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Influence of Motor Imagery on Learning under Complex External Dynamics

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Abstract—**Humans are remarkable in their ability to adapt to changes in the dynamics of a movement. The mechanisms by which the brain controls body movements are important in the fields of robotics and neurosciences. Robots are largely used to study the adaptive properties of human motor system. If rehabilitation robots are used in conjunction with techniques for functional brain imaging, in principle the motor learning can be facilitated for rehabilitation purposes. In this study, we use motor imagery technique to improve the learning rate in a robot-based adaptation task. We tried to determine whether humans can learn an internal model of a complex mixed force field (V+P) that was the sum of a velocity-dependent force field (V) and a position-dependent force field (P). The results suggest that the motor learning can be influenced by mental practice and could be used to increase the rate of adaptation.**

I. INTRODUCTION

Humans have exceptional abilities to behave adaptively even in diverse and complex environment in various types of behaviors. The manipulating adaptive properties of the motor system have been studied in experiments in which robots deliver forces that may be made dependent on position, speed and/or acceleration, thus allowing to simulate specific dynamic environments ('force fields'). In simple force fields, the central nervous system (CNS) can acquire a neural representation (internal model, IM) of the relation between motor commands and external dynamics. For example, when subjects are exposed to a velocity dependent force field that systematically disturbs arm motion, they are capable of gradually recovering their original movements, by cancelling the disturbance by means of pre-planned patterns of forces. This control modality is revealed by characteristic after-effects, the subjects make these errors when the perturbing forces are unexpectedly removed, suggest that internal models are built with practice [1]. An alternate strategy for compensation is used in some cases where external dynamics are not stable. For example, in movements made under divergent perturbing forces the subjects do not learn the IM, but compensate for the force by increasing the mechanical impedance of the arm. This strategy is called impedance control, and it does not need to acquire models of the physical environment [2]. Recent studies have shown that the CNS prefers using IMs when the external dynamics is stable. In contrast, it prefers impedance control when the dynamics is unstable [3].

In relation to the movement, motor imagery (MI) is an internal reproduction of a specific motor action without any overt motor output and represents conscious access to the content of the intention of a movement. However, mere perception of the movement is not enough for learning [4]. A substantial number of studies suggest that MI and movement execution share common neural mechanisms [5] and MI may affect motor performance [6].

These studies suggest that if motor imagery and movement execution share common neural mechanisms, then mental rehearsal of movement should have an impact on motor learning. In this study we investigate the effect of motor imagery on learning complex dynamics. We used a mix force field which is the sum of a velocity-dependent force field (V) and a position-dependent force field (P). In such complex field, the movements were corrected by both internal model control and impedance control strategies.

II. MATERIALS AND METHODS

A. Experimental setup

The experimental apparatus is shown in Fig.1. The robotic manipulandum (x and y axes) was actuated by a couple of linear direct drive motors (M-E099EM0T2-003, NSK Ltd, Japan), which were controlled by the digital servo at 2 kHz sampling rate. The axes positions of the robotic arm were detected by digital encoders at a sampling rate of 2 kHz. The subject was seated on an adjustable-height chair in front of the manipulandum, the shoulder was fixed on the back of the chair by a strap. The right hand and elbow were locked in place with a support rack at the same height as the shoulder, and the wrist was held in a stiff brace made of thermoplastic. Thus, the subject's right arm could only move in the horizontal plane. The hand, start and target positions were indicated on the screen before the movements.

B. Experimental protocol

Ten subjects made point-to-point movements (12.5 cm amplitude) towards the target represented by a circle (1.5 cm) on the computer monitor. Subjects made movements in eight directions (0, 45, 90, 135°, 180, 225, 270, and 315°); all the movements were started from origin and were made in outward directions. The subjects were encouraged to complete the movements in 300±50 ms. The visual feedback of the hand position was suppressed, but the entire hand path and the duration of the movement was shown after the

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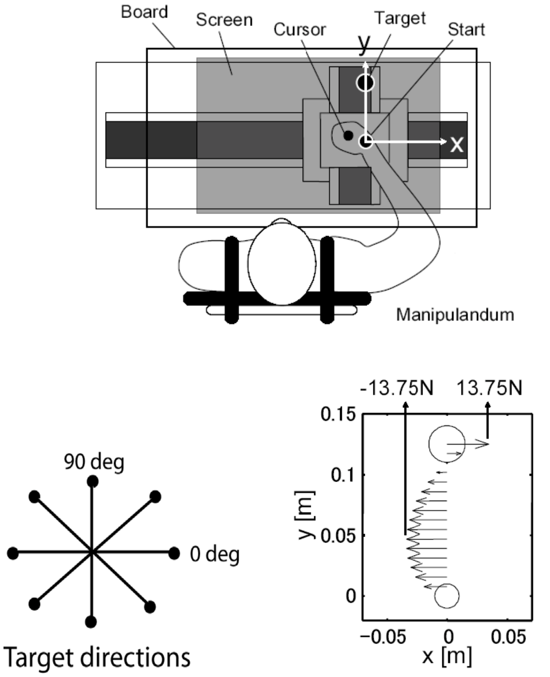

