

# Combining Firing Rate and Spike-Train Synchrony Features in the Decoding of Motor Cortical Activity

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**Abstract**— Decoding of directional information in the motor cortex traditionally utilizes only firing rate information. However, information from other features could be extracted and combined with firing rate in order to increase classification accuracy. This study proposes the combination of firing rate and spike-train synchrony information in the decoding of motor cortical activity. Synchrony measures used are Event Synchronization (ES), SPIKE-Distance, and ISI-Distance. All data used for analyses were obtained from implanted electrode recordings of the primary motor cortex of a monkey that was trained to manipulate a motorized vehicle with 4 degrees of freedom (left, right, front and stop) via joystick control. Firstly, synchrony features could decode time periods, which were otherwise incorrectly decoded by firing rate alone, above chance levels. Secondly, using an ensemble classifier design for offline analysis, combining firing rate and ISI-distance information increases overall decoding accuracy by 1.1%. These results show that synchrony features in spike-trains do contain information not carried in firing rate. In addition, these results also demonstrate the feasibility of combining synchrony and firing rate for improving the classification accuracy of invasive brain-machine interface (BMI) in the control of neural prosthetics.

## I. INTRODUCTION

Brain-Machine Interface (BMI) translates neuronal information into a voluntary motor output [1]. For patients suffering from Completely-Locked-In Syndrome (CLS) or other similar diseases such as Amyotrophic Lateral Sclerosis (ALS), BMI is important for replacement of lost motor outputs. Several groups have recently extracted neuronal spikes from motor areas of non-human primates for controlling computer cursor or robotic arm [2-6]. Since neurons communicate with each other through spikes [7], most motor cortical representations are based on firing rates of spike trains [5]. The independent-coding hypothesis holds that neuronal signals are independent of each other, while the coordinated-coding hypothesis suggests some form of synchrony between neuronal signals is important for neural representation [7]. Neural synchronization is common throughout the visual and auditory cortexes [8-10], and may carry significant information in the motor nervous system. For the primary motor cortex, predicting movement direction based on independent population coding is well-established [11]. Studies have shown that there is sufficient information in independent neuronal signals for predicting movement direction [12]. It was also reported that the coincidence of

spikes has been shown to carry approximately 10% of the information carried by firing rate in the motor cortex, and adding numbers of synchronous spikes did not increase information carried by spike counts [13]. However, such studies did not employ the use of the synchrony measures we are investigating.

In this paper, we investigate whether adding synchrony features to firing rate features will improve decoding performance in an invasive BMI. We compare 3 measures of spike-train synchrony, SPIKE Distance [14, 15], ISI-Distance (Inter-spike Interval) [16], and Event-Synchronization (ES) [17] in the context of decoding directional information in the primary motor cortex. We subsequently employ an ensemble classifier design to combine firing rate and ISI-distance information for decoding.

## II. COMBINING SYNCHRONY AND FIRING RATE

Combining synchrony and firing rate involves 4 main stages (Spike Detection, Synchrony/Firing Rate measure, Feature Selection, and Classification) that perform a selection of session-specific discriminative firing rate and synchrony features, and classification for 4-class invasive BCI.

### A. Spike Detection

Spike detection was performed after filtering of raw data. Continuous raw data were filtered with an elliptic band pass filter between 300 and 3000 Hz. Threshold was determined using an automatic threshold [18]:

$$Thr = 5\sigma_n \quad \sigma_n = \text{median}\left\{\frac{|x|}{0.6745}\right\}, \quad (1)$$

where  $x$  is the bandpass filtered signal, and  $\sigma_n$  is an estimate of the standard deviation of the background noise [19]. Spike sorting was not performed because it did not substantially improve online decoding accuracy, and required more computational time.

