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RESEARCH ARTICLE

Evidence for predictive control in lifting series of virtual objects

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Abstract The human motor control system gracefully behaves in a dynamic and time varying environment. Here, we explored the predictive capabilities of the motor system in a simple motor task of lifting a series of virtual objects. When a subject lifts an object, she/he uses an expectation of the weight of the object to generate a motor command. All models of motor learning employ learning algorithms that essentially expect the future to be similar to the previously experienced environment. In this study, we asked subjects to lift a series of increasing weights and determined whether they extrapolated from past experience and predicted the next weight in the series even though that weight had never been experienced. The grip force at the beginning of the lifting task is a clean indication of the motor expectation. In contrast to the motor learning literature asserting adaptation by means of expecting a weighted average based on past experience, our results suggest that the motor system is able to predict the subsequent weight that follows a series of increasing weights.

Keywords Motor control · Internal models · Grip force · Motor memory · Predictive control

Introduction

Internal models are neural mechanisms that can mimic the input/output characteristics—or their inverses—of the motor apparatus and of the external environment. Forward internal models can predict sensory consequences from efference copies of motor commands. Inverse internal models, in contrast, can calculate necessary feed-forward motor commands from desired trajectory information (Kawato 1999; Wolpert and Kawato 1998). Some researchers do not use the term internal model (Foisy and Feldman 2006; Gribble and Ostry 2000); however, even in their studies, it is clear that the motor system can adapt to external perturbations and, in that general sense, can generate internal representations of the external environment. Understanding the structure and capabilities of these internal representations is essential for understanding the motor system.

In this line of study, it has been demonstrated that internal representations employ state representations rather than time representations during adaptation to force perturbations (Conditt and Mussa-Ivaldi 1999; Karniel and Mussa-Ivaldi 2003), and the learning of these representations has been modeled in various conditions of force distribution between trials (Scheidt et al. 2001; Smith et al. 2006; Thoroughman and Shadmehr 2000). Several studies have examined adaptation to stochastic environments. Takahashi et al. (2001) asked subjects to make elbow flexion and extension movements against a viscous load, the strength of which was drawn randomly from a Gaussian distribution in each trial. In that randomly varying environment, subjects learned the average of the loads they experienced. Scheidt et al. (2001) observed similar adaptation to the mean during a planar reaching movement in which a velocity-dependent force field of varying amplitude was applied to the hand by a robotic manipulandum. They showed that the subject's estimate of the expected force was based on the weighted average of performance over the previous few trials. They also examined trials in which the amplitude of the force field was drawn from a bimodal distribution. In that situation, subjects tended to learn the mean rather than the most frequently experienced

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amplitude. Witney et al. (2001) examined the development of the anticipatory response: when one hand pulls on an object held in the other, the restraining hand generates an anticipatory increase in grip force (GF) and thereby prevents the object from slipping. They found that when the properties of the object were randomly changed between trials, the anticipatory modulation of the GF depended on the weighted average of the object's properties, as experienced over the previous three trials. These results suggested that in a randomly varying environment, a short-time averaging process underlies the representation of the task in the motor working memory and that learning may not represent the statistics of how perturbation changes over a longer time scale (Davidson and Wolpert 2003). Current models of motor learning are typically based on gradient descent learning and predict that the next object is going to be similar to the average of the previous objects. Here, we challenge this mechanism and demonstrate that these models should be extended to account for the possibility of extrapolating and predicting environments that were not experienced in the recent past or do not represent an average of past experience.

The aims of the present study were to investigate the predictive capabilities of the motor system in a simple motor task of lifting a series of objects with increasing weights and to test how past experience can help us to predict the future. The lifting movement was chosen, since it has commonly been used as a tool for learning about forward models or internal models in general (Bracewell et al. 2003; Flanagan and Lolley 2001; Flanagan and Wing 1997; Johansson and Cole 1992). In such studies, the maintenance of an accurate GF is clean evidence for the existence of predictive control and a forward model: When manipulating an object, one must adjust the GF to the movement trajectory as well as to the physical properties of the object to prevent slip. As described below, to determine the GF, we used an augmented reality environment with haptic capabilities that enable subjects to see and feel virtual objects.

