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REVIEW OF EMG SIGNAL CLASSIFICATION APPROACHES BASED ON VARIOUS FEATURE DOMAINS

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Abstract

Electromyography (EMG) is a widely used analytical practice that relays the health-status of the muscles or the nerve cells by monitoring their electrical impulses. However, it inherits the poor signal-to-noise ratio in addition to occasional signal distortions that significantly challenges the efficacy of this technique. Therefore, since the advent of this technology, numerous researchers have dedicated their study to improve the signal quality by reducing inherent noise in addition to offering its automated classification. In the present work, the authors have presented an overview of various existing researches in the field of electro-myographic signals classification involving various state-of-art techniques. A comprehensive survey has been provided while discussing the EMG signal analytic techniques involving different domains along with their performance. In the process, research not published before 2010 in various authenticated sources, such as Elsevier, PubMed, Springer, IEEE, and other articles and reports that are under the coverage of Web of Science and Google Scholar were analyzed. The review examined the suitability of various existing techniques to empower the healthcare sector based on the

interpretation of EMG signals. Detailed comparison of nature-inspired approaches for segmentation is also involved while comparing their demonstrated accuracies. Further, the time domain is also found to be more preferred as compared to the frequency domain for signal evaluation. The authors tried to provide an excellent understanding and evolution of the existing EMG signal classification techniques to guide for more influential, efficient, and flexible applications in the future.

Keywords

EMG, Muscular, Feature, Pattern, Signal Classification

1. Introduction

EMG signals are very complex and inherit several types of noises that pose greater challenges to the medical community. It has been widely used as a diagnostic technique to access muscular health and related disorders. The technique involves the placement of electrodes over the muscle to monitor its muscular activity via electrical signals. It is practiced as a popular clinical application for human-computer interface involved in the diagnosis of myopathy that involves muscle cramps, spasm, stiffness, and dysfunction. The skeletal muscles represent the largest group of muscles that manages body posture, motion, heat generation, and directly controlled by the brain in decision making. Also, growing awareness and concerns about physiological and psychological health significantly lead to a rise in the EMG device market over the globe.

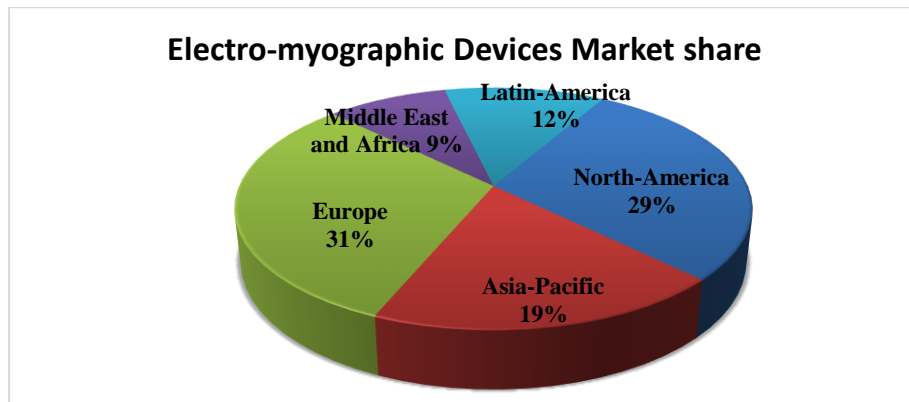


Figure 1: EMG Device Market Share 2017 by Regions

Based on the regional platforms, the market is segmented into five major regions. Figure 1 shows the CGAR of the device market in 2017, specifically for EMG devices. It was predicted that the proportion of EMG devices was significantly higher in North America and European countries among the five regions (Electromyography Devices Market By Modality, 2020). Another report dedicated to

the analysis of the market share of medical devices states that the popularity of EMG along with other medical devices such as ECG, EEG, ERG, etc. in diagnostics is predicted to constantly rise. The prediction report for medical analytic devices from 2014 to 2025 is shown in Figure 2 (Electrodes For Medical Devices Market Size, 2017). U.S. electrode market report had forecasted the trend of market value in USD millions for coming years to steeply rise.

