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Electromyogram (EMG) based fingers movement recognition using sparse filtering of wavelet packet coefficients

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Abstract. Surface electromyogram (EMG) signals collected from amputee's residual limb have been utilized to control the prosthetic limb movements for many years. The extensive research has been carried out to classify arm and hand movements by many researchers. However, for control of the more dexterous prosthetic hand, controlling of single and multiple prosthetic fingers needs to be focused. The classification of single and multiple finger movements is challenging as the large number of EMG electrodes/channels are required to classify more number of movement classes. Also the misclassification rate increases significantly with the increased number of finger movements. To enable such control, the most informative and discriminative feature set which can accurately differentiate between different finger movements must be extracted. This work proposes an accurate and novel scheme for feature set extraction and projection based on Sparse Filtering of wavelet packet coefficients. Unlike the existing feature extraction-projection techniques, the proposed method can classify a large number of single and multiple finger movements accurately with reduced hardware complexity. The proposed method is compared to other combinations of feature extraction-reduction methods and validated on EMG dataset collected from eight subjects performing 15 different finger movements. The experimental results show the importance of the proposed scheme in comparison with existing feature extraction-projection schemes with an average accuracy of 99.52% $\pm$ 0.6%. The results also indicate that the subset of five EMG channels delivers similar accuracy (>99%) to those obtained from all eight channels. The resultant accuracy values are improved over the existing one reported in the literature, whereas only one-third numbers of channels per identified motions are employed. The experimental results and analysis of variance tests ($p < 0.001$) prove the feasibility of the proposed work.

Keywords. EMG; sparse filtering; quadratic discriminant analysis; WPT; wavelet denoising.

1. Introduction

The loss of forearm intensely limits everyday competencies and interactions of people with upper limb amputation [1]. The use of myoelectric controlled (MEC) prostheses facilitates to restore capabilities of the forearm. The surface electromyography (EMG) signals, collected from the residual limb of the forearm, are used to control prosthetic devices [2]. Typically, a myoelectric based pattern classification framework is employed, whereby selected features extracted from EMG signals are used to train the classifiers to predict the intended gesture to be performed by the prosthetic hand. As per the experiment carried out by Al. Timemy [3], it is proven that the accurate movement controls of single, as well as multiple fingers, are required to improve the dexterity of the current prosthetic hand. The accurate controlled movement of fingers improves daily intricate tasks which in turn increases the quality of life of upper limb amputees.

The major challenge in developing such prosthetic arm is the difficulty in accurate identification of the user's intended finger movement. Controlling multi-finger movements is more challenging as compared to the hand movements. Firstly, weaker EMG signals are generated by muscles during finger movements (flexion and extension) as compared to those generated during gross hand movements (pronation, supination, etc.) [3]. Secondly, finger movements involve the most intricate combinations of muscle activation which lies in the deep layers of the forearm. Therefore, EMG signals collected at the skin surface go through nonlinear attenuation caused by forearm tissues. Consequently, a large number of electrodes are required to identify finger movements [2, 3].

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Towards improving forearm dexterity by controlling single as well as multiple finger movements of hand prosthesis, many studies have been carried out. The EMG based pattern classification should include some basic processing steps such as data preprocessing, data segmentation, feature extraction, dimensionality reduction and classification [4]. A careful selection of these techniques results in improved class separability [5].

Jiang *et al*. [6] used four EMG channels/electrodes to classify six finger movements using Artificial Neural Network classifier. However, multiple finger movements were not considered. Tenore *et al*. [7] classified 12 finger movements using multi-layer perceptron MLPNN. He reported 98% accuracy, using 32 EMG channels. Recently, Tara *et al*. [8] utilized 12 channels to identify nine finger gestures using a mixture of expert's model within a Bayesian framework. However, both of these utilized more number of channels than the number of movements. Ali Timemey *et al*. [3] have classified 15 finger movements using an Orthogonal Fuzzy Neighborhood Discriminant Analysis (OFNDA) for the feature set reduction and Linear Discriminant Analysis (LDA) for classification. He reported 98.25% accuracy with six channels for 15 single and multiple finger movements. Nevertheless, he did not include gross movement (hand close) in his study since gross movement generates a more confusing signal as compared to single or multiple finger movements [3]. Rami N Khushaba *et al*. [9] used mutual information based Principal Component Analysis (PCA) as a feature selection and projection scheme to classify 15 movements of single and multi-fingers with an average accuracy of 95% using eight channels across eight subjects. However, no results regarding computational time have been reported.

In the feature extraction step, the extracted features should possess relevant information and discard irrelevant/noise information. The classifier performance mainly depends on the quality of the extracted features [10, 11]. The EMG features are generally categorized into three types, namely time domain (TD), frequency domain and time-frequency domain (TFD). The TD feature set is widely used due to its computational simplicity. A number of TD features like Waveform Length (WL), Mean Absolute Value (MAV), Number of Zero Crossings (ZC), Integrated Absolute Value (IAV), Slope Sign Changes (SSC), Integrated EMG (IEMG), and Root Mean Square (RMS) have been effectively used in many EMG based classification problems previously [2–5, 12]. Hudgin *et al*. [2] obtained 91% average accuracy, using WL, SSC, ZC, and MAV feature set in recognition of four forearm movements. Auto-regressive coefficients of order 4 (AR4) have been combined with TD features to extract effective features from nonlinear EMG. Angkoon *et al*. [10] showed that the MAV and AR4 modeling coefficients [13] are suitable for the classification of 10 upper limb movements. However, TD features are limited to classify a smaller number of finger movements (e.g., 6 [6], 9 [8], 10 [10]) since they are calculated from EMG, assuming the signal to be stationary while EMG is a non-stationary signal. Hence, the TD features may fluctuate significantly for a large number of movement classes. The Frequency Domain (FD) features, calculated from spectral properties of EMG, are not much suitable for EMG based classification [10]. For analyzing more complex, multichannel EMG, representing a large number of movement classes, TFD based feature extraction methods have been proposed. Some of them are Short Time Fourier Transform (STFT) [10], Wavelet Transform (WT) [14] and Wavelet Packet Transform (WPT) [15]. WPT has been adopted in this paper.

