Turkish Journal of Electrical Engineering and Computer Sciences

Volume 24 | Number 3 Article 61

1-1-2016

Comparison of AR parametric methods with subspace-based methods for EMG signal classification using stand-alone and merged neural network models

MEHMET RECEP BOZKURT

ABDÜLHAMİT SUBAŞI

ETEM KÖKLÜKAYA

MUSTAFA YILMAZ

Follow this and additional works at: https://journals.tubitak.gov.tr/elektrik

Part of the Computer Engineering Commons, Computer Sciences Commons, and the Electrical and Computer Engineering Commons

Recommended Citation
BOZKURT, MEHMET RECEP; SUBAŞI, ABDÜLHAMİT; KÖKLÜKAYA, ETEM; and YILMAZ, MUSTAFA (2016) "Comparison of AR parametric methods with subspace-based methods for EMG signal classification using stand-alone and merged neural network models," *Turkish Journal of Electrical Engineering and Computer Sciences*: Vol. 24: No. 3, Article 61. https://doi.org/10.3906/elk-1309-1
Available at: https://journals.tubitak.gov.tr/elektrik/vol24/iss3/61

This Article is brought to you for free and open access by TÜBİTAK Academic Journals. It has been accepted for inclusion in Turkish Journal of Electrical Engineering and Computer Sciences by an authorized editor of TÜBİTAK Academic Journals. For more information, please contact academic.publications@tubitak.gov.tr.

Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2016) 24: 1547 – 1559
© TÜBİTAK
doi:10.3906/elk-1309-1

Comparison of AR parametric methods with subspace-based methods for EMG signal classification using stand-alone and merged neural network models

Mehmet Recep BOZKURT[1,*], **Abdülhamit SUBAŞI**[2], **Etem KÖKLÜKAYA**[3], **Mustafa YILMAZ**[4]

[1]Department of Electrical and Electronics Engineering, Faculty of Engineering, Sakarya University, Sakarya, Turkey
[2]Department of Computer Science, College of Engineering, Effat University, Jeddah, Saudi Arabia
[3]Department of Electrical and Electronics Engineering, Faculty of Engineering, Gazi University, Ankara, Turkey
[4]Department of Neurology, Faculty of Medicine, Gaziantep University, Gaziantep, Turkey

Received: 01.09.2013 • **Accepted/Published Online:** 03.04.2014 • **Final Version:** 23.03.2016

Abstract: This research introduces an electromyogram (EMG) pattern classification of individual motor unit action potentials (MUPs) from intramuscular electromyographic signals. The presented technique automatically classifies EMG patterns into healthy, myopathic, or neurogenic categories. To extract a feature vector from the EMG signal, we use different autoregressive (AR) parametric methods and subspace-based methods. The proposal was validated using EMG recordings composed of 1200 EMG patterns obtained from 7 healthy, 7 myopathic, and 13 neurogenic-disordered people. A feedforward error backpropagation artificial neural network (FEBANN) and combined neural network (CNN) were used for classification, where the success rate was slightly higher in CNN. Among the different AR and subspace methods used in this study, the highest performance was obtained with the eigenvector method. The following rates were the results achieved by using the CNN. The correct classification rate for EMG patterns was 97% for healthy, 93% for myopathic, and 92% for neurogenic patterns. The obtained accuracy for EMG signal classification is approximately 94% for CNN. The rates for FEBANN were as follows: 97% for healthy patterns, 92% for myopathic patterns, and 91% for neurogenic patterns. The obtained accuracy was 93.3%. By directly using raw EMG signals, EMG classifications of healthy, myopathic, or neurogenic classes are automatically addressed.

Key words: Electromyography, motor unit potentials, autoregressive spectral estimation method, subspace-based methods, combined neural network

1. Introduction

Electromyography (EMG) is a neurological study method that is performed by examining the electrical potentials of nerves and muscles. Once pathologic conditions occur in the motor system, the properties of the muscle's electrical signals change. Therefore, accurate analysis of EMG signals can be beneficial for determining abnormalities in the muscles, and better yet in the motor system. The rapid development of technology has a direct impact on all aspects of life as well as on recording and analyzing EMG. Disposable concentric EMG needle electrodes are widely used to diagnose neuromuscular disorders. In the last decade, EMG signals have been digitized and recorded on mobile devices and presented as the researcher desires. [1]

EMG consists of discrete discharges known as motor unit action potentials (MUPs). MUPs from different motor units (MUs) have a tendency for different shapes. The resultant knowledge is used to label the source of

*Correspondence: mbozkurt@sakarya.edu.tr

deficiency, such as neurogenic or myopathic diseases [2–4]. Neurophysiologists commonly use an oscilloscope and assess MUPs by carefully listening to their sounds. Thus, an experienced neurophysiologist is able to distinguish irregularities with reasonable accuracy.

However, in the case of less noticeable or mixed pattern deviations, subjective MUP assessment may not be enough. Therefore, for a valuable automated EMG signal classification, a methodical handling of EMG signals must be made [5]. Nowadays, automated EMG analysis is possible owing to computer-based EMG analysis algorithms. However, it has not obtained approval for routine clinical use. Some of the commercially available algorithms are as follows: Pattichis and Elia classified EMG signals using time domain measures, autoregressive (AR) spectral measures, AR coefficients, and cepstral coefficients with an artificial neural network (ANN) [6]. Pattichis et al. performed sequential parametric pattern recognition classifier and used time-domain, waveform-related MUP parameters as input. They also used a parametric pattern recognition algorithm that facilitates automatic MUP feature extraction. ANN models are combined for providing an integrated system for classification [7]. Loudon et al. studied the decomposition of EMG signals (composed of superimposed MUPs) into their constituent MUPs, using both procedural and knowledge-based methods. They also studied the statistical pattern recognition procedure for classification. Eight MUP features were used as input [8]. Hassoun et al. performed classification by using the time domain waveform as input into a 3-layer ANN with a "pseudo-unsupervised" learning algorithm [9,10].

