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ROBUST MOVEMENT DIRECTION DECODERS FROM LOCAL FIELD POTENTIALS USING SPATIO-TEMPORAL QUALITATIVE PATTERNS

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ABSTRACT

A major drawback of using Local Field Potentials (LFP) for Brain Computer Interface (BCI) is their inherent instability and non-stationarity. Specifically, even when a well-trained subject performs the same task over a period of time, the neural data observed are unstable. To overcome this problem in decoding movement direction, this paper proposes the use of qualitative information in the form of spatial patterns of inter-channel ranking of multi-channel LFP recordings. The quality of the decoding was further refined by concentrating on the statistical distributions of the top powered channels. Decoding of movement direction was performed using Support Vector Machines (SVM) to construct decoders, instead of the traditional spatial patterns. Our algorithm provides a decoding power of up to 74% on average over a period of two weeks, compared with the state-of-the-art methods in the literature that yield only 33%. Furthermore, it provides 62.5% direction decoding in novel motor environments, compared with 29.5% with conventional methods. Finally, a comparison with the traditional methods and other surveyed literature is presented.

Index Terms— Brain Computer Interface, Local Field Potentials, Support Vector Machines.

I. INTRODUCTION

The main problem with using invasive neural-recording modalities is their instability and non-stationarity over time [1]. Only a fraction of the single units have stable activity over a period of two weeks [2]. However, most pattern-recognition algorithms rely on stationary features that show little or no change over time. Hence these characteristics (instability and non-stationarity) pose problems in developing robust decoders that can be trained only once. Many studies have used 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 [3], [4]. In others, daily re-training is needed to improve the performance of the same task [5].

This paper will focus on the following issues: 1) Overcoming the instability and non-stationarity concerns of the data, 2) Providing stable decoders over two week time frame, and 3) Studying the spatial and temporal organization of the motor cortex when performing motor tasks. The inherent non-stationarity of the LFP data can be tackled by transforming the data into a pseudo-stationary space in the form of relative inter-channel rankings. The main contribution of this paper lies in developing robust features from the non-stationary neural data and using them to build consistent decoders, thereby eliminating the need for re-training. The novelty lies in first extracting the spatial distribution of the high energy channels over time and using a non-linear decoder to decode the direction. Using this methodology, the movement directions were decoded at an average of 74% over a period of two weeks. Similar robust performance was observed when this algorithm was tested across sessions with varying external field forces.

The remainder of the paper is organized as follows: Section II discusses the experiment and the data acquisition; Section III describes the methods used for analysis, and is followed by results and discussion in Section IV; and finally concluding remarks are presented in Section V.

II. DATA

Two male rhesus monkeys (H464, H564) were trained to perform the center-out-target-reach task with a robotic manipulandum. The subjects were implanted in the primary and the dorsal pre-motor areas, with two 64-grid Utah micro-electrode arrays. The experimental paradigm and the preprocessing are the same as in [6]. For one subject (H464), the initial sessions were performed over a two week period with the following chronology; session 1 on day 1, sessions 2 and 3 on days 8 and 9 (a week from session 1) and sessions 4 and 5 on days 13 and 14 (two weeks from session 1) respectively. The following sessions were performed with varying external field forces against movement, such as Viscous Clock wise (VCW), Viscous Counter Clock wise (VCCW), Stiffness Clock Wise (SCW) and No Force (NF). The use of external forces aids in investigating the changes in the neural patterns in novel environments. All the trials

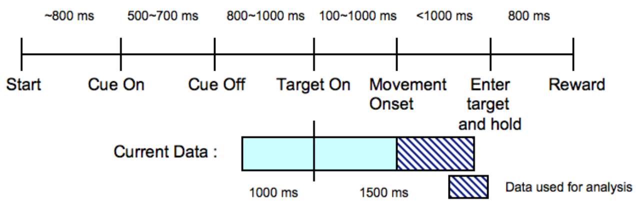

Fig. 1: Time-line of the neural data to be used in the analysis.

in a particular session were performed in a randomized fashion. Figure 1 shows the pseudo-random time spent by the subject at each cue of a single trial. At the successful completion of such a trial subjects were given a juice reward and only these trials were included in the analysis. The number of successful trials varied from 10 per direction in the least successful session to 35 in the most successful one. During the preprocessing stage time-frequency analysis and histograms were used to remove channels that had low Signal to Noise Ratio (SNR) or high baseline wander, thus retaining 61 channels for H464 and 98 for H564.

