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Interactive Rehabilitation and Dynamical Analysis of Scalp EEG

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Abstract— **Electroencephalography (EEG) has been used for decades to measure the brain's electrical activity. Planning and performing a complex movement (e.g., reaching and grasping) requires the coordination of muscles by electrical activity that can be recorded with scalp EEG from relevant regions of the cortex. Prior studies, utilizing motion capture and kinematic measures, have shown that an augmented reality feedback system for rehabilitation of stroke patients can help patients develop new motor plans and perform reaching tasks more accurately. Historically, traditional signal analysis techniques have been utilized to quantify changes in EEG when subjects perform common, simple movements. These techniques have included measures of event-related potentials in the time and frequency domains (e.g., energy and coherence measures). In this study, a more advanced, nonlinear, analysis technique, mutual information (MI), is applied to the EEG to capture the dynamics of functional connections between brain sites. In particular, the cortical activity that results from the planning and execution of novel reach trajectories by normal subjects in an augmented reality system was quantified by using statistically significant MI interactions between brain sites over time. The results show that, during the preparation for as well as the execution of a reach, the functional connectivity of the brain changes in a consistent manner over time, in terms of both the number and strength of cortical connections. A similar analysis of EEG from stroke patients may provide new insights into the functional deficiencies developed in the brain after stroke, and contribute to evaluation, and possibly the design, of novel therapeutic schemes within the framework of rehabilitation and BMI (brain machine interface).**

I. INTRODUCTION

A. Background

The EEG signal, due to its high temporal resolution, is the most commonly used signal to analyze brain function. The complexity of the EEG is paralleled with the complexity of the brain's operation [1]. Arguably, processing of EEG in terms of time-locked activities has not advanced greatly over the past decades. Event-related potential (ERP) analysis in the frequency domain [2]–[4] typically looks at two parameters: event-related synchronization (ERS) and event-related desynchronization (ERD). Based upon these measures, prior studies have been able to identify cortical locations that play a role in the planning and execution of certain movements [5]. ERPs have been used to create cortical current density maps corresponding to movement planning and execution [6], as well as to quantify learning of a novel movement [7]. In addition, surface EEG coherence analysis [8]–[10] has been used to investigate the cortical connections that are present during the planning and execution of simple motor tasks which are either absent or spatially shifted in stroke patients [11].

It is believed that these techniques fail to capture all of the complexity of the EEG signal and, by extrapolation, the underlying cortical activity. The EEG is characterized by limit cycles, bursting behavior, jump phenomena, amplitude dependent behavior, and frequency harmonics. Because of these nonlinear, and possibly chaotic characteristics of the EEG signal, nonlinear dynamic analysis of the EEG may be employed to capture additional and/or essential characteristics of the signal [12].

B. Mixed Reality Rehabilitation

This study was conducted with Arizona State University's School of Arts, Media and Engineering mixed reality rehabilitation (MRRehab) system and School of Biological and Health Systems Engineering EEG recording systems. The MRRehab system provides continuous, real-time auditory and visual feedback using state-of-the-art motion capture analysis of the subject's reach, with feedback coding for numerous parameters including reach trajectory, hand velocity, and wrist rotation. The EEG system is capable of sampling at 2 kHz per channel up to 64 EEG channels.

II. METHODS

A. Experimental Setup

This study involved 19 non-impaired right-handed subjects (see Table I) performing a reaching and grasping task with their right arm to three targets. Each subject participated in one session segmented into four blocks. Each block consisted of 30 reaches, resulting to a total of 120 reaches per subject. At the beginning of the session, the subject had EEG electrodes applied to the head (scalp) and IR reflective markers to the right arm. Next, the subject was placed in the

TABLE I
PARTICIPANT DEMOGRAPHICS

# Subjects		Age Range	Mean Age
Male	Female		
10	9	19–58 years	24.1 years

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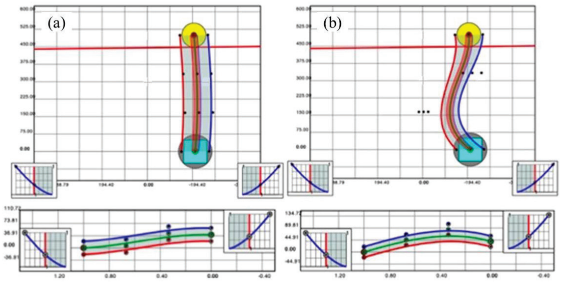

Fig. 1. Visual of normal and altered reach hulls. (a) Normal reach trajectory and supination hulls. (b) Altered reach trajectory and supination hulls.

