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MOVEMENT DIRECTION DECODING OF LOCAL FIELD POTENTIALS USING TIME-EVOLVING SPATIAL PATTERNS

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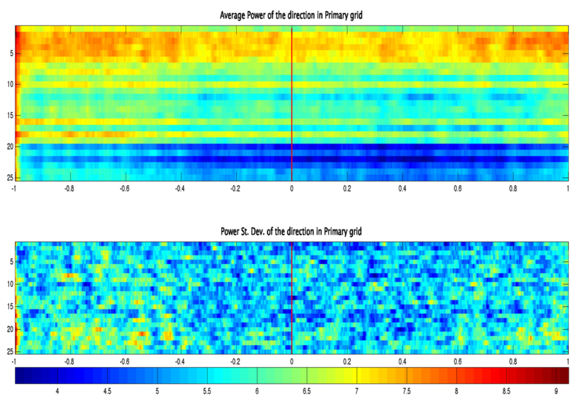
***Abstract*— A main disadvantage of using intra-cortical recordings for Brain Computer Interface (BCI) is their inherent non-stationarity and instability. Thus developing direction decoders for Local Field Potentials (LFP) that are robust over time becomes a difficult task. In this paper, we show the superior performance of qualitative information over the absolute power of the recorded signals by introducing a novel method,that uses time-evolving spatial patterns. This method over-performs the baseline method by 30% on an average over a two week testing period and provides a bit-rate of 0.98 per trial. Further, these spatial-patterns provide robustness against learning when new field-forces are introduced.**

I. INTRODUCTION

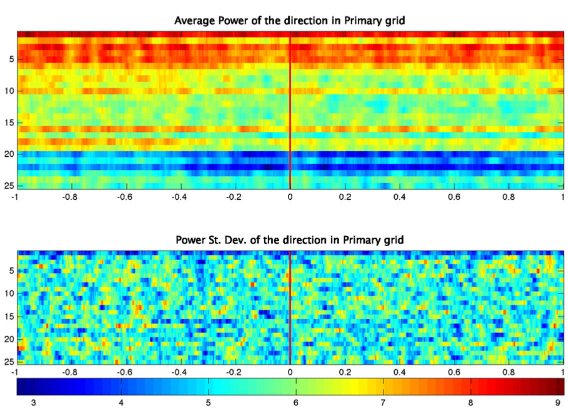
Movement direction can be decoded using intra-cortical recordings such as Local Field Potentials (LFP) and Single Unit Activity (SUA) and the history of such decoding can be traced to [1] where the neuronal spike activity was tuned to preferred direction of movement. In recent times LFP was shown to supplement the SUA in direction decoding [2], [3]. Even non-invasive modalities like electroencephalogram (EEG), Magnetoencephalogram (MEG) [4] and electrocorticogram (ECoG) [5] were used to decode movement directions. However, due to their poor spatial resolution and low Signal to Noise Ratio, the non-invasive modalities provide low performance in such decoding tasks.

Most of the studies relating LFPs and movement parameters have followed methods of analyses borrowed directly from SUA studies. These studies are ineffective in the case of LFPs because the distribution of preferred directions of SUA's are uniform while it is not the case in LFPs [6], [7]. Recently, multi-channel LFPs were used to accurately decode movement direction using spatial patterns [8]. However, the main problem plaguing LFPs is their instability and non-stationarity over time [9] as shown in Figure 1. These characteristics pose problems in developing robust models that do not use retraining since most of the pattern recognition algorithms depend heavily on the stationarity of the measured features. Retraining the model online on the non-stationary data [10] and searching for robust features [11] have been suggested to overcome the non-stationarity. Most of the studies related to such experiments are evaluated in a cross-validation setting where the training and testing sets are re-sampled from a huge pool of data and the average performance is reported.

This paper deals with 1) Overcoming the instability and non-stationarity concerns of the data 2) Provide stable models over two-week time frame 3) Provide models that are robust over learning due to external field forces. In [12], authors show that using relative information about the electrodes provides better decoding capabilities over using the absolute power. The main contribution of this paper is to use a multi-classification technique to improve the decoding power, by using time-evolving spatial patterns, to improve the average performance by more than 30% over two weeks.



(a) Session 1 (Day 1)



(b) Session 2 (Day 8)

Fig. 1: Average (top part) and standard deviation (bottom) of logpower distribution for multi-channel recordings of multiple recording of the same behavior across a week . The vertical scale represents the channel number and the time scale is in seconds. The log-power distribution across sessions is shown here to illustrate the variability across sessions and is not used in our proposed method.

