ROBUST LONG TERM NEURAL SIGNAL DECODING BY ESTIMATING UNOBSERVED FEATURES

Vijay Aditya Tadipatri, Ahmed H. Tewfik

Dept. of Electrical and Computer Engineering
The University of Texas at Austin
Austin, TX

James Ashe

Department of Neuroscience
University of Minnesota, Twin Cities
Minneapolis, MN

ABSTRACT

Chronic effects of electrode implantation in the brain tissue alter the neural channel signal-to-noise ratio (SNR) over time. Variability of signal quality over time poses a difficult challenge in long-term decoding of neural signals for Brain Computer Interface (BCI). Specifically, all channels observed during a neural recording session may not be observed during the next recording session. This paper describes a novel approach that effectively overcomes these challenges by identifying reliable channels and features in any given trial, estimating unobservable or unreliable features and adapting the neural signal classifier with no user input in real time. The proposed decoder predicts one of eight arm directions with an accuracy, unmatched in the literature, of above 90% in two monkeys over 4-6 weeks, achieving robustness against time and also varying environmental conditions. Application of these decoders reduces neural prosthetic training time and user frustration thus improving the usability of BCI.

Index Terms— Brain Computer Interface, Partial Observations, Signal Variability, Local Field Potentials

1. INTRODUCTION

Arm movement for Brain Computer Interface (BCI) can be decoded from intention through intra-cortical recordings like single unit activity (SUA) and local field potentials (LFP) [1, 2, 3, 4, 5]. Recent neural engineering advances improved the recording capabilities of LFP over multiple months [6]. For example, Simeral et al., showed the long-term (1000 days) recording capability of LFP [7]. While these studies establish the long-term recording capability of LFP, their use in long-term decoding applications has not received much attention. Day-to-day signal variability poses a difficult challenge in long-term decoding from LFP. These variabilities manifest in various forms: variations in signal power, change in spatial patterns, etc., and result in variation in derived features [8]. Recent studies show the success of advanced signal processing techniques to overcome such long-term variability. For example, extracting robust feature parameters [9], or rapid prototyping [10] help overcoming such variabilities. Daily re-training of closed-loop LFP decoders also achieves long-term decoding [11]. However, such pauses to recalibrate BCI cause user frustration [12]. While a BCI user learns to modulate neural patterns to match the BCI [13], this process requires effort and sometimes users are incapable of learning these patterns [12]. Moreover, these studies ignore the variability of neural signals over multiple days. We also observed that the signal-to-noise ratio (SNR) of LFP electrodes varies over days due to acute and chronic effects of electrode implantation in brain tissue [14]. Hence a practical BCI system should cope with changes in signal variabilities, including signal SNR over multiple days. In this paper, we present a novel model that overcomes LFP variability by first identifying and then evaluating only high quality (high SNR) channel recordings.

A BCI system that requires fewer calibration sessions helps users focus on rehabilitation tasks rather than neural exertion to provide stable neural patterns [12]. Our approach focuses on extracting useful neural patterns through out BCI performance and incorporating these patterns in the decoder. One of the challenges during such reinforcement learning is the variation in the signal quality in terms of SNR [15]. While studies showed the efficacy of BCI adaptation for stable performance [11, 16], the effect of variable channel SNR was not studied. Specifically, we observed loss of recording channels as channels that have a high SNR during a session might have a low SNR during the next session and vice-versa. However, we noticed that the spatial patterns of the common channels (with high SNR) remained consistent. The current paper takes advantage of this observation and overcomes the variability in signal quality. We also present a method to estimate unobservable channel features by tracking the neural pattern evolution in term of auto-regressive models.

The main contributions of this paper are 1) introducing an arm direction decoder that automates channel selection by virtue of SNR; 2) estimating unknown feature parameters by modeling neural pattern evolution and; 3) adapting the obtained decoder across multiple sessions to overcome signal variability. These include channel quality and variability in subject behavior due to both model latency and environmental

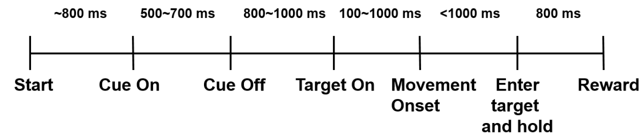

Fig. 1: Timeline of the neural data to be used in the analysis.

effects. This adaptive decoder obtained above 90% decoding of eight movement directions over 4-6 weeks of recordings in two monkeys and required only a single session of dedicated BCI training. Decoders that adapt to these changes reduce user frustration with BCI and increase their practicality [12].

