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Review of Electromyography Signal with Detection, Decomposition, Features And Classifier Theories

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Abstract—Muscle is an essential organ of the body accountable for movements. EMG has a wide range of research from electrode design to recording methods, analytical methods, and various applications. The aim of this paper is to review EMG to understand and decomposition in a concise manner. Extraction and classification of features are has considered demanding tasks as it allows a consistent assessment of the neuromuscular diseases. This manuscript has described various methods of extraction and classification of features that would help to understand their nature and process of adoption. In the evaluation of EMG signals, a number of analysts had tried their hands, so in this paper, we have tried to integrate best of the best researchers that could be advantageous for further analysis. Comparison of the traditional researchers by J. L. Betthauser et al., O. W. Samuel Zhou Hui et al. and Xiangyang Zhu et al. has been conducted to interpret the optimum techniques for the evaluation Betthauser et al. has shown 89% of accuracy with Enhanced Adaptive Sparse Representation Classification (EASRC) technique, O. W. Samuel Zhou Hui et al. has shown 92% of accuracy with LDA and ANN technique and Xiangyang Zhu has used LDA-CA technique with 91% of accuracy.

Keywords—Electromyography, Motor Unit Action Potential, Detection, Decomposition, Features, Classifiers

I. INTRODUCTION

The worldwide increase in the number of diseases such as arthritis, stroke, and paralysis has posed new challenges to the healthcare field. Conventional artificial rehabilitation training cannot meet current medical needs. Robot technology provides a new solution for the rehabilitation and support of people with disabilities [1]. With all kinds of rehabilitation therapy, the human-robot interface stands out because we can simulate the structure and movement of the human body accurately and quickly. Usually, there is a development of compound human limb models that amalgamates the neural signals including kinetic and kinematic data to analyze the human control schemes. Though, because of the intricacy, the computational blocks within the model could be executed independently [2]. For the accommodation of disparity and amendment, tuning methods are needed that sluggish the processing time and build the complex to be utilized in real-time applications. In this era, numbers of researches are utilizing novel techniques to fit into real-time applications that result as a hurdle in the human-robot interface development. This article aims to analyze and examine an EMG (Electromyography) signal which is considered as a significant tool in the diagnostic estimation of peripheral neurological disorders.

A. EMG Signal origination

EMG is a representation of the current produced by ionic flow in the muscle fiber membrane which proliferates via the superseding tissues to reach the destination surface. Muscle fibers innervate in groups known as motor units being activated to attain neural signals from the nervous system and generating a Motor Unit Action Potential (MUAP) [3]. Activation MUAP with the central nervous system is iterated continuously for as long as the muscle is needed to produce the action or action. MUAP from simultaneously active motor units overlays to generate EMG signal. The diagrammatical illustration of MUAP genesis is shown in figure 1. EMG signal is problematic in nature and its amplitude ranges from 0 to 10 mV. The range of dominant energy is from 0 to 500Hz frequency range [4]. These signals are generally influenced by internal and external noise sources. The attainment of the EMG signals is from the surface pre-processed from the precise display, analysis, and recording. Below equation (1) depicts an EMG signal model:

$$x(m) = \sum_{s=0}^{M-1} i(s)e(m-s) + v(m) \qquad (1)$$

As shown in equation (1), x(m) is modeled EMG signal, em is the point processed that illustrated the firing impulse, i(s) illustrates the MUAP, v(m) is the zero mean additive white Gaussian noise and M is the number of motor unit firings. EMG signal has an amplitude range of 0-10V before amplification. These signals attain noise when traveling via varied tissues. It is significant to recognize the electrical noise characteristics that might influence the EMG signals and its categorization is into below types [6]:

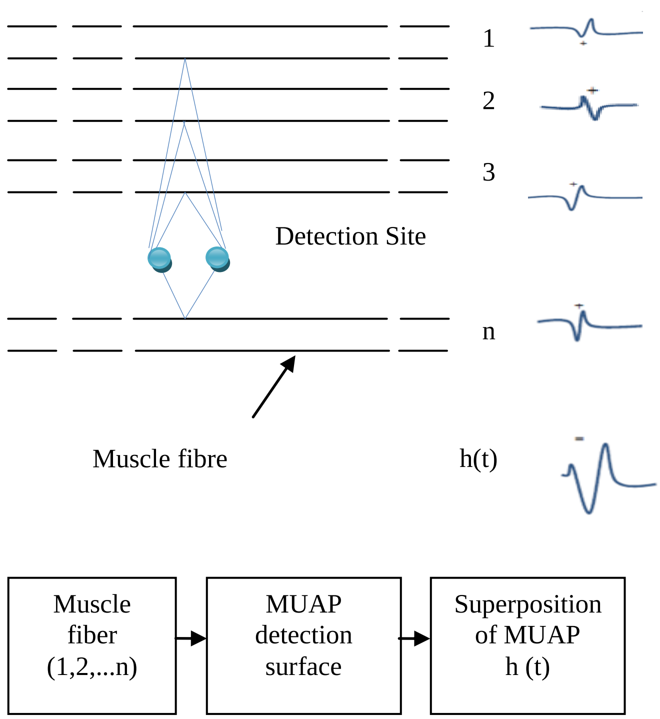

Figure 1.Superposition of MUAP to form EMG signals [34]

1. Inherent noise in electrical equipment: The electronic equipment can obtain noise that cannot be eradicated. It can only be reduced by the electronic components of high quality.
2. Ambient noise: The electromagnetic radiation is considered as the noise source for this type of noise. The surface of the human body is continually being immersed by electromagnetic radiation, and it is almost unfeasible to evade exposing it to the earth surface earth. The magnitude of the ambient noise can be one to three orders of magnitude larger than the EMG signal.
3. Motion artifact: As motion artifacts are considered into the system, information can be biased. Motion artifacts might cause data to be irregular. Generally, two major motion artifacts are considered, namely, electrode interface and electrode cable. The reduction of motion artifacts is according to the appropriate electronic circuit setting and designing.
4. Inherent signal instability: The EMG amplitude is essentially random. The EMG signal is influenced by the firing rate of the motor unit that usually fires with a 0 to 20 Hz frequency range. This noise is acknowledged as unnecessary, though, the noise removal is considered as a significant task.

The features which affect the EMG signals might be classified as well. The aim of classification is to optimize the signal analysis algorithms that could be designed in a reliable way [7]. The factors that influence the EMG signals are classified into three general categories as depicted in tabular form in Table 1.

