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Characterizing EMG data using machine-learning tools

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ABSTRACT

Effective electromyographic (EMG) signal characterization is critical in the diagnosis of neuromuscular disorders. Machine-learning based pattern classification algorithms are commonly used to produce such characterizations.

Several classifiers have been investigated to develop accurate and computationally efficient strategies for EMG signal characterization.

This paper provides a critical review of some of the classification methodologies used in EMG characterization, and presents the state-of-the-art accomplishments in this field, emphasizing neuromuscular pathology.

The techniques studied are grouped by their methodology, and a summary of the salient findings associated with each method is presented.

Contents

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1. Introduction

Electromyography, the study of the electrical currents generated in a muscle during its contraction, provides data describing both neuromuscular activity, as well as muscular morphology [1,2].

Over the last twenty years, electromyography (EMG) has been widely used by researchers and clinicians as a valuable tool for an accurate diagnosis of neuromuscular disorders [3,4]. Neuromuscular disorder is a general term that refers to diseases that affect any part of the nerve or muscle including motor neurons, neuromuscular junctions, and muscle tissue. Myopathy and neuropathy are two critical neuromuscular disease types, and discerning between these, as well as between a disease and non-disease state, are typical objectives of a classifier based EMG characterization systems.

Myopathy describes a group of diseases that affect skeletal muscle tissue directly, and are independent from any disorder of the nervous system. Neuropathy, conversely, refers to any of a number of diseases that cause damage to the nerves involved in muscular control, or in sensation [2,4,5]. Accurate and correct characterization of these two types of diseases becomes an important first step in the diagnostic process.

While historically EMG data has been approached qualitatively [3,4], in recent years a great deal of interest has been found in quantitative EMG analysis, called QEMG [6–11], in which a series of quantitative measures of the EMG signal are analyzed for their diagnostic information, as described in Section 2.3.

To characterize a muscle using QEMG data, the acquired signals must be analyzed, decomposed and classified. In diagnosing neuromuscular disorders, the classification of EMG signal into different groups is used in the detection of abnormalities. This paper presents several classification techniques used for EMG signal classification for diagnosis of neuromuscular disorders, in particular, myopathy and neuropathy types.

In Section 2, we briefly review EMG signals and their attributes. In Section 3, we present a review of EMG classification methods. Discussion is presented in Section 4.

Table 1
Methods, data evaluated, and resulting accuracies (part I).

Year	Technique		$N_S(N_M)$[a]	Accuracy (%)
Artificial neural networks				
1992	[36]	Self-organizing feature map (SOFM)	114	76–83
1995	[37]	Integration of parametric pattern recognition algorithm (PPR) and artificial neural network (ANN)	44	80–90
1996	[31]	SOFM and learning vector quantization (LVQ)	50	60–80
1998	[38]	Modular ANN	40(800)	79.6
1999	[33]	SOFM, LVQ and statistical methods based on Euclidean distance	(1213)	90
2004	[39]	Continuous wavelet transform (CWT) and a multi-channel ANN	13(260)	–
2005	[40]	Multi-layer perceptron (MLP)	12	91.6
2006	[41]	Wavelet-based neural network (WNN)	(1200)	90.7
2007	[42]	Radial basis networks (RBN) and decision trees	62(365)	89
2012	[43]	SOFM and LVQ	11	97.6
2012	[44]	Principal component analysis (PCA) and probabilistic neural network (PNN)		91.72
2013	[45]	PCA and PNN	12	68–94.3
Fuzzy				
2001	[46]	Fuzzy logic	(29)	88.4
2006	[47]	Adaptive fuzzy *k*-NN classifier (AFNNC)	(11)	96.6
2012	[48]	Fuzzy logic	97	97
ANN hybrids				
1996	[49]	Combined ANN and genetics-based machine learning (GBML) models	34	80
2004	[50]	Fuzzy integral of multiple ANN	80	88.58
2010	[35]	Neuro-fuzzy system (NFS)	177	90

[a] N_S indicates the number of subjects, N_M indicates the number of MUPs, thus "40(800)" indicates 40 subjects and 800 MUPs total.

Table 2
Methods, data evaluated, and resulting accuracies (part II).

Year	Technique		$N_S(N_M)$	Accuracy (%)
Support vector machines				
2002	[12]	Support vector machine (SVM) with one against one training algorithm	(231)	89
2005	[40]	SVM	59	92.3
2009	[51]	Multiclass SVM	12	100
2010	[52]	Binary SVM	12	100
2010	[52]	Fuzzy support vector machine (FSVM)	12	99.6
2010	[53]	SVM	27	70.4
2012	[54]	SVM with wavelet technique for feature extraction	300	99.4
2012	[55]	SVM with same technique as used in [54]	433(8660)	99.3
2012	[57]	FSVM classifier combined with statistical features extracted from discrete wave transform (DWT)	27	97.67
2013	[58]	Hybridization of the particle swarm optimization (PSO) and SVM	27	96.75
Others				
1995	[28]	Principle component analysis and multivariate discriminant algorithm	302(6828)	70.4–76.5
2008	[24]	Bayesian aggregation	57	88.7
2012	[56]	Decision tree	27	96.33–96.50

Tables 1 and 2 provide a summary of all the techniques discussed, broken down by the type of classifier used. This is divided into two tables due to page size constraints. Through these tables and the accompanying discussion, both newer results and important historical context are provided, in order to better understand recent trends in EMG classification.

2. EMG signal analysis

An EMG signal is a biological signal obtained by measuring voltages associated with the electrical currents generated in a muscle during its contraction, providing a measure of neuromuscular activity [1].

2.1. EMG signal structure

The collection of muscle fibres innervated by a single α-motor neuron is referred to as a motor unit (MU), and this is the smallest functional unit of a muscle that can be activated by neural control [4,12,13]. Muscular force production within an MU is achieved through activation of the α-motor neuron, causing tension to be produced in the associated muscle fibres as the action potential propagates along the length of these attached fibres. Relaxation occurs as the α-motor neuron ceases activity.

A motor unit potential (MUP) is the summation of the action potentials of these contraction of the muscle fibers in an MU, and is measured either by inserting an electrode into the muscle tissue, or, in the case of surface electromyography (sEMG), by placing an electrode array on the overlying skin surface. The voltages detected by the electrode represent the summation of the activity of all of the active MUs (the sum of the contributions of all MUPs). MUPs from MUs whose territories are close to the electrode will be the most easily discerned, due to the spatial filtering effects arising from the dissipation of energy from distant MUP sources [14].

Signals recorded in this fashion will unavoidably contain noise, both from other biological sources within the body, as well as equipment noise [1,4,14]. Mathematically, the signal using a single electrode gathered from a single contraction can therefore be represented as follows:

$$\mathrm{EMG}_t = \sum_{m=1}^{N} \mathrm{MUPT}_m(t) + n(t), \qquad (1)$$

where MUPT_m refers to the function describing the voltage contribution, as measured over the time of the contraction, of a single MUP m of a total of N MUPs. As this function represents the contribution from potentially many MUPs produced by the same MU over time, this is referred to as a MUP train (MUPT). The function $n(t)$ represents all components of the signal not associated with the MUPs, understood to be the contributions of biological and environmental noise in the recorded signal. Both of these functions are parameterized by time (t) [1].

2.2. Signal decomposition

EMG signal decomposition is a method for studying the structure, organization and function of individual motor units. The objective of decomposition is to identify the contributions of each MU within the overall acquired signal [15–17].