The rest of this paper is organized as follows: Section 2 summarizes the neural and behavioral data; Section 3 discusses the method and algorithms used for decoding; Section 4 presents the obtained results and discussion, and Section 5 provides concluding remarks and related future work.

2. EXPERIMENTAL SETUP

We trained two male rhesus monkeys (Macaca mulatta), H464 and H564 to sit in front of a screen and perform an instructed-delay center-out task. During this task the subject moved a manipulandum in a horizontal plane to move a cursor from a central location to one of eight circular targets highlighted on the screen. The targets are equal spaced around a circle of 9cm from the center. A timeline for each trial with a median time spent at each epoch is shown in Figure 1. To receive a juice reward the subject had to perform the task within the time limits. We recorded and saved behavioral data (sampled at 200Hz) including hand position, velocity, forces and torques exerted at arm joints.

During this behavior task neural signals were recorded using two silicon based electrode arrays (Cyberkinetics, Foxboro, MA) implanted in the contralateral arm areas of primary motor (M1) and dorsal premotor (PMd) cortices. Each array recorded from 64 electrodes arranged on a 10x10 array with an inter electrode distance of $400\mu m$. We recorded both Single Units (SU) and local field potentials (LFP) during these sessions. The analysis in this paper focuses on LFP signals filtered in $0.3 - 200$Hz sampled at 1KHz.

We recorded several sessions of neural activity spread over 6 weeks for H464 and 4 weeks for H564. Once the monkeys gained expertise, we introduced external perturbations on the manipulandum during target reach. All the reaches in that session experienced the same curl forces that acted in a direction perpendicular to the arm movement. Two types of forces were exerted viz. Viscous forces that are proportional to the velocity of the hand movement, and; Stiffness forces proportional to the position of the hand. These forces were applied in both clockwise and counter-clockwise direction. We chose forces to cause perceivable perturbations to the hand, while allowing the monkey to complete the hand reach [17]. Any successful decoder should overcome

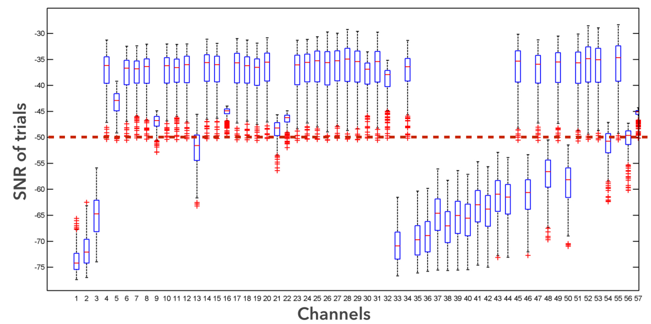

Fig. 2: SNR$_s$ of LFP channels recorded on the first session in monkey H464.

the non-stationarities introduced by the different experiment variations. Such a direction decoder is presented in the next section.

3. METHOD

Human behavior, including arm movement, is inherently variable and non-repetitive [18]. Each repetitive movement of the arm involves a unique set of motor patterns. As there exist multiple ways to perform a same task, we hypothesize that arm position is encoded effectively by multiple neural patterns that generate multiple motor patterns. Since, neural adaptation changes the spatial and temporal patterns of the brain activity, we proposed that the decoding model also needs a suitable adaptation strategy to track them [13, 19]. Identifying suitable neural patterns during BCI use and intelligently incorporating them in the decoder accomplishes decoder adaptation [16].