Table 1.Factors influence EMG signals

Factors	Narration
Causative factors	These factors impose a direct influence on the signals and are categorized into two types, namely, Extrinsic and Intrinsic.
	Extrinsic
	It occurs because of the electrode placement and structure. Factors such as electrode shape, an electrode surface, distance amongst the detection surface of the electrode, electrode location by means of muscle surface motor points and by means of muscle lateral edge, detection surface orientation as per the muscle fiber effects the EMG signal.
	Intrinsic
	Factors such as biochemical, anatomical and physiological occur because of the varied fiber type composition, a number of active motors, fiber diameter, blood flow, location and depth of active fiber and number of tissues among the electrode and muscle surface.
Intermediate factors	These are the physiological and physical phenomenon from one or more causative features. The motive behind this could be the aspects of bandpass filtering of the electrode lone with the action potential superposition, detection volume, action potential conduction velocity that proliferates with the muscle fiber membrane. Though, intermediate factors could be caused by the crosstalk of nearby muscle.
Deterministic factors	These factors are persuading with intermediate factors. The number of motor firing rate, active motor units and even the mechanical interaction among the muscle fiber has straight EMG signal bearing information. Duration, shape, and amplitude of the motor unit action potential could even be accountable.

The quality of EMG signals could be enhanced by considering one of the below methods [8]:

- The highest amount of information should be contained by signal to noise ration from EMG signal as probable and contamination of less noise amount.

- EMG signal distortion should be less as feasible with no redundant filtering and signal peak and notch filter distortion.

The remaining paper is scripted as follows. Segment number 2 has proposed the detection of EMG signals. Segment 3 covers the Literature insights of EMG. Segment 4 prescribed the comparison of existing Work of EMG. The crux of an article has been explored in section 5 following the references.

II. Detection of EMG signal

Accurate detection of discrete events in sEMGs (such as phase transitions in active modes associated with fast motion response initiation) is a significant issue in motor system analysis. Numbers of methods are considered for the detection of on and off muscle timings [9].

The most general techniques of resolving motion-related events from EMG signals include trained observers visual inspection. Single threshold method contrasts the EMG signals to arbitrary thresholds is the most instinctive and general technique for computer-based temporal positioning of muscle contraction activity and is dependent on a contrast of the rectified original signal to an amplitude threshold with the value that relies on the average power of the background noise. It could be used to surmount a few problems associated with a visual inspection. Though, this method is usually unsatisfactory because the measurement result largely relies on the threshold choice. This approach typically relies on overly inspired standards and does not permit the user to autonomously set detection and false positive possibilities [10].

$$P_{el} = \exp\left(\frac{\ln(P_\delta)}{1+10^{SNR/_{10}}}\right) \quad (2)$$

Equation (2) is the case of single threshold methods, the relationship among the detection P_{el} probability and the P_δ shows the probability in which the noise sample is over the threshold δ.

It has been mentioned earlier by DA Winter in 1984 that the above method is unacceptable as it is dependent on the threshold choice. Therefore, later, double threshold detection was given by P. Bonato in 1998. These methods are better than that of the single threshold methods as double threshold methods has more detection probability [11]. Its detectors permit the user to consider the link among the false alarm and detection possibility having freedom of high degree as contrasted to a single threshold method. The user can modify the detector as per varied optimal criterion, therefore, by acclimated the characteristics performance of every application and signal [12].

$$P_e = \sum_{l=s_0}^{n} \binom{n}{l} P_{el}^{l} (1 - P_{el})^{n-l} \quad (3)$$

As depicted in equation (3), the (Surface EMG) sEMG signals recoding while intended dynamic contractions might be contemplated as a Zero-mean Gaussian process $t(u) \in M(0, \gamma_s)$ being modulated with muscle activity and is corrupted with independent zero-mean Gaussian additive noise $m(t) \in M(0, \gamma_n)$. When the detection probability is P_e, equation (3) corresponds to the double threshold method. The double threshold method behavior is rigid with the parameters, such as s_0 with the n as observation window length. The selection of the values is to lessen the false alarm probability and to enhance P_e for every appropriate Signal-to-noise-ratio (SNR). Lanyi and Adler in 2004 have observed that the discovery of Bonato is composite and is expensive as well. So, they have presented an authentic technique which is a replica of double threshold method is more stable, efficient and sensitive with less computation cost. It also provides more reliable and fast muscle on-off detection [13].

III. Decomposition of EMG signals

EMG signals are the superposition of the activities of different motor units. It is evident to disintegrate the EMG signals to acknowledge the methods related to nerve control and muscle. Numbers of methods are created by means of EMG decomposition that could be executed according to Principal Component Analysis (PCA) and wavelet spectrum matching of wavelet coefficients [13]. As per to J. Fang et al. in 1997, one or more Single Motor Unit (SMU) are registered at a similar timespan related to each other, particularly, while the contraction of strong muscles. The researchers have discovered a method by utilizing wavelet transform for the classification of SMU potentials and for the decomposition of EMG signals into basic SMU potentials. The method has a characteristic that it computes the SMU waveform similarity from the wavelet domain being very beneficial. This method is dependent on the wavelet domain for spectrum matching. The technique of spectrum matching is more efficient as compared to the techniques of waveform matching, generally, when there is an induction of interference with less frequency baseline drift. The method is originated for the multi-unit EMG signal decomposition with four varied strategies, namely, Spike detection, Signal de-noising, spike separation and spike classification as per the appropriate method. From the previous studies, it has been observed that the wavelet coefficient of fewer frequency bands is significant in the Action Potential (AP) differentiation as compared to higher bands [14].

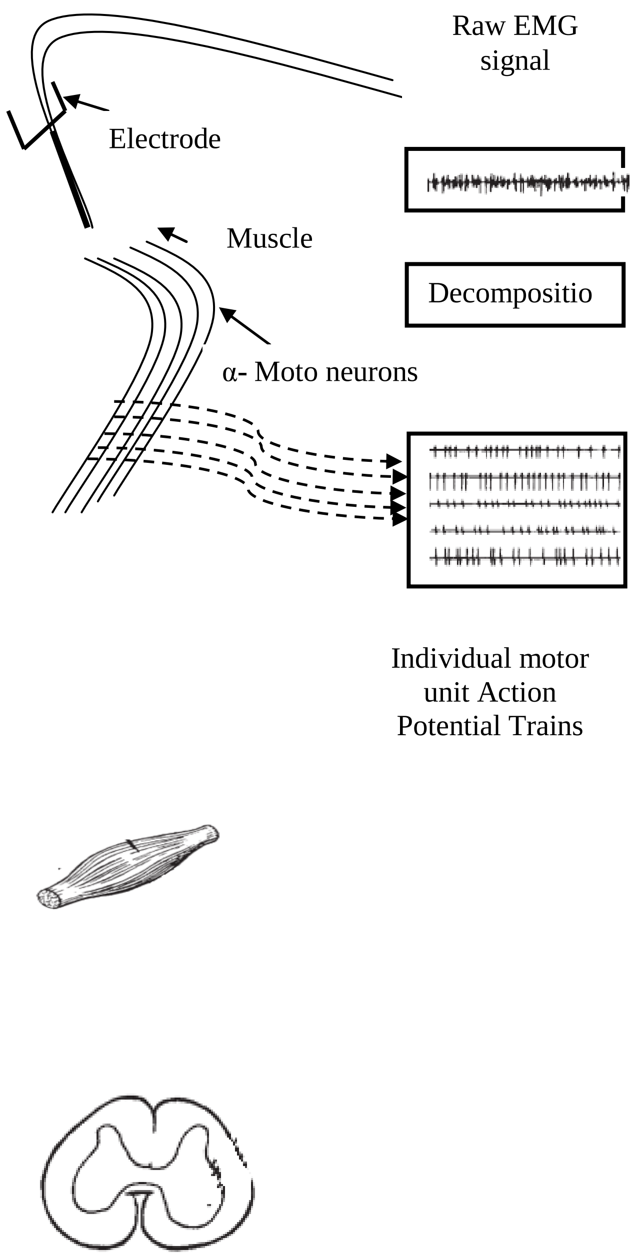

Figure 2. EMG signal decomposition [35]

