Pattern Classification of High-Dimensional Myoelectric Signals Using Wavelet Two-Directional Two-Dimensional Principal Component Analysis

Hongbo Xie, Jianhua Wu, and Lei Liu

***Abstract*—We present a wavelet two-directional two-dimensional principal component analysis (WT2D^{2}PCA) method for the efficient and effective extraction of essential feature information from high-dimensional signals. Wavelet multi-scale matrices constructed in the first step incorporate the spatial correlation of sub-band signals among channels. In the second step, the two-directional two-dimensional principal component analysis operates on the multi-scale matrices to reduce the dimension, rather than vectors in conventional principal component analysis (PCA). Results are presented from an experiment to classify 20 hand movements using 89-channel myoelectric signals (MES) recorded in stroke survivors, which illustrates the efficiency and effectiveness of the proposed method for high-dimensional signal pattern recognition.**

***Index Terms*—Time-frequency analysis, wavelet transform, two-directional two-dimensional principal component analysis, myoelectric signals, pattern classification.**

I. Introduction

Myoelectric signal (MES) is an electrical manifestation of skeletal muscle contractions. Classification of MES patterns can be utilized to control prosthetic hands or other human-machine interfaces [1]. Wavelet transform combined with principal component analysis (WT-PCA) has been one of the most powerful approaches for simultaneously extracting discriminative features and reducing the dimension for MES classification tasks [1]-[6]. Although the time-frequency (TF)-PCA algorithm, particularly WT-PCA, has achieved great success in the analysis of MES, most of these applications have been based on single site or multiple channel (typically <10) recordings. More recently, with the improvements in physiological measurement equipment, new technology permits registration of up to 256 channels using high-density multielectrode arrays. If the scheme of WT-PCA is duplicated directly to high-dimensional data, concatenating the huge number of wavelet coefficients into a 1D array leads to a high-dimensional vector space, where it is difficult to evaluate the covariance matrix accurately due to its large size as well as the relatively small number of training samples. Furthermore, there are other issues such as numerical instability in the subsequent pattern recognition as well as lowering down the computational complexity and storage requirements, among others.

In fact, a two-dimensional time-frequency plane can be regarded as an image. It is thus feasible to apply image processing techniques to indicate time-frequency matrix (TFM) characteristics. Two-dimensional principal component analysis (2DPCA) developed by Yang *et al*. [7] is a 2D image representation and reduction technique, in which an image matrix does not need to be transformed into a 1D array. The purpose of this study is to develop an efficient and effective time-frequency feature extraction method for fully exploiting the spatial-time-frequency (STF) information of high-dimensional MES. The key idea is to divide the wavelet representation of high-dimensional signals into multi-scale matrices using wavelet transform. 2D^{2}PCA is then performed to reduce the dimension of multi-scale matrices in a highly efficient manner for pattern classification. The method is, therefore, termed as wavelet two-directional two-dimensional principal component analysis (WT2D^{2}PCA). To illustrate the efficiency and effectiveness of the proposed method, results are presented on the recognition of 20 hand movements from 89-channel myoelectric signals recorded in stroke survivors.

II. Methods

A. 2D^{2}PCA

Without loss of generality, we consider an m by n time-frequency matrix $\mathbf{A}$ obtained from any time-frequency decomposition. 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. 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

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

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

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

and

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

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

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

Similarly, in order to obtain the $p \times n$ matrix $\mathbf{C} = \mathbf{Y}^T\mathbf{A}$ by projecting $\mathbf{A}$ onto $\mathbf{Y}$, the vertical covariance matrix $\mathbf{G}_v$ can be constructed. Zhang and Zhou [7] demonstrated that 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.

