Neural Signal Processing and Motion Capture as a Feedback Mechanism to Improve Interceptive Human Movement

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***Abstract*—In this paper, we present a framework to explore the role of motion capture and neural information processing in a coordinated execution of movements in the sporting context. We discuss the perception-cognition-action coupling from a motor function consideration. For this, we present a generic experimental design for brain source connectivity estimation. We show the visualisation of the brain connectivity using a sample Electroencephalography (EEG) data-set. We propose to extrapolate the application of similar design to study sporting movements such as cricket batting. We present the case for the use of portable and mobile EEG sensors to study such a low latency decision-making task. Finally, we describe a preliminary framework on how to use and validate the efficacy of neurofeedback in coaching skilled human movement. Taking a multi-modal approach, we included motion capture data to study the skilled movement. From this, we present the wrist movement variation in a shadow batting task by a novice batsman.**

***Keywords*—*Interceptive*; *Movement*; *Neural*; *Neurofeedback*; *Motion-capture*.**

I. INTRODUCTION

Humans could perform complex movements, e.g., in sports, dance, and other skilled activities. Although the actions manifest in physical dynamics, specific internal mental models precede most of these movements. The human brain together with the peripheral Central Nervous Systems (CNS) dictates the quality of motion. The quality, in turn, depends on training and feedback, especially in the case of skilful execution of movement patterns, e.g., in a sporting context.

Brain-Computer Interfaces (BCI) are systems where the signals from the brain are used to control a computation platform directly. This paper presents the theoretical background and validation of the computational model that explores the role of neural circuitry in interceptive action execution as a BCI feedback system. We also present a video analytics method for studying the pattern of movement involved in a defensive cricket shot - the so-called forward defence.

Fundamental models of skilled actions in the human movements are well known [1]. To get a full picture of skilled movement execution and the sensory dynamics of the human agent, both internal and external influences should be considered. The internal models refer to the neural processes that govern the CNS in preparation and execution of the concerned movement patterns, while the external processes are the physical manifestation by the subject performing the same movement tasks.

In cricket, a batsman has to move the bat to the right place at the right time to intercept a fast moving ball; the mental models influence the outcome. Indeed, motor control follows an internal forward model [2]. In the case of such an interceptive movement, the batsman, the bat, and a travelling ball form a closed loop feedback-feedforward system. Feedback from internal and external agents helps the subject to evaluate the past performance, while the internal feedforward models help anticipate the unknown variables before task execution.

Feedback plays a critical role in human motor activities [3]. For example, an improper feedback would induce inefficiencies in the movement mechanisms, and that would cause the motor activity to suffer. Self-adjusting instructions in an automatic system are equivalent to influencing the part of the brain that generates a particular motor behaviour. Hence, finding the source localisation as described in existing literature, could help the training process to achieve the desired mental state [4] [5]. This research takes a multimodal approach. The sub-sections below provide a brief introduction on various modalities.

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A. *The Neurofeedback Approach*

Neurofeedback refers to the method of identifying the brain regions that get triggered during a functional task execution and then to use the information to provide feedback to the subject via visual or auditory cues. For this, different sensor data are collected, e.g., Electroencephalography (EEG), Magnetoencephalography (MEG), and functional Magnetic Resonance Imaging (fMRI), etc. In the real world sporting context, a portable EEG device is ideal. We present connectivity analysis on a sample dataset. EEG allows to carry out high temporal resolution studies, which implies that we can see what happens in the brain when the subject performs a task in near real-time.

B. *The Motion Capture Approach*

The spatial and temporal components of the movement (position, velocity, and acceleration) carry biomechanics signature of action and can be used to compare the quality of movement variation in a single subject or across subjects [6]. Active marker systems, such as the Optotrak [7], allow to place markers on the subject and to observe individual parts of the movement. We present a preliminary movement analysis from Optotrak Motion Capture System (MOCAP).

