Fuzzy Wavelet Packet based Feature Extraction Method for Multifunction Myoelectric Control

Rami N. Khushaba, Adel Al-Jumaily

***Abstract*—**The myoelectric signal (MES) is one of the Biosignals utilized in helping humans to control equipments. Recent approaches in MES classification to control prosthetic devices employing pattern recognition techniques revealed two problems, first, the classification performance of the system starts degrading when the number of motion classes to be classified increases, second, in order to solve the first problem, additional complicated methods were utilized which increase the computational cost of a multifunction myoelectric control system. In an effort to solve these problems and to achieve a feasible design for real time implementation with high overall accuracy, this paper presents a new method for feature extraction in MES recognition systems. The method works by extracting features using Wavelet Packet Transform (WPT) applied on the MES from multiple channels, and then employs Fuzzy c-means (FCM) algorithm to generate a measure that judges on features suitability for classification. Finally, Principle Component Analysis (PCA) is utilized to reduce the size of the data before computing the classification accuracy with a multilayer perceptron neural network. The proposed system produces powerful classification results (99% accuracy) by using only a small portion of the original feature set.

***Keywords*—**Biomedical Signal Processing, Data mining and Information Extraction, Machine Learning, Rehabilitation.

I. Introduction

THE fields of human-computer interaction and robotics emphasize the necessity of humanizing machine interaction thus calling for more intuitive interfaces. The Electromyography (EMG) signal, also referred to as the myoelectric signal (MES), acquired from the forearm skin surface provides valuable information about neuromuscular activities and has been recognized as an efficient and promising resource for human-machine interface (HMI) that can be used for the rehabilitation of people with mobility limitations and those with severe neuromuscular impairment. The MES is utilized in a noninvasive control scheme, and used in many diverse applications including clinical diagnosis, a source of control of assistive devices, and schemes of functional electrical stimulation [1].

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The MES is a complicated signal controlled by the central nervous system (CNS). It is affected by anatomical and physiological properties of muscles, the control scheme of the peripheral nervous system, and the characteristics of the instrumentation used to detect and measure the signal [2, 3].

There has been considerable research in the development of control strategies and techniques for controlling multiple degree-of-freedom (DOF) prosthesis. The ultimate goal of these systems is to produce a control system which can perform simultaneous coordinated control of several DOFs [4]. One of the control strategies being extensively researched is known as myoelectric control strategy, in which a prosthetic arm is controlled by utilizing pattern recognition to classify the MES patterns based on either a priori knowledge or on statistical information extracted from the patterns to select a specific robot arm movement. The MES patterns exhibit distinct differences in their temporal waveforms for different actions. Within a set of patterns derived from the same contraction, the structure that characterizes the patterns is sufficiently consistent to maintain a visual distinction between different types of contraction. Hudgins [5, 6] aligned the patterns using a cross-correlation technique and managed to show that the ensemble average of patterns within a class preserves this structure.

One of the limitations of the current myoelectric control systems is the huge amount of data extracted from the myoelectric signal required to be processed and used as a control input for the prosthesis [7]. The processing of the huge amount of data introduces a time delay in the myoelectric control system which hinders the development of a continuous control. The second limitation is imposed by the first one, as in order to reduce the computational cost of such a system, several techniques are utilized but many of them do not take into account the interaction of the features with specific class labels thus decreasing the accuracy of such systems. This paper focus on multifunction myoelectric control of prosthetic devices, and introduce a new method on feature extraction utilizing fuzzy c-means algorithm in judging on wavelet packet based features suitability in classification, thus maximizing the class separability of the features, which are later projected linearly into a smaller dimension using PCA, a method of features projection.

The paper is organized as follows: section II presents the background and related work. The fuzzy wavelet packet algorithm proposed is described in section III. In section IV, experimental results are presented. Conclusion is given in section V.

II. Background

A. Continuous Multifunction Myoelectric Control

Controlling prosthetic devices can be performed on continuous steady state or transit MES signals. Initial attempts were based on the utilization of transit MES signals, but recent studies proved that the MES classification is enhanced when performed on a continuous steady-state data, switching from one contraction type to another, and reflected in more natural control to the robot arm movements by means of pattern recognition.

The first stage in any pattern recognition system is the features extraction. Although the literature includes many published works which explore the extraction of features from the MES for controlling prosthetic limbs, there have been few works which make quantitative comparison of their quality. Recently, most of the attempts to extract features from the MES can be generally classified into two categories: temporal and spectral approaches[8]. Some of the temporal approaches attempts employ zero crossing rate [9], mean absolute value [5], and Cepstrum coefficients [10] methods. Multiple temporal feature parameters extracted for MES pattern classification were also the focus of many researchers in this field. The justification behind using multiple features parameters is that each of the temporal approach methods can reflect a specific property of the signal in the generated feature set, thus the grouping of those sets might work best together presenting a better image of the information contained in the signal. Park & Lee[11] combined Integral Absolute Value (IAV), Difference Mean Absolute Value (DAMV), Variance (VAR), Autoregressive Model Coefficients (ARC), Linear Cepstrum Coefficients (LCC),and Adaptive Cepstrum Vector (ACV), to prove that the desired motions were recognized efficiently.