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

$$\mathbf{F} = \mathbf{Y}^T\mathbf{A}\mathbf{X}. \qquad (6)$$

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

B. *WT2D²PCA*

In this section, we describe the wavelet two-directional two-dimensional principal component analysis algorithm as follows:

1) High-dimensional signals in channels 1 to S are first segmented by a moving window. Choose an appropriate mother wavelet function and decomposition depth. The discrete wavelet transform is then employed to decompose each time-segment of individual channels into details $D_1, D_2, \cdots, D_L$ and approximate A_L under the same decomposition level L.
2) The multi-scale matrices are constructed: The wavelet approximation coefficients A_L from each of the S decompositions are collected into one matrix $\mathbf{A}_L$, where the gth ($g = 1, 2, \cdots, S$) row of $\mathbf{A}_L$ consists of the approximation coefficients of channel g. Similarly, the wavelet details D_1 to D_L for each of the S decompositions are collected into L matrices $\mathbf{D}_1$ to $\mathbf{D}_L$, where the gth row of D_h $(h = 1, 2, \cdots, L)$ consists of the detail coefficients of channel g at scale h. It should be noted that the sizes of matrices $\mathbf{A}_L$ and $\mathbf{D}_L$ are equal, whilst the sizes of $\mathbf{D}_1$ to $\mathbf{D}_L$ vary. A total of (L+1) matrices is formed, each containing the spatial-time-frequency correlation information within the signal channels at the corresponding scale.
3) $2D^2PCA$ is subsequently carried out on each of the (L+1) matrices to extract the most informative features, as well as reduce the dimension based on the user-specified threshold of total energy preserved.
4) The reduced feature matrices are sequenced into a vector.
5) 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 [8].
6) Only those PCs with high discriminant ability are retained and others are discarded.
7) Finally, the performance of the algorithm can be evaluated by feeding the vector of optimal PCs obtained into a classifier.

C. *Experimental Protocol and Performance Evaluation*

Data used to validate the proposed algorithm are 89-channel high-density myoelectric signals recorded from 12 stroke subjects. The experimental protocol for each subject consisted of 20 functional finger, hand, wrist, and elbow movements. Details relating to electrode placements and 20 arm/hand movements are described in Zhang and Zhou [9]. Each experimental trial contained five repetitions of one movement. The MES were sampled at 2000 Hz per channel, filtered with a fourth-order Butterworth band-pass filter (30–500 Hz) to remove movement artifacts and high-frequency noise. For each movement, the recorded MES was composed of five active segments corresponding to five repetitions of muscle contraction. For each active segment, the 89-channel MES were further segmented into a series of overlapping windows (window length: 256 ms, overlap step: 128 ms). A mother wavelet was employed to simultaneously decompose 89-channel signals over five levels. The remaining procedures for $WT2D^2PCA$ described in Section II.B were employed to extract the PCs. Two typical classifiers, support vector machine (SVM) [10], extreme learning machine (ELM) [11], were employed to evaluate the classification performance of the proposed algorithm. The accuracy for each test was the percentage of correctly classified windows over all the testing windows including all the movements. Since the recorded MES consisted of five active segments for each movement, for each subject, the performance was evaluated as the averaged accuracy across the fivefolds. An overall performance was then evaluated as the mean and standard (SD) of classification accuracies across all the subjects.

III. Results

A. *Spatial Multi-Scale Muscle Activity Patterns*

Using the proposed multi-scale spatial matrix technique, the spatial MES activity at each scale was obtained. Since approximate coefficients at level 5 contained considerable low-frequency artifact, whilst the detail coefficients for level 1 corresponded to high-frequency components greater than 500 Hz, both of these were discarded in the analysis. Fig. 1 shows the typical contour plots obtained for the twenty movements for subject 5 at scales D2-D5 of Coiflet 4 mother wavelet. The five panels from left to right in the first row corresponded to the spatial-time-frequency activities of intended movements corresponding to ulnar wrist up, fingers 3-5 flexion, index-finger flexion, thumb extension, and wrist extension. With each intended movement, a significant difference between the intensity of the myoelectric signals at D2 over the upper limb muscles can be readily discerned in these contour plots. The second row of Fig. 1 indicates the STF distributions of hand open, elbow flexion, wrist supination, index-finger extension, and wrist pronation at scale D3. The third row displays MES activities corresponding to wrist flexion, elbow extension, hand closing, tip pinch, thumb flexion at scale D4. The final row of Fig. 1 displays the specific characteristics of the five remaining movements, namely fingers 3-5 extension, lateral pinch, fine pinch, gun posture, and ulnar wrist down. Similar to the panels in the top row, there was significant discrepancy in the intensity distributions of the remaining contour plots, indicating useful discriminant information in the multi-scale matrices.

