Bill-EVR: an Embodied Virtual Reality framework for rewardard-and-error-based motor rehab-learning

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***Abstract*— VR rehabilitation is an established field by now, however, it often refers to computer screen-based interactive rehabilitation activities. In recent years, there was an increased use of VR-headsets, which can provide an immersive virtual environment for real-world tasks, but they are lacking any physical interaction with the task objects and any proprioceptive feedback.**

Here, we focus on Embodied Virtual Reality (EVR), an emerging field where not only the visual input via VR-headset but also the haptic feedback is physically correct. This happens because subjects interact with physical objects that are veridically aligned in Virtual Reality. This technology lets us manipulate motor performance and motor learning through visual feedback perturbations.

***Bill-EVR* is a framework that allows interventions in the performance of real-world tasks, such as playing pool billiard, engaging end-users in motivating life-like situations to trigger motor (re)learning – subjects see in VR and handle the real-world cue stick, the pool table and shoot physical balls. Specifically, we developed our platform to isolate and evaluate different mechanisms of motor learning to investigate its two main components, *error*-based and *rewardard*-based motor adaptation. This understanding can provide insights for improvements in neurorehabilitation: indeed, rewardard-based mechanisms are putatively impaired by degradation of the dopaminergic system, such as in Parkinson's disease, while error-based mechanisms are essential for recovering from stroke-induced movement errors.**

Due to its fully customisable features, our EVR framework can be used to facilitate the improvement of several conditions, providing a valid extension of VR-based implementations and constituting a motor learning tool that can be completely tailored to the individual needs of patients.

I. Introduction

Virtual Reality (VR) is a promising technology for rehabilitation, as it provides a safe and controlled environment for patients to practice and learn new skills. In particular, this tool has been proved to facilitate motor learning [1]–[3], as it presents substantial benefits, such as the possibility of controlling feedback and repetitions, as well as the articulated customisation that can be implemented. Moreover, visual manipulations can be easily introduced, making VR an incredible resource for motor learning improvements and rehabilitation.

This technology has been shown to be effective for rehabilitating the motor functions of patients affected by stroke [4]–[7], brain injury [8] and several neurodegenerative diseases, such as Alzheimer [9] or Parkinson's disease [10], [11], for which it was linked to an enhancement of balance, gait, and functional abilities [12], [13].

VR systems can be customized to meet the individual requirements and goals of patients, constituting thus a versatile tool in rehabilitation. For example, these systems can provide feedback on movement speed, range of motion, and accuracy, which can be particularly useful in rehabilitation programs targeting upper limb motor function in patients [14]. Furthermore, VR systems can simulate real-life environments and activities, such as grocery shopping or cooking, allowing individuals to practice functional activities from their daily life [15].

Various types of virtual environments have been used in VR-based rehabilitation and training, including gaming [16] and sport [17], [18]. Each environment has its own advantages and disadvantages and can be tailored to the specific needs of the patient, such as games that can provide a high level of engagement and motivation. However, the current state-of-the-art of Virtual Reality studies has multiple limitations.

First, a significant proportion of studies are not properly held in Virtual Reality, but include only interactions with screens [10], [19] or virtual environments without the use of any immersive headset [20]. Moreover, traditional VR paradigms used for rehabilitation lack any physical feedback, which can make it difficult for patients to transfer the skills learned to real-world situations.

To overcome these limitations, the extension of VR into *Embodied Virtual Reality* (EVR) can be beneficial. Unlike traditional VR, which involves sitting or standing and using handheld controllers to interact with virtual objects, EVR requires whole-body movements that closely simulate real-world actions. This feature can be particularly useful for individuals with motor impairments, as it allows them to practice and improve their motor skills in a safe and controlled environment, favouring generalisability [14], [21].

As body-related visual feedback can be given in real-time, alone or in combination with other multisensory stimulations (e.g. tactile or auditory), EVR can deliver sensorimotor training that can activate brain motor and perceptual areas, having a potential impact on neurorehabilitation [22], [23].