### B. Calculating Firing Rate and Synchrony Measures

Firing rate was calculated using a binwidth of 500ms. For calculation of synchrony measure, we did not consider the use of measures- such as the Victor-Purpura Distance [20] and van-Rossum Distance [21] - because they are not time-resolved. In addition, these measures require setting of parameter for time scale which might result in human errors and dilute comparisons between sets of results with differently tuned parameters. The ISI distance is a symmetric and time-scale adaptive measure of the relative firing rate profile. It is based on the relative length of simultaneous ISIs and quantifies the similarities in neurons' firing rate profiles. The SPIKE-Distance is similar to the ISI-Distance except that

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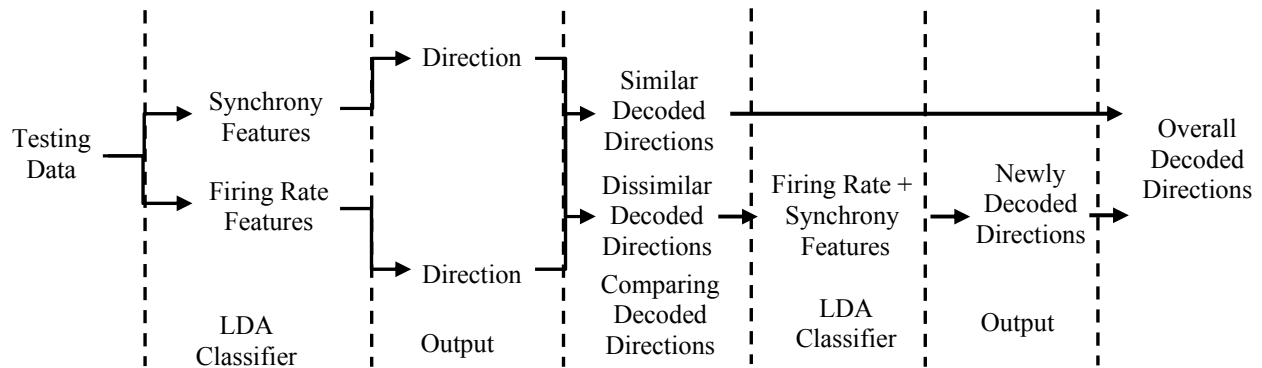


Figure 1: Architecture of the ensemble classifier design used for offline analysis. Individual directional outputs from synchrony and firing rate features are decoded and compared. Similar directional outputs are kept, while different directional outputs are classified using a concatenated matrix with both firing rate and synchrony features. Overall decoded directions are obtained by considering the similar decoded directions and newly decoded directions.

it considers exclusively on spike-timing rather than ISIs [14]. SPIKY GUI [15] was used to calculate SPIKE-Distance and ISI-Distance. Time bins of 500ms were used for the calculation of SPIKE and ISI-Distance. ES measures the number of quasi-simultaneous events, using a changeable time scale that adapts to local firing rates. Both SPIKE-Distance and ISI-Distance do not automatically adapt to the local firing rate. Mathematical equations and explanations can be found in the reference papers.

### C. Mutual Information-based Best Individual Features Algorithm (MIBIF)

Feature Selection was done using the Mutual Information-based Best Individual Features (MIBIF) algorithm [22] on the training data set. This algorithm selects the best features that results in the highest estimate of mutual information for the 4 classes. Both firing rate and synchrony features were ranked in descending order of bits independently using this algorithm. 26 firing rate features and 325 synchrony features were ranked.

If the set of features and true class labels is denoted as,  $F = [f_1^T, f_2^T, \dots, f_m^T]$ , where  $f_k^T \in R^{n \times 1}$  is the  $k^{\text{th}}$  column vector of  $F$ ,  $m$  is the number of features,  $k$  is the channel number (for firing rate) or channel pair (for synchrony) and  $n$  is the number of time bins, mutual information between feature  $f_k$  with the class label  $\omega = \{1,2,3,4\}$  is given by the equation:

$$I(f_k; \omega) = H(\omega) - H(\omega|f_k) \quad (2)$$

where  $H(\omega)$  and  $H(\omega|f_k)$  denote the entropy and conditional entropy respectively. Details of equations can be found in [22].

### D. Classification via Linear Discriminant Analysis

Multiclass Linear Discriminant Analysis (LDA) was performed using the MATLAB classify function.

### E. Architecture of ensemble classifier design

The ensemble classifier design was used for offline analysis. Synchrony and firing rate features were individually decoded to produce directional outputs. Similar directional outputs represent concurrence of synchrony and firing rate features, and their respective time bins are retained. Time bins with different directional outputs are reclassified using a concatenated feature matrix comprising of both firing rate and synchrony features. Overall decoded directions are

obtained by considering the similar directional outputs, which were previously retained, and the newly decoded directions.

## III. EXPERIMENT, RESULTS AND DISCUSSION

All procedures described were approved by the Institutional Animal Care and Use Committee of the Agency for Science, Technology and Research (A\*STAR) and conformed to the Guidelines for the Care and Use of Laboratory Animals.