Christodoulou and Pattichis's MUP classification techniques used 2 different pattern recognition methods: the self-organizing feature maps algorithm and learning vector quantization [11].

Subasi et al. used time-frequency methods for fatigue detection with independent component analysis (ICA) and ANNs [12]. Diab et al. received EMG signals' AR model from uterine muscle and used it as input to ANN for classification in order to calculate the risk of preterm birth in pregnancies [13]. Subasi used particle swarm optimization jointly with a support vector machine to perform a study that increased the accuracy of EMG classification [14]. Sueaseenak et al. used two-channeled EMG to control virtual hand prosthesis with 12 degrees of freedom. In particular, they took 2 channel EMG signals via surface electrodes and separated them by ICA. Feature extraction and classification was conducted by using an eigenvector (EIG) [15]. A similar prosthesis problem was solved by Young et al. using linear discriminant analysis [16]. Ibrahimy et al. used single-channel surface electrodes to receive EMG signals. Five different ANNs were used for classification and comparison of the results [17].

Recently developed techniques for spectrum estimation allow EMG signal classification. There are 2 spectrum estimation procedures: parametric and nonparametric. Of these, the AR method is used more often because there are established techniques for estimating AR parameters. In addition, the approximations of the system are calculated by solving linear equations. Estimation of the AR procedure parameters can be performed with Yule–Walker, covariance, modified covariance, and Burg estimation methods [18,19].

Multiple signal classification (MUSIC) [20–25] and EIG [25–29] techniques are subspace − based techniques that are utilized for acquiring power spectral density (PSD) signal estimations.

Until now, the estimation of the frequencies of different signals was conducted with subspace-based techniques. However, there are still some dilemmas to be solved, even though the previous studies demonstrated good performance. In general, there are not many available EMG patterns for classifier training. Therefore, the generalization ability of a classifier directly affects the success of real-time EMG classification.

In this paper, the CNN model is adopted to obtain a more robust classifier. Furthermore, the method in most previous studies used only one type of feature vector. However, due to a large variation in EMG pattern distribution, different feature extraction methods need to be used. Therefore, we used 6 different feature extraction methods to obtain a better performance. The classification of real EMG signals is a common supervised learning pattern classification problem. Since it will be used for clinical purposes, any computerized method for EMG analysis must have certain quality and regulations such as high speed, sturdiness, and dependableness, and the method must attain a high success rate.

The presented technique was successfully applied in the classification of EMG signals through records from healthy (H), myopathic (M), and neurogenic-disordered (N) people. It consists of 2 stages. The first stage involves preprocessing the EMG signal in order to extract EMG features. In this stage, model-based and subspace-based methods were used. In the second stage, neural networks were used to classify an anonymous EMG signal as H, M, or N. The intention of this study is to develop and test a methodology that is helpful for the neurophysiologist to diagnose neuromuscular disorders. We describe how our findings may turn into an advantageous tool when the neurophysiologist's opinion is dependent on high-priced, invasive tests, as well as by decreasing biomedical-based errors in the medical decision-making process.

Figure 1 illustrates how 6 different feature extraction methods affect a healthy human EMG. Similarly, Figure 2 shows the effects of the same methods on myopathic EMG samples. Figure 3 shows the effects of the same methods on neurogenic EMG samples.

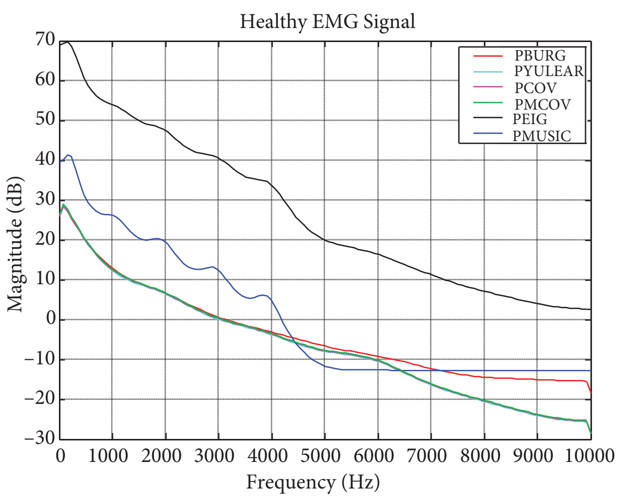

Figure 1. PSDs of EMG signal taken from a healthy subject.

