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Phase-based Cortico-Cortical Connectivity Mapping in Motor Cortex of Nonhuman Primate

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Abstract—In this study we analyze the brain signal phase components to understand patterns of interactions in the motor cortex. Nonhuman primate motor-cortical activity was recorded with electrocorticography (ECoG) arrays along with intramuscular electromyography (EMG) during natural reaching and grasping hand movements. This study investigates phase relationships between each ECoG electrode pair to decode neural signal propagation. We propose a method to cluster recording channels that have similar phase characteristics and suggest a mapping of the signal pathway in motor cortex. This technique can facilitate further studies on cortico-muscular coherence and development of effective prosthetics for motor impairment in patients.

I. Introduction

Communication patterns and neural connectivity in the brain is still a largely unknown territory due to complex parallel computation pathways and lack of methods that can offer the necessary spatiotemporal resolution for documenting neural activity. Recording methods are highly dependent on factors including electrode dimensions and placement, which determine the spatial resolution as well as the signal-to-noise ratio (SNR) [1]. The golden standard in measuring brain oscillations consists of electroencephalography (EEG) and ECoG methods. Current methods for brain signal monitoring not only involve passive observation of the signals but also stimulating and creating them under controlled situations [2]. While invasive, ECoG measures local field potentials (LFP) with both higher resolution and SNR compared to non-invasive methods such as EEG. To determine connection patterns and pathways mediating cortico-muscular dynamics, preliminary cortico-cortical communication analysis with ECoG data can be valuable.

Brain waves can be classified in four primary frequency bands - alpha, beta, low gamma and high gamma. Each band is related to various functions in the brain, and multiple studies have suggested that the beta band is closely correlated with voluntary motor functions such as hand movement [3-7]. Experiments have shown that the dominant frequency bands in the lower frequency range (less than 40 Hz) include the mu and beta bands [8-11]. Mu (8–12 Hz) and beta (14–26 Hz) rhythms are oscillations that are believed to represent post-synaptic potentials associated with thalamocortical modulation of motor cortex.

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Here we look at the cortico-cortical patterns within the ECoG array which will help us better understand cortico-muscular communication dynamics. The phase information between individual electrodes of an array is determined to elucidate signal propagation patterns in the motor cortex. If an accurate mapping of the motor cortex can be established for different movements, it will facilitate the translation of signals between ECoG-EMG.

II. Data acquisition

A monkey was trained to sit calmly in a primate chair, with its head restrained at a neutral, comfortable position, facing forward. One of the monkey's arms was restrained at the elbow and the wrist, at a neutral position (elbow flexed at a 90 degree angle, wrist straight). The experimenter presented a treat at a random location in the monkey's extra personal space, within its reach. Using its free arm, the monkey started from rest to reach for the treat. The treat was either kept at the location originally presented, in which case the monkey would simply reach and grab it, or was moved around inside the monkey's visual field, in which case the monkey would "chase" it up to 3 seconds, before grabbing. ECoG and intramuscular EMG were recorded during both "reaching/grasping" and "resting" periods of each recording session. The "reaching/grasping" and "resting" periods are also called as ON and OFF periods respectively.

A micro-grid of cortical surface array of 4×8 electrode with dimensions of 7.0×13.5mm, platinum-iridium contacts and 75 µm exposed electrode diameter was implanted in the monkey's motor cortex. Each of the arrays was placed on the pia overlying the precentral gyri, as close to the arm/hand representation as possible, based on anatomical landmarks and cortical stimulation mapping.

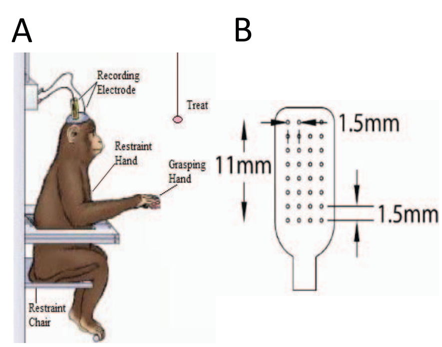

Figure 1: a) The monkey is seated where it can reach for the treat. A 30-channel ECoG array and a 9-channel EMG array are placed over the motor cortex and forearm respectively. b) The ECoG microelectrode array with 75 µm diameter electrodes.