Although pattern recognition using features extracted by those time domain methods were successful to some limit, However the pattern recognition results using these feature vectors have not had a high success rate because such methods assume that MES signal is stationary, while the MES signal is non-stationary in its nature [12, 13], thus changing the researchers trend toward the use of information contained in frequency domain as it leads to better solution for encoding the MES signal, that guide to the spectral approach. Many researchers investigated various time frequency approaches to signal processing in myoelectric control problem ranging from Fast Fourier Transform (FFT) [14] , Short Fourier Transform (STFT) [15], the Wigner–Ville distribution (PWVD), the Choi–Williams distribution (RWED), the Continuous Wavelet Transform (CWT) [16], and finally the wavelet packet transform (WPT) that has been adopted in this paper [1].

The second stage in a pattern recognition system is the dimensionality reduction stage. It is required with this approach to deal with the reduction of problem dimensionality, which is generally fundamental to increasing the classification performance. It works to preserve as much of the relevant information as possible while reducing the number of dimensions. The wide variety of existent techniques for feature extraction presents two problems: which techniques should be used and how to select from among of the features that each extraction technique generates.

Selected features are "best" only by some standard (i.e. criterion): therefore techniques for generation of features tend not to be very portable from one pattern processing problem to another. Many techniques do not generate independent features; therefore there is redundancy in the data, which potentially affects both efficiency and accuracy in pattern recognition. The two main strategies for dimensionality reduction are feature selection and feature projection [17]. In the field of myoelectric control, PCA proved to present powerful results, this was shown by many researches done in this filed [1, 18, 19]. A variation to the approach of using PCA alone was introduced recently, in which PCA is combined with Kohonen self organizing feature map (SOFM) to produce a linear-nonlinear projection of data proving to be very suitable for real time implementation [20]. It is true that using PCA on time frequency features provide good classification accuracy, but it is noticed that when the number of motion classes to be classified increases the performance of the MES pattern recognition system starts degrading. This paper deals with this problem by proposing a new fuzzy wavelet packet based feature extraction method in MES driven systems, for which the functionality will be proven to outperform other methods in this field.

III. Methodology

A. Myoelectric Signal Dataset Acquisition

The MES dataset used to test the proposed method was acquired by the University of New Brunswick in Canada [21]. The dataset consisted of ten motions associated with three degrees of freedom (DOF's) of the wrist, two different hand grips, and a rest state. In particular they were: forearm pronation, forearm supination, wrist flexion, wrist extension, radial deviation, unlar deviation, key grip, chuck grip, hand open, and a rest state, as shown in Fig.1. Each session of the database consisted of two trials or two repetitions of each motion. Six subjects (AW, KS, LH, MW, SM, and WM) were prompted to complete medium force isometric contractions of 5 seconds duration followed by a brief rest period. Each record was 256 ms in duration (256 points sampled at 1024 Hz, pre-filtered between 10-500 Hz using the 4th order Bessel band pass filter with a gain of 2000 and a CMRR greater than 96 db/channel).

B. Wavelet Packet for Feature Extraction

Wavelet packets (WP) were introduced by Coifmann, Meyer and Wicker Hauser [22]. It works by generalizing the link between multiresolution approximation and wavelet bases. A signal space V_j of a multiresolution approximation is decomposed in a lower resolution space V_{j+1} plus a detail space W_{j+1}. The decomposition is achieved by dividing the orthogonal basis $\{\phi_j(t-2^j n)\}_{n\in Z}$ of V_j into two new orthogonal bases $\{\phi_{j+1}(t-2^{j+1}n)\}_{n\in Z}$ of V_{j+1} and $\{\varphi_{j+1}(t-2^{j+1}n)\}_{n\in Z}$ of W_{j+1}, were $\phi(t)$ and $\varphi(t)$ are scaling and

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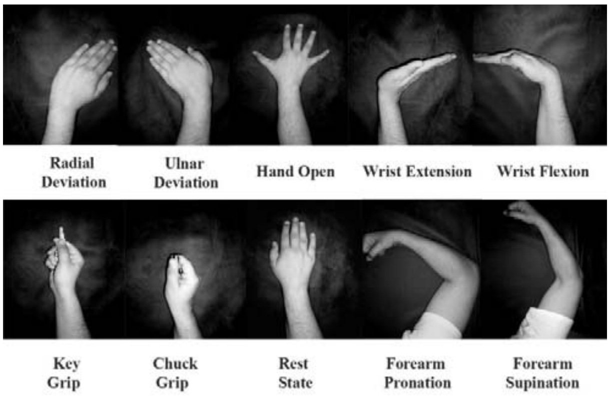


Fig. 1 Ten classes of motion used in this research acquired from 16 MES surface electrodes.

wavelet functions respectively.