Our results support the hypothesis that the motor system predicts the succeeding weight that follows a series of increasing weights and refute an alternative hypothesis by that the motor system employs the average of the previous weights to form its prediction. We believe that the ability to predict the future state of the motor system is both feasible and essential for skilled movement.

Method

Subjects

Five healthy subjects (two women and three men, 24–27 years old) naïve as to the purpose of this study participated in the study after signing an informed consent form, as required by the local Helsinki Committee. The subjects were paid for their participation.

Experimental apparatus

An augmented 3D environment was used to create a grip and lift task. The system (Fig. 1a) creates both visual and haptic feedback providing the impression of interaction with a real object. For each subject, the index finger and thumb of the dominant hand were each connected to a robotic arm (PHANTOM® Desktop™ by SensAble) using firmly fixed thimbles (Fig. 1b). The system measures the position of each finger, calculates the acceleration of the object, updates the position of the object, and computes the resultant forces on the fingers. These forces are applied to the fingers by torque motors to create the appropriate feedback. The visual feedback combined with the force feedback creates the impression of interaction with a real object.

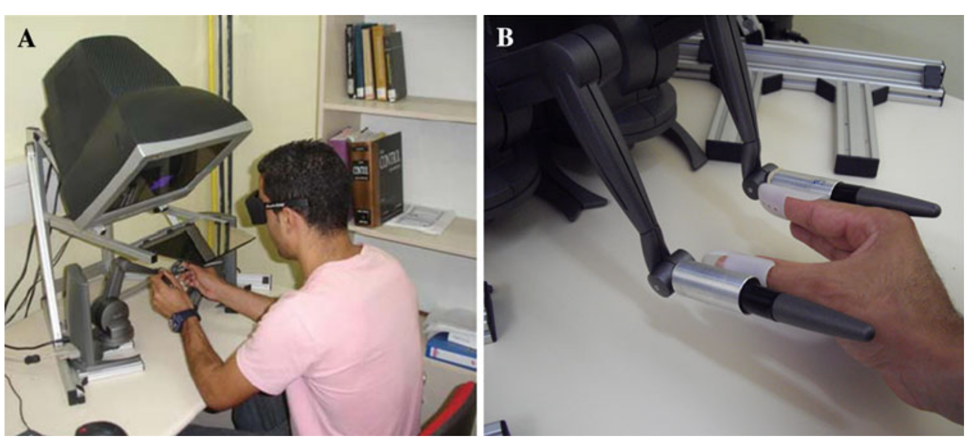

Fig. 1 **a** The dual Reachin/Sensegraphics display system is based on two robotics devices and an augmented reality display that allows subjects to see and feel objects with both hands within a small workspace. **b** Two thimbles each connect the index finger and the thumb to a robotic arm

Experimental procedure

Each subject was asked to grasp and lift, with his/her dominant hand, a virtual object up to a target point, 21 cm above a table. The object was grasped by using two phantoms attached to the index finger and the thumb. The Reachin Display (Fig. 1) with the Sensegraphics software integrates virtually the haptic device with stereo graphics for a 3D-augmented reality experience. A purple box (9 × 12 × 12 cm) represented the object, and a small red circle (1.5-cm radius) indicated the location of the target toward which subjects were instructed to move the object (Fig. 2).

Each subject performed 99 lifting trials; the object weights were selected randomly in each trial and ranged between 100 and 400 g. A series of four trials with increasing weights (100, 200, 300, 400 g), followed by a catch trial (250 g), appeared randomly eight times during the experiment with no overlapping (Fig. 3). It is important to note that the shape of the object did not change during the trials.

