Developing a Novel fMRI-Compatible Motion Tracking System for Haptic Motor Control Experiments

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Abstract: Human neuroimaging can play a key role in addressing open questions in motor neuroscience and embodied cognition by linking human movement experiments and motor psychophysics to the neural foundation of motor control. To this end we designed and built fMOVE, an fMRI-compatible motion tracking system that captures 3DOF goal-directed movements of human subjects within a neuroimaging scanner. fMOVE constitutes an ultra-low-cost technology, based on a zoom lens high-frame rate USB camera and, our adaptation library for camera-based motion tracking and experiment control. Our motion tracking algorithm tracks the position of markers attached to a hand-held object. The system enables to provide the scanned subjects a closed-loop real time visual feedback of their motion and control of complex, goal-oriented movements. The latter are instructed by simple speed-accuracy tasks or goal-oriented object manipulation. The system's tracking precision was tested and found within its operational parameters comparable to the performance levels of a scientific grade electromagnetic motion tracking system. fMOVE thus offers a low-cost methodological platform to re-approach the objectives of motor neuroscience by enabling ecologically more valid motor tasks in neuroimaging studies.

1 INTRODUCTION

On a daily basis, humans acquire new motor skills or enhance their performance on already encountered motor tasks. Occasionally, they may also re-acquire skills, which are difficult to perform or cannot be executed because of injury or disease. The motor learning experience in all these cases involves a number of different processes, which support motor behaviour through interacting and/or hierarchical roles.

At the level of information extraction, skilled performance is based on the efficient gathering of information from the environment. Humans use task dependent attentional mechanisms to actively select (Friston, Daunizeau, and Kiebel, 2009; Friston, 2010) and integrate multisensory stimuli. They uncover the dynamics of a task by learning key properties of their body and the world (Faisal Syladi and Faisal, 2012; Brayanov, Press, and Smith, 2012). Crucially, they determine the necessary motor commands so as to optimize their performance according to task goals, e.g. to minimise variability and noise (Todorov and Jordan, 2002; Todorov, 2004; Faisal and Wolpert 2009; Faisal et al, 2008). This process ranges from high-level decision making that dictates the structure of an effective control policy to low-level optimization of the execution of the selected policy.

Although motor behaviour has been systematically studied for more than 100 years, the mechanisms that underlie motor learning and the formation of control policies remain unclear. A large body of research has examined motor behaviour through motor psychophysical experiments, which provide insight into the patterns of adaptive responses in tasks that introduce changes in the target, the workspace or the force-field (Shadmehr and Moussavi, 2000; Shadmehr and Mussa-Ivaldi, 1994; Wolpert, Diedrichsen, and Flanagan, 2011; Faisal and Wolpert, 2009). Such studies have relied primarily on high-resolution behavioural data and have inspired a number of computational approaches that describe abstract mechanisms of the interplay between perception and action, as well as mechanisms of generalisation of learned activity (e.g. optimal feedback control, reinforcement learning, Bayesian inference).

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A novel strand of research in the field has focused on ecologically more valid tasks shifting away from strict lab protocols and thereby enabling subjects to move freely (within the confines of their task and calibration) in naturalistic settings (e.g. flint stone tool making). Such settings were used in motor studies carried out in parallel with neuroimaging approaches, which investigated the related demands on the brain (e.g. Faisal et al, 2010; Hecht et al., 2014). This work provided insight into human natural movement statistics (Ingram et al 2008, Faisal et al. 2010), as well as into the predictable structure and sequence of movements with immediate implications for Brain-Machine Interface and prosthetic control (Thomik et al, 2013; Haber et al 2014).

