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Sliding Window Nonnegative Matrix Factorization (SW-NMF) for Robustness Low-Density Myoelectric Signals Decoding Against Electrodes Shift

Zhien Xian, Zhiguo Zhang, Fei Tang, Li Zhang, Gan Huang

Abstract—**In this paper, the problem of electrodes shift is studied in low-density surface electromyographic (sEMG) based prosthetic control with the proposed Sliding Window Nonnegative Matrix Factorization (SW-NMF) algorithm. By artificially switching the electrode positions clockwise for $\pi/8$, the 8 channel sEMG signals of 10 gestures were recorded before and after the electrodes shift. It is found that electrodes shift makes the feature space of the sEMG signal non-stationary, which has a great influence on the classify accuracy. Besides, all kinds of existing algorithms for electrodes shift in the high-density electrode environment have limited effect in the low-density electrode environment. In the proposed SW-NMF method, we firstly place the sum constrain on the coefficient matrix $\boldsymbol{H}$ to reduce change of the sample distribution in the feature space. Secondly, a sliding widow strategy is applied accompany with the sum constrain on $\boldsymbol{H}$ to make the algorithm can be run online. Finally, a self-enhanced version of Linear Discriminant Analysis (LDA) is included in the SW-NMF algorithm to make the classifier be able to follow the change of sample distribution in the feature space for further improve the decoding accuracy. Compared with the traditional TD+LDA, and the other type of NMF based methods, the result of the proposed SW-NMF shows a high robustness for electrodes shift.**

I. Introduction

Electromyographic (EMG) signal, the electrical activity by muscle contraction, can be collected by electrodes on the skin for prosthetic hand control [1]. In the recent decades, with the use of advantage pattern recognition methods, such as Bayesian statistics, artificial neural network and support vector machine, the result of pattern recognition has been greatly improved. However, the relatively ideal recognition rate in laboratory environment is in sharp contrast to the high rejection rate for the use of intelligent prosthetics in practice. In addition to the problems of weight, battery life, power [2] etc., the low robustness of existing pattern recognition algorithms is also an important reason. The electrodes shift, change of arm position direction, muscle contraction force, and poor electrode contact in the daily use will all make the recognition result deteriorate seriously [3].

Without these interference factors, a high recognition rate can be achieved in laboratory environment, because all the analysis is performed in a stationary feature space. However, take the electrodes shift for example, the feature space for the sEMG signal would be changed in the daily use. To solve this problem, several methods have been proposed. Variogram (Variog), a statistical measure of the spatial correlation, is a robust feature in the high-density sEMG signals for electrodes shift [4]. Gray-Level Co-occurrence Matrix (GLCM), which provides a well description of spatial distribution of pixels in image processing, can discard information sensitivity to shift and keep as much as useful information in electrodes shift [5]. Common Spatial Pattern (CSP) algorithm, based on the multiple channels signal analysis, can maximize the difference between the variance of two classes [6]. All these methods show robustness to electrode shift for the prosthetic control with high-density sEMG. High-density electrode can improve both the recognition rate and the quality of control. However, with the increasing number of the electrodes (>100 electrodes), the system will take more time to be worn, increase the risk for a single electrode broken. Furthermore, it will make higher requirement for the performance of the signal acquisition, amplification, transmission and calculation, hence the system will become more expensive. For these reasons, currently high-density electrode EMG system is widely used in laboratory environment but seldom used in the daily use. Instead, the commercial EMG device with low-density electrode, like Myo armband with commonly 8 electrodes, is more preferred in daily use for its lower price, easy to ware and also the good performance. Unfortunately, the algorithm developed based on high-density electrodes, like Variog, GLCM and CSP, do not have a good performance for electrodes shift. The lack of methods to cope with the problem of electrodes shift in the low-density electrodes system limits its repeated use in daily use.

In this paper, Sliding Window Nonnegative Matrix Factorization (SW-NMF) algorithm is proposed to improve the robustness for the problem of electrodes shift in low-density sEMG pattern recognition application. With the sum constrain on the coefficient matrix $\boldsymbol{H}$, the sliding window strategy in Nonnegative Matrix Factorization (NMF), and the self-enhanced version of Linear Discriminant Analysis (LDA) in SW-NMF, we can reduce and also follow the change of sample distribution in the feature space to improve the decoding accuracy. The experiment design and the algorithm of SW-NMF is introduced in Session II. The result of SW-NMF, compared with the other existing methods is arranged in Session III. Finally, the conclusion is given in Session IV.