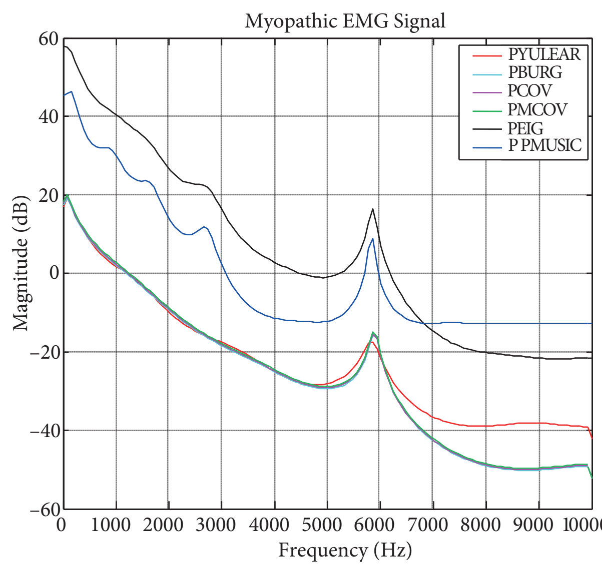

Figure 2. PSDs of EMG signal taken from a myopathic subject.

2. Materials and methods

2.1. Test subjects and obtaining data

Measurements took place in the Neurology Department of Gaziantep University for all patient and control groups. EMG was recorded from the biceps brachii muscle, which is a large muscle positioned at the front of the upper arm. The test subjects were asked to make a slight voluntary contraction for 5 s. EMG was recorded using a concentric needle electrode and an EMG measurement system. The signal was sampled with 12-bit ADC resolution at 20 kHz.

The recording spots in the muscle were standardized; EMG segments were recorded from up to 5 different needle insertions. Before recording, the electrode was inserted at least 3–5 mm into the muscle. In addition, between recordings, the electrode was maneuvered at least 3–5 mm to confirm that the recorded MUPs were in fact different. Insertion of the electrode was performed until the medial or posterior border of the muscle was attained. After the electrode was withdrawn to the fascial, it was inserted into a new radial direction. Usually, 1–2 MUPs were simultaneously active within the pick-up radius of the electrode. Recording more than 2 MUPs simultaneously is more common in pathological cases.

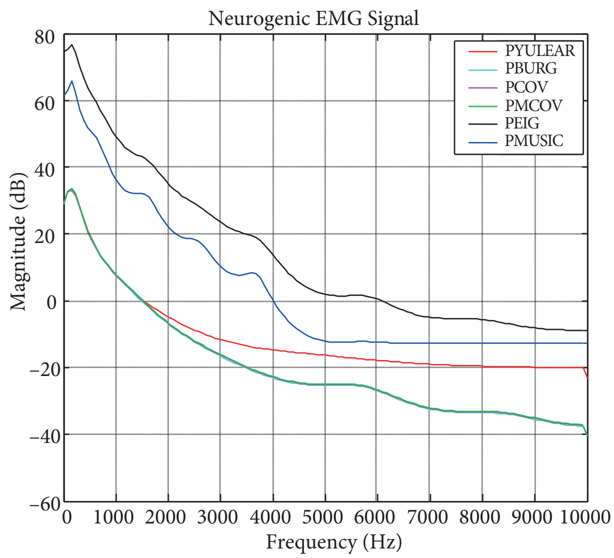

Figure 3. PSDs of EMG signal taken from a neurogenic subject.

In addition to the patient's general examination and clinical history, expert clinicians diagnosed neuromuscular diseases, such as myopathy and neurogenic disorders, through EMG and nerve conduction tests.

This research uses EMG data obtained from 27 subjects. The data were recorded from 7 healthy subjects (4 females, 3 males) between the ages of 10 and 43 years (mean age (MA): 30.2, standard deviation (SD): 10.8 years), 13 neurogenic subjects (5 females, 8 males) between the ages of 7 and 55 years (MA: 25.1, SD: 17.2 years), and 7 myopathic subjects (3 females, 4 males) between the ages of 7 and 46 years (MA: 21.5, SD: 13.3 years), as in [30,31].

2.2. Subspace-based spectral analysis

The model-based (parametric) techniques model the data sequence $x(n)$ as the output of a linear system described by a rational structure. In parametric techniques, spectrum approximation is composed of 2 steps. The first step involves parameters of the parametric technique that are estimated from a given data sequence $x(n)$, $0 \leq n \leq N-1$. In the second step, the estimation of the PSD is performed using the estimated AR model parameters. The AR technique is used more often, since approximation of AR parameters is accomplished without difficulty by solving linear equations.

In the AR technique, white noise is the input, and data can be represented as the output of a causal, all-pole, discrete filter. The AR model of order p is defined by the following equation:

$$x(n) = -\sum_{k=1}^{p} a(k)x(n-k) + w(n), \tag{1}$$

where $w(n)$ is white noise with variance equal to σ^2 and $a(k)$ are the AR model parameters.

In order to obtain the most stable and proper AR method, selection of the model order, length of the modeled signal, and stationary level of the data must be considered [18,19].

When we compare the 4 different AR methods used in this study, the difference between them is as follows: the modified covariance technique minimizes the forward and backward prediction errors in the least square sense. On the other hand, the Burg technique minimizes the forward and backward prediction errors in the least square sense with the AR coefficients constrained to satisfy the L-D recursion. The Yule–Walker and covariance techniques are very similar. They both minimize only the forward prediction error in the least square sense. Their difference is that the Yule–Walker technique applies window to data; however, unlike the other 2 techniques, the covariance technique does not apply window.

