SPECIAL SECTION ON DATA-ENABLED INTELLIGENCE FOR DIGITAL HEALTH

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Discrete Hand Motion Intention Decoding Based on Transient Myoelectric Signals

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ABSTRACT In the application of human–robot interaction (HRI) rehabilitation exercise controlled by Electromyogram (EMG), if the discrete motion intention decoded by EMG signals is within the range of electromechanical delay (EMD), through the rehabilitation training, it will largely enhance the user's feeling feedback and fully activate the brain plasticity. So the decoding of hand movement intention by transient EMG is investigated to reach ideal characteristics needed in the HRI. The high-density EMG signal (HDEMG) database CapgMyo was used to decode the motion intention based on the transient EMG signals within the EMD rather than the whole recorded signals. We investigate the impact of the different decoding window lengths (WL) and training sets constructing methods when using several machine learning algorithms. In addition, the transient EMG signals decoding performance of the sparse multi-electrode EMG signal database NinaPro performing the same hand movement was compared. The visual inspection of the EMG map was used to determine the onset of HDEMG. The proposed approach was tested on EMG decoding window length of 150 ms, demonstrating a mean±SD testing performance of 94.21%±4.84% after voting. However, it is worth noting that sparse EMG signal did not achieve the desired decoding accuracy. The result showed that the high-density EMG signal could be used to decode the motion intention within EMD by simple machine learning algorithms, and extending the window length of training set could improve the decoding accuracy.

INDEX TERMS EMD, EMG, intention decoding, machine learning, pattern recognition, transient.

I. INTRODUCTION

Robot-assisted training provides an effective approach to impairment of hand function, such as neural prosthesis and exoskeleton rehabilitation robot generally controlled by neurophysiological signals, such as EEG [1] and EMG [2], [3]. The surface EMG is a non-invasive bioelectrical signal containing rich motion information that reflects users' motion intentions. EMG-based motion intention decoding is widely used in the brain-muscle computer interface (BMI), or called muscle-computer interface (MCI). The key of human-computer interaction through EMG is to recognize the users' motion intentions accurately, including discrete and continuous situations. The discrete decoding is limb discrete motion classification, such as hand fist, palm extension. The continuous decoding is joint continuous motion estimation, such as joint torque, joint angle and other continuous quantities. As the extension of continuous motion estimation, the estimation of softness such as joint stiffness and impedance is also important to improve the natural interaction ability of human-machine. In order to realize the hierarchical control as the human brain, only the effective synergy of discrete and continuous intent decoding can realize the natural control of human-machine.

The motion of the human limb is achieved by muscle contraction, where the motor control signal is delivered by motor intent from central neural system. The whole motion generation process is not instantaneous. Research shows that the time duration between the onset of the EMG signal and the onset of force production during a muscle contraction is

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about 10-300ms, which defined as electromechanical delay (EMD) [4], [5]. Regardless of discrete or continuous situation, in order to decode intent from peripheral nerve in the human-computer interaction based on EMG, it is necessary to fulfill decoding within EMD after the human brain motion intention is generated in order to prevent the user from feeling delayed. The decoding result is accordingly used to control the neural prosthesis or the robot, thereby enhancing users' sensing feedback, which in turn can fully activate brain plasticity in the neurological rehabilitation system.

Discrete EMG classification is the first step of human-machine control based on motion intention decoding. As the core technology of MCI, the basic steps of EMG pattern recognition are preprocessing, windowing, feature extraction and classification [6]. The correct classification is achieved by selecting appropriate features [7], [8] and classifiers, such as the commonly used machine learning methods [9]–[13] and the state-of-the-art learning methods [14]–[16]. The EMG pattern recognition has achieved a high accuracy in the traditional EMG signal classification. For example, Lucas et al. [17] proposed an approach based on support Vector Machines (SVM) to classify six kinds of hand movements, achieving the accuracy higher than 95%. Chu et al. [18] recognized nine kinds of hand movements and achieved 97.4% accuracy through a multilayer perceptron classifier. Geng et al. [2] introduced the concept of an EMG image spatially composed from high-density EMG. They presented that the resultant recognition accuracy of an 8-gesture based on EMG images with a classification scheme of a deep convolutional network reached 89.3% on a single frame of EMG image, besides, the accuracy of 99.0% was obtained by simple majority voting over 40 frames with a 1,000 Hz sampling rate. The above studies have achieved a high decoding accuracy for intent decoding of EMG signals, but the EMG signals used to train and test the classifiers in the reports are the steady state EMG. Actually, in the process of human-computer interaction, the desired motion of the human intent has already started before the steady-state EMG. In the steady-state EMG duration, continuous decoding rather than discrete decoding is required. That is, the continuous prediction of joint torque and angle is expected to ensure the safety and compliance control of the human-machine system. Accordingly, in order to perform discrete intent decoding, namely to detect attention awareness, the decoding should begin from the onset. There is even a more stable spatiotemporal pattern than the steady-state EMG in the transient EMG, which uses only the data contained in a short window associated to a muscle contraction, which is known as containing a deterministic structure [19]. Therefore, discrete gestures can be decoded by the transient EMG within the EMD starting from the onset of muscle contraction, the prediction result can be used to plan the robot control scheme, and then realize the hierarchical control of the human brain nervous system combined with the continuous decoding result.