The decomposition for WP can be implemented by using a pair of Quadrature Mirror Filter (QMF) bank that divides the frequency band into equal halves. Due to the decomposition of the approximation space (low frequency band) as well as the detail space (high frequency band), the frequency division of the MES signal take place on both the lower and higher sides. This recursive splitting of vector space is represented by admissible WP tree.

Features are usually generated by taking the energy of the wavelet coefficients in the subband according to the normalized filter bank energy $S(l)$ that is given by.

$$\log(S(l)) = \log(\sum_{m=1}^{\infty} Wx(l,m)^2 / N_l) \qquad (1)$$

Wx = Wavelet packet transform of signal .
l = Subband frequency index.
N_l = Number of wavelet coefficients in the $l'th$ subband.

The wavelet packet transform have received more considerable attention in the analysis of non-stationary signals like the MES because the time-frequency analysis produces a high dimensional feature vector thus providing more information about the signal. However the high dimensionality of the feature vector causes an increase in the learning parameters of the pattern classifier, and the convergence of the learning error deteriorates. Therefore, dimensionality reduction is essential before applying the feature vector, to the pattern classifier.

First of all a sliding window is incremented in position by a specific amount and passed on the MES signal records to choose portions of signal each time. In addition to the type of feature set to be used; the parameters which affect the classifier's performance include the record length and the window increment. The response time of a myoelectric hand control system should be less than 300 ms, so that the user operates the hand without perceiving a time delay [23]. In our system the record length was N = 256 samples and the windows increment was M = 32 samples (Blackman type window). WPT was applied on each sample window to extract features.

There are two categories of classification methods employing WPT in features extraction. The first uses abstract aggregates of the original wavelet packet features such as: energy, distance, or clusters[24]. The second category is based on using the decomposition coefficients to form a feature space by merging specific nodes of the WPT tree and splitting others in order to produce a WPT tree that represent the best reflection of the properties of the signal. The features are then extracted as the energy of wavelet coefficients in the terminal nodes of the resultant optimized tree. The common methods known, in the second category, are the joint best basis (JBB), the local discriminant basis (LDB) methods, and fuzzy wavelet packets based features extraction method (denoted as FWP throughout the rest of this paper) that was developed in [24] and proved to outperform both the JBB and the LDB methods in classification of biomedical signals. The FWP used FCM to determine the optimal wavelet packets decompositions and ranked the features based on their membership in the classes, thus that forming a kind of features selection method. Although the FWP proved very successful on certain kinds of biomedical signals, but using such method based on features ability to separate different classes alone doesn't perform well on the MES signals, due to the high variance of the signal and consequently of WPT features [1], This situation was analyzed by Englehart [25], as he compared feature selection and feature projection (employing PCA) on MES patterns and proved that PCA outperformed feature selection methods in MES pattern recognition.

Recently, Chu et al [13, 20] proved that the approach of extracting the features by WPT followed by dimensionality reduction by PCA could not provide an effective result in recognition accuracy because PCA learning merely produces a well-described coordinate system for the distribution of all features without consideration of the separation of class distribution, and proposed their approach of using PCA followed by a self organizing feature map (SOFM). The use of such linear-nonlinear feature projection method in real time control of a prosthetic arm achieved an accuracy of 97% in average across 10 subjects. In the linear-nonlinear projection approach a SOFM is utilized along each channel. If the same method is applied on the MES dataset with 16 channels it will require 16 SOFM to be trained, thus increasing the overall complexity of the problem and the computational cost. Another point in the SOFM based approach is that, in their approach they recognized that the problem is caused by PCA because it doesn't take into account the relation of features with the class, but they apply PCA and later try to remove the error induced by PCA through the utilization of SOFM. It would be preferred if care is taken before applying PCA and not after that, so as to reduce the probability of error before it actually take a place. This paper presents a new technique to reduce the computational cost and increase the MES recognition performance in an efficient simple manner.

The block diagram of the proposed system of this paper is shown in Fig.2. It consists of four stages. In the first stage, WPT is applied on the MES records to generate a wavelet tree, through decomposing the original signals using a Symmlet family, with four level of decomposition for the wavelet tree and taking the energy of wavelet coefficients

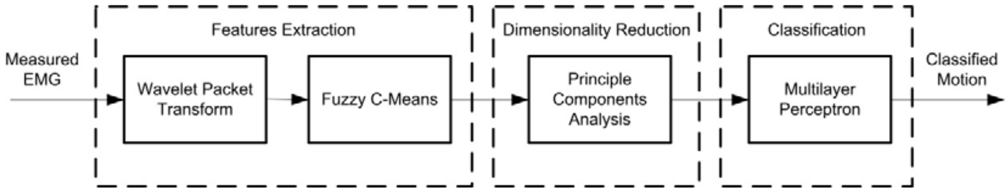


Fig. 2 The proposed MES recognition system.

