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Time Robust Movement Direction Decoding in Local Field Potentials using channel ranking

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Abstract— **Movement direction for Brain Machine Interface (BMI) can be decoded successfully using Local Field Potentials (LFP) and Single Unit Activity (SUA). A major challenge when dealing with the intra-cortical recordings is to develop decoders that are robust in time. In this paper we present for the first time a technique that uses the qualitative information derived from multiple LFP channels rather than the absolute power of the recorded signals. In this novel method, we use a power based inter-channel ranking system to define the quality of a channel in multi-channel LFP. This representation enables us to bypass the problems associated with the dynamic ranges of absolute power. We also introduce a parameter based ranking system that provides the same rank to channels that have comparable powers. We show that using our algorithms, we can develop models that provide stable decoding of eight movement directions with an average efficiency of above 56% over a period of two weeks. Moreover, the decoding power using this method is 46% at the end of two weeks versus the 13% using the traditional approaches. We also applied these models to decoding movements performed in a force field and again achieved significantly higher decoding power than the existing methods.**

I. Introduction

In Brain Machine Interface Local Field Potentials (LFP) and Single Unit Activity (SUA) have been recognized to hold information regarding the movement direction and velocity parameters. It has been long discovered that neuronal spike activity was able to predict the movement direction and was observed to tune into preferred directions [1]. There has been great interest recently in decoding the movement direction using different neural modalities. Mehring et al., [2] showed that LFP could be used as a supplementary data to SUA in direction decoding. In [3], Schalk et al., provided proof that even electrocorticograms (ECOG) can also be used to decode the directions. Recently [4], non-invasive modalities like electroencephalogram (EEG) and Magnetoencephalogram (MEG) activity were also used for the decoding of four movement directions.

While these results are extremely encouraging, there have been few advances in the field towards developing decoders that are robust in time. The instability and non-stationarity of the intra-cortical recordings has been well documented in the literature [5]. There have been various suggestions made to address this problem. In [6], the authors search for robust features from a non-stationary environment. Also [7], suggests the use of online retraining to model the non-stationary data. These studies are very encouraging, though were performed in a very constrained way. In general the decoding performance was evaluated in a cross-validation setting or by adding some testing trials as a calibration.

This paper addresses the following problems: 1) Overcoming the non-stationarity and the instability of the data, 2) The stability of models over a time period of two weeks, 3) The stability of the models when an external force opposing the movement is applied. Our main contribution is the use of inter-channel power ranking system to develop stable spatial patterns in multi-channel LFP. These spatial patterns in turn aid in discriminating the different directions. As described in the following sections this method provides an improved performance of above 46% versus the baseline method that provides around 13% at the end of 2 weeks.

The rest of the paper is arranged in the following sections: Section II discusses the experimental paradigm and the data collection process; Section III describes the algorithm, followed by the results and discussion in Section IV.

II. Data Acquisition

Two male rhesus monkeys were instructed to perform a center-out-target-reach task. The subjects were implanted with two 64-grid Utah microelectrode grid arrays, one in the Primary and other in the dorsal Pre-motor cortex area of the brain. The subjects were trained to move a robotic manipulandum to one of the eight targets on a horizontal plane. These targets were in a circle separated by an angle of 45°. Their direction labels designate these targets as {0,45,90,135,180,225,270,315}. The experimental paradigm proposed by [1] is adopted in our experiments and is shown in the Fig. 1.

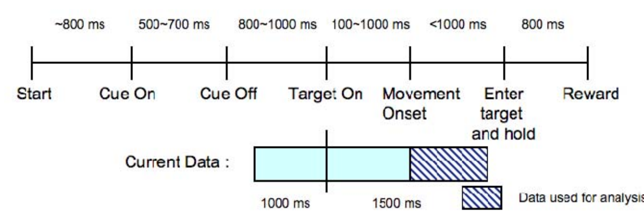

Figure 1: The timeline for each trial of the experiment indicating the median time to be spent in each phases of the experiment.

The LFP data collected from the 128 electrodes is then low-pass filtered in 0.4 – 200 Hz, at a sampling rate of 1

KHz. By means of visual inspection of spectrograms, artifacts like power line noise and large DC wanders were identified and then removed. Channels with such noise were then eliminated from the analysis. In this analysis, we use 1s of data after the movement cue. The data is then down-sampled by a factor of 2. Previous analysis [8], revealed that the δ–band i.e. 0.4 – 4Hz, contained discriminating information of the eight directions of movement. We focus only on this band for our analysis.

The monkey 'H464' performed the experiment spreading over two weeks. Table I shows the timeline of the experiment. In all of the analysis, we use only session 1 (data from day 1) for training our models. All the rest of the sessions are used for testing.