The idea of using pattern recognition of transient EMG for decoding is not new. Pizzolato et al. [20] classified all 52 movements in NinaPro DB4, and the best average accuracy obtained is 69.13% with marginal discrete wavelet transform feature and random forests classifier. There were literatures considered EMG from onset [20]–[23], yet, the steady-state EMG was included. Although the signals fed into the classifier were not clarify in the study, the proportions of transient signals are low in the duration of the entire data. Besides, the data of the transient signals are sparse and unbalanced with respect to the steady state EMG signals duration, so the steady state characteristic is still in effect. Additionally, other authors already proved that it was feasible to use transient EMG signals for discrete motion intention decoding and even for real-time control of the prosthetic hand. Gandolla et al. [24] proposed a cascade artificial neural network to predict 3 grasp functional tasks with the EMG signals measured in a 100ms window after the EMG onset. The accuracy for intact subject was 76%±14%, which was achieved using 5 channels. The motion intention decoding accuracy of the literature is lower compared to motion classification based on steady-state EMG signals. Recently, Gunter et al. [19] validated that EMG patterns at the onset of a contraction can be used for real-time control of a prosthetic hand. The maximum accuracy for four hand tasks was 94%, which achieved using 15 channels with EMG signal measured in a 300ms window.

Despite the rather direct relation between a motion (or an intended motion) and the expressed transient EMG signals, however, there remain several open issues before the decoding of hand movement intention by transient EMG will reach the ideal characteristics needed in control of prostheses in human-robot interaction. For example, 1) the different effect of the decoding window length on the decoding accuracy, 2) how to construct the training set, and 3) whether the acquisition method of myoelectric signal affects the decoding result. In view of the superior performance of machine learning in pattern recognition, this paper focuses on solving the above problems of decoding transient EMG signals with it.

Although the duration of transient EMG is short, fortunately, the high-density EMG signals have rich spatial characteristics to provide more conducive features for decoding within EMD in the shortest possible time. In this paper, the high-density EMG signal (HDEMG) database CapgMyo was used to decode of discrete hand motion by machine learning algorithms. We investigated the influence of decoding window length and training set constructing method. In addition, we compared the feasibility of sparse EMG signal for intention decoding by using the sparse EMG database NinaPro which performs the same hand movement as CapgMyo.

II. MATERIALS AND METHODS

A. DATABASE

Surface HDEMG data obtained from CapgMyo [2] DB-a database which contains 8 isometric and isotonic hand gestures obtained from 18 intact subjects was analyzed in

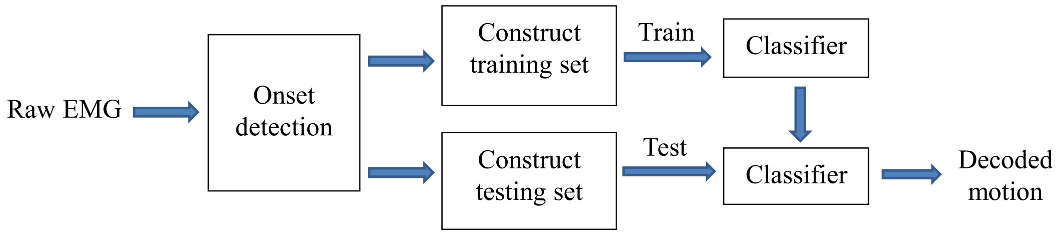

FIGURE 1. Block diagram of Motion Intention Decoding with Transient EMG Signal.

this study. Each gesture was held for 3 to 10 seconds and repeated 10 times. The 128 electrodes were recorded around the circumference of the forearm. The database contains raw data of the HDEMG signal as well as pre-processed data. Both sets were band-pass filtered at 20-380 Hz and sampled at 1,000 Hz and used in this study to investigate the effect of intention decoding. In particular, The pre-processed data set contains only the steady-state part of the HDEMG which has been reported to decode and achieved high recognition accuracy [2].

In order to discuss the decoding performance of sparse EMG signal under the same gesture conditions, we select publicly available database NinaPro [25] DB-4 for comparison, where the EMG is recorded by a total of 12 electrodes and the sampling frequency of 2kHz, and the movement labels and onset have been corrected [26]. The NinaPro DB-4 contains 52 kinds of motions of 10 subjects, each movement repeating 6 times. The gestures of numbers 13-20 in the NinaPro database correspond to the HDEMG database CapgMyo DB-a.

B. FRAMEWORK OF MOTION INTENTION DECODING WITH TRANSIENT EMG SIGNALS

All approaches of EMG pattern recognition have the fundamental processing parts including data preprocessing, data windowing, feature extraction and classification [6]. In this paper, we propose to construct different training sets for training classifier, and test different window length for decoding. Data windowing and feature extraction work on the training set and the testing set separately. Prior to the train and test, the onset detection is conducted. The structure of intent decoding is shown in Fig. 1.