The perception is designed pragmatically. R. Yamada et al. in 2003 has observed that high-frequency information is also evident for MUAP classification. To control the feature selection subjective criterion, the researchers have developed PCA for wavelet coefficients. The algorithm has four processing phases; Segmentation, Wavelet transforms, PCA with clustering. The benefits are that it does not need standard coefficient selection and consider the frequency information. The conceptual framework of EMG signal decomposition is depicted in Figure 2 and shows the relationship amongst the decomposed EMG signal and individual motor unit activity. It shows the procedure of discovering considerable essential MUAPTs which contributes to EMG signal detection [15].

$$\mathrm{MUAPT}_k(u) = \sum_{l=1}^{N_j} \mathrm{MUAPT}_{kl}(u - \vartheta_{kl}) \qquad (4)$$

Equation (4) is a representation of MUAPT of the kth motor unit, $\mathrm{MUAPT}_{kl}(u)$ is the MUAP achieved while lth motor unit; N_j shows the time when the motor unit fires and ϑ_{kl} is the firing time of the kth motor unit.

IV. EMG Features and Classifiers

A. EMG Features

Features are the characteristics of the representation of a signal with fewer dimensions. The purpose of the extraction is to discover fewer features that are chiefly informative and distinguishing. EMG features are analyzed in Time Domain (TD), Frequency Domain (FD) and Time / Frequency Domain (TFD) as well. The depiction of TD is the representation of the characteristics of the signal compared to the time. The features of TD recognize the characteristics of the signal that characterize its temporal structure. The illustration of the characteristics of the signal against frequency is the representation of the FD [16]. The frequency spectrum of some signal shows what frequency relies on that signal. TFD features administer the information for temporal and spectral characteristics as well of the signal. For EMG signal classification, varied features could be considered and every feature particularly lies in varied features as in TD, FD, and TFD.

1) Time Domain (TD)Features: The extraction of TD features is usually from the basic EMG signal for apparent implementation that becomes the pros for the EMG signals and the cons appear from the active EMG signals property, variation in algebraic properties on time, although, TD presumes the data as fixed signals. TD features are computed from the values of signal amplitude; therefore, much interference is obtained via a recording from other cons of the features. Varied features utilized in TD are defined below [17]:

- Mean: It is easy to implement and is a common feature of TD. It only discovers the EMG amplitude means with the signal sample length.

$$\mathrm{Mean}\ (\mu) = \frac{1}{M}\sum_{m=1}^{m} x_m \qquad (5)$$

- Variance: It is also known as the general statistical method utilized for TD feature extraction.

$$\mathrm{var} = \frac{1}{M}\sum_{m=1}^{m} (x_m - \mu)^2 \qquad (6)$$

- Standard Deviation

$$\mathrm{Std}\ (\sigma) = \sqrt{\frac{1}{M}\sum_{m=1}^{m}(x_m - \mu)^2} \qquad (7)$$

- Skewness: It is considered as a measure of irregularity of measure or signal of third order cumulative.

$$\mathrm{skewness} = \frac{\frac{1}{M}\sum_{m=1}^{m}(x_m-\mu)^3}{\sigma^3} \qquad (8)$$

- Kurtosis: It is a computation of the probability distribution peakness or it is the computation of fourth order cumulative.

$$\mathrm{Kurtosis} = \frac{\frac{1}{M}\sum_{m=1}^{m}(x_m-\mu)^4}{\sigma^4} \qquad (9)$$

- Mean Absolute Deviation: It is the average of data point's absolute deviation from their mean.

$$\text{Mean Absolute Deviation} = \frac{1}{M}\sum_{m=1}^{m}|x_m - \mathrm{ORT}| \quad (10)$$

- AR Co-efficient: These coefficients are the most accepted feature extraction for EMG signals. AR modeling achieves the signal that resides in the signal. It attempts to model the signal according to the prior signal data points.

$$y[m] = \sum_{l=1}^{q} b_l y[m-l] + f[m] \qquad (11)$$

As shown in equation (11), q is the AR model degree, $y[m]$ is the data signal with m data points, b_l is the AR coefficients real value and $f[m]$ is the white noise being independent of prior samples.

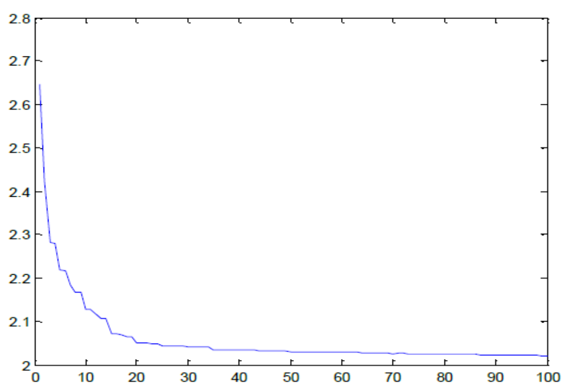

Figure 3. AR model selection criteria plot

AR model selection is considered as a significant issue as the AR model lower order cannot depict signal precisely, AR model high order is overfitted and produces more noise. It has been shown in Figure 3 that there is no variation after 20th order until 100th order. Therefore, the AR model can be used till 20th order. More changes are noticed till 10th order and some changes can be seen from 10th to 20th order.

2) Frequency Doman (FD) features: The wide utilization of FD features is because of Power Spectral Density (PSD). Usually, six FD features are utilized and their mathematical expressions are provided beneath [17]:

- Mean Frequency: This is an average frequency that is computed by dividing the EMG power spectrum product and frequency division by the total spectrum intensity.

$$\textit{Mean Frequency} = \frac{\sum_{l=1}^{N} e_l Q_l}{\sum_{l=1}^{N} Q_l} \qquad (12)$$

As depicted in equation (12), e_l is the spectrum frequency, Q_l is the power spectrum of EMG and $N$is the frequency length.