III. FEATURE GENERATION

This section discusses the feature generation and decoding algorithms used in this paper. The data in the LFP recordings consists of several trials, each consisting of N simultaneously recorded channels. The neural field potential in each channel is sampled T times. Thus, each trial of the neural data can be represented as a matrix $X \in \mathbb{R}^{T\times N}$. During each recording session, movement to various directions are repeated K times and can be represented as $\mathcal{X} = [X_1...X_k...X_K] \in \mathbb{R}^{K\times T\times N}$. These trials have class labels of 0,45,90,135,180,225,270,315. In order to account for this variation in the raw neural data recorded over different sessions, the quantitative neural data was transformed into qualitative information in the form of inter-channel power ranks [6]. It was observed that certain groups of electrodes have relatively high and low power levels depending on the direction of movement. To extract this observation, the following algorithm was used:

1) Calculate the power of each channel in W overlapping time windows.
2) In each time window, sort the channels based on their power calculated above.
3) Then rank the channels such that the highest powered one has the highest rank in that time window.
4) Replace the raw neural data with the corresponding inter-channel power ranks calculated.

By using this transformation, a $\mathbb{R}^{K\times T\times N}$ is projected to a $\mathbb{N}^{K\times W\times N}$ that spans $\mathbb{N}^N$. This projection eliminates any variations in dynamic range by bounding it to N and provides us feature vectors to train stable decoders. Common Spatial Patterns (CSP) is traditionally used to identify existing task dependent spatial patterns [6], [7], [8]. In this paper, this concept is extended to the spatial distribution of high powered channels. As shown in Figure 2, there exists certain patterns that are common to one direction and are absent in the others. These patterns were observed in at least 50% of the repeated trials for reaching a particular target and were observed in at most 30% of the trials corresponding to other target reaches. To extract these patterns from the qualitative information the spatial distribution of only the top ranked (or high power) channels was empirically calculated. If $X \in \mathbb{R}^{T\times N} = x(t,n)$, is the neural data at time t and channel n of a single trial as indicated above, and $p(t,n) = PowerRank(x(t,n))$ is the power rank of the channel as obtained from the algorithm above, then the rank patterns RP are defined as

$$RP(t,n) = \begin{cases} 1 & \text{if } p(t,n) \geq R_{th}, \\ 0 & \text{otherwise} \end{cases}$$

where R_{th} is a predefined rank threshold.

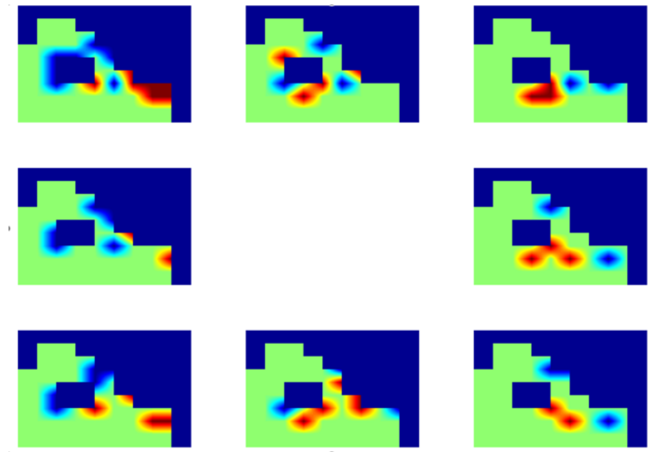

Fig. 2: Discriminative Spatial Distribution in the Motor cortex grid for the eight movement direction (placed at their corresponding target locations). Spatial Locations indicated by the red spots have relatively higher power than those in blue. The neural recordings were from the area shaded green; electrodes from the blue-shaded area were not sampled.

