conclusive statements about the impact of force feedback on the transfer of motor skills (Rosati et al., 2014; Williams and Carnahan; 2014).

With regard to fine motor skills training (such as force exertion), Sewell et al. (2007) proposed the use of haptic feedback for force skills transfer, and they analyzed the transference of force skills learned in a haptic-enabled virtual environment to performance on a surgically task (drilling a bone). Meli, Pacchierotti and Prattichizzo (2016) used haptic feedback to train a needle insertion and palpation task, and Xiong et al. (2016) used force feedback for basic surgical skills training by using a medical robot. In all cases, haptic feedback significantly improved task performance and accuracy. One of the terms most often used to describe these haptic training procedures is haptic guidance (Williams and Carnahan; 2014), and the term refers to a variety of procedures aimed at helping a learner move through a sequence of movements by pulling or pushing the learner through the sequence using a haptic device. Previous works used haptic guidance to train motor skills such as temporal patterns (Feygin, Keehner and Tendick, 2002; Teo, Burdet and Lim, 2002) and visuo-manual trajectory tracking (Bluteau, Coquilart and Payan, 2008) based on the idea that a specific force profile (pattern of forces) will produce a specific trajectory, delivering to the learners the sensations that would be felt by an expert correctly executing the task.

Force skill training has been analyzed through other sensory channels, such as vision. Hasan, Yano and Buss (2008) tested their Hybrid Trainer Model and they focused on analyzing force skill transfer under three paradigms: the user was active via force feedback (haptic tutoring), the user was active via visual feedback (visual tutoring) or the user was passive via the combination of force and visual feedback (haptic guidance). Although their results indicate that all methods bring skill improvement, the learning of forces was accelerated and remembered better when the trainees were trained with the visual feedback condition. Additionally, the haptic tutoring condition yielded the worst results. Morris et al. (2007) explored the use of three training modalities (haptic feedback, visual feedback and the combination of the two) to learn a sequence of forces. They observed that the users trained with the visuo-haptic modality obtained the best experimental results, and the users in the visual feedback group reproduced the force pattern better than the users of the haptic feedback group. Rissanen et al. (2007) demonstrated the use of VR based on visual and haptic feedback to teach experts' force exertion to novices using the "shaping" strategy, which provides information about the power and duration of a force during the training stage.

In all the above studies, the feedback cues provided "punctual information" about the task's execution. In this study, the punctual information approach means trainees only obtained information related to the current time step. This means that learners received information about the level of force that they had to learn (or that they had applied) at each moment. From the authors' point of view, a drawback of the punctual information approach is that it does not help users to create an accurate force profile (mental model) of the whole target/applied force pattern, i.e. how the target/applied forces change overtime. "Mental model" is a term from cognitive psychology (Gentner, 2002) that refers to the way people represent specific instance of knowledge in their mind. Several studies have demonstrated that mental models can improve learning (Cañas, Antoli & Quesada, 2001; Taagten et al., 2008). In this study, the term "mental model" refers to the force profile that learners have to create in their mind. The objective of this work is not to measure how users create this model in their mind; nevertheless, according to Swinnen (1996) and Iwasako et al. (2014) feedback is important in motor skills learning in order to help trainees create a correct mental model of the task (they can recognize errors and improve their performance), while Santos (2016) concludes that multimodal systems should have to provide information about the whole task and the progress of the trainee throughout the training session. According to Williams and Carnahan (2014), training procedures that allow trainees to understand the whole task should be more helpful for learning. Along these lines, in order to facilitate the development of correct and useful mental models for the force profile, in this work the authors propose a new approach that is based on providing contextual information about the task execution. This approach will provide users not only with information about the current time step (i.e. the level of the target/applied force at a particular time) but also information about the past (how the target/applied force have changed over-time) and the future (how the target force will change).

To implement the contextual approach, visual cues were used to provide information about how the force changes overtime. This decision was based on 1) previous studies (Hasan, Yano, and Buss, 2008; Morris et al., 2007; Rissanen et al., 2007) that have demonstrated that visual feedback may accelerate and improve the learning of force profiles, and 2) previous studies that have shown that visual feedback contributes to the formation of mental models because it can influence adaptation to a dynamic environment (Rosati et al., 2014).

This new contextual approach, which is called "contextual visual feedback" in this study, is based on the display of a dynamic chart in which the evolution of the tutor's target force and trainee's performance (applied force) over time are shown on-line within the same render area. In this way, users receive information not only about what will happen in the next seconds, but they can also easily compare their entire performance with the target force. Consequently, they can correct their errors (Swinnen (1996); Iwasako et al., 2014), which contributes to their understanding of the level of force (Rosati et al., 2014) and improves learning throughout the training (Santos, 2016).