3.1. Estimating SNR surrogate of LFP channels

Since the actual signal and noise powers of LFP signal are unknown, we estimate a surrogate SNR statistic (SNR$_s$) of a given channel by measuring its deviation from the trial average. SNR$_s$ is calculated as a function of the deviation of a single trial LFP x_{tr}, from the signal averaged over multiple trials conducted in a given session, $\langle x_{tr} \rangle$, as shown in (1).

$$\begin{aligned} \sigma_{tr} &= \sqrt{\frac{1}{T}\sum(x_{tr} - \langle x_{tr} \rangle)^2} \\ SNR_s &= 20\log(\frac{1}{\sigma_{tr}}) \end{aligned} \tag{1}$$

The SNR$_s$ of different channels over the session is presented in Figure 2. All channels that have an SNR$_s$ more than -50dB are deemed non-noisy signals and used to train and test the decoding models. We observed that 82 ± 5 channels in H464 and 120 ± 2 in H564 had high SNR$_s$.

3.2. Model robustness against loss of LFP recordings

The decoding model, $\mathcal{M} = \{X, w, \phi_{\mathbf{x}}\}$, is trained only over a single session and its scope is limited to the electrode locations identified in that session. Here $\phi_{\mathbf{x}}$ calculates the similarity only over the channels ($\mathbf{x}$) in training data X and w represent the corresponding model weights. For example, $\phi_{\mathbf{x}}$ could be a radial basis function, or a linear correlation model that compares two feature vectors. During BCI use the model evaluation to predict the arm position p corresponding to a neural data Y is computed as

$$p = \sum_i w_i \phi_{\mathbf{x}}(X_i, Y) \quad (2)$$

Without loss of generality, the neural data extracted on the testing day, Y, and the training day, X, could be decomposed as

$$X_{\mathbf{x}} = \begin{bmatrix} X_c \\ X_x \end{bmatrix}, Y_{\mathbf{y}} = \begin{bmatrix} Y_c \\ Y_y \end{bmatrix} \quad (3)$$

,where $._c$ represents the common recordings from the training and testing spatial patterns. The other subscripts represent the electrode locations observed only on that particular session. Ignoring uncommon channels (X_x, Y_y) in both sessions, the pattern similarity $\phi_{\mathbf{x}}$ calculated only over these common channels predicts the arm position as

$$\begin{aligned} p &= \sum_i w_i \phi_c(X, Y) \quad (4) \\ \phi_c(X, Y) &= \phi(X_c, Y_c) \end{aligned}$$

3.3. Estimating Partial Neural Spatial Patterns

The above method discussed in 3.2, estimates the similarity of two neural pattern by selecting channels with high SNR$_s$ in both sessions. Ignoring channels with low SNR$_s$ limits noise creep and the model improves decoding accuracy. However, this strategy ignores any information from the remaining high quality channels. We estimate the similarity measure over all locations $\mathbf{x}$ as $\phi_{\mathbf{x}}(X, Y)$, shown in eq (5).

$$\begin{aligned} \phi_{\mathbf{x}}(X, Y) &= \phi(X_c, Y_c) + \phi(X_x, \hat{Y}_x) \\ \phi_{\mathbf{x}}(X, Y) &= \phi(X_c, Y_c) + \hat{\phi}(X_x, Y_x) \quad (5) \end{aligned}$$

We find estimating model similarity efficient than estimating the neural features $\hat{Y}_x$. Recognizing that the similarity calculated using the common channels is only a fraction of the total estimate, we hypothesize that prior knowledge gained from the channel and spatial pattern interaction provides additional decoding information. We track the local correlations between spatial patterns in the form of auto-regressive functions. The observation and auto-regression are written as

$$\begin{aligned} \phi_c(t) &= \mathbf{H}\phi_{\mathbf{x}}(t) + \vartheta \quad (6) \\ \phi_{\mathbf{x}}(t+1) &= \mathbf{F}\phi_{\mathbf{x}}(t) + \eta \quad (7) \end{aligned}$$

Table 1: Decoder performance and comparison across different phases of the recordings. For monkey H564 the average decoding is presented across all 20 recording sessions spread of 4 weeks. For monkey H464 the average decoding is calculated over 37 sessions spread over 6 weeks.