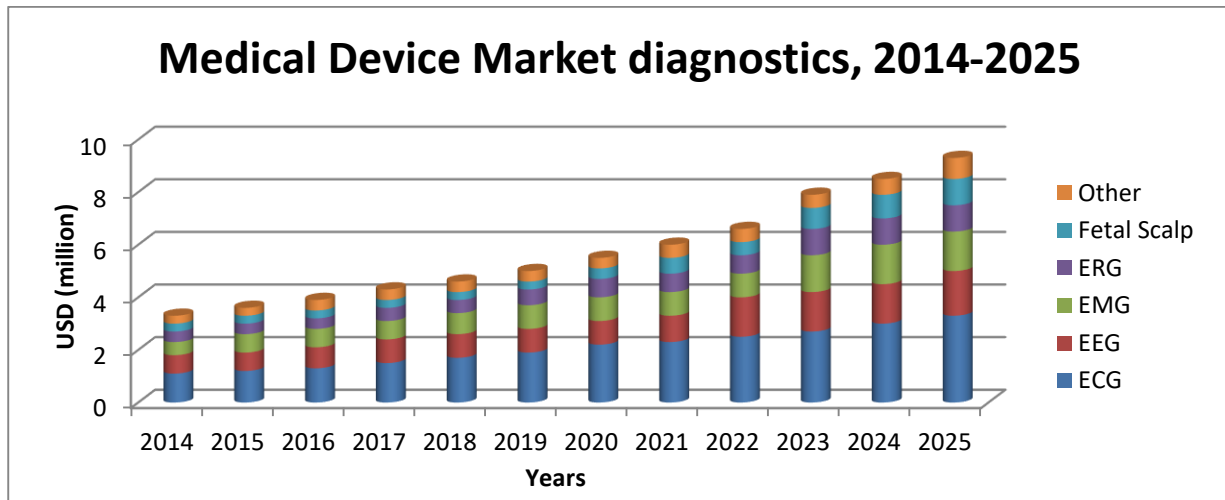


Figure 2: Medical Device Market Predictions 2014-2025

1.1. Electromyography (EMG) Sampling

The muscular electrical impulse reflecting the biomedical activity of the muscle is monitored by using EMG electrodes. There are two general methods for recording EMG (Ibrahim, Gannapathy, Chong & Isa, 2016) as surface EMG and intramuscular EMG. Waris et al. had employed both the methods in their EMG classification study based on ANN to evaluate the effectiveness of the sampling methods. They demonstrated that intramuscular recording results in lower classification errors (Waris et al., 2018).

1.1.1. Surface EMG

This involves monitoring and recording the muscular activity by placing the electrode over the surface of the muscle or the skin. This technique could only provide limited information about the muscular activity. This non-invasive technique was used by Abu et al., 2020, for EMG classification using ANN (Abu et al., 2020). To increase efficiency, multiple electrodes can be involved in a sampling of the signals. This is important because the EMG signal reflects the potential difference between electrodes. Limitation: It can be used to monitor only superficial muscle activity, and it varies when sampling for inner-muscles that considerably depends on the body weight and physique of the subject influenced by the discharge from adjacent muscles (Ravariu, 2011).

1.1.2. Intra-muscular EMG

It is performed by inserting electrodes into the muscles. Traditionally, a monopolar needle is used as an electrode. It can be a single fine wire or multiple wires used to monitor the muscle activity in addition to a reference surface electrode. This technique is usually employed for kinesiological studies or research purposes, as also demonstrated by Waris (Waris et al., 2018).

1.2. EMG signal Features

The feature extraction process is very significant in analyzing EMG signals. Its features are either analyzed using Time Domain (TD) features, Frequency Domain (FD) or together to offer a precise classification of the EMG signals (Altin & Er, 2016).