The main research question addressed by this paper is the following: does force skill training based on contextual visual information about the execution task provide better user performance than training based on punctual information? To analyze this question, the experiment presented in this work compares the performance obtained with both approaches. In order to widen the scope of the experiment, for the punctual information approach three sensory channels (visual, haptic and audio) were tested. Thus, this experiment analyzes four multimodal training conditions: 1) contextual visual feedback, 2) punctual visual feedback, 3) punctual haptic feedback, and 4) punctual audio feedback.

In addition, the authors were interested in analyzing the performance under two different experimental scenarios. The first one is concerned with "variable exerting force patterns", which are used in certain medical tasks such as drilling a bone, blunt dissection, palpation or needle insertion, and the main goal of the scenario would be to learn the evolution of forces over time. The second scenario is concerned with "constant exerting force patterns", which are used in industrial tasks such as inserting/removing machine components or plugging and unplugging cables; the main goal in this case would be to learn force magnitudes with accuracy. To analyze these scenarios, the test users had to reproduce both variable and constant force patterns after training under one of the four training conditions explained above.

This paper is organized as follows: Section 2 describes the experiment and the experimental task, the experimental set-up, the experimental conditions, the participants, the experimental design and the performance measures. Section 3 presents the results of the experiment. Lastly, Section 4 discusses the main findings and draws conclusions from this study.

2. Method

2.1. Experimental task and scenarios

The experimental task selected for this study was a fine motor skill, namely learning a pattern of exerting forces. Each participant had to memorize and then reproduce a pattern of force after training under one of the training paradigms.

Specifically, this experiment analyzed the two different scenarios of exerting force patterns. The first scenario was related to learning variable exerting force patterns. In this case, the goal was for users to improve their ability to control the change of applied force over time. For example, to remove a tumor from the brain, the surgeon has to drill the bone. But it is not enough for surgeons to practice the correct trajectory to be successful in this task; they also have to apply the correct level of force at each moment in order to avoid causing damage to any other organ. In this task, the level of applied force changes over the time, where the surgeon starts at a specific value (usually zero) and then has to improve their ability to increase the force until the constraint level is reached. In this first scenario, two variable force patterns were tested. Both patterns had similar features: the same duration (17 seconds) and the same typology (two segments, the first one corresponding to an incremental force and the second one to a constant force). The only difference between them was in the maximum constant force value.

The second scenario was related to constant exerting force patterns. In this case, the goal was for participants to learn and understand magnitudes of forces with accuracy. This skill is necessary, for example, in maintenance tasks where components need to be removed/inserted with different types of weights and constraints but without damaging the machine or other components. In this second scenario, two constant force patterns were tested. They had similar features: the same duration (32 seconds) and the same typology (three segments, each one corresponding to a different value of force). The main difference between them was the target force values.

Figure 1 shows the four patterns tested (two with variable forces and two with constant forces) in this study. The graphs represent the magnitude of the force that participants had to learn. In all cases, the target force was applied in the same direction: the downward direction (i.e. the negative y-axis). After a training session, participants were required to reproduce the force patterns as accurate as they could.

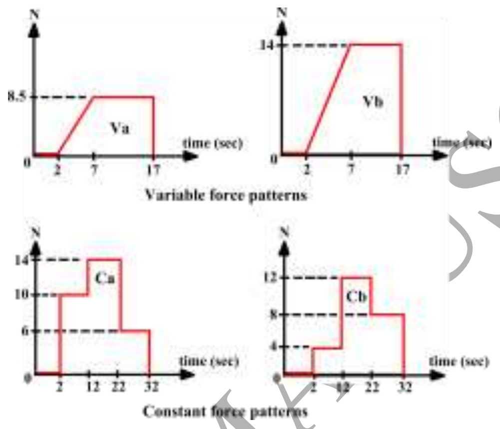

Fig. 1. The graphs represent the magnitude of the force that participants had to learn; at the top, Va and Vb are the variable exerting force patterns with a duration of 17 seconds; at the bottom, Ca and Cb are the constant exerting force patterns with a duration of 32 seconds.

2.2. Hardware and software set-up

The experimental setup is shown in Figure 2 (on the left); it was comprised of a projector screen (for visual feedback), the six-DOF LHIfAM haptic device developed by CEIT (for haptic feedback) and a pair of speakers (for audio feedback).

The LHIfAM haptic device (Borro et al., 2004) was selected because it is able to deliver a sustained force up to 20 N and the maximum level of force required for this experiment was 14 N. An SI-80-4 force sensor (by ATI Industrial Automation[1]) was installed in the LHIfAM's stylus to measure and record the level of force applied by users (see Figure 2, right).