C. *Background on Motion Capture and Brainwave Data Analysis*

The motion capturing system, as used in the experiment presented in this paper, uses markers on different body parts and allows to find granular variations in different body regions undergoing movement. Similarly, brainwave sensors allow capturing functional correlates of different wave- bands generated during a task execution. The firing of neural circuits gives rise to electrical activities in the brain. The sensors (EEG) placed on the scalp can detect and measure the electric component of the electromagnetic waves from the electrical dipoles in these circuits. Similarly, MEG measures the magnetic component in the signals. To use a neurofeedback paradigm in training movement, in is necessary to find the location of the sources related to a particular functional activity. Source localisation from the detected signals forms the Inverse problem. These brainwave signals fall into different groups based on their frequency ranges that correspond to different functional mental states. Typical frequency ranges dominant in EEG are **alpha**, **beta**, **delta**, and **theta**. Fig. 1 shows different groups and their associated functional correlates.

The organisation of the rest of the paper is as follows. In Section II we present the methodologies followed in collecting the sample data [11]. In Section III we describe the connectivity metrics followed by the experimental design of the Motion Capture system in Section IV. Section V concludes with a summary of the benefits, advantages and limitations of our approach and describes the future direction for this work.

II. EXPERIMENTAL DESIGN METHOD: NEUROIMAGING

We present the experimental design for neuroimaging example dataset below.

A. *Connectivity Analysis Protocol in EEG and MEG*

The brain source localisation could be used to visually display the neural network connectivity for functional task performance [8]. The brain network connectivity analysis using EEG and MEG for a high temporal resolution extend the neurofeedback modality. Combining EEG and MEG will make it possible to distinguish the mechanisms that are the event-related from that evoked potential. Thus allowing precise identification of the brain areas during a successful and failed execution of the batting task described in Section IV.. Hence, the connectivity patterns during the successful performance of a cricket shot could be used to provide feedback in future performance. It is possible to gamify the feedback-feedforward loop by designing a rewarding and penalising the subject in a scoring scale. The gamification part will be explored further in future work. The neuroimaging is then to be combined with MOCAP data analysis to provide feedback on, e.g., ideal hand and wrist movement in a defensive cricket batting stroke.

B. *The Sample Dataset*

The MGH/HMS/MIT Athinoula A. Martinos Center for Biomedical Imaging at Massachusetts General Hospital (MGH), Harvard Medical School (HST), and Massachusetts Institute of Technology(MIT) acquired and made available the example dataset captured with the Neuromag Vectorview system. EEG data from a 60-channel electrode cap was obtained simultaneously with the MEG. The raw data refers to the continuous time series, the Epochs imply the collection of time-locked trials and averaged data over trials, e.g., storing Left Auditory, and Right Visual in a single file is the averaged data known as Evoked. Details of the data collection protocol are available in the literature. The methodology follows one subject's brainwave recording associated with triggered finger movement [4]. An occasional appearance of a smiley face was the stimulus at the centre of the subject's visual field. The instruction to the subject was to press a key with the right index finger as soon as possible after the face appeared. Tab.-I lists the trigger codes [9].

TABLE I
TRIGGER CODES FOR THE SAMPLE DATA SET.

Name	Code	#Contents
LA	1	Response to left-ear auditory stimulus
RA	2	Response to right-ear auditory stimulus
LV	3	Response to left visual field stimulus
RV	4	Response to right visual field stimulus
Smiley	5	Response to the smiley face
Button	32	Response triggered by the button press

C. *Brainwave Data Analysis Protocol*

Cortical surface-based functional brain imaging involves segmentation and surface reconstruction [10]. To cortical constraint, the EEG/MEG source, the data analysis protocol uses the MRI of the subject. The computational algorithm covers the following stages and analysis [9] [11]:

- Preprocessing and denoising

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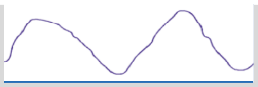
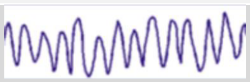
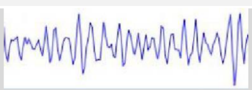
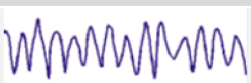
Power Spectral Density	Band	Frequency (Hz)	Correlates
	Delta	< 3	sleep
	Theta	3 – 7	memory creation
	Alpha	8 – 13	relaxation, closed eyes, intrinsic focus, reflection
	Beta	13 – 30	intense concentration, cognition
	Gamma	30 +	multi-sensory, euphoria, high focus
	Mu	8 – 12 (over sensorimotor)	suppression has been linked with empathy

Fig. 1. Comparison of EEG frequency bands and corresponding mental state activation. Please see Section C. for more details

- Source estimation
- Visualisation of sensor- and source-space data
- Time-frequency analysis
- Statistical testing
- Estimation of functional connectivity
- Applying machine learning algorithms

We validate the example relevant to the functional connectivity analysis after performing the preprocessing steps.