III. DATA PROCESSING

The phase relationship between ECoG channels is compared to better understand the interactions among these locations. Another approach is to use cross correlation to determine signal similarities as suggested by Rohde et al. [12]; however we consider phase comparison a more accurate method due to the possibility of signals generated by different sources. As the brain has a non-linear

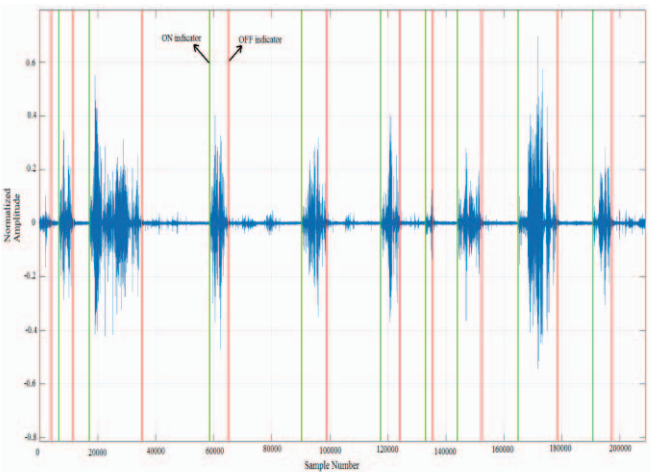

Figure 2: Examples of raw EMG data showing the onset of movement (ON, green lines) and the end of movement (OFF, red). The pulse between each ON and OFF indicators is described as one data segment, or the ON region.

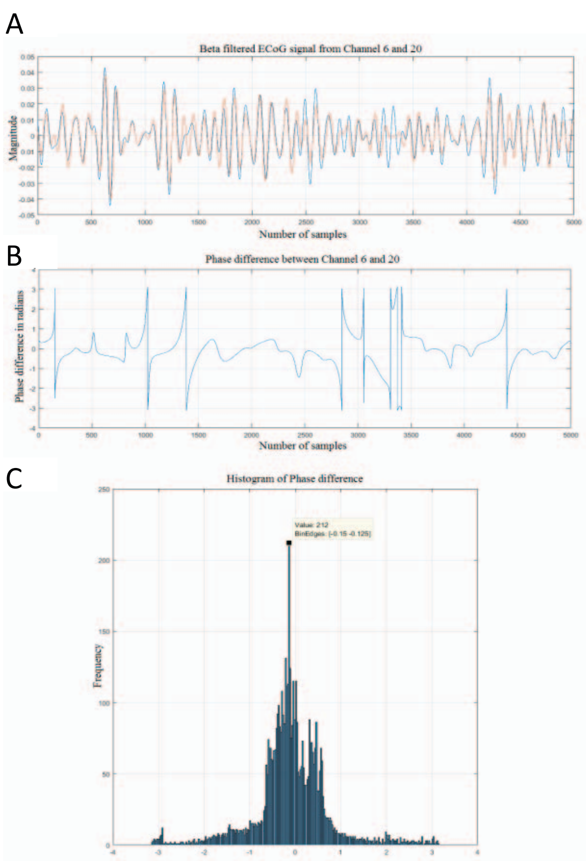

Figure 3: a) ON segment filtered signals from ECoG channel 6 and ECoG channel 20 (see Fig. 6) are superimposed and plotted over 5000 sample points b) Phase difference plot between the two signals obtained from Hilbert transforms c) The histogram of the calculated phase values between channels 6 and 20. The most recurring “dominant” bin is selected and used as the driving phase between two channels. In this case the bin with edges -0.15 to -0.125 radians is selected, thus the driving phase between channels 6 and 20 is -0.1375.

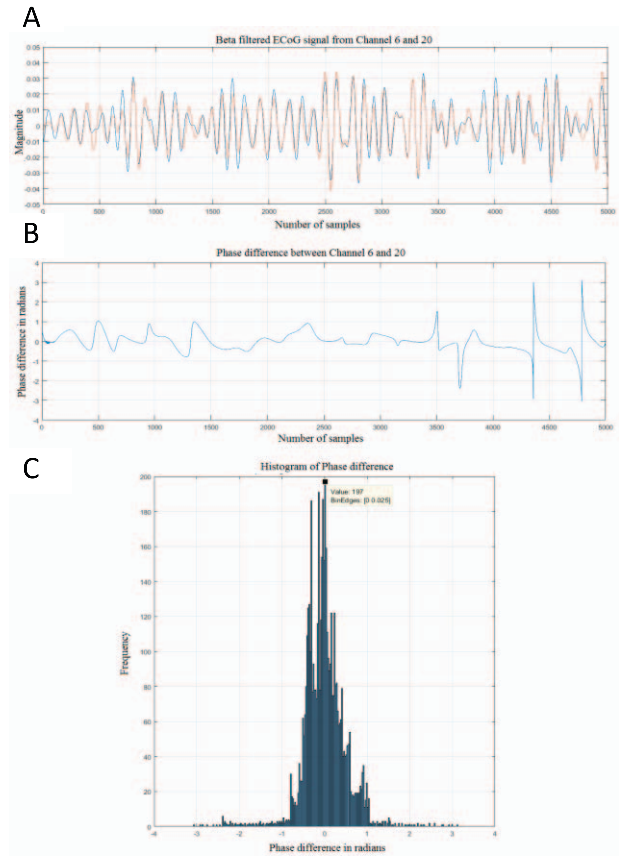

Figure 4: a) OFF segment filtered signals from ECoG channel 6 and ECoG channel 20 are superimposed and plotted over 5000 sample points b) Phase difference plot between the two signals obtained from Hilbert transforms c) The histogram of the calculated phase values between channels 6 and 20. The most recurring “dominant” bin is selected and used as the driving phase between two channels. In this case the bin with edges 0 to 0.025 radians is selected, thus the driving phase between channels 6 and 20 during OFF segments is 0.0125.