All the forces that users had to learn in the experiment were in the downward direction (negative y-axis, which runs perpendicular to the floor; see Figure 2, left). For this reason, the x-axis (which runs from the participant's left to right, parallel to the floor) and the z-axis (which runs toward the user, in and out of the user's view plane) were jammed mechanically to prevent users from moving the device in these directions. Figure 2 shows how users held the stylus of the haptic device in order to feel or apply the target force during the experiment.

[1] [1] The technical characteristics of this sensor can be found on the web at http://www.ati-ia.com/products/ft/ft_models.aspx?id=Mini40

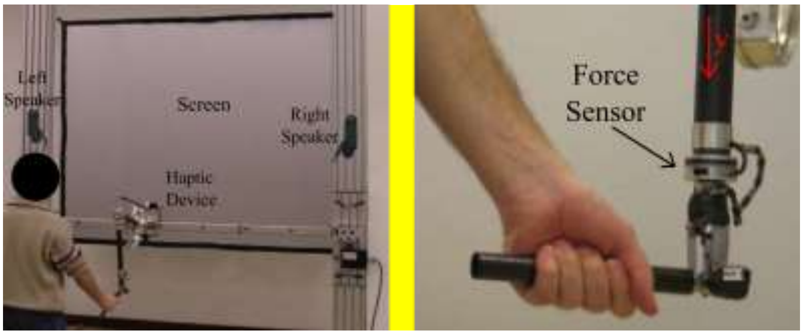

Fig. 2. On the left, the experimental setup comprising of a projector screen, the six-DOF LHIfAM haptic device and a pair of speakers. On the right, users hold the LHIfAM's stylus in the form of force grip.

In order to achieve the greatest accuracy possible, the LHIfAM force sensor was calibrated to obtain the equation and the line of best fit to describe the response of this sensor (see Figure 3).

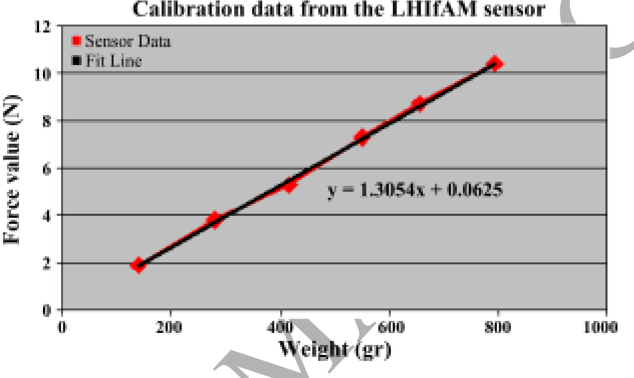

Fig. 3. Line of best fit to describe the LHIfAM's force sensor response.

A midi synthesizer module was included to provide audio feedback. This module uses the internal sound card of the PC to generate a continuous sound signal (a beep sound) whose frequency (pitch) can be changed. In this way, an initial sound (middle note C4) can change to either a higher pitch (note C5) or a lower pitch (note C3). Additionally, the sound can be enabled/disabled easily.

The test software was developed in C++ and run on a core duo CPU 3GHz with 4G RAM. The visual and audio feedback control loop rate operated at 35 Hz, while the haptic feedback was controlled and displayed at 1 kHz. The users' forces were recorded in a data file for later analysis.

2.3. Experimental conditions

The goal of the experiment was to compare the efficiency of both approaches by providing punctual or contextual information about the task execution in order to train fine motor force skills.

As described in the introduction, in the punctual approach the multimodal system only provides information about the current levels of force, while in the contextual approach the platform provides the users with information about the evolution of their performance in the past and present and about the next target forces. In this experiment, three learning conditions were tested under the punctual approach, each one based on a different sensory channel: visual feedback, audio feedback and haptic feedback. In the case of the contextual approach the learning condition was based on visual feedback. Below, the four learning conditions are described in detail.

1) Punctual Visual Feedback (VFp): this provides information about the target and user' forces at the current moment via two arrows displayed on the screen (see Figure 4). The length of the target arrow (orange arrow) changes automatically according to the target force pattern while the user's arrow (green arrow) changes according to the level of force applied by the user and is measured by the force sensor placed on the stylus of the haptic device. If the user applies less force than the target, then their arrow will be rendered smaller than target's arrow (see Figure 4, left). In contrast, if the user applies more force than the target then their arrow will be rendered bigger. When both arrows are the same height, it indicates that user is applying the correct level of force (see Figure 4, right).