- Median Frequency: It is the frequency according to which the spectrum could be categorized into two regions with equivalent amplitude.

$$\sum_{l=1}^{MDF} Q_l = \sum_{l=MDF}^{M} Q_l = \frac{1}{2}\sum_{l=1}^{N} Q_l \qquad (13)$$

- Maximum to Minimum Drop in Power Density Ratio: It is the proportion of average mean power density value and minimum power density value including a user-defined frequency band.
- Signal to Noise ratio: It is a proportion of noise power and signal power and usually, computed independently.
- Power Spectrum Deformation: It is sensitive to the variations in spectral symmetry and gives a spectral deformation indication.

$$\text{Power Spectrum Deformatio} = \frac{\sqrt{N_2/N_0}}{N_1/N_0} \qquad (14)$$

As shown in equation (14), N_n is the nth spectral moment and is described as:

$$N_n = \sum_{j=0}^{j_{max}} Q_i e_i^m \qquad (15)$$

Q_i is the density value of power spectral at a frequency e_i as shown in equation (15).

- Signal to Motion Artifact Ratio: As mentioned above motion an artifact is an artifact of low-frequency EMG signals. They are below 20Hz. The signal-to-noise artifact was calculated as the ratio of power densities of all frequencies to below 600 Hz, and the sum of every power density in excess of a straight line along with the axis coordinates and the largest value of the average power density at frequencies above 35Hz.

3) Wavelet transforms (WT): It is designed to consider the issue of non-stationary signals. It considers time functions by means of fixed building blocks, wavelets and simple building blocks [19].

Figure 4 and Figure 5 is a representation of EMG signals of patients for neuropathic and myopathy diseases. The fixed building blocks, wavelets, and simple building blocks are derived from a generating function known as Mother Wavelet with dilation and translation operations. 1-dimensional WT can mathematically be defined as [20]:

$$W_g = \frac{1}{\sqrt{e}} \int_{-\infty}^{\infty} g(u)\, \vartheta^*\left(\frac{u-n}{e}\right) dt \qquad (16)$$

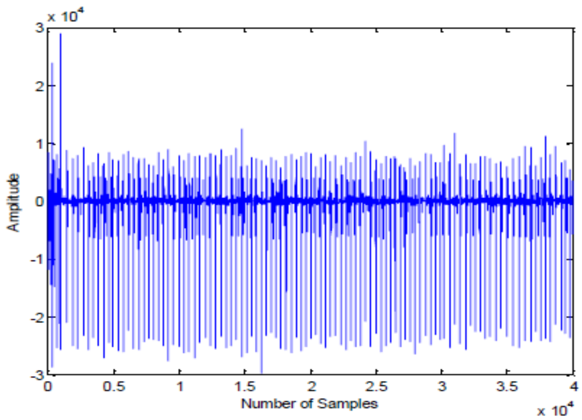

Figure 4. Neuropathic disease EMG signal [19]

Equation 16 shows ϑ^* as a conjugate function of $\vartheta(u)$ as

mother wavelet and e,nis termed as scale and shift parameter correspondingly.

4) Principal Component Analysis (PCA): PCA is known as one of the most reliable outcomes from applied linear algebra. It can be utilized in copious from for analysis from neuroscience and computer graphics as it is a non-parametric and simple technique for the extraction of persistent information from confusing dataset. It is utilized for discovering the data patterns similarity [20].

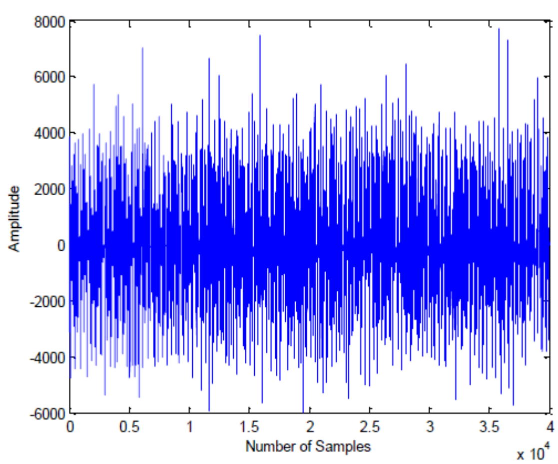

Figure 5.Myopathy diseases EMG signal

For some dataset, $Y = [y_1, y_2, y_3, \dots \dots y_n]$. Assume Y has n data a point, the novel set of data points is provided by below mathematical expressions:

$$Z_i = y_i - \tau \quad ; \quad i = 1,2, \dots, n \qquad (17)$$

As shown in equation (17), τ is the mean vector and to discover the covariance matrix of Z_i can be articulated as:

$$C_{mxm} = cov(y_i, y_z); i = 1,2,3, \dots \dots \dots m; k = 1,2,3, \dots m \qquad (18)$$

$$C = \sum_{k=1}^{n} (y_i - \tau)\, y_i - \tau^T \qquad (19)$$

In equation (19), n are the data points. The Eigen value μ_i and Eigen value ϑ_i of covariance matrix c, captivates:

$$C_{\vartheta_i} = \mu_i \vartheta_i \qquad (20)$$

$$D = [\vartheta_1, \vartheta_2, \vartheta_3, \dots \vartheta_n] \qquad (21)$$

Dataset W can be projected into Eigenvalues, then, the following expression is achieved:

$$Q^{nxm} = F^T W^T \qquad (22)$$

Equation (22) shows Was $W_1, W_2, .. W_n]$ and mapping of Q can be done in original coordinates, and [21]:

$$W^T = FQ \qquad (23)$$

F is an orthogonal matrix and $F' = F^T$

$$W^T = F'Q' \qquad (24)$$

B. EMG classifiers

Numbers of classification algorithms were considered in the past for EMG signal recognition. This segment analyzes the most accepted classification algorithm with the significant properties for EMG recognition. The classification algorithm estimates the data class as illustrated by feature vector by depicting the novel signal in condensed dimensionality [22].

K-Nearest Neighbour (KNN): The most common nearest neighbor technique version classifies the unknown sample on k vote's f its nearest neighbor than on single nearest neighbor. The classification procedure of K-nearest neighbor is termed as k-NN. When the error cost is equivalent for every class, then the unknown sample estimated class is selected as a class being symbolized as KNN collection sample. It does not acknowledge a priori assumptions for the distributions from the arrangement of training instances. It considers classification class training and a novel sample can be classified with the Euclidean distance calculation to nearest training case and then the sample classification is determined with the point sign. The idea has been extended by considering K-nearest points and with the assignment of majority signs [23]. The enhanced values of K assists in lessening the noisy points effects in the training datasets and the k selection is generally considered via cross-validation. Accordingly, with the input test sample vector of y features of n dimension:

$$p(y, x) = \sqrt{\sum_{k=1}^{m} (y_j - x_j)^2} \qquad (25)$$

- The training instances are the vectors in the space of multidimensional features with a class label. The algorithm's training phase merely stores the class labels and feature vectors of training samples. While classification, K is considered as user-defined constant the classification of the unlabelled vector is according to the label assignment between the k training samples adjoining to query point.
- Support Vector Machine (SVM): SVM has been developed by Vapnik as a classification technique. It is related to the kernel based classifier family. It totally maps the data in the form of feature space in which the decision boundary divides the classes which might exist. An illustration of SVM is shown in Figure 6 that shows that when the data is linear, there is a separation of a hyperplane in form of the linear kernel that could be utilized for the classification of data and is termed as Linear SVM. h hyperplane divides the two regions §- and §+ with two points classes correspondingly the margin has been represented by the dotted line [24].
- For the high transitional and non-linear data, the liner hyperplane formulation is enhanced to develop a non-linear SVM kernel that converts the input data into high dimensional feature space. For high dimension feature space, the data could be linearly divided by using linear SVM formulation.