An additional feature of EVR is the ability to capture

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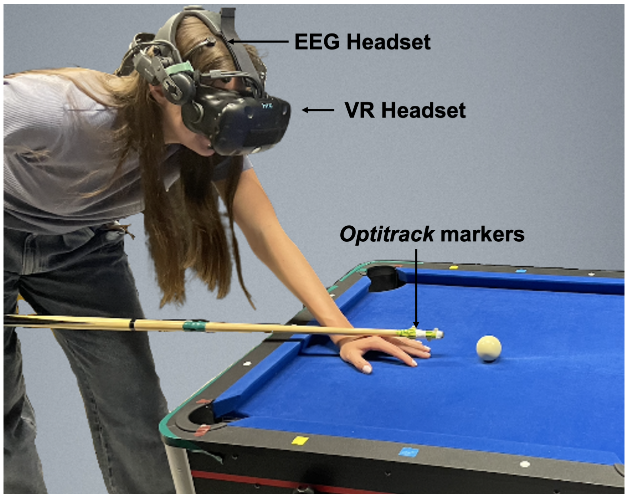


Fig. 1: *Bill-EVR* experimental setup with a real pool table and equipment (cue ball and stick), an *HTC Vive* VR headset, an EEG *eMotiv* EPOC+ headset and *Optitrack* markers for the cameras.

natural behaviour, which makes it a great candidate for the study of motor learning. Specifically, the current way this topic is investigated lacks generalisability of results, as lab-based experiments are often highly controlled and artificial and may not extend well to real-life situations [24]–[27]. By studying natural behavior, researchers can better understand how individuals perform daily activities and can design interventions that more closely mimic real-life contexts [28].

Finally, the outcomes of motor skills rehabilitation achieved up to now might be explained by the limited knowledge we have of the brain and its underlying processes. Indeed, further understanding of the neural mechanisms related to movement would be beneficial to increase the potentialities of recovery and improvement, and for that, it is fundamental to correctly capture the complexity of reality. Therefore, the need of investigating real-world situations for rehabilitation purposes is extremely clear.

In order to pursue the objectives described above, in the past few years we established a billiard task as a valid and engaging way to study motor learning [26], [27] and created *Bill-EVR*, an innovative Embodied Virtual Reality setup [21]. It filled the gaps of the real-world task limitations while preserving the possibilities of introducing manipulations and customising the environment, and maintaining the subjects' sense of embodiment. The features of this setup make it not only a useful tool to study real-world motor learning, but also a promising tool for VR-based rehabilitation.

Multiple mechanisms have been shown to underlie the motor learning processes which involve the synergic interaction of adaptive and strategic processes, respectively referred to as *error-based* and *reward-based* learning [29].

Error-based learning concerns the adaption to the error that we commit, which is quantifiable and distinguishable in measure, i.e. a small error can be clearly separated by a big error, making the brain aware of the degree of correction needed to improve the movement performance [30]. Specifically, this mechanism is driven by sensory-prediction errors as visual and haptic feedback are fundamental for the classification of the error and the choice of consequent actions needed to adapt for it [31]. On the other hand, *reward-based* learning is driven by reinforcement of model-free successful actions [32], which induces subjects to perform movements based on strategies that can be rewarding, based on past successes and improvements.

These two learning mechanisms have been usually studied separately in motor learning experiments where tasks are typically designed with the objective of isolating one or the other. However, their coexistence was shown with our billiard paradigm [27], identifying different groups of subjects with diverging behavioural and neural signatures.

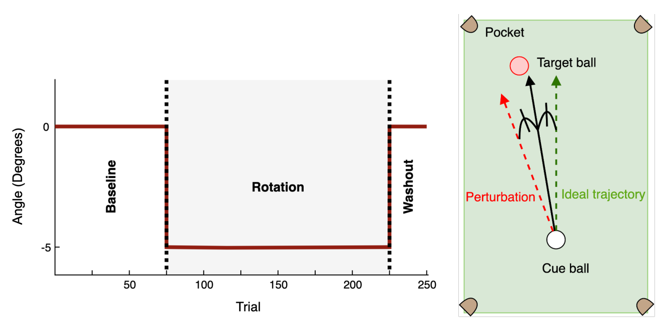
Here, we use our previously introduced EVR setup [21] to create specific tasks, with the aim of limiting the visual feedback and force to use individual learning mechanisms. This enables us to ask whether such a complex real-world task could be learned with only one of those feedback mechanisms, and how those two learning processes differ. This can be significantly insightful for a wider understanding of neural processes underlying the learning of motor skills, which would have consequences in the progress of neurorehabilitation.

