A review of Various Classification Algorithms of EMG Signals

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ABSTRACT

Electromyography (EMG) signals are muscles signals that enable the identification of human movements without the need of complex human kinematics calculations. Electromyography (EMG) signals are becoming increasingly important in many applications, including clinical/biomedical, prosthesis or rehabilitation devices, human machine interactions, and more. Classification analysis in electromyography (EMG) is very desirable because it allows a more standardized and precise evaluation of the neurophysiological, re-habitational and assistive technological findings. The proper algorithm to classify human movements from raw EMG signals has been an interesting and challenging topic to researchers. Different pattern recognition-based classification algorithms are applied on extracted features to classify the gestures. In current years, many academics have focused on finding suitable features and classifiers to realize high precision. Recent Computational Intelligence studies show that EMG signals can be processed by machine learning methods and more classification analysis in electromyography (EMG) is very desirable because it allows a more standardized and precise evaluation of the neurophysiological, re-habitational and assistive technological findings. The classification accuracy varies according to different classifiers. This paper reviews the common types of classifiers favored by researchers to recognize human movements based on EMG signals. In this paper, Various machine learning methods, like support vector machine (SVM), k-nearest neighbors (KNN), artificial neural network (ANN) and Extreme Learning Machine (ELM) are displayed as classification algorithms. In the present work, the paper has presented an overview of various existing researches in the field of electromyographic signals classification involving various state-of-art techniques.

Keywords: electromyography EMG; classification; Surface electromyogram (sEMG); Finger movements classification; Machine learning; ANN; SVM; KNN.

1.INTRODUCTION

The term EMG is known since the 1943 when presented by Weddell et al. for the description of clinical application [1]. A further progress was made due to limited technology at the time until several decades later that. During the late 1960s to mid-1970s the first pattern recognition systems were developed using myoelectric inputs, however once again technology proved to be a significant limiting factor. The next major step forward occurred when Hudgins et al., presented a multifunctional myoelectric control system in 1993, which achieved good performance in classifying multiple movements using multiple signal features and an artificial neural network classifier [2]. Electromyography (EMG) is an electro diagnostic medicine technique to measure muscle responses or electrical activity produced by skeletal muscles [3]. In other words, EMG is a bio-potential signal acquired through the muscle fiber body by electrodes to analyze muscle activity and these signals measure the electrical activity during contraction and relaxation phase of the muscle fiber [4]. Electromyogram (EMG) signals have been progressively more used for hand and finger gesture acknowledgment. However, most studies have concentrated on the wrist and whole-hand gestures and not on individual finger (IF) gestures, which are considered more challenging [5]. Electromyography (EMG) signals can be used to:

1- Control of powered upper-limb prostheses.
2- Make device control commands for rehabilitation (prosthesis) equipment such as robotic prostheses and in generic man-machine interfaces for Human Computer Interface (HCI) [6].
3- Diagnose various muscle related diseases, follow the disease process, estimate the effect of treatment [**7**].
4- Obtain several information related to muscle activity.
5- Find the effect of symptoms such as muscle weakness, deformity, stiffness, and shrinkage.
6- Test the problem of the motor like involuntary muscle twitching and nerve compression, injuries such as muscle degeneration [4].

In fact, EMG signals consist of two types: surface EMG to control prosthetic devices, and intramuscular EMG [6].

2. Surface-EMG

There are two methods to measure EMG signals: invasive and noninvasive. For invasive methods, it uses needle electrodes while a noninvasive method uses electrodes above the skin surface of the patient's body [4]. Different types of sensors are used, but surface electromyography (sEMG) sensors are the most important ones to perform the recognition of the specific hand movement [8]. Surface electromyogram (sEMG) refers to a bio-signal acquired from the skin surface during the contraction of skeletal muscles, and a different signal waveform is generated, depending on the motion performed [9]. Surface EMG is a kind of non-stationary signal, and its strength is sensitively proportional to the degree of muscle activity, which makes it can accurately represent the gesture of fingers [10]. From other side, it is the product of all the action potentials which are selected from the muscles below skin surface electrode.