Fig. 1. Experimental setup: A robotic Manipulandum was used to deliver the forces during the movements in eight directions. The forces was generated first towards left (perpendicular to the target direction) and then towards right.

movements had finished. The subjects were allowed to take rest during the experiment. The movements were distributed into trials and sets, each trial consisted of 8 movements (1 movement per direction), and 4 trials (4 movements per direction) were grouped to form one set.

Adaptation task: In the experiment, the subjects had to made point-to-point movements in a mixed force field (V+P), i.e. sum of a velocity-dependent force field and a position dependent force field. The applied forces were proportional to both the hand velocity and the hand position according to the following equation.

$$F = B\dot{x} + Kx \tag{1}$$

where x = $[x, y]^T$ is the hand position. In these two equations, the coefficient matrix B equals [0 -25;25 0] (Ns/m), and K equals [0 110;-110 0] (N/m). (Fig.1) shows force patterns of two force fields. At first, V+P generates a force to the left depending on the hand velocity (the peak level: Fx ≈-13.75 N), and then the direction of the force is reversed to the right depending on the hand position (the peak level: Fx ≈13.75 N). These force pattern characteristics are the same when reaching in the other movement directions.

The subjects were assigned two groups randomly; one group (N=5) performed reaching movements without motor imagery (No-MI) while the other group (N=5) performed reaching movements with motor imagery (MI).At first, all subjects in both groups practiced point-to-point reaching arm movements during which no force field was applied (200 movements). This condition is called the "null field".

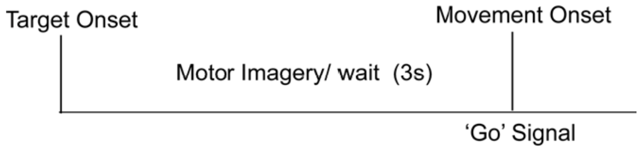

Fig.2. After onset of the target, during first 3 seconds the subject has to stay still and imagine the subsequent movement or wait for the 'Go' signal. The "Go" signal indicates the start of the movement.

After the practice, both groups learned the V+P (200 trials) force field. During later 64 movements, for eight movements (one movement in each direction) the force field was unexpectedly switched off to check for after effects.

For each movement, subjects had to hold the cursor at the starting position (initial position of the target), at the center of the workspace. Then the target shifted to one of the eight outer locations. At this point, the 'MI' group subjects were required to 'imagine' the subsequent hand movement toward the target for 3 sec. A 'Go' signal (target color turning into green), indicating that the actual movement could start. On occurrence of the 'go' signal, subjects had to move immediately as fast and accurate as possible. During imagery interval, the subjects in the 'No-MI' group simply had to wait for the appearance of the 'Go' signal Fig.2.

C. EMG

We also recorded surface EMG activity of two biarticular muscles: the triceps long head and the biceps long head. The EMG recorded on the skin surface was A/D converted with a sampling frequency of 2 kHz.

EMG analysis: The amplified signal was band pass filtered (17–530 Hz) and processed through a 50 Hz notch filters. To facilitate averaging across movements, data were aligned on the basis of the movement onset, which was defined as when the tangential speed first crossed a threshold (0.03 m/sec). The absolute EMG activity during 50 ms before movement onset to 100 ms after movement onset was calculated.

Polar analysis: We used polar analysis to evaluate changes in EMG. These polar plots summarized the function mapping of target direction into initial EMG activity. The analysis was done by computing the movement initiating activation for each direction in each trial. The resultant 8x1 scalar matrix for a trial was multiplied by respective unit vectors pointing in the direction of movement. For each trial we added these vectors to form one resultant vector. This resultant vector pointed towards the mean of all eight directions. The orientation of this resultant vector indicates the preferred direction of the muscle in the dynamic environment. The details of EMG analysis are explained in [7].

