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Myoelectrical signal classification based on S transform and two-directional 2DPCA

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Abstract. In order to extract discriminative information, time-frequency matrix is often transformed into a 1D vector followed by principal component analysis. This study contributes a two-directional two-dimensional principal component analysis ($2D^2PCA$) based technique for time-frequency feature extraction. $2D^2PCA$ is directly conducted on the time-frequency matrix obtained from the S transform rather than 1D vectors for feature extraction. The proposed method can significantly reduce the computational cost while capture the directions of maximal time-frequency matrix variance. The efficiency and effectiveness of the proposed method is demonstrated by classifying eight hand motions using four-channel myoelectric signals recorded in health subjects and amputees.

1 Introduction

Pattern recognition of biomedical signals has been broadly applied for robotics control, human/brain-machine interface, disease diagnosis, wearable devices, and rehabilitation programming. Most biomedical signals, for example myoelectric signal (MES), an electrical manifestation of skeletal muscle contractions, are typically nonlinear and nonstationary. Time-frequency (TF) analysis offers simultaneous interpretation of biomedical signals in both the time and frequency domains, allowing the elucidation of local, transient or intermittent components at various scales [1]. However, there are typically a large amount of TF coefficients generated from such a two-dimensional analysis. Concatenating TF coefficients at various scales into a 1D array often leads to a high-dimensional vector space, where it is difficult to evaluate the covariance matrix accurately due to its large size and the relatively small number of training samples if it is followed by principal component analysis for feature extraction.

In fact, a two-dimensional time-frequency plane can be viewed as an image. It is thus feasible to apply image processing techniques to indicate time-frequency matrix (TFM) characteristics. In this study, inspired by the success of two-directional two-dimensional principal component analysis ($2D^2PCA$) in imaging processing [2, 3], we investigate the feasibility of using $2D^2PCA$ to efficiently and effectively extract feature information from the signal time-frequency representation. S transform (ST), integrating the strengths of both short time Fourier transform (STFT) and wavelet transform (WT), is selected to decompose the discrete time signal into time-frequency matrix. The key idea is that $2D^2PCA$ is applied to reduce the dimension of ST coefficient matrix in a highly efficient manner for pattern classification. The method

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is, therefore, termed as S transform-based two-directional two-dimensional principal component analysis (ST2D^{2}PCA). To evaluate the performance of the proposed method, results are presented on the recognition of eight hand motions from four-channel myoelectric signals recorded in both health subjects and amputees, aiming for the prosthetic hand, robot, and human man interface controlling.

2 Methods

2.1 S transform

The S transform established by Stockwell et al. [4] in 1996 can be regarded as an extension of the STFT and WT. Different from fixed resolution of STFT, S transform provides good localization in the frequency domain for low frequency components whilst good localization in time domain for high frequency components. On the other hand, compared with WT, S transform preserves the phase information of the signal as in STFT. Therefore, the S transform integrates the strengths of both STF and WT.

2.2 2D^{2}PCA

Without loss of generality, we consider an m by n time-frequency matrix $\mathbf{A}$ obtained from the S transform. Let $\mathbf{X} \in \mathbb{R}^{n\times q}$ and $\mathbf{Y} \in \mathbb{R}^{m\times p}$ be matrices having orthonormal columns $n\times q$ and $m\times p$, respectively. We can simultaneously project $\mathbf{A}$ onto $\mathbf{X}$ to yield the $m\times q$ matrix $\mathbf{B}=\mathbf{AX}$, and onto $\mathbf{Y}$ to yield the $p\times n$ matrix $\mathbf{C}=\mathbf{Y}^T\mathbf{A}$. In contrast to conventional PCA for one-dimensional array applications, 2D^{2}PCA operates on a matrix in both horizontal and vertical directions. The total scatter of the projected samples, a measure of the discriminatory power of a projection matrix, can be characterized by its trace of the covariance matrix of the projected matrix. From this point of view, maximisation of the generalised total scatter is the criterion adopted to find the optimal projection. Considering the $m\times q$ matrix $\mathbf{B}=\mathbf{AX}$ obtained by projecting $\mathbf{A}$ onto $\mathbf{X}$, the horizontal covariance matrix is denoted by

$$\mathbf{G}_h = E[(\mathbf{A}-E(\mathbf{A}))^T(\mathbf{A}-E(\mathbf{A}))], \tag{1}$$

which is an $n\times n$ positive semi-definite matrix.