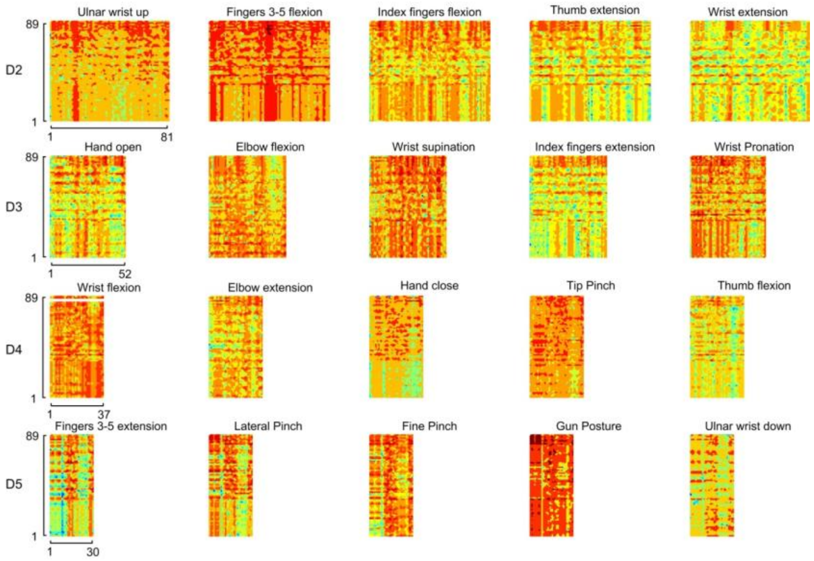

Fig. 1. Contour plots of multi-scale matrices for 89-channel myoelectric signal traces of 20 hand movements obtained from subject 5.

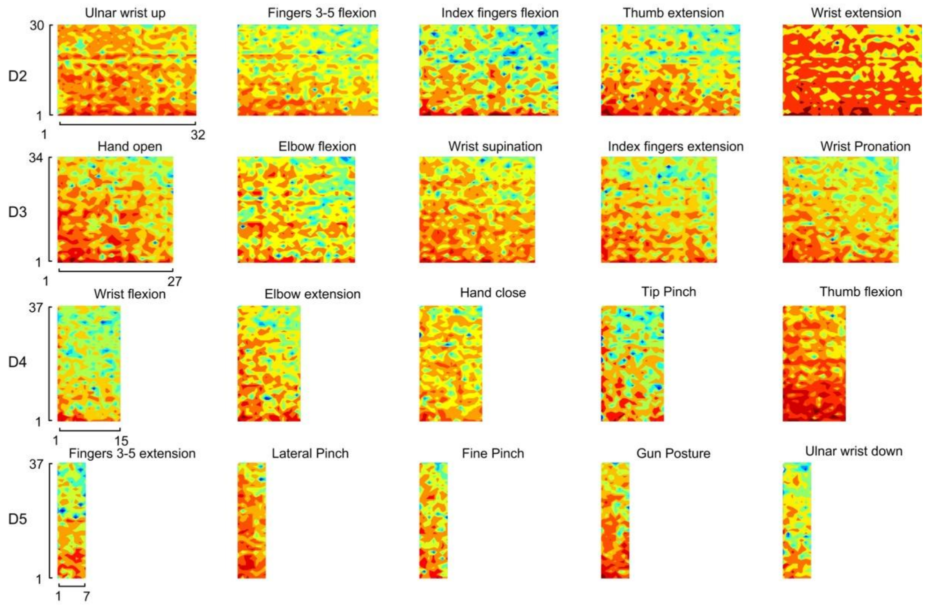

Fig. 2. The contour plots of multi-scale matrices reduced using 2D2PCA for 89-channel myoelectric signals of 20 hand movements obtained from subject 5.