II. Methods

This section provides a detailed account of the EVR experimental setup, extended from [21], the experimental design, participant selection, and data collection and analysis.

A. Experimental Setup

The *Bill-EVR* setup (figure 1) is composed of a real pool table. The use of a real scenario lets the subjects maintain a connection with reality while having all the advantages of the VR in terms of measurements and manipulations that can be introduced. The subject is playing pool in real life while seeing task-dependent visual feedback inside the virtual environment, including manipulations that vary based



(a) (b)

Fig. 2: (a) Experimental Structure: in the initial baseline phase the feedback was veridical and no rotation was applied; the angle of the ball was rotated by 5° during the perturbation phase and a task-dependent visual feedback was provided; the final washout block had the same conditions as the baseline; (b) Graphical representation of the visuomotor rotation applied in the perturbation phase of the game.

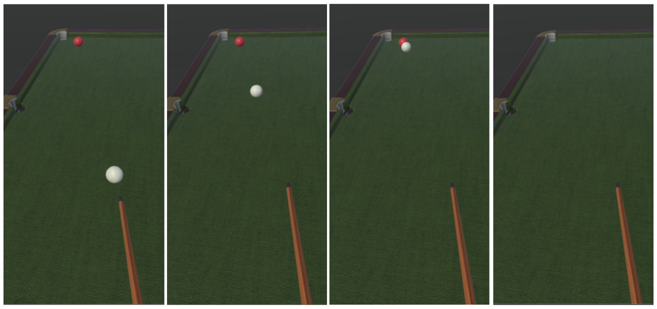


Fig. 3: Task-dependent visual feedback showed in Virtual Reality for *Error feedback*: the two balls disappear after their collision.

on the experimental features. The game is performed with a real stick, which is reconstructed in VR using geometric characteristics and the position of four markers placed on top of it; the stick is streamed in VR using *Optitrack* cameras with high precision (± 0.2mm accuracy), letting the subjects see it as a virtual object in the game.

The embodiment of the setup allows the participants to physically interact with real-world objects, receiving the full somatosensory and proprioceptive feedback of the real-world task. Indeed, the haptic feedback is preserved making the participants shoot a real cue ball, as well as through the provision of the real collision sound when the ball is shot and an artificial sound when the cue ball collides with the target ball. This latter object is only virtual, as its features are completely manipulated through VR, although its dynamics comply with the real physics of the ball, similarly to all the objects in the virtual environment (for validation of the pairing VR/real-world see [21]). The dimensions of the virtual and real table match to be even more realistic and this correspondence is achieved through a pre-experiment calibration via the four cameras and the VR controllers. The VR headset is an HTC Vive on which an eye-tracking device has been implemented by *SensoriMotor Instrument* (SMI), resulting in an additional source from which data are collected during the experiment to gain further insights on learning. The whole paradigm in virtual reality was created in Unity and coded in C#.

Furthermore, we embedded into the EVR paradigm an electroencephalogram (EEG) device which records brain activity during the experiments. We used the *eMotiv* EPOC+, a 14-channel wireless device that can be easily set on the head with the VR headset. To focus on the rehabilitation aspects of the setup and due to the fact that the data analysis has not been completed yet, the eye movement and EEG data will not be discussed here.

B. Experimental Design

16 healthy right-handed volunteers (9 men and 7 women, ages 20 to 25), with normal or corrected-to-normal vision, participated in the study. A baseline phase (75 trials, divided into 3 blocks of 25 trials), a perturbation phase (150 trials, 6 blocks of 25 trials), and a final washout block (25 trials) were all part of the 250 trials that made up a session in the lab (fig. 2a). Each trial was a single shot, where the cue ball and the target ball are starting at a constant location. Since the shooting was not timed and participants performed at their pace, the trials length could span between a couple to more than 10 seconds. Each participant attended 2 sessions. The target ball was placed close to the far-left (or right) corner of the pool table, and the same shot was repeatedly executed with the goal of pocketing. The cue ball trajectory was rotated, during the perturbation phase, by 5° (fig. 2b); therefore, in order to correct for this trajectory change and successfully pocket, the participants had to change their aim towards the centre of the table.