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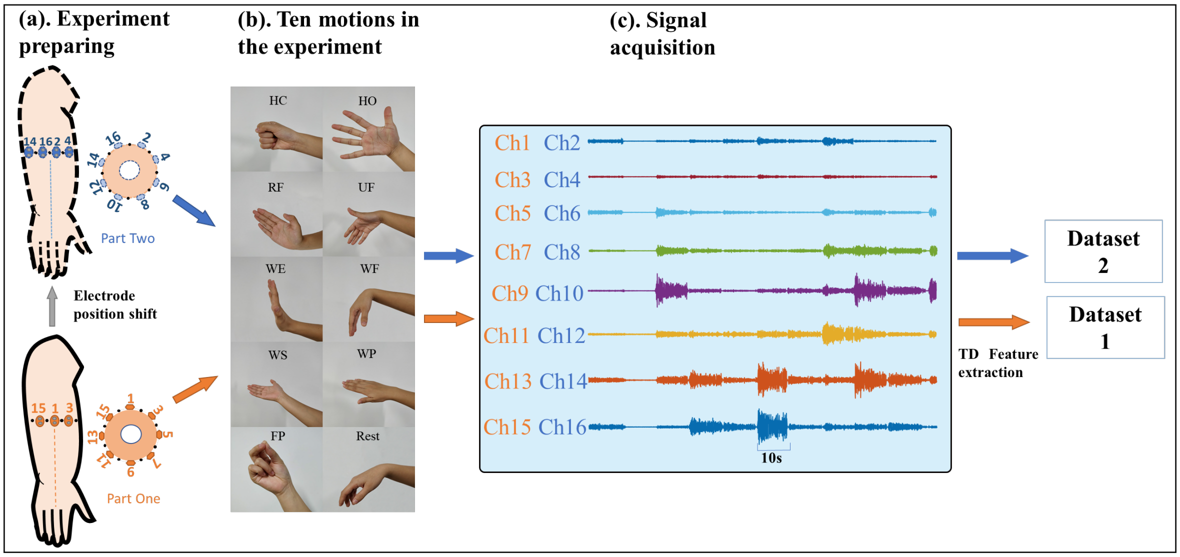

Fig 1. Acquisition schematic of EMG with 8-channel bipolar differential EMG sensor electrodes.

II. Method

A. Experiment Design

Twenty-five subjects participated in this experiment (18 males and 7 females, age ranging from 20 to 25 years). All subjects were informed of the experimental process and signed informed consent before the experiment. Eight-channel sEMG signals are collected from subjects' right-hand forearms by DataLINK (Biometrics Ltd., Newport, UK) with a sampling rate of 1kHz.

In the experiment preparation, the circumference of the arm was measured for each subject. From the back side of middle finger as the origin, the upper arm circumference was divided into 16 equal parts and marked the endpoints clockwisely as 1, 2, 3, …, 15, 16 (Fig. 1). The experiment was divided into two parts, in which the subjects were asked to perform exactly the same task but with the different electrode montage for EMG recording. In the first part of the experiment, eight electrodes were placed at the position of 1, 3, 5, …, 15. For the second part of the experiment, we rotated the electrode positions clockwise for $\pi/8$ to artificially produce the lateral electrodes shift. Hence as illustrated in Fig. 1a, the electrodes in the second part of the experiment were placed at the position of 2, 4, 6, …, 16.

During the experiment, the subjects sat in a comfortable chair and kept their arms straight down. Each part of the experiment is consisted of 10 sessions. For each session, the subjects were asked to complete 10 motions continuously with 80% mean cumulative voltage for 10 seconds. For each time, the 10 motions, which are hand close (HC), hand open (HO), wrist flexion (WF), wrist extension (WE), radial flexion (RF), ulnar flexion (UF), wrist pronation (WP), wrist supination (WS), fine pinch (FP) and rest, were arranged in a random order and prompted to the subjects by MATLAB program (Fig. 1b). The subjects would have an adequate rest as he/she want between the two sessions in the experiment. After the completion of the first part of the experiment, the position of the electrode was adjusted for the EMG recording in the second part of the experiment (Fig. 1c).