MRRehab system and allowed to investigate the space freely. By moving the arm in various ways, the subject became accustomed to the audio and visual feedback the MRRehab system provided. Following the free exploration of the space, each subject was guided through feedback examples and a single test trial was run to confirm understanding. Once the subject gained an understanding of the system, Block 1 began.

In Block 1 the subjects reached to and grasped a cone placed at three different locations. These reaches were designed to be conducted using a normal trajectory (see Fig. 1 (a)). Following the completion of the 30 reaches (10 reaches per cone in a random order), the subjects were allowed a voluntary rest period. Block 2 began following the rest period and the reaches greatly differed from those in Block 1. The subjects were forced to learn to complete a reach with a novel, highly perturbed trajectory and wrist rotation having the cones placed at the same positions as in Block 1 (see Fig. 1 (b)). The altered reach consisted of an initial deviation to the left and over-rotation of the wrist. Following 30 reaches, the subjects were allowed another voluntary rest period. Next, Block 3 was performed as a repetition of Block 1. Following another voluntary rest period, Block 4 was performed as a repetition of Block 2.

Although the trajectory and wrist rotation differed between Blocks 1 and 2, and Blocks 3 and 4, the sequence of events was identical within and across reaches. Approximately seven seconds before a Go-Cue is given the trial begins with a complete image displayed on the screen. Six seconds before the Go-Cue, the image explodes into numerous pieces. Three seconds before the Go-Cue, one of the three cones lights up, indicating the specific target for the upcoming trial. Finally, the Go-Cue is issued by the appearance of a green box on the screen.

B. Data

Scalp EEG recordings from 19 subjects were acquired and analyzed. Measurements of head dimensions and electrode placement were performed by professional EEG technicians and electrode impedances were kept below 5 kΩ. EEG signals were recorded by a Neuroscan EEG machine (Neurosoft Inc., VA, USA) from 19 electrodes overlaying 6 brain regions using a standard EEG montage (international 10-20 system)

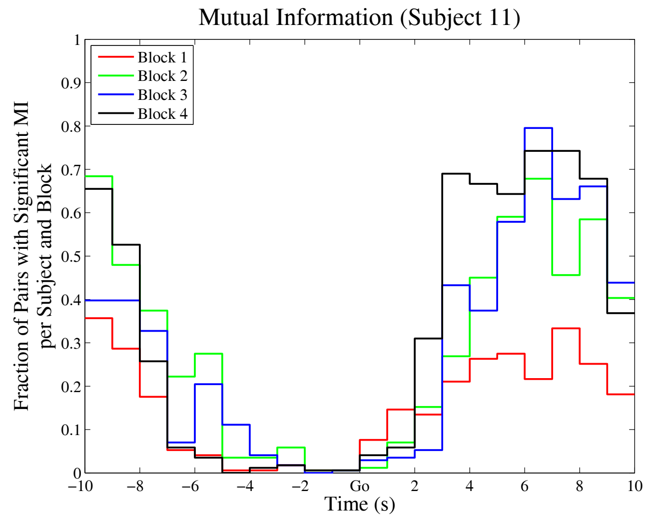

Fig. 2. Fraction of pairs with significant mutual information across reaches over time per block for all four blocks in one subject. The brain's functional connectivity, derived from statistically significant MI profiles, is depicted over time (with resolution of 1 sec) per block (different color per block). At approximately $t = -7$ sec the visual feedback begins the initiation of a new reach. At precisely $t = -3$ sec the cone (one of three possible) the subject must reach to is highlighted. At $t = 0$ sec the Go-Cue is presented to the subject. The subject initiates the reach to the cone (at about $t = +0.5$ sec), grasps the cone, and returns (within 5 to 10 sec) to the rest position.

including averaged mastoid references. The analog data were low-pass filtered at 500 Hz and then digitized at 2000 Hz (sampling frequency) with a 16 bit A/D and stored on a digital hard drive in Neuroscan data format.

C. Mutual Information

Shannon first introduced the concept of mutual information, which two random variables X and Y may share, as the entropy (uncertainty) that remains about them after their joint entropy is subtracted from the sum of their individual entropies. In mathematical terms, MI can be expressed as:

$$MI(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}, \tag{1}$$

where $p(x,y)$ is the joint probability density of X and Y, and $p(x)$ and $p(y)$ are the marginal probability density functions of X and Y, respectively [13], [14]. MI can capture the information shared between two variables even if they are nonlinearly related.

