State-Based Decoding of Force Signals From Multi-Channel Local Field Potentials

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ABSTRACT The functional use of brain-machine interfaces (BMIs) in everyday tasks requires the accurate decoding of both movement and force information. In real-world tasks such as reach-to-grasp movements, a prosthetic hand should be switched between reaching and grasping modes, depending on the detection of the user intents in the decoder part of the BMI. Therefore, it is important to detect the rest or active states of different actions in the decoder to produce the corresponding continuous command output during the estimated state. In this study, we demonstrated that the resting and force-generating time-segments in a key pressing task could be accurately detected from local field potentials (LFPs) in rat’s primary motor cortex. Common spatial pattern (CSP) algorithm was applied on different spectral LFP sub-bands to maximize the difference between the two classes of force and rest. We also showed that combining a discrete state decoder with linear or non-linear continuous force variable decoders could lead to a higher force decoding performance compared with the case we use a continuous variable decoder only. Moreover, the results suggest that gamma LFP signals (50-100 Hz) could be used successfully for decoding the discrete rest/force states as well as continuous values of the force variable. The results of this study can offer substantial benefits for the implementation of a self-paced, force-related command generator in BMI experiments without the need for manual external signals to select the state of the decoder.

INDEX TERMS Brain-machine interface, local field potential, force decoding, state decoding, common spatial pattern.

I. INTRODUCTION

Technology advances of cortical signal processing and microelectrode array fabrication can enable the practical use of intra-cortical brain-machine interface (BMI) systems, applied for the movement restoration after spinal cord injury (SCI) and stroke. It is also thought that a high information transfer rate from the brain to a neural prosthesis and the long-term stability of the brain signals are supposedly the key factors toward designing real-world BMI systems [1]. Different applications of BMIs were demonstrated in rats [2]–[5], non-human primates [6]–[10], and humans [11]–[20].

It is generally assumed that the kinematic trajectories of limb position or velocity are directly decoded from the intracortical signals and converted to a command signal to control an external device or prosthetic limbs [17]. However, the accurate neural control of a prosthetic hand, especially for reach-to-grasp movements, requires the decoding of kinetic information such as hand grasping force in addition to kinematic trajectories of the shoulder and arm.

For this reason, various studies have been devoted to the possibility of decoding different types of kinetic parameters such as grasping force [21], [22], joint torque [8], and muscle activities [23], [24]. In most force-based BMI studies, continuous changes of the force variable are decoded from the intra-cortical signals only in specific time segments of the experimental trials. However, real-world tasks require a self-paced command decoder to detect active and resting states of the system and produce a continuous command signal accordingly. Hence, decoding the discrete state of the action and combining it with a continuous force decoder can produce a more accurate neural command signal for the real-world BMI systems.
Different combined state detectors and continuous decoder methods have been suggested for the kinematic-based BMI systems [25], [26]. Suway et al. combined an idle state decoder with a continuous brain-controlled prosthetic arm. They obtained spike activities from 96-channel arrays implanted in the primary motor cortex of monkeys to detect idle and active states and produce continuous movement commands during the active state. They found that incorporating a state detector with a continuous decoder can significantly decrease the unwanted or jitter movements during the idle state compared with the traditional continuous variable decoders [25]. Kao et al. demonstrated that incorporating a hidden Markov model (HMM) into a continuous brain controller can enhance the performance of neural prostheses. In a reaching-then-target clicking task on monkeys, the HMM state classifier combined with a continuous decoder, increased the performance of the neural prosthesis in terms of communication rate [27].