D. Hand-path errors

The adaptation to the force fields was quantified by calculating the error relative to a straight line joining the centers of the start and the target circles. The absolute hand path error T.E was calculated as follow

$$T.E = \int_{t_s}^{t_f} |a(t)| \, |\dot{b}(t)| \, dt \qquad (2)$$

Here, T.E represents the area between the actual movement path and the straight line and 'a' is the deviation of the hand position to the direction perpendicular to the target direction and $\dot{b}$ is the hand velocity to the target direction. The errors were calculated from the start time, ts (20 ms before crossing a hand velocity threshold of 0.05 m/s), to the termination time, tf (20 ms after recrossing a hand velocity threshold of 0.05 m/s). The error measures were adjusted for any bias that may have been present during the last null field set. Therefore, errors in a field set always refer to changes from errors in the null set. We also compared the errors of the after effects for the subjects of both groups and in-between the groups.

III. RESULTS

Fig.3 shows the learning curves of both groups in force field trials. The horizontal axis represents the trial number, and the vertical axis represents the error in each group. The error bars represent standard deviation. In both groups, the average error substantially decreased across trials. There was a significant difference between the average error of the last set (last 32 movements) and that of the first set (first 32 movements) in both groups (MI: $p<0.03$; NO-MI: $p<0.01$), suggesting that the subjects learned to move in the force fields. We recorded the after effects to determine how the compensation for the force was achieved. We compared the errors of the after effect trials with the errors of last set in the force field in both groups. The data shown in the figure are the average of each group. The error bars represent standard deviation. We found no significant after effects within NO-MI group; however, strong after effects were present within MI group ($p<0.04$). In general the after effects in MI group was greater than NO-MI group ($p<0.01$). Fig. 4 shows activation of each muscle in a certain "preferred" direction. For the null field (gray line), the resultant vector (mean±SD) in the biceps (MI, -29°±7°; NOMI,- 35°±8°) and in the triceps (MI, 138°±6°; NO-MI, 148°±7°) was measured, presuming a sinusoidal fit of the data. The muscle preferred direction was changed with adaptation in both biceps (MI,-72°±8°; NO-MI,-28°±6°) and triceps (MI, 113°±7°; NO-MI, 130°±7°). After adaptation, the resultant vectors (black line) rotate in a clockwise direction for all subjects in the MI group in both muscles. However, in the NO-MI group the biceps muscle showed no rotation in two subjects and counter clockwise rotation in 3 subjects; the triceps muscle showed clockwise rotation similar to MI group but the results were not significant ($p=0.187$).

IV. DISCUSSIONS

In reaching movements, the CNS combines two elements of control: feedforward elements generate neural commands based on information available before the movement (e.g., desired trajectory); and feedback elements, which generate neural commands based on delayed visual and proprioceptive information available during the movement. During this experiment the visual information was suppressed, so the movements were mainly under the influence of feedforward elements. The subjects in both groups showed discrepancy between expected and actual movement as indicated by high errors during the early phase of learning, and with training they learn to make correct movements under force field. The magnitude of the observed error was decreased gradually with the practice period in both groups. To quantify whether subjects develop an IM, we removed the force field in few movements unexpectedly, the subjects in both groups produced trajectories opposite to the direction of removed force field. However the after effect errors were larger in MI group. We also performed EMG analysis to spot any effect of learning on muscle preferred direction. Previous studies developed the hypothesis that practicing in a field at a given arm configuration results in a change in the pattern of muscle activations (or forces) as a function of movement direction (or desired motor state). The change may be quantified as a rotation in the spatial tuning curves, or preferred directions,