EMG signal decomposition involves five steps: signal acquisition; segmentation; feature extraction; clustering of detected MUPs; and MUP assignment.

Before it can be characterized computationally, a signal, EMG_t, must be decomposed into the contributions from each active MUPT; once this is accomplished, the firing behaviour of each MU, along with the shape of the associated MUPs, can be determined. A typical MUP is shown in Fig. 1; the shape of all MUPs forming a train will be similar, and is due to the specific placement of the muscle fibers of the motor unit and the neuromuscular junctions along the muscle fibres with respect to the electrode placement.

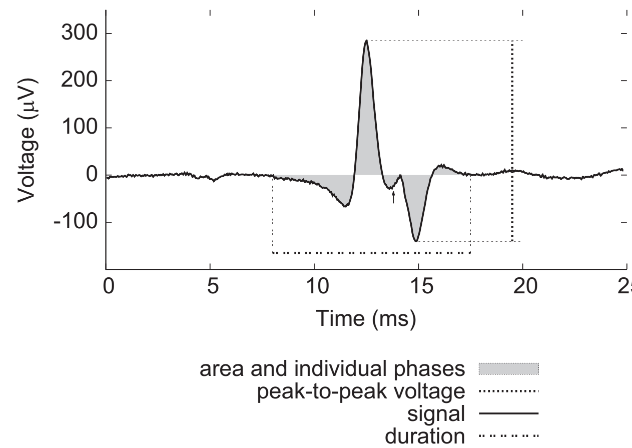

Fig. 1. A typical MUP, with several features shown.

2.3. Decomposed MUP features

There are many features that can be extracted from EMG signals, however several features have commonly been used to classify EMG signals in studies of neuromuscular diseases. These features include duration, (peak-to-peak) amplitude, number of phases, turns, as well as area.

Fig. 1 displays several of these features, which are well defined in several other works [7,13,18–20], however for the convenience of the reader a short summary follows. All the following definitions have been adapted from [7]:

- Duration is the time between the onset and the termination of an MUP. It is related to the time taken between the origin of the muscle fiber action potentials in the innervation zone and their arrival at the ends of the fibers.
- Peak-to-peak amplitude is the difference between the maximal and minimal peak values for the MUP, measured in mV.
- The number of phases in an MUP is generally equal to the number of baseline crossing plus 1, as shown in Fig. 1.
- A turn is a positive or negative peak that is separated from a previous and a following peak of opposite polarity by some threshold voltage. In Fig. 1 a turn is shown at the arrow near 14 ms.
- MUP area is calculated by integrating the rectified MUP over its duration.
- Thickness is the ration of area to amplitude. It may be useful in detecting myopathies.
- Size index is defined as $2 \times \log_{10}(amplitude) + (area/amplitude)$. It can be viewed as a weighted-thickness measure.

In Fig. 1, the area of the curve has been shaded; each shaded section on alternate sides of the baseline constitutes a single phase of the MUP.

Several other features based on combinations of these can be constructed, such as spike, and spike duration [21]; other information related to the firing rates and firing variability may also be extracted [7].

Using all, or subsets of, these quantitative feature values, it is possible to produce a tabular summary of the contents of a signal in the form that is typically used as input to an automated classification system. If trained to discriminate between disease classes, typically between neuropathies and myopathies, then such a classifier can be used as the basis for a decision support system, and may then be used to assist physicians and researchers with the diagnosis, treatment and management of neuromuscular disorders [22–25].

In practice, ambiguity in the interpretation of MUPs detected from a muscle makes discrimination between these two types of disease a challenging task [7].

3. EMG classification approaches

Several studies have employed classification methods including Bayesian techniques [26–30], neural networks [31,32], multilayer perceptrons [33], fuzzy approaches [34], support vector machines [12], and neuro-fuzzy systems [35]. In the following section, we discuss some of the works which explore the EMG classification problem in the domain of neuromuscular pathology.

All of the techniques discussed in this and later sections are summarized in Tables 1 and 2 which provides a breakdown by classifier type, and year of publication.

3.1. *Artificial neural networks approach*

In the last decade, artificial neural network (ANN) tools have been of interest to many researchers in the field of EMG classification. ANNs have several advantages such as their ability to learn from examples and their tolerance for vagueness and uncertainty, which are significant characteristics of EMG signals. ANNs are also well known for their generalization ability, which is important when working in high dimensional input spaces. The learning capability of an ANN is its strength, but this is limited by their inability to explain the reasons for conclusions reached [59]. This issue aside, their ability to learn directly from large data sets that have high feature variability is a strong advantage for EMG classification, and therefore many researchers have successfully applied ANNs to the diagnosis of neuromuscular disorders.

Pattichis et al. [37] used an integrated system composed of a parametric pattern recognition algorithm (PPR) and an ANN model to classify EMG signals for the diagnosis of neuromuscular disorders. This system employed ANNs under both supervised and unsupervised training paradigms. Back-propagation (BP) [60] was utilized in Pattichis' work for supervised learning, and the Kohonen self-organizing feature maps (SOFM) algorithm [61] were used for unsupervised learning. SOFM, also known as vector quantization, is an unsupervised learning technique based on competitive learning. It is a dimensionality reduction technique which transforms a high-dimensional data set into a low dimensional space. In such a projection, SOFM techniques have been shown to preserve the topological properties of the training set [61].

Different ANN architectures were investigated in Pattichis' work. EMG signals were acquired from *biceps brachii* muscle during a voluntary contraction. The classifiers were trained on MUPs obtained from 44 subjects (14 healthy patients, 16 neuropathic and 14 myopathic patients). The means and standard deviations of 7 features (duration, spike duration, amplitude, area, spike area, number of phases and number of turns) were used as input.

The resulting classification performances were compared against a *k*-means cluster analysis classifier. Kohonen SOFM model and the *k*-means cluster analysis algorithm achieved the same level of accuracy: between 80% and 85%. The ANN models trained with the BP algorithm, with an accuracy of 80–90%, appeared to be more accurate than the two other models.

The results from BP models are also tend to be more consistent, meaning that in different training sessions, different MUP may be classified incorrectly even when the overall classification accuracy is reported to be the same.

This paper discovered the (now well-understood) pattern wherein myopathic muscles frequently have MUPs with short duration, low amplitude and small number of phases, while neuropathic patients have MUPs with long duration, high amplitude, and a large number of phases. This study also showed that no clear boundaries for each group can be suggested.

The SOFM model, as contrasted to the BP model, has two advantageous properties [37]: the first advantage is its comparison ability, allowing comparison between the data of one patient and another, or between two studies of the same patient; the second advantage claimed for the SOFM model is the lower number of epochs required for adequate training of a neural network.

The main disadvantage of ANN models is the difficulty they have in achieving generalization, and associated problems of overfitting the training data.

Pattichis' results show that training with the combination of the mean and the standard deviation of the EMG parameters significantly improves the learning process. The advantages of this approach are as follows: the minimization of observer bias and the provision of information for physicians to reach an accurate diagnosis.