Surface EMG signals collected from the upper hand muscles show specific patterns for a particular finger movement, which is also true for combined (more than one) finger movements [11]. sEMG accurately identify the body's movement intention by sEMG signal. Today, the control of finger movements with sEMG signals is widely studied because are widely used in the recognition of finger movements [7].

3. Classification of finger movements

Classification of finger movements using EMG signals has not received much attention, most studies are either focused on gross hand movements or a combination of finger movements. Finger movement classification is a necessary precursor to control individual finger movements of an EMG-controlled prosthetic hand [12].Finger movements classification and prediction are one of the hot-topic research areas for biomedical engineering, machine learning and computer sciences [7], because the detected signal has a lot more difficult to distinguish between movement classes due to the reduced amplitudes of the already inherently weak signals that are generated and cross over where the same muscle control multiple fingers i.e., mid, ring and little fingers [13].

Classification analysis in electromyography (EMG) is very desirable because it allows a more standardized and precise evaluation of the neurophysiological, re-habitational and assistive technological findings [14]. Different factors, such as electrode position, muscle fatigue and sweat, cause variations in the EMG pattern over time and result in misclassification; hence, a classifier should be able to cope with these flaws. Moreover, the classifier must be fast and proficient enough to meet real-time restraints and classify the novel patterns during the online training [15].

4. Various Classification Algorithms of EMG Signals

The classification of sEMG signals can be achieved using a wide range of classification algorithms like support vector machine (SVM), k-nearest neighbors (KNN), artificial neural network (ANN), convolutional neural network (CNN), etc., [16].

4.1 Artificial Neural Networks

ANNs are computational models used in machine learning, consisting of a large group of simple interconnected processing units called artificial neurons. They are an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. Similar to other machine learning means, ANNs are used to resolve a wide variety of tasks within areas that are problematic to solve. A simple ANN is given in figure 2 [17].

The collection of neurons can be divided into three types of layers:

1-The input layer

2-The hidden layer(s)

3-The output layer.

The neurons in the input layer and output layer are connected to the outside environment. The weights are regulated to try to bring the network's output nearer to the environment providing the inputs. A network can have n hidden layers, hence the use of the term Deep Learning. An ANN is a supervised learning, if the desired output is known. In unsupervised learning, the network learns by input data with no associated output [3].

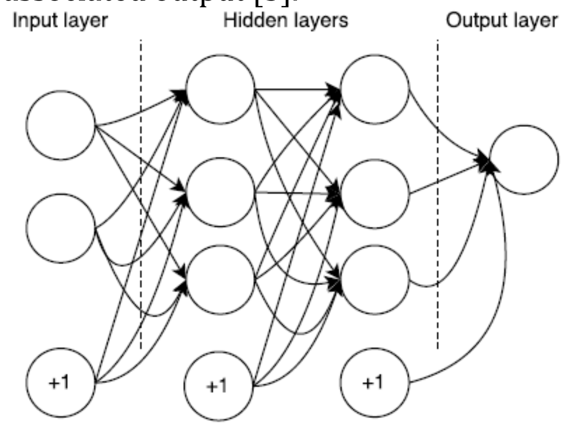

Figure 2: A simple Feed-Forward Neural Network with two hidden layers. The circles labeled "+1" are called bias units.

[18] Mochammad Ariyanto et al. focused on the feature extraction and pattern recognition of five finger movement classification using EMG raw signals based on one channel EMG signals. The 16 utilized features in time domain fed up to the input of network and classified using Back Propagation Artificial Neural Network with two layers feed forward network. The training of ANN pattern recognition used Levenberg-Marquardt training algorithm and the performance utilizes mean square error (MSE). The accuracy of each finger movement is 100%. The confusion of each finger movement is 0% that means there is no miss classification during training process. The overall performance is 100 % and overall error is 0 %. It is noticed that no miss classification during training process. Besides that, Matlab provided easy way to design, create and implement neural networks. The disadvantages of the used neural network is that it needs training to operate and requires high processing time for large neural networks. Back Propagation algorithm minimizes error in the output by making adjustments to the weights in the network. Besides that, it is easy to implement, and can maintain the efficiency of the network.