as features, without applying the JBB and LDB method to optimize the tree. In stage two, our version of the FCM based measure for removing nondistinguishing features is presented, which represents an enhanced version of the measure used in [24] as their measure of removing nondistinguishing features took into consideration the distance between only the maximum and minimum class centers along each feature, but the fact that certain centers might be close to one of either the maximum or minimum centers deviates this measure from a true indication of the feature suitability in classification. This paper propose to remove only the features that prove to be absolutely has no significance in classification, and retain other features even if they have small power in separating the clusters (to account for robustness in features), as shown in the next section. The features that are not very important are retained because such features might not work well alone, but with the inclusion of them in a set of features with other they might prove very successful. Finally, PCA (stage three) is employed to reduce the dimensionality of the features retained after removing the nondistinguishing features and use a multilayer perceptron (stage four) to classify them into classes.

C. Fuzzy C-Means based Cluster Separation Index (FSCI)

Fuzzy logic proved to bring new possibilities into control, modeling, data analysis, decision making, and other fields in biomedical sciences. One problem in using clustering-based classification is setting the number of clusters to use in each class. An optimal number does not always exist but one is satisfied with a number that is large as necessary to yield perfect classification of the samples, and yet as small as possible so that the ensuing generalization is acceptable [26]. The approach of using fuzzy c-means algorithm in MES classification was found in many attempts in the literature, each reported excellent classification accuracy yielded from using fuzzy logic to cluster the data into varying number of motion classes [27-29].

The fuzzy c-means algorithm attempts to cluster measurement vectors by searching for local minima of the generalized within group sum of squared errors functions (WGSSE). It was proposed by Trivedi and Bezdeck [30] and is given by:

$$J_m(U,v)=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m \left|x_k-v_i\right|_A^2 , \quad 1<m<\infty \tag{2}$$

Where

c : is the number of clusters,

n : is the number of vectors,

x_k : is the $k'th$ measurement vector, $x_k \in R^n$

v_i : is the $i'th$ centroid vector,

m : is the fuzzy coefficient,

$|.|_A$: is an inner product norm,

$|Q|_A^2 = Q^T AQ$, and A is a $d*d$ positive definite matrix where d is the dimension of the pattern vectors.

When $m=1$, the objective function J_m in (2) is the classical WGSSE function and the algorithm reduces to the crisp k-means clustering algorithm. For $m>1$ under the assumption that $x_k \neq v_i$, (U,v) may be a local minimum of J_m only if:

$$u_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{\left\|x_k-v_i\right\|_A}{\left\|x_k-v_j\right\|_A}\right)^{2/(m-1)}} \quad \forall\ i,k \tag{3}$$

and

$$v_i=\frac{\sum_{k=1}^{n}(u_{ik})^m x_k}{\sum_{k=1}^{n}(u_{ik})^m}, \quad \forall i \tag{4}$$

In the proposed approach, the centers across each feature are normalized to [0, 1] and denote $FSCI_{ij,k}$ as the fuzzy cluster separation index along feature k is given by:

$$f_{ij,k}=\begin{cases} f_{ij,k}+1 & if \left|v_{ik}-v_{jk}\right|>r \\ f_{ij,k}+0 & otherwise \end{cases} \tag{5}$$

$$FSCI_k=\sum_{j=i+1}^{c}\sum_{i=1}^{c-1} f_{ij,k} \tag{6}$$

Where $0<r<1$, as r approaches 0, more features will be retained. This measure indicates the relative ability of feature k to separate all distinct pairs of the c subclasses, where as a comparison with the approach adopted in [24] their cluster separation measure took into account only the difference between $\left|v_{\max k}-v_{\min k}\right|$. Only features with $FSCI_k=0$, are removed and not used in classification. Fig.3 shows an example after applying the FCM method to the features tree generated by WPT with four levels of decomposition, retaining only part (depending on r value) of the original feature set produced by the WPT (gray). The PCA is applied after removing the nondistinguishing features, thus further reducing the dimensionality.

The justification for our approach is as follows: WPT was employed to generate a tree with large number of features to provide more descriptive information about the signal,