2.2.1. Yule–Walker technique

In the Yule–Walker technique, the AR parameters need to be estimated. The estimation process is performed by minimizing an estimate of prediction error power. PSD estimation is constructed by the predictions of the AR parameters, as shown in the formula below [25–28]:

$$\hat{P}_{YW}(f) = \frac{\hat{\sigma}^2}{\left|1 + \sum_{k=1}^{p} \hat{a}(k)e^{-j2\pi fk}\right|^2}. \tag{2}$$

AR Yule–Walker PSDs of EMG signals are presented in Figures 1, 2, and 3. For more information about this method, please see the references.

2.2.2. Covariance technique

If there are compound data, a resembling estimator can be formed by minimizing the forecast of the prediction error power. Covariance and autocorrelation techniques are very similar. The range of summation in the prediction error power estimate distinguishes them from one another. Based on the estimates of the AR parameters, PSD estimation is formed as [25–28]:

$$\hat{P}_{COV}(f) = \frac{\hat{\sigma}^2}{\left|1 + \sum_{k=1}^{p} \hat{a}(k)e^{-j2\pi fk}\right|^2}. \tag{3}$$

AR covariance PSDs of EMG signals are presented in Figures 1, 2, and 3. For more information about this method, please see the references.

2.2.3. Modified covariance technique

In this technique, the averages of the estimated forward and backward prediction error powers are minimized to estimate the AR parameters.

As with the covariance method, the sums of the observed data samples are more than the prediction errors.

The difference between the modified covariance and covariance techniques is in the definition of the autocorrelation estimator. Based on the estimates of the AR parameters, PSD prediction is expressed with the formula below [25–28]:

$$\hat{P}_{MCOV}(f) = \frac{\hat{\sigma}^2}{\left|1 + \sum_{k=1}^{p} \hat{a}(k)e^{-j2\pi fk}\right|^2}. \tag{4}$$

AR modified covariance PSDs of EMG signals are presented in Figures 1, 2, and 3. For more information about this method, please see the references.

2.2.4. Burg technique

The Burg technique performs the minimization of the forward and backward prediction errors and estimates the reflection coefficient. From the estimations of the AR parameters, PSD estimation is expressed as [25–28]:

$$\hat{P}_{BURG}(f) = \frac{\hat{e}_p}{\left|1 + \sum_{k=1}^{p} \hat{a}_p(k)e^{-j2\pi fk}\right|^2}, \tag{5}$$

where $\hat{e}_p = \hat{e}_{f,p} + \hat{e}_{b,p}$ is the total least squares error.

AR Burg PSDs of EMG signals are presented in Figures 1, 2, and 3. For more information about this method, please see the references.

2.2.5. Selection of AR model orders

Selecting the model order is a fundamental issue for model-based techniques. Much work has been done and experimental results have been given in the literature regarding this issue [25–28]. The Akaike information criterion (AIC) is the most recognized criterion for selecting the model order [32]. In our research, the model order of the AR technique was achieved by utilizing AIC.

2.3. Subspace-based spectral analysis

To estimate the frequencies and the power of signals from noise-corrupted measurements, subspace-based techniques are used. These are characterized by eigendecomposition of the correlation matrix of the noise-corrupted signal. The subspace-based techniques provide high resolution frequency spectra. Even if the signal-to-noise ratio (SNR) is low, they can still provide good PSD estimations. The mentioned techniques are most applicable to signals that might be assumed as the composition of some specific sinusoids buried in noise [20–29]. In this research, 2 subspace-based procedures (MUSIC and EIG) were chosen to generate the PSD estimates. The polynomial $A(f)$ was run through to predict the PSD.

$$A(f) = \sum_{k=0}^{m} a_k e^{-j2\pi fk} \tag{6}$$

According to the formula, the desired polynomial is symbolized with $A(f)$, a_k stands for coefficients of the desired polynomial, and m stands for the order of the eigenfilter, $A(f)$ [24].

2.3.1. MUSIC technique

The MUSIC technique is a noise subspace frequency estimator that was designed by Schmidt [33]. Schmidt intended to distinguish the desired zeros from the spurious ones and used the mean spectra of entire eigenvectors matching to the noise subspace. The PSD is obtained from the formula below:

$$P_{MUSIC}(f) = \frac{1}{1/K \sum_{i=0}^{K-1} \left|A_i(f)\right|^2}. \tag{7}$$

According to the formula, K stands for the dimension of noise subspace and $A_i(f)$ stands for the desired polynomial that corresponds to all the eigenvectors of the noise subspace [21–24,33].

MUSIC PSDs of EMG signals are presented in Figures 1, 2, and 3. For more information about this method, please see the references.

2.3.2. EIG technique

The process of distinguishing the desired zeros from the spurious ones is performed by using the EIG technique [26–28]. This method brings down spurious zeros into the unit circle and calculates an acceptable noise subspace vector a out of the noise or signal subspace EIGs.

Along with the MUSIC technique, the EIG technique was also explored [26–28]. It is possible to distinguish between spurious zeros and real zeros. After the EIG technique forces spurious zeros inside the unit circle, it calculates a desired noise subspace vector from either the noise or the signal subspace EIGs. The formula from using the EIG for the PSD is shown below:

$$P_{ev}(f) = \frac{1}{\left(\sum_{i=0}^{K-1} \left|A_i(f)\right|^2 / \lambda_i\right)}. \tag{8}$$

EIG PSDs of EMG signals are presented in Figures 1, 2, and 3. For more information about this method, please see the references.

Before MUSIC and EIG PSD are calculated, a technique is used for finding the dimension of the noise subspace K. The AIC or minimum description length (MDL) criteria are mostly used [25].

