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A synchronous and multi-domain feature extraction method of EEG and sEMG in power-assist rehabilitation robot*

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***Abstract*—To propose a synchronous and multi-domain feature extraction method of electroencephalogram (EEG) and surface electromyogram (sEMG) signals is of great significance to power-assist rehabilitation robot control with human-computer interface (HCI). In this paper, nonnegative Tucker decomposition which is one model of nonnegative tensor factorization (NTF) is used to fuse two kinds of bioelectricity signals (EEG and sEMG) and extract multi-domain features of EEG and sEMG signals for classification which contain time, frequency, and space domains. In the first step the EEG and sEMG data are transformed into multidimensional information using continuous wavelet transform and the 4-D EEG-sEMG tensor is established. Then the tensor is decomposed into four components (spatial components, spectral components, temporal components and category components) and the core tensor is the feature extracted. The feature after being eliminated and compressed are fed into KNN, LDA and SVM classifiers for pattern recognition, and a comparison is done in single EEG analysis, single sEMG analysis and both EEG and sEMG analysis. An experiment about 10 healthy participants' upper limb movements was carried out to verify the validity of this algorithm. The result implied that NTF is a meaningful and valuable synchronous and multi-domain feature extraction method which may be promising in power-assist rehabilitation robot control.**

I. INTRODUCTION

ACCORDING to the World Health Organization, stroke is one of the major diseases which seriously threaten humans health and more than half of the stroke patients suffer from hemiplegia [1]. Clinical trials prove that through timely rehabilitation training, the motor function of most stroke patients can be recovered gradually and even healed. Recent years, the technology of hemiplegia rehabilitation assisted by robot has been introduced and gradually acquired the recognition of doctors and researchers. Various types of rehabilitation robots have been developed to assist physicians, which have improved the recovery efficiency signifycantly [2, 3]. However, most of these rehabilitation robots are no-power or simple mechanism with movement fixed, and the subjective intention and rehabilitation status of patients are ignored. The weakness of lacking flexibility and adaptability in robot control limits the application of rehabilitation robot. With the ideas of human-computer interface (HCI) appearing, human-centred design of power-assist rehabilitation robot has already become the hotspot of research and front field [4].

sEMG signals which represent neuromuscular activity are effective biological index for expressing movement intention and obtaining muscular system information. EMG-based HCI have been widely used in rehabilitation. For example, Osamu proposed a sEMG-control method based on log-linearized Gaussian mixture network (LLGMN) which assisted the patient's limb motion [5] and a neuromuscular method based on muscle reflex was proposed by Wu to control rehahilitation robot [6]. It is of great importance to find methods for decoding intended action from sEMG signals and extracting the feature information from sEMG accurately. Healthy people's sEMG signals can primely reflect the motion movement intention, however, for stroke patients with hemiplegia, the contraction and strength of affected side muscle are very faint which makes the sEMG so weak that it's difficult to acquire the movement intention of patient. What's more, the sEMG under dynamic movement is non-stationary and transient, which also brings difficult to motion recognition. EEG is considered, therefore, to be combined with the sEMG.

EEG is the reflection of electrophysiological activity from a group of nerve cells, which contains numerous physiological information. EEG from the cortical region of motion perception will have a corresponding change when people perform motor and control information from operator's intention can be obtained by analyzing EEG, in order to control object. Brain-computer interfaces (BCI) technology in rehabilitation robot has shown impressive progress in the last few years. Yoshikatsu used the cross-correlation functions of EEG to drive assistive robotic system [7], and the power density of frequency bands from the EEG are used by Ela as features to control the robot after classifing using LDA [8]. These robots with BCI technology are humanized and innovative, but the recognition rate still cannot meet the demand of precisely control. Nevertheless, more and more evidences suggest that there are complex mapping relations between EEG and sensory-cognitive processes, so studys on multichannel EEG signals and EEG-sEMG synchronous analysis are particularly important, especially for the central nerves injury patients with movement disorder.

