ADAPTATION TO VISUAL PERTURBATIONS WHILE LEARNING A NOVEL VIRTUAL REACHING TASK

By

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ABSTRACT

ADAPTATION TO VISUAL PERTURBATIONS WHILE LEARNING A NOVEL VIRTUAL REACHING TASK

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The movements we do to perform our day-to-day activities have always been riddled with perturbations, to which we adapt and learn. The studies looking at this aspect of motor learning should consider, the biomechanical differences that exist between individuals and create a novel task that can test every individual without any bias. This was achieved in our study by using a virtual environment to perform a novel motor skill in order to investigate how people learn to adapt to perturbations. 13 college age participants (females = 7, *Mean* = 21.74 ± 2.55) performed upper body movements to control a computer cursor. Visual rotation of the cursor position was introduced as a perturbation for one half of the practice trials. Movement time and normalized path length were calculated. One way repeated measures ANOVA was performed to analyze significance between the performance at different times of the task. Significant learning seen while learning the initial baseline task (p<0.0001) and significant drop in performance upon immediate exposure to the perturbation (p =0.005). No significant adaptation over practice with the perturbation (p = 0.103) or significant after-effects on removal of the perturbation (p = 0.383). Results suggests differences in adaptation when the task is novel, when compared to other adaptation studies and such novel tasks trigger a different type of learning mechanism when compared to adaptation.

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CHAPTER 1

INTRODUCTION & REVIEW OF LITERATURE

While learning and performing motor skills daily, we see that there exist various disturbances to our movements, to which we constantly try to adjust and adapt with ease. This process of adjusting or modifying our movements to new demands by gradual trial-to-trial basis using the feedback from the errors, in order to reduce the same is called motor adaptation and this gives rise to motor learning (Martin *et al.*, 1996; Bastian, 2008). These demands or disturbances may be external, such as environmental conditions/forces, use of certain devices like prisms, or internal like muscle fatigue or injuries (Krakauer, 2009). Common examples of adaptation are walking on slippery or snowy surfaces, where our walking patterns would have to adjust to the change in the nature of the surface or trying to use computers which have different mouse sensitivities, to name a few.

Motor adaptation in research

In order to help us understand the effects of adaptation in our real life movements, studies have extensively used tasks based on error-based paradigms, such as visual or mechanical perturbations (Shadmehr *et al.,* 2010; Mazzoni & Krakauer, 2011). Study-specific examples of such paradigms being used include perturbations being introduced to the upper body such as, reaching and pointing movements. Studies with visual perturbations include visuomotor transformations using prism goggles (Helmholtz, 1962; Newport & Schenk, 2012; Redding & Wallace, 1996; Rossetti et al., 1998) or virtual rotation of the hand or finger displacement using a mouse cursor on the computer screen (Wigmore et al., 2002; Scheidt et al., 2011). Alternatively, mechanical perturbations can be used in the form of lateral external forces being brought about using a robot arm manipulandum. In these studies, there are constant modifications to the movements in the task from trial-to-trial, where the movement retains the identity of action, but over practice, changes in terms of other parameters such as movement direction or intensity of force (Martin et al, 1996).

Visuomotor adaptation

Between the two types of perturbations, a lot of studies have used visuomotor rotations and visual perturbations to study adaptation and the subsequent learning associated with it. There are many reasons and findings that support this. First, many studies using this type of perturbation have provided results that provide important results regarding procedural learning and memory. Second, rotational learning is implicit, which means that the participants tend to adapt to the perturbation even without awareness and without any explicit strategies regarding the perturbation being provided. Visuomotor adaptation studies also have tasks that are predominantly reaching based, which has a significance that the human nervous system plans reaching movements as a vector consisting of separate details for extent and direction (Gordon *et al*., 1994; Vindras and Viviani, 1998; Ghez *et al*., 2000). Reaching tasks primarily involve arm movements and visuomotor rotation works by introducing a direction based change in the reach target position, which in turn is related to the arm movement. Therefore, this can be used to study the adaptation in important movements such as reaching (Krakauer, 2009).

In such adaptation studies using visual perturbations, we see certain common trends in the structure of the experimental protocol used. There is a primary, task familiarization phase, where the participant learns to perform a certain movement for the task in hand. This phase usually consists of a certain number of trails, after which the participant is exposed to the perturbation of the task. Then there is a series of trials where the participant performs the task with the perturbation influencing the movements and it is over this period of performance where people study the effects and rate of adaptation taking place. After a considerable period of practice under the perturbation, it is taken off, and the task becomes similar to the initial familiarization task. This “washout” block is to see how the effects of the adaptation get carried over to the baseline movements.

Performance in visuomotor adaptation studies

Looking at the performance in such adaptation studies, we see that initially in the familiarization block, the participants perform well with minimum errors in the task parameters. This was because most of the tasks involve movements that participants already have some idea about. Then, upon introduction of the perturbation, the participant has a significant drop in performance and a rise in the errors, as they are not aware of the perturbation and do not yet know how to develop counter-measures to adapt. With practice over several trials, the participants gradually get better in performing the task with the perturbation, showing the presence of adaptation. This is seen in many studies by the trial-by-trial reduction in the errors made during the perturbed phase (Buch *et al*., 2003, Shadmehr *et al*., 2011). On removing the perturbation in the washout block, it is seen that there are significant after-effects, which are seen in the form of a sudden increase in the occurrence of errors. The presence of after-effects indicates that the participant does not merely react to the perturbation that has been introduced but also gradually adapts and anticipates the expected dynamics of the visually rotated environment. This therefore shows that motor adaptation appears to work by updating the internal model of an existing baseline environment, when changes are made (Huang and Krakauer, 2009).

Lack of task novelty in existing studies

However, in the tasks performed in most of the visuomotor adaptation studies done earlier, there is always the possibility of some participants having prior knowledge about the task. For example, if it is a dart-throwing task, some participants who have been prior experience throwing darts, or if they are trained in dart-throwing before. This would make these participants use strategies that they already know to result in better performance that all the other participants who have not experienced dart-throwing before. Another potential issue is that, there might exist certain biomechanical body differences between various participants, which might cause the them to get an edge over others. This for example can be understood in reaching tasks, where people with longer arms might be able to reach further when compared to people with shorter arms. In short, most of the previous studies involve tasks which try to look at adaptation through re-parameterization of an already existing, well-learn movement coordination pattern (Lee *et al*., 2018). These two aspects of prior task experience and the biomechanical differences play a crucial role in every task because these might prevent studies from looking at true learning from scratch. Therefore, tasks that are novel enough in the movements executed by the participants, so that they have no prior experience advantage, nor do they have any edge in the performance due to biomechanical differences, should be used.

Studies using novel tasks

To overcome these issues, there have been newer few studies that have taken task novelty into consideration and have structured a task which involves the learning of a novel movement coordination patterns such as using a split-belt treadmill to perform walking based adaptation tasks (Reisman *et al*., 2007) or the use of a data glove (Liu *et al*., 2011). But even in these studies, for example in Liu *et al*., 2011, the movements performed by the data glove were not completely novel and exploratory. The participants were made to wear a data glove and control a cursor on the screen, but when calibrating the movements, they were not given complete freedom to explore and define their movements, but rather made to perform repetitions of a random sequence of 24 hand postures corresponding to the static finger spelling characters from the American Manual Alphabet (AMA). Further, subjects were provided with photographic images of an expert in AMA performing these postures. This therefore restricted participants from completely exploring and defining their own set of movements for calibration.

Need for this study

Therefore, it was critical for us to investigate the effects of visual perturbations when learning a novel, exploratory motor task to understand the true effects of adaptation and give us a better understanding in real life. To achieve these task goals of novelty and lack of biomechanical differences, we used a Body Machine Interface (BoMI). There are various kinds of

Body Machine Interfaces which basically help to connect body movements and transform them to perform new functional tasks such as controlling a computer cursor, a prosthetic arm or even a wheelchair. A body-machine interface does not take account of previous biases: subjects perform novel virtual tasks that are independent from their prior experience and their biomechanical characteristics (Casadio et al., 2012). We used one such interface, which uses upper body movements to control a cursor on a computer screen (Casadio, Ranganathan, & Mussa-Ivaldi, 2012). With this, we focused on answering our following research questions.