The MDL principle produces a coherent approximation of the quantity of signals. On the other hand, the AIC principle does not produce a consistent approximation.

Because it gives coherent estimates, the MDL principle was used and the dimension of the noise subspace K was calculated according to the MDL criterion in our study. The dimension of the noise subspace K is the value that minimizes MDL (k), which was taken as 10 for all subjects [34].

2.4. Combined neural network models

ANNs are mostly used for classification problems in biomedical engineering. In particular, analyzing biomedical signals requires a capacity of real-time parallel signal processing. The training of ANNs is not done with rules; instead, they are trained by giving examples, and they are not interrupted by personal factors such as a person's emotional state, fatigue, or external factors. ANNs are very effective for the analysis of conditions, fast recognition, and real-time diagnoses [35]. Even though there are many neural network algorithms for training in the literature, the backpropagation (BP) algorithm is the most frequently used algorithm for training in classification problems, and it is also employed in our study [36,37].

If we combine neural network models, we can obtain a better result in classification accuracy than that of the single models. This development is known as a combined neural network (CNN) and it is based on a stacked generalization. Training data generally reveal high distribution in the search space due to the inefficiency of the low-level measuring aspects in illustrating the model briefly. The learning process can be made easy by converting the data into a more suitable model.

Therefore, for each feature set in the data model, it is essential to calculate approximately the difficulty of learning the main ideas using those training data. As a next step, the learning system needs to transform the models into a space that is easier for the learning objectives [38–40]. Wolpert's stacked generalization idea [41] runs ahead of the mentioned ideas and points to schemes for feeding data from one set of generalizers to another. The referring process is performed prior to building the final predicted output value. The stacked generalization scheme might be thought of as a more complex form of cross-validation. It was proved that the stacked generalization scheme performs better than stand-alone neural networks and improves the generalization skill of ANN models. Figure 4 shows the CNN model used in this study.

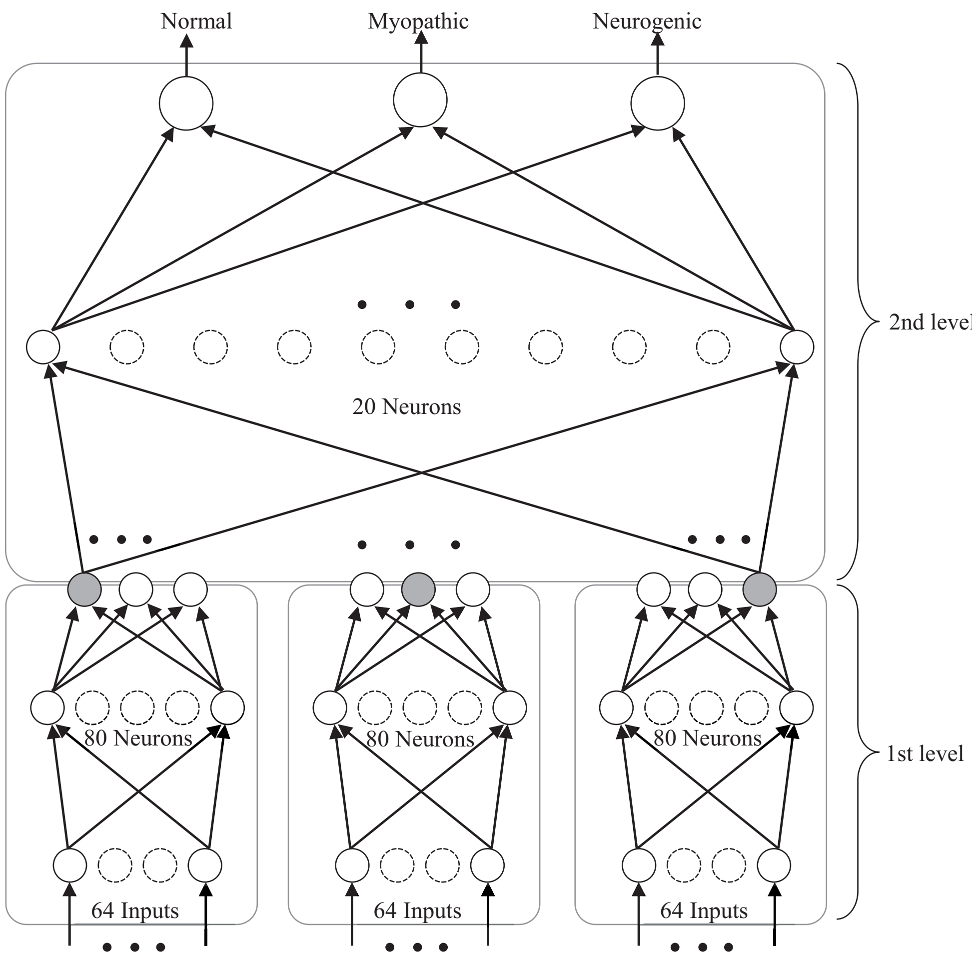

Figure 4. A combined neural network topology used for EMG signal classification.

At the first level, the feedforward error backpropagation artificial neural network (FEBANN) was used, and the second level was used for the implementation of the CNN [38]. In this study, the FEBANN and CNN are used for designing classifiers.