B. Feature Extraction

For signal preprocessing and feature extraction, the recorded sEMG signals were firstly filtered by 20-450Hz band-pass filter. In order to avoid the impact of transient data, we only analysis the data of the intermediated 8 seconds (from 1 second to 9 second). Using a sliding window with 100ms window length and 100ms sliding step, we segmented the sEMG signals into 8000 ($(8000/100)\text{windows} \times 10\text{ motions} \times 10\text{ sessions}$) epochs in each part of the experiment. For each epoch, the TD features [2], which are mean absolute value, waveform length, zero crossings and slope sign changes, were extracted from the 8 channels of the sEMG signals. Hence, in each part of the experiment, we have 8000 samples with the feature dimension 32 ($4\text{ features} \times 8\text{ channels}$). In the following, we denote 8000 samples from the first part of the experiment (before electrodes shift) as Dataset 1, and 8000 samples from the second part of the experiment (after electrodes shift) as Dataset 2.

C. NMF and LDA

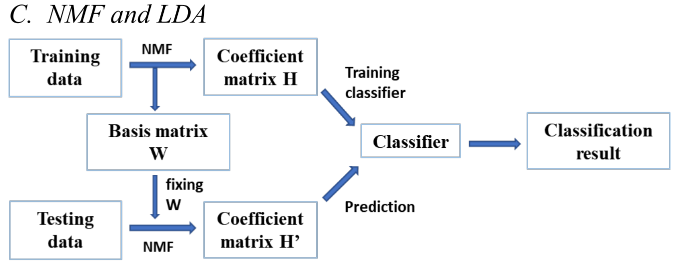

Fig 1. Flowchart of pattern recognition based on NMF and LDA.

The Flowchart of NMF and LDA used in sEMG pattern recognition is shown in Fig. 2. With the TD features in the training data, NMF algorithm is performed to get the basis matrix W and the coefficient matrix H. Fixing the basis matrix W, we can also obtain the coefficient matrix H' based on the testing data. Then LDA classifier is used for patter recognition. In the following, a brief introduction of NMF and LDA is given.

Non-negative Matrix Factorizations is an algorithm use to reduce the dimensionality by matrix factorization [7], which is applied to extract the cooperative information for Muscle Synergy-based Discrimination for Simultaneous Control (MSDSC) of dexterous figure movements with high-density sEMG [8].

Training:

(1) Initialize the matrices $\boldsymbol{W}$ and $\boldsymbol{H}$ as random nonnegative matrices;

(2) for $\boldsymbol{iter} = \mathbf{1, 2, \ldots, l}$

$$\boldsymbol{W_{mk}} \leftarrow \boldsymbol{W_{mk}} \left(\sum_{i=1}^{M} \frac{\boldsymbol{X_{mi}}}{(\boldsymbol{WH})_{mi}} \boldsymbol{H_{ki}}\right)$$

$$\boldsymbol{W_{mk}} \leftarrow \frac{\boldsymbol{W_{mk}}}{\sum_i \boldsymbol{W_{ik}}}$$

$$\boldsymbol{H_{kn}} \leftarrow \boldsymbol{H_{kn}} \left(\sum_{i=1}^{N} \boldsymbol{W_{ik}} \frac{\boldsymbol{X_{in}}}{(\boldsymbol{WH})_{in}}\right)$$

end

Testing:

(1) Fix the basis matrix $\boldsymbol{W}$ obtained from training and initialize the matrices $\boldsymbol{H'}$ as random nonnegative matrices;

(2) **for** $\boldsymbol{iter} = \mathbf{1, 2, \ldots, l}$

$$\boldsymbol{H'_{kn}} \leftarrow \boldsymbol{H'_{kn}} \left(\sum_{i=1}^{N} \boldsymbol{W_{ik}} \frac{\boldsymbol{X_{in}}}{(\boldsymbol{WH'})_{in}}\right)$$

end

Algorithm 1: the original NMF algorithm with the sum constrain on W.