D. *Preprocessing*

Preprocessing eliminates the defective EEG channels to make sure that errors due to incorrect data do not propagate further in the pipeline. Signal Space Projection (SSP) and Independent Component Analysis (ICA) routines suppress the artefacts [12]. Fig. 2 shows the result of the covariance matrix estimates.

III. CONNECTIVITY METRICS

Dynamic statistical parametric mapping (dSPM) [13] and MNE [14], sLORETA estimates source activation from MEG and EEG data. To study the brain region connectivity, both model-based and data-driven approaches are applicable, respectively in the time and frequency domains. Connectivity analysis provides a way to perform multivariate analysis of brain region in response to different stimuli such as auditory and visual. Another area to study is the connectivity within the brain and brain-CNS regions. The example of connectivity between a seed-gradiometer close to the visual cortex and all other gradiometers as shown in Fig. 3 uses the metric Squared Weighted Phase Lag Index [15].

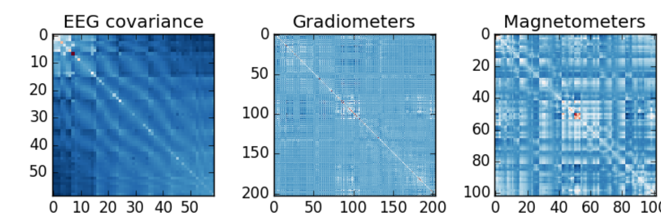


Fig. 2. Covariance matrix estimation on the raw data with Signal Space Projection

Fig. 4 shows the connectivity computed between 4 labels across the spectrum between 5 and 40 Hz.

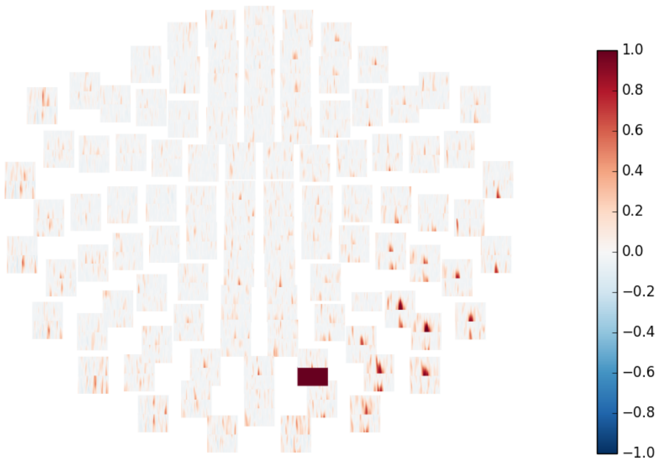


Fig. 3. Connectivity map of a seed gradiometer using Squared Weighted Phase Lag Index

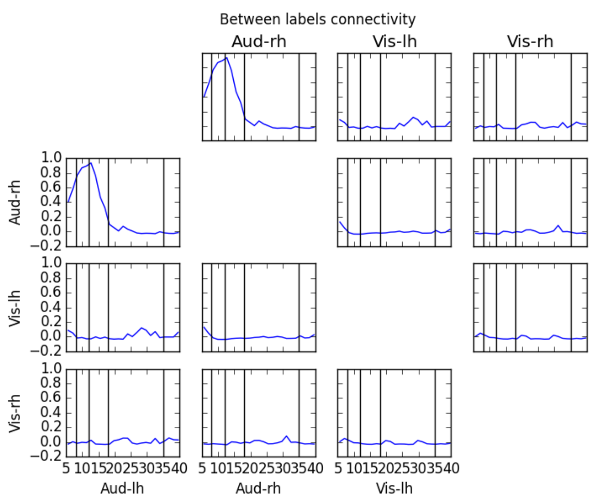


Fig. 4. Inverse Connectivity Spectrum

A. *EEG BCI Motor Imagery And Real Time Feedback*

In this section, we discuss some preliminary results from a motor imagery data available at PhysioNet [16]. The data collection is as per the experimental protocol described in [17].