From the above, the strategy integrating sEMG and EEG signals can avoid the disadvantages of single sEMG or single EEG strategy, however, few relevant researches in this field have been published at present, particularly in rehabilitation robot study. Armando designed a EEG-EMG HCI system classifies biosignals into mouse functions by

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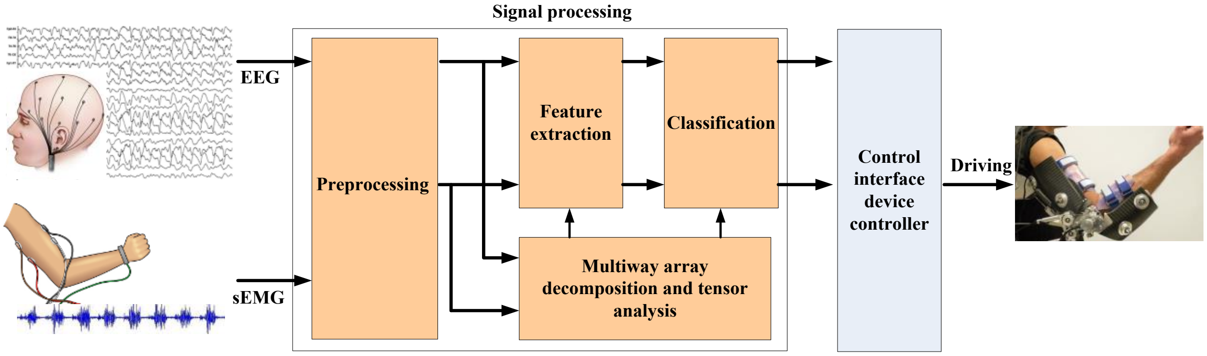

Fig.1. EEG-sEMG power-assist rehabilitation robot system.

applying amplitude thresholds and PSD which obtained a better result than the previous [9]. Robert fused the16-channel EEG and 4-channel EMG by Bayesian method to classify left and right hand movements, which was comfirmed to be better than classification only relied on EEG or sEMG [10].

In view of the above mentioned problem, this paper presents a synchronous and multi-domain feature extraction method of EEG and sEMG in upper-limb rehabilitation robot which is the signal processing part of rehabilitation robot system (Fig 1). In this study, we first use nonnegative Tucker decomposition (NTD) [11] which is one model of nonnegative tensor factorization (NTF) to extract multi-domain features of sEMG and EEG signal simultaneously for classifycation. Firstly, we pretreat the acquired sEMG and EEG signals and construction the spectral tensor by wavelet transform. Then the feature tensor is obtained by decomposing using NTD. Futhermore, the sEMG-EEG feature is classified by KNN, LDA and SVM. An experiment was conducted to confirm the validity and high performance of the algorithm.

II. Materials and Methods

A. Subjects

A sample of 10 subjects (6 males and 4 females) was recruited in this study. Subjects' ages ranged from 20 to 30 years old (mean ± standard deviation [SD], 25.2 ± 2.3y). All subjects were healthy without previous problems in nerve or physiology.

B. Instrumentation

During the experiments, EEG and sEMG were digitized simultaneously at a sampling frequency of 1kHz by a data acquisition equipment with a 16-bit Analogue-to-Digital converter and an amplifier (1000 ×). The scalp EEG signals of 32 channels referenced to the common linked electrodes at the earlobes were recorded. Signals from C3, C4, CP3, CP4, which represent the sensorimotor cortex were selected for further investigation. Two-channel sEMG with the 5-500Hz bandwidth were acquired simultaneously during the task. The participants were asked to do particular movements to find these target muscles (biceps brachii (BB) and triceps brachii (TB) or flexor carpi ulnaris and extensor carpi radialis). The signals were acquired using Ag-AgCl disposable sEMG electrodes, the diameter of which was 15mm. Two surface electrodes were connecters in two differential configurations separately placed on the bulge of the muscle with a reference electrode at the elbow. The arrangement ensured that two electrodes were along with the muscle fiber and the inter-center-electrode distance was 20mm. The skin at the electrodes sites were prepared by shaving and rubbing with alcohol. Fixing the lead wires appropriately in order to decrease the interference which dangling wires brought. The off-line data were further processed and analyzed using Matlab2011a.

C. Data acquisition

The test was performed with the subject sitting, and the elbow joint of dominant arm at the edge of the bench. The EEG and sEMG data were then recorded at 6 movement conditions- wrist flexion, wrist extension, fingers flexion, fingers extension, elbow flexion and elbow extension. For 6 movement conditions, each subject performed 4-sec long action ten times with 4-sec of rest in between. 1200 data sets of EEG and 600 sets of sEMG were recorded in total. The same procedure was repeated for each subject and condition (Fig.2). We cut the trials into 8s segments and manually discarded the segments trials contaminated with sensor jumps.