Suppose that the training feature set is $\mathbf{\Omega}=(\mathbf{A_1},\mathbf{A_2},\cdots,\mathbf{A_N})$, where each $\mathbf{A}_i\,(i=1,2,\cdots,\mathbf{N})$ denotes the ith $m\times n$ time-frequency matrix and $\mathbf{N}$ is the number of training samples. The average TFM is given by

$$\bar{\mathbf{A}} = \frac{1}{N}\sum_{i=1}^{N}\mathbf{A}_i \tag{2}$$

Denoting the kth row vectors of $\mathbf{A}_i$ and $\bar{\mathbf{A}}$ by $\mathbf{A}_i^k$ and $\bar{\mathbf{A}}_h^k$, respectively, these TFMs can be represented by

$$\mathbf{A}_i = [(\mathbf{A}_i^1)^T,(\mathbf{A}_i^2)^T,\cdots,(\mathbf{A}_i^m)^T]^T, \tag{3}$$

and

$$\bar{\mathbf{A}} = [(\bar{\mathbf{A}}_h^1)^T,(\bar{\mathbf{A}}_h^2)^T,\cdots,(\bar{\mathbf{A}}_h^m)^T]^T. \tag{4}$$

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The horizontal covariance matrix can then be obtained from the outer product of these TFM row vectors:

$$\begin{aligned}\mathbf{G}_h &= \frac{1}{N}\sum_{i=1}^{N}(\mathbf{A}_i - \overline{\mathbf{A}})^T(\mathbf{A}_i - \overline{\mathbf{A}}) \\ &= \frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{m}(\mathbf{A}_i^k - \overline{\mathbf{A}}_h^k)^T(\mathbf{A}_i^k - \overline{\mathbf{A}}_h^k)\end{aligned} \tag{5}$$

Similarly, we can construct the $m \times m$ vertical covariance matrix $\mathbf{G}_v$ in the same manner using the training samples. The optimal projection matrices $\mathbf{X}$ and $\mathbf{Y}$ are composed of the orthonormal eigenvectors $\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_q$ of $\mathbf{G}_h$ corresponding to the q largest eigenvalues and $\mathbf{Y}_1, \mathbf{Y}_2, \cdots, \mathbf{Y}_p$ of $\mathbf{G}_v$ corresponding to the p largest eigenvalues, respectively. The value of p or q can be controlled by simple threshold settings. In practice, we set a ratio γ of total energy preserved as in PCA (for example >85%) and then set $\alpha = \beta$, each corresponding to the energy conservation rate.

After obtaining the projection matrices $\mathbf{X}$ and $\mathbf{Y}$, $2D^2PCA$ projects the m by n TFM $\mathbf{A}$ onto $\mathbf{X}$ and $\mathbf{Y}$ simultaneously, yielding the reduced p by q matrix

$$\mathbf{F} = \mathbf{Y}^T\mathbf{A}\mathbf{X}. \tag{6}$$

Using the above procedure, an $m \times n$ dimensional feature matrix $\mathbf{A}$ is projected into a $p \times q$ dimensional feature matrix $\mathbf{F}$.