Specific aims

Using a novel and exploratory virtual reaching task, we investigated

Aim 1: Adaptation on introduction to visual perturbation with practice.

Aim 2: After-effects of the adaptation to perturbation on its removal.

Proposed hypothesis

For Aim 1, we expected to see an initial drop in the performance upon introduction of the visual perturbation, but also expect to see a gradual improvement in the performance over practice over a period of reaching trials. For our second aim, we expected to see significant after-effects when the visual perturbation is removed, which would see a sudden drop in the performance similar to the drop seen on the onset of perturbation (Helmholtz, 1867; Liu and Scheidt, 2011; Pierella *et al*., 2015).

CHAPTER 2

METHODOLOGY

Participants

In order to answer our research questions, we had 13 healthy college-age adult participants (*Mean* = 21.74, *SD* = 2.25) with no recent history of upper body disabilities, out of which 7 were females. All the participants were undergraduate and graduate student from the Department of Kinesiology in Michigan State University (East Lansing, Michigan) and received an extra credit in one of their courses to perform the experiment as compensation. The procedures were approved by Michigan State University Human Research Protection Program (MSU HRPP) and all the participants were given consent forms to sign and a copy of the signed consent form was given to them. In this study, all the participants performed the same task with the same experimental protocol and were all exposed to the visual perturbation when they were performing a novel and exploratory virtual reaching task using a Body Machine Interface (BoMI).

The body machine interface

The Body Machine Interfaces are a means for the human body to interact with an external device. These interfaces play an essential role in assisting the people with reduced motor skills on a daily basis. The main aspect of this Body Machine Interface that makes it significant in our study is that it does not take account of previous biases: subjects perform novel virtual tasks that are independent from their prior experience and their biomechanical characteristics (Casadio *et al*., 2012). General scheme for a body machine interface is shown in the following figure:

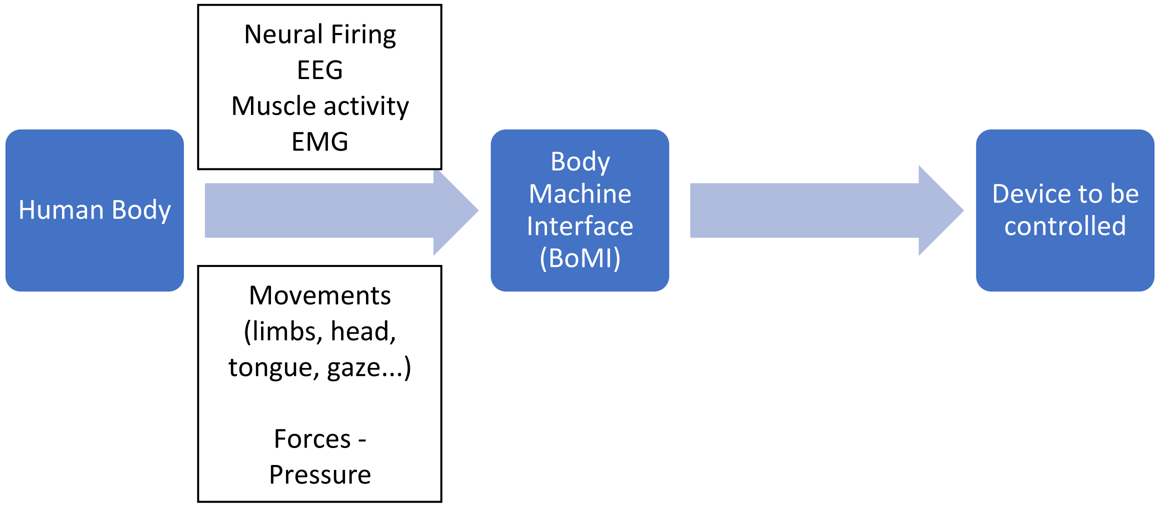

Figure 1. Schematic Diagram of a BoMI (adapted from Casadio *et al*., 2012)

A typical Body Machine Interface consists of three main components. The body being the first, refers to the human body from which signals are obtained. The second component is the machine, which refers to the device or machine that is to be controlled. The final component is the one that links these two, which is the interface. The interface plays an important role in the functioning of the BoMI by receiving and transforming the body signals into commands for controlling the device.

The general aim of a body-machine interface is to enable the user to retain a complete or shared control over the device (e.g a prostethic limb, a wheelchair or the cursor position on a computer monitor) through signals derived from the user's body. These signals may be extracted directly from body motions, using goniometers, magnetic or infrared sensors, accelerometers, cameras, force sensors and pressure switches.

Structure of a body machine interface

Signal acquisition

The initial part of a BoMI involves acquiring the signals from the body, which is done using various measuring devices and, in our case, we use four wireless Inertial Measurement Units (IMUs). These IMU sensors are placed on the shoulders of the participants (two on each shoulder) to record the movement.

Transformation of body signals into control space

The acquired body signals are mapped onto the control space, i.e. the space defined by the commands of the external device. This mapping process is typically obtained by executing a dimensionality reduction which allows mapping the n-dimensional body signal into the m-dimensional control signal (with $m<n$). This dimensionality reduction exploits several machine learning algorithms, such as PCA, independent component analysis (ICA), and the Isomap method. These algorithms rely on the extraction of key features, selected basing only on input signals' statistical properties. Among these, we use PCA, which is an unsupervised machine-learning algorithm that allows to find the directions, i.e. the principal components (PCs), of the greatest variance in the input data. These PCs are orthogonal lines of best fit to the input dataset. Only the first two PCs are generally used in our study to create the control space because they explain the biggest percentage of variance of the dataset. PCA returns an eigenvectors matrix that has the same dimension as the input matrix's independent variables. Each eigenvector is associated with an eigenvalue that is used to order the eigenvectors matrix (first eigenvector is

the one which has the highest eigenvalue). The eigenvectors are used to create the map that allows the projection of the input dataset into the PC dataset.

Substantially, PCA projects those input variables, i.e. body signals $q = [q_1\ q_2\ . .\ q_N]$, in a new Cartesian system in which the new x-axis is the 1st PC (the one that explains the highest amount of variance), $h_1 = [h_{11}\ h_{12}\ . .\ h_{1N}]$, and the y-axis is the 2nd PC (the PC with the second highest amount of explained variance) , $h_2 = [h_{21}\ h_{22}\ . .\ h_{2N}]$, and so on. To control a cursor on a monitor it is enough to have a map H made up only by the first two eigenvectors.

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & .. & h_{1N} \\ h_{21} & h_{22} & .. & h_{2N} \end{bmatrix} \cdot \begin{bmatrix} q_1 \\ q_2 \\ .. \\ q_N \end{bmatrix}$$

Figure 2. Cursor coordinates mapping equation

The control interface

Once the cursor map has been generated, we built a control mechanism which consisted of a task, which served as an interface between the body signals and the signals for the control of the external device. This is done using custom programs in MATLAB (R2014a) and Simulink.

Experimental setup

For our experiment, the participants sat comfortably and faced a 23” (58.4 cm) computer display monitor positioned at about 70 cm in front of them, at eye level. The participant was asked to wear a customized vest with Velcro strips near the shoulder region. Four wireless inertial measurement units (IMUs) (3-space, YEI Technology, Ohio, USA) were attached to the vest on the Velcro strips to capture the shoulder's scapular retraction. protraction, elevation and depression (Farashchiansadegh *et al*., 2014). The position of the sensors was on the anterior and posterior ends of the acromioclavicular joint of the shoulder, on both the left and the right sides (Figure 2) . The number of sensors was chosen in order to balance the need to capture a rich set of movements and be able to use low cost instruments that can be adopted for a more home-based setting in the future.