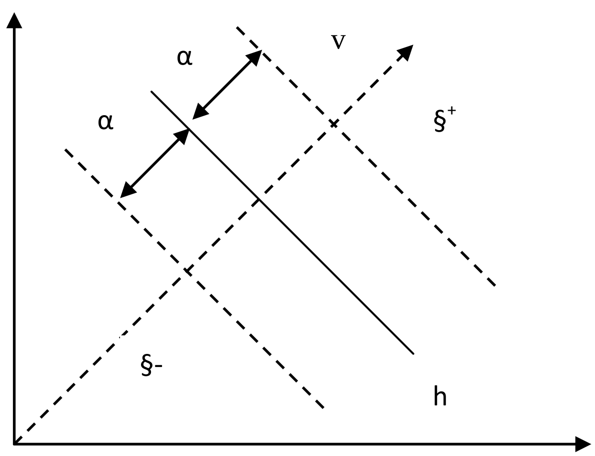

Figure 6. SVM classifier with h hyperplane [38]

The data mapping is done implicitly to a different space, usually with more dimensionality with the kernel function. It though discovers the best decision boundary by enhancing the margin among the different class boundaries which are controlled with regularization constant.

- Fuzzy Logic (FL): In current years, Fuzzy logic has proven to bring new potential to problem analysis of biomedical signals. The fuzzy theory is composed of membership functions and fuzzy sets of variables that subsist in rule bases and fuzzy sets to describe uncertainty, fuzzification procedure to discover the defuzzification process and output value to achieve crisp value from the fuzzified output value.

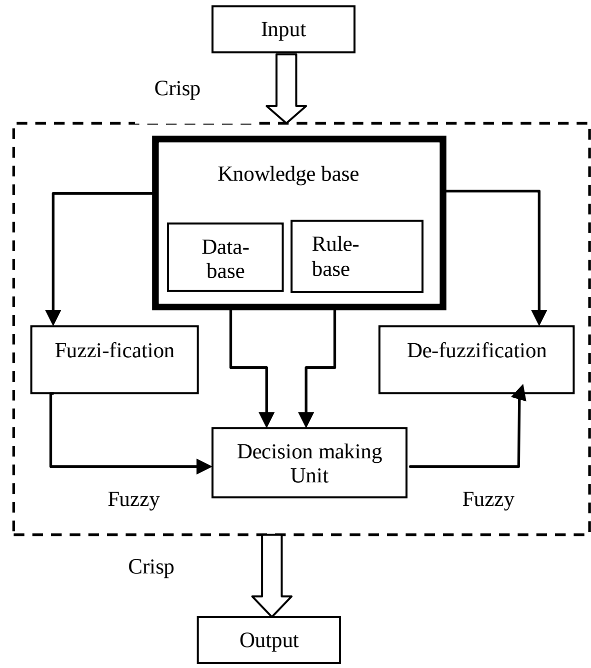

Figure 7. Fuzzy Logic Classifier [39]

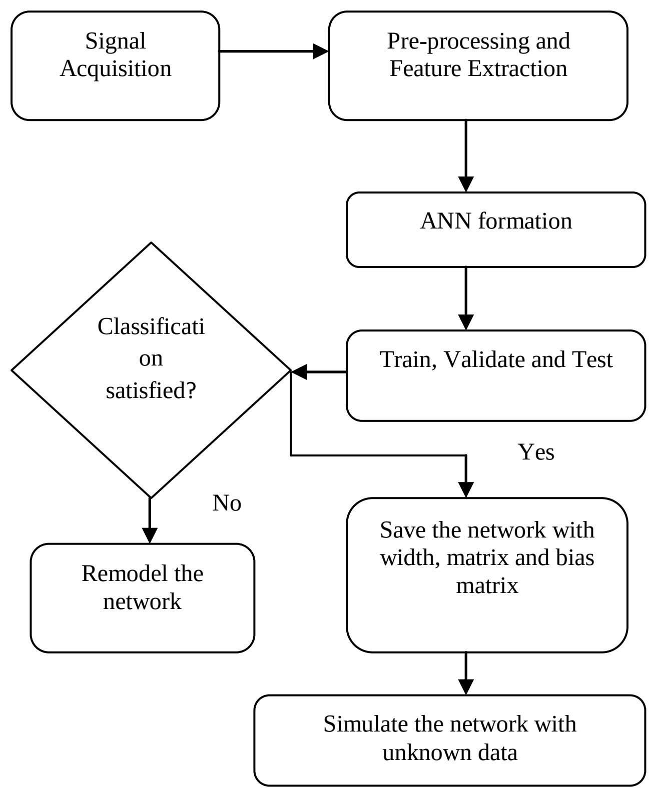

Figure 8.ANN based EMG signal classification [40]

Fuzzy sets show uncertainty associated with some variable in a problem with language variables like, low, medium, high, frequent, few and so on. Membership function has different levels of membership degrees like. .5, .7, etc., the values among the real interval (0, 1), these values symbolize fuzziness. Few essential membership functions forms are trapezoidal, triangular and Gaussian [25]. The rules are the foundation for fuzzy logic to get the output and also change the crispy inputs to the fuzzified output. These rules have the universal form "IF X is then Y is B" in which A and B are the fuzzy sets. A diagrammatical representation of fuzzy logic classifier is shown in Figure 7.

III. RELATED WORK

Below an established and existing theory of EMG signals has been described that indicates the hypothesis that would help in filling a noticeable hole.