During this rotation phase, condition-specific feedback was provided in VR. To force subjects to learn with a specific mechanism, we designed the task to hide the visual information contributing to the opposite mechanism. Indeed, the trajectories of the balls in the *error*-based feedback condition were hidden after they collided (fig. 3), allowing individuals to progress solely based on the error of the cue ball trajectory, as they could not see the target ball pocketing. In contrast, in the *reward* feedback condition, the balls were hidden after the cue ball was shot. When a shot was *successful*, the subject was given a reward by being shown a fictional successful trajectory, constituting a reinforcement independent of any possible error correction.

A reward zone to define a shot *successful* was defined by the combination of two distinct criteria: (i) shooting inside a success funnel around the pocket (coherently with the baseline condition) or (ii) when the shot was more precise than the median of the past 10 rewarded trials. The perceived successful trials have been modulated to guide the subjects towards the perturbation, given that otherwise, without error feedback, they would have never guessed the new direction of the ball. This was following a success region method that is well established in computer-based motor learning tasks (e.g. [33]) that here we generalised to our pool task.

The 16 subjects performed the experiment in both conditions, over 2 sessions with at least 48 hours in between. Participants were randomised by the order of feedback provided and target pocket, in order to counterbalance the potential effects of individual game features.

C. Data Analysis

Data have been pre-processed to handle extreme values: a threshold for the outliers removal of the directional errors was set on the baseline ($\mu \pm 3\sigma$), and applied to the perturbation learning zone.

As regards the methodology used, in order to correctly capture the repeated measurements each subject had, the various tasks were compared using mixed-effects ANOVA: these were performed on the quantities of interest separating the different phases, *baseline*, *perturbation* and *washout* and reported through their F scores, after testing for normality.

All the principal results were evaluated by grouping trials in blocks of 25 to increase the robustness and reliability of the trends detected. No significant difference between target

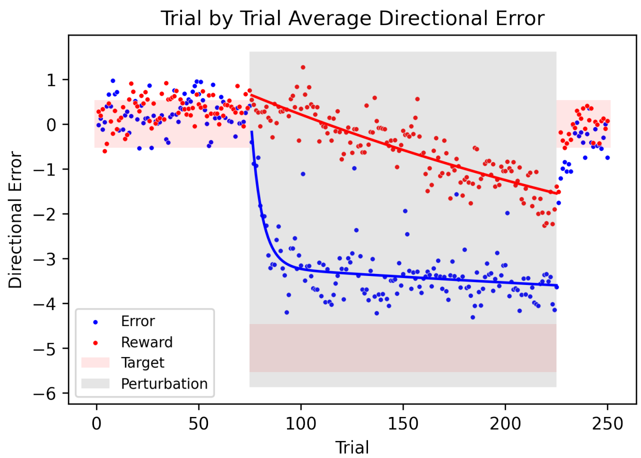


Fig. 4: Mean cue ball trial-by-trial directional error of *error-based* subjects (blue) and *reward-based* subjects (red). Grey area represents the presence of perturbation, while pink area indicates the successful angles. Double exponential fit is in bold. $N = 16$

pockets was found, allowing us to aggregate the samples to have bigger statistical power.

III. Results

A. Learning Structure

Our framework successfully probed the learning structure of the individual subjects following the visual manipulation. All participants learned the task in both learning conditions (error and reward) but had very different learning patterns as a result of the visual feedback (fig. 4). The trial-by-trial directional error was obtained by averaging the errors made by each of the 16 subjects, separating between the error and the reward tasks. During the baseline phase, in both conditions, the participants were presented with full visual feedback of the tasks and no perturbation and showed similar behaviour. In the learning phase, during which the participants were presented with varying visual feedback in the different conditions and a perturbation to learn, they showed different learning patterns, which also affected their performance during the washout phase, with no perturbation and full feedback.