3.1.1. *SOFM models*

Abel et al. [31] examined the use of different ANN architectures and learning algorithms in the EMG diagnosis of neuromuscular disorders. They investigated the performance of three supervised and one unsupervised neural networks using combinations of parameters including turns analysis, small segments, and frequency analysis. EMG inference patterns (IP) were acquired from the biceps muscle during maximum voluntary contraction from a total of 50 subjects (12 healthy, 18 myopathy, 15 neuropathy and 5 both myopathy and neuropathy). Supervised networks including the Levenberg–Marquardt optimized back-propagation network (LBPN) [62], radial basis network (RBN) [63], learning vector quantization network (LVQ) [64] and unsupervised Kohonen SOFM were compared. LVQ is a supervised version of vector quantization, similar to SOFM. LVQ performs its classification based on the distance between input vectors [64] .

Tan-sigmoid, radial basis, and competitive algorithms were used to train the hidden layer of LBPN, RBN, and LVQ respectively.

Using different parameter combinations, LBPN, RBN and LVQ gave diagnostic yields of 75–80%, 50–80%, and 70–80% respectively. The results of this study did not show that any of the neural networks were superior to any other in terms of accuracy. However, it has been noted that the LBPN and RBN networks trained faster than their counterparts.

All parameters were weighted equally in this study. Some parameter combinations produced lower scores than using a single parameter, however this study found that closely interrelated parameters (i.e., those that are functions of amplitude and frequency) could produce a comparable diagnostic accuracy.

Two years later, Christodoulou and Pattichis [38] proposed a modular ANN for the same problem. This system was designed to mimic the decision making process an expert neurophysiologist would invoke when analyzing MUP features. Six different feature sets, including time domain parameters, frequency domain parameters, cepstral coefficients and three different wavelet coefficients, were computed and used as inputs to multiple SOFM classifiers. The results from all individual classifiers were then combined through majority voting. The contribution of each of the feature sets and classifier to the final diagnosis was weighted according to its confidence measure. As noted in the paper [38], the confidence measure "is calculated based on the number of input patterns assigned per class to the nearest neighbours on the self-organizing map during the training phase."

Experiments were carried out on a total of 40 subjects (12 healthy, 13 myopathy, and 15 neuropathy) where 20 MUPs were recorded from each subject. The success rate observed for the individual feature sets was 69.1%, whereas when combining the six classifications using a confidence measure, the success rate rose to 76.9% for an improvement of "approximately 3%" reported. This study proved that the use of a combination of multiple ANN classifiers in conjunction with a confidence measure significantly increases the overall classification performance. Time domain parameters yielded better results than other parameters. This approach additionally increases the reliability and robustness of the system by reducing the error variance of the final result.

Another notable attempt using SOFM for the classification of EMG signals for diagnosis of neuropathies is presented in [36]. Experiments were conducted on a total of 114 subjects of which the data of 84 subjects was used for training and that of 30 subjects for testing. Results were then compared with the doctors' interpretation where accuracy and kappa coefficients were computed for each case. (The kappa coefficient [65] measures the agreement between the categorizations produced by two different classifiers.)

The classification accuracy varied with the size of the map. The optimal map size was between 10×10 and 12×12. Classifiers with lower size achieved accuracy between 70% and 76%, while classifiers with higher map size achieved higher accuracy between 76% and 83%. This work reported that network control parameters, such as the number of iterations, and neighbour parameters do not impact classifier accuracy. Conversely it also demonstrated that adding further input variables increases classifier performance. This study proved that an SOFM neural network is an efficient applicable model for EMG classification tasks.

Christodoulou and Pattichis [33] proposed two different pattern recognition techniques for the classification of EMG signals to diagnose neuromuscular diseases. An unsupervised ANN trained with a modified version of the SOFM algorithm and LVQ and a statistical classifier based on the Euclidean distance were developed in this application. Experiments were carried out on a total of 1213 MUPs, and 97.6% accuracy was achieved using the ANN, while the statistical approach achieved 95.3% accuracy.

The additional use of LVQ improved the classification performance by defining the class borders. Each input was presented to a network only once. Using one learning epoch for training increased the performance and speed of the learning process and makes this algorithm appropriate for most real-time applications [33].

The statistical approach used Euclidean distance within the feature space in order to identify and group similar MUPs using a constant threshold. They also used baseline and slide correction to improve the accuracy of the statistical classifiers. Baseline and slide correction is a technique that measures the significant changes of the system compared to the previous states. The threshold values were determined heuristically.

Using a constant threshold for classification is one of the drawbacks of the statistical method because it is not flexible enough for EMG signals with high variability. Another disadvantage found with this statistical approach was that the computational time geometrically increased with the size of data set. These two disadvantages result in a lowering of both speed and accuracy rates for this approach compared to using an ANN. This study shows that ANN techniques are more appropriate for the classification of MUPs because of their ability to model complex decision boundaries.

3.1.2. RBN and decision trees

Katsis et al. [42] used the combination of RBN and Decision Trees (DTs) to classify MUP template for the diagnosis of neuromuscular disorders.

EMG signals were acquired from the *biceps brachii* muscle under constant isometric conditions and up to 30% of the Maximum Voluntary Contraction (MVC) level. The classifiers were trained on 365 template MUPs obtained from 62 subjects (20 healthy patients, 22 neuropathic and 20 myopathic patients).

This approach used a minimal number of tuned parameters, and was able to provide interpretable decisions. This classification process was implemented in two stages. In the first stage, a radial basis function was employed to classify MUPs into healthy and pathological classes. In the second stage, a decision tree was used to classify the pathological MUPs into myopathy and neuropathy classes.

For the first stage, a multilayered probabilistic neural network (PNN, a class of RBN) was trained with heuristically selected training vectors (143 MUP templates) following an iterative trial-and-error method. The input to the first hidden layer was the Euclidean distance between a connection weight w and the input value v, multiplied by a bias b. The second hidden layer presents the classification probabilities computed through the summation of the outputs of the previous hidden layer. The final output was produced by applying a compete transfer function on the second hidden layer. This transfer function identifies the labelling with the maximum probability. Using RBN usually requires a more neurons than standard feed-forward neural networks (FFNNs) for the same classification problem. RBN techniques do, however, provide better speed and the performance, when used with a smaller training set.

In the second stage, a decision tree was used to classify the pathological MUPs into myopathy and neuropathy classes. Decision trees are able to provide decision interpretation, especially when dealing with the structure of decision rules. Information gain is used as a measure of the effectiveness of the features used. Five feature sets (amplitude, duration, rise-time, area, and number of phases) extracted from pathological MUPs were employed as inputs for the training of the radial basis function (RBF) network and were used to build the decision tree. The discrete valued features were dynamically defined based on continuous feature values. A pessimistic post pruning method was then applied on the induced decision tree to avoid over-fitting. In the testing phase, the inputs to the decision tree were the pathological MUPs classified by the RBN classifier. Thus, the decision tree classified the pathological MUPs into myopathic or neuropathic. This approach was able to provide interpretable decisions. The authors report that this technique achieved 89% accuracy. Decision trees can greatly increase transparency in diagnostic systems, but this approach performs well only when the available features have a high information content. By increasing the number of features, the accuracy of the decision tree decreased. Also, the greedy characteristic of decision tree construction leads to over-sensitivity to noise and the possibility of over-fitting the training data.

3.1.3. Wavelets

Gazzoni et al. [39] proposed an automatic system for the classification of surface EMG signals to diagnose neuromuscular disorders. Their experiments were performed on MUPs recorded from "healthy" and "pathological" subjects.