In the aforementioned studies, spike activities, representing single neuron activation, were used to detect the state of behavior and produce a continuous kinematic variable depending on the detected state. Nevertheless, spike-based decoding techniques on multi-channel electrodes require complex and time-consuming procedures of signal thresholding and spike sorting. To overcome the challenges associated with spike-based decoders, we offer a state-based continuous decoder that uses multi-channel LFPs as a source of information. The rationale is that the previous studies have already revealed that LFPs can provide more long-lasting movement-related information compared to spikes [28], [29]. Moreover, the lower-bandwidth of LFPs (1-400 Hz) compared with spikes (400- up to 5000 Hz) can significantly decrease the required hardware resources and battery power consumption. Furthermore, the BMI-based studies have introduced LFPs as an optimum choice because it can provide the same stability and higher task-related information compared to Electrocor-ticography (ECoG) and electroencephalography (EEG) [30].

In the same vein, Aggarwal et al. proposed a combined state detector with a continuous kinematic decoder using multi-channel LFPs and spikes [31]. They used 55 LFP channels and spikes to classify the states of behavior in a reach-to-grasp task on monkeys. To extract input LFP features, they computed the power of different LFP frequency bands and used a linear discriminant analysis (LDA) method to classify four states of the behavior including baseline, reaction, movement, and hold. They showed that incorporating an LFP-based state decoder into a spike-based continuous kinematic decoder can significantly enhance the performance of the decoder in terms of the correlation coefficient between the actual and predicted movement.

In our study, we used 16 LFP channels to investigate the detection of force/rest states in rats. To enhance the performance of state detection from the low number of LFP channels, we extracted the input features using a filter-bank common spatial pattern (FBCSP) algorithm [32]. The objective of our study was to combine the proposed state detector with a continuous variable decoder using multi-channel LFPs to enhance the decoding accuracy of the output signal compared to conventional continuous decoders. We also investigated the idea of using state-based continuous decoder with both linear and non-linear regression algorithms.

II. MATERIALS AND METHODS

Previously reported procedures for animal training, micro-array implantation, and brain data acquisition were used [33]. Here, we present more details related to the current study to support data analyses. We will first explain the experimental task and LFP data recording and processing in free moving rats. Then we will present the procedures used for decoding the behavioral states (force and rest time periods), and we will finally show the strategy of integrating the discrete state decoder into the continuous variable decoder.

A. ANIMALS

Three Wistar rats (300-400 g) were used in this study. The local ethics committee of animal care at Iran University of Science & Technology checked and approved animal care and surgical procedures. All the protocols in this study were in accordance with the NIH protocols for animal research [34].

B. INTRACORTICAL ARRAY IMPLANTATION AND DATA ACQUISITION

All surgical survival procedures were conducted under aspetic conditions. To prevent hypothermia, the body temperature was maintained at 37 °C using a heating pad. As depicted in Fig. 1A, under anesthesia, a 16-channel microwire array created with Platinum/Iridium wires and coated with Teflon (25 μm diameter, 500 μm electrodes distance, Microprobes Inc., Gaithersburg, USA, 500–800 KΩ) with 4 × 4 configuration was implanted in the forelimb sensorimotor cortex of the left hemisphere and inserted in 1.5 mm depth from the brain surface to record pyramidal neuron activity in the layer five of the motor cortex. Meloxicam (0.2 mg/kg) was administered for two days after the surgery. Two weeks after the array implantation, the brain data were recorded with a multi-channel data acquisition system (Microprobes Inc., Gaithersburg, USA) at a 10 kHz sampling rate and stored on the PC for further analysis. Simultaneously, force data were recorded at a 30 Hz sampling rate and synchronized with the brain data using a TTL-pulse triggering both brain and force data acquisition systems. To extract multi-channel LFP signals, raw brain data were bandpass filtered through 0.1-500 Hz band (4th order Butterworth, forward and backward) and re-sampled with the rate of 1 kHz. The common noise of all channels was removed using a common average reference (CAR) algorithm. Recording sessions have been done in different days. In each experiment session, different number of trials have been selected from the whole data. The data points that animals were not engaged in the task were removed from the analysis. To obtain different trials in each session, 1.5 s before and 2 s after the force threshold crossing (0.15 N) was selected as a trial. The number of sessions for
rats 1, 2, and 3 was 5, 7, and 5, respectively. Overall, 74, 79, and 80 trials were obtained from these sessions, respectively.