2.5. Development of neural network models

Classifying EMG signals into groups is a typical problem of pattern classification. In our study, the collected EMG data were analyzed by different neural networks. Data were recorded from a total of 27 subjects. Among these subjects, 7 were healthy (H), 7 were myopathic (M), and 13 were suffering from neurogenic disorder (N). The AR and subspace-based methods were used for a particular EMG signal epoch (1024 samples). The model order for AR was chosen as p = 15, and for subspace-based methods it was k = 10; the size of the window was taken as 128. Neural network classifier inputs were the PSDs. The intention of the modeling phase in this practice was to differentiate the 3 classes, H, M, and N. In order to build up the neural network classifiers, the feature vectors were extracted by using AR parametric methods and subspace-based methods from each EMG signal frame (1024 separate samples).

Our results yielded 1200 feature vectors for each feature extraction procedure. Among the 1200 distinct EMG signal patterns, 900 were randomly chosen and used for training the networks. The remaining 300 were utilized to confirm the validity of the developed models. The class distribution for each data set is shown in Table 1.

Table 1. Class distribution of the samples in the training and test data sets.

Class	Training set	Test set	Total
Healthy	300 (5 subjects)	100 (2 subjects)	400 (7 subjects)
Myopathic	300 (4 subjects)	100 (3 subjects)	400 (7 subjects)
Neurogenic	300 (9 subjects)	100 (4 subjects)	400 (13 subjects)
Total	900 (18 subjects)	300 (9 subjects)	1200 (27 subjects)

In the input layer, the neural network models were designed with features composed of various EMG signal patterns. The number of hidden neurons was 80, and the output layer contained 3 nodes representing H, M, or N. In our experiment, [0 0 1] values for H, [0 1 0] values for M, and [1 0 0] values for N were used as indicators. In order to merge the assumptions of the first-level networks, we trained second-level neural networks in the CNN. There were 9 inputs in the second-level network. This corresponds to the outputs of the 3 groups in the first-level networks. The targets for the second-level network and the original data were identical. The numbers of outputs and hidden neurons were chosen as 3 and 20, respectively. We also implemented the same classification issues with the FEBANN. Hence, we were able to compare the performance of the 2 classifiers.

3. Results and discussion

The classifiers suggested for the classification of the EMG signals were applied using MATLAB. In order to appraise classifier performance, all classifiers introduced in our research were trained with the identical data set. All classifiers were also tested with the evaluation data set. Pattern classification problems were solved through ANN, employing the backpropagation training algorithm. As an advantage, this type of neural network allows a better comprehension of system behavior and efficiency in the training algorithm. It must be said that when using a neural network, the division of the data into 2 sets (training and test) must be decided. In our research, 18 of 27 subjects were used for training and the others were used for testing. As a practical way of enhancing the common capability of the neural network, data from different subjects were used to form the training and test sets.

PSD was computed for each EMG signal frame from the 1024 samples. After training with 900 data, 300 testing data were used to confirm the accuracy of ANN models for EMG signal classification. The aim of the classification was to appoint the input patterns to one of the different classes. This representation of the probability of class membership was done by restricting the outputs to a range of 0 to 1. Classification was carried out by the classification features selected for a specific class, and a specific pattern was appointed for that class. This application consisted of 3 classes: H, M, and N.

The performance of our approach was calculated by dividing all the EMG data into 2 sets. The training set and the test set were used to create a classification model and to verify it, respectively. Subsequently, k-fold cross-validation was used. We chose k-fold cross-validation since it is a widely recognized evaluation method that many researchers use in order to reduce the bias related to random sampling. k-fold cross-validation is done by randomly splitting the whole data set into k mutually exclusive subsets (folds) that are of almost the same size. After the classification model is trained, it is tested k times. Videlicet, the classification model, is trained on whole folds except for a single fold. That single fold is used for tests. The cross-validation accuracy (CVA) is the average of the k individual accuracy measures.

$$CVA = \frac{1}{k}\sum_{j=1}^{k} A_i \tag{9}$$

The number of folds used is denoted by k (10 in this case), and A_i is the accuracy measure of each fold, $i = 1, \ldots, k$ [42]. In this research, all EMG data were stratified into 3 classes: H, M, and N. As with those in the whole data set, each of the 10 folds contains equivalent proportions of H, M, and N.

By computing the following statistical parameters, the test performances of the ANNs were determined:

Specificity: number of correctly classified healthy subjects / total healthy subjects.

Sensitivity (*myopathy*): number of correctly classified myopathic subjects / total myopathic subjects.

Sensitivity (*neurogenic*): number of correctly classified neurogenic subjects / total neurogenic subjects.

Total classification accuracy: number of correctly classified subjects / total subjects.

The comparisons of the different feature extraction methods for FEBANN and CNN are given in Tables 2 and 3, respectively.

Table 2. Comparison of different feature extraction methods using FEBANN for EMG signal classification.

Statistical parameters	AR Yule	AR Burg	AR COV	AR MCOV	MUSIC	EIG
Specificity (%)	94	95	96	97	90	97
Sensitivity (%) (myopathic)	88	88	89	90	80	92
Sensitivity (%) (neurogenic)	80	81	85	86	83	91
Total classification accuracy (%)	87.3	88	90	91	84.3	93.3

Table 3. Comparison of different feature extraction methods using CNN for EMG signal classification.