Fitting two distinct learning curves for the perturbation data, we found a difference between the two conditions, with the error sample showing a significant fast learning component and then a persistent slow one ($\tau_{fast|error} = 588.24$, $\tau_{slow|error} = 5.40^{(\dagger)}$), whereas the reward sample did not show an exponential trend over time, but linear ($\tau_{fast|reward} = 1$, $\tau_{slow|reward} = 303.03^{(\dagger)}$).

Grouping the trials into blocks of 25 (figure 5a), we found a similar pattern, with a significant discrepancy between the two learning trends during the perturbation phase ($F_{mode|pert}(1, 30) = 29.11^{***}$; $F_{int|pert}(5, 150) = 2.39^{*}$). Indeed, as a result of the visible trajectory, the error subjects did compensate for the perturbation right away. In contrast, the reward subjects were more inclined to move in the direction of the rotated trajectory, and while showing slower learning it was still substantial.

Nevertheless, in both conditions, subjects learned how to compensate for some of the visuomotor rotation.

B. Success Rate

Coherently with the directional errors, the feedback manipulation influenced how the participants were able to perform in terms of success rate. Its definition is feedback-dependent and intrinsic to the specific task. In particular, for the error task it is the ratio between pockets and total number of shots, whereas for the reward experiment it is defined as the number of *perceived* successes over the total, as the participants experienced a successful trajectory every time they got rewarded. Therefore, in this case, the real pocketing rate cannot be used as the appropriate measure to capture success. In baseline and washout conditions the success rate is the standard measure for both tasks, corresponding to the error feedback one.

Considering the dynamics of the two conditions (fig. 5b), we can observe a varying trend depending on the phase. Indeed, whereas in the baseline and washout blocks the success rates were similar ($F_{mode|base}(1, 30) = 0.14$; $F_{mode|wash}(1, 30) = 0.42$), in the perturbation phase the behaviour of the two curves was roughly opposite ($F_{mode|pert}(1, 30) = 5.75^{*}$; $F_{int|pert}(5, 150) = 3.67^{**}$).

C. Variability

In order to understand which effect the game feedback had on the performance, we wanted also to measure the uncertainty of the shots over the different conditions. To do so, we investigated the mean variability of the directional error within blocks (*intra-block* variability), which then was grouped by task and averaged across subjects (fig. 5c).

To take into account and remove potential linear trends, the chosen measure for variability was the *corrected variability*, i.e. the standard deviation of the residuals of a linear regression model that was fit at a block level on the angle data (for further methodological details see [26]).

The subjects had an evolution similar to the success rate. In particular, despite the same trend during baseline and washout ($F_{mode|base}(1, 30) = 0.09$; $F_{mode|wash}(1, 30) = 0.02$), the two conditions have almost opposing dynamics over time during the perturbation phase ($F_{mode|pert}(1, 30) = 1.32$; $F_{int|pert}(5, 150) = 2.90^{*}$).

IV. Discussion

Our study introduced *Bill-EVR*, an Embodied Virtual Reality framework to develop a highly manipulable task in a real-world environment, which allows capturing natural movement while changing the physics and appearance of the game. The incorporation of a visuomotor perturbation

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$^{*}: p < 0.05$; $^{**}: p < 0.01$; $^{***}: p < 0.001$
base: baseline; *pert*: perturbation; *int*: interaction; *wash*: washout
$^{(\dagger)}$ the τ's represent the fast and slow components of the learning curves