C. BEHAVIORAL TASK TRAINING
A novel force-based training task was designed to record the endpoint force signal while animals were pressing an object. The behavioral setup comprised a translucent box with a circular hole to receive the liquid reward. As shown in Fig. 1B, a load-cell sensor was placed in the wall of the front panel. To reach the water reward, the animals had to press the force sensor to a pre-specified threshold (0.15 N). When the applied force by rats reached the pre-specified threshold, the water pump was activated for 200 ms, and the animal received a liquid reward from the tip of a tube. Fig. 1B shows an example of a bell-shaped force signal produced by pressing the force sensor. The rising section of the force pattern corresponds to the force sensor pressing, and the falling section corresponds to the sensor releasing. There was no go or end cue to define the beginning or the end of each trial. Animals were free to move in their experimental setup. After 20-30 successful trials, animals had unlimited access to water for 30 minutes at the end of each session. Then, they were water restricted for the next day’s experimental session.

D. FORCE AND REST STATE CLASSIFICATION
As shown in Fig. 1B, each trial comprised force and rest sections. In the force section, the animal continuously pressed the force sensor that produced a bell-shaped signal. In the rest section, the animal did not press the force sensor, and so the force value was equal to zero. In the classification step, the data were divided into 500 ms windows. The windows with force amplitude higher than two centinewtons were considered as force, and those less than two centinewtons were considered as rest. This threshold was selected because sometimes the animals hold their hand on the sensor without applying any force on the sensor. Fig. 2 shows the procedures of state classifications in the training and test phases.

Quadratic discriminant analysis (QDA) classifier was used to classify the force and rest states based on the LFP information in each 500 ms time windows. FBCSP algorithm was used to obtain the input features of the classifier [35]. In this method, multi-channel LFP signals were filtered using zero-phase bandpass filters (4th order Butterworth) through multiple frequency bands: \( \delta \) (1-4 Hz), \( \theta \) (4-8 Hz), \( \alpha \) (8-12 Hz), \( \beta \) (12-30 Hz), \( \gamma_1 \) (30-50 Hz), \( \gamma_2 \) (50-100 Hz) and \( \gamma_3 \) (100-200 Hz). Each multi-channel bandpass filtered signal was spatially filtered using the CSP method. CSP can maximize the difference of the variance between the two classes of brain signals. In summary, consider \( X_i \) as multi-channel bandpass filtered signals corresponding to frequency band \( i \). This input signal can be spatially filtered employing the CSP algorithm:

\[
Z_i = W_i^T X_i
\]
The schematic representation of the proposed state-based continuous force decoder. In the first step, the multi-channel LFPs were filtered using the CAR algorithm to increase the signal-to-noise ratio of the recorded channels. In the classification step, the FBCSP method was used to increase the separation of spectral neural features. In FBCSP, the CSP method was applied to the bandpass filtered signals of multiple frequency bands leading to better discriminative features compared with traditional CSP algorithms. A feature selection algorithm was used to select the most discriminative features. QDA algorithm was then used to classify the input features into two classes of rest and force. In the regression step, two different PLS regression models were computed for each class of rest and force. The output of the PLS regressor continuously decodes the output by multiplying neural features by the PLS weight corresponding to either class of rest or force.