From the literature, it is evident that the recognition rate of a large number of finger movements is greatly influenced by the number of channels. To increase the usability of EMG based prosthetic hand by amputees, it is necessary to minimize the number of EMG channels/electrodes used. The literature observes the fact of an increase in the number of channels for identifying more finger movements. Channel reduction is also beneficial with the aim of reducing the cost and complexity of hardware as well as reducing the processing time of myoelectric controller required to identify a gesture [3] while simultaneously achieving a very high classification accuracy of a large number of finger movements. For accurate identification of a large number of finger movement classes, more information about class discrimination from raw EMG must be extracted. This information has a tendency to be spread over the original feature set due to the high variance nature of the EMG signal. Feature projection-based dimensionality reduction can consolidate this information [16]. To this end, Principal Component Analysis (PCA) has been extensively used [3, 12]. However, PCA has its own limitations that are described in the subsequent section.

In this paper, Sparse Filtering (SF) of Wavelet Packet transforms coefficients is proposed as a feature extraction–projection method to reduce the classifier burden and achieve maximum class separability. Wavelet Packet Transform is used to get multi-resolutions of complex and non-stationary EMG in the time – frequency domain, whereas Sparse Filtering is used to protect the structural representation of the projected/learned features in an efficient manner and to reduce the dimensionality of high dimensional feature vector formed by wavelet packet coefficients.

The primary focus of this research work is to develop a framework for fast and accurate identification of multi-finger movements with a small number of EMG channels. Towards the attainment of the goal set, six state-of-the-art dimensionality reduction and classification schemes are proposed as shown in figure 1. The best scheme identified for EMG multi-finger classification with rigorous experimentation is used for the rest of the study, which prominently includes optimum channel selection to reduce the computational/time complexity. The proposed methodology shows various TD, TFD, AR4 and RMS features that

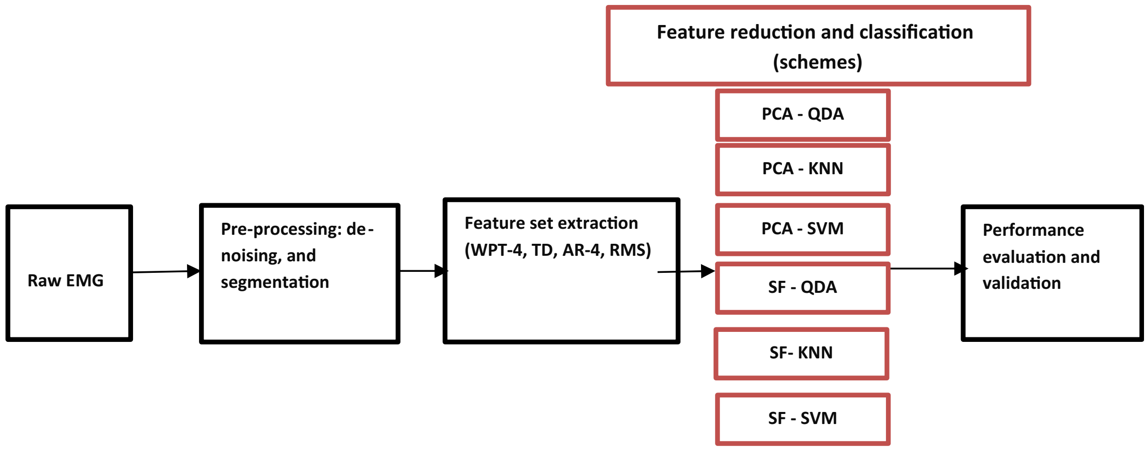


Figure 1. Schematic of the experimental evaluation of the proposed EMG pattern classification system.

are calculated and grouped into different feature sets. For the dimensionality reduction step, two unsupervised feature reduction methods: PCA and SF have been employed in combination with three state-of-the-art classifiers: Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM) and K-nearest neighbor (KNN). The performance of the proposed algorithm is assessed using percentage classification accuracy and statistical tests like analysis of variance (ANOVA).

2. Background

2.1 *Sparse filtering*

Sparse filtering (SF) is a two-layer unsupervised feature learning algorithm that focuses on the sparsity optimization of the learned representation rather than learning input data distribution [17]. It is frequently very well used to scale with the dimension of the input data [18]. It is very simple to use as it requires only a single parameter to tune which is a number of reduced features that guarantee optimal solution convergence. It is computationally very efficient and has been successfully applied to image and phone classifications [19]. The sparsity optimization is achieved by using the following properties of the feature distribution matrix.