C. ONSET DETECTION

Visual inspection of EMG signal is not only the earliest method for detecting EMG onset, but also a gold standard for verifying the other onset detection methods [27], [28]. Usually for single-electrode or sparse multi-electrode EMG signals, the onset can be determined directly by visually observing the signals of each channel. As for HDEMG signal, however, direct observation is not applicable due to the large number of channels. HDEMG signal depicts the temporal and spatial distribution of muscle electrical activity in the electrode coverage area, showing a global view of the state of the electric field changes that muscle activity produces on the skin surface [2]. EMG map formed by EMG signal then reflects the distribution of the potential in space. Thus, in this paper, the Jet coloring scheme is adopted to produce EMG map [29]. Namely, the feature extracted from HDEMG was converted into RGB pixel value to form a color image. Then the onset of the myoelectric signal was recognized by visually observing the EMG map, considering the difference between the rest and contraction potentials of the myoelectric signal in the spatial distribution.

D. CONSTRUCTING TRAINING SETS AND TESTING SETS

For HDEMG, three of ten trials were selected as the testing set. The remaining seven trials constituted the training and validation sets. For sparse multi-electrode EMG, one of six trials was selected as the testing set. The remaining 5 trials constituted the training and validation sets. The 7-fold and the 5-fold cross-validation were utilized for HDEMG and sparse multi-electrode EMG.

It is generally considered that users will not feel delayed within 300ms because of the delay between the onset of the EMG signal and the onset of force production [30], hence we selected the EMG signal of 300ms from onset, as shown in Fig. 2 for every channel. Five training sets were obtained from the selected EMG segments, starting from onset and the lasting length varying from 100ms to 300ms in steps of 50ms. In addition, in order to investigate the effect of steady-state EMG signals on decoding transient EMG signals, and make the steady-state part occupy the same proportion of the training set, we selected 150ms steady-state and 150ms transient signal respectively to obtain the sixth training set.

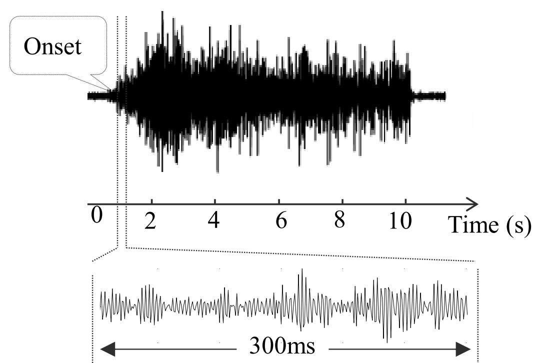

FIGURE 2. Segment data of 300ms from onset for constructing.

In order to study the influence of decoding window length on the accuracy, six test sets with different decoding window length varied from 50ms to 300ms in steps of 50ms, also starting from onset, were formed to test the classifiers.

E. FEATURE EXTRACTION

The method of overlapping windows can solve the decision error caused by the non-stationary of EMG signal [31]. The number of windows (N_{win}) can be calculated as:

$$N_{win} = \frac{L-\Delta L}{L_s-\Delta L}, \tag{1}$$

where, L is data length, ΔL is window increment, and L_s is the sampling window. In this paper, the L_s and ΔL are set as 10ms and 5ms, respectively.

As a representative time domain feature, the average of the absolute values (MAV) of the EMG signal amplitude in the time window is comparable to the output of clinically available EMG sensors [19], so we chose the common time domain feature average of the absolute values in our study, the calculation of which is shown in Equation (2) below [7]:

$$MAV = \frac{1}{N} \sum\nolimits_{i-1}^{N} |x_i|, \tag{2}$$

where x_i, $1 \leq i \leq N$ represents the ith point in the window, and N is the total number of sampling points within a window length.

F. CLASSIFIER

The aim of this paper is to study the influence of the decoding window length, training set constructing methods and the myoelectric detection type on the discrete decoding of transient EMG signals, so the selection of feature quantities and classifiers are not selected preferably under this premise. Instead, classifiers were trained and cross-validated for the first seven repetitive using the CLASSIFICATION LEARNER toolbox in MATLAB R2018b that published by the MathWorks company. Then according to the decoding accuracy obtained by cross-validation, the best three classification models, cubicSVM, LDA and fineKNN were selected. BP neural network previously applied to EMG analysis and showing good performance was also chosen as classifier in our study.

G. EVALUATION METHOD

A majority vote (MV) [32] was used to further improve the reliability and accuracy of the classification. More specifically, the classification result with the highest number of votes in all the samples of a testing set is the final decision result, and the classification accuracy (ACC) [33] is the ratio of the number of correctly classified test sets to the total number of testing sets:

$$ACC = \frac{TP + TN}{TP + FP + TN + FN}, \tag{3}$$

where TP represents the number of true positives which means testing pattern x classified as belonging to pattern x; FP represents the number of false positives which means any other patterns classified as pattern x; FN is the number of false negatives which means pattern x classified as belonging to any other patterns; and TN is the number of true negatives which means any other patterns that are not classified as belonging to pattern x.