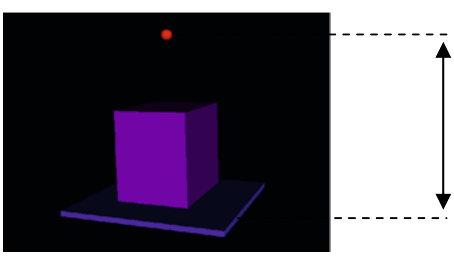

Fig. 2 Augmented reality display that includes target point (*circle*), object (*box*), and table

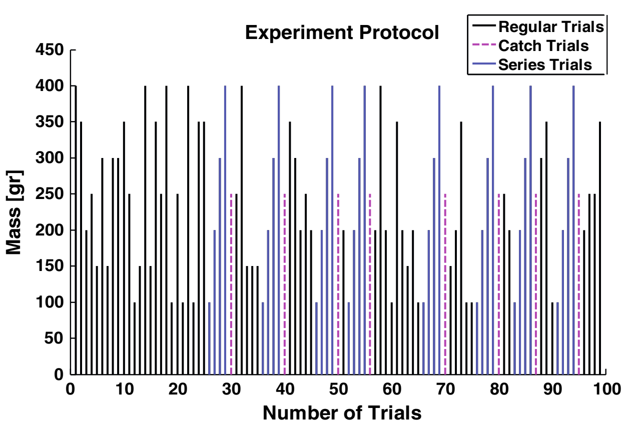

Fig. 3 Experiment protocol comprising 99 trials; the object weights were selected randomly in each trial and ranged between 100 and 400 g (*black lines*). A series of four trials with increasing weights of 100, 200, 300, 400 g (*gray lines*), followed by a catch trial of 250 g (*dashed lines*), appeared randomly eight times during the experiment with no overlapping

To probe the subjects' awareness to the sequences, we asked each subject the following questions in the order given below after she/he had performed all the trials of the experiment.

(1) Did you observe any changes in the object's weight?
(2) Did you observe a random change in the object's weight?
(3) Did you observe any similarity between the trials?
(4) Did you observe a sequence of change in the object's weight?

Data analysis

The GF was calculated as an average of the forces produced by the index finger and the thumb along the horizontal axis, in the direction of the squeeze that prevented the object from slipping. The vertical position of the object in each trial was analyzed to detect the onset time (t_0) of the movement by using an algorithm based on a minimum acceleration criterion with constraints (MACC) (Botzer and Karniel 2009). The MACC suggests that the first phase of the movement is characterized by a constant jerk, i.e., it fits well with a cubic power of time (Karniel and Ben-Itzhak 2008). Here, we assumed that the first part of the vertical movement can be approximated by the following trajectory:

$$x(t) = \begin{cases} x_0 & t \le t_0 \\ x_0 + \frac{1}{6}U_m(t-t_0)^3 & t_0 \le t \le t_1 = t_0 + \Delta T \end{cases}$$

And we used the MACC-based algorithm to fit U_m and t_0 to each trial. We set $\Delta T = 70\ ms$. Then, for each trial, the GF at the onset of the movement was recorded for further statistical analysis, since it represents the prediction about the object and is not contaminated by feedback generated only after the onset of the movement.

Results

Figure 4 demonstrates the grip force (GF) and vertical position in a single lifting trial under a load of 300 g. The dashed line indicates the onset of the movement as detected by the MACC-based algorithm (Botzer and Karniel 2009).