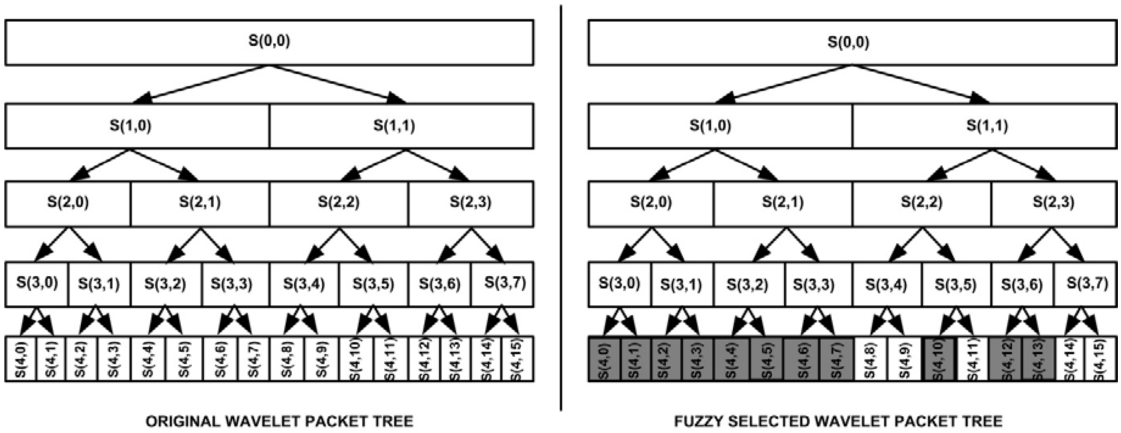


Fig. 3 Example of WPT features selection based on the fuzzy cluster separation index (FSCI).

after this stage, the FCM method was used to select only the features that maximizes the class separability, thus removing features that play no role in the classification results, thus retaining only features that does contribute to the problem, even if they have small contribution to account for interaction between features. Till this point the best features from the interaction with class point of view were selected, but this doesn't ensure that there is no redundancy between the selected features. Thus PCA is employed to remove redundancy by projecting the features onto their eigenvectors and retaining those which corresponds to the largest eigenvalues. As a result of this process specific features are extracted, because our motivation is toward the evaluation of MES features in ways which are not tied to accurate estimates of signal characteristics, but rather to the intrinsic quality of those features as control signals for a desired device, in our case the prosthetic arm device.

The resultant features comply with the high quality MES features properties, suggested by Boostani [31], and providing the following qualities:.

- ***Maximum class separability***. A high quality feature space results in clusters that have maximum class separability or minimum overlap. This ensures that the resulting misclassification rate will be as low as possible; this is achieved in the proposed system using the (FCM) method.
- ***Robustness***. The selected feature space should preserve the cluster separability in a noisy environment as much as possible, as was explained in section III.
- ***Complexity***. The computational complexity of the features should be kept low so that the related procedure can be implemented with reasonable hardware and in a real-time manner that is achieved by employing PCA technique in the proposed method.

IV. Experimental Results

During the experiments, WPT was applied on the MES records of 256 samples each, to generate a wavelet tree presenting us with 16 features (level 4 of decomposition) for each channel, for a 16 channel problem this process produced a total of 256 features concatenated from different channels. Due to the size of the feature vector it is impractical to consider using all 256 in the classification process directly. the *FCSI* measure was applied to remove non-significant features, and PCA to reduce the dimensionality of what is left of features. The value of r varied to range from 0.1 to 0.5 after which any further increase in r can lead to a negative impact on classification accuracy (subject dependant as a value of $r = 0.5$ can degrade classification accuracy on certain datasets while increasing the accuracy for other – AW datasets results), as it was seen from experiments. Each of the six person's datasets was tested to study the impact of this method on the testing accuracy on each subject. Only the first 20 principle components were used in the analysis. Testing was performed employing a back propagation neural network with 20 nodes in the hidden layer. The results acquired from each person datasets are shown in Fig.4, for which only the results for three values of r are plotted that shows the most significant differences in their results (to produce clear graphs).

In the experiment that were carried out, large number of features were utilized first and moved toward smaller number of features that were projected into their eigenvectors, this is done by taking different values for the variable r. Usually the experiment started with small values for r thus keeping most of the features, and later increasing the value of r slightly, till a point that actually degrades the performance of the system is reached. In most cases, the maximum value was $r = 0.5$, although for some datasets (like AW dataset) the value of $r = 0.5$ did show an enhanced performance, but further increase lowered down the testing accuracy for all the datasets. When plotting the trade-off between the number of principle components used and the classification accuracies of the neural network, it was shown (for all the datasets) that a value of $0.3 \le r \le 0.4$ can represent a common value that have a good effect on the final results, even if it does not represent the optimum value for each of the datasets, but this value is reasonable as it does not necessitates removing large number of features, so that the system can generalize better on unseen data during the real time process. To better understand the effect of choosing the value of r, Table I include in the percentages of the features number retained with varying values for r, showing that certain values of r might remove more features from one subject dataset than another making the exact amount of features retained subject dependant.

In another experiment, the value of $r = 0.35$ was fixed, and a search, for the regions from which the features were removed mostly, was run. It was found that most of the features that were dismissed from classification (depending on the value of r) were actually from the region of the channels (4, 5,6,7,8,12,13,14, and part of channels 2, 3, and 11). When looking at the original figure for the channels distribution around the forearm[21], that is represented here in this paper in Fig.5 (for the sake of comparison), it appeared that most of the features the method retained were acquired from surface electrodes placed over the extensors/supinator, flexor carpi ulnaris, and flexor digitorum subliminus. This is a significant foundation, as those are the most interesting locations on human forearm on which three surface electrodes achieved an accuracy of 97% by using time domain features concatenated with 6th order AR model, reduced in dimensionality with PCA [21]. Thus the suggested system functions in an accurate way by removing features from non important channels.