Yet despite this substantial progress in the study and understanding of motor control processes and in the predictability of movements, less methodological advancement has been achieved in linking motor psychophysics and computational models of behaviour to their underlying neurophysiological correlates. Brain imaging based on fMRI, one of the predominant technological paradigms to access the neural implementation level, has been primarily used in studies that examine purely cognitive tasks. In the less common cases, in which fMRI has been employed in motor neuroscience research, the examined functions refer to very simple, lab-constrained movements (e.g. finger-tapping) and the designed experiments instruct non-realistic open-loop tasks, which do not provide any sensory feedback of performance so as to encourage learning. The main reason for this restriction lies in the technical constraints, which are interwoven with the fMRI function and which often make its use incompatible to most advanced motion tracking systems.

Here we designed and built an fMRI-compatible motion tracking system that allows us to examine how humans learn complex motor tasks. Our system, fMOVE, constitutes a technology capable of acquiring information about 3D motion inside an fMRI scanner in a three-degrees-of-freedom context. The designed platform can host closed-loop motion studies by establishing continuous motion tracking and providing human subjects with online virtual feedback of their motor behaviour and performance. fMOVE thus provides an expansion of conventional motion tracking methods used in fMRI studies, which are trying to improve the analysis of fMRI data (compensation for head and/or body motion), or to adjust the block design to the actual motion start and pause.

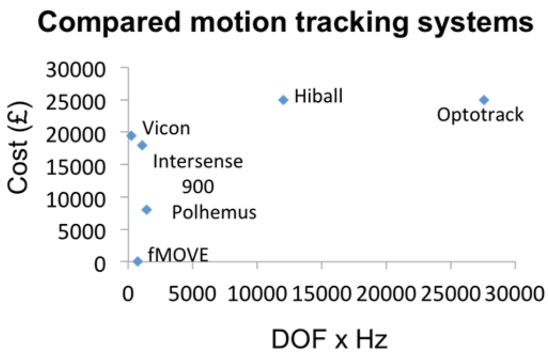

Figure 1: Comparison of fMOVE and commercial motion tracking systems. fMOVE corresponds to the lowest cost level and possesses motion tracking performance within the range covered by established motion trackers (e.g. Polhemus, Vicon). The processing power of the displayed systems is estimated as the product of DOF and sampling frequency (both of which should be maximised, but are often treated as trade-offs in conventional motion tracking systems).

At the same time fMOVE possesses motion tracking performance in the same range as established fMRI-incompatible motion tracking methods (e.g. Vicon with motion tracking at 1DOF and 250Hz, Intersense 900 at 6DOF and 180Hz, Polhemus Liberty at 6DOF and 240Hz) and is significantly cheaper than other fMRI-incompatible technologies with better information processing features (e.g. Hiball with motion tracking at 6DOF and 2000Hz, Optotrack at 6DOF and 4600Hz, see Fig. 1). The development of our software that supports this platform makes use of ARToolkit, a software library for building Augmented Reality applications. The motion tracking setup was developed inside a simulated fMRI environment to match the deployment in the Clinical Imaging Facility at Hammersmith Hospital, London.

2 MATERIALS AND METHODS

2.1 Hardware Development

Our system consists of the motion tracking installation inside the fMRI environment and the software that runs the experiment by adapting its phases and provided feedback to the subject's captured performance. In particular, subjects lay inside the fMRI-scanner holding the fMOVE object in their dominant hand. The fMOVE adjusted camera is installed at the distal end of the scanner room with its telezoom lens facing the foot-end view of the scanner cylinder with the hand-held object clearly visible (Fig. 2B). Camera images are processed in real-time by a laptop-based system which controls the experiment and can present real-time feedback to the patient via the scanner's visual display setup. We used a PlayStation 3 Eye camera (SONY, Tokyo) to track the motion of markers attached to a hand-held object. This camera is able to work with frame rates of 120Hz at a 320 x 240 pixel resolution and can also work with frame rates of 60 Hz at 640 x 480 if more resolution is needed. In addition, this device can be set for close up framing at 56º field of view or 75º for long shot framing. All these features provide the camera a satisfying image acquisition quality for the needs of our motion tracking setup. Its single component price of 23£ (at time of printing) constitutes the sole cost of fMOVE and therefore establishes the latter as the cheapest 3DOF motion tracking technology amongst a number of commercially available systems (Fig. 1).