- Population sparsity: Each example is represented by a few activated features.
- Lifetime sparsity: Each feature is activated for only a small subset of the examples.
- High dispersal: All the features should have a uniform contribution.

The SF incorporates an objective function optimization with nonlinear transformation for mapping between input features and as few as possible output features. This ensures lifetime sparsity and population sparsity [18]. High dispersal is achieved by considering mean squared activations of each feature (resulting in almost equal values) calculated by averaging the squared values in the feature matrix across the examples.

For a given training set, $\{Y^i\}_{i=1}^{M}$ where$Y^i \in R^{N\times L}$ is a sample value of the M^{th} sample and $N \ll L$. The convention used here is the rows of the matrix corresponds to the features, the columns to the samples; particularly N is the number of original features and the L is the number of samples. The training set is used to train the sparse filtering model to obtain weight matrix $W \in R^{N\times P}$. Sparse Filtering maps the samples onto their features $Z^i \in R^{P\times L}$ using a weight matrix $W \in R^{N\times P}$. P is the number of learned features the original features should reduce to. Hence $P \ll N$.

For each sample, linear features are computed using Eq. (1).

$$Z_l^i = W_l^T Y^i \tag{1}$$

where Z_l^i denotes l^{th} feature of i^{th} sample.

Sparse Filtering optimizes a function using its ℓ_2-normalized feature. The Z_l^i forms a feature matrix. The normalization of rows and columns of feature distribution matrix is done successively so that the features lie on the unit ℓ_2-ball.

Equation (2) shows row normalization and Eq. (3) shows column normalization of the matrix.

$$\tilde{Z}_l = Z_l / \|Z_l\|_2 \tag{2}$$

$$\hat{Z}^i = \tilde{Z}^i / \left\|\tilde{Z}^i\right\|_2 \tag{3}$$

Finally, the solution of the weight matrix W is obtained by cost function optimization shown by Eq. (4).

$$\sum_{i=1}^{M} \left\|\hat{Z}^i\right\|_1 \tag{4}$$

The term $\left\|\hat{Z}^i\right\|_1$ measure sparsity of ith sample [17]. Since features $\hat{Z}^i$ are constrained to unit ℓ_2-ball, the cost function minimizes when the features are sparse. Hence the objective function optimizes for population sparsity. As all the features are divided by their ℓ_2-norm across all samples, normalized features are uniformly active satisfying high dispersal property. Lifetime sparsity is achieved by optimizing population sparsity and high dispersal both. This can be explained as population sparse means many entries are zero in the feature distribution matrix and high dispersal means there is an almost uniform distribution of these zero entries. Therefore, every feature is a lifetime sparse because it has many zero entries. More details of sparse filtering are described in [17].

3. Materials and methods

3.1 *EMG dataset*

The EMG dataset used to test the proposed scheme is available publically by Rami [9]. It is the same dataset used in the evaluation of EMG classification by Rami *et al.* [9]. It comprises eight channel EMG datasets collected from forearms of eight normal subjects (6 males and 2 females aged from 20 to 35). The electrode positions to collect dataset are shown in figure 2. The raw EMG signals are amplified by the gain of 1000 and band-pass filtered (Finite Impulse Response Butterworth – order 10) between 20 and 450 Hz and also a notch filtered at 50 Hz for the removal of power line interference. The filtering is necessary to remove motion artifacts and high-frequency random noise. An analog-to-digital converter (National Instruments – BNC2090) with a 12-bit resolution and sampling frequency of 4000 Hz is used.

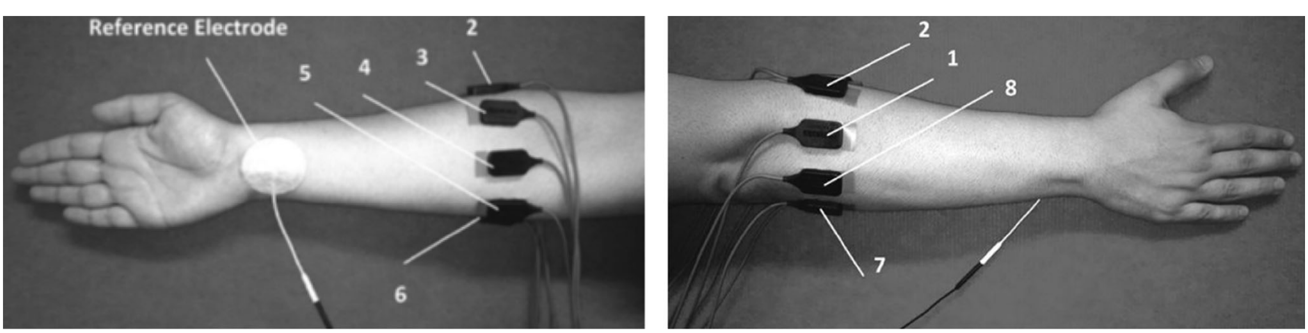
Fifteen classes of finger movements are considered which include flexion of each of the single and multiple fingers, i.e. Thumb (IF1), Index (IF2), Middle (IF3), Ring (IF4), Little (IF5), Thumb-Index (CF1), Thumb-Middle (CF2), Thumb-Ring (CF3), Thumb-Little (CF4), Index-Middle (CF5), Middle-Ring (CF6), Ring-Little (CF7), Index-Middle-Ring (CF8), Middle-Ring-Little (CF9) and a gross movement Hand Close (G) for the experiment. The details of data collection, subjects and experiments are reported in table 1.