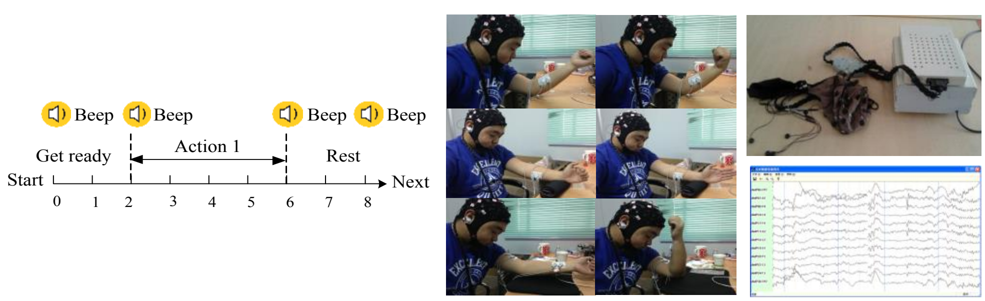

Fig.2. Pictures of experimental process and setup.

D. Nonnegative tensor factorization

(a) NTF

Nonnegative tensor factorization (NTF) is an effective approach to extract features of high-dimensional data. It is a multiway extension of nonnegative matrix factorization (NMF). Hidden latent characteristics in data structures can be extracted using this method. Ideally, the features extracted by NTF have the character of nonnegative and sparse, which ensures the physical significance of features and benefits the local feature extraction. A multiway array is regarded as a tensor. A vector is a 1-order tensor, a matrix is a 2-order tensor, and a cube is a 3-order tensor. One of the most promising factorization of NTF is the nonnegative Tucker decompositions (NTD).

(b) Nonnegative Tucker Decompositions

The NTD model [12] is a restricted form of Tucker model which imposes nonnegativity performs decomposition of N^{th} -order tensor $\underline{Y} \in \mathbb{R}^{I_1 \times I_2 \cdots \times I_N}$ as

$$\underline{Y} = \underline{G} \times_1 U^{(1)} \times_2 U^{(2)} \cdots \times_N U^{(N)} + \underline{N} \tag{1}$$

Where, $\times_N$ denotes mode - n tensor-matrix product. $U^{(n)} = [u_1^{(n)}, u_2^{(n)}, \cdots, u_{J_n}^{(n)}] \in \mathbb{R}^{I_N \times J_N}$, $n(n = 1, 2 \cdots N)$ is the nonnegative component matrix or common factors, and $\underline{G} \in \mathbb{R}^{J_1 \times J_2 \cdots \times J_N}$ is a core tensor (normally, lower dimension than tensor $\underline{Y}$. The nonnegative component matrix captures the variation along the N modes and the core tensor captures the interaction between them. $\underline{N}$ is a tensor representing error or noise.

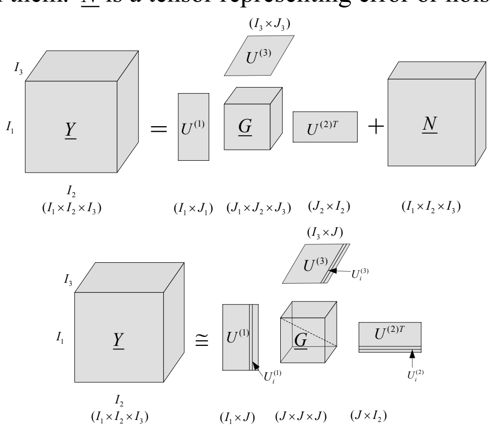

Fig.3. (a) Illustration for a 3-D Tucker decomposition (b) The NTD model.

Given a nonnegative tensor $\underline{Y}$, the objective is to seek a nonnegative core tensor $\underline{G}$ and nonnegative component matrix $U^{(n)}$ such that $\underline{Y} \cong \underline{G} \times_1 U^{(1)} \times_2 U^{(2)} \cdots \times_N U^{(N)}$. In this model, the core tensor $\underline{G}$ is specially reduced to a diagonal tensor with $J_1 = J_2 = \cdots = J_N = J$. The models are showed in Fig.3.