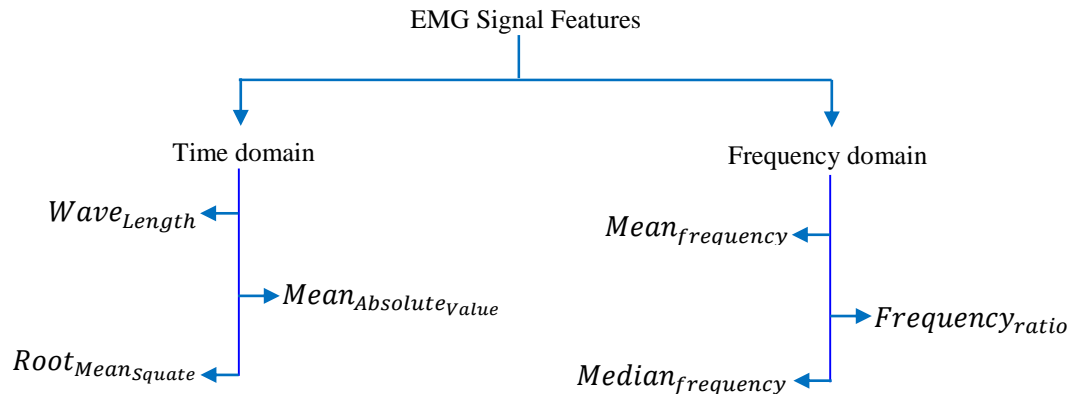


Figure 3: EMG Signal Feature Domains

1.2.1. Time Domain (TD) features

These are the type of features that are extracted from the EMG signal (x) in the time representation. The most popular features in this domain are wavelength ($Wave_{Length}$) (Kim, Cho, Lee, Koo, Choi & Kim, 2017), root mean square ($Root_{MeanSquare}$) (Cunningham, Plow, Allexandre, Rini & Davis, 2016) and mean absolute value ($Mean_{AbsoluteValue}$) (Yamanoi, Morishita, Kato & Yokoi, 2015). They are also characterized by an instrumentally high processing speed for classification and are calculated as follows:

$$Wave_{Length} = \sum_{i=1}^{N-1} |a_{i+1} - a_i| \quad (1)$$

$$Mean_{AbsoluteValue} = \frac{1}{N} \sum_{i=1}^N |a_i| \quad (2)$$

$$Root_{MeanSquare} = \sqrt{\frac{1}{N} \sum_{i=1}^N a_i^2} \quad (3)$$

Where, $Wave_{Length}$ represents the cumulative length of the waveform over the segments, $Mean_{AbsoluteValue}$ represents the average of all the absolute value of the EMG signal, $Root_{MeanSquare}$

represents the amplitude modulated Gaussian Random process. The variables, x_i represents the amplitude of i^{th} EMG sample and N represents the length of the signal analysis window. In 2013, several authors, including Phinyomark et al., and Matsubara et al., had analysed the EMG TD features to recognize muscular patterns (Phinyomark et al., 2013; Matsubara & Morimoto, 2013).

1.2.2. Frequency Domain (FD) Features

These features are extracted against the frequency representations that also illustrate the EMG signal Power Spectrum Density ($Power_{SD}$). It comprises features such as frequency ratio ($Frequency_{ratio}$), median frequency ($Median_{frequency}$) and mean frequency ($Mean_{frequency}$) (Phinyomark, Phukpattaranont & Limsakul, 2012). These features involve high computation time as compared to TD features and are specifically employed in the estimation of muscle force and fatigue (Thongpanja, Phinyomark, Phukpattaranont, & Limsakul, 2013). FD descriptors are calculated as follows:

$$Mean_{frequency} = \sum_{j=1}^M \frac{P_j}{M} \quad (4)$$

$$Median_{frequency} = 1/2 \sum_{j=1}^M P_j \quad (5)$$

Where, $Mean_{frequency}$ represents the average frequency, P_j represents the power spectrum, M is the length of $Power_{SD}$ and $Median_{frequency}$ corresponds to the frequency at which the power spectrum is divided into two parts.

$$Frequency_{ratio} = \frac{\sum_{j=Lower_{lowfr}}^{Upper_{lowfr}} P_j}{\sum_{j=Lower_{highfr}}^{Upper_{highfr}} P_j} \quad (6)$$

Where, $Frequency_{ratio}$ is used to distinguish the difference between contraction and relaxation of muscle, $Upper_{lowfr}$ and $Lower_{lowfr}$ the upper and lower cutoff frequency at low frequency, $Upper_{highfr}$ and $Lower_{highfr}$ are upper and lower cutoff frequency at the high-frequency band.

1.3. Feature Size Reduction

In the signal analysis, features are the source of vital information that needs to be precisely extracted for processing. However, it is not wiser enough to use every feature to perform further processing or classification. Hence, a process called feature reduction is involved in reducing the dimensions of the signal data to a small feature set that contains the most important features. These reduced features are believed to reflect the feature set that could demonstrate good performance. Genetic Algorithm (GA) is a nature-inspired optimization approach that searches for a single solution while evaluating various potential solutions. Practically optimization strategies have recently been

implemented by various researchers to address a variety of issues in addition to feature reduction. It works by addressing the error rate of the classifier in its fitness function and, over time, tries to reduce it. It was implemented by Majidnezhad and Kheidorov for feature reduction followed by SVM based classification (Majidnezhad & Kheidorov, 2013). Following this, Rodriguez et al. had taken advantage of cosine similarity to classify EMG signal data categorized into subjects with muscle fatigue and non-fatigue. Here, cosine similarity metrics were implemented to reduce the size of feature-based data (Rodriguez et al., 2014). However, in 2018 researchers took advantage of PCA-based feature reduction that works by searching best mapping representation for the distribution of data. Therefore, a signal representation criterion is used for the reduction of high-dimensional feature data. It also preserves the variance and randomness in the high dimensional space. However, it has a major limitation that classes are not separately considered in PCA as it does not consider the class labels of feature vectors under study (Too, Abdullah, Saad, Ali & Zawawi, 2018).