Consider the matrix $X \in R^{M\times N}$ with all element nonnegative, in which M is the feature dimension and N denotes the sample size used in NMF. The NMF can linearly factorized the matrix X into the basis matrix $W \in W^{M\times K}$ and the coefficient matrix $H \in R^{K\times N}$,

$$X_{mn} \approx (W \cdot H)_{mn} = \sum_{k=1}^{K} W_{mk} H_{kn}$$

in which K is the intermediate dimension of factorization with $(\mathrm{N}+\mathrm{M}) \times K < N \times M$. The original NMF algorithm for training and testing can be performed as the following iteration:

Since the feature dimension $M = 32 << N$, we set $K = 31 < \frac{NM}{(\mathrm{N}+\mathrm{M})} < M$ in our application. The iteration number l is set to be 400 since we find $l = 400$ can already guarantee the converge of the result in practice.

LDA classifier aims to project the samples in a higher-dimensional feature space into a lower-dimensional space for a good class-separability. For the two-class classifier problem, suppose that we have a set of N samples with feature dimension M, N_1 in the subset D_1 with label ω_1, and N_2 in the subset D_2 with label ω_2. We have the within-class scatter matrix S_{w} by

$$S_{\mathrm{w}} = \sum_{i=1}^{2} S_i \text{ and } S_i = \sum_{x\in D_i} (x-\mu_i)(x-\mu_i)^T,$$

in which $\mu_i = \frac{1}{N_i}\sum_{x\in D_i} x$, for $i = 1,2$. If the prior probabilities $P(\omega_i)$ are the same for ω_1 and ω_2, the linear discrimination function would be

$$g(x) = \omega^T x + \omega_0$$

where

$$\omega = S_{\mathrm{w}}^{-1}(\mu_1 - \mu_2)$$

$$\omega_0 = -\frac{1}{2}(\mu_1 + \mu_2)^T S_{\mathrm{w}}^{-1}(\mu_1 - \mu_2).$$

If $g(x) > 0$, $x \in \omega_1$, else $x \in \omega_2$. For the multiple classification problem, One-versus-One strategy is applied to divide the c-class problem in $c \times (c-1)/2$ binary problems. The classification results come from the majority voting rule.

D. SW-NMF method

Due to electrodes shift, the sample distribution in the feature space would be changed. In the SW-NMF algorithm, there are mainly three improvement from the original NMF+LDA method to handle the change in feature space.

Training:

(1) Initialize the matrices $\boldsymbol{W}$ and $\boldsymbol{H}$ as random nonnegative matrices;

(2) **for** $\boldsymbol{iter} = \mathbf{1, 2, \ldots, l}$

$$\boldsymbol{W_{mk}} \leftarrow \boldsymbol{W_{mk}} \left(\sum_{i=1}^{M} \frac{\boldsymbol{X_{mi}}}{(\boldsymbol{WH})_{mi}} \boldsymbol{H_{ki}}\right)$$

$$\boldsymbol{H_{kn}} \leftarrow \boldsymbol{H_{kn}} \left(\sum_{i=1}^{N} \boldsymbol{W_{ik}} \frac{\boldsymbol{X_{in}}}{(\boldsymbol{WH})_{in}}\right)$$

$$\boldsymbol{H_{kn}} \leftarrow \frac{\boldsymbol{H_{kn}}}{\sum_{i=1}^{n} \boldsymbol{H_{ki}}}$$

end

Testing:

(1) Fix the basis matrix $\boldsymbol{W}$ obtained from training and initialize the matrices $\boldsymbol{H'}$ as random nonnegative matrices;

(2) **for** $\boldsymbol{iter} = \mathbf{1, 2, \ldots, l}$

$$\boldsymbol{H'_{kn}} \leftarrow \boldsymbol{H'_{kn}} \left(\sum_{i=1}^{N} \boldsymbol{W_{ik}} \frac{\boldsymbol{X_{in}}}{(\boldsymbol{WH'})_{in}}\right)$$

$$\boldsymbol{H'_{kn}} \leftarrow \frac{\boldsymbol{H'_{kn}}}{\sum_{i=1}^{n} \boldsymbol{H'_{ki}}}$$

end

Algorithm 2: the NMF algorithm in SW-NMF with the sum constrain on H.