connectivity structure, regions in close proximity do not necessarily possess the same function. In our analysis, we want to know whether certain channels are consistent in their phase characteristics with respect to the others. Since the measured potential from a single electrode is obtained from the activity of many neurons in the vicinity, we are monitoring the overall signal over an area rather than individual neurons. If the pattern of a propagating signal between particular electrode sites is found, a further analysis of neuronal connectivity in the motor cortex can be made. One way of achieving this is through isolating neuron groups that exhibit comparable phase characteristics. To determine the phase component of each channel, we initially considered the beta wave band in the ECoG measurements and band-pass filtered the 15-25 Hz range using Remez FIR filter. Previous coherence studies [3-7] found the greatest overlap between beta range and EMG signals, and thus we chose the 15-25 Hz for our analysis. We then applied Hilbert transform to the filtered signal to extract the phase information that was used to calculate the delay between electrode channels. Hilbert transform is appropriate in calculating instantaneous attributes of a time series, specifically the frequency component for our phase calculation. It is a commonly used method in other works on neural synchrony and ECG signal analysis [13-14]. Channels 1 and 25 are deemed noisy and a total of 28 channels with 15 segments per channel are compared. A segment is the signal between ON and OFF markers, as shown on Figure 2. First, the phase of each channel during ON segments (hand movement) was plotted with respect to the others as shown on Figure 3, and grouped according to their magnitudes. Channels that had 0.01 – 0.1 phase shift were grouped together and each group is considered to contain the same oscillation and thus designated as a new, single channel. This range is determined according to the variance and phase distribution of the each electrode among all data segments. Similarly, the phase information is plotted for OFF segments (idle/rest) as shown in Figure 4. The difference in behavior between ON-OFF segments could be helpful in isolating particular muscle motions and their mapping on the motor cortex. It is seen that the phase oscillations during OFF segments are much smoother than ON segments and closer to 0. This shows that the behavior of channels changes during actual movement sessions and validates that this phase analysis can be useful for cortico-muscular mapping. When translated into a delay in the time domain, a 0.1 radian phase shift corresponds to roughly 0.7 ms delay, which is compatible with the time scale of cortico-cortical dynamics [15]

IV. RESULTS AND DISCUSSION

The average phase of each group is determined, as well as whether it was leading or lagging compared to other groups. The grouping allowed us to reduce the processing among 28 working channels considerably, and estimate possible signal trajectories along the array. Each electrode group is reduced into a single electrode in the following manner: (3,4,5,11,12,13,19,20,21) ->12, (23,24,26,27,28,29,30,31,32) -> 27, (7,8) -> 7, (14,15) -> 15 and (17,18) -> 17. The remaining channels that do not belong to a group are: 2,6,9,10,16 and 22. We calculated the average phase between these grouped and single channels, and then estimated the overall phase acting on each one by averaging contributions from all other channels. This was repeated on a single

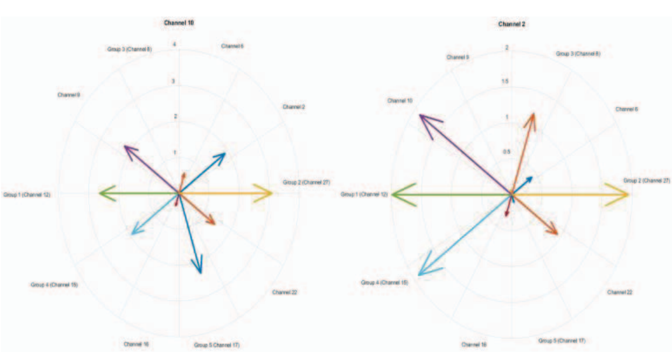

Figure 5: Absolute phase of each channel is plotted with respect to the other channels on a compass plot. Arrow lengths depend on the phase magnitude. Channel groupings are included and indicated. Left compass is channel 10 vs. other channels and right compass is channel 2 vs. other channels. These two channel plots are provided here as examples.