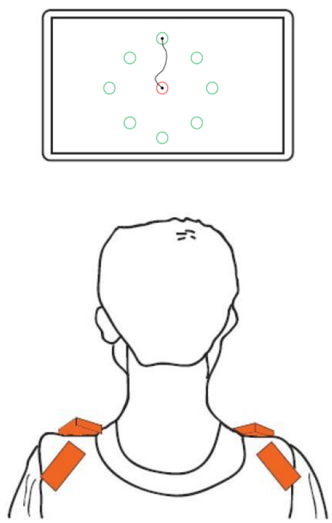

Figure 3. IMU position and experimental setup

The orientation of the sensors was estimated using a sensor-fusion algorithm through the combination of measurements derived from three types of sensors within these IMUs: a gyroscope, an accelerometer and a magnetometer. Each IMU measured three real-time signals, corresponding to the Euler angles: roll, pitch and yaw. The IMU signals were captured at the rate of 50 Hz and then mapped into the position of a computer cursor using a custom program in

Matlab/Simulink (Mathworks, Natick, MA). No filtering or pre-processing was applied to the IMU signals. In IMU design, the earth magnetic field is used to stabilize the yaw (heading angle). Therefore, the heading angle is unreliable when the earth‟s magnetic field is disturbed. This phenomenon takes place when ferromagnetic materials are in proximity of the sensors or when the sensor is subject to magnetic fields other than the Earth‟s magnetic field. For this reason, only the roll and the pitch were used as input signals for the interface.

Dimensionality reduction

The significance of BoMI lies in its ability to convert the countless number of body signals of such a high dimension and map it to get a low dimensional control space signal (a cursor). In order to define this body-to-cursor map for our task, the eight-dimensional body space vector defined by the signal values coming from the four IMUs ($\underline{h}$) is made to undergo dimensionality reduction using PCA to reduce to a two dimensional coordinate system of task space (cursor x and y on the computer monitor) ($\underline{u}$), which is referred to as the Euclidean domain.

A calibration phase was required to compute the transformation matrix needed to perform the dimensionality reduction. During this phase the participant had to execute a “body dance” for 70 seconds in which he was asked to perform exploratory movements with his upper body while maintaining a comfortable range of motion. Then, PCA was applied and the transformation matrix A was constructed using the coefficients of the first two principal components (PCs):

$$\underline{u} = A\underline{h} + p_0$$

where *p* is the 2-D cursor position vector, *h* is the 8-D body space vector, *A* is the individual's map and p0 is the offset term (Farschiansadegh et al., 2014). The individual map *A* will be determined using a calibration method where the participant shall perform exploratory movements for 60 seconds. They will be told to perform all kinds of upper body movements while staying seated, to let the computer know their boundary of motion. This calibration data will be dimensionally reduced using PCA and the first two vector components will be extracted (containing most of the variance) and scaled by a gain factor that shall be equal to their corresponding eigen vectors. The offset p_0 will be added finally to set the cursor roughly to the center of the screen. The map can be further rotated to get the most relatable and intuitive map between the body motion and cursor movement.

The task interface

The Body-Machine Interface software comprises of two different programming levels: a higher level, the Matlab G.U.I (Graphic User Interface), which allows both the experimenter to execute the program and the participant to perform the experiment; a lower level, the Simulink model, not visible to the participant, through which the experimenter has direct access to the program. Both the programming levels were previously developed by the Northwestern University (Chicago, U.S.A.) and were subsequently edited in order to conduct this study.

The G.U.I

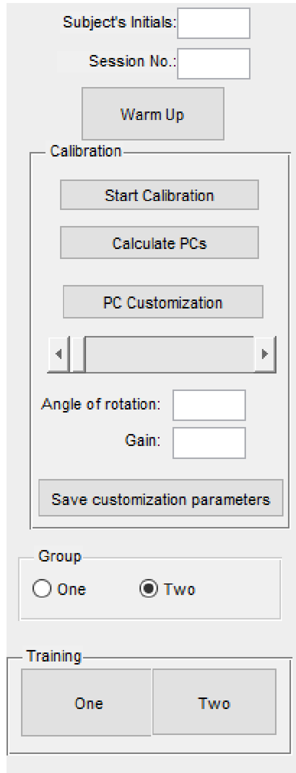

Figure 4. Matlab G.U.I to set experimental parameters and control overall task protocol

The Matlab G.U.I was used to help the experimenter control the overall protocol and interact with the interface and start/stop the Simulink part of the program when necessary.

Experimental flow

Before beginning to run the program, the experimenter has to update the destination folder name in the Simulink program in the corresponding “To File” destination and save the model.

Once the program is started, the G.U.I pops up and the participant ID and session number data are inserted into their respective slots. This will lead to the creation of a customized folder in which the data collected during the experiment will be saved. Subsequently, the user selected the “Warm up‟ button.

This action starts both the Simulink model and connects the wireless sensors to the computer. This connection process usually takes about one minute, during which all the sensors and the dongle connected to the computer blink constantly, signifying successful connection.

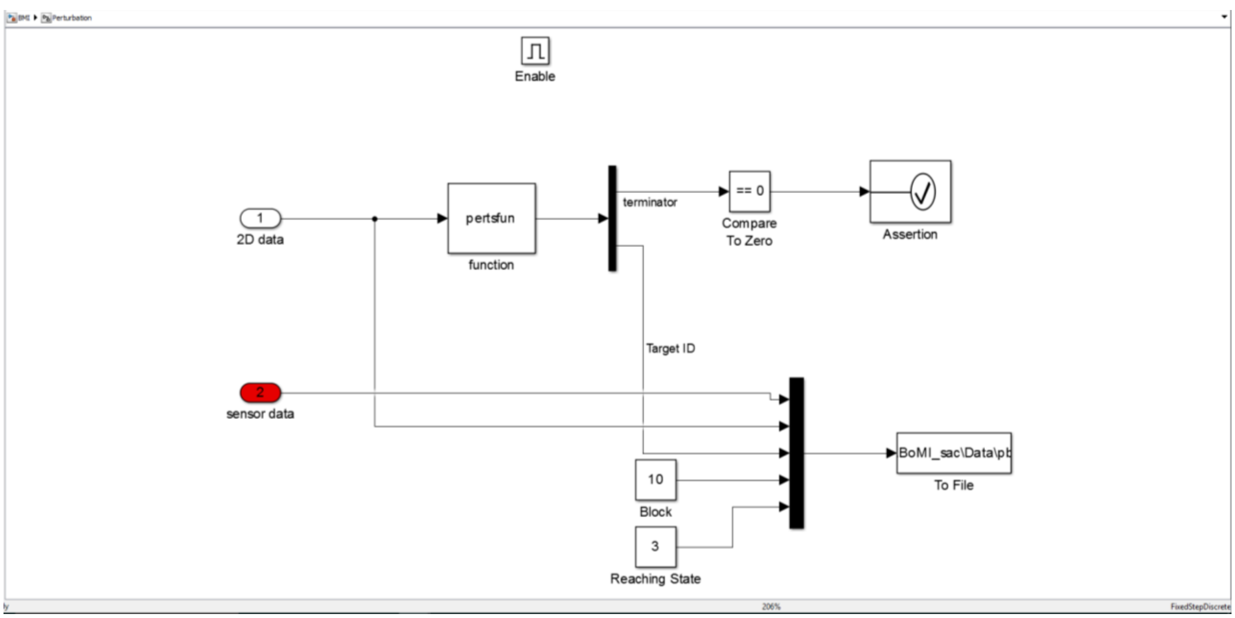

Figure 5. Simulink layout of the perturbation block

By clicking “Start Calibration” the calibration phase will start. A “calibration window“ showing the floating values of the yaw, pith and roll angles will appear and, at the end of this phase, the transformation matrix (A) will be computed. The participants were instructed on doing all different kinds of shoulder and upper body movements for the given period.