fMOVE's motion tracking accuracy was tested for 3 different camera lenses in order to examine whether the markers are captured successfully both for smaller and larger distances to the camera. We selected the variable lens focal lengths taking into account three different distances to the camera (0.5m, 1m, 2.5m) based on:

$$f = \frac{w_{CMOS} \cdot D}{FOV} \tag{1}$$

where f denotes the focal length, w_{CMOS} the width of the CMOS sensor (3.98mm), FOV the Field Of View (400mm), D the distance between the camera and the tracked marker. The focal lengths for the different distances were estimated as 6.35mm, 12mm and 35mm.

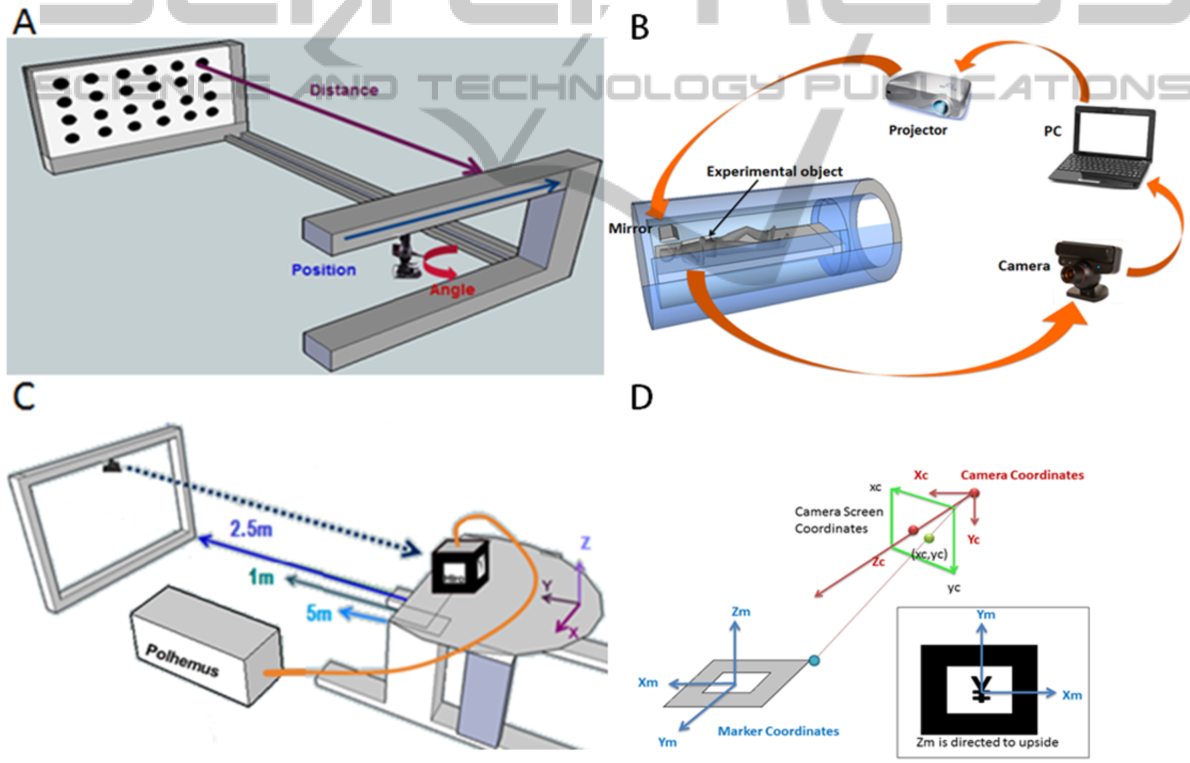

Figure 2: (A) Setup for the one-time calibration for any camera system to be used with fMOVE system. Rigid aluminium frames allow mounting of camera and target calibration pattern at defined position and orientation. (B) fMOVE system in use: healthy subject lying inside the fMRI-scanner holding the fMOVE object in the dominant hand. Camera installed at the distal end of the scanner room with its telezoom lens facing the foot-end view of the scanner cylinder with the hand-held object clearly visible. Camera images are processed in real-time by laptop-based system which controls the experiment and can present real-time feedback to the patient via the scanner's visual display setup. (C) Set-up to measure the motion tracking performance of the fMOVE system against a commercial electromagnetic (i.e. non-optical) motion tracking system used as reference gold-standard (LIBERTY polhemus). A reference fMOVE object (black cube) which contains the magnetic motion-tracking sensor is moved at defined distances and orientations (see text for details). (D) The coordinate systems used by fMOVE include the camera coordinates (X_C, Y_C, Z_C in red), the coordinate system of the camera view (x_C, y_C in green) and the relative coordinates of the fMOVE object surface(s) (X_m, Y_m, Z_m in blue).