3.2 *Pre-processing*

EMG pre-processing step includes de-noising and segmentation.

3.2a *Wavelet denoising*: Since the EMG signal when recorded by electrodes on the skin surface, it captures the biological signals from other neuromuscular activities like eye blinking, cardiac activity, brain activity, etc. [20]. Traditional filtering methods separate signal and noise, according to their different frequency bands. However, for overlapping signal and noise spectra, wavelet-based methods prove to be very effective due to its time-frequency localization property [14]. The high-frequency noise generally obeys Gaussian distribution, which can be very well minimized using the wavelet de-noising method [16]. The popular methods of wavelet denoising are a module maximum of the wavelet transform, noise cancellation, based on the scale coherency of wavelet transform and the wavelet thresholding [14]. The accurate selection of decomposition level and type of mother wavelet leads to the perfect reconstruction of the EMG signal [16, 20]. We have reconstructed EMG from the 5th decomposition level of the db2 mother wavelet family using the SURE thresholding method and soft thresholding technique [20]. The detailed procedure for wavelet denoising of EMG can be found in [16].

3.2b *Segmentation*: To get the most intrinsic property of EMG, data segmentation is a necessary step. Data segmentation is performed using two techniques: adjacent windowing and overlap windowing. The previous study reported that the overlapped windowing outperformed adjacent windowing for better classification [9, 21] and to meet real-time constraints of EMG based controllers. In the



(a) **(b)**

Figure 2. (**a**) Anterior electrode position. (**b**) Exterior electrode position [9].

Table 1. EMG dataset: details about subjects and experiment.

Specifications	Dataset [9]
Number of electrodes	8
Number of finger movements/classes	15
Number of repetitions/class	3
Total number of repetitions/subject	45
Number of subjects	8
Total number of repetitions	360
Time for each repetition	5 s
Sampling rate	4000 Hz
Resolution	12 bit
Analysis window length	250 ms with 125 ms overlap

proposed EMG pattern classification system, the features are extracted from overlapped windowing where an analysis window size of 250 ms which was incremented by 125 ms [5] is used.

3.3 *Feature extraction*

Eight feature extraction methods: seven from TD group (MAV, WL, IEMG, RMS, ZC, SSC and AR4) and one from TF group (WPT) are selected for this study. The TD set (MAV, WL, ZC, and SSC) also called as Hudgin's [2] feature set is baseline feature set, generally used to compare other feature sets in EMG based classification system. The RMS feature is selected to get the force applied and non-fatiguing contraction level of the EMG signal.

Based on the literature, TD-AR features [1–3, 5, 9, 22] have been proved to be useful in the EMG based hand movement classification as they exhibit a great deal of intra-class variability due to the existence of random components. Although, TD features are widely used for hand movement classification problems by many researchers, the large degrees of nonlinear overlapping exist between the pattern associated with the single finger movement and same finger when combined with another finger. To separate such complex movement classes effectively, more signal information needs to be extracted. Time-Frequency Domain (TFD) analysis has been used in such cases [22, 23], specifically, wavelet packet transform (WPT) is more advantageous than wavelet transform (WT) feature extraction since it not only decomposes the approximation coefficients but also the detail coefficients of the EMG signal.

The mathematical expression of each of the extracted features is given below:

1. Root mean square (RMS)
   Root Mean Square (RMS) is a popular feature used to analyze EMG signals [10–12]. Mathematically it is expressed as

$$\mathrm{RMS} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{x_i^2}} \tag{5}$$

   where x_i is the magnitude of i^{th} the sample of x and N are a total number of samples in the segment.
2. Auto-regressive coefficients (AR)
   EMG signal is represented by an auto-regressive model, a predictive model that represents the signal as a linear combination of past value x_{i-q} and additive white Gaussian noise w_i. AR coefficients are given as

$$x_i = \sum_{q=1}^{Q} a_q x_{i-q} + w_i \tag{6}$$

   where Q is model order and a_q is model coefficients. Fourth-order AR coefficients [5, 12, 13] were extracted as EMG features in this work.
3. Mean absolute value (MAV)

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{7}$$

   where $|x_i|$ is the magnitude of a i^{th} sample of x and N are the total samples in a segment.
4. Waveform length (WL)
   Waveform length is defined as the wavelength of an EMG signal over a segment. [2, 7, 24] The mathematical expression is

$$\mathrm{WL} = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{8}$$

5. No. of zero crossing (ZC)
   ZC gives frequency information of an EMG signal. It suggests that how many times the signal has crossed the zero level. To remove low-frequency variations due to noise, a threshold is used.

$$\mathrm{ZC} = \sum_{\mathrm{i=1}}^{\mathrm{N-1}} \{\mathrm{sgn}(\mathrm{x_i} \times \mathrm{x_{i+1}}) \cap |\mathrm{x_i} - \mathrm{x_{i+1}}| \geq \mathrm{Threshold}\}$$
$$\mathrm{sgn}(x) = \begin{cases} 1 & \text{if} \quad x \geq \text{Threshold} \\ 0 & \quad\quad \text{otherwise} \end{cases} \tag{9}$$

6. Integrated EMG (IEMG)
   IEMG is related to the firing point sequence of the EMG signal which is mostly used in non-pattern recognition and clinical applications [11, 21, 25]. It is defined as the sum of the EMG signal over the length.