By selecting the "Calculate PCs" button. Another window will appear showing the results of the dimensionality reduction. This will display both the Variance Accounted For (VAF) by the PCs and the calibration data projected on the two-dimensional PC space, allowing the experimenter to understand if the participant will be able or not to perform the task.

Then, it goes on to the customization phase. This is started by selecting the "PC Customization" button. During this phase, a grey window appears, and the participant controls a red dot on the screen by moving his upper body. At this level, the experimenter asks the participant to hit all four sides of the screen moving his upper body. If the participant cannot touch one or more sides, the calibration must be repeated.

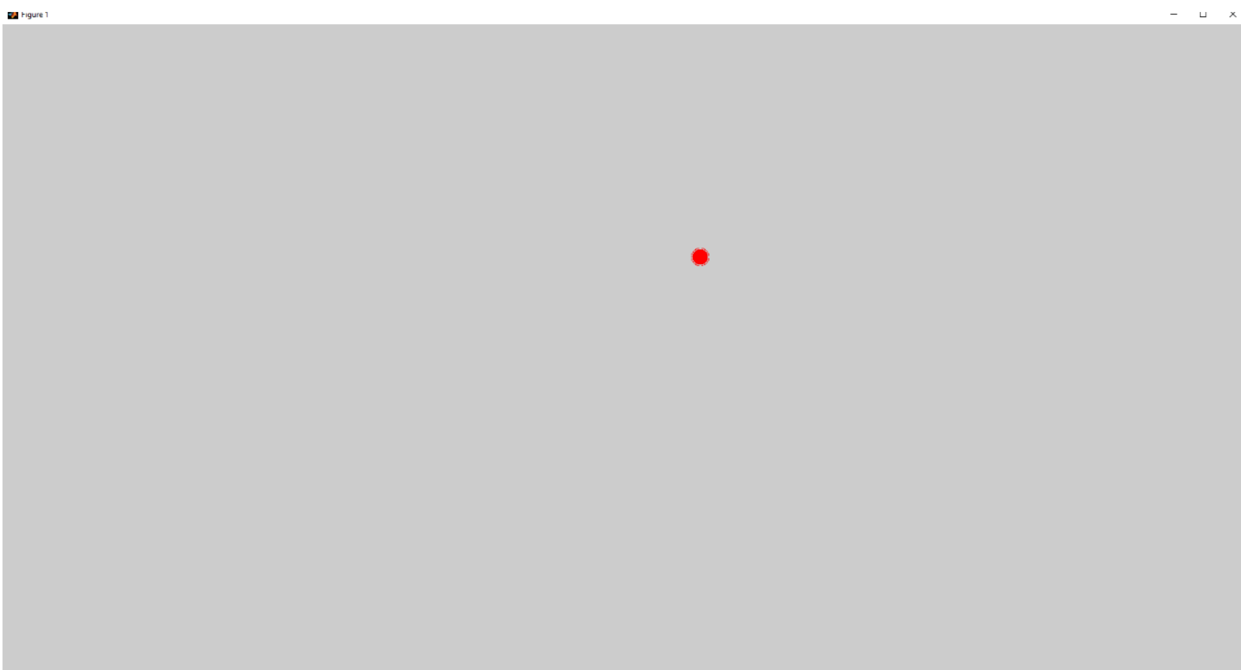

Figure 6. Customization window with the red dot task

During this, it is possible to modify the map multiplying it by a gain, adding and offset or applying a rotation. The gain will allow to stretch (if gain >1) or contract (gain <1) the workspace, whereas the offset and rotation values will allow respectively the translation and rotation of the workspace. For our study purposes, we use a Gain of +1 and an Offset value of 0.

Both parameters are selected in accordance to participant's preferences, in order to let them move the cursor in the entire workspace more intuitively. After selecting the "Save customization parameters" button, the user must select a group (Group 1, Group 2). Each group is characterized by a different protocol and the selection must be done according to the protocol that the participant must follow.

The experimental protocol

The participants were told to move their upper body (shoulders and torso) to control a cursor on the monitor and perform a center-out reaching task, designed in the custom made Matlab/Simulink program. The overall goal of the participant was to move the cursor into a specific target circle as fast and as close to the center as possible. On reaching the target circle, they would have to stay in it for at least 500ms. All participants performed 12 training blocks each consisting of 24 trials where the target circles appeared in random order in both the cardinal and diagonal directions at 11.5 cm from the center of the screen. They went back and forth between these peripheral targets and a central base target. In these blocks, the participant received a score that reflected their individual performance for each trial. Among the 12 blocks, the first five blocks were without any kind of visual perturbation, but rather a baseline or familiarization block.

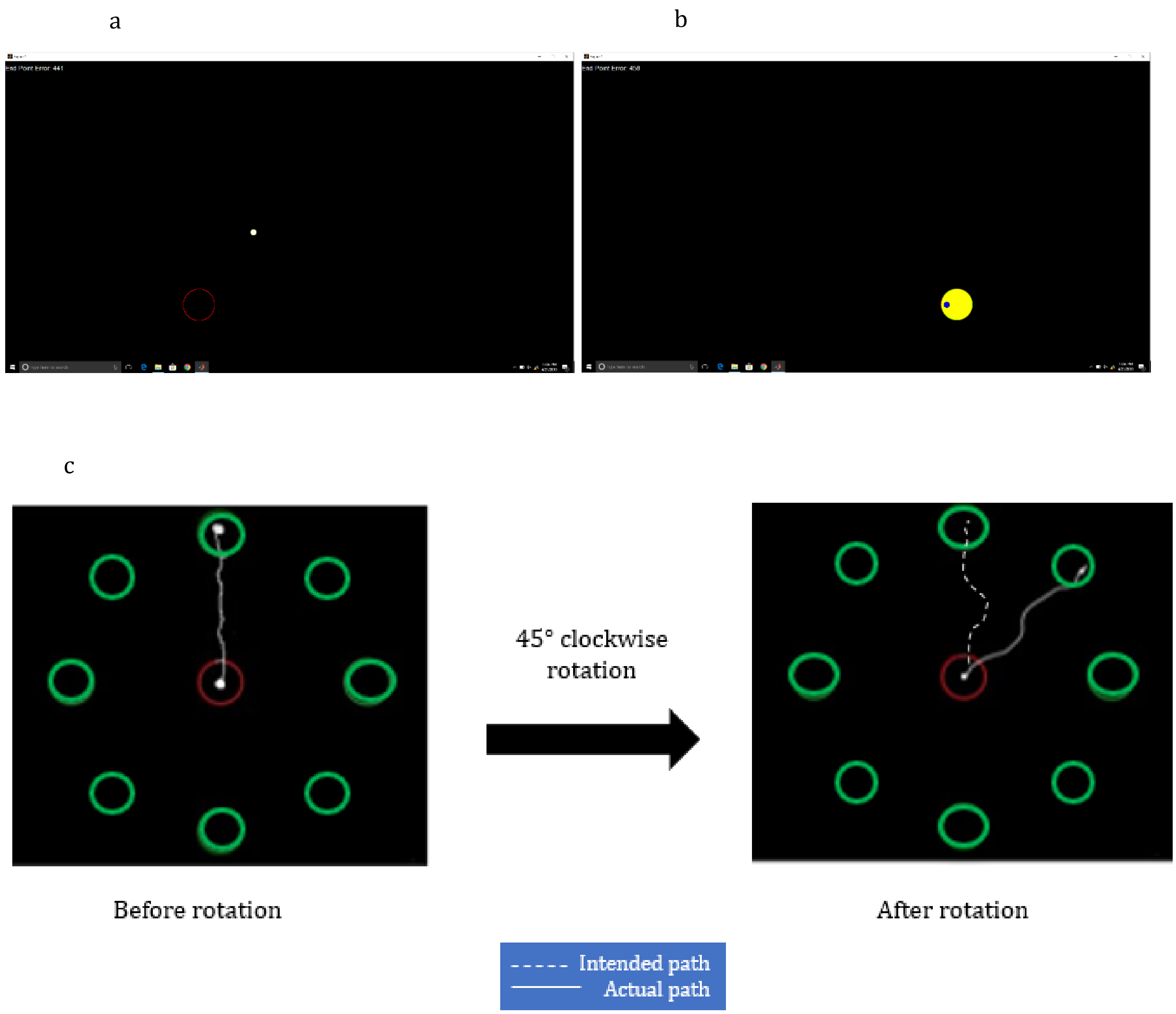

Figure 7. The task interface **(a)** Cursor while reaching to a peripheral target. **(b)** Cursor upon reaching a target and holding there for 500 ms **(c)** Position of all eight targets with the effect of visual perturbation seen while reaching for the top target