2.2 Calibration

The camera was calibrated in a setup, which consists of two reference planes; one marker based and one camera based (Fig. 2A). The marker plane remained fixed throughout the calibration whereas the camera plane could be rotated around a reference point and translated away from or closer to the marker plane. The camera was positioned at a fixed height on the camera plane and at variable distances to the camera plane's rotation axis. Altogether in each calibration we tested three different camera positions with regard to the camera plane rotation axis (11.5cm, 18.5cm, and 25.5cm), three different camera plane rotation angles (29º, -17º, 19º or/and 65º) and three different camera plane distances to the marker plane (either 33cm, 49.5cm, 41cm or 56.5cm, 45cm, 37cm).

2.3 Coordinate systems

fMOVE takes three coordinate systems into account: a camera screen based (2D), a camera based (3D) and a marker based (3D) (Fig. 2D). The marker coordinate system uses as reference the centre of the marker, having X_m and Y_m parallel to the borders of the marker, and Z_m pointing away from the marker.

The marker centre is defined as $(X_m, Y_m, Z_m) = (0,0,0)$. The relationship between the camera and marker coordinate system is determined through rotational and translational operations. In particular, we used the following transformation, which reflects a rotation followed by a translation:

$$\begin{pmatrix} X_c \\ Y_C \\ Z_C \\ 1 \end{pmatrix} = \begin{pmatrix} R_{11} & R_{12} & R_{13} & T_1 \\ R_{21} & R_{22} & R_{23} & T_2 \\ R_{31} & R_{31} & R_{31} & T_3 \\ 0 & 0 & 0 & 1 \end{pmatrix} \cdot \begin{pmatrix} 0 \\ 0 \\ -V/2 \\ 1 \end{pmatrix} \qquad (2)$$

where R_{ij} and T_i determine the values of the rotation and translation matrices respectively (Kato & Billinghurst, 1999) and V denotes an edge of the cubic component of the object; it has a negative sign due to the orientation of the axes in the camera based coordinate system.