Session	Using Fixed Electrodes	Updating Electrodes	**Estimating Partial Observations**
H464			
Average Decoding (6 weeks)	89.8	93.5	**93.5**
Before Field Forces (2 weeks)	96.6	97.6	**96.7**
During Field Forces (4 weeks)	89	93	**93.1**
New Field Forces (9 sessions)	85	89.5	**89.8**
H564			
Average Decoding (4 weeks)	86.3	88.9	**89.7**
Before Field Forces (1 weeks)	81.1	79.9	**81.8**
During Field Forces (3 weeks)	86.9	89.9	**90.6**
New Field Forces (4 sessions)	83.8	85.3	**88.4**

, where t represents the time step of target reach; $\mathbf{F}$ is the auto-regressive parameter describing the evolution of spatial patterns; $\mathbf{H}$ is the observation parameter that models ϕ_c as a fraction of the variable $\phi_{\mathbf{x}}$. ϑ and η are zero mean gaussian white noise variables representing the neural variability observed in the measurements over days. Under perfect observability, we expect that observations follow the spatial correlations. However, due to changes in neural patterns the observations deviate from the modeled evolutions. These equations follow the Kalman filtering dynamical model system. Using the "**Predict**" and "**Update**" phases of the Kalman filter, the observation is filtered closer to the model estimates. The design of the Kalman filter parameters, involves calculating the auto-regressive parameters, $\mathbf{F}$ and the respective noise covariance on the neural samples recorded on the training session. For this application we design the observation matrix, $\mathbf{H}$, as a scalar under the assumption that all spatial filters are partially observed.

4. RESULTS AND DISCUSSION

The objective of the project is to design long-term decoding capability that provides stable performance, with minimal re-training sessions to mitigate BCI user frustration. All the decoding models were initially trained on the first session with no field forces and applied over chronological sessions spread over 4-6 weeks that included sessions with novel exter-

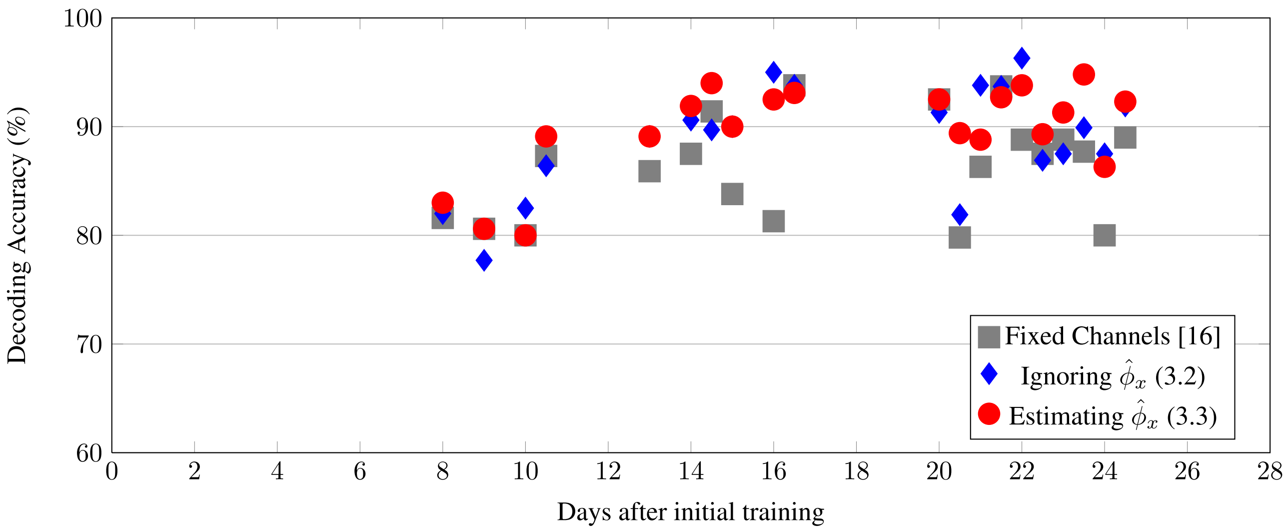

Fig. 3: Decoding Accuracy over multiple testing sessions recorded from subject H564 for decoders presented in the paper. We train the decoders on neural data recorded on day 0. Field forces are applied on sessions after day 10 and vary on different sessions. We observe that decoding accuracy is stable over 20 sessions and using high quality LFP signals improves decoding especially on day 15,16 and 20 (by 10%).