III. RESULTS

A. HIGH-DENSITY EMG SIGNAL ONSET DETECTION

Firstly, the approximate positions of the onset are found through some more obvious channels of the raw HDEMG, then the EMG maps before and after the approximate point are produced. Then the onset of the HDEMG is determined by visual inspection of EMG maps. Since the CapgMyo data are collected by an electrode grid of 16 rows and 8 columns, a color image with a pixel of 16 × 8 is generated. The EMG maps before and after the approximate onset of the first subject are shown in Fig. 3. When there is no contraction, the amplitude of the EMG signal is almost zero, and the EMG color is darker, as in the picture 1–8 of Fig. 3. As soon as the muscle contraction starts, the amplitude of the EMG signal gradually increases. Then the bright color area of the presented EMG is gradually increasing, as shown in the picture 9–15 of Fig. 3. Therefore, the position of the onset can be determined from the change in the brightness of the myoelectric image, where we can find that changes begin from the ninth color map, so the point corresponding to the ninth map is determined as the onset.

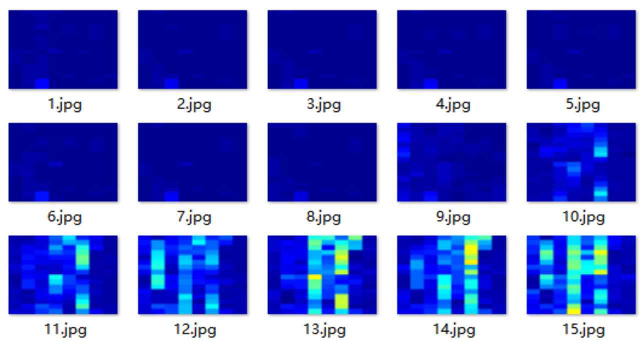

FIGURE 3. HDEMG maps for the onset detection of the first subject.

B. ANALYSIS RESULTS OF DIFFERENT TESTING SETS

Studies have demonstrated that the decoding window length of 300ms achieved the best accuracy in the situation when the decoding window length is restricted within 300ms with latencies short enough to be perceived as real time by the individuals [19]. However, we still don't know how and to what extend the decoding window length of the EMG signal affects the decoding accuracy.

In this section, the classifiers were trained by the transient EMG within EMD of 300ms, and then tested by different decoding window length from 50 to 300ms with 50ms step. Fig. 4 displays the test results of HDEMG decoded by SVM, LDA, KNN and BP. For all the four decoding modes, as the decoding window length increases, the accuracy increases