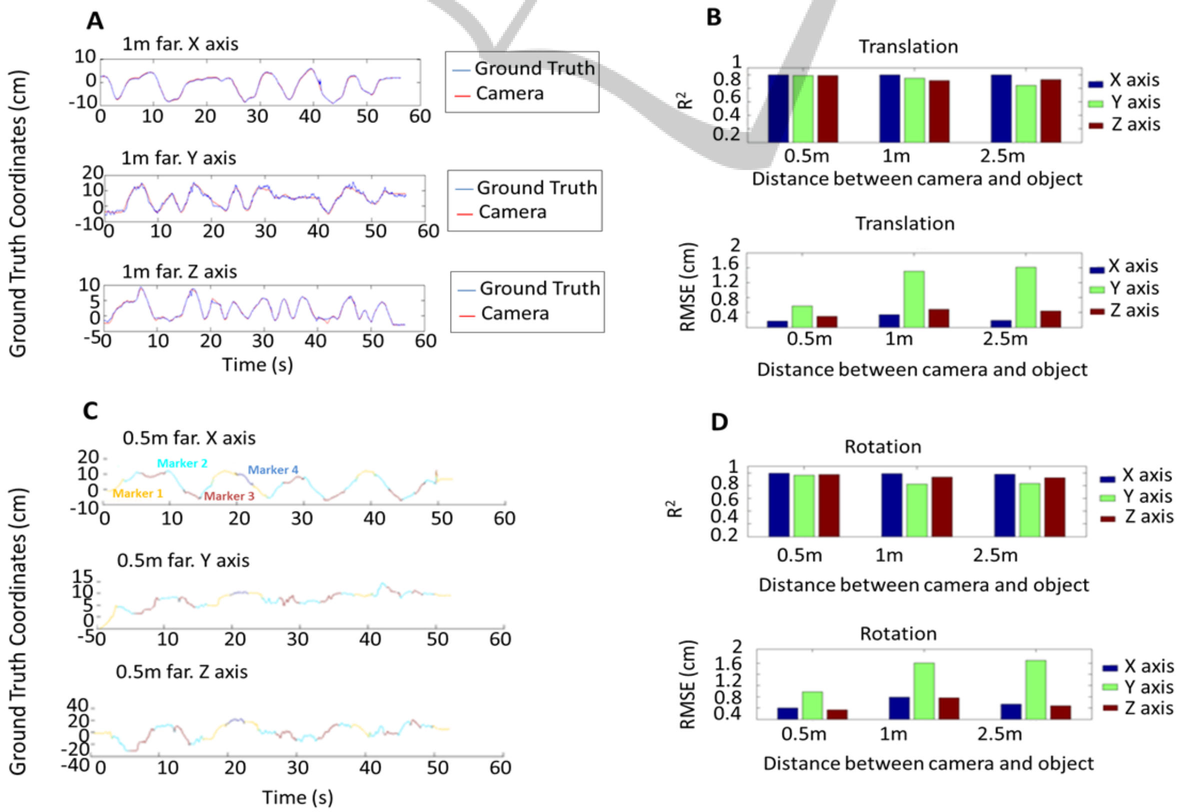

Figure 3: (A) Spatial and temporal alignment of fMOVE and Polhemus data during translational movements in the X, Y and Z axis. (B) fMOVE and ground truth comparison based on R^2 and Root Mean Squared Error (RMSE) for translational movements in the X, Y and Z axis. (C) Spatial and temporal alignment of fMOVE and Polhemus data during rotational movements in the X, Y and Z axis. (D) fMOVE and ground truth (Polhemus, Liberty) comparison based on R^2 and RMSE for rotational movements in the X, Y and Z axis.

2.4 Testing the Tracking Accuracy

In order to assess the tracking accuracy of fMOVE, the system was compared with Polhemus Liberty, a commercial electromagnetic motion tracker (Fig. 2C). One Polhemus sensor was positioned exactly in the centre of an exemplary multi-marker object. The designed object was free of metal so as to suit usage inside the fMRI scanner. It consisted of a wooden handle and a plastic cube at the surfaces of which we attached four different ARToolkit compatible markers. These markers can be identified by the image-processing algorithm of our system and assigned to a different label according to the pattern they display. Labelling the different patterns enabled the identification of rotational movements.

In this setup, the object's 3D position could be tracked simultaneously by the calibrated camera of fMOVE and the electromagnetic sensor. The two streams of motion data were subsequently compared after their respective reference coordinate systems were aligned. The estimated error between them was used as a performance measure for fMOVE's motion tracking accuracy in translational and rotational movements of the object.