2.3 ST2D²PCA and performance evaluation

In this section, we describe the S transform-based two directional two-dimensional principal component analysis algorithm for extracting discriminant feature information from these matrices as follows:

1. Multiple-channel signals are first segmented by a moving window with width d.
2. Set the frequency band width and the decomposition interval in time and frequency domain, the S transform is then employed to decompose each time-segment of individual channels into time-frequency matrix with size $d \times L$.
3. 2D2PCA is subsequently carried out on each of the $d \times L$ dimension matrices to extract the most informative features, as well as reduce the dimension based on the user-specified threshold of total energy preserved.
4. Since the discriminant abilities of principal components (PCs) at various scales are different, a simple distance-based technique is applied to re-order all PCs [1].
5. The performance of the algorithm is evaluated by feeding the optimal PCs obtained into a classifier.

The proposed algorithm was evaluated using the myoelectric signals collected from the following experiment. Eight distinct wrist and hand motions were used: grasp (GR), hand open (OP), wrist flexion (WF), wrist extension (WE), ulnar deviation (UD), radial deviation (RD), pinch (PN), and thumb flexion (TF. The initial purpose of this data collection was to recognise arm and hand movements from MES for prosthetic hand control to improve the hand function of amputees.

The four-channel myoelectric data were recorded and further segmented into a series of overlapping windows (window length: 256 ms, overlap step: 128 ms). The procedures for ST2D²PCA described in Section 2.2 were employed to extract two-

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dimensional PCs. Support vector machine (SVM) was employed to evaluate the classification performance of the proposed algorithm [5]. After the classification, the accuracy was further improved by a post-processing procedure using majority vote (MV) [6]. A conventional wavelet packet-principal component analysis (WPTPCA) algorithm to analyse the same data set was also conducted for comparison [6].

3 Results

3.1 Multi-Scale Muscle Activity Patterns

The myoelectric signal at each channel was first transformed into time-frequency matrix. Fig. 1 shows the typical contour plots for eight motions for subject 8, each row corresponding to a motion type. With each intended motion, a significant difference between the intensity of the myoelectric signals over the upper limb muscles can be readily discerned in each column of the contour plots, indicating useful discriminant information in the S transform matrices.

The ST2D^{2}PCA algorithm was then used to reduce the dimension of each matrix. Fig. 2 shows the contour plots of each matrix in Fig. 1 following dimension reduction using 2D^{2}PCA when the total energy preserved was 90%. Compared with Fig. 1, the intensity difference between certain sub-panels in Fig. 2 is further enhanced. More important, the matrix size at each channel was significantly decreased, which were 19×6, 24×7, 26×5, and 19×6, respectively. If conventional PCA was used with all time-frequency coefficients arranged into a 1D array, the size of the covariance matrix would be $(256\times129)\times(256\times129)$.

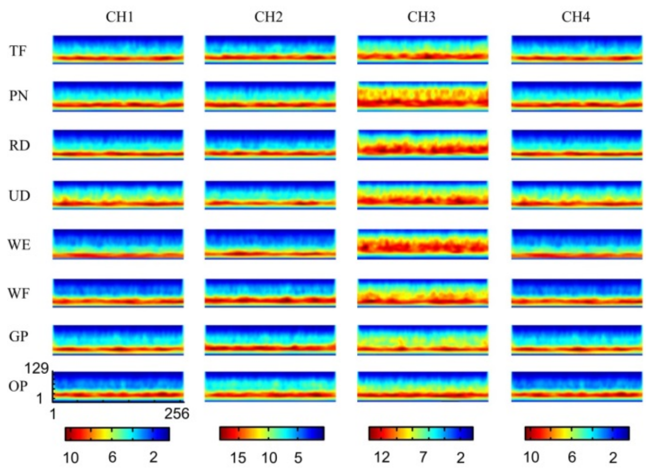

Fig. 1: Contour plots of S transform matrices for 4-channel myoelectric traces of eight hand motions obtained from subject 8.

3.2 Effect of total energy conserved

For PCA analysis, a typical recommendation is to set the threshold of total energy conserved between 0.8 and 0.95. Fig. 3 shows the classification accuracy for the subject 8 for three threshold values of total energy conserved, i.e., 95%, 90%, and 85% versus the PCs. With the reduction in threshold, there was no significant difference in the accuracy for SVM. Findings on the effect of total energy conserved for the remaining subjects were similar. The insensitivity of SVM to the total energy preserved may be due to its adaptive ability to map input features to high-dimensional feature space.