E. Data analysis

(c) Pretreated

EEG and sEMG signals are very weak, inevitably contaminated by the presence of artifacts. Such as EOG, inadequate skin-electrode contacts, baseline drift, low-frequency movement artifact, the power line interference (50Hz and its higher harmonics), etc. In order to remove any artifact, a scheme of pretreatment was designed in this study. An adaptive high-pass filter (digital 8th-order Butterworth) was used to remove baseline drift and movement artifacts were isolated by 0.5-75Hz(EEG) and 0.1-200Hz(sEMG) band-pass filters (digital 8th-order Butterworth). The power line interference and EOG were suppressed using Independent Component Analysis (ICA). Examples of pretreated signals are depicted in Figure 4.

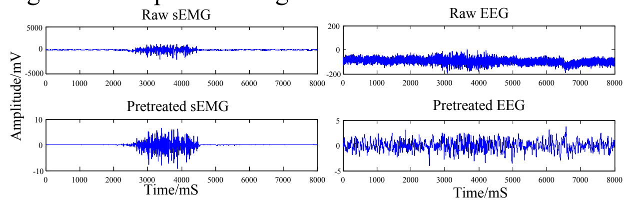

Fig.4. Contrast diagrams of raw signals (top) and signals after pretreating (bottom)

The method of NTF needs the tensor more than 2 coordinates, however, EEG and sEMG signals acquired by the equipment are both stored in the form of one dimensional data in time domain. In order to use NTF to analysis multi-domain features including EEG and sEMG, multichannel and multisubject, time-frequency-space domain and multi-way classification, the data should be transformed into multi-dimensional information and the EEG-sEMG tensor should be established first.

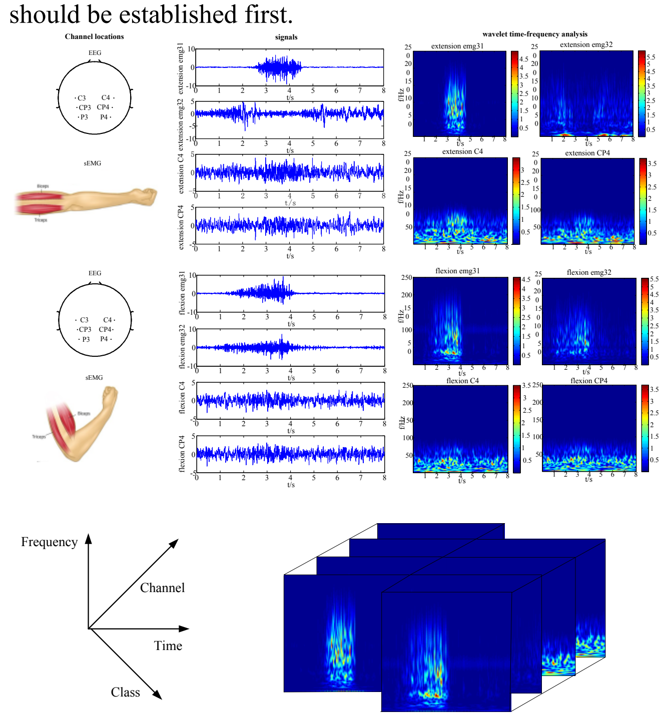

Fig.5. 4-D tensor construction and visualization of EEG and sEMG data.

Transformation of signals into the time-frequency domain is a standard technique to augment dimensionality. All the EEG and sEMG signals were transformed into the time-frequency domain using the complex Morlet wavelets CMOR6-1 with the bandwidth parameter fb=6 Hz, and the wavelet center frequency fc=1 Hz. Since the movement conditions have significant correlation with the energy of sEMG and EEG, the modulus of wavelet coefficient is selected as the representation of time-frequency character.

The data for each trial formed a 3-D spectral tensor with the modes of 4 channels × 200 frequencies × 8000 times. Take left elbow movement for example (so does the following part), BB muscles and the TB muscles are two sEMG channels, C4 and CP4 are two EEG channels, and elbow flexion and elbow extension are two classes. Hence, the full data is a 4-D tensor of size 4 channels × 200 frequencies × 8000 times × 2 classes. Fig.5 shows the procedure of transformation.

For classification, the whole data set is divided into 2 parts. That means the training data $\underline{Ytr}$ is a 4-D tensor of 60 sub-tensors for each subject and two classes (elbow flexion and elbow extension) : 4 × 200 × 8000 × 2. The test data is 140 sub-tensors $\underline{Yts}$ of 4 × 200 × 8000 × 2.