Firstly, instead of W, we place the sum constraint on the coefficient matrix H. As comment by Daniel et. al., the sum constraint is a convenient way of eliminating the degeneracy associated with the invariance of WH in the iteration. But the sum constraint on the coefficient matrix H can be treated as a normalization among the samples, which is better for decreasing the change in feature space caused by electrodes shift. Hence the NMF algorithm in the SW-NMF method is as follows,

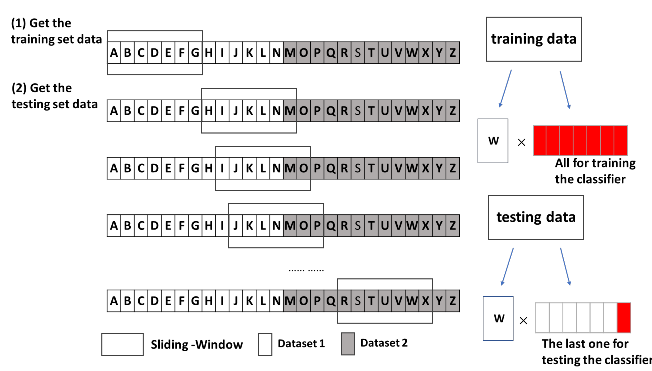

Fig 2. Illustration of the sliding window strategy in SW-NMF.

Secondly, a sliding window strategy is applied in the SW-NMF. With the sum constrain on basis matrix, the coefficient for each sample in testing only depends on the testing sample itself. However, with the sum constrain on coefficient matrix, the coefficient for each testing sample in H' also depends on the other samples in the testing. For online sEMG patterns recognition, the sliding window is used in SW-NMF methods, in which the coefficient for the testing sample in H' is obtained with a certain number of previous samples together (Fig. 3), and the window length is set to be 800 in practice for a tradeoff between the performance and the computational complexity.

At last, Self-Enhanced LDA (SE-LDA), the LDA algorithm with self-enhanced strategy that can compensate the slow changes in the features space of myoelectric signals in the day [9], is applied in the LDA classifier updating to track the feature space changing by electrodes shift. Once a testing sample x_t is predicted as class i, the mean vector μ_i and the scatter matrix S_i of the class i is updated as follows,

$$\mu_i' = \frac{n_i \mu_i}{n_i + 1} + \frac{x_t}{n_i + 1}$$

$$\mathrm{S}_\mathrm{i}' = S_\mathrm{i} + \frac{n_i}{n_i + 1}(x_t - \mu_i)(x_t - \mu_i)^T$$

in which n_i is the number of samples in class i.

II. Results

A. The Influence of Electrodes Shift

As is shown in Fig.4, without electrodes shift, the average accuracy based on TD feature is 98.74±1.18% for 10 motions, but it decreases to 55.04±11.85% when the electrode shift occurs. The existing methods, which are robust to the electrodes shift with the high density sEMG, do not work well in the low-density environment, as GLCM 25.63±6.99%, Variog 28.04±9.54%, CSP 43.61±10.28%.

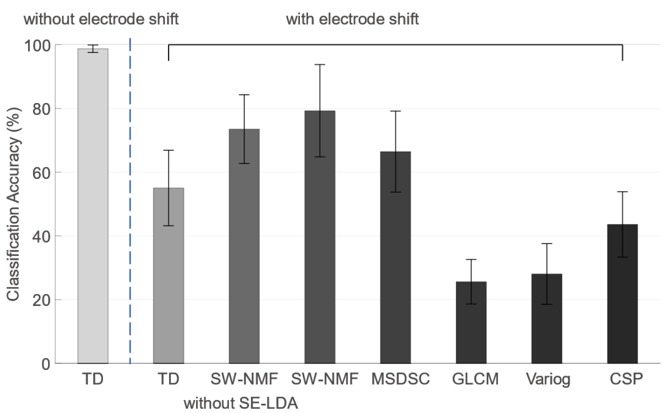

Fig 3. The comparison of the classification accuracy with different methods for electrodes shift.