Matthew W. Flood et al. (2019) have discovered the differences in Surface EMG (SEMG) with idiopathic Parkinson's disease (PD) and age-matched controls. SEMG has been recorded in isometric leg extension in PD patients before and after the Locomotor training program and in age-matched controls. The quantification of EMG structure is done with Determinism (%DET), sample entropy (SampEn) and inter-muscular coherence. The dissimilarity has been examined are reliable with more synchrony between motor units in and across the leg muscles in PD. The dissimilarity among the EMG signals is recorded before the therapy and improvement have been seen in walking capacity. Andras Hegyi et al. (2019) has found proximal- distal and inter-muscular EMG activity patterns for hamstring muscles while general hamstring exercises. 19 amateur athletes with no hamstring injury have performed nine exercises whereas EMG activity has been recorded with Biceps femoris long head (BFlh) and semitendinosus (ST) muscles with fifteen channels high- density electromyography (HD- EMG) electrodes. The normalization of EMG activity levels is into the Maximal Voluntary Isometric Contraction (%MVIC) has been observed for concentric and eccentric phases of every exercise and is contrasted among varied regions and muscles in every muscle. The upright hip extension, leg curls, and Straight-knee Bridge has demonstrated more hamstring activity in concentric phases (69% o 85%MVIC) and eccentric (40% to 54%MVIC). These researches have demonstrated inter-muscle and proximal-distal activity patterns being exercise dependent and are affected with contraction mode. Sidharth Pancholi and Amit M. Joshi (2018) have developed effective multi-channel EMG signals for UL prosthetic application. For the attainment of EMG signals from the five varied arm muscle for developed hardware, a number of arm exercises are conducted. Palpation method is utilized for the selection of muscle position. Moreover, the researchers have observed classification algorithm for seven varied activities. For the attainment of EMG data, 29 subjects are selected. The researchers have extracted the nine-time domain, recorded EMG dataset with seven frequency domains. Contrast has been conducted for varied classifiers for varied electrode muscle positions. The classification range by means of accuracy for varied classification algorithms is from 57.69% to 99.92% for each subject. J. L. Betthauser et al. (2018) has proposed a classification method of sparsity-based adaptability which is considerably less susceptible to signal deviation from untrained situations. The researchers have contrasted the method in online and offline ways of untrained UL positions for able-bodied and amputee subjects for the demonstration of robustness as a contrast to other myoelectric classification techniques. The results have shown an improvement in the untrained limb position for each subject group. The proposed work assists in providing better untrained better performance form less training conditions. The proposed technique is able to provide real-world clinical pros for amputees, lessen training burden, better tolerant performance by means of duration and frequency with enhancing myoelectric prostheses adoption. O. W. Samuel Zhou Hui et al. (2018) has presented three novel TD features for the performance improvement of EMG-PR scheme in the classification of arm movement. The recording of EMG signals is from the residual arms with eight amputees while executing varied UL movements. The features that are proposed were extracted and classified the limb movements. The outcome has shown that the novel features have attained a mean classification accuracy with $92.00\% \pm 3.11\%$ is 6.49% more than that of generally utilized TD features. By utilizing more measures, the presented features have performed well and have implied more potential in EMG-PR prostheses clinical performance. Mohsen Ghofrani Jahromi et al. (2018) have reviewed cross-comparison of feature extraction methods. Using the classification accuracy and decomposability index of the KNN classifier with class features, common information for the evaluation of discriminative power are employed for various feature extraction techniques morphology, including time domain, frequency domain, and discrete wavelet. In terms of data, 45 analog signals and 82 real EMG signals were used. The results show that in the time domain feature, the first derivative of the time sample shows the best separability. For morphological features, slope analysis provides the most discriminating power. The discrete Fourier transform coefficients provide the best separability between frequency domain features. Though, morphology and frequency domain techniques are no better than time-domain features. When compared to other feature extraction techniques, the detail 4 coefficients in the discrete wavelet decomposition are exceeded in the evaluation measurements. PCA slightly improved the results, but it was time-consuming. Li Lizhi et al. (2018) has assimilated an EMG-based classification method to organize the auxiliary robot arm and carry out the interactions in human arm motion. The system is based on SVM that classifies the movement of upper limbs on the basis of EMG signals being recorded from the diaphragm, biceps and anterior deltoids. As per the proposed method, six types of human arm movements have been analyzed and therefore, the classification results are transmitted remotely for controlling the auxiliary robot to mimic the motion of the human arm. The novel work has identified the performance by considering 72 of the 5 second EMG signals from both subjects. Based on the selected EMG characteristics of each measured muscle, the overall accuracy can reach 94%. The results indicate the importance of feature selection based on the morphology of the EMG waveforms recorded from different muscle bundles. The performance of the proposed method has been quantitatively evaluated, and the auxiliary robot arm can be remotely controlled using an EMG signal with enhanced accuracy. Nida Sae Jong et al. (2018) has observed the performance of suggested speech proposed sEMG (Surface electromyography) in the classification of 12 Thai syllables by lessening the variety of electrodes. sEMG signals were obtained from five facial muscles of seven volunteers. Every sEMG signal is filtered with a band-pass filter having a cutoff frequency of 20-450 Hz. The features extraction is done with frequency domain features, statistical domains features and time domain features as well. Spectral regression extreme learning machines (SRELM) are considered for the reduction of data dimension of the data and keep the significant information. Feedforward neural network (FFNN) is taken as a classifier. The outcome has shown that with the amalgamation of 2, 3, 4 and 5 channel electrodes, the average classification accuracy obtained is 87.05%, 94.77%, 97.81%, and 99.01% correspondingly. Yuh-Ren Tsai and Jia-Hao Ko (2018) has developed a portable multi-channel EMG signal detection system intended for Android-based smartphones. The communication interface among the connected microcontroller and smartphone unit is a Universal Serial Bus (USB) On-The-Go (OTG) interface. Therefore, the proposed system could be considered for random Android-based smartphone effortlessly with no issue of compatibility. Muhammad Zahak Jamal and Kyung-Soo Kim (2018) has introduced an EMG detection surface by fine processing of solid silver to obtain millimeter-scale toothed electrodes. The toothed electrode surface has a higher surface area than its flatter counterpart. The surface not only improves contact with the skin, but it also improves signal quality. This research has provided an assessment of electrodes with gel-type EMG electrodes and silver surfaces of a similar size but with flatter surfaces. One more significant factor in the efficiency of EMG depends on the skin impedance of the electrodes. Thus, using a flat silver surface of the same size and a gelled EMG electrode provides a comparison of the surface of the introduced EMG electrode in terms of electrode-skin impedance. A detailed description of the comparison indicates that the proposed electrode surface results are close to the gelled EMG electrode and superior to the flat silver surface. Ayse Tasdogen Kocak and Atila Yilmaz (2018) have distinguished events on the uterine EMG signal and classified the premature birth predictions for contraction events. In accumulation with premature birth, pregnancy, and normal childbirth, one can discover maternal and child breathing, muscle movements caused by the baby, and noisy signals generated by the electrodes when recording signals. Contraction of the events on the signal can provide information for normal childbirth, premature birth or pregnancy signals that need to be inaccessible from varied events. The identification and segmentation of signals obtained from the database according to the purpose are analyzed systematically using wavelet transforms and Teager energy operators. As a result of this analysis, 491 events were detected. At this stage, within the framework of expert evaluation and labeling results, fragments with similar shrinkage were determined by using neural networks, and classification was achieved using 79.4% accuracy, and shrinkage type detection had a %86.4 performance ratio in the isolated events found. Premature contractions, normal birth contractions, differences in pregnancy contractions were observed using different time records of the same individual, and premature contraction signals were classified by using artificial neural networks, with an overall success rate of 82.6%.