(d) Feature extraction and classification

In order to extract features from spectral tensor, we decompose the 4-D training tensor $\underline{Ytr}$ along its first three dimensions to find 3 basis factors for spatial components, spectral components and temporal components. Features of a 3-D tensor are coefficients of this tensor in the subspace spanned by estimated basis which are expressed by the core tensor in the NTD [13].

$$\underline{Ytr} \cong \underline{Gtr} \times_1 U^{(1)} \times_2 U^{(2)} \times_3 U^{(3)} \tag{2}$$

Then, the Laplacian Tensor Discriminant Analysis [14] is employed to further eliminate redundant features, and the most distinct basis factors are preserved. So the estimated factors $U^{(n)}, n=1,2,3$ are reduced to 4, 45 and 36 components. The size of core tensor is 4 × 4 × 4. Features for training and test data are core tensors in NTD with the same basis factors $U^{(n)}$

$$\underline{Gtr} = \underline{Ytr} \times_1 U^{(1)T} \times_2 U^{(2)T} \times_3 U^{(3)T} \tag{3}$$

$$\underline{Gts} = \underline{Yts} \times_1 U^{(1)T} \times_2 U^{(2)T} \times_3 U^{(3)T} \tag{4}$$

A spectral tensor is compressed to a feature tensor of size 4 × 45 × 36. Matricization of the feature tensors for training and test data and matrices of features are acquired.

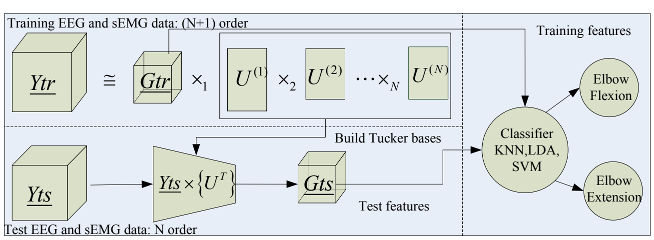

Fig.6. Tensor factorization for the training data and projection of the test data to extract features

A trial has in total 4 × 45 × 36 features which are still large and redundant for classification. In fact, Fisher scores are selected to seek dominant features, and then, leading Fisher feature is identified as the feature extracted which are available to train a classifier and predict labels for test data. Classifiers: KNN, LDA and SVM are used to evaluate the classification performance. The whole steps are showed in Fig.6.

III. RESULTS

First, the 4-D tensor of size 4 channels × 200 frequencies × 8000 times × 2 classes is decomposed by NTD to show the meaning of each component. Four factor matrices in the space, frequency, time, and class domains are shown in the figure. The first column represents the channel (spatial) component, which is described by the brain electrical activity mapping (BEAM) and topographic map of power spectrum of sEMG. The component in the second, third, and fourth columns are the frequency (spectral) component, time (temporal) component and class (category) component. The result shows the weight coefficients on each component. In Fig.7, component 1 mainly corresponds to BB muscle from the muscle maps of arm, and the fourth column of component 1 has larger amplitude in class 1. Component 2 indicates that the spatial amplitude distribution is lower on the left hemisphere than the right, and the centre of the distribution is around CP4 which is considered to be related with class 1 showed in column 4. So these two components are recognized as the elbow flexion condition. Similarly, component 3 illustrates the movement condition with a spatial distribution of larger amplitude on the TB muscle and lower amplitude on the BB muscle, hence the larger amplitude in class 2 and lower amplitude in class 1. Therefore, the component 3 represents elbow extension condition. From the figure we can see that component 4 also belongs to class 2, however, the BEAM of component 4 doesn't have significant different with component 2. In addition, there is a phenomenon that the peak of spectrum of component 1 is mainly in the 80-100 Hz frequency band; however, that is 40-60 Hz in component 3. Component 2 has a little wider frequency band than component 4 at the same time.