To examine whether predictive feed-forward control is used to predict the succeeding weight that follows a series of increasing weights, we measured the GF at the movement onset for each trial in the series and for each catch trial. Figure 5a,b shows the GF at the movement onset for lifting in one series and one catch trial in a healthy subject. From the Figure, we can see that the GF at the movement onset increases as the weight increases, namely, the subject applies a proper GF under each load condition. The highest

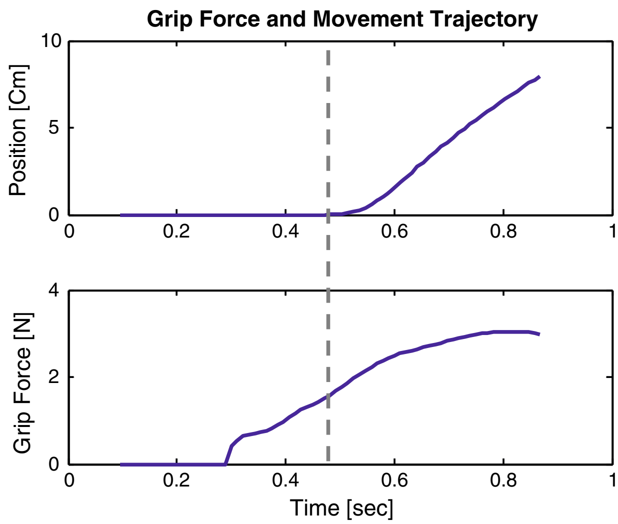

Fig. 4 Single trajectory movement and GF records from one subject lifting a load of 300 g. *Dashed vertical line* indicates the onset time of the movement using the MACC-based algorithm

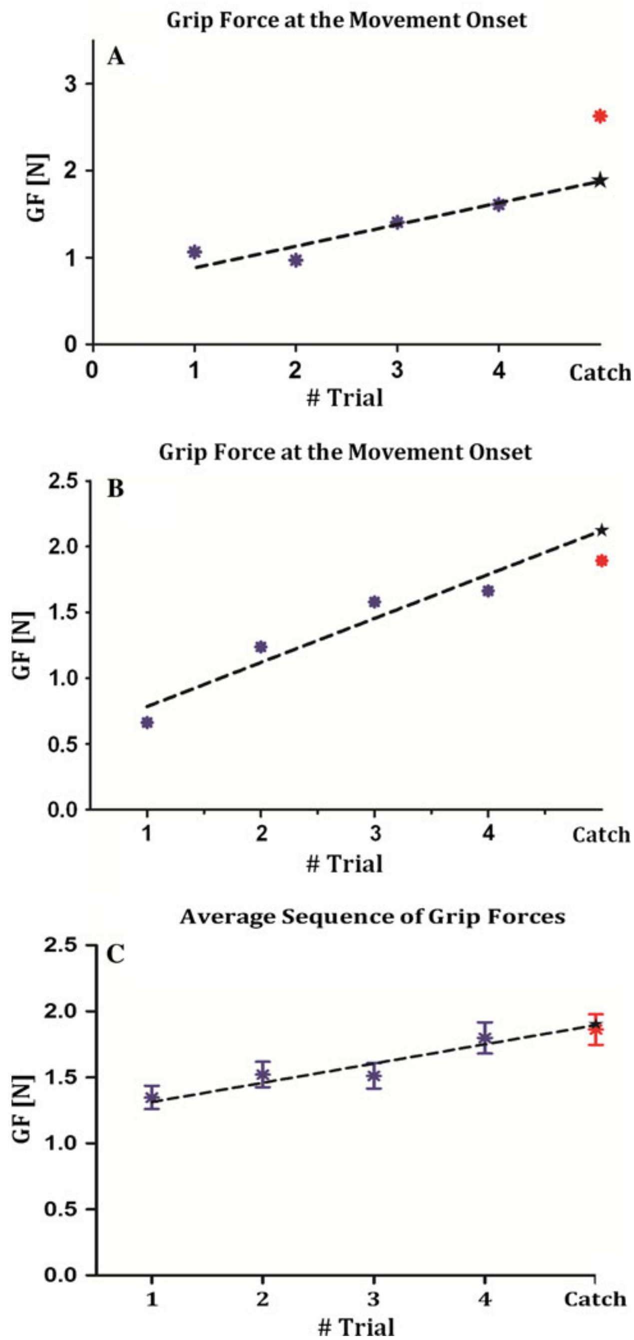

Fig. 5 **a**,**b** GF at the movement onset records from two subjects for one series and one catch trial. *Gray points* represent the GF while lifting a series of increasing weights of 100, 200, 300, 400 g. *Last gray point* represents the GF in the catch trial (250 g). *Black dashed line* indicates the linear regression model that fits the four data points. *Black star* indicates the estimation of the GF according to the regression model. **c** Average sequence of forces across all the series of increasing weights in all subjects (Mean ± SEM)