The visual perturbation blocks

From the sixth block, the visual perturbation was introduced. The perturbation was in the form of a constant clockwise rotation of 45° of the cursor position (Figure 6.c). Previous literature on cursor rotation tasks show that the response time. error reduction and adaptation rate are maximum at 45° (Krakauer, 2009; Newell, 2012). The cursor rotation was brought about by applying a rotation matrix on the final 2-D task space vector. The participants were not given any information about the perturbation and were completely oblivious to its onset. Such a perturbation was applied to the next five blocks (training blocks 6-10). At the end of these five perturbed training blocks, the participants performed two more blocks of the original unperturbed condition, which was a washout block to investigate the presence of after-effects of the perturbation. The overall layout of the study is shown in Figure 5.

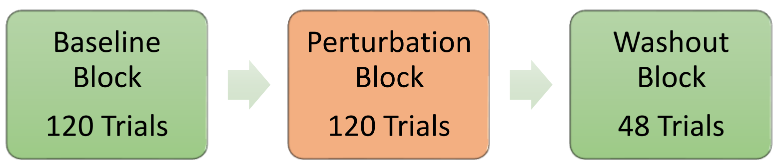

Figure 8: Overall protocol common for all the participants

Data analysis

The data that we received was in the form of .mat files, with sensor information and cursor position and time information in the files. Based on this, we will be looking at two different parameters to evaluate the participant's performance.

Performance metrics

The two different performance metrics we will be using are movement time and normalized path length, where movement time was our primary variable because all the targets were equidistant from one center target and we also looked at path length to check for the straightness in the path. We used such these measures because previous literature has shown that there is a gradual straightening of the path in reaching tasks over practice (Shadmehr and Mussa-Ivaldi, 1994; Mosier *et al.*, 2005).

Movement time is defined as the time at which the cursor leaves the center target to the time at which the cursor reaches the destination target and stays inside the target for the next 500 ms. Normalized path length between two targets is defined as the ratio of the actual distance travelled by the cursor from the center target to the destination target, to the straight line distance between the two targets.

We use normalized path length as our secondary measure to analyze how the cursor has travelled, especially when there have been high movement times. If the path length has also been correspondingly large, it means that the participant did not have a very good control of the cursor during that trial. If the path length was comparatively smaller, it would mean that the participant moved slowly, but still tried to maintain a straight line. This therefore gives us a better idea as to how participants reach and learn the task.

Statistical analysis

In order to answer our research questions, we analyzed the performances of all the twelve training blocks and investigated the effects of learning and adaptation across these.

First, we wanted to confirm if learning of the baseline task had taken place, therefore we compared the performance between training 1 and training 5, i.e. the first and last training blocks of the baseline version of the task. Next, in order to see if the introduction of the perturbation has affected the participant's performance, we look at the performance between training 5 and training 6, i.e. the last baseline training block and the first block of perturbation. Then, to study the rate of adaptation, we would compare training 6 and 10, which are the first and last blocks of perturbation. This would be followed by the washout blocks. Here, we would compare training 10 and 11 to check for the presence of after-effects upon the removal of the perturbation. Also, in order to check for any immediate after-effects upon the removal of the perturbation, we closely investigated the last cycle of target reaches of training 10 (last perturbation block) with the first cycle of target reaches of training 11 (first washout block).

For all these comparisons, we ran individual one-way repeated measures ANOVA with the training block (baseline, perturbation and washout) being our independent variable and taking the performance measures (movement time and normalized path length) as our dependent variables. Since all participants performed both the baseline and the perturbation blocks, there were no separate groups or group-effects. Post-hoc Tukey's tests were done to analyze the significance of the comparisons. The significance levels were set at $p < .05$. All the statistical analyses were performed using Jamovi version 0.9.6.9.

CHAPTER 3

RESULTS

Movement time

Baseline (Training 1 to training 5) : As we see from Figure 8, there was significant improvement in the performance initially between training blocks 1 and 5 (df = 48.0, t = 5.943, P_{tukey} <.001), which shows that considerable learning of the baseline task has happened. This was supported by a significant drop in the movement time.

Perturbation (Training 6 to training 10) : Upon introduction of perturbation, we saw that there is a significant drop in performance, which was shown by the sudden increase in movement time between trainings 5 and 6 (df = 48.0, t = -3.699, P_{tukey} = 0.005). Over the period of five training blocks under the visual perturbation, we noticed that there was a gradual reduction in the movement time, although not statistically significant (df = 48.0, t = 2.518, P_{tukey} = 0.103).

Washout (Training 11 and training 12) : Upon removal of the perturbation, at the end of training 10, we saw that there was no significant change in the movement time curve, which in fact reduces a little bit. We saw that the performance from training 10 to 11 (last block of perturbation and first block of washout) was not significant (df = 48.0, t = 1.804, P_{tukey} = 0.383). We also looked to see if there were any gender-related differences with movement time and found that there were no significant differences at any point through the 12 training blocks (df = 11.0, t = 0.320, P_{tukey} = 0.755).