In our analysis, the MI was calculated from 1 sec (2000 samples) non-overlapping, sequential EEG segments over the duration of a trial (10 sec before to 10 sec after the Go-Cue signal), for all electrode pair combinations, resulting in 171 MI values per second per reach. The fraction of statistically significant MI pairs at each time point (1 sec EEG segment) per block and subject was estimated as follows. First, the statistical threshold for significant MI values per subject was established from Block 1. This was performed by estimating the MIs from all electrode pairs at all time points across reaches in Block 1 for each subject. The mean, M, and standard deviation, SD, of all thus estimated MIs were then

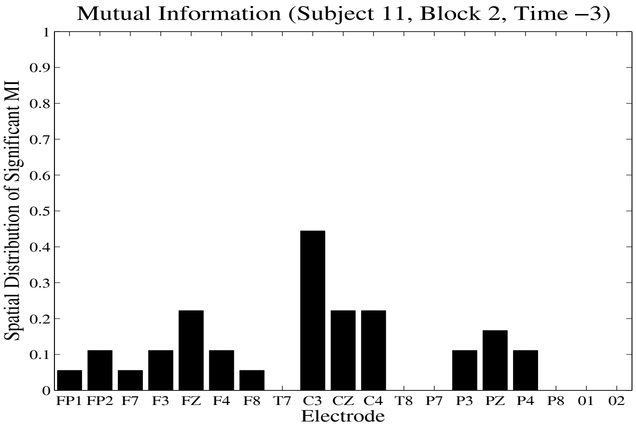

Fig. 3. Histogram of the electrode sites that exhibit significant MI with the rest of sites during the planning period (-3 to -2 sec) for the same block and subject as in Fig. 2. The contralateral to the right arm motor cortex (C3) is shown to be clearly most active of all brain sites during that period for planning of movement.

calculated. Second, the mean of each electrode pair's MI at a time point across all reaches per block was calculated. Third, if this mean MI value was greater than $M + 0.5SD$, this electrode pair's MI was considered significant at that time point. Finally, for each time point and block, the number of electrode pairs with significant MI was summed and divided by the total number of electrode pairs (19C2 = 171) to produce the fraction of pairs of brain sites with significant MI at a time point per block and subject.

III. RESULTS

A. Information Exchange

The probabilistic measure of MI can capture the common information present within a pair of brain sites. MI may reflect linear or nonlinear interactions between sites without any a priori assumption (e.g., number or width of power frequency bands) or particular patterns in the EEG that may constitute information. Thus, it can theoretically provide information about the functional connectivity of brain regions that participate in the planning and execution of movement. Fig. 2 shows the fraction of electrode pairs with statistically significant MI estimated for non-overlapping 1 second segments of EEG data from $t = -10$ sec to $t = +10$ sec around the Go-Cue signal at $t = 0$ sec, for one of our subjects. These same general trends were found across all 19 subjects. Fig. 2 clearly shows that long before (-10 sec to -8 sec) the Go-Cue is presented to the subject, a large number of pairs of brain sites are functionally connected (statistically significant MIs). As the subject prepares for the reach (-5 sec to 0 sec), a progressive reduction in the number of the functionally connected pairs is observed, with a parallel maintenance of the ones that are relevant to the brain's operation at the time, for example, planning in the motor cortex (see topographical histogram in Fig. 3 and map in Fig. 4). Following the reach (+5 sec to +10 sec), the connectivity returns with a spatial spread to the elevated levels per block that existed long before the reach.

B. Information Network

For every 1 sec, MI was used to produce network connectivity plots. These plots show the functional connections between brain sites that have significant MI values. In Fig. 4 we show such a plot for one subject in Block 2 at (a) $t = -10$ sec and (b) $t = -3$ sec. Based on such plots, the brain's functional network at work during the experiment can be monitored.

IV. CONCLUSIONS AND FUTURE WORK

The results presented herein demonstrate the application of a promising signal processing technique, MI, in order to measure the functional connectivity between brain sites over time during reaching and grasping tasks. The technique provides valuable information as to the brain's operation at specific times (e.g., planning in the motor cortex following target identification; -3 to -2 sec). It is expected that results from the application of this technique to EEG from stroke patients during reaching and grasping tasks would contribute to a better understanding of the impaired network, as well as be used as a valuable monitoring tool for the progress of the process of rehabilitation.

Employment of directional information flow measures may shed more light than MI on the involved brain interactions. Expanding upon the bidirectional information flow measure of MI, cross Lyapunov exponents and transfer of entropy [15], [16], both directional information flow measures, are expected to elucidate the directionality of the observed functional connections of the brain sites over time, and hence also the localization of brain activity during the planning and execution of a motor task.