They used continuous wavelet transform (CWT) for the segmentation and a multi-channel ANN that was a modified version of a multi-channel adaptive resonance theory network (MART) for classification. MART is an ART-based neural network which commonly is used as an unsupervised network. The ART2 neural networks use the first example pattern as the template for the first cluster. This template then changes when new examples are introduced to the neural network. Each time a new example is not matched by any of the stored patterns, a new cluster will be created. The advantage of a MART neural network is that it reduces the influence of noisy channels. One of the limitations of this approach is that superimposed MUPs are not classified correctly because MUPs are assumed to be non-overlapping.

Subasi et al. [41] developed a wavelet-based neural network (WNN) and compared it against a custom MLP with a back-propagation based learning method for the classification of MUPs to diagnose neuromuscular disorders. A WNN combines advantage of the time–frequency localization characteristic of wavelets and the learning ability of an ANN into a single unit. They are well-known for their ability to provide fast training through heuristics and also their capability of handling non-stationary signals [66]. Because MUP features have the properties of large variability and lack stationarity, the WNN seems to be an interesting and appropriate choice compared to other neural network types for MUP classification.

For the MLP, Subasi used a three layer feed-forward neural network (FFNN), where the hidden layer employs a dyadic discrete Morlet wavelet basis function as an activation function. They used the linear discriminant portion to improve the function approximation and train the WNN to approximate only the wave-like components in the function. The input provided to the WNN was an autoregressive (AR) model of MUPs, and the output nodes represented healthy, myopathic and neurogenic disorders.

The FFNN was designed with three layers, and to avoid over-fitting, they used the same number of nodes which were used in the hidden layer of the WNN. Experiments were carried out on a total of 1200 MUPs, and 90.7% accuracy was achieved by WNN, while a simple feed-forward back-propagation neural network achieved 88% accuracy. Therefore, we come to the conclusion that a WNN is a more robust classifier, which can add weight to neuromuscular diagnosis with the use of MUPs. Further, it was suggested by Subasi that a WNN can handle waveform variability better than other classifiers.

3.1.4. Other ANN approaches

Kaur et al. [67] used an ANN model to classify MUPs for the diagnosis of neuromuscular diseases.

The MUPs were extracted using an algorithm that automatically detects and eliminates the areas of EMG signal with low activity and possible noise. The candidate MUPs were clustered using a statistical pattern recognition technique, where the Euclidean distance is used to identify and group similar MUP waveforms. Then the group average was calculated and used for the classification of MUPs using a constant threshold. Time domain and auto-regressive features were extracted from the MUP clusters. A back-propagation neural network classifier was used to classify the time domain and AR features of the MUP clusters. Experiments were carried out using 12 subjects: 3 healthy, 5 myopathic, and 4 neuropathic. The success rate for the clustering method was 93.13%, while that of the ANN was 66.72% when using time domain parameters and 75.06% with AR parameters. The authors of the study conclude that the classification accuracy is significantly higher with the AR features compared to the time domain features, which is interesting in the context of the WNN setup used in Subasi et al., above [41].

Bhardwaj et al. [43] proposed an ANN technique based on the SOFM algorithm with LVQ to classify MUPs for the diagnosis of neuromuscular disorders. This method is implemented in three phases. In the first phase SOFM is used. Then in the second phase LVQ is applied to increase the performance of the ANN. The actual classification takes place in the third step. Experiments were carried out on a data set consisting of 11 subjects (2 healthy, 4 myopathic, 5 neuropathic). The success rate for this technique was 97.6%.

Shaw and Bagha [44] proposed using principal component analysis (PCA) a technique for feature extraction, followed by a probabilistic neural network (PNN) technique for classification of MUPs for the diagnosis of neuromuscular disorders. PCA is a useful statistical technique for pattern recognition in high dimensional data spaces. PCA can be used as a nonlinear dimensionality reduction technique, because it can reduce a large set of correlated variables into a smaller set of uncorrelated variables [68].

PNN is a supervised ANN that implements a Bayesian decision strategy for classification, called kernel discriminant analysis. In Shaw and Bagha's work, a four-layer PNN was employed. The PNN training process is faster than the back propagation method, and the convergence to an optimal classifier is guaranteed as the size of training set grows. Additionally, a PNN can overcome the local minima issue. An average accuracy of 91.72% was achieved using a PNN. This study shows that the selection of network input parameters is an important factor in classification performance.

Acevedo and Mogollon [45] used a PCA method for feature extraction and a PNN for classification of a set of MUPs of patients with foot drop. The results were then compared to those of an MLP. The experiments were carried on a set of MUPs extracted from EMG signals acquired during isometric contractions in the tibial anterior muscles. In total 60 EMG signals recorded from 12 subjects were used for experiments. PCA and PNN each achieved a higher degree of accuracy for classification of healthy (94.3%) and injured cases (68%) compared to MLP with the accuracy of (60%) for healthy and (64%) for injured. However this work shows promising results from both neural networks, but the author does not mention what features extracted from MUPs have been used.

ANN models are not transparent because they do not reveal how they reach their conclusions. The large number of neurons means that a large number of arithmetic operations are used to transform the features making ANNs essentially black box classifiers. Studying a large number of models proved that the learning of a training set does not guarantee successful diagnostic behaviour when using an evaluation set.

3.2. Fuzzy systems

Since the early 1990s, more attention has been given to fuzzy systems. Fuzzy systems can be used for both function approximation and pattern classification applications. Fuzzy rule-based classification systems have been successfully applied in both these domains, providing high explanation ability for the input/output data behaviour [69].

Chauvet et al. [46] proposed a fuzzy logic method for decomposing an EMG signal into its constituent MUPs (72.4%). The algorithm was evaluated on both sEMG and needle EMG data. The rate of successfully classified MUP for EMG signals was 88.4% and for sEMG, the algorithm identified correctly 21 out of 29 MUPs tested.

Rasheed et al. [47] proposed an adaptive fuzzy k-NN classifier (AFNNC) for EMG signal classification for neuromuscular diagnosis. The results for the AFNNC classifier were compared with its adaptive certainty classifier (ACC) counterpart. The AFNNC classifier generalizes the k-NN classifier, assigning a fuzzy membership function to each input pattern. The AFNNC uses fuzzy nearest neighbours to estimate the membership function. The combination of MUP shapes and two modes of MU firing patterns (passive and active) is used to determine the similarity criterion for grouping MUPs.

The AFNNC has the advantage of dealing with vagueness and uncertainty, as well as providing a confidence measure with respect to the classification results. The mean performance for AFNNC was 96.6% and for the ACC it was 86.9%. Increasing data set size resulted in higher classification accuracy for AFNNC. This study shows that the AFNNC model performs better than the ACC when the variability of MUP shapes within MUP trains was high. It also shows that the k-NN assignment model has the ability to improve the classification accuracy for unstable MUPs.

Disselhorst-Klug [48] used a fuzzy approach for classification of high-spatial-resolution-EMG (HSR-EMG) signals for the diagnosis of neuromuscular disorders. Seven features extracted from HSR-EMG signals were used for classification. These features are divided into three groups regarding the excitation spread, the entire signal course in time as well as the shape of isolated peaks within the signal.

Different weighting factors were used, each with a range of [0⋯50] to control the contribution of each feature to the classification result. The weighting factors were then optimized by classifying a training data set generated with a specially developed muscle model. The training data set consisted of different HSR-EMG signals simulated using muscle structures with no pathological changes, muscle structures where a loss of muscle fibres had occurred (muscular disorders or myopathies), and muscle structures where a loss of entire MUs had occurred (neuronal disorders – neuropathies).