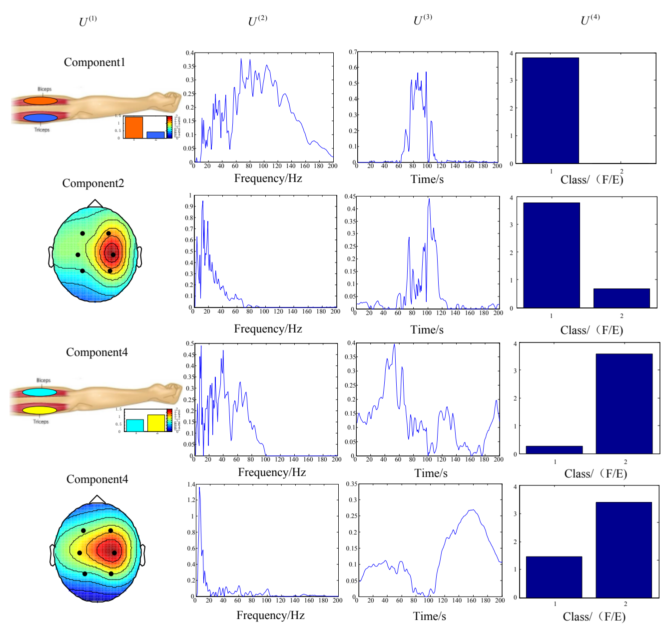

Fig.7. Decomposition of 2 channels sEMG and 2 channels EEG signals into basis components. Experimental results using 4-D tensor decomposition of data (channel × frequency × time × class)

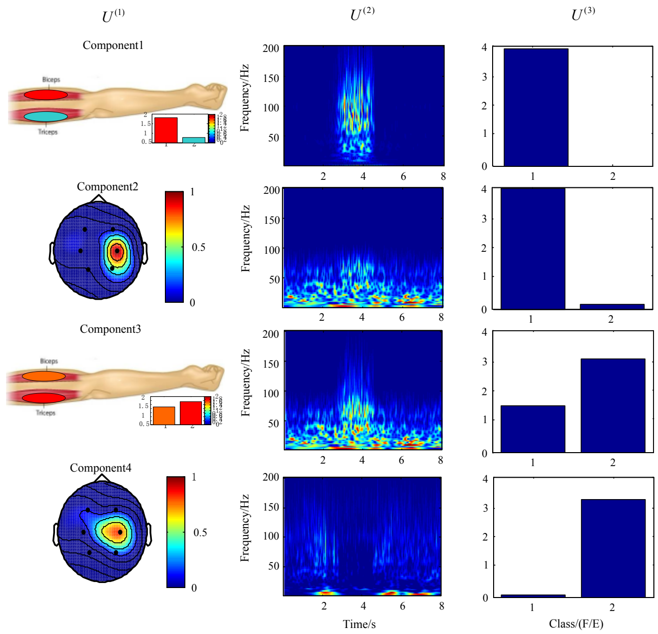

Fig.8. Visualization of components of the NTD model using 3-D tensor.

There is another method to do the decomposion that the time and frequency domains can be reshaped and combined into one dimension. A 3-order tensor with the size 4× 1600000× 2 is gained. The decomposion result of NTD is depicted in Fig.8, in which we can clearly see the component 1,2 and component 3,4 represent class 1 and class 2 respectively. From the time-frequency spectrum component we verify the conclusion about frequency band in the method mentioned above.

The training tensor $\underline{Ytr}$ and testing tensor $\underline{Yts}$ are then operated. There are three classifiers including KNN, LDA and SVM. And for SVM, the 'RBF' kernel is trained. The average accuracy is used to evaluate the classification performance. The accuracies of three movement conditions using EEG signals, sEMG signals, or both EEG and sEMG signals are shown in Tab.1 corresponding to KNN, LDA and SVM respectively.

TABLE I. ACCURACY RATE OF SIX MOVEMENT CONDITIONS

Accuracy rate		EEG only	sEMG only	EEG+sEMG
Wrist F/E[a]	*KNN*	69.50%	89.38%	89.96%
	LDA	76.50%	90.42%	91.52%
	SVM	74.00%	91.44%	92.14%
FingerF/E	*KNN*	75.92%	80.81%	86.47%
	LDA	78.46%	82.05%	88.23%
	SVM	80.10%	82.78%	89.78%
ElbowF/E	*KNN*	62.80%	88.25%	90.63%
	LDA	67.24%	88.75%	92.50%
	SVM	65.85%	90.56%	93.75%

a. F:flexion, E:extension

IV. DISCUSSION

Exploring the synchronous usage of EEG and sEMG, and fusing all channels' feature are very important for achieving a good robot control. Generally, EEG and sEMG signal are stored in the form of one dimensional. However, the information only in time domain is not enough to extract discriminative features from different conditions. Much useful latent information is hidden in other domains including trails, conditions, subjects, space, time, and frequency. To propose a synchronous and multi-domain feature extraction and multidimensional data mining method is increasingly important.