In the final test, experiments employing the FWP method mentioned earlier were carried out. In order to produce a competent comparison to prove that using the new measure with PCA can produce better results than that in [24] by using the separation measure followed by a method of ranking features based on their classes membership. *FSCI* measure is first applied rather than the one they proposed, as the FSCI takes into consideration the feature ability to separate all distinct classes rather than the maximum and minimum along each feature, and later ranked features according to their total membership value in all classes. The results are given in Fig.6 for each of the six datasets, plotting the FWP results in conjunction with the proposed new method denoted as NFWP-PCA. It is clear from the figures that the new method outperform the FWP method, as the later one does not take into consideration the relationship between features, but only the membership of features in each class, in which the case there exist a large amount of redundancy of information. Thus it requires more features to be used to achieve the same results as those achieved by the NFWP-PCA method which takes into account the relationship between features and classes, and adds to that it further reduce the redundancy by employing the principle components analysis method. Thus achieving higher accuracies at smaller number of principle components used. The smaller number of principle components reduce the total computational cost for such a system when implemented in real time.

In general 20 principle components were enough to produce a classification accuracy of 99% for the NFWP- PCA method, while it took 40 – 65 features (depending the dataset used) using the FWP method to achieve the same results achieved by our new method.

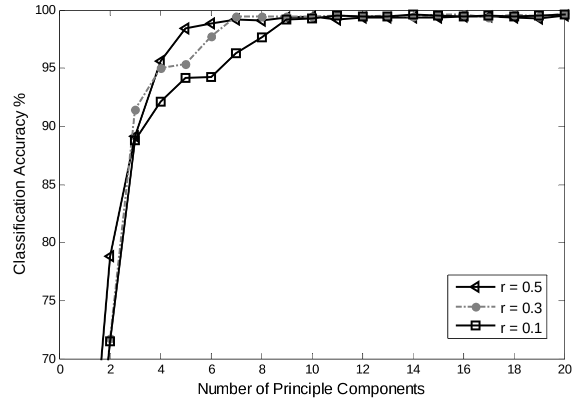
TABLE. I
PERCENTAGES OF THE NUMBER OF FEATURES RETAINED WITH DIFFERENT VALUES FOR r

Datasets	AW	LH	KS	MW	WM	SM
	Percentage of features left %					
r = 0.5	91	45	114	85	103	53
r = 0.4	133	101	129	143	146	130
r = 0.3	175	194	178	188	173	196
r = 0.2	227	256	242	221	227	245
r = 0.1	250	256	256	251	253	256

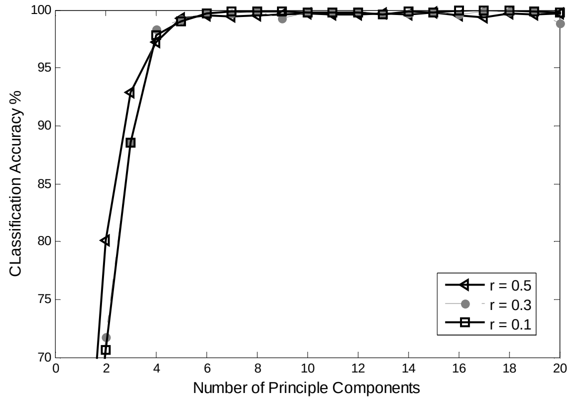
When comparing to the classification results that were acquired by Levi *et al*., that originally used those databases they achieved an average accuracy ranging between 95% and 99% using the first 40 principle components in the final decision making [21]. In our case an average accuracy of 99% was achieved when using the first 20 principle components in final decision making when using the fuzzy clustering method followed by PCA, and also various results are achieved depending on the number of features kept as shown in Fig.4. This proves that the features extracted using wavelet packets gives comparable results (even better) to those obtained using the AR coefficients if the features used in classification are selected with the proper approach. It was also proved that the proposed system computational cost was less than that in [21], and also was more accurate than the work in [20] as they achieved an average of 97% across nine classes of hand motion, were as 99% of accuracy was achieved for ten classes of motion in this proposed system, also in their system a SOFM was utilized along each channel, were as proposed system used one FCM algorithm along the whole features extracted from 16 channels, thus our system being of less computational cost that SOFM based one.