As part of the performance of the fuzzy classification process, all parameter values are initialized to a mean of zero and a unit variance. Starting the classification process, three clusters representing the groups “neuronal disorder,” “muscular disorder” and “healthy” are defined using a hierarchical clustering process such as the nearest-neighbour algorithm. Each HSR-EMG signal is assigned to the cluster with the highest membership-value. The training data set was classified with all possible combinations of weighting factors.

The optimal combination of weighting factors was selected when the classifier achieved the highest classification accuracy.

Disselhorst-Klug's fuzzy approach correctly classified 100% of all healthy subjects, 100% of all subjects with muscular disorders, and 87% of all subjects with neuronal disorders. On average, in 97% of all investigated children the diagnosis by means of the non-invasive HSR-EMG was correct, however there is a strong bias in errors toward neuromuscular disorders.

This study shows that the diagnostic selectivity of HSR-EMG signals falls into the same range as, and could even exceed the selectivity of, commonly used needle EMG techniques, though the HSR-EMG methodology is limited to superficial muscles and MUs. Clearly, this approach has achieved promising results.

3.3. *Hybrid systems*

EMG signals have the properties of non-stationary and large variability of features within each class [70]. The variability of the signal is in part due to the existence of redundancy in the neuromuscular system, which cause many combinations of muscle activity to produce the same movements. Hence whether the EMG signals are recorded from one subject for different tasks, or from different subjects within the same task, this variability will be observed [71]. It is difficult for a single network to learn non-stationary data such as EMG signals, because of local minima problems, and vagueness within the data and its classification.

3.3.1. *Neuro-fuzzy systems*

A neuro-fuzzy system (NFS) is a combination of a fuzzy system and an ANN that incorporates the advantages of both methods. Both ANNs and fuzzy systems have some disadvantages, however their combination can overcome drawbacks present in each approach.

An NFS takes the advantage of the “learnability” of the ANN and the capability of fuzzy reasoning in dealing with imprecise information. One of the most important advantages of a NFS is that the knowledge of experts can be incorporated in the fuzzy linguistic rules of the system. This advantage is a significant one over the ANN. Classifiers based on fuzzy logic can potentially be more robust in comparison with ANNs. Recently, using NFS approaches for EMG classification has been of interest for many researchers.

Koçer [35] used an NFS classifier to classify EMG signals obtained from 177 subjects. The main characteristic of this approach is including AR analysis coefficients of an EMG signal. A special three layer MLP was employed. The rule learning algorithm was fed by an initial fuzzy sets for each input node. A simple heuristic method was used for tuning the membership functions. Rule pruning and variable pruning methods were applied to the rule base in order to improve the accuracy of the classifier. Experiments were carried on for a group of 177 subjects including 60 myopathic, 60 neuropathic, and 57 healthy subjects. An accuracy of 90% was achieved. This study shows that classification accuracy is highly dependent on the number of rules. The experiments showed that pruning fuzzy rules and variables significantly improve the accuracy of the classifier. This study confirmed that the application of AR coefficients of EMG signals in neuro-fuzzy systems produce a new and reliable classification system for neuromuscular diagnosis.

3.3.2. *Fusing classifiers*

It has been proven that a combination of the outputs of many different neural networks can be a powerful technique to improve classification accuracy [72]. The reason this occurs is because each network makes generalization errors on different subsets of the input space, and these errors cancel out in aggregation with other classifiers. There are different techniques of combining several neural network outputs into an aggregate output, such as majority vote or fuzzy integrals.

Xie et al. [50] have used a hybrid decision support system based on fusing multiple ANN outputs to utilize multiple feature sets to improve the accuracy of neuromuscular diagnosis.

The fuzzy integral approach was used to combine the outputs of three back propagation neural networks. Experiments were carried out on a group of 80 subjects consisting of 20 healthy, 30 myopathic, and 30 neuropathic participants. The fuzzy integral method, with 88.58% accuracy, outperformed majority voting by 8.58%. Also it outperformed all the individual classifiers by 14.29%, 34.29% and 25.72% for time domain features, AR coefficients, and cepstral coefficients, respectively. This study proved that applying a hybrid method to multiple feature set can produce more accurate and reliable diagnosis results compared to the use of an individual classifier and a single feature set. The study also reported that the fuzzy integral method can achieve higher accuracy compared to majority voting. An important practical question in the design of the fuzzy integral classifier is the selection of the fuzzy measures, which is an integral part of the classifier, so performance is directly related to this choice.

3.3.3. *Other hybrids*

In [49], Pattichis and Schizas proposed a hybrid approach which combines an ANN and a genetics-based machine learning (GBML) algorithm for classification of EMG signals for diagnosing neuromuscular disorders.

Several GBML control parameters including message length size, number of classifiers, “lifetax”, the period of genetic algorithm (GA), crossover probability, and mutation probability were used to build the GBML model. The period of GA is expressed in iterations, showing how often the classifier system calls the genetic algorithm. More than a thousand GBML models were developed using different combinations of all parameters. A total of 28 models were selected that achieved a diagnostic yield better than 95% and 70% for the training and evaluation sets, respectively.

This study showed that a GBML model is a promising classification method in a clinical study.

Pattichis and Schizas also investigated the effect of different factors such as architecture, gain, and momentum on the performance of a back propagation neural network [49].

Experiments were performed on 680 MUPs collected from 12 healthy participants, 11 with motorneuron disease, and 11 myopathic subjects. Each subject was described by a 14-element feature vector consisting of the mean and the standard deviation of each of the following MUP parameters: duration, spike duration, amplitude, area, spike area, phases, and turns. GBML models, back propagation neural networks, and the SOFM achieved similar diagnostic performance of the order of 80%. Pattichis reports that models with small architectures require more epochs during training, and thus more computation cost, while for models with bigger architectures, the number of epochs and training time are reduced. The SOFM model had the lowest computational cost compared to the back propagation and the GBML algorithms. The diagnostic performance of the neural network and GBML models is enhanced by the hybrid system, hence using two learning principles together makes this model more robust and reliable for diagnostic tasks.

3.4. Support vector machine (SVM)

SVMs are a remarkably robust classification method in disease diagnosis. Katsis et al. [73] suggested a SVM classifier for the classification of individual MUPs from intramuscular EMG signals.

A one-against-one method was used to train the classifier, in order to deal with the problems with more than two classes. It constructs $k(k-1)/2$ classifiers (where k is the number of classes) and each classifier is trained using data from two classes. Parameters were chosen heuristically.

An experiment on 231 MUPs led to an accuracy of 86.14%. This was 9% higher than the closest other classifier tested. Results show that SVM improves classification accuracy. Two advantages of these works were that tuned parameters and data driven calculation were minimized. Advantages of using SVMs include the low training time required and also their comparable performance.

Koçer and Guler [40] proposed using the MLPs and SVMs to classify EMG signals into healthy, myopathic, and neuropathic. The results for the SVM classifier were compared with its MLP counterpart. The SVM classifier with 92.3% accuracy outperformed the counterpart MLP classifier with an accuracy of 91.6%. It was shown that the SVM accuracy is high in comparison with the MLP. Some drawbacks for SVMs are the complexity of the selection of the kernel function, and the speed and size of the classifiers both during training and testing [74].

In addition, the extensive memory requirements during the learning process when trained with large data set is a major issue with SVMs [75], however once training is completed, SVMs operate in a very efficient manner.