$$\mathrm{IEMG} = \sum_{i=1}^{N} |x_i| \tag{10}$$

7. Slope sign changes (SSC)
   SSC gives the spectral information of EMG. It measures the number of times the signal has changed the slope

from positive to negative. To cancel the background noise, the threshold level is used.

$$SSC = \sum_{i=2}^{N} \{ f(x_i - x_{i-1}) \times (x_{i+1} - x_i) \} \tag{11}$$

where $f(x) = \begin{cases} 1 & \text{if } x \geq \text{Threshold} \\ 0 & \text{Otherwise} \end{cases}$

8. Wavelet Packet Transform coefficients (WPT)
In the orthogonal wavelet decomposition method, the signal is split into two parts: approximation and detail coefficients. In the WPT method [1], the signal space Y_j is divided into lower resolution Y_{j+1} and detail space W_{j+1}. The orthogonal function $\{\varphi_j(t-2^j n)\}_{n\in z} Y_j$ is divided into two new functions, $\{\varphi_{j+1}(t-2^{j+1}n)\}_{n\in z}$ of Y_{j+1} and $\{\phi_{j+1}(t-2^{j+1}n)\}_{n\in z}$ of W_{j+1} where $\varphi(t)$ and $\phi(t)$ is scaling and wavelet functions respectively. For WPT decomposition, a smaller decomposition level gives poor resolution for effective feature extraction, whereas a larger depth increases computational complexity [20, 23]. Adhering to this trade-off, the decomposition depth of 4 is selected [24]. This work has empirically selected Symlet 5 mother wavelet producing 31 coefficients in total from 4 decomposition levels. The energy values of all 31 coefficients are calculated by the logarithmic value of the root mean square of WPT coefficients. The logarithmic transform is selected for its better performance in EMG classification [9].

The myoelectric classification toolbox provided by Chan [26] is used for implementing the feature extraction algorithms using Matlab 2017b software (Mathworks).

3.3a *Feature sets*: It should be noted that, the predictive power of individual feature may not be able to describe finger movements solely; however, the classification performance can be improved by combining multiple features in one set. To compare the performance of various feature sets, five previously reported feature sets along with individual feature WPT are evaluated in this study

- **TD**: IAV, MAV, WL, ZC, SSC, IEMG [2, 5]
- **TDAR**: IAV, MAV, WL, ZC, SSC, IEMG, AR4 [5, 7, 14]
- **TDRMS**: MAV, WL, ZC, SSC, IEMG, RMS [5, 12]
- **TDTFD**: MAV, WL, ZC, SSC, IEMG, WPT [5]
- **ALL**: MAV, WL, ZC, SSC, IEMG, AR4, RMS, WPT
- **TFD**: WPT

The extracted features provide meaningful information such as the signal amplitude, power, frequency complexity, time-series model parameters and time-scale parameters of the EMG signal. The TD feature set combines signal amplitude (IAV, MAV, WL, IEMG) and frequency related (ZC and SSC) information, whereas TDAR combines signal amplitude and frequency with time series modeling parameters of order 4 (AR4). The time-scale features are combined with TD features to give a better image of EMG signal in the TDTFD feature set. All the important information about the EMG signal is collected under feature set i.e. ALL. The total dimension size of each feature set is given in table 2. The total dimension is calculated considering all eight channels.

3.4 *Dimensionality reduction and pattern classification*

The wavelet analysis provides more meaningful information about non-stationary EMG signals, but also provides high dimensional feature vector, increasing the classifier burden in terms of its learning parameters. However, dimensionality may be reduced by applying an appropriate feature projection/reduction method. This paper proposes SF, a novel method for dimensionality reduction (DR) of EMG feature space, for its simplicity and efficiency in scaling multidimensional datasets. The performance of SF is also compared with other well-known DR technique, Principal Component Analysis (PCA) [3, 9, 12, 27]. SF has been successfully used as a feature learning technique in classifying image and video [17] previously. This is the first reported study in which SF has been applied for dimensionality reduction of EMG feature space in the classification of intended finger movements. SF aims at protecting the structural representation of data by preserving mutual information between original and learned features by entropy maximization of the learned representations. In the classification step, three different classifiers are employed: Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM) and KNN. The selection of QDA is encouraged by its merits of being computationally efficient, the simple approach of statistical implementation, reusability and robustness [25, 27]. SVM, a state-of-the-art classifier, is implemented with a "one-vs-one" strategy. It searches for hyper-planes with the largest margins to classify the multi-class problem. It works well with the high dimensional feature space. KNN was employed with k = 5 as implemented in [3]. For identification of the best feature or feature set and the best mixture of feature reduction and classification technique, six combinations of two feature reduction and three classifiers are used (see figure 1). The classification Schemes 1, 2 and 3 are composed of PCA for dimensionality reduction and QDA, SVM, and KNN for classification, respectively. The 3rd, 4th, and 5th schemes included SF for feature reduction; and again QDA, SVM, and KNN for classification, respectively. In summary, the six "Schemes" evaluated in this study are as follows: (1) PCA + QDA, (2) PCA + SVM, (3) PCA + KNN, (4) SF + QDA, (5) SF + SVM and (6) SF + KNN. All the data processing algorithms are implemented using MATLAB 2017b (Mathworks, USA) software with 16GB of RAM and i7 processor.

Table 2. The dimension size of all feature set.