4.2. Support Vector Machine (SVM) model

Support vector machines are machine-learning algorithms. SVM is a tool that is frequently used in order to classify a particular input data into various groups. In order to ensure proper classification, the classifier is trained with some training data [17]. Support vector machine can classify EMG signals correctly with a higher classification rate suitable for designing prosthetic and assistive devices, therefore, this classifier has been widely used for EMG classification [19].

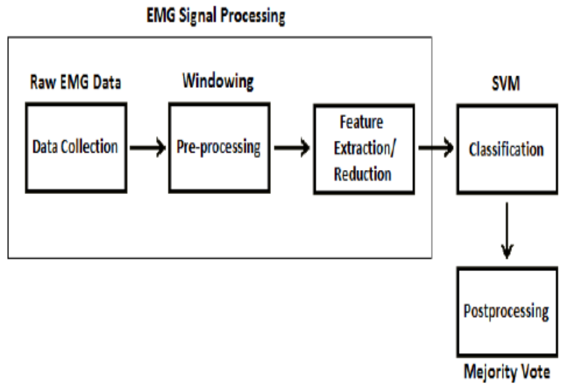

Fig. 5: Step-by-step procedure of EMG pattern recognition using SVM.

[20] Maryam Alimohammadi Soltanmoradi et al introduced a new method for surface electromyography (EMG) classification that it is used for controlling robot by using two EMG electrodes located on the human forearm. SVM is used as a classification method with accuracy approach to 80%. The results of the study provide a basis for the development of prosthesis devices that it is utilized less EMG channels. The limitations of their study that the SVM pattern recognition method is hard to implement with many features without feature reduction.

4.3. KNN (K-Nearest Neighbor) model

KNN algorithm is a supervised machine learning method widely used in clustering problems and non-generalizing learning where these models won't construct a general internal model, however, they store different instances of the training data. The optimal value for k is based on the type of data [21].

In this method features are classified based on their nearest neighbors' class, and it rates a pattern by regarding the most similar labeled training samples. The number of adjacent samples which are taken into account is defined by the parameter k (number of nearest neighbors) [20]. **Turker Tuncera et al [7].** presented a novel MCBP based sEMG signal classification method and can be used in prosthetic device control. The proposed classification method evaluates by three cases. In the first case, the raw sEMG signals are utilized as input. In the second and third case, sEMG signals are divided into frames and these frames are utilized as input. In the classification phase, k-nearest neighbor (k-NN) and support vector machine (SVM). The proposed MCBP based method achieved 99.17%, 99.70% and 99.62% classification rates using SVM classifier according to Case 1, Case 2 and Case3 respectively. The results show that the study is a highly accurate method. The SVM pattern recognition method is hard to implement with many features without feature reduction. Additionally, the kNN classifier requires large memory to store all the training patterns to compare each testing sample based on distances.

4.4. GB Classifier

GB is a supervised learning algorithm based on the principles of tree boosting. Boosting can be defined as an ensemble algorithm that creates its predictors sequentially rather than independently. In the boosting technique, each new tree is an addition on a modified version of the original data set. Boosting algorithms combine the results of the sequential predictors using a weighted averaging technique to make a final decision. This basic boosting process is shown in Fig. 6. This step-by-step operation allows the algorithms to learn from the mistakes of the previous predictors and this knowledge helps the algorithm to interpret the actual class with fewer iterations [11].

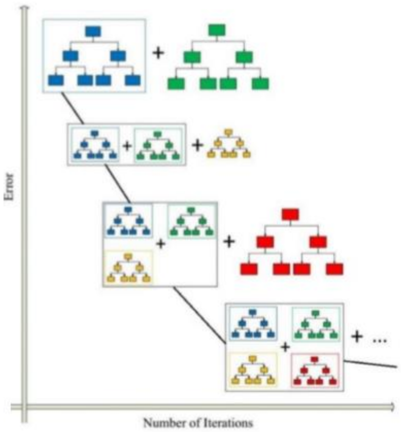

Fig. 6. The estimation process of GB classifier.