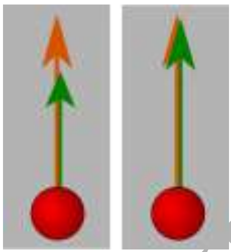

Fig. 4. Punctual information using visual feedback; on the left, the user (green arrow) is applying less force than the target (orange arrow); on the right, the user (green arrow) is applying the same level of force as the target (orange arrow).

2) Punctual Audio Feedback (AFp): this provides information about the difference between the target and user's forces at the current moment ($f_{dif} = f_{user} - f_{target}$) through audio feedback. The audio signal is generated using the midi synthesizer module described in the previous section. The sound pitch is determined through the value of the force difference (f_{dif}), meaning that if the difference increases/decreases then the pitch increases/decreases proportionally to the magnitude of the difference (i.e. the sound changes from bass to treble or vice versa). When the users apply the same level of force as the target force, the system does not send any audio feedback.

3) Punctual Haptic Feedback (HFp): this condition allows users to physically feel the target force at each moment through the stylus of the haptic device. The system replicates on the trainees the opposite force (upward direction) that they have to learn at that moment. Consequently, the learners have to apply the correct level of force (downward direction) in order to balance the system, so if the trainees apply less/more force than the target one then their hand will be moved upwards/downwards, respectively. When the system is at its equilibrium point it means trainees are applying the correct level of force.

4) Contextual Visual Feedback (VFc): in this condition the system displays the contextual information about task execution through a dynamic chart that shows both the evolution of the magnitude of the trainee's forces (red graph in Figure 5) and target forces over time (blue graph in Figure 5); in other words VFc uses visual cues to show the trainee's performance in the past and present. This chart also provides information about the next target forces. This chart also provides quantitative information about the force magnitudes and time. Additionally, the participant feel the level of force exerted through the stylus of the haptic device. The level of force applied by users was measured using the force sensor installed in the LHIfAM's stylus.

Fig. 5. Contextual information in a dynamic chart with the evolution of the target and the trainee forces overtime, along with quantitative information about magnitudes and duration.

2.4. Participants

Sixteen right-handed subjects participated in this experiment. The group consisted of five women and eleven men between the ages of 23 and 40. All participants reported normal sense of touch, vision and hearing. Each participant was informed about the purpose of the experiment before starting it.

2.5. Experiment design

The four training conditions were grouped into two groups and each participant was randomly assigned to one of the two groups. Given that the main research question addressed in this paper is whether force skill training based on contextual information about the execution task can provide better user performance than training based on punctual information, in order to answer this question group A tested the punctual visual feedback and contextual visual feedback conditions. However, in order to extend the scope of our research, group B was added. This group tested the punctual force feedback and the punctual audio feedback. This would allow the study to corroborate the advantages of the use the contextual approach in comparison with the punctual approach. In addition, each participant in each group tested the same learning condition using both variable and constant force patterns. To minimize the learning effect, in each group the force patterns and the learning conditions were counterbalanced. The participants tested each learning condition following the same protocol (Figure 6): familiarization with the learning condition, training in the target force pattern, and final test.

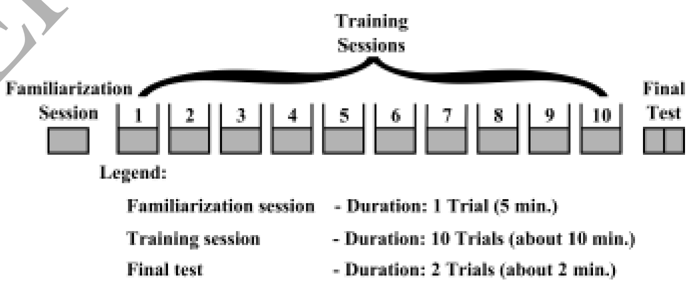

Fig. 6. Participants tested each learning condition following the same protocol: familiarization (participants were given instructions regarding the task and how to use the platform), training in the target force pattern (participants received feedback according to the training condition) and test condition (participants did not receive feedback).

In the familiarization session, participants were given instructions regarding the task and then they received a brief description and demonstration of how the corresponding training condition worked. For example, in the case of the audio feedback, the evaluator explained the difference between a treble or bass sound; in the case of punctual visual feedback, the evaluator explained the difference between the length of the two arrows, etc. When users performed the familiarization session, to avoid the learning affect they used a different force pattern than the one used in the training sessions. The objective of this session was to make sure that participants understood how they should interact with the system and how to interpret the level of force in each training condition of their experimental group.