Gabriele Borelli et al. (2018) have developed short time Fourier transforms and spectral distance calculations to notice muscle activation from signals recorded using capacitive sensors. This technique has been tested on five young healthy subjects. To consider the reliability of the method, the researchers have quantified the delay among the detection algorithm output and the gold standard protocol results created by expert bioengineers. The achieved outcome has depicted reliable offline EMG detection. Sang Wan Lee et al. (2017) has proposed an exceptional Sensing Unit (SU) for electrode placement and reliable data acquisition placement. The researchers have experimented on the analysis of non-parametric statistics on class-separability values for EMG feature with an analysis of model considering the trade-off among the class dimensionality and class separability. Empirical analysis has been performed to consider the issue of the generalization of datasets and independent systems on six classification techniques. Histogram and Absolute value as feature types are combined to be vigorous for electrode location variations. System organization developments are considered on a case basis with the trade-off system complexity for the capability for online adaptation. On and all, it has been concluded that the analysis has shown a prototype to develop a reliable walking assistant system on the basis of EMG signals in smart home development. Xiangyang Zhu et al. (2017) has considered the limiting factors like algorithm degradation because of intrinsic non-stationary in EMG signals with the consequential requirement for regular re-calibration and re-training. For the reduction of re-calibration time needed for doffing and donning among the sessions and has shun away the requirement to re-calibrate with provided session with the process of donning and has presented Cascaded

Adaptation(CA) structure on the basis of Linear Discriminant Analysis (LDA) that considers the prototypes from existing sessions to combine with the present sessions. The novel mechanism has also updated the prototype measures as pee the novel data samples with the equivalent recognized labels. Offline analysis and online testing with nine intact limbed subjects have been considered for the evaluation of the proposed mechanism. It has been seen that LDA with CA that is LDA and CA has classified eleven motion types with small training data sets while experimenting the second session. Better results have been obtained while comparing the performance with three different techniques. The proposed outline of myoelectric control with less calibration burden can move the MPR prostheses from intellectual research to clinical application. Namita Sengar et al. (2017) has detected neuro-muscular disease with varied features in the wavelet domain with the utilization of continuous wavelet transform and as per p-values score, the features of discriminatory are chosen. Few EMG signal features like amplitude mean, root mean square and amplitude are classified and quantified with the utilization of SVM for the automation of amyotrophic lateral sclerosis disease diagnosis. The proposed mechanism has been tested on EMG database in the United States, EMG lab. The obtained results have an accuracy of 93.75%.

Yogesh Paul et al. (2017) have examined the features that extract constructive information being hidden in signals taken from different types. These signals could be speech, EMG, ECG, EOG and EEG and so on. In this research, the researchers further studied the EMG signal and discussed the relative assessment of time domain features among linear SVM and KNN classifiers. For successful classification, the EMG signal carefully selects the function. In this paper, seven basic time domain features are implemented because they are often used for the same features. N. Srisuwan and P. P. Limsakul (2017) has shown a performance assessment of fourteen feature extraction and four classifiers for combined Thai word classification on the basis of EMG signals for the discovery of near-optimal classifier and criteria. Their research has captured ten subjects with eleven Thai number words in silent and audible modes whereas the EMG signals consist of five positions of the neck and facial muscles. After the process of pre-processing and classification, twenty-two EMG features are utilized and are computed by means of fourteen assessment criteria with Dependent Criteria (DC) and Independent criteria (IC) for feature selection and feature evaluation. Consequently, nine features are considered for every criterion and are utilized in the form of input for the classifiers. There is the employment of four classifier types and are considered as a performance of Petoestimate classification. It has been concluded that the selected features with DC on a Fisher's least square linear Discriminant classifier (D-FLDA) with linear Bayes normal classifier (LBN) has provided better results by means of average accuracy inaudible and silent modes as 93.25% and 80.12%. Jian Wu et al. (2016) has utilized a wearable system for the identification of American Sign Language (ASL) during real time. The information has been fused from sEMG and inertial sensors. There is a utilization of gain based feature selection method for choosing the best feature subset. The researchers have considered classification algorithms for 80 generally utilized ASL signs with four subjects. The accuracy came out to be 85.24% and 96.16 % for the evaluation of intrasubject evaluation with a chosen feature subset and SVM classifier. Sirinee Thongpanja et al. (2016) have estimated statistical descriptors used to identify noisy EMG signals as of pdfs, particularly robust measures of kurtosis, negative entropy, L kurtosis and kurtosis as KR1 and KR2. The outcome has depicted that at minimum SNR (<5 dB), each noise types influence the statistical descriptor of the noise EMG signal pdf. Furthermore, KR2 performs best in these descriptors in identifying noisy EMG signals from its pdf because it is calculated based on the quantile of the data. Therefore, it can evade the influence of outliers, so that the pdf shape of the noise EMG with each contamination types and all SNR levels can be correctly identified. Khairul Anam and Adel Al-Jumaily (2015) proposed a novel dimensionality reduction constituted from the integration of extreme learning machine (ELM) and spectral regression (SR). The ELM in the proposed method is built on the structure of the unsupervised ELM. The hidden layer weights are determined randomly while the output weight is calculated using the spectral regression. The flexibility of the SR that can take labels into consideration leads a new supervised dimensionality reduction called SRELM. In this paper, SRELM is implemented in the finger movement classification on the basis of EMG signals from two channels. The outcome has depicted that SRELM has enhanced Spectral Regression Linear Discriminant Analysis (SRDA) performance. Additionally, the performance also comes out to be better as contrasted to Principal Component Analysis (PCA) and Unrelated Linear Discriminant Analysis (ULDA). A. B. M. S. U. Doulah et al. (2014) has developed two classification methods of EMG signal neuromuscular diseases by means of Discrete Wavelet Transform (DWT) features. In the first system, several high energy DWT coefficients and maximum values are extracted frame with given EMG data. Researchers not only consider such local information obtained from a single frame but as a replacement for using global statistics, which are based on information gathered from some successive frames. In the second scheme, the Motion Unit Action Potential (MUAP) is initially extracted from the EMG data by a template matching based decomposition technique. It is well known that not all MUAPs obtained by decomposition can uniquely represent a class. Therefore, a new idea of selecting explicit MUAP based on energy criteria is proposed, and instead of all MUAPs, only dominant MUAPs are used for classification. A feature extraction scheme based on the statistical characteristics of the dominant MUAP DWT coefficients is proposed. For the purpose of classification, the K-nearest neighbor (KNN) classifier is used. The clinical EMG database was extensively analyzed for the classification of neuromuscular diseases, and the proposed method was found to provide very satisfactory performance in terms of specificity, sensitivity and overall classification accuracy. Tahereh Kamali et al. (2014) have come up with a new classification strategy based on a set of SVM classifiers in a hybrid serial/parallel architecture to find the class label for a specified MUAP. The novel system utilizes the Time Domain (TD) and Time-Frequency Domain (TFD) characteristics of the MUAP being extracted from the EMG signal decomposition system. Varied classification strategies were studied with a lone classifier and different classifiers with different feature subsets. The outcome has utilized a set of authentic EMG signals that depicts the best performance of the proposed multi-classifier approach. In the method, a multi-classifier using multiple feature sets and a combination of trainable and non-trainable fusion techniques to integrate the general classifiers with the best performance with an average accuracy of 97%, being considerably more as compared to Single Average accuracy of SVM - based on classifier system. Jan Sedlák et al. (2013) have contrasted two varied methods for EMG segmentation with the aim to identify muscle activation pattern. Existing linear EMG envelope method has been contrasted with the novel designed method on the basis of the video in marker detection. The evaluation of the results is by means of the contrast of the intervals of muscle activity. The EMG segmentation is based on the video processing being robust for EMG Signal varied types. Takamitsu Matsubara and Jun Morimoto (2013) have presented a multi-user electromyography interface that has adapted new users easily. Different EMG signals are computed as the user performs the varied motion. Dissimilar EMG signals are also computed when different users perform a similar motion. So, it is difficult to design a myoelectric interface that can be utilized by multiple users to execute multiple motions. To resolve this problem, the researchers have proposed a bilinear model consisting of two linear factors for the EMG signal; namely; dependent on user and motion dependence. By decomposing the EMG signal into these two factors, the extracted motion-related factors can be used as features that are not relevant to the user. The researchers have developed a motion classifier for extracted feature space for the development of a multi-user interface. For new users, the adaptive method guesstimates the user correlation factors with similar interaction. The bilinear EMG model with an approximate user co-relation factor could extract the features of user independence for the recognition of robotic hand control task with four-channel EMG signal computed from the subject forearm. The accuracy came out to be 73% is different from standard non-multi user interface accuracy as an outcome of two-sample t-test at 1% level.