### A. Data Acquisition

4 microelectrode arrays (MicroProbes, Gaithersburg, MD, United States) were implanted anterior to the central sulcus into the arm area of the primary motor cortex (MI) contralateral to the trained right arm. A total of 96 single-electrodes (two arrays of 32 electrode and two arrays of 16 electrodes) with tip impedance of  $\sim 0.5 \text{ M}\Omega$  were used. Spiking activity from arrays was recorded with a 100 channel in-house neural recording system [23]. A sampling rate of 25 kHz was used. Units with firing rate below 1 Hz were discarded. Simultaneous joystick signals corresponding to monkey wrist movement were also recorded. After manual calibration of joystick signals, the 4 different movements (front, left, right and stop) were defined with appropriate corresponding voltage range. For offline analysis, joystick signals and neuronal spiking activities corresponding to the 4 different classes were extracted and segmented as inputs.

### B. Experimental Protocol

Data was collected from an asynchronously intracortical brain-computer interface which allows monkey to continuously drive a mobile robot in real time [24]. One male rhesus macaque was seated in a primate chair placed on a mobile robot. The monkey was trained to use a joystick to perform four movements (front, left, right and stop) in two-dimensional space on the mobile robot. The feedback of self-movement together with mobile robot is delayed because of the physically limited acceleration time of the engine [24]. At the beginning of each trial, the trainer visually cued the monkey to indicate prescribed direction of motion by using a liquid reward. The monkey was allowed to move asynchronously through the use of a joystick to reach the target. The trial repeats with the trainer indicating a new direction of motion within the 6m by 4m workspace. This

Measure	Left (%)	Right (%)	Forward (%)	Stop (%)	Overall (%)
FR	74.8± 3.75	94.1± 6.1	86.7± 7.95	78.2± 3.76	83.1± 0.61
ISI-Distance	57.9± 2.41	80.2± 9.86	62.7± 13.04	66.8± 1.73	67.5± 3.46
SPIKE-Distance	42.64± 1.29	61.5± 8.4	57.0± 1.23	55.8± 2.56	54.6± 3.58
ES	44.51± 0.94	77.3± 4.53	57.1± 11.89	67.4± 1.66	63.1± 2.11

Table 1: Table showing mean overall decoding accuracies (%) of the 4 approaches – Firing Rate (FR) only, SPIKE-Distance, ISI Distance, Event Synchronization (ES) - of the 3 testing sessions with standard deviations

behavioral task is similar to pursuit tracking task where the monkey follows a visual target by operant conditioning [25].

### C. Comparing Different Synchrony Measure – Individual Decoding Accuracy

Offline Analysis was performed on 26 units (each representing one spike train) after spike detection. Analysis was done using data from 4 different sessions on a single test date. 1 session was used for training while the other 3 sessions were used for testing. For the firing rate approach, mean firing rate was calculated using a 500 ms time-bin. Therefore, for each time stamp, there are 26 values corresponding to firing rate information and  $325 \left( \frac{26 \times 25}{2} \right)$  values corresponding to synchrony information. Event Synchronization was calculated using the same bin-width; MATLAB code for Event Synchronization was provided by Kreuz [17]. Table 1 shows the respective decoding accuracies for firing rate, ISI-Distance, SPIKE-Distance, and Event Synchronization. Firing rate information consistently yielded the highest decoding accuracy with an average of 83.2% while SPIKE-Distance yielded the lowest decoding accuracy with an average of 54.6%. Both ISI-Distance and Event Synchronization yielded similar decoding accuracies of 67.5% and 63.1% respectively. The results validate the firing rate as the best measure for decoding directions in the motor cortex.

### D. Comparing Different Synchrony Measures – Decoding Accuracy of Synchrony Features in decoding mis-decoded time periods from firing rate

If synchrony contains redundant information with respect to firing rate information, decoding mis-decoded time periods from firing rate using synchrony features would yield performance below chance. Mis-decoded time periods are time periods where the directional output produced from using firing rate for classification is not the same as the real direction of movement. Figure 3 shows the overall decoding accuracies for the 3 synchrony feature. All 3 synchrony measures produce decoding accuracies above chance level of 25%, showing that synchrony features do carry information not carried in firing rate. All 325 synchrony features were considered in this analysis. Similarly, 1 session was used for training while the other 3 sessions were used for testing.