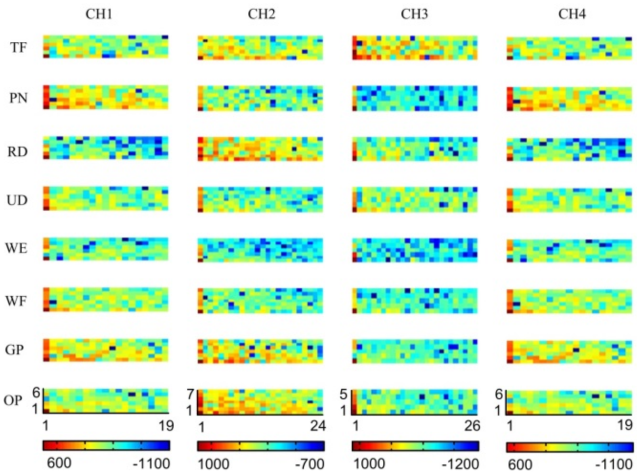

Fig. 2: The contour plots of S transform matrices reduced using $2D^2PCA$ for 4-channel myoelectric signals of eight hand motions obtained from subject 8.

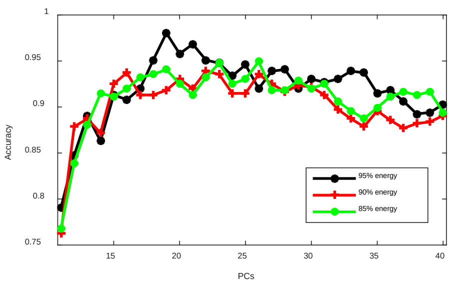

Fig. 3: The effect of total energy conserved of $ST2D^2PCA$ on the myoelectric signals classification for the subject 8.

3.3 Recognition of intended motions

Pattern recognition analysis was performed using the optimal number of PCs previously determined. Table 1 summarizes the subject-specific classification accuracy for all eight intended upper-limb motions. Across all subjects, there is significant difference between the accuracy of $ST2D^2PCA$ and WPTPCA ($p<0.05$) with lower average accuracy for WPTPCA in both cases of with or without majority vote. On the other hand, due to the amputees can only perform grasping, opening based on imagination, the related muscle activities were not as strong as the health subjects. The accuracy for two amputees was lower than the health subjects.

4 Conclusion

A novel S transform-based two-directional two-dimensional principal component analysis for feature extraction has been proposed and examined in this study. We used ST2D^{2}PCA to extract and classify specific time-frequency patterns in four-channel myoelectric signals from ten health subjects and two amputees for identification of eight hand motions. Compared with conventional WPTPCA, enhanced recognition accuracy were obtained by using ST2D^{2}PCA, indicating its potential in a broad range of applications in biomedical engineering.

Table 1. Classification results of all twelve subjects by ST2D^{2}PCA and WPTPCA based feature subsets

Subject	Before MV		After MV	
	ST2D^{2}PCA	WPTPCA	ST2D^{2}PCA	WPTPCA
1	93.38	83.38	98.49	88.38
2	87.27	84.69	95.62	94.06
3	90.29	90.58	96.94	95.75
4	92.72	86.09	97.52	92.81
5	90.28	80.94	95.53	84.06
6	92.61	83.44	98.95	91.56
7	94.40	88.75	98.85	98.16
8	92.66	83.28	96.67	86.72
9	92.15	91.04	96.45	97.29
10	89.28	81.25	95.32	86.35
11*	80.32	73.65	86.88	79.16
12*	72.29	69.63	77.31	74.04
Average	88.97±6.4	83.06±6.4	94.54±6.3	89.02±7.4

*amputee

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