Reducing the dimensionality of the data while retaining the maximum amount of variability present in the date set can help to develop more accurate classification methods. The fast Fourier transform (FFT) and principal component analysis (PCA) are two common methods for producing the frequency spectrum of EMG signals [40]. In several EMG signal studies, FFT parameters have been used as feature sets. The FFT parameters are ranked based on their variance, hence they reflect the importance of each feature with respect to their ability to capture variations of the original data set [40].

PCA extracts the features with reduced dimensionality by computing the eigenvalues and eigenvectors of the covariance matrix. Hence PCA with its ability to reduce dimensionality of the data is widely used in pattern recognition applications.

Guler and Koçer [40] investigated using FFTs and PCA for classification of EMG signals. The EMG signals were recorded from biceps and hypothenar muscles of 59 subjects (19 healthy, 20 neuropathic, and 20 myopathic). The FFT analysis was applied to each EMG signal in order to break down a signal into different segments and estimate the spectrum of each segment. FFT produced a large number of coefficients, which were then reduced by PCA. PCA coefficients were then used as input parameters to train and test SVM and MLP classifiers. Using PCA parameters reduced the computing expense and improved the performance and speed of the classifiers.

The results of both classifiers were very similar. The SVM classifier obtained an 82.45% accuracy, showing a higher performance in the diagnosis of neuromuscular disorders compared to the MLP. This study shows that SVMs can have significant advantages over MLPs. Regardless of initial conditions or data set, the SVM algorithm will converge to a solution that is not prone to overfitting problems; moreover, SVMs can handle classes with complex nonlinear decision boundaries.

Kaur et al. [51] developed a multi-class SVM classifier to classify EMG signals for the diagnosis of neuromuscular disorders. They used a statistical pattern recognition technique for clustering MUPs and the one-against-all strategy to adapt the SVM for the multi-class problem. A number of SVM models were constructed equal to the number of classes.

The experiments were run on 12 EMG signals collected from 5 myopathic, 4 neuropathic and 3 healthy subjects. The highest success rate, 96.07%, was reported for clustering MUPs with the statistical approach and an accuracy of 100% was reported for the SVM classifier.

In [52], Kaur et al. developed a binary SVM classifier to classify EMG signals to diagnose neuromuscular disorders. First, a binary SVM classifier was used to classify the healthy subjects and the subjects with disease. If the signal was classified as diseased, then another binary classifier was used to classify myopathic and neuropathic signals. The analysis was completed using 12 EMG signals obtained from 3 healthy, 5 myopathic and 4 motor neuron diseased subjects. The means and standard deviations of the feature values of each subject were computed as the input feature vector of the binary classifier. Using autoregressive features has the advantage of reducing the amount of data needed and total processing time. The accuracy reported for this model was 100%.

Although a 100% accuracy is reported in this work, the small data set size (12 signals, used for both training and testing) indicates that further evaluation of these techniques may be in order, and raises the question of whether over-fitting has occurred that was not identified by the testing procedure.

Subasi [57] compared six machine learning classification methods to classify EMG signals into healthy, myopathic, and neuropathic. They suggested using a fuzzy support vector machine (FSVM) classifier combined with statistical features extracted using discrete wave transforms (DWTs). The results were compared with those of linear discriminant analysis (LDA), MLP, RBN, C4.5 decision tree, and SVM classifiers.

In order to decrease the dimensionality of the input space, four statistical features calculated over the set of the wavelet coefficients were used. A FSVM is an extension to a SVM with a fuzzy membership function [76]. The theory behind FSVMs is that every input point can contribute to the decision making task. The main advantage of FSVMs is using membership functions instead of fixed weights, which produce narrower margins, thereby better representing noisy data.

This study was conducted using EMG signals from 27 subjects, including 7 healthy, 7 myopathic, and 13 neuropathic subjects. The results for the FSVM classifier were 3% better than the other methods. This study confirms the importance of the selected features with regard to the EMG classification accuracy, as statistical analysis was performed during training to evaluate the provided features in order to compensate for noisy data.

The results show that FSVMs can provide superior performance compared to all of the other classifiers tested with regard to at least three points: classification accuracy, reliability, and insensitivity to over-fitting. Internal cross validation based on AUC, defined as the area under the received operating characteristic (ROC) curve, was used to assess the accuracy of the classification methods. A FSVM using DWT features achieved a higher classification success rate for internal cross validation with AUC and accuracy equal to 99.6% and 97.67%, respectively. This study shows that a FSVM using DWT features has the potential to become a promising classification method for EMG signals in neuromuscular pathology.

Istenic et al. [53] proposed a SVM classification approach to classify surface electromyograms (sEMGs) for the diagnosis of neuromuscular disorders. The sEMGs were recorded from *biceps brachii* muscle of 9 healthy, 9 myopathic, and 9 neuropathic subjects.

40-dimensional vector of entropies were extracted from each EMG signal and used as input to the classifier. Leave-one-out cross-validation was used for binary classification (healthy/patient) and three-class classification (healthy/myopathic/neuropathic). The accuracy for binary classification was 81.5% (77.8% sensitivity at 83.3% specificity). For three-class classification, the accuracy decreased to 70.4% (myopathies were recognized with a sensitivity of 55.6% and a specificity of 88.9%, neuropathies with a sensitivity of 66.7% and a specificity of 83.3%). This method is suitable for distinguishing between healthy and neuromuscular patient, but it fails to classify the type of neuromuscular pathology.

Tomczykiewicz, Dobrowolski and Wierzbowski have proposed an SVM based technique based on wavelets used for feature extraction and SVMs for the classification of neuromuscular disorders. This technique has been evaluated on two pools of data [54,55]. The analysis of scalograms determined by the Symlet 4 wavelet technique was used for feature extraction. For feature extraction, first the scalograms in 5 selected scales were calculated for each individual MUP. Then a single 5-dimensional feature vector per subject was calculated by taking the maximum values of the scalograms in the 5 selected scales, and averaging across the MUPs. The 5-dimensional feature vector per subject then will be used as a data set for the SVM classifier. Because a single SVM classifier is able to distinguish between only two classes, two SVM classifiers were used to deal with the three-class problem. The first classifier separated the myogenic cases from other cases (i.e., neurogenic and healthy), while the second one separated the neurogenic cases from other cases (i.e., myogenic and healthy). The third (healthy) case was to be distinguished based on negative outputs of the two classifiers. In a rare case identified by the authors, both classifiers might produce positive values for a case, when that case belongs to both myogenic and neurogenic classes at once.

One set of experiments used training data consisting of 800 EMG signals collected from deltoid muscle of 300 subjects. Three features including duration, amplitude, and area were extracted from each MUP. For validation, they used MUPs acquired from three other muscles including the 1st dorsal interosseous, vastus lateralis and tibialis anterior from the same subjects. This method yielded the accuracy of 99.4%. The sensitivity at 100% of specificity amounts to 98.4% for myogenic cases and to 98.7% for neurogenic ones. The results demonstrated high accuracy in discrimination between pathological and non-pathological cases.

This group performed another set of experiments on a variety of muscles [55] using 1015 EMG signals obtained from deltoid, first dorsal interosseous, vastus laterals, and anterior tibial, gathered from a total of 433 subjects including 362 neurogenic and 71 myogenic cases. A total of 8660 MUPs were obtained from the EMG signals used in this set of experiments. The same three features used above (duration, amplitude, and area) were again used here. The average value of each set of the features over all MUPs for an individual muscle was calculated and compared with the exemplary feature value ranges to classify the muscle as normal, myogenic, or neurogenic. This study yielded 99.3% diagnostic accuracy, specificity of 100% and sensitivity of 98.6% for myogenic muscles and 98.4% for neurogenic muscles.