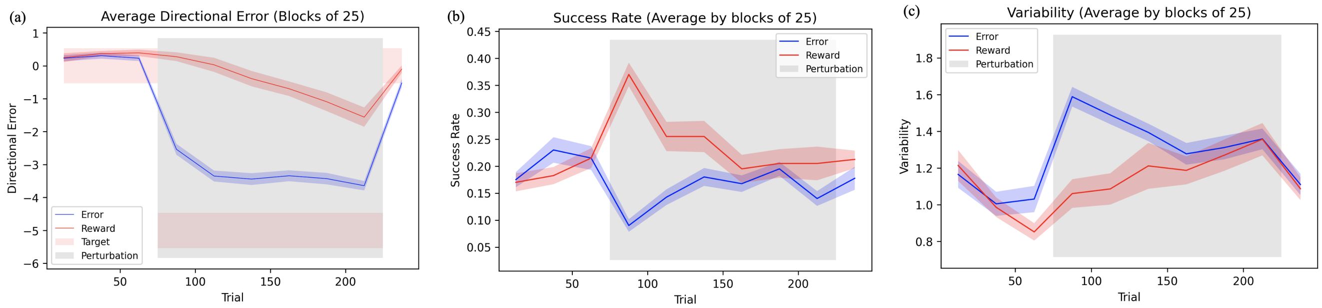

Fig. 5: (a) Mean cue ball directional error over blocks; (b) Success rate over blocks (includes the entire reward zone during perturbation for the reward condition). (c) Corrected standard deviation (after removal of linear trends within blocks). All calculated over blocks of 25 trials and averaged over subjects within condition. Shaded areas represent inter-subjects variability. Blue: *error-based* subjects; Red: *reward-based* subjects. $N = 16$

enabled us to investigate the relationship between learning and visual feedback manipulation in Virtual Reality, while maintaining the complexity of natural movement unchanged. Furthermore, the partial concealment of ball dynamics forced subjects to learn with a specific mechanism, influencing their improvement prospects.

From a learning perspective, the distinction between error-based and reward-based tasks was significant, although both showed significant training. Notably, in the error-based condition, subjects adapted to the rotation of the cue ball faster than in the reward-based condition, due to the difficulty of learning from the latter feedback and due to the enhanced success feedback.

Our results are consistent with previous research indicating that adaptation to error is faster than adaptation to reward [34], [35]. These findings contribute to our understanding of the effectiveness of Embodied Virtual Reality in investigating motor learning mechanisms in real-world environments.

The manipulation of learning magnitude was reflected in the success rate of the subjects. As they became more proficient in the task and narrowed their range of shots, the dynamics of the error performances were consistent with typical adaptation experiments (e.g., [36]), indicating successful learning. In contrast, the reward condition exhibited the opposite pattern, due to the definition of the incentive regime. As the dynamic reward zone shrank over time, the task became more challenging, leading to a decreasing trend of successful trials.

Moreover, the different feedback provided to the subjects resulted in different exploration dynamics, as indicated by the variability trends. In the error-based condition, the participants showed a high exploration initially that decreased over trials, while in the reward-based condition, they saw this tendency rise throughout the game due to the increasing difficulty of the task.

However, this disparity in exploration dynamics may also be interpreted as a distinct rate of learning, as the reward subjects may have become aware of the perturbation much later than the error ones, likely due to the difference in trajectory visibility. Nonetheless, the dynamic reward zone was designed to guide subjects towards the perturbed direction without excessive or insufficient reward, consistent with the paradigm as established.

Overall, our Embodied Virtual Reality paradigm helped us to gain insights into the motor learning mechanisms of the human brain. Indeed, its customisable learning dynamics in a real-world task make it a potentially useful tool for personalised training aids that could enhance the learning abilities of patients in an EVR-based rehabilitation framework for neurological disorders.

Furthermore, *Bill-EVR* holds the potential to manipulate patients' neural signatures through the change of visual feedback. In a previous study [27] we found that, while learning a pool shot in a real-world setting (without the use of VR), participants tend to show one of two different patterns in their neural activity - their increased synchronisation in beta (13-30Hz) oscillations at the end of the movement, known as *Post-Movement Beta Rebound* (PMBR), was either increasing or decreasing during learning. This was then linked to the main learning mechanism used. With *Bill-EVR* we would be able to validate this assumption. This would imply that neural activity could potentially be influenced by the visual feedback presented during the task, further underscoring the potential of our system, particularly for individuals with neurological diseases.

In addition, the possibility of complete customisation of visual feedback within our EVR framework could serve as a tool for motor learning. This customisation allows for the tailoring of the environment to each individual patient, including personalised data-driven manipulations to increase task difficulty and enhance generalisability [37]. Personalisation would capture the unique features that each subject requires, with the aim of maximising retention of information and improving their ability to perform movements. Taken together, our results suggest that the *Bill-EVR* paradigm represents a promising tool for neurorehabilitation.

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