**FIGURE 2.** The schematic representation of the proposed state-based continuous force decoder. In the first step, the multi-channel LFPs were filtered using the CAR algorithm to increase the signal-to-noise ratio of the recorded channels. In the classification step, the FBCSP method was used to increase the separation of spectral neural features. In FBCSP, the CSP method was applied to the bandpass filtered signals of multiple frequency bands leading to better discriminative features compared with traditional CSP algorithms. A feature selection algorithm was used to select the most discriminative features. QDA algorithm was then used to classify the input features into two classes of rest and force. In the regression step, two different PLS regression models were computed for each class of rest and force. The output of the PLS regressor continuously decodes the output by multiplying neural features by the PLS weight corresponding to either class of rest or force.

where $Z_i$ are spatially filtered signals of frequency band $i$ with $N$ channels and $L$ samples. The spatial filter matrix, $W_i^T$, can be obtained using the CSP algorithm by maximizing the ratio of average variances between two different classes after spatial filtering [32], [36]. The $m$ first and last row of the matrix $Z_i$, i.e. $Z_i'$ are generally selected to produce the feature vector $f_i$ as follows:

$$f_i = \log \left( \frac{\text{var}(Z_i')}{\sum_{j=1}^{2m} \text{var}(Z_j')} \right)$$

(2)

where $j$ corresponds to the row index of the matrix $Z_i'$. Here, four features in each frequency band were obtained from each 500 ms time window. In the next step, the most discriminative features were selected and fed into a classifier. To select the most discriminative features, features were ranked based on the Wilcoxon statistical test, and the five top-ranked features were selected as the input of the QDA classifier. QDA algorithm can classify the input feature to the class of interest. QDA is similar to a linear discriminant analysis (LDA) algorithm except that the covariance matrix of each input can be different. In this method, the quadratic discriminant function, $g_k(X)$, is computed as follows:

$$g_k(X) = (X - \mu_k)^T \Sigma_k^{-1} (X - \mu_k) + \log |\Sigma_k| - 2 \log |\pi_k|$$

(3)

where $k$ is the class index, $X$ is the input feature matrix, $\mu_k$ is the mean vector of each class, $\pi_k$ is the prior probability, and $\Sigma_k$ is the covariance matrix of input features. The decoded state $Y(t_k)$ in each time-window $t_k$ was identified as the class with the highest quadratic discriminant function:

$$Y(t_k) = \arg \max (g_k(X))$$

(4)

The classification accuracy was computed with a ten-fold cross-validation method repeated ten times after shuffling the order of trials.

**E. STATE-BASED CONTINUOUS FORCE DECODING**

In this phase, force values were decoded continuously from the multi-channel LFPs using a partial least square (PLS) regression algorithm [37], [38]. Fig. 2 presents the procedures of state-based continuous decoding of force signals in training and test phases. The LFP signals were bandpass filtered through the same frequency bands as section B: $\delta$ (1-4 Hz), $\theta$ (4-8 Hz), $\alpha$ (8-12 Hz), $\beta$ (12-30 Hz), $\gamma_1$ (30-50 Hz), $\gamma_2$ (50-100 Hz) and $\gamma_3$ (100-200 Hz). Then, the envelopes of these filtered channels were computed to produce input features. Furthermore, the time lags of the features over 500 ms before the current time with 100 ms time-steps were added to the feature vector. With six channels, seven frequency bands and six time lags, $16 \times 7 \times 6 = 672$ features were obtained, z-score normalized, and fed into the PLS model. PLS is a powerful algorithm for high-dimensional regression problems. In this method, both input and output data are projected into a new low-dimensional subspace by maximizing the covariance between the projected input and output data. Hence, PLS not only captures the input and output components that maximize the covariance but also ignores the non-output-related components due to the noise.

In the training stage, the temporal-spectral-spatial features corresponding to the force class were concatenated, and a PLS model was obtained between input LFP features and output force signal. Similarly, the features corresponding to the rest class were concatenated, and a different PLS model
was obtained between input LFP features and output rest signals. In the test phase, depending on the identified class (force or rest) by the QDA classifier in each 500 ms time windows, the continuous output signal was decoded by selecting its corresponding PLS model (Fig. 2). This decoder is called state-based PLS (S-PLS), showing that a state decoder can be combined with PLS regression:

\[ F(t) = \sum_{j=1}^{16} \sum_{k=1}^{7} \sum_{t=0}^{-500 \text{ ms}} \beta_f(j, k, \tau) S_f(j, k, \tau) \]

\[ R(t) = \sum_{j=1}^{16} \sum_{k=1}^{7} \sum_{t=0}^{-500 \text{ ms}} \beta_r(j, k, \tau) S_r(j, k, \tau) \]  \hspace{2cm} (5)

where \( F(t) \) and \( R(t) \) represents the output signal corresponding to the force and rest section, respectively. The regression coefficients \( \beta_f \) and \( \beta_r \) were identified using PLS algorithm optimization for each force and rest state, respectively [38]. The regression algorithm was computed as follows:

\[ \beta_f(j, k, \tau) = \frac{\sum_{t=0}^{T} (F(t) - \bar{F}(t))(f(j, k, \tau) - \bar{f}(j, k, \tau))}{\sqrt{\sum_{t=0}^{T} (F(t) - \bar{F}(t))^2} \sqrt{\sum_{t=0}^{T} (f(j, k, \tau) - \bar{f}(j, k, \tau))^2}} \]

\[ \beta_r(j, k, \tau) = \frac{\sum_{t=0}^{T} (R(t) - \bar{R}(t))(r(j, k, \tau) - \bar{r}(j, k, \tau))}{\sqrt{\sum_{t=0}^{T} (R(t) - \bar{R}(t))^2} \sqrt{\sum_{t=0}^{T} (r(j, k, \tau) - \bar{r}(j, k, \tau))^2}} \]

\[ R = \frac{\sum_{t=1}^{T} (f(t) - \hat{f})(f(t) - \bar{f})}{\sqrt{\sum_{t=0}^{T} (f(t) - \bar{f})^2} \sqrt{\sum_{t=0}^{T} (f(t) - \bar{f})^2}} \]

\[ R^2 = 1 - \frac{\sum_{t=0}^{T} (f(t) - \hat{f})^2}{\sum_{t=0}^{T} (f(t) - \bar{f})^2} \]  \hspace{2cm} (6)

where \( f(t) \) and \( \hat{f}(t) \) are the actual and decoded output at time sample \( t \), respectively. \( \bar{f} \) and \( \bar{f} \) are the average of the actual and decoded output signal in a test fold with \( T \) time samples.

We used ten-fold cross validation method with ten repetitions after shuffling the order of trials to evaluate our decoder under different data combination. The importance of each frequency band in decoding the continuous output signal using different regression algorithms was computed as follows:

\[ \% C(k) = \frac{\sum_{j=1}^{16} \sum_{k=1}^{7} \sum_{t=0}^{-500 \text{ ms}} |\beta(j, k, \tau)|}{\sum_{j=1}^{16} \sum_{k=1}^{7} \sum_{t=0}^{-500 \text{ ms}} |\beta(j, k, \tau)|} \]  \hspace{2cm} (7)

where \( \% C(k) \) shows the contribution of the \( k \)th frequency band in the decoding of continuous force and rest signals.

In addition to the linear PLS algorithm, different non-linear regression methods were also considered to investigate the effect of combining state detector with continuous regression strategies. The non-linear regression methods include regularized extreme learning machine (RELM) [39], support vector regression (SVR) with RBF kernel, SVR with the polynomial kernel, and SVR with the linear kernel [40].

### III. RESULT

The results are divided into two sections. First, we will describe the results of the force state classification. We will also compare the contribution of different frequency bands in the classification of the output states. Second, we will present the results of integrating the discrete state classifier into the continuous decoder. We will compare the performance of the state-based continuous decoder with the conventional continuous decoder in terms of \( R \) and \( R^2 \) decoding performance. We will also compare the result of state-based continuous decoder employing both linear and non-linear regression methods.