In the training stage, participants had 10 trials to learn one of the force patterns (variable or constant) under one of the four training conditions. They were required to memorize both the magnitude of the target force and the duration, in the case of the variable patterns, and in the case of the constant patterns they only had to memorize the magnitude of the target force.

In the test condition, the participant's hand was pulled to the initial position and then, at the evaluator's signal, they were required to reproduce the same force pattern as accurately as possible, but without receiving any feedback from the system. For the variable patterns, the participants had to keep track of the timing, meaning they decided when and how they had to change the force. For the constant patterns, the evaluator told participants when they had arrived at the end of one of the segments and it was time to start the next one, i.e. they were told when they had to change of magnitude of force. In all cases the participants had to reproduce each pattern twice. After each attempt, the participant's and the target patterns were shown in a chart on the screen.

2.6. Performance measures

In order to analyze participant performance, the duration and the force applied by the users were recorded automatically by the system with a frequency of 100 Hz. A different performance measure was defined for each type of exerting force pattern (variable or constant) as a function of its goal. Each performance measure is described in detail below.

The goal of the variable force patterns was to learn the evolution of the forces over time. Therefore, the performance measure for the variable force patterns was defined by the similarity between the target force pattern and the user's force pattern, taking into account time variability aspects. To comparing two sequences, sometimes it is sufficient to use standard measurements such as the Mean Square Error (MSE) or the Root Mean Square (RMS). However, these measurements may fail to capture a correct analysis of similarity between two sequences since they are very sensitive to small distortions on the time axis (two sequences can have approximately the same overall shape and obtain a high deviation since they are not aligned over time). Consequently, Dynamic Time Warping (DTW) algorithms were used to solve this problem.

DTW is a method that allows an optimal match between two given sequences (e.g. time series) to be found, though with certain restrictions (Wang and Gasser, 1997). DTW algorithms have been used in previous works to verify signatures based on writing forces. For example, Jiao, Wang and Zhang (2009) carried out an experiment to compare the verification performance between different force components using DTW algorithms, while Fang et al. (2005) compared three modified DTW algorithms with the general DTW algorithm. In both works the results demonstrate the DTW algorithms are a suitable tool for verifying and classifying a signature using vector forces.

The DTW algorithm implemented in this study warped the target and user's force patterns non-linearly in the time dimension to calculate a measure of similarity independent of certain non-linear variations in the time dimension, and it had as a "cost function" the difference between the forces at each time step. Using this DTW algorithm, a DTW error value was obtained to classify each user's test trial. Figure 7 shows that the more similar the target pattern and user's pattern are, the smaller the DTW error value.

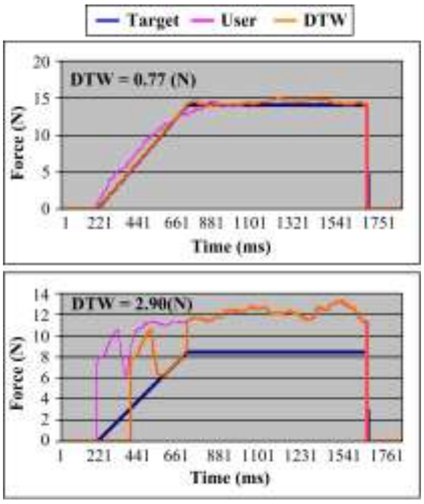

Fig. 7. DTW error to measure user performance in reproducing variable force patterns. The more similar the target pattern and user's pattern, the smaller the error.

The goal of the constant force patterns was to learn and understand magnitudes of force and therefore the time factor was not relevant. The constant force patterns had three segments, each one with a different level of force and a duration of 10 seconds (32 seconds in total including start and end of pattern). Therefore, the performance measure for the constant force patterns was defined by the similarity between the target forces and the users' forces in each of the three segments (without considering time variability). This means that only the magnitude of both forces at each point of the segment was compared. The duration of each segment was 10 seconds and the data acquisition frequency was set at 100 Hz, and thus there were 1000 points for each segment. But in order to avoid the instability effect that comes from changing from one segment to the next one, the first two and last two seconds of each segment were dismissed, so that only the six middle seconds (600 points) of each segment were compared (see Figure 8).

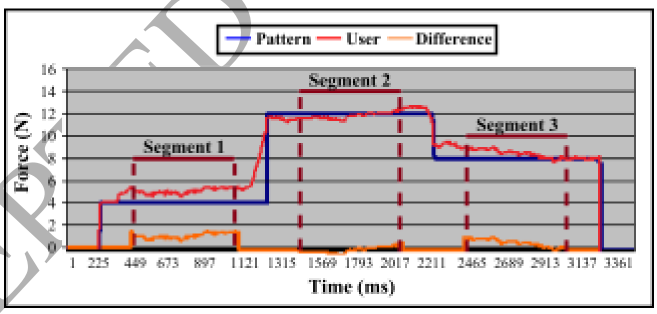

Fig. 8. Error is measured as the difference between the force of the user's pattern and the target pattern at each time step. The first two and the last two seconds of each segment are dismissed. If the error is equal to zero, it means that the user is applying the same level of force as the target one.