TABLE I: Session Number and the day on which the experiment was performed counted from the 1st session

Session	1	2	3	4	5
Day	1	8	9	13	14

For the monkey 'H564', the experiments focused on the effects of force fields on movement direction. Sessions were performed with different types of opposing fields of force viz., viscous counter clockwise (VCCW), smooth clockwise (SCW) and viscous clockwise (VCW) and sometimes no fields (NF). Table II shows the distribution of the force fields for different sessions. As above, we use only the first session for training and the rest to evaluate the performance.

TABLE II: Sessions of monkey H564 and the force fields applied

Session	Day	Force Field
15	1	VCCW
16	1	NF
17	2	VCCW
18	2	VCCW
19	3	VCCW
20	3	SCW
21	4	VCCW
22	4	SCW

III. CHANNEL POWER RANKING

To analyze multi-channel data Common Spatial Patterns (CSPs) are used extensively in literature [9]. These spatial patterns are generalized Eigen Vectors of covariance estimates of two directions. In general CSP is a binary feature extraction and classification algorithm. To use this in our setting of 8 different classes (corresponding to 8 different movement directions), error correction output codes (ECOC) are employed [8]. A block diagram of the system is shown in Fig. 2.

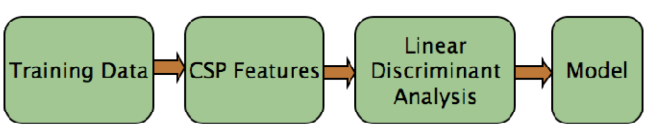

Figure 2: A block diagram of the classification training system

Method I – Channel Power Ranking

The results in [8] indicate towards the existence of a spatial pattern corresponding to the movement directions in LFP. This implies that the channels are arranged in a unique fashion when a particular target needs to be reached. We investigated this by observing the power patterns of each channel in a small time window. For this purpose we employed rectangular moving windows sliding by one time sample to evaluate the power. When the power of each channel was visualized on the electrode grid map, a pattern over time unique to a direction was observed. However, the power level across the trials was not consistent. This tends to be a challenge in the consistency of feature extraction. Normalization techniques can be used to tackle this, but usually require prior knowledge of the test data.

To overcome the dynamic range of the trials, we ranked the channels of each trial according to their power. Thus, at each time sample, the channel with the highest power will have a rank 1, the next channel rank 2 and so on. In this manner, the total number of the channels in the analysis is the upper bound value of the channel. By following this process, the dynamic range of the channels is bypassed, however the relative information between the channels is retained.

Fig. 3 shows a typical trial. Plot A shows the power of all the channels over the one second of movement, which starts at 0s. Plot B shows the relative ranking of the channel based on the power at each time sample in the same time period.

Two important observations can be made in this trial. During the actual movement i.e. from 0-0.45s the order of the channels is very consistent. It can also be observed that at around 0.6s there is a change in the ranking order. Interestingly, this is the time point just after the target is reached as shown by the vertical line. This implies a change in the cognitive state after reaching the target. This is our motivation to use the trials in the rank domain.

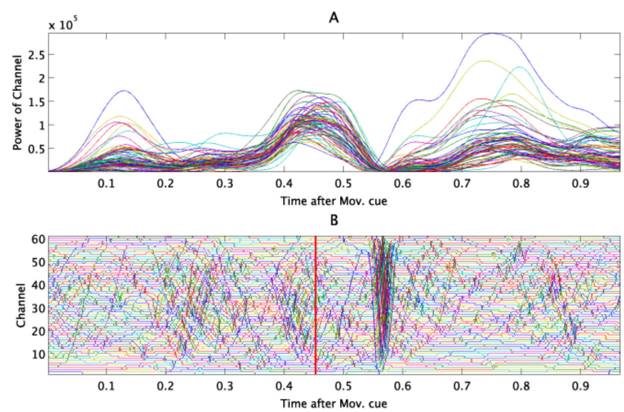

Figure 3: A typical trial with all the channels is shown. Plot A shows the power of the channels over time. Plot B displays the ranking of the powers at each time sample. The vertical line represents the target reach cue.

Method II – Standard Competition Ranking

An alternate way of ranking that is typically used is the standard competition rankings. In this process, the competitors with the same score would get the same rank and a gap is left in the ranking numbers [10]. This enables a fairer ranking in a competition.

In our data setting, the power of each channel is a real number and it is very unusual that two channels have the same power at a time point. To adapt this ranking system in our context, we use a fractional threshold (F_{th}). The process is described below:

1. The ranking is done from the top-down. The channel with the highest power (P_{max}) is identified.
2. All the channels that have a power $P_{max}*(1-F_{th})$ are then given the same rank. A gap equal to the number of channels identified is left in the ranking system.
3. Then, the channel with the next highest power is identified and the same process is applied.
4. This process is done until all the channels have a rank.