GF that the subject applied was that in the catch trial; this finding indicates that in this case the subject expected higher weight (recall that in the catch trial, the weight was "unexpectedly" lowered to 250 g; see Fig. 3). Figure 5c shows the average sequence of forces across the entire series of increasing weights in all subjects. From this Figure, we can see that prediction of the next weight is a general phenomenon. All the subjects were not consciously aware of the sequences, and all observed that there was a random changing in the object's mass but no regularity or sequence.

We considered three alternatives for the expected GF in the catch trials and calculated three different errors. The first error (designated 'Next' error) was the difference between the GF in the catch trial and the estimated linear regression model that fits the GF data for the series trials. The second error ('Last' error) was the difference between the GF in the catch trial and the GF in the last trial of the series. The third error ('Average' error) was the difference between the GF in the catch trial and the average of the previous GFs. We then repeated this analysis for any set of three increasing weights in the data and for any set of two increasing weights in the data.

Figure 6 shows that the group analysis clearly demonstrated predictive control after three trials of increasing weights. An analysis of the four increasing weight trials compared with the fifth catch trial revealed a significant difference between errors (ANOVA; $F = 3.87$, $P = 0.0236$). The t-test was used to assess the difference between each pair of errors. The 'Next' error was lower than the 'Average' error ($P < 0.001$); the 'Last' error was lower than the 'Average' error ($P < 0.001$); and the 'Next' error was lower than the 'Last' error ($P < 0.032$).

We can see that even in sequences of three increasing trials the motor system uses predictive control and appear to better predict the subsequent weight than the average weight ($P < 0.01$) and to better predict the subsequent

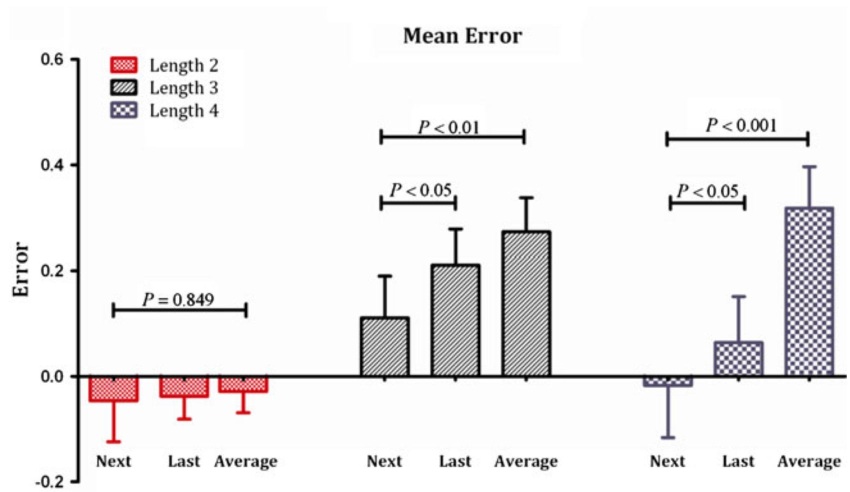

Fig. 6 Mean ± SEM errors during each series of trials across all subjects. *Left bars* represent the errors in series of two trials in a row with increasing weights. *Middle bars* represent the errors in a series of three trials in a row with increasing weights. *Right bars* represent the errors of four trials

weight than the previous weight ($P < 0.05$). In sequences of two trials, the predictive phenomenon did not appear in our data ($P = 0.849$).