The rest of the paper is as follows: Section II describes the algorithm, Section III discusses the experiment and the data acquisition, Section IV deals with the Results and is followed by conclusion in Section V.

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II. ALGORITHM

Common Spatial Patterns (CSP) [13] is used as both an analysis and a feature extraction tool, especially in analyzing multi-channel recordings. The spatial weights generated by the algorithm are the generalized eigen vectors of covariance estimates of the discriminant groups. Previous studies [8] reveal the existence of such spatial patterns that can decode the movement directions in LFPs. While CSP is usually a binary classifier, additional logic can be developed to deal with multiple classes. For this purpose, we develop redundant binary classifiers and output the final result via a decoding matrix using error correction output codes (ECOC). This redundant hierarchical strategy involves grouping the directions into diametrically opposite groups of neighboring directions as shown in Figure 2 and then basing the final decision using ECOC.

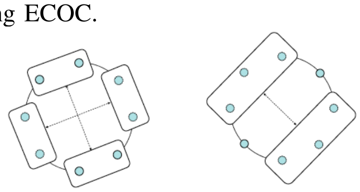

Fig. 2: The grouping of the diametrically opposite groups based on their neighborhood. In this example we show a group of 2 directions per group and the 3 per group.

The algorithm Common Spatial Patterns (CSP), requires that there be variability in the training dataset to produce a generalized model [14]. In the study [12], this signal variability and instability were overcome by capturing the relative behavior of the electrodes and revealed that the inter-electrode ranking system bypasses the time variability and improves the performance of the same underlying classifiers. The algorithm for evaluating the rank patterns of a single trial data as in [12] as:

1) For each channel, calculate the power of the signal in a pre-defined time window that is determined by cross-validation in training data.
2) At this time-window, rank all the channels based on their power. For example, a channel with the highest power at that time-window would have rank 1, the next channel rank 2 and so on.
3) Replace the raw data in the trial with the respective rank of the channel.
4) Move the time-window with or without overlap and go to step 1, until the trial is completed.
5) Using the obtained data (raw data projected on the rank space), build the CSP models for all the hierarchical groups.
6) In the testing stage, evaluate all the CSP models and evaluate the final decision based on ECOC of the hierarchical classifiers.

The algorithm discussed in [12] and the CSP algorithm assume that the correlation of the electrodes, which determine the spatial weights, would remain constant over the length of the trial. We hypothesize that this inter-electrode correlation evolves over the trial, which mandates developing spatial weights over the trial time. The goal of this new algorithm is to investigate if there is indeed an evolution of spatial patterns over time and then extends our decoding results using an evolution paradigm. We developed spatial patterns based on smaller time-windows in order to incorporate the change in spatial patterns over time. Each trial is first split into a number of non-overlapping time-windows of equal size, say Tms, the length of the which will be calculated using cross-validation on the training data. Spatial Patterns will then be computed using the CSP method for each of these time-windows that discriminate the directions. We also compute the spatial patterns using adjacent time-windows as shown in Figure 3 which allows us to investigate the change in them across time as shown in Figure 4. Once the spatial patterns have been computed, the testing stage starts by splitting the trials into similar time-windows for evaluation based on the spatial patterns of the corresponding time-window. For each time-window the distance of the LDA classifier is evaluated and stored as the final decision on the direction is based on the sum of all these LDA distances. The direction that has the smallest cumulative LDA distance will be labeled as the direction of the trial.

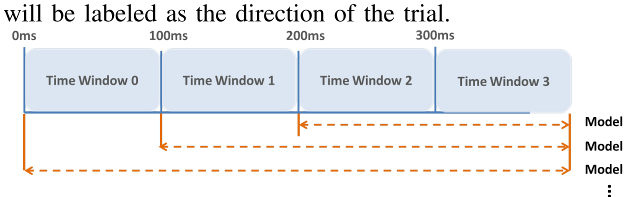

Fig. 3: The process used to calculate the models at each time window is shown. In this figure, we show the models calculated when evaluating Time Window 3, which involves determining the spatial patterns using ranks from windows (2,3), (1,2,3) and (0,1,2,3). The same process is repeated for all the time-windows.

The proposed algorithm can be presented as follows:

Training Stage:

1) For each channel calculate the rank based on its instantaneous power as discussed in [12].
2) Divide the trial into overlapping or non-overlapping time-windows of length Tms, determined by cross-validation.
3) At each time-window, calculate the spatial-pattern models of the rank patterns, based on its previous windows as shown in Figure 3.