Method III – Rank Variance Sampling

Another challenge with the experiment is the variation of the trial times. It is observed that the trials, even from the same session are performed at different speeds. In other words, the subject takes different times to reach the same target. Also, we observe that the trial could be broken up into zones where the variance of the rank is high and low.

To provide consistency in the time duration, we use a modified sampling algorithm. This is accomplished by collapsing all the time samples having similar rank patterns. The similarity is measured as the maximum change in the rank pattern of all channels between two successive points. Consider $R \in N\{T \times Nch\}$, as the Rank Patterns of the channels across time, where T is the total time samples and Nch the total number of channels. The distance between these patterns at time t and (t+1) is then measured as maximum of R(t)-R(t+1).

A threshold (V_{th}) is used to detect the change in patterns. Using this method, the high variance zones are represented by a high number of samples and the zones that vary slowly are represented by lesser number of samples. Fig. 4 shows this process for multiple variance threshold parameters (V_{th}). As the variance threshold parameter is increased, we are tolerating more change in the ranks, the total number of samples goes down, but the original pattern is retained.

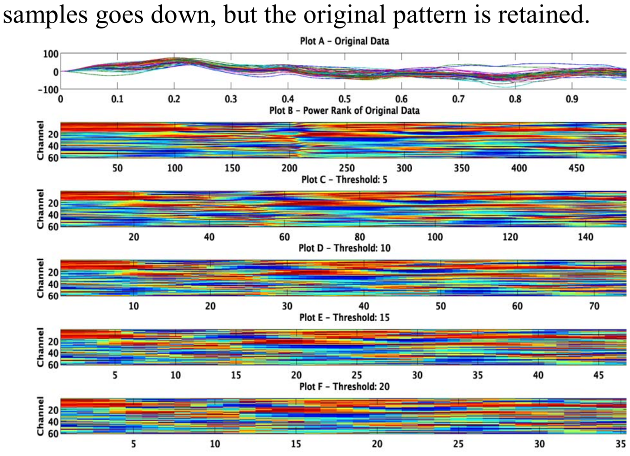

Figure 4: Use of different variance thresholds. Plot A shows the original data of a single trial. Plot B is the power rank of each channel at each sample. Plot C-F show the effects of threshold change. It can be observed that though the number of samples changes the pattern is still held intact.

IV. Results and Discussion

The measure to evaluate the performance of the algorithms is defined as the decoding power (DP). It is the ratio of trials that are correctly decoded to the total number of trials that are evaluated. Since there are eight different directions, the decoding power at chance level is 12.5%.

The analysis consists of training and test phase. In the training phase, first the rank patterns of single trials are evaluated. Using these the spatial weights for all the ECOC classifiers are designed. These features are used to then design the linear discriminant analysis (LDA) classifiers. The spatial weights for a typical classifier are shown in Fig. 5; they reflect the difference in the spatial weights in the original data domain and the rank domain.

In the testing phase, the spatial weights are applied and the extracted features are then passed through the classifiers. A decoding matrix is used to decode the final result from the individual classifier outputs.

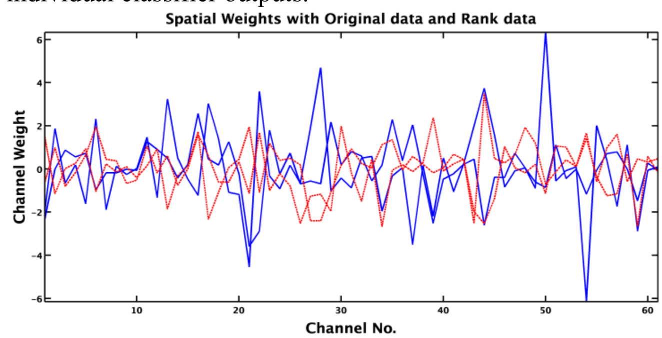

Figure 5: The spatial weights of the channels for the original data (in solid blue) and the power rank data (in dashed red)

To evaluate the performance of this method, we use the same CSP and ECOC set on both the original data and the data in the rank domain. Since the main focus of this paper is the relative rank algorithm, we use consistent classifiers to compare the performance. Other non-linear classifiers might provide higher decoding, and they will be pursued in the future. The results from using the rank method on monkey H464 are presented in Fig. 6. Here we used only trials from session 1 for training and the rest of the sessions were used for testing purposes. From the illustration we can gather that this method over performs the traditional method in all the sessions. Further, we observe that there is consistency of performance in the first two test sessions.