Studies of the past decade reflect a significant rise in the applications based on biomedical signals that have been popularly used in Human-computer interfaces. EMG representing electro-myoelectric signals generates unidirectional patterns representing muscular activity that proves to be very informative and reveal depth information when interpreted by experts. The precise analysis of EMG holds great significance not only in neuromuscular malfunctioning but has also been widely implemented in numerous biomedical applications focusing on exoskeleton designs (Stein, Narendran, McBean, Krebs & Hughes, 2007), prostheses (Kuiken et al., 2009), rehabilitation robots (Kiguchi, Imada & Liyanage, 2007) and wearable. Despite technological advances, still, the research in the field of diagnosis via EMG may not be enough for precise identification of minor variations and therefore require manual assessment by an expert. Hence, it is essential to advent an automated classification approach that can detect even minor variations from the normal patterns. To guide the scientific community and developers, the authors have presented a survey that discusses the suitability of existing techniques and their effectiveness in resolving issues related to EMG analysis are discussed.

1.4. Organization of the Paper

Section 1 highlights the significance of EMG signals and their rising popularity reflected by recent trends prevailing in the medical device market. Section 2 discusses the mechanism involved by the authors for data mining while analyzing various authenticated platforms to conduct a constructive survey. Section 3 summarizes the various classification approaches involving variable mechanisms and metrics to aid EMG signal analysis and classification. This is followed by section 4 that shares the

outcomes of the survey. Finally, the review is concluded in section 5, trailing with a list of references used in the paper.

2. Methodology

The present section discusses the research methodology employed for surveying existing approaches to EMG signal analysis and classification. Many classification approaches have been proposed to achieve better classification accuracy. To achieve this; many researchers also involved some optimization techniques while focusing on time and frequency domain metrics both separately and in combination.