Statistical parameters	AR Yule	AR Burg	AR COV	AR MCOV	MUSIC	EIG
Specificity (%)	94	95	97	97	93	97
Sensitivity (%) (myopathic)	89	89	90	90	81	93
Sensitivity (%) (neurogenic)	82	83	85	87	85	92
Total classification accuracy (%)	88.3	89	90.6	91.3	86.3	94

As seen from the tables, the average success rate for CNN with EIG was the highest (94%). However, the FEBANN with MUSIC technique had the lowest success rate (84.3%). Our examination of the classification performance of each class yields that the highest performance was acquired for the H group using AR covariance, AR modified covariance, and EIG. However, the lowest performance was acquired for the H group using MUSIC. The complex and variable waveform shapes are attributed to the low performance of the N group. Thus, the CNN model obtained higher accuracy rates compared to the FEBANN model.

By referring to the results contained in the present paper as well as to our awareness of EMG signal classification problems, we draw attention to the following points:

i) Due to the high classification accuracy of the CNN classifier, we obtained insight into the features used to define the EMG signals. The conclusions demonstrate that the EIG PSDs are the features that best represent the EMG signals. Moreover, a good distinction between classes was obtained by using these features.

ii) To diagnose myopathic and neurogenic disorders, the first-level networks were applied in the CNN. The different features were used as inputs. Diagnostic accuracy was improved by training the second-level networks through implementing the input data as the outputs of the first-level networks. The CNN models reached a slightly higher performance compared to the FEBANN.

iii) EMG is a useful method for diagnosing different diseases in muscles. In order to test this hypothesis, CNN and FEBANN were trained to identify 3 groups of MUPs derived from EMG spectrums; these were the healthy, myopathic, and neurogenic disorder groups. The classification accuracy that was demonstrated by the ANN was 97% for healthy, 93% for myopathic, and 92% for neurogenic disorders. After the ANN was trained adequately and the values of the biases were stored, testing and succeeding realization was rapid. This is an advantage of ANN over existing methods of EMG signal analysis. In addition, the EMG waveform is interpreted through pattern recognition, whereas feature vectors are created from the EMG PSDs to distinguish the data to be classified. The features of the classifier inputs determine the performance of the classifier. Six different feature extraction methods were utilized to obtain the features that most accurately represented EMG signals. Our research suggests that determining the best classifier for EMG signals is feasible through the AR and EIG methods.

iv) In a previous study [30], the FEBANN employing a backpropagation training algorithm was used to identify the myopathic and neurogenic disorders. Spectral analysis of EMG signals was performed by AR method to determine the FEBANN inputs. The total classification accuracy was 88%. For our experiment, we used different features in the CNN, and slightly higher classification accuracies were obtained. This result shows that CNN classification accuracy is slightly improved with the usage of EIG feature.

The results obtained from our experiments are encouraging, in that they suggest that the CNN approach is feasible for EMG signal classification. The ANN diagnostic system has a satisfactory success rate in testing, and the evaluation of EMG signals is performed objectively. Its automated functions bring rapidness as well as efficiency. All these features make the system eligible for use in clinical practice.

4. Conclusion

A CNN was used in the present study. In the first layer, the ensemble neural networks were used for the classification and decomposition of EMG signals. In order to combine the decisions of these networks, another neural network was used. An ANN that classifies people as suffering or not suffering from neuromuscular diseases ensures a useful tool for physicians to perform diagnostic decisions. To classify EMG signals, 2 types of neural networks were trained: FEBANN and CNN. Identical data sets and targets were used to train networks within each group. By training new neural networks to merge with the original network predictions, an improvement in the accuracy of the classification of EMG signals was observed. This merged neural network was trained and tested with features using parametric and subspace-based methods. Compared to the stand-alone neural network model, the merged neural network model achieved higher performance for the classification of EMG signals. Therefore, the diagnostic decision support system is a very valuable tool that allows the physician to make a better judgment without relying on other expensive tests. Most importantly, diagnostic decision support systems permit higher decision accuracy.

References

[1] Henneberg K. Principles of electromyography. In: Bronzino JD, editor. The Biomedical Engineering Handbook. Boca Raton, FL, USA: CRC Press, 2000. pp. 242–251.

[2] Katsis CD, Goletsis Y, Likas A, Fotiadis DI, Sarmas I. A novel method for automated EMG decomposition and MUAP classification. Artif Intell Med 2006; 37: 55–64.

[3] McGill KC. Optimal resolution of superimposed action potentials. IEEE T Biomed Eng 2002; 49: 640–650.

[4] Krarup C. Pitfalls in electrodiagnosis. J Neurol 1999; 246: 1115–1126.

[5] Richfield EK, Cohen BA, Albers JW. Review of quantitative and automated needle electromyographic analyses. IEEE T Biomed Eng 1981; 28: 506–514.

[6] Pattichis CS, Elia AG. Autoregressive and cepstral analyses of motor unit action potentials. Med Eng Phys 1999; 21: 405–419.

[7] Pattichis CS, Schizas CN, Middleton LT. Neural network models in EMG diagnosis. IEEE T Biomed Eng 1995; 42: 486–496.

[8] Loudon GH, Jones NB, Sehmi AS. New signal processing techniques for the decomposition of EMG signals. Med Biol Eng Comput 1992; 30: 591–599.

[9] Hassoun MH, Wang C, Spitzer AR. NNERVE: Neural network extraction of repetitive vectors for electromyography—Part I: Algorithm. IEEE T Biomed Eng 1994; 41: 1039–1052.