In our future work, we also plan to identify the key predictive EEG features in motor learning integrating our findings with the available ones from kinematic analysis. One route is to first use kinematic features to mine the motor learning patterns for individual subjects, as well as groups of subjects, and then correlate them with corresponding features from the EEG analysis for each pattern (both individual and group). In this experiment, three kinematic parameters (trajectory error, supination error, and number of phases of the velocity profile [17]) were calculated and recorded in parallel with the EEG. We will use these three features of kinematics to identify motor learning patterns at the two levels of individual and group of subjects.

At the individual level, we will investigate periods that clearly show different patterns in a subject's kinematic performance after a transition compared to before. Initial kinematic analysis along these lines has revealed the presence of a transition time for certain kinematic parameters that may denote learning. Computationally, the transition time can be detected by using a mixture of linear regression fits to the data. Fig. 5 shows an example where a subject has two phases in terms of trajectory error over reaches (a two-piece linear regression has a better fit than a single linear regression in this case). This piecewise regression implies that, within a subject and within a block, there is a transition in the motor learning, possibly the point where the subject

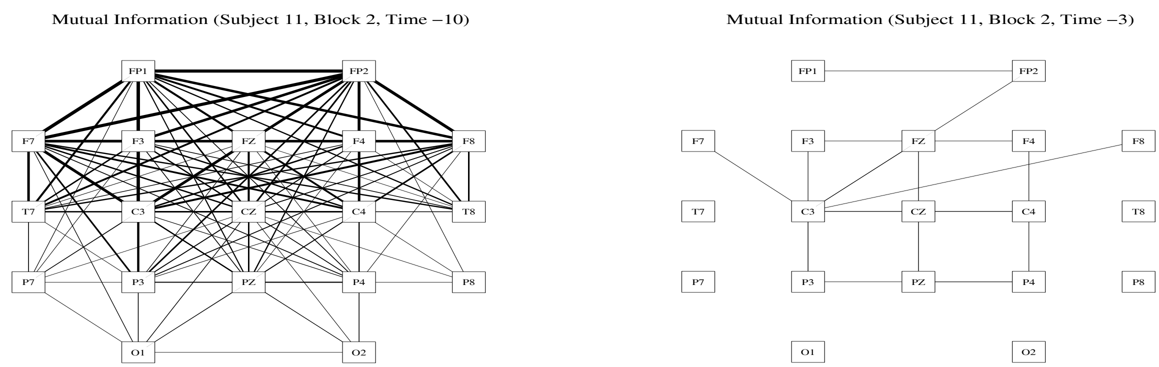

Fig. 4. Functional connectivity plots in Block 2 for the same subject as in Fig. 2. (a) Network at $t = -10$ sec. (b) Network at $t = -3$ sec. Only the significant MI pairs of sites are connected by lines. The thickness of the line corresponds to the value of MI.

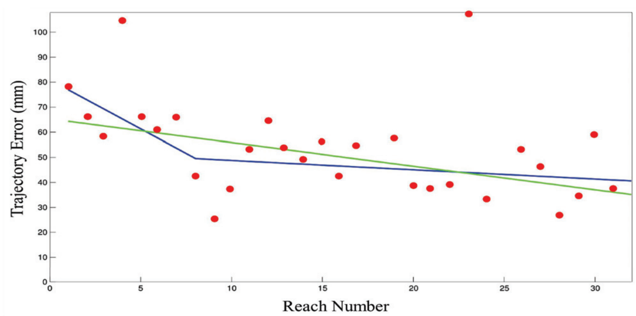

Fig. 5. Trajectory error versus reaches and its best-fit regression. The trajectory error values from kinematic analysis for a subject's reach versus all 30 reaches in Block 2 are shown. They are fit with two different best-fit strategies: lines with (blue curve), and without (green curve) piecewise robust regression.

has learned the novel motor plan and from then on is just recalling the plan.

At the group level, we will apply clustering techniques to identify subject clusters where each group shares a similar motor learning strategy. Initial analysis of the kinematic parameters has revealed the presence of multiple different groups of learners; some subjects appeared to focus on correcting their trajectory error, others on their supination error, and others on their velocity. Clustering will be based on trends kinematic features exhibit across reaches. Once such an analysis of kinematics is complete, features from the EEG (e.g., MI values and trends) will be mined to further determine correlations at both the individual and group levels.

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