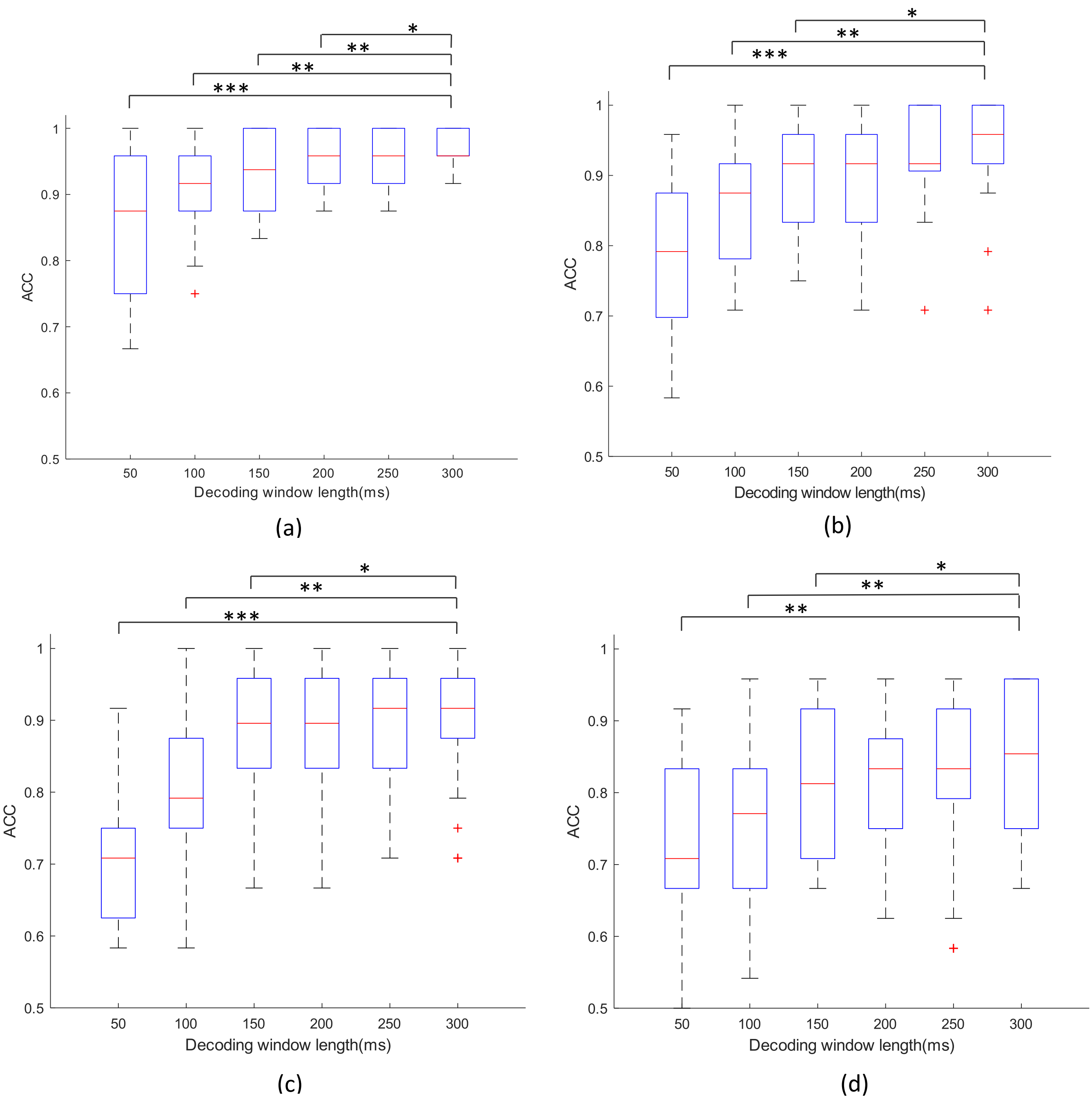

FIGURE 4. Boxplot of the decoding accuracy for high-density electrodes EMG of different decoding window length that show a statistically significant difference with the longest window length as determined by the ANOVA (*: $p > 0.05$;**:$0.001 < p < 0.05$;***: $p < 0.001$). The window length which equals to 300ms was utilized to train the classifiers. (a) Boxplot of the SVM decoding accuracy. (b) Boxplot of the LDA decoding accuracy. (c) Boxplot of the KNN decoding accuracy. (d) Boxplot of the BP decoding accuracy.

apparently, then improves slightly, and finally reaches the maximum when the decoding WL = 300ms. Further, a one-way Analysis of Variance (ANOVA) was used to perform this analysis in MATLAB R2018b that published by the MathWorks company. Fig. 4(b), (c) and (d) indicate that for LDA, KNN, BP classifiers, there is a significant difference between the decoding window length of 300ms and less than 150ms ($0.001<p<0.05$). Whereas the accuracy is no longer significantly improved when the decoding window length is equal to or greater than 150ms ($p>0.05$). However, slightly unlike LDA, KNN, BP, until the decoding window length is equal to or greater than 200ms, the decoding accuracy of SVM is no longer significantly improved ($p > 0.05$), as shown in Fig. 4(a).

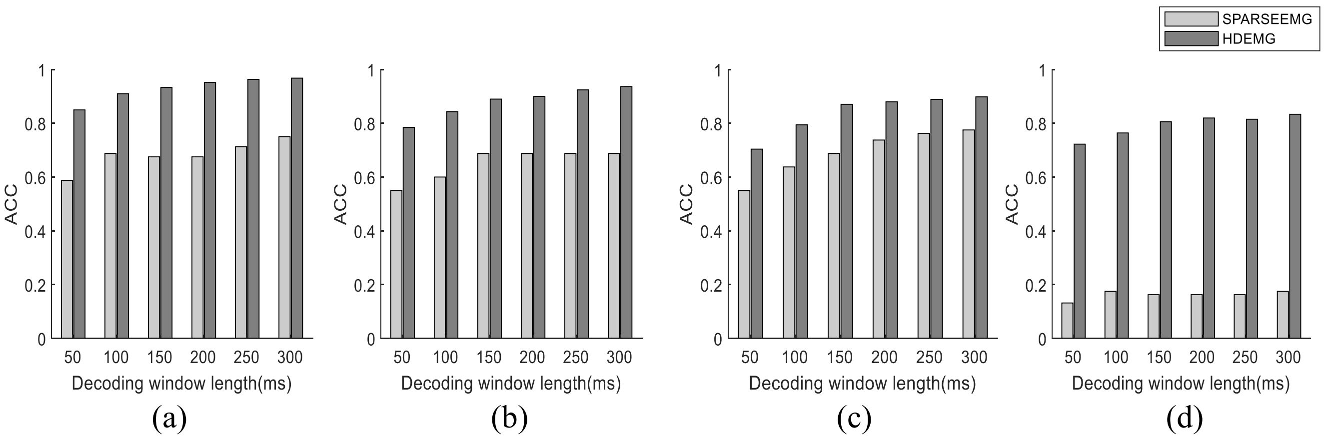

FIGURE 5. The average accuracy with SVM (a), LDA (b), KNN (c) and BP (d). The classifiers were decoded by different decoding window length for sparse and high-density electrodes. The window length which equals to 300ms was utilized to train the classifiers.

As mentioned earlier, the decoding accuracy increases as the window length increases, and reaches the maximum when the decoding window length is 300ms. However the longer decoding window length leads to longer delay. Fortunately, accuracy of decoding window length 150ms and 300ms shows no significant difference with LDA, KNN and BP except for SVM, which is shown in Fig. 4. And the accuracy of SVM shows no significant difference between the decoding window length 150ms and 200ms ($p = 0.3095$) by the ANOVA. Accordingly, In order to decode the motion intention of the HDEMG signal as short as possible and also with adequate accuracy, we finally chose decoding window length as 150ms to evaluate the influence of different training window length in the subsequent analysis.