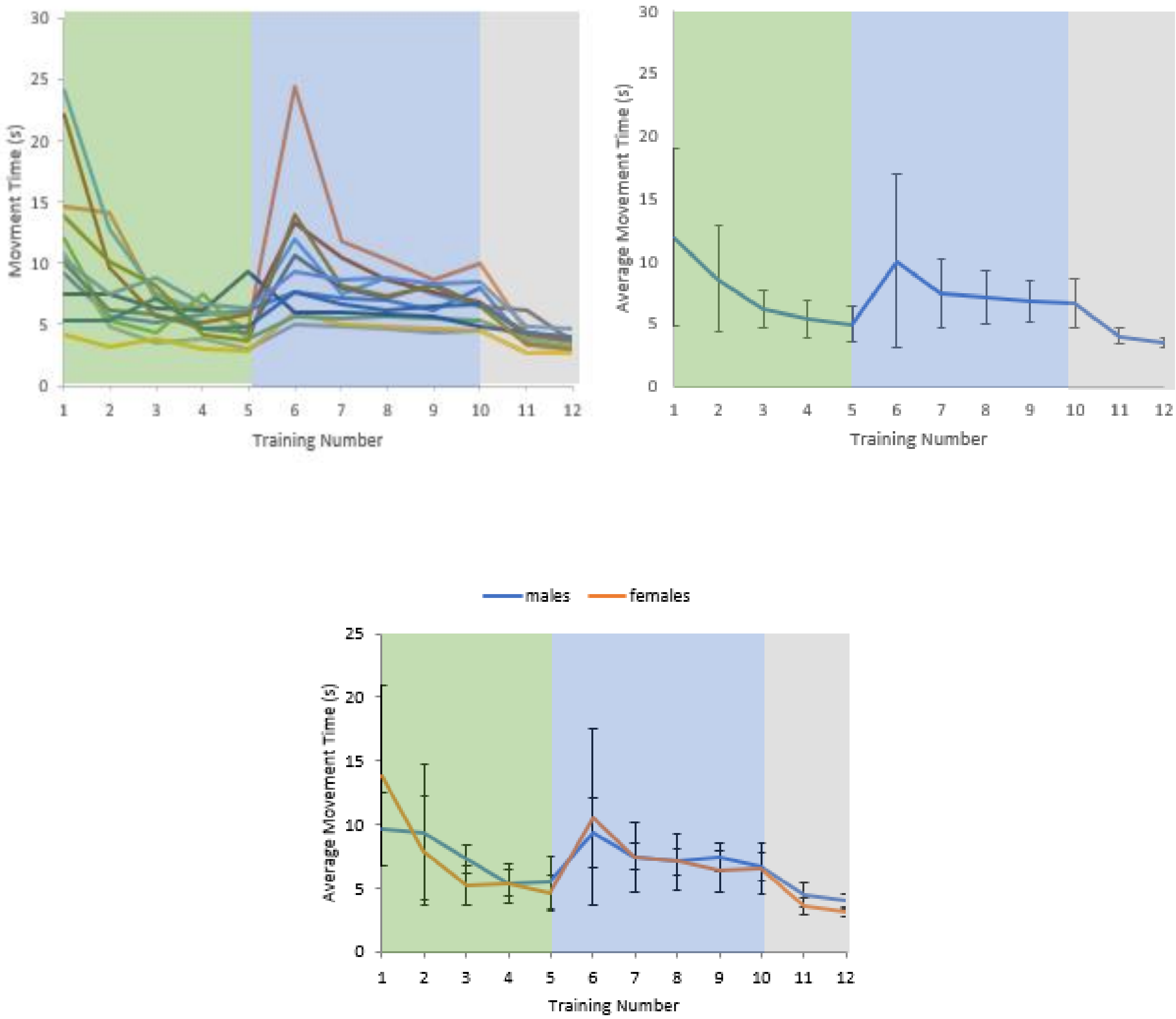

Figure 9. Performance graphs plotted for movement time against training number. The green part of the graph focuses on the baseline blocks, the blue part on the perturbation blocks and the grey part on the washout blocks. **(a)** Movement times (s) of individual participants plotted with respect to the training block number. **(b)** Movement time (s) averaged across all participants, represented with respect to the 12 blocks **(c)** Movement time comparison between males and females averaged across the participants plotted with respect to the training blocks

Path length

Baseline (Training 1 to training 5) : From Figure 9, we saw that path length followed a trend that was similar to movement time. There was significant improvement in the performance initially between training blocks 1 and 5 (df = 48.0, t = 4.79269, P_{tukey} <.001), which shows that considerable learning of the baseline task had happened. This was supported by a significant drop in the normalized path length.

Perturbation (Training 6 to training 10) : On introducing of perturbation, we saw that there was not such a significant increase in the normalized movement time, which indicated that there was no significant drop in performance between training blocks 5 and 6 (df = 48.0, t = -1.64893, P_{tukey} = 0.475). Over the period of five training blocks under the visual perturbation, we saw that there was a gradual reduction in the normalized path length almost to near baseline performance, which was not statistically significant (df = 48.0, t = 1.8334, P_{tukey} = 0.367).

Washout (Training 11 and training 12) : When the perturbation is taken off at the end of training 10, we saw that there was almost no change in the normalized path length curve, which stayed almost exactly at the same level. We saw that the performance from training 10 to 11 (last block of perturbation and first block of washout) was not significant (df = 48.0, t = -0.19362, P_{tukey} = 1.000). Even for normalized path length, we did not see any significant gender-related differences at any point through the 12 training blocks, although we saw that the females had slightly lower normalized path length than the males (df = 11.0, t = -2.00, P_{tukey} = 0.070).

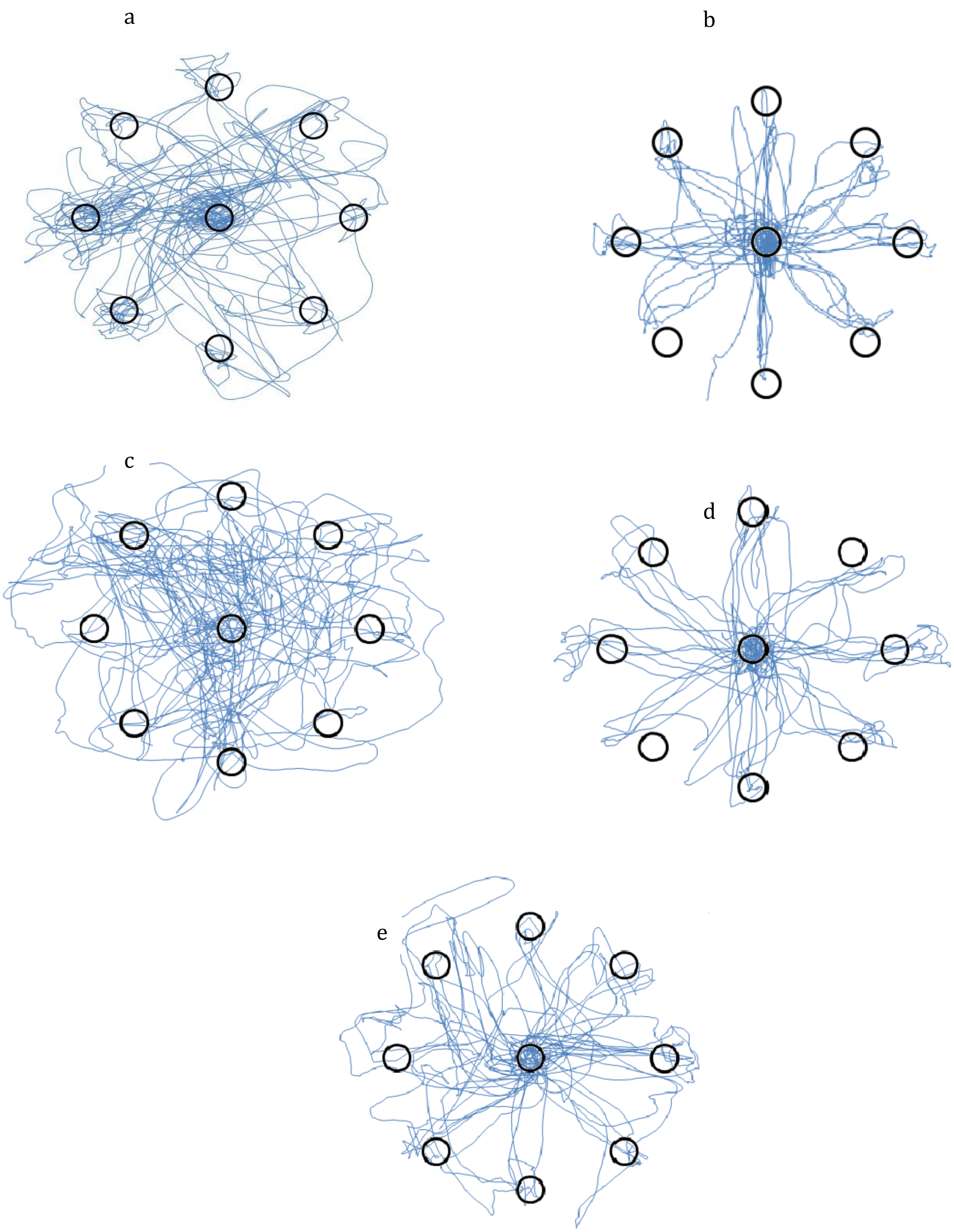

Figure 10. Path length trajectories at various stages of the protocol **(a)** Training 1 (first baseline block) **(b)** Training 5 (last baseline block) **(c)** Training 6 (First block of perturbation) **(d)** Training 10 (last block of perturbation) **(e)** Training 11 (first block of washout). This clearly shows that gradual learning has happened to an extent along the perturbation block but there are no big differences on removal of the perturbation.