To test the sensitivity of the results to the onset detection, we repeated the analysis for a GF that was measured at $t = t_0 - 10$ *ms* instead of at $t = t_0$ and observed similar effects, both qualitatively and statistically.

Discussion

We found that the GF at movement onset fits well with the next weight of an object in a short series of objects with increasing weights. Since the GF at movement onset represents the internal expectation, we conclude that this expectation is based, at least partially, on extrapolation and not solely on the average of past experience.

Several studies have shown that people are able to predict subtle variations in the dynamic state of their arms. Ariff et al. (2002) hid subjects' arms from view and asked them to make reaching movements without visual feedback. They were asked to track the position of their unseen hand with their eyes. Subjects made saccadic movements to a location that was predicted to be the position of the hand 196 *ms* into the future. A brief force pulse was then applied to the hand, thereby altering the state of the arm. After the pulse, saccades were suppressed for 100 *ms*, and then accurate predictive saccades re-emerged. This inhibition period may reflect the time taken to recompute the estimate of hand position. However, after the dynamics of the arm were altered by applying a novel velocity-dependent force field, the subject's subsequent saccades were inaccurate. These findings suggest that subjects rely on an internal estimate of arm dynamics to generate their predictions. Flanagan and Lolley (2001) showed that when sliding an object across a frictionless surface in different directions subjects vary the force they apply normal to the surface in anticipation of the direction-dependent change in initial hand acceleration. This indicates the presence of a predictive model that allows for the effects of anisotropic inertia.

We all know from personal experience and introspection that mental excursions can be made not only to the past, but also into the future. It has even been speculated that the ability to contemplate future scenarios was a driving force in the evolution of episodic memory (Dudai and Carruthers 2005). In contrast to traditional understanding of memory as mechanism to store the past, contemporary studies of human memory suggest that memory is better equipped to handle the future than the past (Dudai and Carruthers 2005; Gilbert and Wilson 2007; Schacter and Addis 2007). To date, this dichotomy between handling the past and the future has been studied only in relation to episodic memory. There are, however, a few clear similarities between motor memory and episodic memory that justify the consideration of this dichotomy for motor memory. For example, two main features of memory, consolidation, and mental practice, have also been studied in the motor control literature (Brashers-Krug et al. 1996; Dudai and Eisenberg 2004; Krakauer and Shadmehr 2006). However, it is possible that procedural memory and episodic memory differ in the way they address the past and the future.

In this article, we distinguish between remembering the past and imagining the future in the context of motor memory where the concept of the forward model is frequently used to describe this phenomenon, namely, using past experience in order to predict the future. The notion of the forward model is being increasingly used in the motor control literature in three different structures: predictor, distal teacher, and state estimator (Karniel 2002). The forward model as a distal teacher is used to train the controller and can also be used without actual execution of the task, e.g., during mental practice (Jordan 1996). Further studies are required to induce mental practice in order to explore the ability of the brain to employ motor memory for recording the past as well as for planning for the future.

We also measured the vertical trajectory and sought to extract the motor command based on the average jerk during the beginning of the movement and on the object weight (load). However, we did not find any significant difference between the motor commands during the sequence and in the catch trials after the sequence. It is indeed possible that the motor command to lift the object is not predictive while the grip force is. However, further study is required to reach such a conclusion and differentiate between the mechanisms responsible for grip and for load force adaptation.

As discussed above, much research has focused on elucidating the constructive nature of episodic memory, and a growing number of recent investigations have recognized the close relationship between remembering the past and imagining the future. However, the possible relationship between constructive memory and past–future issues remains almost entirely unexplored (Schacter and Addis 2007). In the motor control arena, we have the tools to carefully study this relationship by means of computational models of the internal representations structure and learning algorithms and here, we demonstrate that these models indeed need to be corrected and extended to account for the prediction of the next object in a series of objects at least in the mechanism responsible for grip force adjustment in a lifting task.

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