B. The Result for SW-NMF

Based on the original NMF algorithm (Algorithm 1) with the sum constrain on the basis matrix W, the classification accuracy is 43.44+9.93% (not shown in Fig. 4), which is even lower than the classical TD methods with 55.04±11.85%. In the SW-NMF algorithm, we placed the sum constrain on the coefficient matrix H accompany with the sliding window strategy, the classification accuracy is improved to 73.51+10.79% (SW-NMF without SE-LDA in Fig.4), which is significantly better than TD method ($p = 6.96 \times 10^{-10}$). Furthermore, with use of SE-LDA in SW-NMF, the classification accuracy can be further improved to 79.29 ± 14.49% ($p = 1.18 \times 10^{-3}$ as compared with SW-NMF without SE-LDA), which is also significantly better than the other NMF based method MSDSC 66.46±12.71% with $p = 5.54 \times 10^{-6}$.

Fig. 5 illustrates the change of the classification accuracy with the increasing number of testing samples. It is shown that the accuracy keeps unchanged for the TD and MSDSC algorithms. But with the sliding window strategy, the accuracy increased in the first 800 samples for SW-NMF algorithm, in which 800 is the window length.

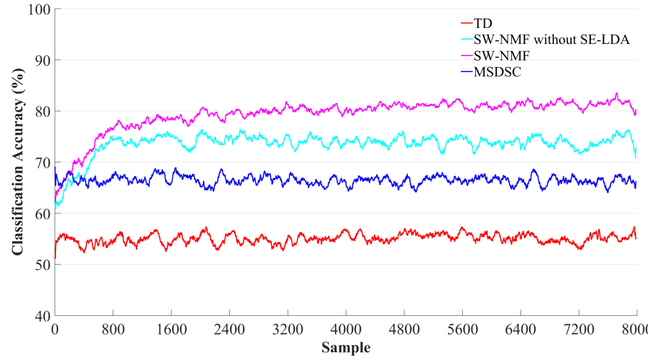

Fig 4. The change of the classification accuracy with the increasing number of testing samples. The results are averaged from 25 subjects and smoothed for every 101 samples.

III. Conclusion

Low-density sEMG, for its low price and easy to wear, is more practical than high-density sEMG for prosthetic control in daily use. However, the problem of electrodes shift influences classify accuracy greatly, and the existing robust algorithms for electrodes shift in the high-density electrode environment have limited effect in the low-density electrode environment. Hence the SW-NMF algorithm is proposed for the robustness low-density sEMG signals decoding against electrodes shift. As a result, the classification accuracy with SW-NMF algorithm is effectively improved as compared with the existing methods.

References

[1] Parker P, Englehart K., and Hudgins B, Myoelectric signal processing for control of powered limb prostheses [J]. Journal of Electromyography and Kinesiology, 2006, 16(6):541-548.

[2] Oskoei M A and Hu H, Myoelectric control systems-A survey [J]. Biomedical Signal Processing & Control, 2007, 2(4):275-294.

[3] Kaufmann P, Englehart K, Platzner M. Fluctuating EMG signals: Investigating long-term effects of pattern matching algorithms [C]//Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. IEEE, 2010: 6357-6360.

[4] Stango A, Negro F, Farina D. Spatial correlation of high density EMG signals provides features robust to electrode number and shift in pattern recognition for myocontrol [J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2015, 23(2): 189-198.

[5] He J, Zhu X. Combining improved gray-level co-occurrence matrix with high density grid for myoelectric control robustness to electrode shift [J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2017, 25(9): 1539-1548.

[6] Pan L, Zhang D, Jiang N, et al. Improving robustness against electrode shift of high density EMG for myoelectric control through common spatial patterns [J]. Journal of Neuroengineering and Rehabilitation, 2015, 12(1): 110.

[7] Lee D D, Seung H S. Learning the parts of objects by non-negative matrix factorization [J]. Nature, 1999, 401(6755): 788.

[8] Zhang S, Zhang X, Cao S, et al. Myoelectric pattern recognition based on muscle synergies for simultaneous control of dexterous finger movements [J]. IEEE Transactions on Human-Machine Systems, 2017, 47(4): 576-582.

[9] Chen X, Zhang D, Zhu X. Application of a self-enhancing classification method to electromyography pattern recognition for multifunctional prosthesis control [J]. Journal of Neuroengineering and Rehabilitation, 2013, 10(1): 44.