Fig. 5 shows the decoding results of the sparse acquisition mode, too. It confirms that the decoding accuracy increases as the decoding window length increases. The decoding accuracy obtained from three decoding modes of SVM, LDA and KNN is lower than 70% when the decoding window length is less than or equal to 150ms, which is shown in Fig. 5 (a), (b) and (c). The decoding accuracy of sparse acquisition mode reaches the maximum when the decoding WL = 300ms with KNN, but still lower than 80% (Fig. 5 (c)). Moreover, Fig. 5 (d) also shows that BP is not suitable for the intended decoding of sparse EMG signal. Remarkably, for HDEMG, the minimum decoding accuracy reaches as high as 70% when the training WL = 300ms and decoding WL = 50ms (Fig. 5 (c)). Consequently, the results revealed that sparse EMG signals can also achieve transient EMG signals intent decoding when the training WL = 300ms, nevertheless, the results of sparse EMG is quite unsatisfactory compared to the HDEMG.

In order to study the effect of feature extraction on the decoding for transient sparse EMG signal, several other time domain features were selected to form feature sets. The feature set consists of MAV, IEMG, DASDV, SSI, VAR, and WL [7] which was popular with decoding. As mentioned before, BP may not be suitable for sparse EMG, so SVM,

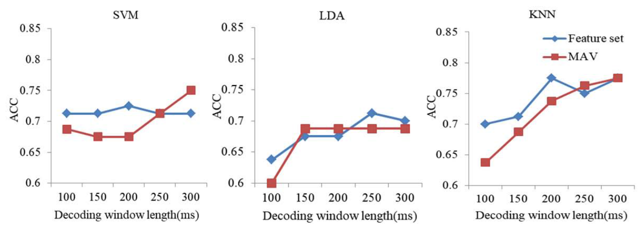

FIGURE 6. Decoding accuracy depending on the testing set for different features and classifiers when the training set is 300ms.

LDA and KNN were used as decoders. In this case, the result is shown in Fig. 6. It shows that for KNN and SVM, when the training set is within 300ms and the testing set is less than or equal to 200ms, the classification accuracy is improved. But as the decoding window length increases, the accuracy decreased. Increasing of feature does not show an advantage. However, the increase of features has little effect on improving the transient decoding performance for LDA.

In addition, for the sparse EMG signal, the window length is increased from 10ms to 50ms. The results obtained by the three classifiers after voting are shown in Fig. 7. As can be seen from Fig. 7, the decoding accuracy of LDA is improved, but the SVM is reduced. The KNN is basically unchanged. It's probably because the effect of increasing the sampling window length on the classification accuracy is weakened by voting.

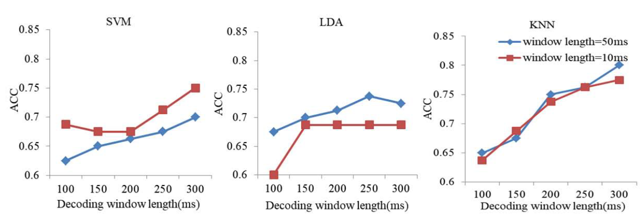

FIGURE 7. Decoding accuracy depending on the testing set for different sliding window lengths and classifiers when the training set is 300ms.

C. ANALYSIS RESULTS OF DIFFERENT TRAINING SETS

Various pattern recognition methods are capable of high performance in myoelectric control under steady-state conditions [2], and most of the classification errors were clustered at the beginning and end of the contractions [21]. The result of literature is confirmed by a preliminary analysis in our study. The SVM classifier was trained by steady-state HDEMG of 100ms and tested when decoding WL = 100ms, obtaining an average accuracy as low as 50%. This fact prompted us to construct training set using transient EMG signals. As the transitional phases of myoelectric signal from relax to steady state, how to construct the training set is problem to be explored in this study.

The statistical difference between different decoding window length and maximum decoding window length of 300ms when training with 300ms for sparse multi-electrode EMG is analyzed by ANOVA. The result shows that there is no statistically significant difference between the testing window length of 100ms and 300ms for all of the three classifiers. However, as shown in Fig 5, the decoding result of decoding window length of 150ms exceeds 65% for all of the classifiers except for BP, which is meaningful for the sparse EMG signal with poor decoding effect. Therefore, decoding window length of 150ms is used to evaluate the influence of different training window length for sparse and HDEMG.

Six different training sets were constructed to train four classifiers which were then tested with decoding window length of 150ms to discuss whether extending the time window length for training can improve the decoding performance of transient EMG signals, as well as the associated effect of steady-state and transient EMG training on transient EMG decoding. Fig. 8 represents the decoding results of different training window length for HDEMG with four decoding methods when decoding WL = 150ms. As we can see, the accuracy reached the maximum of 94.2%, 90.2%, 87% and 80.8% when training WL is equal to 200ms, 100ms, 300ms, and 250ms for SVM, LDA, KNN and BP respectively. In the four decoding modes, different decoders have different trends associate to the training set within EMD. The decoding results with SVM and BP have a rising trend with the increase of the training window length. Remarkably, the accuracy begins to decrease from training window length of 200ms and 250ms respectively. As for KNN decoder, the decoding result increases rapidly when the training window length from 100ms to 150ms, then increases slightly until the WL = 300ms. It indicates that the length of the transient EMG signals for training cannot be increased indefinitely. Conversely, the decoding result of LDA decoder decreases with the increase of the training window length, then it is stable. Especially, the increased steady state portion seems to negatively affect the decoding accuracy with four decoding methods. Moreover, The BP decoding method achieves the lowest decoding accuracy in the training set with steady-state components, and it is the lowest accuracy in the four decoding modes too, but also 72%. In summary, Fig. 8 confirms that the decoding performance of HDEMG can be improved by extending the window length of training set except for LDA.