[11] Chyon Krishno Bhattachargee et al. described a method utilizing Digital Signal Processing (DSP), Machine Learning (ML) techniques and a dataset in the public domain shared by Rami N. Khushaba. After creating an operational dataset from the EMG signals, the next step is to extract desired features from them to classify ten different hand gestures based on the extracted features form EMG signals collected from eight participants using GB classifier. To reduce complexity and make the signals more understandable to the algorithm statistical and frequency features were extracted from the raw EMG signals and used for classification. Fig. 7 provides a graphical view of the described methodology.

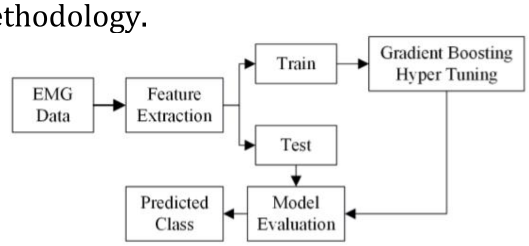

Fig. 7. Block diagram of the proposed EMG classification method.

It is noticed that the effectiveness of the method is proven by testing it on a practical EMG dataset. However, there remains room for improvements through selecting more relevant features, calibrating the classifier's internal parameters, as well as providing a larger dataset with more accurate EMG information. Through some modifications, the model can be used for real-time hand gesture classification.

4.6. Extreme Learning Machine

ELM is a learning scheme for single-hidden-layer feedforward networks (SLFNs) whose hidden layer does not need to be tuned. It needs fewer optimization constraint, better generalization functioning and faster learning time than SVM. The hidden parameters can be independently determined from the training data, and the output parameters can be determined by pseudo-inverse method using the training data.

[22] Khairul Anam et al. used Spectral Regression Discriminant Analysis (SRDA) to extract more features and Extreme Learning Machine (ELM) instead of SVM for the classification. This combination, SRDA and ELM along gives a fast and good classification system for individuated and combined finger movements with the classification accuracy of 98.45 % by using only two EMG channels. The use of SRDA gives chance to add more features in order to increase the classification accuracy with reasonable time processing.

In appendix A, Table 1, list important EMG dataset for the classification methods that used at above.

5.CONCLUSIONS

Various machine learning methods, have been implemented as classification algorithms. Most studies achieved at least a 90% accuracy in classifying. EMG signals were classified using SVM, received excellent average accuracy which is helpful for arm prosthesis research. SVM classifier can be effectively trained for classification of EMG datasets. But, the limitations of the SVM pattern recognition method is hard to implement with many features without feature reduction. ANN is one of the most popular Machine Learning Method has been widely used to classify the EMG data. In order to increase the classification success, ANN can combine the best of both time and frequency domain measures. Although of these advantages, the achievement of both high accuracy and low response time is still a challenge. kNN classifier requires large memory to store all the training patterns to compare each testing sample based on distances. The effectiveness of GB classifier is proven by testing it on a practical EMG dataset and through some modifications, the model can be used for real-time hand gesture classification. ELM is a fast and accurate identification of multi-finger movements with a small number of EMG channels. The learning of ELM can be carried out extremely fast compared to the other learning algorithms. kNN classifier requires large memory to store all the training patterns to compare each testing sample based on distances.

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Appendix A

Table 1. EMG Classification for various algorithms.

Ref.	Number of electrodes	Number of finger movement //classes	Number of repetitions /class	Total number of repetitions/ subject	Number of subjects	Total number of repetitions	Time for each repetition (s)	classifier
7	8	15	3	45	8	20	20	SVM
11	2	10	10	100	8	800	5	GB
20	2	2	6	12	8	5	5	SVM
22	2	10	3-6	30-60	8	240-480	3-5	ELM