Testing Stage:

1) Use step 1 from above to calculate the rank patten of the trial. Use step 2, to evaluate the models with their corresponding time-windows.
2) At each time-window, retain the LDA distance of each of the model. Final direction decision is given as the direction that has the minimum cumulative LDA distance of all the models that are evaluated.

III. DATA ACQUISITION

Two male rhesus monkeys, H464 and H564 were trained and instructed to perform a instructed-delay-center-out-target-reach task. When an appropriate cue is provided, the subject

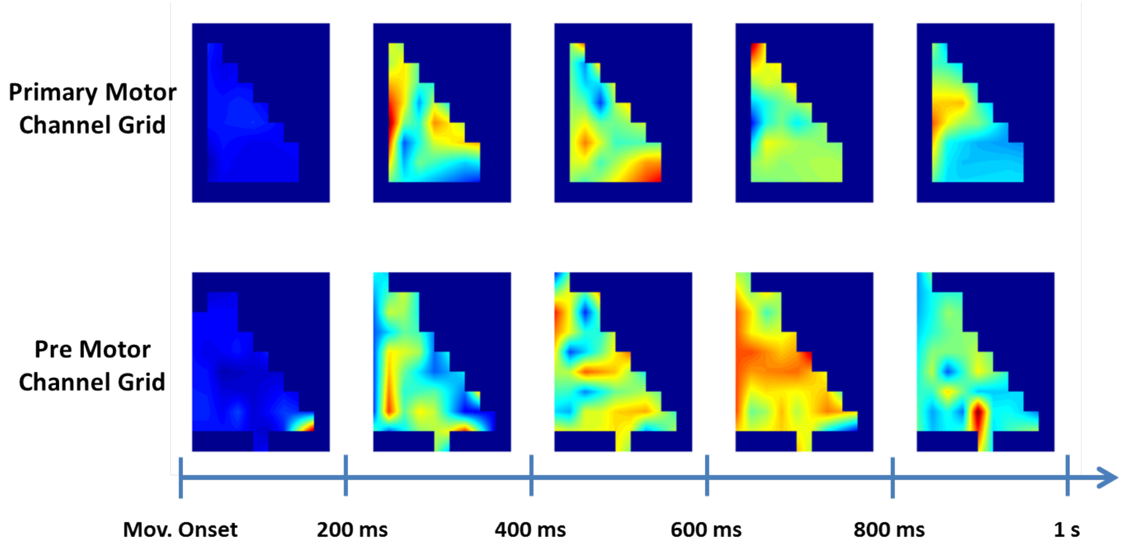

Fig. 4: The time evolution of spatial patterns as observed for the direction 0 movement in Session 1 performed by subject H464. The top part corresponds to the evolution in the grid placed over the primary motor and the bottom shows the evolution in the pre-motor grid. The spatial patterns computed every 200ms after the movement onset are shown here.

was trained to move a robotic manipulandum to one of the eight targets on a horizontal plane. The targets were arranged in a circle separated by an angle of 45 . The experimental paradigm proposed by [1] is adopted in our experiments and is shown in Fig.5. In most of the trials, the subjects were able to reach the target within 1s of stimulus. To record the neural activity, two 64-grid Utah micro-electrode grid arrays, one in the Primary and other in the dorsal Pre-motor cortex area of the brain were implanted in both the subjects.

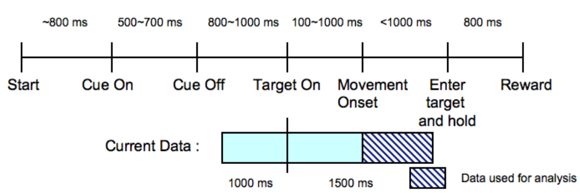

Fig. 5: The timeline for each trial of the experiment indicating the median time to be spent in each phases of the experiment.

The recordings from the both the subjects were recorded over multiple weeks. To assess the learning involved, various field forces against the movement were applied in some sessions viz. No Force (NF), Viscous Counter Clock-wise (VCCW), Viscous Clock-wise (VCW) and Stiff Clock-wise (SCW). Figure 6 shows a calendar time-line of the recordings for subject H464, and the field forces applied in those sessions. 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. Several trials were recorded and only those that had accurate responses were considered in the study. The LFP data acquired from the 128 electrodes is then filtered in 0.4 - 200 Hz, at a sampling rate of 1 KHz. Artifacts like power line noise and large DC wanders were identified by means of visual inspection of power spectrum and duly removed. In this analysis, we use 1s of data after the movement of the manipulandum began. It was shown that lower frequency bans 0.4 - 4Hz, i.e., the δ-band contained discriminating information of the eight movement directions [8]. We focus only on this band for our analysis.