For leg based EMG, Nurhazimah Nazmia et al. (2019) has proposed his research with the machine learning approach. With the usage of machine learning approaches, feasibility in discriminating and swing phases have been observed. I. Elamvazuthia et al. (2015) have identified a neuromuscular disease for hands using Multi Perceptron (MLP) tool for the classification of EMG signals with three diverse groups, like, neuropathy, myopathy and healthy. S.M. Mane et al. (2015) has identified hand movement by classifying the single channel sEMG. M. Gandolla et al. (2016) has designed and implemented an EMG based controller for a hand robotic assistive device
and tested on eight healthy control subjects (4 females; age range 25–26 years), each participant has performed 20 trials of each hand grasp task. Giho Jang et al.(2016) has used surface EMG signals from face muscles for the electric powered wheelchair control system using Root mean squares (RMS) operation and normalization for signal processing for paralysis of all four limbs. Nurhazimah Nazmi et al. (2016) has provided an overview of the numerous methods available to recognize motion patterns of EMG signals. Muhammad Ibn et al. (2013) has investigated the classification of different movements based on the SEMG pattern recognition method using an artificial neural network- Levenberg-Marquardt and scaled conjugate gradient learning algorithms. Ali Boyali and Naohisa Hashimoto (2016) has worked on recognition of hand gestures using raw surface EMG signals using Spectral Collaborative Representation based Classification (SCRC). Mads Jochumsena et al. (2018) has observed the effect of arm position on motion class discrimination was investigated using intramuscular EMG (iEMG) using Hudgins'time domain features and a Bayes classifier. Peng Xia et al. (2017) has identified a novel model to estimate kinematic (motion) information for myoelectric control from multi-channel electromyogram (EMG) signals using convolutional neural networks (CNNs) and recurrent neural networks (RNNs). Asim Waris et al. (2018) has investigated changes in EMG classification performance over time using Linear discriminant analysis and the classification error quantified within (WCE) and between (BCE) days. Ivan Vujaklija et al. (2018) has developed Autoencoding (AEN) of EMG for myocontrol(control of muscle) using Seven able-bodied subjects without any neuromuscular disorders (5 M, 2 F, age: 29 ± 3 yrs).

IV. Comparison of existing work of EMG

The comparison of existing work performed by authors J. L. Betthauser et al. (2018), O. W. SamuelZhouHui et al. (2018) and Xiangyang Zhu et al. (2017) in the EMG signal classification by using different techniques such as Adaptive Sparse Representation Classification (EASRC), LDA and ANN and LDA-CA respectively have been demonstrated in Table 3.

Table II. Classification of Accuracy of existing work

Authors	Accuracy (%)	Proposed technique

Betthauser et al. (2018)	89	EASRC
Samuel et al. (2018)	92	LDA and ANN
Zhu et al. (2017)	91	LDA-CA

Figure 9 has illustrated a comparison graph of classification accuracy (%) for the EMG signal evaluated by J. L. Betthauser et al. (2018), O. W. SamuelZhouHui et al. (2018) and Xiangyang Zhu et al. (2017) and displayed by black, brown and gray color.

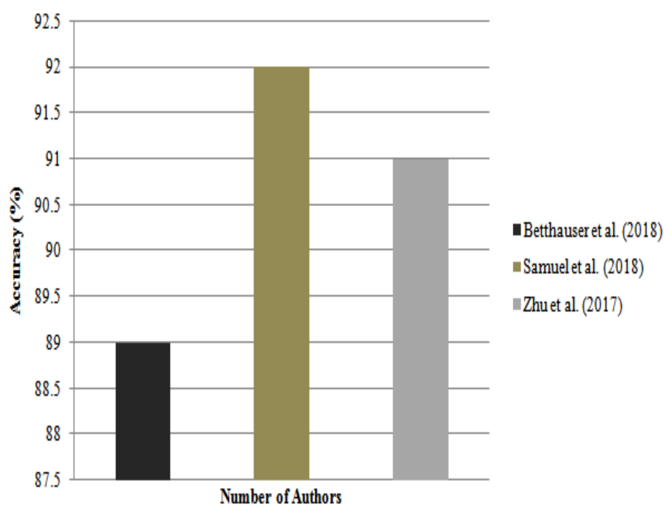

Figure 9. Comparison of Classification Accuracy (EMG)

The graph indicated that the accuracy obtained by O. W. SamuelZhouHui et al. (2018) by integrating two machine learning techniques namely, Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) is about 92 %, which is higher than other existing techniques proposed by J. L. Betthauser et al. (2018) and Xiangyang Zhu et al. (2017) respectively.

V. Conclusion

EMG signals have come out as significant field in biomedical and clinical applications. The detection, processing, feature extraction, and classification are deceivable as it concedes the regulated estimation to differentiate neuromuscular diseases. To understand the depth of EMG signals, we have presented a survey that covers on an all every aspect of it. Varied characteristics concerning with EMG signals with the methods of detection, decomposition, feature extraction, and classification has been discussed. The purpose is to divulge the methods to evaluate the signal. Discussion of varied existing researchers has been elaborated to analyse the effectiveness for prospective outlook by means of accuracy. It has been noticed that the traditional work by Betthauser et al., Samuel et al. and Zhu et al. has speculated the prominent techniques for further evaluation.

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