Therefore, the performance measure for constant patterns is based on the error between the users' force (Fu) and the target force (Ft) at each one of the 600 intermediate points of each segment of the pattern:

$$Error_{ij} = Fu_{ij} - Ft_{ij} \quad \text{(Equation 1)}$$

In Eq. 1, i indicates the number of segments (i=1, 2 or 3) and j indicates the number of points at each segment (j=1, 2, .., 600). It is important to point out that this performance measure does not use average values of the force errors at each segment, but rather it takes into account the force errors at each point of the segment one by one. The disadvantage of using the average of the user's performance as a measure is that it hides the real performance. For example, in Figure 9 the mean force applied by the user in the first segment has a value of 3.94 N and the target force magnitude is 4.00 N; this fact would indicate good performance, but an observational analysis of the user's performance in the first segment shows bad performance. Analyzing the errors of the forces at all the points (point by point) instead of only the mean performance provides more reliable information. At the same time, this approach provides not only quantitative information about the error made but also qualitative information; for example, it is possible to know if the forces applied by the participants are larger or smaller than the target ones.

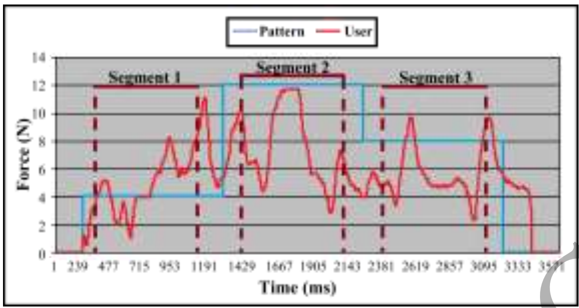

Fig. 9. Example of bad user performance (punctual audio feedback group). The mean user force for the first segment is 3.94 N, while the target force is 4.00 N, which indicates good performance, where an observational analysis would suggest bad performance.

3. Results

3.1. Variable force patterns

During the experiment's test condition, the multimodal system recorded the level of force applied by the users every 10 milliseconds. The performance measure for these patterns was defined by the DTW error described in the previous section. The DTW error represents the difference between the user's force and the target force by taking into account the magnitude of the force and the time at which the force was applied. A DTW error equal to zero means that at every moment the user applied the correct level of force. Figure 10 shows the mean DTW error for each training condition. The contextual visual feedback (VFc group) condition resulted in the best performance (0.94 N mean DTW error and 0.42 standard deviation). In contrast, the worst performance was obtained by users in the audio feedback group (AFp), with a mean DTW error of 2.50 N and the highest standard deviation value, 1.36. The data were also analyzed using an analysis of variance (ANOVA) with the learning conditions as within-subjects factors. The ANOVA analysis yielded a significant difference among the four training conditions ($F=4.62$; $p=0.006$).

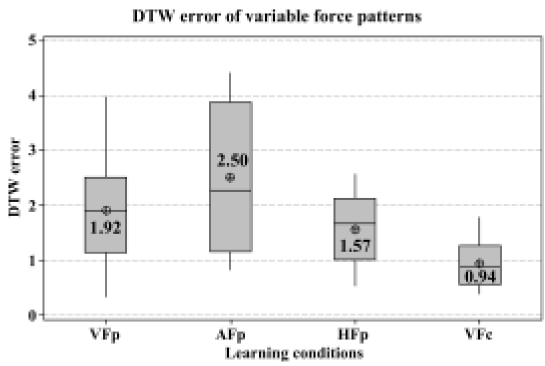

Fig. 10. Mean DTW error for each training condition in reproducing the variable force patterns: punctual visual feedback (VFp), punctual audio feedback (AFp), punctual haptic feedback (HFp) and contextual visual feedback (VFc).

3.2. Constant force patterns

As in the above case, the multimodal system recorded the level of force applied by users every 10 milliseconds. As explained in the previous section, the performance measure for these patterns was defined by the error between the users' force and the target force at the 600 intermediate points of each segment of the patterns. This means that for each learning condition, 230,400 values of force errors were analyzed together. Figure 11 shows the statistical analysis of these force errors for each learning condition. If the value of the force error is positive or negative, it means that the force applied by the user at this time is larger or smaller than the target force. On the other hand, a value of force error equal to zero means that the user is applying the correct level of force.