V. CONCLUSION

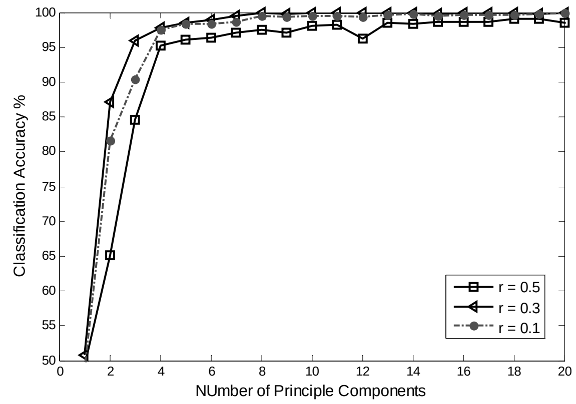
A new approach for wavelet packet based features extraction was presented in this paper. The approach was based on the use of FCM algorithm to judge on features suitability in classification by measuring the degree of overlapping between the clusters, thus measuring the ability of each feature to separate between the different problem classes. Accurate results were obtained from the system using different number of features selected from the original 256 features that represents the total number from 16 channel myoelectric signals concatenated with each other. It was proved that by using WPT method with fuzzy logic followed by PCA, the use of only the first 20 principle components (although achieved with smaller number of principle components but included to account for generalization) achieved an accuracy of 99% across six subjects who participated in the MES dataset collection.



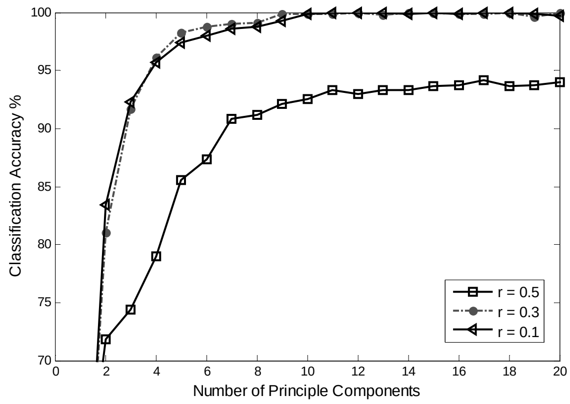
i. Accuracy of testing using AW datasets.



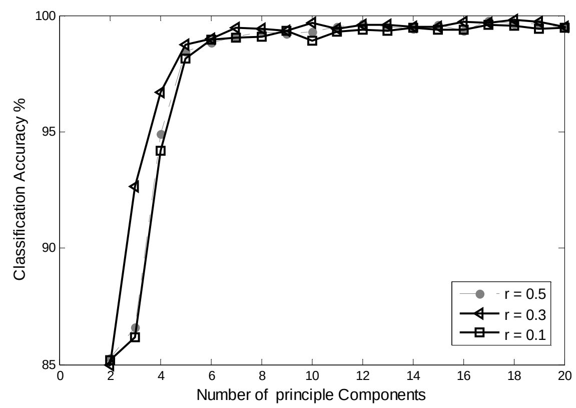
ii. Accuracy of testing using KS datasets.



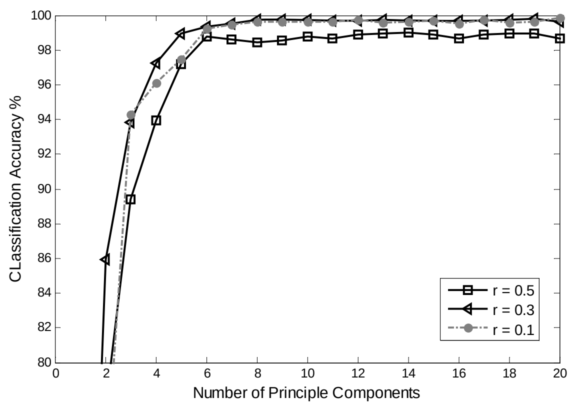
iii. Accuracy of testing using MW datasets.



iv. Accuracy of testing using LH datasets.



v. Accuracy of testing using WM datasets.



vi. Accuracy of testing using SM datasets.

Fig. 4 Plot of the tradeoff between the number of principle components retained and classification accuracy achieved by MLP.

It was also found that most of the features retained were from specific regions on the human forearm, for which it is currently known from research in this field till day that those regions are the most important for consideration in MES classification, thus proving the efficiency of the proposed fuzzy wavelet packet method.

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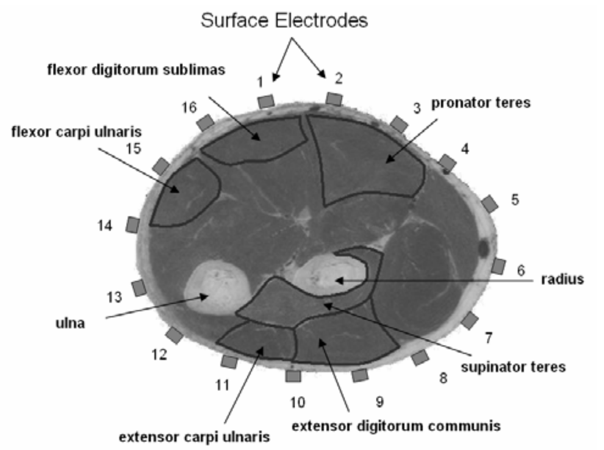

Fig. 5 A cross-section of the upper forearm showing the surface electrodes locations on human forearm.