Various EEG and sEMG signal processing algorithms, such as wavelet transforms [15], wavelet packet transforms [16] and EMD [17], have been proposed to discover features in two domains- time and frequency. Nonetheless, there will be more available factors if multi-domain information is taken into consideration. What's more, in order to analysis EEG and sEMG parallelly, a fusion method is needed at the same time. Many data fusion approaches are using simple method to synthesize information such as weight fusion, however, how to determine the weight of EEG and sEMG feature is a hard problem to solve. In addition, in previous works, EEG and sEMG features are extracted separately first and then fused by forming feature vector in feature level as the input of classifier which may underutilize the information in data level [10].

One of the most promising method of multidimensional data analysis is the tensor-based method which can extract latent components with different dimension in each mode and investigate complex interactions among them. Multi-domain information can be transformed and organized into a tensor (multiway arrays). NTF is an effective approach to extract features of high-dimensional data which is a multiway extension of NMF. In many practical engineering problems, the involved data are often negative. The components decomposed by NTF have the character of nonnegative, which ensures the physical significance of features. PCA, ICA are viewed as generalizations of component analysis and dimensionality reduction methods, however, these conventional approaches don't have nonnegative restriction, which makes it difficult to explain the results after factorization. For example, the time, frequencies, and channels are hard to account for if they are negative. Another advantage is sparse which makes the separation of local feature simple; therefore, it is beneficial for classification. Recently, the NTF has been used in the study of bio-informatics, image understanding and neuroscience. NTF has been used in EEG analysis about cognitive analysis and motor imagery [18, 19], whereas, NTF in synchronous and multi-domain feature extraction of EEG and sEMG in neural control is less intensively studied.

In this study, we have presented a method of synchronous multi-domain feature extraction of EEG and sEMG signal on the basis of NTF. In our experiments using NTF, we chose the promising NTD model. High-order data across time, frequency, space (EEG or sEMG channels) domains and are decomposed into multiple components with distinct modalities through this method. Components are factorized to identify common across different domains, and the projecttions are calculated as the feature to discriminate different conditions in a lower dimension space. Because of the capacity of tensor to retain the information of time-frequency-space domain and the relation of multi-domain, the tensor algorithm is more effective to extract implicit and multi-domain characteristics in the EEG and sEMG data. At the same time, NTF can discriminate different conditions without prior knowledge of the frequency bands and temporal windows for a specific subject. What's more, like other scholars say, NTF has the advantage of overcoming the low SNR weakness of EEG and sEMG signals for the reason that a component can simply be removed if it is not correlated with the specific task. From Tab.1 we can see that no matter what classifier is used, the recognition rates of using both EEG and sEMG signals are higher than using either EEG signals or sEMG signals and the average classification accuracy of the EEG-sEMG feature extracted by NTD is 90.55%, which implied that the synchronous multi-domain feature extraction method of NTF is applicative to EEG-sEMG analysis and the EEG-sEMG approach is more stable performance compared to the single conditions. Research shows that integrated feature extraction of EEG and sEMG and the quantitative description of the multi-domain characteristics of EEG and sEMG are helpful to increase the recognition rate of the movement conditions classification. Especially for the patients with movement disorders, whose residual muscle force is so weak that it's difficult to identify the movement intentions of affected limbs effectively. What's more, the NTF method can be seen as combining the different biological electrical signals in data fusion level, which may also take full advantage of each source and improve the efficiency of classification and control.

V. CONCLUSION

In conclusion, NTF is a meaningful and valuable approach for EEG-sEMG feature extraction which is one of the most important parts in this EEG-sEMG-based power-assist rehabilitation robot system. This comprehensive method with synchronous and multi-domain analysis of EEG and sEMG signals is significative for the developing of power-assist rehabilitation robot. In future works, a control strategy of the upper limb power-assist rehabilitation robot will be proposed, and the feature extracted by the NTF will be used to control the movement trail of the robot mechanism. In addition, an experiment about the stroke patients will be performed. The internal relation of EEG and sEMG will be considered, and the complementary fusion feature of EEG and sEMG associated with the mechanism of motion will be considered to apply in power-assist rehabilitation robot.

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