The motor imagery could be decoded from this type of dataset by separating the signal into additive components, which have maximum differences in variance between the windows of the multivariate signal. This method is known as the Common Spatial Pattern (CSP). Work is underway on this dataset to improve the classification accuracy and to use the method in real-time data analysis similar to the imagery protocol described above.

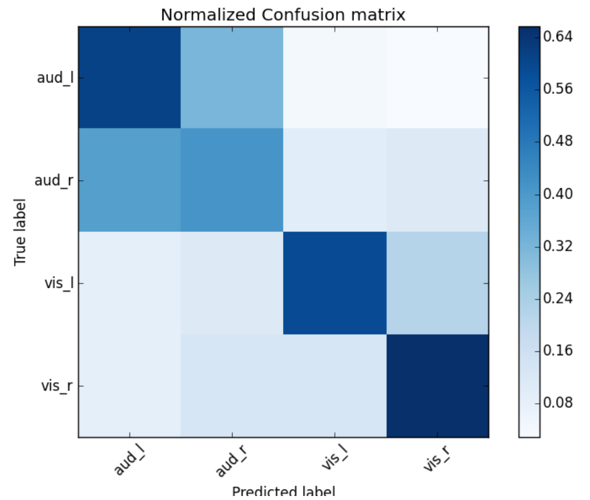


Fig. 5. Labels for rescaled channels for left and right motor imagery stimulus

Event Related Potential (ERP) is decoded with xDAWN is as shown in Fig. 5 [18], [19]. For each event type, a set of spatial xDAWN filters is trained and applied on the signal. Channels are concatenated and rescaled to create feature vectors. They are fed into a Logistic Regression. The real-time feedback mechanism with a client–server setup could be used for feedback. The server is started so that future stimuli for the classification task are presented via the client. This is predicted less accurately, and an on-demand adaptation of the stimuli is issued to improve the performance of the classifier to compute various statistics in real-time. Currently, we are exploring the simulated data with a plan to extend the pipeline to include real experiments in future.

IV. EXPERIMENTAL DESIGN: MOCAP

We present the experimental design for MOCAP dataset below.

A. *Method*

The aim of the study is to perform an initial test for verification of the experiment design using the passive motion capture system with an inter-reliability test.

B. *Participant*

A novice (with no experience in cricket), a right-handed male student in the Department of Animation and Game Design in Shu-Te University volunteered. We followed the health and safety briefing, risk assessment, and obtained informed consent as per Bath Spa University and Shu-Te University standard protocols. The participant's age is 24 years old, using his preferred right hand to perform the task.

C. *Apparatus*

We conducted the experiment in the motion capture laboratory in Hengshan Innovation Base in Shu-Te University, Taiwan. We initially assessed four participants in a single batch, thanks to the maximum capability of the laboratory. But for the result presented here, we included data from only one participant. The rest of the data will be used for a comparative analysis of the movement patterns among participants in future work. OptoTrak Inc. provided the passive motion capture system shown in Fig. 6 and Fig. 7.

Fig. 6. On body marker on subjects. Only one subject's data is presented here.

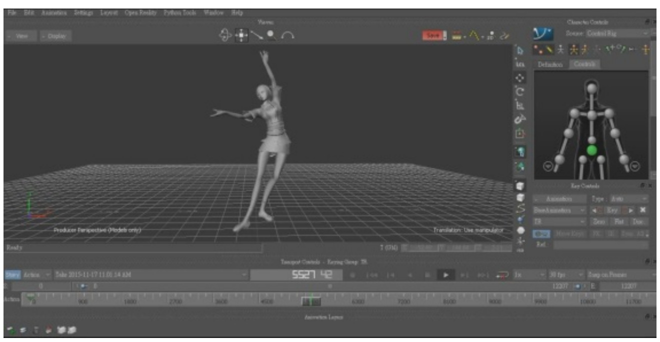


Fig. 7. Screenshot of the MOCAP software renderer.