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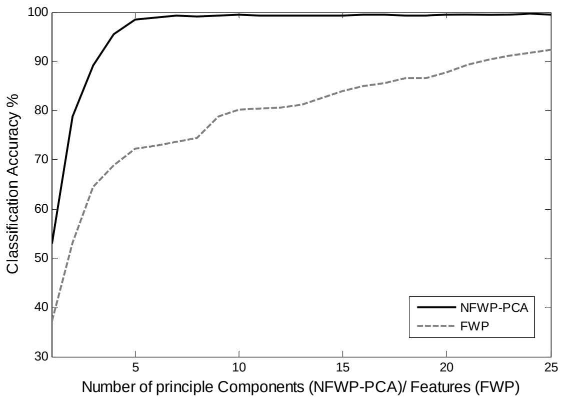
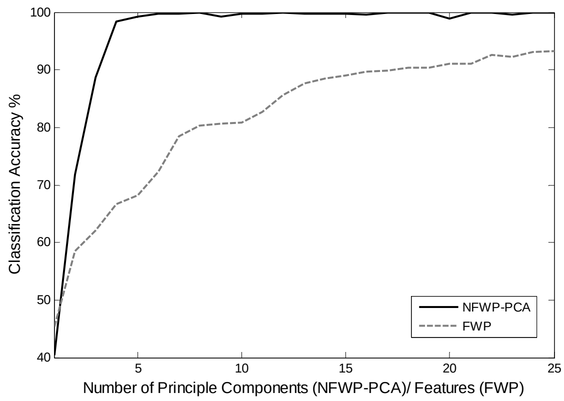


i. Accuracy of testing using AW datasets.



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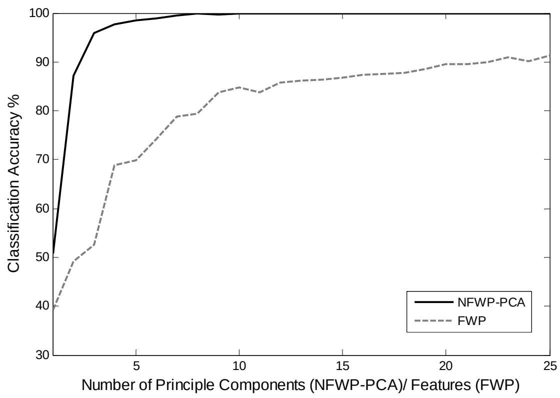

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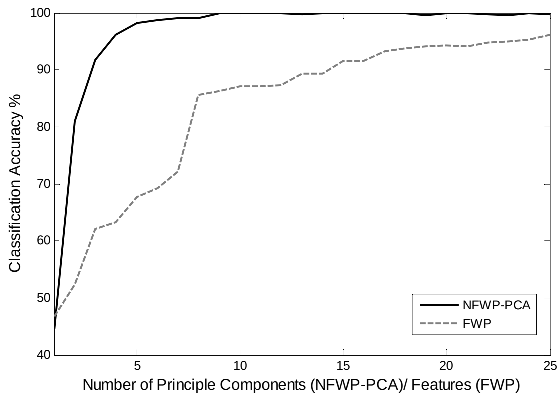

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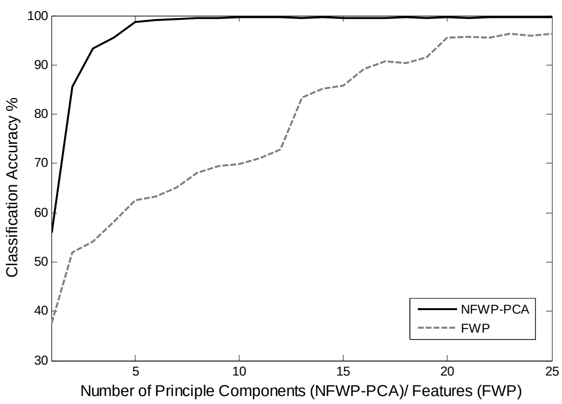

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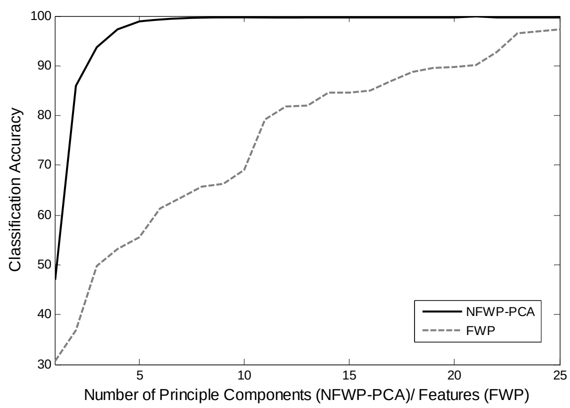

vi. Accuracy of testing using SM datasets.

Fig. 6 Comparison between the classification results acquired from NFWP-PCA method and the FWP method on the same datasets for the same value of r