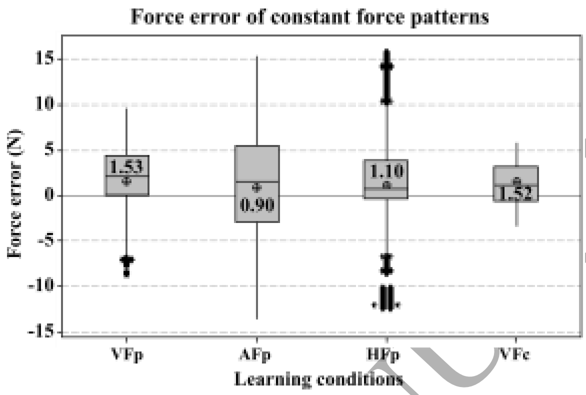

Fig. 11. Force errors for each training condition in reproducing the constant force patterns: punctual visual feedback (VFp), punctual audio feedback (AFp), punctual haptic feedback (HFp) and contextual visual feedback (VFc).

Figure 11 shows the audio feedback group (AFp) were the worst at reproducing the constant force patterns, while the contextual visual feedback (VFc) yielded the best results. Moreover, the lowest value of variance (2.83) was obtained by users in the VFc group with respect to users in the VFp, AFp and HFp groups (3.41, 5.51 and 5.10 respectively). Additionally, Figure 11 shows that in the case of the punctual visual feedback (VFp) and punctual haptic feedback (HFp), outliers are obtained (the data display surprisingly high maximums and surprisingly low minimums). The ANOVA analysis confirmed a significant difference among all the conditions ($F=109.3$; $p=0.001$). The results of Figure 11 also demonstrate that in all the learning conditions most of the participants applied more force than the target value.

4. Discussion and conclusions

4.1. Discussion

In this study, participants were required to memorize and reproduce two variable exerting force patterns and two constant exerting force patterns in order to analyze whether there was any benefit in training based on contextual information with respect to training based on punctual information. The results show (see Figures 10 and 11) that the contextual information condition (VFc) provides the lowest value of variance relative to the punctual conditions in reproducing the force patterns in both scenarios (variable and constant patterns). With regard to the average, in the case of the variable force patterns (see Figure 10), the contextual approach (VFc) provides the lowest mean value. In the case of the constant force patterns (see Figure 11), although the VFc condition does not have the lowest mean value, it provides the lowest value of variance and does not have outlier values in comparison with the other conditions. From this point of view, the contextual approach yields the best user performance when learning force profile (fine motor skills) in both scenarios. Thus, the answer to the main research question addressed by this study is that force skill training based on contextual information does result in better user performance than training based on punctual information when learning force patterns.

This result is in line with Williams and Carnahan (2014), namely that visual cues (observational learning) can be useful in facilitating cognitive processing, especially for novices performing complex tasks. In other words, the contextual approach allows trainees to observe the errors made (and possibly the correction). The observational learning literature has shown that observing a "model" that represents the goal of the task can be better for learning than only observing an explanation by an expert (Laguna, 2008). Moreover, according to Andrieux and Proteau (2013), observational learning interspersed with physical practice of the task, as compared to observational learning alone, leads to superior learning (learners are able to observe errors in action with appropriate feedback). In this case, the contextual strategy allows the learners to practice the task, and they can receive information about how their performance has evolved from the past along with information about how the target force will change (including quantitative information about the magnitudes of the forces).

Additionally, Figure 11 shows that a drawback of using the punctual approach is that user performance could result in an outlier value. According to comments made by participants, the advantages of the contextual approach over the punctual approach were that the contextual information allowed them to: 1) visualize their performance through time and therefore better understand the forces applied and correct their errors, 2) obtain information about the upcoming forces, so they could be ready for the next change of force and try to be "pro-active" in applying the correct force (in the punctual visual condition users only knew the target force at the last time step), and 3) reinforce the quantitative information about the magnitude of the applied/target forces and reinforce their force profile of the target force pattern.

On the other hand, the Figures 10 and 11 show that the worst user performance in both scenarios was obtained under the audio condition. This condition provided the users with information about their performance through a sound whose pitch indicated the difference between the target and the applied forces. According to comments made by participants, the drawbacks of this approach are: 1) most users did not know how to interpret the information provided by the sound feedback in order to understand the target force pattern and correct their mistakes (i.e. Figure 9 shows the applied forces by a user trained under the audio condition; this user not only applied the wrong forces but he also reproduced a totally different pattern); 2) users were more focused on understanding how the audio feedback worked than on memorizing the pattern. These findings are in contrast with the outcomes in Matsumura and Sakaguchi, (2008), which supports the use of auditory feedback for perceiving the timing of body movement; and in Oscari et al., (2012), where audio feedback, when properly delivered, influences both motor performance and motor adaptation.