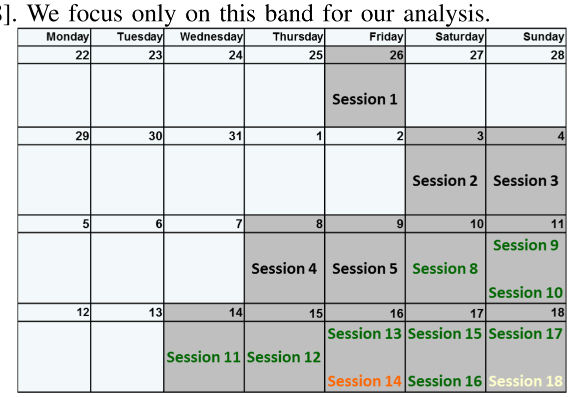

Fig. 6: Calendar time-line of the data collection for subject H464. The session in the black font are sessions without any external forces. Green font represents the VCCW sessions, the orange font VCW sessions and yellow font SCW sessions.

IV. Result

We use two measures to evaluate the performance of the algorithms. 1. Decoding Power (DP): The ratio of the total number of correctly decoded trials to the total number of trials in the testing session. 2. Bitrate per trial: It is defined by the following formula according to Shannon's theorem as $I := \log_2 N + p \log_2 p + (1-p) \log_2 (1-p)/(N-1)$, with number of classes N and classification accuracy p [15].
Please note that the CSP filters are all trained using only one session, and the sessions following the training session

chronologically are used to evaluate the performance of the different algorithms. For all the algorithms, the same CSP and ECOC methodology are used. Also, note that the accuracy with a random classifier for an 8 class problem would be 12.5% and a bit information rate of 0. Table I shows the decoding power proposed method, for the subject H464, with different time-windows and overlaps, and it outperforms the baseline methods. To achieve the same bit information rate of 0.98 (highlighted result with a window of 30ms)with a two class classification problem would require an accuracy of over 99%. For subject H564, we observed that the decoding powers were 65.5% and 60.2% in comparison with 53.3% and 51.5%, with traditional methods, on days 7 and 8 respectively. For both these subjects, the training was performed on session 1.

We have also observed similar results in sessions with field forces against movement as shown in Figure 7. It is observed that all the techniques fail to perform when the field forces in the testing session are in the opposite direction to that of the training session. However, when the same field forces are presented after this interruption the models continue to perform with high decoding power. These results show that using the time evolving method performs better than a static spatial pattern. These results highlight the need of using evolving spatial patterns of electrode ranks in the context of robust movement decoding in LFPs.

TABLE I: Decoding Power and Bit-rate(BR),in subject H464 over 4 testing sessions, with the day indicated in parenthesis. For comparison, the decoding powers from the baseline method, the best performance for the Rank CSP (using the optimal time-window) is presented.

Alg. \ Sess	2(8)	3(9)	4(13)	5(14)	Avg.	BR
Only CSP	43.2	50.9	20.7	9.1	30.9	0.16
Rank CSP	63.5	70.2	52.01	44.32	57.5	0.81
Time Evolving						
250ms (25%)	67.3	65.9	52.6	43.2	57.2	0.80
250ms (50%)	67.3	68.9	54.3	46.6	59.2	0.87
100ms (25%)	68.8	66.5	56.3	50	60.4	0.91
100ms (0%)	73.8	68	56.6	48.8	61.8	0.96
75ms (0%)	69.9	66.2	57.8	50	60.9	0.93
50ms (0%)	69.6	66.8	57.8	48.9	60.7	0.93
30ms (0%)	71.1	69.2	58.3	50	62.1	0.98
15ms (0%)	70.7	68.6	58.6	50	61.9	0.97

V. CONCLUSIONS

In this paper we have introduced a time-evolving spatial pattern algorithm to build robust classifiers and hence improve the efficiency in movement decoding in LFPs. We have shown that by using this method, the decoding power is almost doubled on an average over 2 weeks of testing data for one subject, in comparison to the traditional method. Using this method the performance is elevated to 0.98 bits per trial from 0.168 bits per trial. These results emphasize the use of evolving classifiers to build a robust classifier. In conjunction with using the qualitative information, in the form of inter-channel ranks, this method is very effective in movement decoding. By using adaptive window-lengths to accommodate the variation in performance of individual trials, this method can achieve even better results.