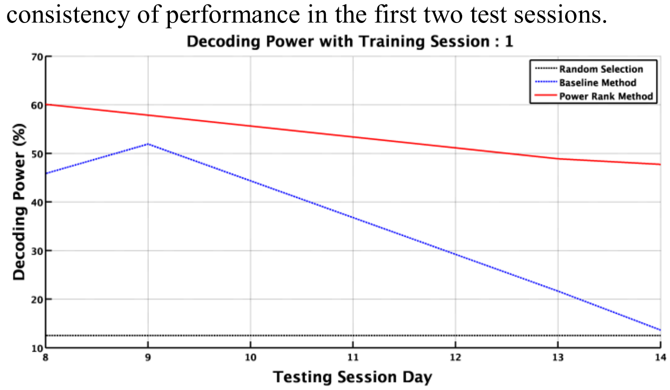

Figure 6: Decoding Power vs. Test Session Day plot for subject H464. The Training session is Session 1 on day 1. The decoding power with the baseline method and random selection is plotted for reference.

Next, we test the performance of the algorithm with varying fractional threshold. The results for different thresholds are presented in Table III.

TABLE III: DP at different fractional thresholds of Method II

Threshold \ Session (Day)	2 (8)	3 (9)	4 (13)	5 (14)
0	60.09	57.87	48.88	47.73
5%	58.56	57.56	50.01	47.73
10%	60.05	56.66	50.59	48.86
15%	60.81	58.81	52.31	46.59
20%	61.16	58.83	52.89	48.86
25%	61.93	59.12	53.75	44.32
30%	60.80	59.42	55.76	48.86
35%	**61.93**	**61.28**	**55.48**	**46.59**

We next evaluated the performance of Method III, with increasing variance thresholds (V_{th}). Again the same CSP and ECOC sets are used. The decoding powers with changing thresholds (V_{th}) are listed in Table IV. The method III is an illustration that the number of samples does not significantly change the performance of the algorithm. We performed t-test on the performance at different threshold and observed no significant change in the mean at the 0.05 levels. While the number of samples goes down, there is not a significant drop in the accuracy of decoding.

TABLE IV: Decoding Power of all testing sessions at different variance threshold (V_{th}) of Method III. The analysis was performed at the factional threshold (F_{th}) of 35% in Method II

Threshold \ Session (Day)	2 (8)	3 (9)	4 (13)	5 (14)
0	61.93	61.28	55.47	46.59
5	59.63	58.81	49.68	44.31
10	57.71	56.35	49.45	42.04
15	60.04	57.88	51.16	44.32
20	56.21	53.90	48.27	44.32

Similarly, the performance for H564 is evaluated. In this case, the model is robust not only in time, but also over the change in the environmental conditions.

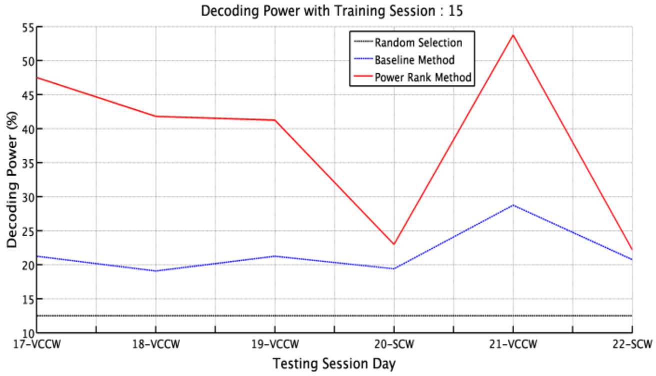

Figure 7: Decoding Power vs. Training Session for subject H564. The force fields for the test sessions are indicated

Fig. 7 shows the performance of the algorithm on the training sessions. This figure illustrates the high performance of the algorithm over the traditional algorithm, even when the experimental conditions are altered by means of external force fields.

V. CONCLUSION

In this paper we present three methods. In method I, we have presented a novel algorithm that evaluates multi-channel recordings based on their relative power. This algorithm proves to over perform the existing technique by an average of 56% from 36% over 4 testing sessions spread over two weeks. Further, a parameter based standardized ranking technique is adapted for the first time in method II, to provide consistent models over a period of two weeks from the training session, for one subject. In the other subject, this model was stable across the changing force fields. In method III we use a similarity based sampling method and overcome the variation in the trial length. Method III illustrates how the patterns can be preserved even if the trial times vary. We intend to use non-linear classifiers in the future to improve the overall performance of the algorithm. The success and stability of these methods implies that movement direction can be inferred with a higher degree of accuracy from the relative rankings of the channels rather than from their absolute values.

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