Feature set	TD	TDAR	TDRMS	TDTFD	ALL	TFD
Total dimension size	5 × 8 = 40	9 × 8 = 72	6 × 8 = 48	36 × 8 = 288	40 × 8 = 320	31 × 8 = 248

3.5 *Performance evaluation*

For each participant, out of the total number of reduced EMG feature sets, 60% of the data is selected as a training dataset and the performance of the selected features was evaluated using the remaining 40% of the testing dataset. For performance evaluation of the proposed system, the quantification of the results is implemented using the following parameter [3, 28]: The average percentage classification rate (%CR) for each individual subject based on testing dataset is calculated as

$$\mathrm{CR} = \frac{\text{Total No.of correct classified samples*100}}{\text{Total No.of testing samples}}$$

4. Results

In the first phase of the experiment, the classification performance of the five multi-feature sets and a single feature is tested for the six proposed classification schemes. Three classifiers, QDA, SVM and KNN are trained and tested using reduced EMG feature sets and the average percentage accuracy of eight subjects is reported in table 3.

The results show that the WPT feature extraction and scheme 4 (SF + QDA) outperformed all other feature set and classification schemes. The best technique for feature extraction, reduction and classification obtained from the initial phase of the experiment, is used throughout the rest of the study.

The second experimental phase focuses on channel number reduction still maintaining the highest classification accuracy for 15 finger movement classes comparable with all eight channels.

Using the channel exclusion technique [28], the minimum number of channels is decided for 15 finger movement classes of eight subjects. To determine the channel subset less computationally expensive, but effective channel exclusion technique is used that recursively eliminates the worst-performing channel at a time. For all eight subjects, eight iterations of the channel exclusion are performed [28]. The average classification accuracy of all subjects for a different number of channels is reported in figure 3. The result shows that a channel subset of four gives 98.72% accuracy, five gives 99.12% and all eight channels give

99.72%.

To compare the two unsupervised feature projection methods, SF and PCA, the number of projected features are varied maximum up to $c - 1$, where c is the number of classes as c is the minimum number of features in the supervised method. Therefore, the number of dimensions reduced is equal to or less than 14 for a 15 class problem. In order to find the effect of dimensionality reduction on the classifier performance, the number of dimension size of WPT features is varied from 1 to 14 and the classification performance of QDA classifier for SF and PCA is illustrated in figure 4.

To evaluate the necessity of wavelet denoising, a comparison between the classification performance obtained when WPT feature extraction and scheme 4 (SF + QDA) is employed with and without de-noised EMG. Figure 5 clearly brings out the effectiveness of using wavelet denoising as a pre-processing step in EMG based classification problems. For a more comprehensive view, the comparison between the confusion matrix obtained from the current problem for with (see figure 5) (5a) and without (5b) denoised EMG of a single subject. The diagonal values indicate the accuracy rate of correct classification wherein non-diagonal entries indicates the misclassification rate.

A two-way ANOVA was performed with p-value = 0.05. The results indicated that there is a substantial difference in the performances when compared the mean classification

Table 3. % Average accuracy of six classification schemes for five multi-feature sets and WPT feature.

Feature set	PCA + QDA	PCA + SVM	PCA + KNN	SF + QDA	SF + SVM	SF + KNN
TD	80.83%	87.30%	78.47%	81.06%	66.43%	55.44%
TDAR	85.51%	86.27%	78.56%	84.17%	68.35%	68.76%
TDRMS	80.53%	87.37%	75.90%	88.78%	56.56%	84.77%
TDTFD	90.54%	87.65%	92.90%	95.24%	70.54%	87.97%
ALL	93.43%	86.93%	91.96%	93.39%	64.87%	75.32%
TFD	**96.65**%	**88.88**%	**93.76**%	**99.79**%	**85.76**%	**96.54**%

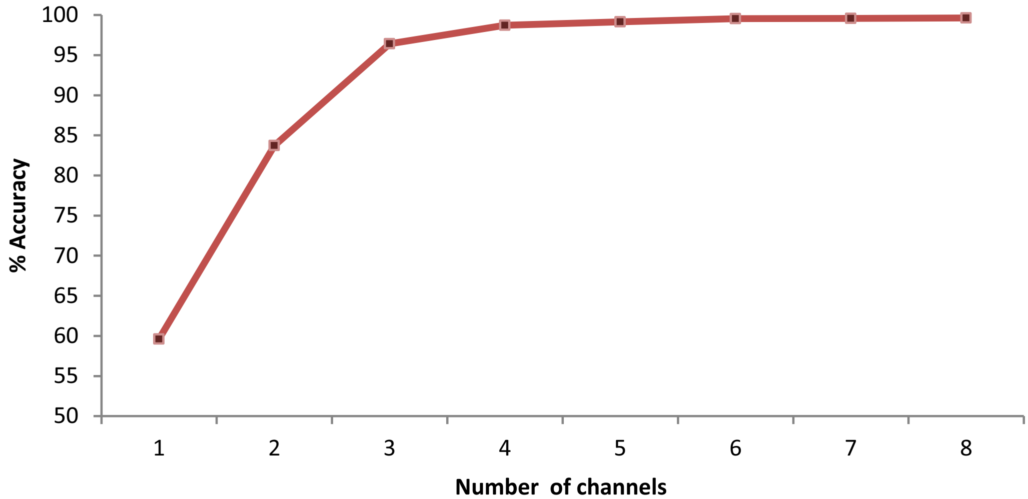


Figure 3. Average classification accuracy of 15 finger Movements for a different number of channels using Scheme 4 for eight subjects.