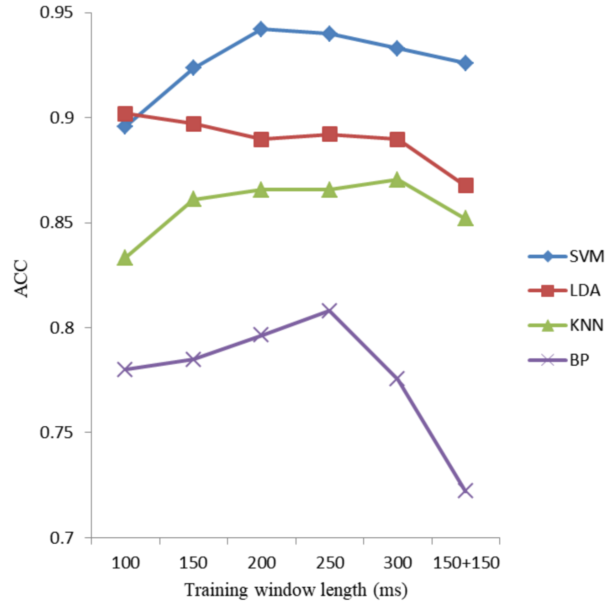

FIGURE 8. Decoding results of different training window length for HDEMG with four decoding methods when decoding WL = 150ms.

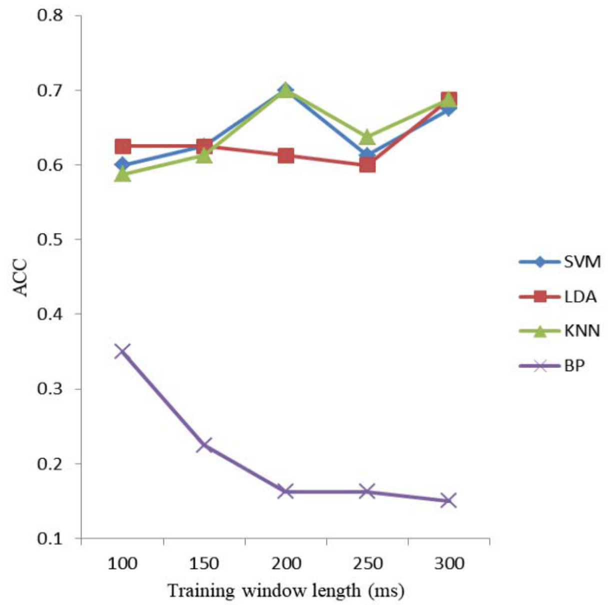

FIGURE 9. Decoding results of different training window length for sparse multi-electrode EMG with four decoding methods when decoding WL = 150ms.

Fig. 9 shows the decoding results of different training window length for sparse multi-electrode EMG with four decoding methods when decoding WL = 150ms. The decoding results of the decoders are different for different training window length, and the best result with BP is less than 40%. This fact suggests that the BP is not suit to achieve transient decoding of sparse EMG signals. The results with LDA reach the maximum of 68.8% when the training WL = 300ms. Importantly, the decoding result of sparse EMG signals reach the maximum accuracy of 70% when the training WL = 200ms with SVM and KNN, unfortunately, it still less than the minimum accuracy decoded by HDEMG.

D. ANALYSIS RESULTS OF DIFFERENT DECODING METHODS

As for HDEMG, Fig. 8 also confirms that compared with the other three classifiers, the decoding result of SVM is the best. The analysis results of different training sets also revealed that although there are differences in the decoding results between different training sets, the differences are not obvious (Within 300ms, the accuracy obtained by the same classifier is about 5% between the minimum and maximum). In particular, a one-way ANOVA was calculated, showing that there was no significant difference between results when training window length equal to 150ms and 200ms with the SVM decoder ($p = 0.3257$). Increasing the amount of training time would make it impractical for clinical applications [21]. Therefore, a shorter training set could be used to achieve better decoding results, and the training time can be shortened while ensuring the accuracy. Besides, the combination of short training set and testing set is more suitable for clinical applications. Importantly, in the case when the training window length and the test window length are both equal to 150ms, the decoding accuracy has reached more than 92% with SVM. Thus the decoding accuracy of 18 subjects with four decoding methods for HDEMG was analyzed in Fig. 10, and the decoding window length is 150ms as same as training window length.

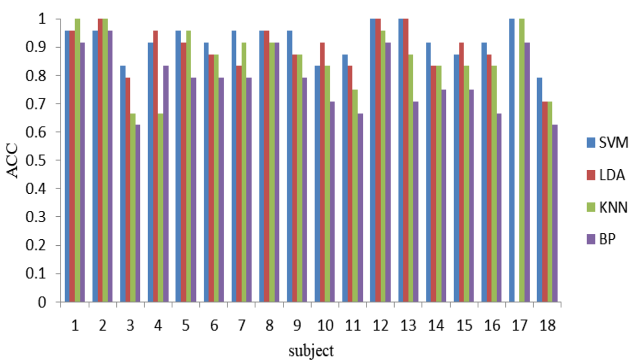

FIGURE 10. Decoding accuracy of 18 subjects with four decoding methods for HDEMG. Both the decoding window length and the training window length are both equal to 150ms.