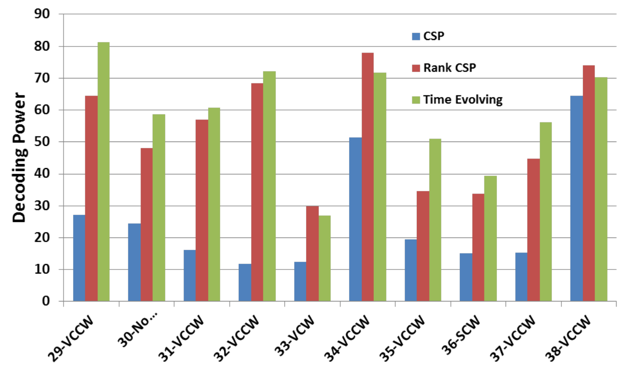

Fig. 7: Decoding Powers of the time-evolving Spatial Patterns in comparison with baseline methods in subject H464. For all these models, the session 28 (VCCW) is used for training, the session number and the field force applied are also indicated.

REFERENCES

[1] A. Georgopoulos, J. Kalaska, R. Caminiti, and J. Massey, "On the relations between the direction of two-dimensional arm movements and cell discharge in primate motor cortex," *J. Neurosci.*, vol. 2, no. 11, pp. 1527–1537, 1982. [Online]. Available: http://www.jneurosci.org/cgi/content/abstract/2/11/1527

[2] M. C, "Inference of hand movements from local field potentials in monkey motor cortex," *Nature Neuroscience*, vol. 6, 2003.

[3] H. S. et al., "Cortical local field potential encodes movement intentions," *Neuron*, vol. 46, pp. 347–354, 2005.

[4] W. e. a. Stephen, "Hand movement direction decoded from meg and eeg," *Journal of Neuroscience*, vol. 3, pp. 1000–1008, January 2008.

[5] G. e. a. Schalk, "Decoding two-dimensional movement trajectories using electrocorticographic signals in humans," *Journal of Neuro Engineering*, vol. 4, pp. 264–275, 2007.

[6] E. Salinas and L. F. Abbott, "Vector reconstruction from firing rates," *Journal of Computational Neuroscience*, vol. 1, pp. 89–107, 1994, 10.1007/BF00962720. [Online]. Available: http://dx.doi.org/10.1007/BF00962720

[7] I. Asher, E. Stark, M. Abeles, and Y. Prut, "Comparison of Direction and Object Selectivity of Local Field Potentials and Single Units in Macaque Posterior Parietal Cortex During Prehension," *Journal of Neurophysiology*, vol. 97, no. 5, pp. 3684–3695, 2007.

[8] N. Ince, R. Gupta, S. Arica, A. Tewfik, J. Ashe, and G. Pellizzer, "Movement direction decoding with spatial patterns of local field potentials," in *Neural Engineering, 2009. NER '09. 4th International IEEE/EMBS Conference on*, May 2009, pp. 291 –294.

[9] W. Jensen and P. Rousche, "On variability and use of rat primary motor cortex responses in behavioral task discrimination," *Journal of Neuro Engineering*, vol. 3, pp. L7–L13, 2006.

[10] N. Murata, M. Kawanabe, A. Ziehe, K.-R. Mller, and S. ichi Amari, "On-line learning in changing environments with applications in supervised and unsupervised learning," 2002.

[11] B. Blankertz, M. K. R. Tomioka, F. U. Hohlefeld, V. Nikulin, and K. robert Mller, "Invariant common spatial patterns: Alleviating non-stationarities in brain-computer interfacing," in *In Ad. in NIPS 20*. MIT Press, 2008, p. 2008.

[12] V. A. Tadipatri and A. H. Tewfik, "Time robust movement direction decoding in local field potentials using channel ranking," in *Engineering in Medicine and Biology Magazine*, vol. 29. IEEE, 2010.

[13] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. robert Mller, "Optimizing spatial filters for robust eeg single-trial analysis," in *IEEE Signal Processing Magazine*, 2008, pp. 581–607.

[14] B. Reuderink and M. Poel, "Robustness of the common spatial patterns algorithm in the bci-pipeline," Enschede, July 2008. [Online]. Available: http://doc.utwente.nl/64884/

[15] G. Dornhege, B. Blankertz, G. Curio, and K.-R. Muller, "Boosting bit rates in noninvasive eeg single-trial classifications by feature combination and multiclass paradigms," *Biomedical Engineering, IEEE Transactions on*, vol. 51, no. 6, pp. 993 –1002, 2004.