nal field forces. We measure performance as decoding accuracy (DA): percentage of accurately predicted targets during each target reach. A random classification results in an accuracy of 12.5%. During each evaluation session, the model is adapted after every K (= 25) trials. Adaptation of the model begins first by predicting the direction from the neural patterns. Under the assumption that the BCI user intends to reach the target in a straight path, we compare the prediction to an expected signal, modeled as a straight line from the center to the predicted target [16]. The adaptation strategy needs only accurate reaches to adapt the decoder by selecting neural patterns that minimize the error between the prediction and the desired straight line approximation. Feedback to the BCI system could be delivered via multiple modes like vocal cues, error related potentials, or residual muscle activity [15, 20].

Figure 3 presents the decoding accuracy over multiple recording sessions for the monkey H564. In monkey H464 field forces were introduced after two weeks of no field movement reaches and in monkey H564 after 10 days. Results from the figures show the improvement of decoding results when decoders consider only channels with high SNR. We observe that using high quality channels consistently performs better than a fixed channel decoder. Overall, the presented decoders improved up to 3% accuracy over decoders with fixed channels. Table 1 presents the performance of these decoders in different phases of recordings. In H564, the fraction of common channels between sessions is $98\% \pm 1$ leading the observation model to follow the auto-correlation model closely. This results in 3% decoding improvement over a fixed channel decoder. In H464 this fraction is only $87\% \pm 4$, resulting in an improvement of 1% of decoding accuracy. Estimating missing unknown neural features improves decoding accuracy to 93%. Especially, the decoder performance is improved in sessions that experience a change in the field force by 5%, as shown in the last row of Table 1. Overall, we infer that using session related high SNR channels improves decoding accuracy. Removing the low SNR channels eliminates any noise in the model without affecting the quality of the neural patterns.

5. CONCLUSION

In this paper, we presented neural decoders that provide robust arm decoding against LFP variabilities over time, environmental conditions like external field forces and also changing channel SNR. We observed that channels exhibit different SNR over multiple recording sessions. This paper introduced a method to estimate a surrogate statistic of SNR that and uses the identified channels with high SNR for direction prediction. The decoder presents a novel way of estimating unobservable neural patterns by modeling the feature correlations and system dynamics. This model provided up to 94% direction decoding in one monkey and 90% accuracy in another over 6 and 4 weeks respectively.

In the presented model we assumed that all spatial patterns are observed at the same fraction and $\mathbf{H}$ is modeled as a scalar. In fact, we can scale it to different observations. Preliminary research suggests that the design of the matrix $\mathbf{H}$ dictates the model observability and improves decoding. We should note that recordings occurred in an open-loop fashion, where the monkey received no feedback on decoder performance. We anticipate that the decoder performance would improve in a closed-loop setting, where subjects learn the dynamics of the model. Such decoders need few calibration sessions and improve the practical usability of BCI.

6. REFERENCES

[1] AP Georgopoulos, AB Schwartz, and RE Kettner, “Neuronal population coding of movement direction,” *Science*, vol. 233, pp. 1416–1419, 1986.

[2] Itay Asher, Eran Stark, Moshe Abeles, and Yifat 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.

[3] Hansjörg Scherberger, Murray R. Jarvis, and Richard A. Andersen, “Cortical local field potential encodes movement intentions in the posterior parietal cortex.,” *Neuron*, vol. 46, no. 2, pp. 347–354, Apr. 2005.

[4] Jörn Rickert, Simone Cardoso de C. Oliveira, Eilon Vaadia, Ad Aertsen, Stefan Rotter, and Carsten Mehring, “Encoding of movement direction in different frequency ranges of motor cortical local field potentials.,” *The Journal of neuroscience : the official journal of the Society for Neuroscience*, vol. 25, no. 39, pp. 8815–8824, Sept. 2005.