#### A. CLASSIFICATION OF FORCE STATES

The main goal of the FBCSP is to provide the discriminate features between the two classes of interest. Adding a feature selection step after FBCSP can ensure that most discriminative features were selected for the classification purpose. The output signal of the test fold was classified to force or rest class on each 500 ms time window. Fig. 3 depicts the average of top five feature values over an example test fold for two classes of the force and rest in three rats. This can clearly show that the introduced feature extraction and selection technique can highly discriminate the features of force and rest classes.

Table 1 presents the classification accuracy of the desired states based on the multi-channel LFPs. Force and rest states were identified with average accuracies of 99.57% and 95.34%, respectively.

**TABLE 1. Summary of force and rest state classification based on the multi-channel LFPs.**

|          | All         | Force       | Rest        |
|----------|-------------|-------------|-------------|
| Rat 1    | 96.8 ± 0.19 | 100 ± 0     | 94.30 ± 0.33|
| Rat 2    | 98.49 ± 0.15| 99.57 ± 0.12| 97.55 ± 0.26|
| Rat 3    | 96.51 ± 0.1 | 99.15 ± 0.2 | 94.37 ± 0.39|
| Mean     | 97.26 ± 0.1 | 99.57 ± 0.12| 95.34 ± 0.22|

Fig. 4 illustrates the average contributions of different frequency bands of LFPs on state decoding. The frequency bands \( \gamma_1 (30-50 \text{ Hz}) \) and \( \gamma_2 (50-100 \text{ Hz}) \) significantly contributed more than other bands in the classification (\( p < 0.001 \), Wilcoxon signed-rank test with Bonferroni correction, three rats).

#### B. STATE-BASED CONTINUOUS FORCE DECODING

Fig. 4 compares the contributions of different frequency bands on continuous decoding of force-only, rest-only (S-PLS), and the whole output signal (conventional PLS). For both force and rest signal decoding, \( \gamma_1 (30-50 \text{ Hz}) \) and \( \gamma_2 (50-100 \text{ Hz}) \) made the most contributions compared to other frequency bands (\( p < 0.001 \), Kruskal–Wallis test with post hoc Bonferroni, three rats). In the case that state decoder was not integrated into the continuous decoder, \( \alpha (8-12 \text{ Hz}) \) and \( \gamma_1 (30-50 \text{ Hz}) \) made greater contributions than other frequency bands.

To evaluate the performance of the state-based force decoder, the correlation coefficient, and the coefficient of
FIGURE 3. Example of top-five feature values for the two classes of force and rest. Each bar shows the mean ± standard error of each feature value on a selected test fold.

FIGURE 4. Contribution of individual frequency bands in the state classification and continuous regression. Each bar presents the mean ± the standard error of contribution obtained from ten folds with ten repetitions averaged over all rat datasets (p-value < 0.001, three rats, Kruskal–Wallis test with post hoc Bonferroni). In the classification analysis, significant contributions were found for the $\gamma_1$ (30-50 Hz) and $\gamma_2$ (50-100 Hz) bands. In the continuous decoding analyses, for the conventional PLS algorithm, significant contributions were found for $\alpha$ (8-12 Hz) and $\gamma_1$ (30-50 Hz). But, in the case of using state-based continuous decoding of both force and rest signals, significant contributions were found for $\gamma_1$ (30-50 Hz) and $\gamma_2$ (50-100 Hz).

determination between the real and decoded force signals were computed. Fig. 5 illustrates the result of continuous force decoding both for each individual rat and the average of all rats using a state-based force decoder. The average correlation coefficient and the coefficient of determination were $R = 0.8 \pm 0.012$ and $R^2 = 0.57 \pm 0.011$, respectively (mean ± SE, three rats, ten times of ten-fold).
To evaluate the effect of incorporating a discrete-state classifier into a continuous variable decoder for different types of regression, we also used non-linear regression methods (RELM, SVR with RBF, SVR with polynomial kernel and SVR with the linear kernel). The same classification methods were used in this section, and only non-linear regressors were used instead of linear ones.