Thus, at any instant, the spatial distribution of the high power channels is given by the location of '1' on the electrode grid. By estimating the location of these channels at successive time instances, a spatio-temporal distribution of the top R_{th} ranked channels can be developed. Further, focus can be shifted to the low powered channels by simply choosing a value of R_{th} closer to the total number of channels N. It has been shown that non-linear classifiers provide better accuracy than simple linear classifiers, especially when dealing in a high dimensional feature space. In BCI applications, the features extensively used in the classification of multi-channel neural data are frequency band power, auto regressive parameters, and wavelet coefficients [7]. For our analysis, a support vector classifier with Radial-Basis kernel was built using the WEKA software [9]. And to improve decoding accuracy with multiple directions, redundant non-linear classifiers similar to the error correction output code (ECOC) strategy are employed, where each classifier tested groups of directions [8]. The grouping of directions is based on the neural correlation observed in neighboring directions. The δ-band (0-4 Hz) provided good movement decoding [8], and that frequency band was analyzed. As shown in the Figure 1, the data 1s after the movement onset is used to perform the analysis. The next section discusses the obtained results from the analysis and some inferences.

IV. RESULTS AND DISCUSSION

As mentioned before, the main objective of this investigation was to develop a robust movement decoder with a single training session. This was tested by using a decoder, learned from a single session, more than a week old than the testing sessions. The measure used for comparison is the decoding power (or decoding accuracy) and is defined as the ratio of number of correctly predicted trials to the total number of trials. The performance is compared with the state-of-the-art CSP method [8] and the Rank-CSP method in [6]. For consistency, the same set of redundant classifiers in the ECOC method for both the CSP methods are used. Note that the decoding accuracy achieved by random selection results in an accuracy of 12.5% for eight different target reaches.

The results of varying channel rank threshold (R_{th}) for subject H464 are shown in Table I. From the table it can be inferred that at least 20 top powered channels need to be analyzed to obtain reliable decoding performance over two weeks. This result underscores the variability existing in the data over multiple days. The analysis of top 5 powered channels results in poor performance highlighting the change in the spatio-temporal locations of this subset. On the other hand, the top 20 powered channels are fairly stable across the two weeks of testing. Also, decoding information was be extracted from the low ranked channels (results from rank 40 and 50). Finally, consistent and superior decoding performance is achieved by the cumulation of all the top rank information. The choice of the number of top rank channels depends on the variability of the data that is being analyzed.

Table I: Decoding Power for different top ranked channels. The decoding power for subject H464 over different testing days after the training day is shown.

R_{th} \ Test Day	8	9	13	14
5	27.38%	32.00%	21.84%	25.00%
10	43.35%	50.46%	47.13%	30.68%
20	66.92%	64.92%	62.93%	47.73%
30	74.52%	75.08%	59.48%	56.82%
40	63.88%	71.07%	58.62%	51.14%
50	63.88%	61.54%	53.74%	54.55%
Cumulative Top Ranks	75.67%	80.62%	70.4%	69.32%

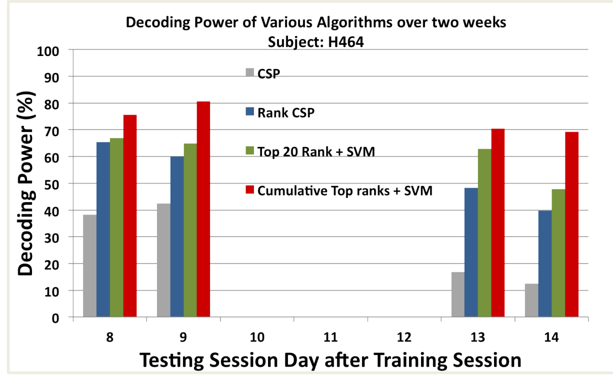

Fig. 3: Comparison of Decoding Powers across various algorithms.

A comparison of the results for various algorithms for subject H464 are provided in the Figure 3 and for subject H564 in Table II. Superior decoding performance of our method was observed when all algorithms were tested on sessions with external field forces, as presented in Figure 4. Here, the decoders were trained on a session where the external force VCCW was applied. It is evaluated on sessions where different field forces were applied. These results indicate the consistency in the spatial location of the top ranked channels. The authors conclude this is a result of extracting the stable spatio-temporal patterns that are responsible for the direction decoding. For the sessions with same field forces as the training session, or no field forces (ex. session 30, 39) the algorithm provided consistent decoding over multiple sessions as seen in Figure 4. However when opposite forces were tested (ex. session 33, 36), although our algorithm's performance trumps the others, the accuracy is poor. This shall be explored in future studies.