Finally, with regard to punctual information, it is important to mention that the findings are not completely congruent with the results of previous studies. For example, in Figure 10, the punctual haptic condition provides better results than the punctual visual condition for learning variable forces patterns. This fact is in line with the findings of Morris et al. (2007), and Sewell et al. (2007) haptic feedback is beneficial for learning a series of forces. In contrast, in Figure 11 the punctual haptic condition (which has outlier values) provides worse results than the punctual visual condition for learning constant forces patterns. In general, in comparing the performances obtained in the punctual information conditions, the outcomes demonstrated that in the case of variable patterns the haptic feedback condition provided the best results, while in the case of constant patterns the performance under the visual and haptic conditions there were no significant differences (although it is important to take into account the outlier values obtained in both groups). Previous studies in the haptic training literature have been designed to compare the performance of visual demonstration and haptic demonstration for learning a novel motor skill. These studies have reported no significant differences between visual and haptic demonstration conditions (Liu, Cramer and Reinkensmeyer, 2006) and that haptic demonstration was superior only for particular aspects of the task (Feygin and Tendick, 2002; Lüttgen and Heur, 2012). Therefore, in order to provide more accurate conclusions in the case where the results of each condition depend on the objective (goal) of the pattern, a new study with more patterns should be carried out.

4.2. Conclusions

The main research question addressed by this paper was whether force skill training based on contextual information about the execution task could provide better user performance than training based on punctual information. The findings from the experiment suggest that the contextual information approach is a useful strategy for training a fine motor skill such as force exertion and it provides better user performance than the punctual information approach.

The advantage of the contextual information approach over other punctual approaches is that users receive information not only about the current time step (i.e. the level of the target/applied force at a specific time), but they also receive information both about the evolution of their performance in the past and about the future (how the target force will change), which also provides quantitative information about the magnitudes of the forces, as suggested by Swinnen (1996), Iwasako et al. (2014), and Santos (2016). All this information could reinforce the user's mental model about the target force pattern and improve user performance. This fact is in line with Williams and Carnahan (2014) and the fact that motor learning research has shown that augmented feedback can be beneficial for learning if it is provided in a way such that the feedback does not become an integral component of the task and learners do not become dependent on it for performance.

In short, the contextual information approach proposed in this experiment is based on a simple visual cue—a dynamic chart—whose information is easy to understand. The outcomes of this experiment show that one drawback of some of the training strategies based on punctual feedback is the difficulty that some users have in interpreting the information. In line with the comments made by the experiment participants, one recommendation for the design of new training strategies is that the information provided to users must be clear and easy to interpret in order to allow efficient knowledge transfer. This ensures that users are more focused on learning the task than on learning how to interpret the information about the task that is provided by the training system.

In addition, the contextual visual approach could be used to extend the capabilities of haptic training procedures based on haptic guidance to provide information about the level of force to be applied during the execution of a specific task, such as the robot-assisted system presented by Meli, Pacchierotti and Prattichizzo (2016) for training needle insertion and palpation tasks or the medical robot presented by Xiong et al. (2016) used for minimally invasive surgery. Moreover, previous research has shown that the haptic feedback helps users to learn a trajectory (Feygin, Keehner and Tendick, 2002; Yang, Walter and Boulanger, 2008). From the authors' point of view, the proposed contextual visual feedback could be used together with haptic feedback to improve the training of motor tasks; for example, the haptic feedback could be used to provide information about the trajectory (gross motor skill), while the contextual visual feedback could provide information about the level of force (fine motor skill) to be applied at each moment in the trajectory.

Lastly, one limitation of the present study is that the performance test was run just after the training sessions. Most studies on haptic training evaluate learning by using post-tests that are administered immediately after training (Bluteau, Coquillart and Payan, 2008; Culbertson, 2016; Lüttgen and Heuer, 2012; Morris et al., 2007; Teo, Burdet and Lim, 2002). However, according to Williams and Carnahan (2014), performance tests administered on the same day as skill acquisition are generally thought to demonstrate short-term retention. Consequently, it is possible that researchers have drawn incorrect conclusions or missed more permanent effects of their interventions if only using a performance test immediately after training has concluded. Hence, future studies should design an experiment in which a retention test (or a performance test) is given a few days after the training sessions to demonstrate long-term retention.

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