[5] John G. O’Leary and Nicholas G. Hatsopoulos, “Early Visuomotor Representations Revealed From Evoked Local Field Potentials in Motor and Premotor Cortical Areas,” *J Neurophysiol*, vol. 96, no. 3, pp. 1492–1506, Sept. 2006.

[6] Adam S. Dickey, Aaron Suminski, Yali Amit, and Nicholas G. Hatsopoulos, “Single-unit stability using chronically implanted multielectrode arrays,” *Journal of Neurophysiology*, vol. 102, no. 2, pp. 1331–1339, Aug. 2009, PMID: 19535480 PMCID: PMC2724357.

[7] J. D. Simeral, S.-P. Kim, M. J. Black, J. P. Donoghue, and L. R. Hochberg, “Neural control of cursor trajectory and click by a human with tetraplegia 1000 days after implant of an intracortical microelectrode array,” *Journal of Neural Engineering*, vol. 8, no. 2, pp. 025027, Apr. 2011.

[8] Vijay Aditya Tadipatri, Ahmed H. Tewfik, Vikrham B. Gowreesunker, J. Ashe, G. Pellizer, and R. Gupta, “Time robust movement direction decoding in local field potentials using channel ranking,” in *Engineering in Medicine and Biology Magazine*. IEEE, 2010, vol. 29.

[9] Benjamin Blankertz, Motoaki Kawanabe Ryota Tomioka, Friederike U. Hohlefeld, Vadim Nikulin, and Klaus-robert Müller, “Invariant common spatial patterns: Alleviating nonstationarities in brain-computer interfacing,” in *In Ad. in NIPS 20*, 2008, vol. 20.

[10] G. Pfurtscheller and C. Neuper, “Motor imagery and direct brain-computer communication,” *Proceedings of the IEEE*, vol. 89, no. 7, pp. 1123–1134, July 2001.

[11] Robert D Flint, Zachary A Wright, Michael R Scheid, and Marc W Slutzky, “Long term, stable brain machine interface performance using local field potentials and multiunit spikes,” *Journal of Neural Engineering*, vol. 10, no. 5, pp. 056005, 2013.

[12] A. Nijholt and D. Tan, “Brain-computer interfacing for intelligent systems,” *Intelligent Systems, IEEE*, vol. 23, no. 3, pp. 72–79, 2008.

[13] Karunesh Ganguly and Jose M. Carmena, “Emergence of a stable cortical map for neuroprosthetic control,” in *Article ID e1000153*, 2009.

[14] W Jensen and P.J. 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.

[15] Eric A. Pohlmeyer, Babak Mahmoudi, Shijia Geng, Noeline W. Prins, and Justin C. Sanchez, “Using reinforcement learning to provide stable brain-machine interface control despite neural input reorganization,” *PLoS ONE*, vol. 9, no. 1, pp. e87253, 01 2014.

[16] Vijay Aditya Tadipatri, Ahmed H. Tewfik, and James Ashe, “Long-term movement tracking from local field potentials with an adaptive open-loop decoder,” in *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2014, Florence, Italy, May 4-9, 2014*, 2014, pp. 5904–5908.

[17] Rahul Gupta and James Ashe, “Offline decoding of endpoint forces using neural ensembles: application to a brain-machine interface,” *IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society*, vol. 17, no. 3, pp. 254–262, June 2009.

[18] Nicholas Stergiou and Leslie M. Decker, “Human movement variability, nonlinear dynamics, and pathology: Is there a connection?,” *Human Movement Science*, vol. 30, no. 5, pp. 869 – 888, 2011, {EWOMS} 2009: The European Workshop on Movement Science.

[19] Steven M Chase, Robert E Kass, and Andrew B Schwartz, “Behavioral and neural correlates of visuomotor adaptation observed through a brain-computer interface in primary motor cortex,” *Journal of neurophysiology*, vol. 108, no. 2, pp. 624–644, July 2012.

[20] M Falkenstein, J Hoormann, S Christ, and J Hohnsbein, “ERP components on reaction errors and their functional significance: a tutorial,” *Biological psychology*, vol. 51, no. 2-3, pp. 87–107, Jan. 2000.