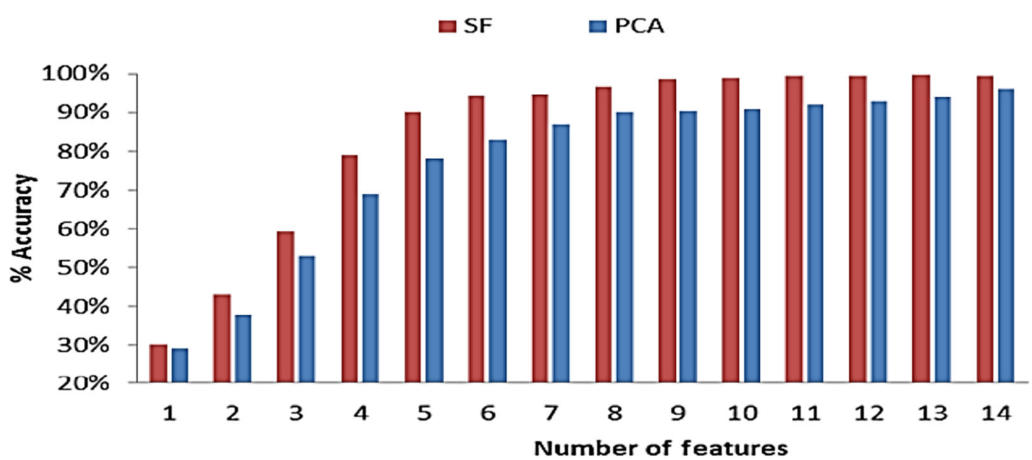


Figure 4. Average classification accuracy of 15 finger Movements for different number of features reduced using SF and PCA.

accuracy for with and without wavelet denoising (*p*-value = 0.00093).

5. Discussion

The average classification accuracy of eight subjects obtained using all six classification techniques for the classification of 15 finger movement classes is shown in table 3. It can be observed that in the current problem of EMG classification, across different feature sets and classifiers, on an average TFD (WPT) as feature extraction and SF as feature reduction obtained better accuracy amongst all other techniques. For classification, QDA was preferred due to the improvement shown in accuracy for 15 finger movements. Additionally, it has a few tunable parameters and lower computational complexity.

In the feature extraction step, better performance of WPT may be justified by its nonlinear decomposition analysis approach which is very much suitable for extracting relevant features from highly nonlinear EMG selected for the current problem. In the feature reduction step, SF outperformed PCA, as it transforms the feature space to maximize the variance along with fewer principal components, but keeping the overall dimension of the same features as the original. Selection of a few numbers of lower-order PCA components for the classification (e.g., 14 features in this case) can cause the loss of important information.

The SF algorithm implemented which considers the intrinsic radial structure of the input data. This assumption enhances the suitability of the algorithm to certain data. However, SF does not suite well with other feature sets utilized in this experiment. The combination of WPT as feature extraction and SF as feature reduction has

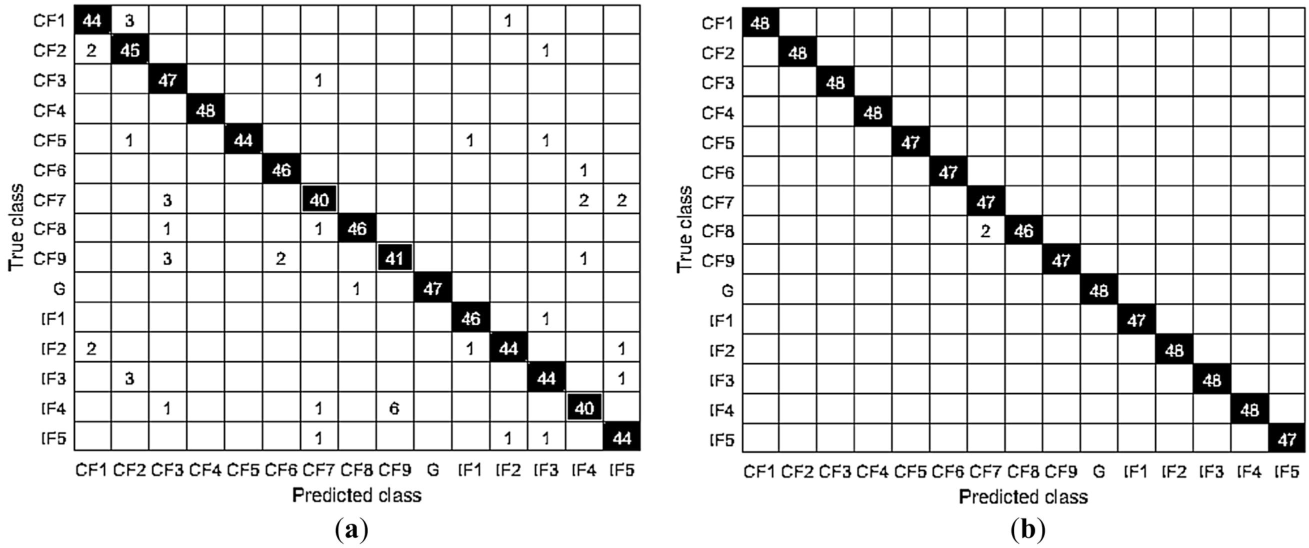


Figure 5. Confusion matrix across all movements using TFD feature set and Scheme 4: (**a**) Without wavelet denoising. (**b**) With wavelet denoising.

performed exceptionally well as compared to other methods. Previous work has used SF as an effective feature learning method in image and video classification [17]. It must be noted that, in contrast to other studies, our results for SF show its suitability for feature reduction step in the recognition of single and multiple finger movements accurately. This results in better preservation of separation amongst classes by the projection matrix generated by SF which outperforms PCA.