The proposed two-directional two-dimensional principal component analysis 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 88%. Compared with Fig. 1, the intensity difference between certain sub-panels in Fig. 2 is further enhanced, including, for example, those in the first row. On the other hand, the matrix size at each scale (row) was significantly decreased. Table I summarise the matrix sizes at all scales before and after 2D^{2}PCA for 93%, 88%, and 83% total energy conserved for subject 5. If conventional PCA was used with all wavelet coefficients arranged into a 1D array, the size of the covariance matrix would be 17800×17800, i.e., $(89 \times (81+52+37+30))^2$. It would be obviously problematic to compute such a high dimensional covariance matrix containing more than 3×10^8 elements.

B. Recognition of Intended Movements

Pattern recognition analysis was performed using the optimal number of PCs and SVM and ELM classifiers with the fivefold cross-validation scheme. Table II summarizes the subject- specific classification accuracy for all 20 intended upper-limb movements. A high average classification accuracy above 95% could be achieved for most subjects. Across all subjects, there was no significant difference in the accuracy of SVM and ELM (p>0.05), although the average accuracy for ELM was slightly lower. Compared with a previous study on the same MES dataset using PCA reduction in the time domain feature [9], $2D^2PCA$ yielded higher average accuracy with much fewer PCs for the same SVM classifier, indicating the efficiency and effectiveness of $2D^2PCA$. Although the PCs needed for ELM was higher than SVM, ELM exhibited better computational efficiency due to its unique learning scheme. In addition, the average accuracy of $WS2D^2PCA$-ELM was also higher than LDA, and SVM classifiers used in conjunction with PCA in [9]. This further suggested that $WT2D^2PCA$ was more effective than PCA for high-dimensional MES classification.

TABLE I: MULTI-SCALE MATRIX SIZE AT VARIOUS THRESHOLD VALUES OF TOTAL ENERGY CONSERVED FOR SUBJECT 5

Size	Total energy conserved (%)			
Scale	100%	93%	88%	83%
D2	89×81	33×32	30×32	25×29
D3	89×52	35×27	34×27	29×25
D4	89×37	43×16	37×15	32×14
D5	89×30	43×8	37×7	30×4

TABLE II: PATTERN RECOGNITION RESULTS (MEAN ±SD) OF 89-CHANNEL MES FOR 12 SUBJECTS, AVERAGED ACROSS FIVEFOLD TESTS FOR EACH SUBJECT (UNIT: %)

subject	SVM	ELM
1	93.04 ± 5.26	94.13 ± 7.34
2	87.39 ± 13.27	86.24 ± 10.89
3	97.49 ± 1.23	96.93 ± 1.42
4	92.26 ± 7.37	91.40 ± 5.25
5	96.30 ± 3.46	95.75 ± 3.38
6	97.64 ± 1.88	96.96 ± 2.31
7	99.81 ± 0.21	99.46 ± 0.16
8	99.90 ± 0.15	99.34 ± 0.92
9	95.68 ± 3.57	95.25 ± 2.86
10	98.55 ± 1.44	98.89 ± 0.98
11	99.48 ± 0.27	99.13 ± 0.37
12	99.45 ± 0.71	98.87 ± 1.02
Average	96.41 ± 3.81	96.02 ± 3.95

IV. CONCLUSION

A novel wavelet two-directional two-dimensional principal component analysis for high-dimensional signal classification has been proposed and examined in this study. Spatial-time- frequency discriminant information from high-dimensional myoelectric electrode array can be effectively extracted and reduced using the proposed method. Compared with the time domain feature extraction in conjunction with PCA, $WT2D^2PCA$ performed better with higher classification accuracy and less PCs in MES classification. The efficiency and effectiveness of the method can be further validated by using other high-dimensional biosignals. Although the present study focuses on high-dimensional signal pattern classification, based on the PCs obtained at multiple scales, it is relatively straightforward to expand $WT2D^2PCA$ for high-dimensional signal compression, denoising, component extraction, and other related tasks.

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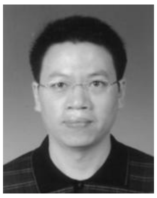

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