The system has 20 pieces of high-speed IR camera (Product ID: Prime 17W), each of the cameras has 70 degree of Field of view (FOV) wide angle, offering true, edge to edge coverage across the camera's image sensor. It has advantages of perfectly matching the imager's resolution, 20 pcs of motion capture IR camera, with an amazing 70^o FOV, 1.7 MP of resolution and a 360 FPS capture rate. Furthermore, the following equipment and tools were employed:

- A $60''$ LCD monitor was provided to play the video showing the movement of the swing movement.
- The data analysis was performed using MATLAB and SPSS version 13.

D. *Procedure*

The objective measurement involves a laboratory-based movement experiment with three repetitions. We captured the movements on 120 frames-per-second (FPS). During the trial, the participant was instructed to perform a cricket bat swing motion based on the video playing in front of him. We performed a five-minute warm-up test before the experiment. It ensures the inherent reliability of the study.

E. *Limitations*

One potential limiting assumption was that the bias might be minuscule and could be normalised. Hence, we ignored any biases because the number of samples collected is large. Thus significantly reducing the bias on frames captured from the system.

F. *Data Analysis*

The motion data collected at the 120 (FPS) resulted in a total of $N = 1,588$ frames, implying a successful recording of approximately $1MB$ of data. Thus, provided enough data for doing an analysis by quantitative method. The variance of velocity is as shown in Fig. 8. The analysis of variance indicated that the mean movement time was no significant difference among three repetitive movements, $p < 0.05$. Thus, the experiment design was consistent.

G. *MOCAP Results*

In the case of cricket batting, for right-handed batsmen, the left hand is the leading side and vice versa for the left-handed batsman. The leading hand is the most important in controlling the bat movement. Hence, we focused on the data from the three markers located at the left-hand wrist on top, bottom and side-on positions. We calculated the position vectors from the Cartesian coordinate values at each instant during the movement as provided by the MOCAP and generated Acceleration Profile for the left-hand wrist as shown in Fig. 8.

One subject was undergoing multiple trials to produce data so that random statistical significance could be detected. In the next phase, the subject will be identifying the ball movement direction as a stimulus presented on a screen. A second task will be to predict the spin and swing direction of the ball concurrently capturing the MOCAP and EEG data.

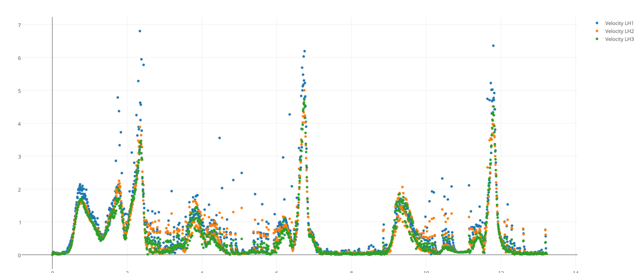


Fig. 8. Variation of velocity with time of the wrist of the leading left hand of a right handed subject performing the shadow forward defence shot

V. CONCLUSIONS, PERSPECTIVES, AND THE FUTURE DIRECTION

In athletic performances, perception and action need to be in a synchronised state. If an athlete is great at perceiving

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and processing a mental model on the sport specific task but unable to perform the required action successfully, that will be of no use in successful execution of the task.

The hypothesis that the action influences perception is one of the ideas we aim to establish a multimodal methodology encompassing neurofeedback and motion capture feedback on task execution.In a case of cricket batting, this implies that a successful hitting of the target at practice could lead to the perception of increased size, and slower movement of the ball against failed execution of interceptive action would result in a perception of smaller size and faster motion of the ball. This research extends the signal processing part from the previous work [4], [8], and also looks at the experimental movement data that could be correlated to neuroimaging data in future as a gamified neurofeedback or as a neurogaming application for training athletes. To attain the level of sophistication to be used in real world situations, we need to improve and develop existing data analytics methods and combine with other movement related modalities to build a practical training framework. We establish the feasibility of connectivity measures in MEG-EEG monitoring and suggest ways measure motor performance from a combination of cognitive states and motion capture in an interceptive movement. To combine these modalities for training interceptive action is the goal and future direction of this research.

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