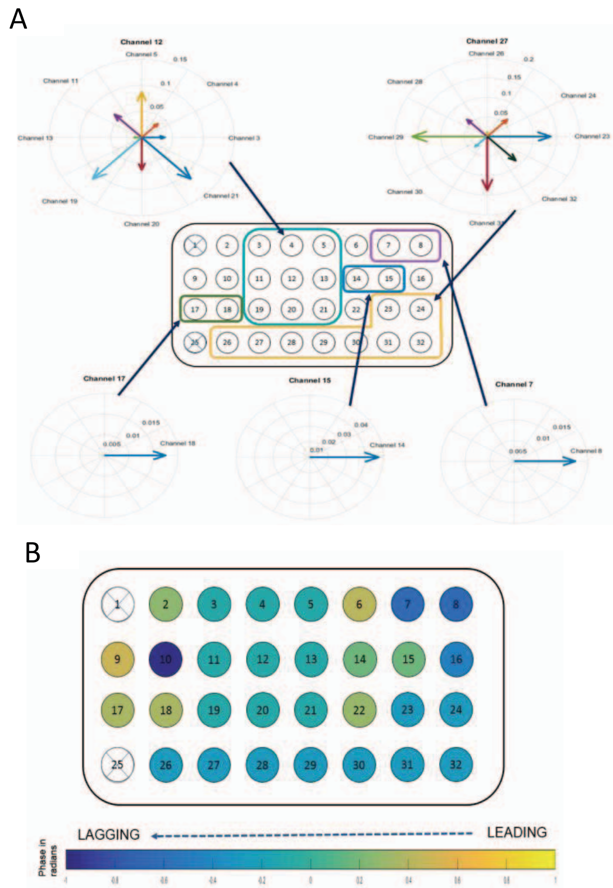

Figure 6: a) Channel grouping is demonstrated on the ECoG array. The channels that have a phase of 0.01 – 0.1 radians between them are grouped together indicated with the boxes. Corresponding compass plots are included with the arrows pointing to relevant groups. b) Phase information between the groups is color coded depending on the direction. This demonstrates how much each group is leading or lagging other groups. In this case channels 6 and 9 lead the most whereas channel 10 lags the most.

segment as well as across all segments. Examples of these calculations are shown on the compass plots in Figure 5, where channel 10 and channel 2 are compared to the other channels after the grouping. The compass plots do not reflect channel positions, but rather the absolute phase difference between each channel. Length of the arrows shows the magnitude of the phase difference.

Figure 6 demonstrates how the channels were grouped on the ECoG array and the corresponding compass plots. Moving forward and calculating the phase difference between these groups and the outlying channels, we were able to create a color-coded mapping of the locations where the signal is lagging or leading compared to other locations, as seen on Figure 6 b). With the help of grouping, we can get an idea of how the neural signal propagates within the measurement area. Multiple signal pathways can be deduced by realizing that channels 6 and 9 are strongly leading while the middle and bottom/rightmost channels are comparatively lagging.

TABLE I. PHASE BETWEEN GROUPED ECOG CHANNELS

ON Segment 1		ON Segments 1-15 Averaged	
Channel (descending phase)	*Phase (radians)*	*Channel (descending phase)*	*Phase (radians)*
9	0.426	2	0.1208
6	0.410	6	0.0701
17	0.397	10	0.0422
22	0.381	9	0.0414
2	0.367	22	0.0302
14	0.163	12	0.0042
12	-0.053	14	0.0037
27	-0.206	16	-0.0910
16	-0.494	17	-0.1028
7	-0.603	27	-0.1407
10	-0.963	7	-0.1613

In Table 1, channels are sorted in descending order depending on their overall phase with respect to all other channels. Left section is calculated on a single segment and the right section is calculated as an average of all 15 segments. The average was calculated to see if certain channels tend to mostly lag or mostly lead. Upon averaging phase values between individual channels over entire (15) data segments we observed that the resulting phase for most channels approached and oscillated around 0. Table 1 shows that the channel ordering is not consistent between single segments and averaged segments. It was also observed that no channel was strictly leading or lagging over the span of these segments. Channel 6 for example showed leading behavior during 8 and lagging behavior during 7 of the 15 measured segments. This indicates that a fluctuating signal flow pattern might exist over the measured area, where the signal changes direction periodically. Since the average value is very close to zero over long segments, it can also be suggested that the signal follows various pathways during the monkey's reaching and grasping motions.

From the perspective of body sensor networks and health informatics, future BMIs could exploit accurate mapping of the neural pathways between the central nervous system and motor connections. This can be translated into implantable devices and prosthetics which will offer treatments for patients with motor neuron diseases. Because ECoG/EEG and EMG signals are inherently different and undergo considerable transformation in the nervous system, establishing reliable relations between them is challenging. Thus, it is important to understand and quantify communication pathways in the motor cortex to decode motor control information from brain signals and vice versa. Our method investigates cortico-cortical dynamics with a phase difference method that can also be extended to cortico-muscular communication in future studies.

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