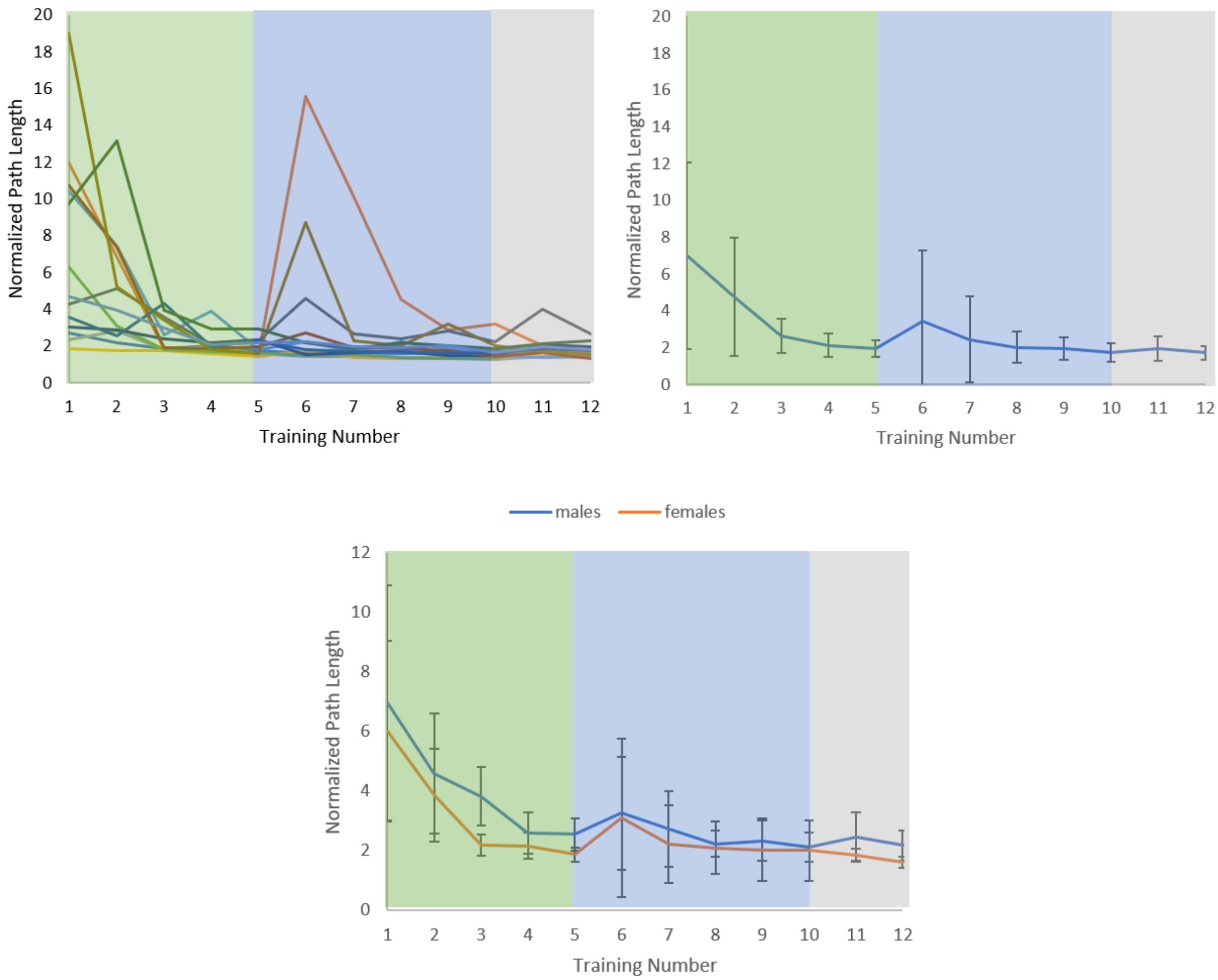

Figure 11. Performance graphs are plotted for normalized path length against training number. The green part of the graph focuses on the baseline blocks, the blue part on the perturbation blocks and the grey part on the washout blocks. **(a)** Normalized path lengths of individual participants plotted with respect to the training block number. **(b)** Normalized path length averaged across all participants, represented with respect to the 12 blocks **(c)** Normalized path length comparison between males and females averaged across the participants plotted with respect to the training blocks

Immediate after-effects

Although we saw that there was no significant results for both movement time and normalized path length between training blocks 10 (last perturbation block) and training block 11 (first block of washout), which showed the absence of after-effects on removal of the perturbation, we wanted to see if there were any immediate after-effects on the first few trials of the washout block. For this, we compared the performance of participants in the last 8 of the 24 trials of the perturbation block (training 10) with the first 8 trials of the washout block (training 11). Eight reaches were chosen because they corresponded to the one cycle of reaches to all the eight targets.

The results showed that the last cycle of target reaches for training 10 (perturbation block) were significantly higher than the first cycle of target reaches for training 11 (washout block) for movement time (df = 7.0, t = 4.76, P_{tukey} = 0.002). For normalized path length, although the reaches in the washout block were more than the ones in the perturbation block for certain targets, they were not statistically significant for us to make a defining conclusion (df = 7.0, t = -0.287, P_{tukey} = 0.435).

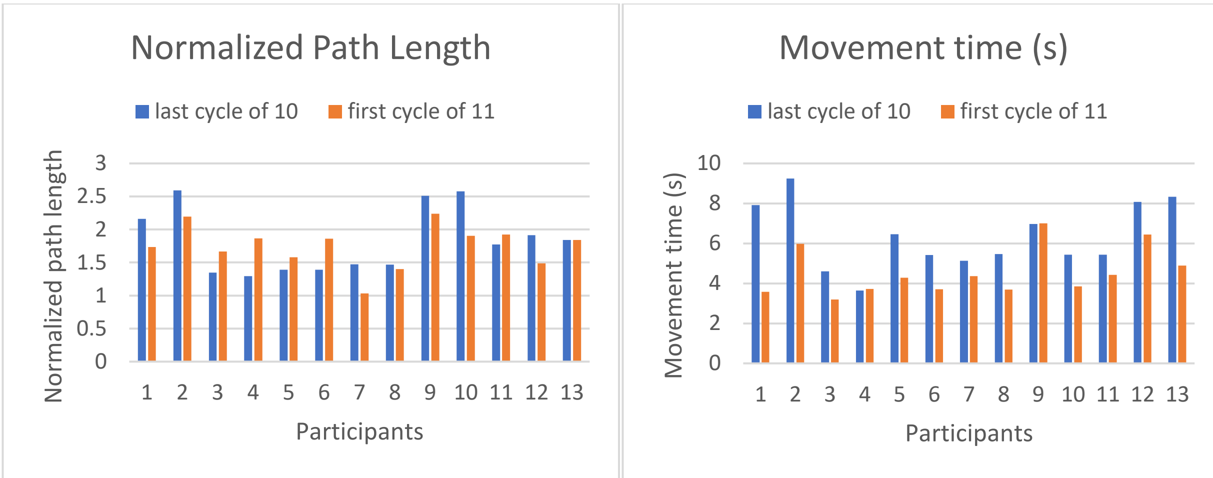

Figure 12. Comparison between the average of reaches for the last cycle of training 10 and the first cycle of training 11. The performance parameters (movement time and normalized path length) have been plotted for each participant, averaged across each cycle.

CHAPTER 4

DISCUSSION

Summary

Learning a motor pattern is one of the most primitive and important processes in human development. This process of motor learning also leads to adjustment of movements, when encountered by forces or changes in the environment, which results in motor adaptation. During adaptation, eventually new motor patterns are learnt, and adaptation always tends to work in the direction of bringing back the performance to near baseline (unperturbed) conditions (Izawa *et al*., 2008). This is done through a feedback process using the errors we commit in the previous trials, which is used to correct movements in future trials (Wei and Kording, 2008).

We initially aimed to investigate motor adaptation in a novel, exploratory virtual reaching task using a visual perturbation (visuomotor rotation). We identified that the lack of task novelty would cause some participants to have undue advantage due to prior task experience or biomechanical differences giving Previous literature has shown that the performance worsens on the onset of the perturbation but over practice, it does get better, which suggests that motor adaptation has taken place. Also, it was seen that once the perturbation is removed and the participant performs the baseline task, the performance goes bad once more, which suggests the presence of after-effects in the washout trials. This is also what we expected to see in our study.