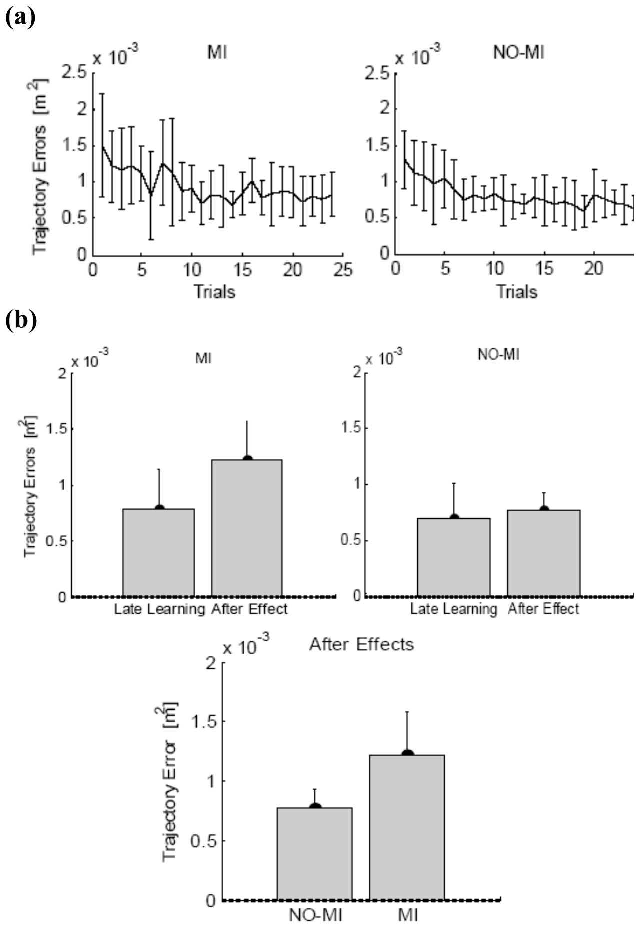

Fig. 3. (a) The learning curves for both groups. (b) comparison of the after effects within groups and in-between both groups. The subjects with motor imagery showed higher after effects.

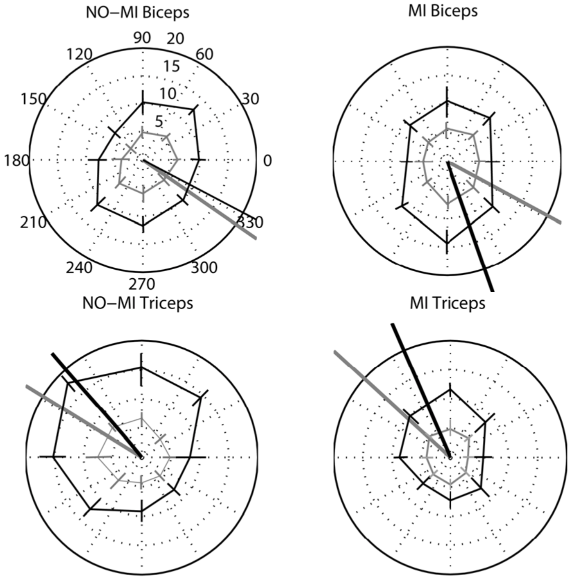

Fig. 4. The polar plots for four conditions are shown in the figure, the resultant gray (black) vectors show the preferred direction of a muscle in null filed (force filed). The data was averaged along all subjects in each group, the error bars shows standard deviation of the averaged data in each direction.

of EMGs [7]. We evaluated the directional bias of EMG by calculating the orientation of the resultant vectors (preferred directions) in both groups from 50 ms before the onset of movement to 100 ms after the movement offset. The muscle activity during this time will include both the feedforward command and the reflex responses. The resultant vectors remained stable in later stage of null field for both groups. However, with training in the force field, the preferred direction of each muscle's EMG function rotates in MI group, while no significant rotation was found in NO-MI group especially in the biceps muscle. The possible explanation is; some force fields are easier to learn than others. Because learning of each field is coupled to a specific rotation in the muscle tuning functions, it is possible that the degree of difficulty in learning a mix force field relates to how much each tuning function needs to rotate. And an incomplete learning leads to partial rotation in the preferred direction of the muscles. Higher after effects and the rotation in muscle's preferred direction in MI group provides evidence that during force field trials the central nervous system gradually composed an internal model of the force field, and used it to predict and compensate for the forces imposed by the environment, while the NO-MI group partially developed the internal model and might used some altered technique (impedance control) as well to correct the movements.

Motor imagery shares the same neural mechanisms with motor preparation and actual movement, and the central changes produced during motor imagery should also have an effect on motor performance. In general, the process of learning novel motor skills is believed to involve three stages: (i) a cognitive stage- we observe the motor skill which has to be acquired; (ii) an associative stage (early *learning)* - we learn to perform and refine the motor skill. Movements are predominantly performed under feedback control mode; (iii) an *autonomous stage (late learning)*, during which the motor skill increasingly becomes automatic and movements are predominantly performed in feed forward control mode. So having in mind that the motor imagery and actual movement shares same neural substrate, it is reasonable to ask whether mental rehearsals of a movement in a given workspace influence the performance. In motor imagery of an action, we use forward model to make movement predictions since an efferent copy of previous motor commands are available for it. The correspondence between these predictions and the behavior helps us to tune our forward model during the movements. In other words the mental practice of a movement can facilitate motor learning by establishing a functional link between internal model and forward model [8].

V. CONCLUSION

In this paper, we examined adaptation of reaching movements to a mixed force field. Both groups managed to perform straight movements with trials, but the after effects were only present in MI group. The NO-MI subjects did not learn the internal model of V+P accurately and they might use impedance control technique to achieve the stability. The increase of learning in subjects who performed movements with motor imagery suggests that motor imagery together with rehabilitation robots may find immediate application in fields like neuromotor rehabilitation and motor skill learning.

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