Another measure to compare the results of decoding is information bit-rate which is calculated by the Shannon's theorem $I := \log_2 N + p\log_2 p + (1-p)\log_2(1-p)/(N-1)$, with number of classes N and classification accuracy p. Using that formulation, the proposed algorithm achieves a bit-rate of 1.44 bits/s, while the traditional algorithms (CSP) achieve 0.59 bits/s. Table III shows a comparison of other surveyed literature which use similar paradigms to decode movement direction. The algorithms available in literature use cross-validation or re-training to test their decoders. Thus the natural (daily) variability of neural recordings is ignored, and an optimistic estimate of the algorithm's performance is shown. The results obtained using our methodology are much closer to practical results with no need of re-training.

Table II: Comparison of Decoding Powers across various algorithms for Subject H564.

Day after Training	8	9
CSP	41.37%	40.38%
Rank CSP	51.44%	48.8%
Top 20 Ranks	56.31%	43.69%
Cumulative Top Ranks	61.17%	48.54%

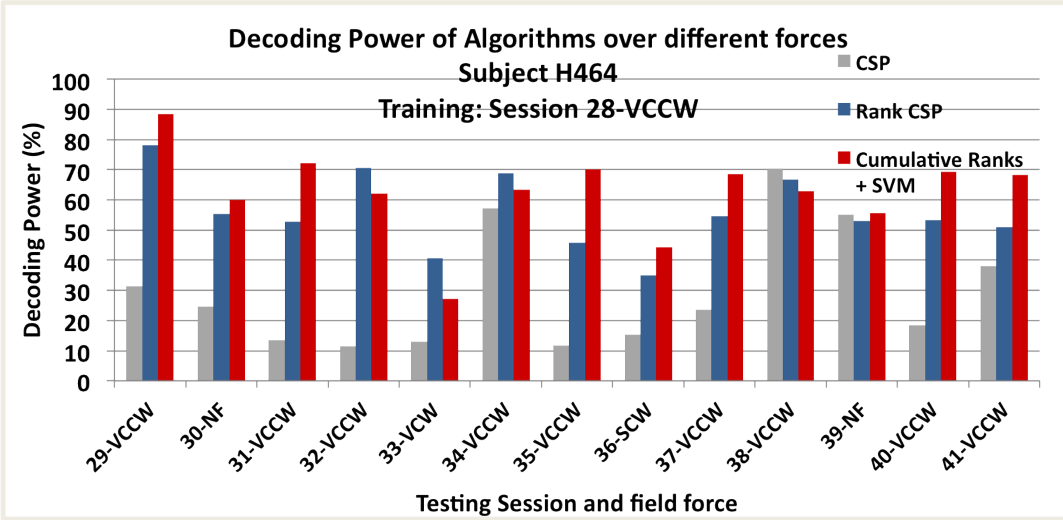

Fig. 4: Comparison of Decoding Powers across various algorithms across sessions with varying external field forces. Training was performed on session 28 which had VCCW external field force.

Table III: Decoding Power (DP) and Bit-rate(BR) of various methods in comparison with the proposed method. Note that the other studies used cross-validation for their analysis.

Algorithm	DP (# directions)	BR
Bayesian Decoding, SVM [3]	40% (8)	0.35 bits/s
Directional Tuning [4]	50% (8)	0.59 bits/s
Bayesian Classification [10]	81.4% (8)	1.78bits/s
Proposed Method	74% (8)	1.44 bits/s

V. CONCLUSION

This paper presents the use of qualitative information, in the form of inter-channel power spatial distribution to provide stable movement decoding over time. Non-linear classification techniques on these features are used to improve decoding performance over time and in novel motor environments. Since these spatial distributions are consistent across various recording sessions, the proposed feature extraction and classification algorithm provides better results than the existing common spatial pattern methods. These algorithms may also benefit from extracting features that utilize multiple frequency bands like wavelet decomposition. Further, feature subset selection algorithms can be used to reduce the high dimensionality of the data sets. Finally, our data offer the possibility of identifying a stable pattern in the neural recordings for real-time neural control. Because this decoder is stable, it is possible to use the same decoding filter over days, without the need for re-training the decoder on a daily basis, and making the BCI technology more user-friendly in a clinical setting.

VI. REFERENCES

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