The authors noted that the greatest advantage of this method is high accuracy and simplified diagnostic process. The other advantages of this method are its capability in dealing with large data sets, as well as its flexibility and adaptability to new information. This method easily can be adjusted and retrained with new, up-to-date clinical data and EMG signals obtained from other muscles. It can also be effectively used in analysis of difficult boundary cases. The author suggested considering other features such as the number of turns, number of phases, spike duration, thickness, and size index in uncertain cases.

The use of SVMs generally provides strong generalization without under-fitting or over-fitting. Despite exhibiting high classification accuracy, this method has some disadvantages such as a high computational complexity and a general lack of transparency.

Subasi [58] proposed a novel particle swarm optimization and SVM (PSO-SVM) model to classify EMG signals into healthy, neurogenic or myopathic. They used a hybridization of PSO and SVM to improve the classification accuracy. The experiments were conducted on EMG signals acquired from 27 subjects. Data were recorded from 7 healthy subjects, 7 myopathic subjects and 13 subjects suffering from a neurogenic disorder. They achieved 96.75% accuracy for the SVM classifier, based on the RBF kernel, 94.08% for the RBN classifier, and 95.17% for the *k*-NN classifier. The results for the SVM based on the RBF kernel were better than those achieved by the RBN and the *k*-NN classifiers. These experiments confirmed that a SVM based on the RBF kernel is superior, when compared to RBN and *k*-NN, with respect to statistical features of EMG signals.

Kamali et al. [77] proposed a novel approach using a serial/parallel hybrid architecture of multiple SVMs classifiers for classification of MUPs into myopathic, neuropathic, and normal classes. This model consists of several base classifiers which take nine time domain features including rise time, duration, spike duration, peak-to-peak amplitude, area, phases, turns, thickness, peak-to-peak samples number, and time–frequency domain features of MUPs extracted from EMG signals. Three different classifiers including single classifier (SC), multiple classifiers multiple features best voting (MCMFBV) and multiple classifiers multiple features all voting (MCMFAV) were used. The base classifiers have been arranged in a novel efficient way. The classification accuracy of those three classifiers was compared to a support vector machine (SVM) classifier with Gaussian radial basis function (RBF) kernel, developed by Vladimir [78]. Multi-classifiers are extension of standard SVM classifiers trained with a sigmoid function. The multi-classifier uses class label of each MUP and maps the SVM outputs to the class posterior probabilities. In a MCMFAV classifier system, a modified majority voting and a weighted majority voting were used. For majority voting all of the base classifiers are contributed in the decision making process about a given MUP but the final decision made using a modified majority voting. For the weighted majority voting, the more competent/confident classifiers are given more power in making the final decision [77].

Kamali et al.'s study [77] showed that multi-classifiers with an average accuracy of 97% achieve significantly higher accuracy compared to a single SVM-based classifier with 88% accuracy. The aim of the author is the production of a model that will be appropriate for other pattern recognition applications through its ability to divide a complex decision into several detailed decisions where the input of each decision node can be separately optimized.

Using a SVM is one of the most accurate classification models, but it has some drawbacks. The main challenge in using SVMs is the selection of an appropriate kernel, and this is of great importance in the performance of the classifier. Another drawback is the selection of the speed and size of the classifiers both in training and testing [74]. Further, the high algorithmic complexity, extensive memory requirements [75], and lack of transparency are other major issues of SVM.

3.5. Other methodologies used

Keleş and Subaşi [56] implemented a decision tree classifier for classification of EMG signals for the diagnosis of neuromuscular disorders. The “consistency subset evaluator” and “principal component” feature selection methods were used to increase the model performance, speed, transparency, and to avoid overfitting problems. Four decision tree algorithms, namely CART, C4.5, random forest and random tree, were analyzed for the classification task. The data set of 129 features extracted from EMG signals was used to evaluate the model. The analysis was applied to MUPs collected from 27 subjects (including 7 healthy, 7 myopathic, 13 neuropathic).

The random forest decision tree classification algorithm, combined with the “consistency subset evaluator,” provided 99.25% accuracy and was the most successful classifier. The C4.5, random tree and the simple CART classification algorithms applied without using feature selection obtained similar accuracies between 89.82% and 96.25%. This study showed that the random forest classification algorithm using the “consistency subset evaluator” feature selection method gave the best accuracy. Other algorithms achieved better accuracy when used without any feature selection method. This study also suggests that the “principal component” method was the worst option for feature selection evaluated, as it decreases the accuracy of classifiers by 7%.

Pfeiffer and Kunze [28] used a multivariate discriminant algorithm for classification and the principal component analysis method for feature extraction to characterize MUPs. The results were compared with a bivariate discriminant algorithm. In this method MUPs are classified by their discriminant scores in two phases. At first, a 2-group discriminant with one discriminant score was used to determine whether a muscle was diseased or not. Then a 3-group discriminant with two discriminant scores per MUP was used to distinguish myopathic, neuropathic, and healthy cases. The conditional probability of a MUP was calculated based on the Euclidean distance of the MUP to the centroids of the respective discriminant score distributions. A MUP belongs to the disease type with the highest conditional probability. Two methods were used to predict muscle classification: the class containing most MUPs and the class with highest mean or median posterior probability.

The analysis was applied to 2323 MUPS collected from 108 *biceps brachii*, 2961 MUPS from 128 *tibialis anterior* muscles and 1544 MUPs from 66 *rectus femoris* muscles. Five features extracted from MUPs including duration, amplitude, area, turns count and centre frequency. This study showed that multivariate discriminant analysis with an accuracy of 74.4% achieves significantly higher accuracy compared to bivariate discriminant function with 60.9% accuracy. One of the disadvantages of this method is the bias caused by the equal prior probability assumption for three cases.

Kaur and Singh [79] proposed a statistical technique for classification of the real time recordings from myopathic, motor neuron disease and healthy cases. A statistical pattern recognition technique also based on Euclidean distance was used for classification MUPs into three different classes. The author mentioned that the results were found to be satisfactory as compared with the available literature, however the accuracy has not been reported.

Pino and Stashuk [80] used four methods to characterize a set of MUPs into normal, myopathic, and neuropathic cases. The four methods include pattern discovery (PD), linear discriminant analysis with minimum Euclidean distance (LDA MED), LDA with generalized Euclidean distance (LDA GED) and naïve Bayes (NB). They measured the correlation between muscle characterization and the corresponding level of involvement of a disorder. To measure this relationship, EMG signals acquired through various contractions of several different muscles with different levels of involvement , and decomposed using QEMG into MUP templates. Seven features including amplitude, duration, area, number of phases, number of turns, size index (SI), and thickness were extracted from MUP templates. Mean and standard deviation of features were used as inputs to the classifiers.

Experiments were conducted using 1500 MUPS including 500 MUPs from normal muscle, 500 from myopathic muscle and 500 from neuropathic muscle with 25%, 50% and 75% disease involvement. PD, NB and LDA GED achieved a similar accuracy of 96%. LDA MED with 93% achieved lowest accuracy. LDA that exhibited inconsistent behaviour across different feature sets was deemed not appropriate to determine the level of disease involvement. This study showed a direct relationship between the characterization measure and the level of disease involvement.