### E. Combining Firing Rate and ISI-Distance features

Classification was performed for the combined synchrony and firing rate features using the architecture described in

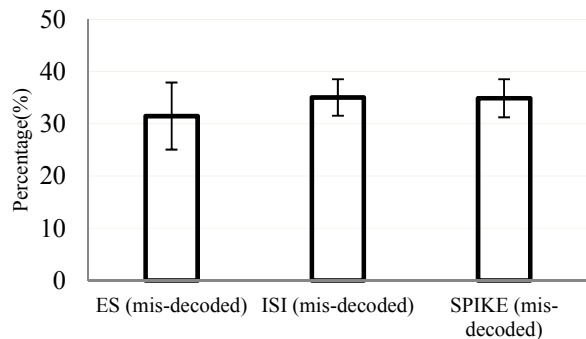


Figure 2: Table showing mean overall decoding accuracies (%) of the mis-decoded time periods for the 3 synchrony features. Mis-decoded time periods are time periods where the directional outputs from using only firing rate are dissimilar from the real directions of movement.

Figure 1. From previous analysis, ISI-distance was chosen as the synchrony feature for analysis because it is the best performing synchrony measure in terms of its individual decoding accuracy and its ability to decode mis-decoded time periods. Session 1 was used for validation to optimize the number of synchrony features. For optimal performance, 26 firing rate features and 150 synchrony features were used. The 150 synchrony features are the top 150 features in terms of mutual information using the MIBIF algorithm.

Table 2 compares the weighted averages of the decoding accuracies for firing rate and for the combination of firing rate and ISI-distance features. Weighted averages and standard deviations were calculated from the 2 sessions used for testing. The architecture for feature combination yielded an increase in overall decoding accuracy of 1.1%. The increases in decoding accuracy are attributed to increases in decoding the “right”, “forward” and “stop” directions.

## IV. DISCUSSION AND CONCLUSION

There has been substantial work on feature combination [26], and these work have shown to improve classification accuracy for Brain-Computer Interface application [27-29]. Most of previous work was performed on EEG data. Thus, this paper investigated feature combination in neural data recorded from invasive electrodes implanted into the cortex. Specifically, we combined both firing rate and synchrony features using an ensemble classifier design and feature selection using the mutual information-based best feature algorithm (MIBIF). Although our results validate that firing rate outperforms synchrony measures in terms of decoding accuracy, we have shown that synchrony features do contain information not carried by firing rate alone. The architecture implemented yielded a significant increase in overall decoding accuracy. Future work should focus on implementing the architecture using different synchrony,

Measure	Left (%)	Right (%)	Forward (%)	Stop (%)	Overall (%)
FR	99.6 ± 0.38	76.5 ± 4.41	83.5 ± 9.62	76.7 ± 4.55	83.5 ± 0.58
FR + ISI-Distance	99.4 ± 0.18	80.3 ± 3.43	84.5 ± 8.65	77.6 ± 2.37	84.6 ± 0.29

Table 2: Table comparing mean decoding accuracies (%) for firing rate only and when firing rate and ISI-Distance features are combined. Values shown are weighted means and standard deviations for the 2 testing sessions

features such as SPIKE-distance and ES. In addition, different structures of the ensemble classifier design could be investigated. The design could also be further optimized by assigning weights to the decoded directions obtained from the firing rate and synchrony. Similarly, the design could use an ensemble of firing rate and 2 or more synchrony features.

Because our analysis focused on sessions from a single test date, further work on non-stationarity of data across different test days should be investigated to ascertain the robustness of the architecture in its implementation across different sessions. Since there are other features that can be extracted from spike trains, such as ISIs and bursting information, the ensemble classifier architecture and feature selection method could be used for combining other features. Because our analysis was done offline, real-time implementation of the architecture could also validate the feasibility of combining firing rate and synchrony features. In addition, our study considered only 4 degrees of freedom, and synchrony might be more important when performing decoding with higher degrees of freedom. Lastly, future work should consider scenarios where there are less neuronal units available for analysis. This is important especially when electrode scarring occurs after a long period of implantation, which renders the electrode unable to pick up substantial signal [30]. Synchrony features might carry additional information useful for decoding in long term use of BMI. Thus, our results motivate further investigation into how adding synchrony features can improve BMI decoding performance

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