Translational movements were constrained between the borders of a specified workspace. During translation, the camera was always tracking the same face and consequently the same marker on the object. On the other hand, during rotational movements within the same workspace borders, the system's motion tracking switched between the different markers positioned on the object surfaces.

3 RESULTS

We assessed the tracking accuracy of fMOVE by testing its position measurements against a widely used electromagnetic motion tracker (Polhemus Liberty). The comparison was performed for three different distances between camera and object plane (0.5m, 1m and 2.5m). For each of these three cases we tested 15 trials of pre-specified motor tasks. In 10 of these the object was translated and in the remaining 5 it was rotated.

After temporally and spatially aligning the position measurements of the marker-based fMOVE and the sensor-based Polhemus Liberty, we noticed that our motion tracking system acquires data streams that accurately match our ground truth. This matching is evident in the overlaid position plots for both translational and rotational trials (Fig. 3A,C). In fact, during rotational movements fMOVE manages to efficiently avoid tracking omissions, by switching from one marker to another (as is evident in the color-coding of Fig. 3).

Two measures of comparison of the acquired data streams (R^2 and RMSE) verify the efficiency of fMOVE in motion tracking (Fig. 3B,D). In translational movements R^2 reflects over 84% accuracy for all tested distances between camera and tracked object. The lowest R^2 level ($R^2 = 0.846$) is estimated for the largest distance (2.5 m) in the y-dimension. The same case produces the highest RMSE (RMSE = 1.6181 cm). Throughout all cases, the y-dimension produces the highest error levels, which reflects the fact that fMOVE is mostly sensitive along the axis that connects the camera centre with the marker centre. Even these instances however, do not significantly affect the R^2 levels as displayed in Fig. 3B.

Similarly, in rotational movements our assessment verifies a matching between the measurements of our system and the ground truth. The lowest R^2 level ($R^2 = 0.8214$) is estimated again for the largest distance (2.5 m) in the y-dimension (Fig. 3C) for which the corresponding RMSE = 1.6181cm (Fig. 3D). As in the translational movements, the largest tracking errors here are noted again in the y-dimension. It is thus evident that fMOVE displays its highest sensitivity in the y-direction for a broader range of movements.

4 DISCUSSION

Based on our experience in designing extremely affordable Neurotechnology for eye-tracking (Abbott and Faisal, 2012, Abbott et al, 2013), wearable motion tracking and muscle signal systems (Gavriel et al. 2013, Fara et al. 2013), we now designed and built fMOVE, a first low-cost fMRI-compatible marker-based motion tracking system capable of capturing 3 DOF movement. The system acquires behavioral data from subjects, while they manipulate a marked object inside an fMRI scanner and it provides to them online visual feedback of motion and task performance.

We tested the efficiency of the system against Polhemus Liberty, a commercial electromagnetic motion tracker, which operates with high accuracy at 240 updates per second. We found that fMOVE achieves high tracking accuracy for both translational and rotational movements of the markers and preserves this accuracy for variable distances of the camera to the moving object.

fMOVE poses technical advantages since it allows high frequency data acquisition inside the fMRI environment which is commonly incompatible to all widely used motion tracking technologies, due to the applied magnetic field. Our system is amenable to further customization depending on the needs of the experimental study, designed to be carried out inside the scanner. Such customization can include developing a multiple-marker tracking algorithm, so as to increase the motion tracking accuracy, avoid false marker detections and cover the motion of multiple body parts or more complex behavioural tasks.

Importantly, apart from its compatibility to the fMRI environment, fMOVE constitutes an ultra-low-cost motion tracking technology, that limits expenses to the price of the used camera. At the same time, the methodological platform it supports, offers promising advantages for future studies of motor behaviour (Wolpert, et.al., 2011, Wolpert and Flanagan, 2010). It namely enables a tight integration of psychophysical and functional imaging studies and can thereby guide investigations of the still unknown neural foundation of cortical action selection and motor learning rules.

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