Baseline performance

We initially saw that there was significant learning of the baseline task, which corresponded well with the results of previous studies done with the same baseline task (Lee *et al*., 2018). The performance curves were similar for both movement time and normalized path length. This suggested that our initial number of blocks given for practice was enough for the participants to learn the task, although it was novel.

Perturbation block performance

Our first aim was to see how participants would react to the perturbation and how the corresponding motor adaptation to the visuomotor rotation of the cursor position would be. We saw that the performance on both parameters, movement time and normalized path length, reduced considerably upon introduction of the visual perturbation. This suggested that all the participants had a significant reaction to the perturbation on its exposure, although none of them were given any feedback or knowledge about the perturbation or it's onset. Over practice, where the number of trials were the same as that of the baseline block (5 training blocks, 24 trials each), we saw that there was a significant improvement in performance which was seen with the reduction in movement time. The normalized path length also gradually reduced although not statistically significant. This suggested that although the task was novel, adults could adapt their movements to visual perturbations after learning a novel task from scratch.

Washout block performance and after-effects

On removing the perturbation, we expected to see considerable after-effects in the movements. The presence of after-effects has been found in most of the previous motor adaptation studies, even the few that have been done in novel tasks (Liu and Scheidt, 2011). It demonstrates that the participant doe not just react to the changes in the environment or the perturbation to movement, but rather also works according to a prediction-based model where he/she tries to anticipate the dynamics of the changed environment and perform movements accordingly. Therefore, there is an update that happens to the existing internal model of the external environment.

In this study, we expected to see significant after-effects, but we found that participants exhibited no after-effects at all when the perturbation was removed. The performance with respect to both movement time and normalized path length remained almost the same after the perturbation was removed like it was before removal. We looked closely to check for any immediate after-effects in the few reaches, by comparing the last cycle of reaches of the final perturbation block with the first cycle of reaches in the first washout block. Even in that case, we found that there was not drop in performance which could indicate any after-effects. We saw that the movement time for the reaches of the last perturbation block was higher than the movement time for the washout block. This shows the lack of after-effects. Also, the performance at the beginning of the washout block was almost at the same level as that of the last block of baseline (both unperturbed conditions).

The lack of after-effects can be attributed to two possible reasons. One, the practice that occurred during the perturbation phase might have helped strengthen the original motor plan of the baseline block. In that case, it is not just adaptation to the visual perturbation but also reinforcement of the existing map. The second possibility could be that the novelty of the task might have made it too difficult for the participant to adapt to the perturbation and this might have caused the them to learn two separate motor plans one for the unperturbed condition and one for the baseline condition.

Limitations

A major limitation of our study was the small sample size. The statistical insignificance of the results can be attributed to the low power of the study, which in turn is related to the sample size. For now, although we see significance for adaptation over the period of visual perturbation, the results are not so conclusive for the after-effects phase, which could be understood better if we had a bigger population.

Future direction

Few suggestions for the future would include trying to look at similar adaptation in different populations, as previous literature has suggested that there are significant age-related differences when the task performed is novel. For children, we expect the populations that are slightly older (around 12 years) to not show any after-effects and perform similar to the adults, whereas expect the younger populations of children to have lower performances with significant after-effects. That being said, this study can be potentially used as an effective tool to investigate the effects of aging on the ability to adapt to visuomotor perturbations an also in understanding motor adaptation, motor planning and execution.

Another suggestion would be to look at the data from a different perspective. Although in this study we have considered movement time to be the primary variable to measure learning, literature has looked at other parameters such as error in path deviation and directional error (Kagerer *et al*., 1997, Buch *et al*., 2003). These are measures of the angle and distance and with our perturbation being a visuomotor rotation, this might give us a better understanding of how it affects movement. This is because, a participant can reach to a target very fast, but can have randomness or deviation in their movement. It is this angular deviation that might give us a better reading about how the visual rotation has affected the movement.

APPENDIX

Data Analysis Tables

Movement Time

Repeated Measures ANOVA

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2
Blocks	923	4	230.7	15.0	< .001	0.398
Residual	739	48	15.4			

Note. Type 3 Sums of Squares

Assumptions

Tests of Sphericity

	Mauchly's W	p	Greenhouse-Geisser ε	Huynh-Feldt ε
Blocks	0.00191	< .001	0.429	0.494

Post Hoc Tests

Post Hoc Comparisons - Blocks

Comparison							
Blocks		Blocks	Mean Difference	SE	df	t	p_{tukey}
Training 1	-	Training 5	9.144	1.54	48.0	5.943	< .001
	-	Training 6	3.454	1.54	48.0	2.245	0.181
	-	Training 10	7.328	1.54	48.0	4.763	< .001
	-	Training 11	10.103	1.54	48.0	6.567	< .001
Training 5	-	Training 6	-5.691	1.54	48.0	-3.699	0.005
	-	Training 10	-1.816	1.54	48.0	-1.180	0.762
	-	Training 11	0.959	1.54	48.0	0.623	0.971
Training 6	-	Training 10	3.875	1.54	48.0	2.518	0.103
	-	Training 11	6.650	1.54	48.0	4.322	< .001
Training 10	-	Training 11	2.775	1.54	48.0	1.804	0.383

Figure 13. One-way repeated measures analysis for movement time averaged for all participants with blocks as the repeated measures factor.

Normalized path length

Repeated Measures ANOVA

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2
Block	256	4	64.11	8.93	< .001	0.330
Residual	344	48	7.18			

Note. Type 3 Sums of Squares

Assumptions

Tests of Sphericity

	Mauchly's W	p	Greenhouse-Geisser ε	Huynh-Feldt ε
Block	2.84e-4	< .001	0.412	0.470

Post Hoc Tests

Post Hoc Comparisons - Block

Comparison							
Block		Block	Mean Difference	SE	df	t	p_{tukey}
Training 1	-	Training 5	5.03545	1.05	48.0	4.79269	< .001
	-	Training 6	3.30300	1.05	48.0	3.14376	0.023
	-	Training 10	5.22927	1.05	48.0	4.97716	< .001
	-	Training 11	5.02584	1.05	48.0	4.78354	< .001
Training 5	-	Training 6	-1.73245	1.05	48.0	-1.64893	0.475
	-	Training 10	0.19381	1.05	48.0	0.18447	1.000
	-	Training 11	-0.00962	1.05	48.0	-0.00915	1.000
Training 6	-	Training 10	1.92627	1.05	48.0	1.83340	0.367
	-	Training 11	1.72283	1.05	48.0	1.63978	0.480
Training 10	-	Training 11	-0.20343	1.05	48.0	-0.19362	1.000

Figure 14. One-way repeated measures analysis for normalized path length averaged for all participants with blocks as the repeated measures factor

Immediate after-effects

Movement time

Repeated Measures ANOVA

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2
block	14.18	1	14.183	22.7	0.002	0.675
Residual	4.38	7	0.626			

Note. Type 3 Sums of Squares

Post Hoc Tests

Post Hoc Comparisons - block

Comparison							
block		block	Mean Difference	SE	df	t	p_{tukey}
training 10	-	training 11	1.88	0.396	7.00	4.76	0.002

Figure 15. One-way repeated measures analysis of movement time, comparing the last eight reaches of the training 10 to the first eight reaches of training 11.

Normalized path length

Repeated Measures ANOVA

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2
block	0.0466	1	0.0466	0.685	0.435	0.019
Residual	0.4760	7	0.0680			

Note. Type 3 Sums of Squares

Post Hoc Tests

Post Hoc Comparisons - block

Comparison							
block		block	Mean Difference	SE	df	t	p_{tukey}
training 10	-	training 11	-0.108	0.130	7.00	-0.827	0.435

Figure 16. One-way repeated measures analysis of normalized path length, comparing the last eight reaches of the training 10 to the first eight reaches of training 11.

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