Hamilton-Wright et al. [24] used a Bayesian aggregation classifier to characterize a set of MUPs collected together from the same muscle. They assumed that MUP parameters have Gaussian distribution. The study was applied to MUPS collected from 57 subjects including (17 with symptoms of non-specific arm pain and 40 healthy). Each subject was described by feature vectors consisting of the mean and the standard deviation of each of the MUP parameters: amplitude, duration, phases, turns, area/amplitude ratio, inter-discharge rate, firing rate, and mean MU voltage. Three classifiers were implemented and compared. First, each individual MUP was classified independently using a Bayesian normal density discriminant function classifier, and the results were used as the baseline. In the second stage, MUPs from the same muscle were classified using a Bayesian probabilistic aggregation model to produce muscle-level characterization results. In the third stage, a majority voting was used to aggregate results for the set of MUPs collected from the same muscle. The results show that the Bayesian aggregation and voting classification of MUPs achieves quite similar accuracy. The author also noted that the distribution underlying EMG data may be significantly different from a Gaussian normal distribution [24].

4. Discussion

In this paper, a detailed review of the common methods of classifying EMG signals for the diagnosis of neuromuscular disorders have been presented. All of the papers cited are presented in Tables 1 and 2, grouped by classifier type, and annotated by their classification performance and year of publication.

The survey shows that using an ANN is the most popular classification method (measured by the number of implementations), for the classification of EMG signals [12,31,33,36–39,41,43,44].

There are several different models of ANN that were used including multi-layer perceptron NN (MLP), feed forward NN (FFNN), modular NN (Mod NN), recurrent neural network, self-organizing feature maps (SOFMs), and probabilistic NN (PNN). Applying an appropriate learning algorithm is very important factor to achieve higher accuracy. For example, back-propagation suffers from long learning times, especially when the data set is large, and it also suffers from poor learning-discrimination performance in EMG classification due to the high variability in the EMG data. SOFM can overcome these drawbacks.

As a consequence of this review it can be realized that the accuracy of the ANN models can be enhanced by using the SOFM learning method combined with LVQ [31,33,43], for example the SOFM combined with LVQ [43] can yield 97.6% accuracy. The additional use of LVQ improves the classification accuracy by defining the class borders [33]. Also, the SOFM model has the lowest computational cost compared to the back propagation and the GBML algorithms [49].

Results obtained by Abel et al. [31] and Katsis et al. [12] demonstrate that using RBF networks usually requires more neurons than required by the standard FFNN for the same classification problem. Although, RBN increases the speed of the classifier with a smaller training set, the reported classification accuracy in most studies is higher when using standard FFNNs.

Furthermore, a WNN [41] with sufficient accuracy (90.7%) and speed was found to be one of the strongest techniques among ANNs to provide clinically useful information. Also a WNN can handle waveform variability better than other classifiers. To date, however, not enough research employing WNNs for EMG classification in neuromuscular pathology has been completed to allow a general statement to be made.

Based on the accuracy reported by Pattichis et al. [37], Pattichis and Schizas [49], and Kaur et al. [52] using mean and standard deviation values of EMG parameters as input to a neural network contributes significantly to the learning process.

Using fuzzy logic for EMG classification [46–48] can greatly improve transparency of the system. The main weakness of this approach lies in the relatively weak learning capabilities of fuzzy systems. Hence the rules must be built using existing domain knowledge.

Constructing fuzzy rules directly from domain knowledge is a very difficult task for human experts if it involves high-dimensional feature spaces, because humans have difficulty in processing data problems based on more than three-dimensions. This is of interest in QEMG data, as machine-generated rules can supplement and extend the expert domain knowledge available.

Decision trees [42,56,57] can greatly increase transparency of a diagnostic system, but this approach performed well only with a few highly relevant feature sets. By increasing the number of features the accuracy of a decision tree will be decreased. Also the greedy characteristic of a decision trees leads to oversensitivity to the training set and to noise.

In all studies examined [42,44,45], PNNs achieved higher accuracy compared to the standard neural networks. The PNN training process is faster than the back propagation method, and convergence to an optimal classifier is guaranteed as the training set size increases. PNN design can additionally overcome the local minima issue. PNN models are derived from a Bayesian network and therefore they require unrealistic simplifying assumptions. Also PNNs are slower than a multilayer perceptron in classifying new cases. The other disadvantage of a PNN is that it requires a large amount of memory space to store its model.

Using a SVM is the second most popular model for classifying EMG signals for neuromuscular pathology [12,40,51–53,57,58]. The ability to generalize beyond the training examples is the main advantage of SVM classifiers [74]. Applying a SVM method assures the best generalization capabilities based on the given training data set and generally results in classifiers that are insensitive to over-fitting problems.

The highest accuracy reported using a SVM was 99.4%, obtained using a wavelet-SVM classifier [54,55]. The average accuracy rate using a SVM approach was 93%. The recent novel approach by Subasi [58] obtained a 96.75% accuracy rate by using PSO combined with SVM.

The highest level of accuracy among all the papers reviewed was 100% reported by Kaur et al. [51,52] using a SVM classifier. This success rate is impressive, however the small size of the data set used in this work is insufficient to be representative of the real world problem. Also, training on such a small size data set is subject to over-fitting.

Despite their high degree of accuracy, the ANN and SVM models suffer from lack of transparency which is an important factor in the success and acceptance of a clinical decision support system.

A FSVM classifier using DWT features [57] has the potential to become a promising approach for classification of EMG signals. This approach is superior to its counterparts including multilayer neural networks, radial bases function NN, decision trees and SVM classifiers in respect to classification accuracy, reliability, and insensitivity to over-fitting. The main advantage of a FSVM is the use of a membership function instead of fixed weights, which produces narrower margins, thereby removing noisy data.

Hybrid systems such as the fuzzy integral combination of the outputs of multiple ANNs [50] and neuro-fuzzy system [35] with accuracy rates between 95% and 98% were found by the authors cited here to be the most efficient methods in terms of accuracy and transparency for EMG classification.

Hybrid systems not only may yield high accuracy, but also can provide transparency which is an important requirement for diagnostic clinical decision support systems [33,81–83].

Some drawbacks of neuro-fuzzy systems are over-fitting, interpretability and time complexity. Neuro-fuzzy systems generate a large number of rules with relatively low significance levels which lead to over-fitting. The large number of rules additionally leads to poor knowledge interpretation. Hybrid systems may potentially provide a promising classification method if they combine with a rule selection method that can select the most representative fuzzy rules.

5. Conclusions

The review demonstrates that ANNs and hybrid neural networks play important roles in EMG classification and yield high accuracy results. Back-propagation generally leads to high accuracy results, but it suffers from poor learning-discrimination performance in EMG classification due to the various noise signals. WNNs with sufficient accuracy and speed were found to be one of the most ideal techniques to provide clinically useful information.

One may also note, based on the materials reviewed, that a SVM is an appropriate model for multi-class classification and, therefore, is a strong candidate for neuromuscular diagnosis, however there remain significant challenges. While selecting a kernel for a SVM is a difficult task, the main disadvantage of the SVM, ANN and WNN approaches is the near-total lack of transparency.

A NFS approach has the potential to become a promising classification method if it is combined with a rule selection method that can select the most representative fuzzy rules. In addition, this technique has very promising transparency possibilities.

Conflict of interest statement

None declared.

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