[10] Hassoun MH, Wang C, Spitzer AR. NNERVE: Neural network extraction of repetitive vectors for electromyography—Part II: Performance analysis. IEEE T Biomed Eng 1994; 41: 1053–1061.

[11] Christodoulou CI, Pattichis CS. Unsupervised pattern recognition for the classification of EMG signals. IEEE T Biomed Eng 1999; 46: 169–178.

[12] Subasi A, Kiymik MK. Muscle fatigue detection in EMG using time–frequency methods, ICA and neural networks. J Med Syst 2010; 34: 777–785.

[13] Diab MO, El-Merhie A, El-Halabi N, Khoder L. Classification of uterine EMG signals using supervised classification method. J Biomed Sci Eng 2013; 3: 837–842.

[14] Subasi A. Classification of EMG signals using PSO optimized SVM for diagnosis of neuromuscular disorders. Comput Biol Med 2013; 43: 576–586.

[15] Sueaseenak D, Chanwimalueang T, Pintavirooj C, Sangworasil M. An accurate forearm EMG signal classification method using two-channel electrode. IEEJ T Electr Electr 2013; 8: 328–338.

[16] Young AJ, Smith LH, Rouse EJ, Hargrove LJ. Classification of simultaneous movements using surface EMG pattern recognition. IEEE T Biomed Eng 2013; 60: 1250–1258.

[17] Ibrahimy MI, Ahsan R, Khalifa OO. Design and optimization of Levenberg-Marquardt based neural network classifier for EMG signals to identify hand motions. Meas Sci Rev 2013; 13: 142–151.

[18] Muthuswamy J, Thakor NV. Spectral analysis methods for neurological signals. J Neurosci Meth 1998; 83: 1–14.

[19] Isaksson A, Wennberg A, Zetterberg LH. Computer analysis of EEG signals with parametric models. P IEEE 1981; 69: 451–461.

[20] Swindlehurst AL, Kailath T. A performance analysis of subspace-based methods in the presence of model errors — Part I: The MUSIC algorithm. IEEE T Signal Proces 1992; 40: 1758–1774.

[21] Swindlehurst AL, Kailath T. A performance analysis of subspace-based methods in the presence of model errors—Part II: Multidimensional algorithms. IEEE T Signal Proces 1993; 41: 2882–2890.

[22] Friedlander B, Weiss AJ. Effects of model errors on waveform estimation using the MUSIC algorithm. IEEE T Signal Proces 1994; 42: 147–155.

[23] Friedlander B. A sensitivity analysis of the MUSIC algorithm. IEEE T Acoust Speech 1990; 38: 1740–1751.

[24] Porat B, Friedlander B. Analysis of the asymptotic relative efficiency of the MUSIC algorithm. IEEE T Acoust Speech 1998; 36: 532–544.

[25] Proakis JG, Manolakis DG. Digital Signal Processing: Principles, Algorithms, and Applications. 1st ed. Upper Saddle River, NJ, USA: Prentice Hall, 1996.

[26] Kay SM, Marple SL. Spectrum analysis—-a modern perspective. P IEEE 1981; 69: 1380–1419.

[27] Kay SM. Modern Spectral Estimation: Theory and Application. Upper Saddle River, NJ, USA: Prentice Hall, 1999.

[28] Stoica P, Moses R. Introduction to Spectral Analysis. Upper Saddle River, NJ, USA: Prentice Hall, 1997.

[29] Subasi A, Erçelebi E, Alkan A, Koklukaya E. Comparison of subspace-based methods with AR parametric methods in epileptic seizure detection. Comput Biol Med 2006; 36: 195–208.

[30] Subasi A, Yilmaz M, Ozcalik HR. Classification of EMG signals using wavelet neural network. J Neurosci Meth 2006; 156: 360–367.

[31] Subasi A. Classi?cation of EMG signals using combined features and soft computing techniques. Appl Soft Comp 2012; 12: 2188–2198.

[32] Akaike H. A new look at the statistical model identification. IEEE T Automat Contr 1974; 19: 716–723.

[33] Schmidt RO. Multiple emitter location and signal parameter estimation. IEEE T Antenn Propag 1986; 34: 276–280.

[34] Wax M, Kailath T. Detection of signals by information theoretic criteria. IEEE T Acoust Speech 1985; 33: 387–392.

[35] Micheli-Tzanakou E. Neural networks in biomedical signal processing. In: Bronzino JD, editor. The Biomedical Engineering Handbook. Boca Raton, FL, USA: CRC Press, 2000. pp. 7–13.

[36] Haykin S. Neural Networks: A Comprehensive Foundation. New York, NY, USA: Macmillan, 1994.

[37] Fausett L. Fundamentals of Neural Networks: Architectures, Algorithms, and Applications. Englewood Cliffs, NJ, USA: Prentice Hall, 1994.

[38] Güler I, Übeyli ED. ECG beat classifier designed by combined neural network model. Pattern Recogn 2005; 38: 199–208.

[39] Hansen JV, Nelson RD. Data mining of time series using stacked generalizers. Neurocomputing 2002; 43: 173–184.

[40] Ting KM, Witten IH. Issues in stacked generalization. J Artif Intell Res 1999; 10: 271–289.

[41] Wolpert DH. Stacked generalization. Neural Networks 1992; 5: 241–259.

[42] Zhang R, McAllister G, Scotney B, McClean S, Houston G. Combining wavelet analysis and Bayesian networks for the classification of auditory brainstem response. IEEE T Inf Technol B 2006; 10: 458–467.