For instance, Khushaba *et al*. classified 15 finger movement classes (same dataset as used by this work) and focused more on feature selection step than feature reduction. He selected relevant features from the TDAR feature set using mutual information entropy and further reduced in dimensionality using PCA. He achieved an average accuracy of >95% with four or more channels. Instead of selecting relevant features, our work focuses on the nonlinear mapping of all relevant features provided by time-frequency analysis of WPT, using feature projection method SF. Hence, our results are improved (>98.5% using four or more EMG channels and >99% with five or more number of channels. The same number of movement classes (same dataset) in this study explains a bigger improvement than reported by Khushaba *et al.* [9]. A pairwise comparisons t-tests confirmed that an accuracy provided by five EMG channels is not significantly different (p-value = 0.543) from that achieved with all eight EMG channels, suggesting that five channels are sufficient to obtain similar performance to that of eight channels. However, there is a difference in the optimal channel locations that achieved the accuracies (>98.5%) between all participants, which may be due to the variation in their anatomy and the manner in which the electrodes are placed. The accuracy calculated for each movement class averaged across all participants, by considering the optimum five channel set is reported in table 4.

These results show improvement over those reported by Ali Timemy [3], where 15 classes of finger movements were classified using six EMG channels, with an accuracy of 98% for 10 participants. In addition to that, the dataset utilized in this [3] study involved 11 single finger movements, only three combined finger movements and a rest state, whereas

in our case only five single finger movements and 10 combined finger movements are used which makes the signal more complicated.

Table 4. Average % classification accuracy and standard deviations (SD) across eight participants for all 15 classes examined by the best identified five channels.

Classes (flexion of)	Classification accuracy and SD (%)
Thumb (IF1)	98.75 ± 3.15
Index (IF2)	97.25 ± 3.18
Middle (IF3)	98.87 ± 3.90
Ring (IF4)	96.67 ± 2.13
Little (IF5)	98.00 ± 2.82
Thumb-Index (CF1)	99.63 ± 0.56
Thumb-Middle (CF2)	94.00 ± 3.26
Thumb-Ring (CF3)	100 ± 0.0
Thumb-Little (CF4)	99.25 ± 0.97
Index-Middle (CF5)	97.62 ± 2.55
Middle-Ring (CF6)	98.87 ± 2.14
Ring-Little (CF7)	99.25 ± 0.83
Index-Middle-Ring (CF8)	99.33 ± 1.68
Middle-Ring-Little (CF9)	98.33 ± 2.35
Hand Close (G)	98.66 ± 3.26

Table 5. Comparison between the results obtained from this work and previous research.

Ref.	Features selected	Methods used	Number of EMG Channels (Nch)	Number of finger movements (Nm)	Number of participants	(%) Avg. Accuracy	Nm/Nch
Al Timemy[4]	TD,RMS,AR6	OFNDA-LDA	6	15 SF & MF	10	98.75	2.5
Rami [14]	TD, AR11, Hjorth	MCA-SVM	4/8	15 SF & MF	8	95/98.7	3.75/1.8
This Work	WPT	SF-QDA	4/6	15 SF & MF	8	98.75/**99.58**	3.75/2.5

SF = single finger, MF = multi-finger.

In our work, we presented WPT feature extraction when combined with SF-QDA, allows for dimension reduction and the amount of channel reduction still providing a higher accuracy for a large number of movements. The above comparisons confirm our assumption about extracting WPT features than TD-AR-RMS features from EMG signal when employed with SF dimensionality reduction, accurately recognizes a large number of finger movements. This approach resulted in a better Nm/Nch ratio (where Nm is the number of finger movements and Nch is the number of EMG channels) than reported in previous studies. The summary of related work has been displayed in table 5 showing the Nm/Nch ratio. Our work achieved a ratio of 3.75 for eight subjects, in comparison with previous values ranging from 1.8 to 2.5 which recommend a reduction in hardware complexity makes it more suitable for hardware implementation.

6. Conclusion

A novel method for EMG feature reduction is proposed after rigorous experimentation. The proposed SF method when applied to WPT features, maps the nonlinear information present in WPT features to a reduced feature set. In SF, the weights of the projection matrix are optimized while preserving the mutual information between original and learned features through the preservation of the data structure.

We investigated EMG dataset from eight subjects recorded using an eight channel EMG system. Our results highlight the crucial role played by the wavelet denoising, WPT features extraction technique and SF feature reduction technique in the EMG signal classification chain. In particular, the results identify the superiority of the SF feature reduction method applied to WPT coefficients calculated from the denoised EMG signal and classified by the QDA classifier in terms of accuracy as compared to previous work reported. The experimental results show higher classification accuracy, with an average of >98.5% for eight subjects in the classification of 15 finger movement classes using only four channels and >99.5 using six channels. The results of our experimental work may be applied in clinical applications to improve the quality of life of the amputee persons and elderly people.

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