Fig. 6 clearly shows that state-based decoder with different types of regressors could lead to significant decoding performance compared with the case that no state classifier was added to the regressor \( p < 0.001 \), Wilcoxon signed-rank test, three rats). Fig. 7 presents an example of a 20 s time segment of the decoded output signal using normal PLS method (no state detection) and the proposed state-based PLS method. As can be seen, using S-PLS, the decoded output signal, when decoded continuously, was more accurate in both force and rest periods compared with normal PLS.

Fig. 8 compares the classification accuracy of the proposed FBCSP method with the feature extraction algorithm used by Aggarwal et al. [31]. Aggarwal et al. computed the band power of 6-14 Hz, 15-22 Hz, 25-40 Hz, 75-100 Hz, 100-175 Hz, and LFP amplitude as input features. They performed LDA classification to classify the state of behavior with band powers as input features. To compare the efficiency of FBCSP on enhancing separability between classes, we applied FBCSP on the same frequency bands and performed LDA classification. As shown in Fig. 8, FBCSP outperformed the feature extraction strategies employed in [31]. Furthermore, FBCSP presents more accuracy compared with using band power of all bands.

**IV. DISCUSSION**

The neural control of external devices such as robotic arms or muscle stimulation requires accurate extractions of motor command signals. Different challenges limit the clinical use of BMI systems. One of the most significant challenges to use BMIs in the clinic is that the human subjects controlling a neural interface need to have a stable, accurate, and always available control signal. In the real-work tasks, a neural controller may need to switch between object reaching, grasping, and holding conditions.

Furthermore, in most situations, the neural interface must automatically identify the rest or non-attention states to avoid producing undesirable control outputs. To address this challenge, different machine learning strategies were devoted to combining the state classifiers with continuous kinematic decoders [25], [26], [41], [42]. In our study, we investigated the effect of combing a state detection with a kinetic decoder. We showed that incorporating a discrete-state decoder into a continuous variable decoder could significantly improve the decoding accuracy of the output command signal. The total performance of the integrated discrete and continuous decoder is highly dependent on the accurate performance of the state decoder. The poor performance of the classifier, especially for the idle state detection, may produce a disturbing and noisy command signal [25], [31]. This problem can decrease the usability of the neural interface for human subjects. In the current study, we showed that the rest and the force states could be classified with a rate of 97% over three rat subjects. Inferring from Fig. 3, the proposed FBCSP feature extraction algorithm can significantly increase the separability of force and rest states; thus, it can improve state detection compared with the conventional feature extraction strategies.

FBCSP method is a powerful strategy for extracting discriminative CSP features that are conventionally used for imaginary motor tasks [32], [35]. The main advantage of FBCSP over conventional CSP algorithms is that the discriminative patterns are produced from multiple bandpass filtered signals. This advantage addresses the challenge of selecting the optimum frequency band in the CSP algorithm. As depicted in Fig. 8, FBCSP lead to a better classification rate compared with using conventional band power features used by [31].

We also evaluated the efficiency of the state-based continuous force decoder using different linear and non-linear regression algorithms. Fig. 6 confirms that the state-based decoding strategy can improve the decoding performance compared with the use of continuous variable decoders only. Fig. 6 also implies that the difference between the performances was more due to the use of a state-based decoding strategy rather than the regression algorithm selection.

The analysis of the contribution of different frequency bands of LFPs presents that both discrete states and continuous variables are significantly encoded in the gamma frequency bands. Bundy et al. found that the beta frequency band of ECoG information could contain the most important neural features of the state of the movement, and the high gamma-band power was important for the continuous kinematic variables [41]. However, our study showed that gamma...
FIGURE 6. Comparing the decoding of output signals using state-based linear and non-linear regressors. The performances of PLS, RELM, SVR with RBF, SVR with polynomial kernel and SVR with linear kernel were compared for state-based decoding and without state-based decoding. In all cases, the state-based linear or non-linear decoders significantly improved the decoding performance in terms of $R$ and $R^2$. Each bar presents the mean ± the standard error of each performance metric computed averaged over 10 test folds with 10 repetitions ($P$-value < 0.001, three rats, Wilcoxon signed-rank test).