Fig. 10 indicates that different subject have different decoding performance with the same classifier, and each subject has a special decoding method. For instance, the decoding accuracy for 17th person is near 100% with SVM and KNN, and the result is also more than 90% with BP, but it can't be decoded by LDA classifier. Table 1 also indicates that SVM decoding is more stable, according to the standard deviation of the four methods.

TABLE 1. Standard deviation of 18 subjects with four decoding methods for HDEMG. Both the decoding window length and the training window length are both equal to 150ms.

Decoding method	SVM	LDA	KNN	BP
SD	0.0578	0.0784	0.1021	0.1014

TABLE 2. Statistical analysis of decoding results between different classifiers and SVM by ANOVA for sparse and high-density EMG signals. Both the decoding window length and the training window length are both equal to 150ms.

p	LDA	KNN	BP
HDEMG	0.1744	0.0397	0.00003
sparse multi-electrode EMG	1	0.8619	0.0001

When training and testing window length are both 150ms, the statistical difference between the classification results obtained from SVM and the other classifiers was analyzed. The result of ANOVA is shown in Table 2. As can be seen from Table 2, for HDEMG signals, although the decoding effect of SVM is better, there is no significant difference from the decoding result of LDA. As for sparse EMG signals, the decoding effect between SVM and other classifiers did not show a significant difference except for BP.

IV. DISCUSSION

The contributions of this paper is that we decode the motion intention with a short window of EMG signal (only 150ms EMG signal after the onset), and provide a reference scheme for reducing the system delay of the neuroprosthesis. In addition, we solve the transient decoding problems with a fast and simple method (the average of the absolute values feature, SVM classifier) that is more suitable for clinical applications. Furthermore, several problems in transient EMG signals are discussed in detail: (a) how to construct the training set, (b) the influence of different test set window lengths, and (c) EMG collection mode on transient decoding.

Based on the fact that low accuracy decoding on transient EMG when the classifier is trained by steady state EMG signal, we constructed training set with transient EMG. Intention decoding on transient EMG can reduce the system delay compared with the traditional method, and the idea of using pattern recognition of transient EMG for intention decoding is not new [34]. With more and more EMG signals are used for the control of prosthetic hands, transient EMG signals have highlighted advantages in the aspect of delay. Recently, many literatures have made efforts in this regard [19], [24]. On the basis of the report [19], we proposed to construct different training sets with transient electromyography specially, realizing the decoding of motion intention. Furthermore, we choose high-density EMG signals which is full of spatial information so as to improve accuracy with 100ms EMG after onset detection [24]. Ideally, the decoding accuracy is improved compared with Gandolla et al. (76%±14%) when the training and testing window length are both 100ms (the accuracy of 91.67%±4.17% with SVM). In addition, we studied the decoding of 8 finger movements unlike the decoding of 3 or 4 movements mentioned in the above literatures.

The construction methods of the training sets are not mentioned in most of the literatures decoded with transient myoelectric signals. As such, different training sets and testing sets were constructed in our study under the premise of ensuring the optimal delay of EMG control equipment, in an effort to quantify the impact of transient EMG on the classifier's performance. In addition, the performance of classifiers which trained by transient EMG was tested by different testing set. Interesting, we find that as the length of the decoding window increases, the accuracy increases. This is in accordance with literature [19]. Moreover, the decoding performance was improved with increasing of the training window length, which compensated for the poor performance of the transient EMG classification by the classifier which trained by steady-state EMG. The results obtained from classifiers which trained by transient combined with steady-state EMG are also better than trained by steady-state EMG, indicating that selecting the appropriate training set improved the decoding performance.

In addition, the proposed decoding methods based on transient HDEMG showed better performance than sparse multi-electrode EMG. This result indicates that high-density EMG signal is more suitable for intentional decoding of transient EMG signal. It is more likely due to the fact that the number of HDEMG signal electrodes is redundant when there is an intentional decoding of the whole process of the EMG signal, which causes problems such as complicated decoding time of data processing. Indeed, the myoelectric signal within 300ms from onset was used in this study, which is extremely short compared to the entire myoelectric signal. This feature makes the decoding time of HDEMG signal reduced greatly. Ideally, high-density spatial signals dominate the short-term EMG signal and provide more information for intent decoding.

The methods for transient EMG signal decoding proposed in this paper are suitable for intact people, and the application in the intention decoding of patients such as stroke is worth trying. Besides, more and more methods of deep learning are proposed in literatures to decode the motion intent. Therefore, the construction method of training set and testing set we proposed can be further applied to the study of deep learning. Although our method is tested under offline conditions, with the advancement of control algorithms [35], [36], the robot controlled by EMG signals has become increasingly mature, so whether it can be used to control neuroprosthesis such as exoskeleton robot is worth considering.

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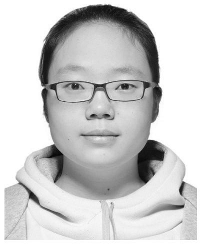

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