FIGURE 7. A) Examples of output signal decoding from multi-channel LFPs using S-PLS and normal PLS algorithms in three rats. The state-based PLS decoder predicted the output signal in both force and rest sections. B) An example of state classification corresponding to the same test fold is clearly shown. In all three rats, the force and rest states were classified with high detection rates.

band (30-50 Hz and 50-100 Hz) contributed significantly to both discrete states and continuous variable decoding. This difference could be explained considering the different representations of kinematic and kinetic information in the motor cortex. But further studies need to be carried out to investigate this issue. Furthermore, similar to the results of our study, Aggarwal et al. found that high gamma-band power of LFPs contained the most neural features of both discrete state and continuous variables [31], but the 100-200 Hz spectral features did not significantly contribute to the state or continuous variable decoding in their study. This discrepancy could be attributed to the fact that 100-200 Hz spectral features in their study may have contained residual spike information, but in our study, the effect of spike information on this specific band
was diminished due to the low number of channels or possibly the low impedance of the used micro-wire array.

An important advantage of this study over other state-based decoding strategies is that we used LFP information for both state detection and continuous variable decoding. This advantage is noticeable since it allowed us to avoid time-consuming and complex spike sorting procedures, which could be regarded as big challenges for the use of BMIs in clinical applications. Furthermore, most state-based continuous decoders were developed for decoding kinematic parameters such as velocity and limb position [31], [43]–[45]. In this study, we investigated the decoding of force information from the multi-channel LFP signals. In many situations, such direct control of applied force on the endpoint of the neural prosthesis or the stimulation of the paralyzed muscle, force information must be decoded from the cortical information. We showed that force information could be accurately distinguished from the rest/idle states. This study offers that it is possible to switch between kinematic and kinetic parameter decoders because, during the rest period, animals had some forelimb movements but with negligible endpoint hand force. Moreover, we achieved the same classification accuracy with only 16 LFP channels compared with other studies that used higher numbers of spike channels [31].

In our future work, we plan to use the proposed state-based kinetic decoder in the online brain controller scheme. Due to the processing advantages of LFP-based decoding techniques, most of the decoder components, including FBCSP spatial filters, envelope extractor, and PLS weight multiplication, can be easily applied in an online phase.

V. LIMITATIONS OF THE STUDY
The current study only presents the effectiveness of the state-based force decoder in an offline study. In the online setting, the parameters of the classifier and regressor need to be updated at the beginning of each session. In this study, we did not investigate the stability of decoder across days or animals and how the robustness of the decoder performance may change by the variability of the decoder parameters. One solution to make a robust state-based decoder is to adaptively update the classifier and regressor parameters using a least mean square filter (LMS) strategy.

VI. CONCLUSION
In this study, we presented a method to continuously decode force information from LFP signals depending on the discrete state of behavior. The filter bank CSP can lead to very high classification rates of force and rest states using the multi-channel LFPs. Combining this high accuracy classifier with linear or non-linear regressors can significantly improve the accuracy of the continuous force-related output signal. The high accuracy of the proposed state detector suggests that it is possible to switch between the force decoder and the movement decoder based on the brain signals without the need for an external command. Overall, the results of this study suggest a useful strategy for controlling the force-related BMI devices needed to provide self-paced and continuous command signals.

ETHICS APPROVAL
The local ethics committee of animal care at Iran University of Science & Technology checked and approved animal care and surgical procedures. All the protocols in this study were in accordance with the NIH protocols for animal research.

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(Amirmasoud Ahmadi and Abed Khorasani contributed equally to this work.)

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