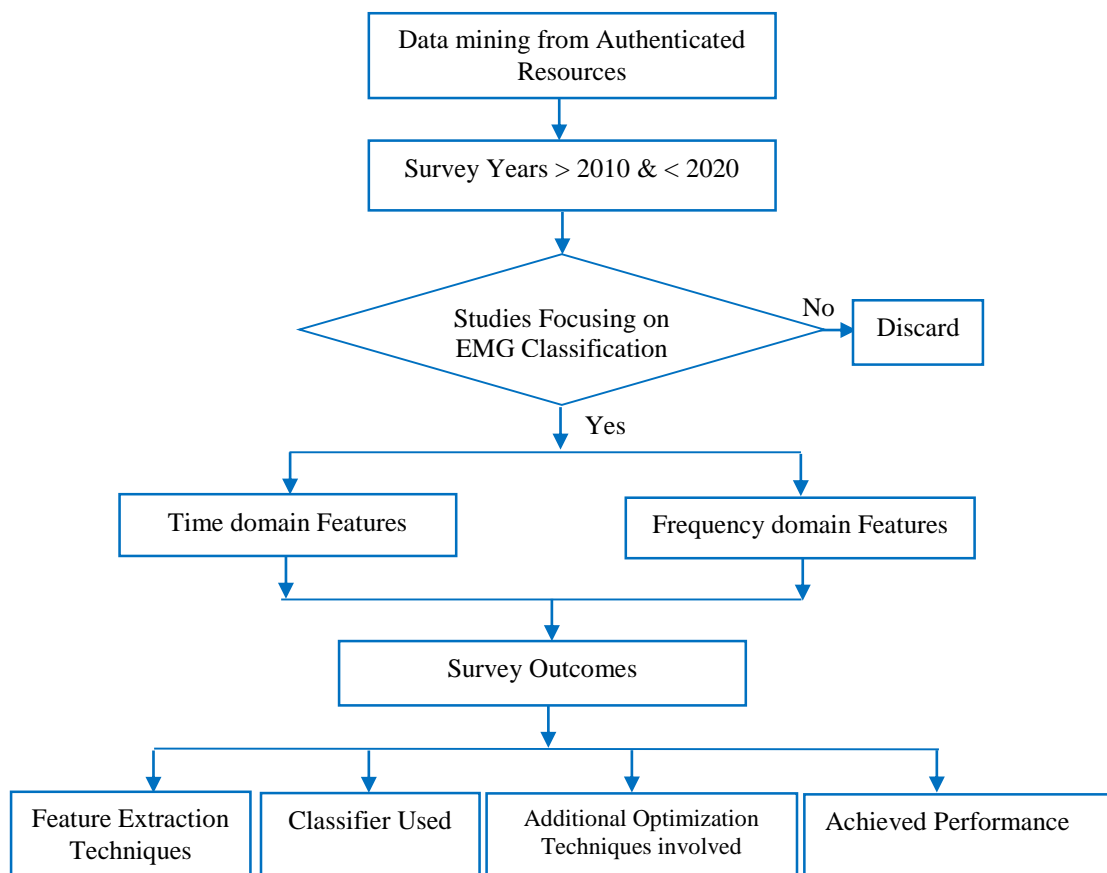


Figure 4: *Outlined Survey Methodology*

The literature is mined that was published in the last decade not earlier than 2010 while analyzing the published research in various authenticated sources, such as PubMed, IEEE, Springer, Elsevier, and articles falling under coverage of Web of Science and Google Scholar. The steps followed are outlined in Figure 4. Here, the preference is given to prepare a comprehensive survey of various classification

techniques proposed for the deployment of real-time applications in analyzing myoelectric patterns generated by EMG.

3. Survey Review

The current section covers the various existing work of the past decade. Khushaba had focused on the various dynamic factors that could significantly challenge the recognition accuracy of EMG signals. They discussed that EMG patterns were very sensitive to change in the electrodeposition (Spanias, Perreault & Hargrove, 2015), muscle orientation, change in limb position (Park, Suk & Lee, 2015), and even muscle contractile levels. The work involved wavelets transform to decompose EMG signal and extract TD features followed by SVM based classification to demonstrate pattern recognition accuracy of 91% (Khushaba, Al-Timemy, Kodagoda & Nazarpour, 2016). However, most of the studies have focussed on either time domain or frequency domain features. Jiang et al., 2019 had implemented classification of the labelled samples of EMG signals into muscle pain levels, such as without pain, mild pain, moderate pain and severe pain. They had implemented an Artificial Neural Network (ANN) as a classifier to achieve a signal based pain classification with an accuracy of 70.6 % (Jiang et al., 2019).

3.1 Myoelectric Signal Classification using Learning Methods

Mishra and co-workers believed that a suitable feature extraction approach was required to achieve an automated classification of EMG signals. To detect neuromuscular disorders, they considered MUAP based approach for EMG signals can be characterized in addition to the direct approach (Mishra, Bajaj & Kumar, 2016). Earlier, Subasi had implemented a direct method for EMG classification in which signal was divided into non-overlapping frames followed by feature extraction of each frame. These extracted features were finally used for the EMG signal classification (Subasi 2012). Performance of various classifiers, namely LDA, NB, KNN, and SVM, was evaluated by Dhindsa while combining TD and FD features with 4 autoregressive coefficients. The study segmented ECG signals with an overlapped window of variable sizes and concluded that quadratic kernel SVM outperformed the other classifiers with an accuracy of 93.07% (Dhindsa, Agarwal & Ryaite, 2019). Similar work was also presented by Too using PSO and KNN in 2019 (Too et al., 2019). Kehri and Awale had dedicated their study to diagnosing muscular dystrophy using EMG signals. They implemented wavelet-based decomposition of the signals followed by a combination of ANN and SVM as machine learning approaches. The experimentation against 140 samples demonstrated that the technique proved to be 95% effective when polynomial kernel SVM was implemented (Kehri & Awale, 2018).

Geethanjali had designed and deployed a cost-effective platform for robotic hand monitored using EMG signal patterns. The success of the design was evaluated using SVM, ANN, SLR, LDA classifier against TD features such as WL, MSV, RMS, and VAR. Additionally, kernel function was applied in SVM based classification that resulted in the best outcome with 92.8% using linear kernel (Geethanjali, 2016). Phinyomark et al. had taken advantage of TD wave features to identify variable EMG muscle signals by employing LDA classifier to achieve a high classification accuracy (Phinyomark et al., 2013). In the same year, Matsubara et al. had proposed another TD based EMG feature for a multi-user myoelectric interface using Support Vector Machine based classification. However, their work could only achieve 73% accurate recognition (Matsubara & Morimoto, 2013). Other researchers, Alkan and Guany, had used EMG signals with high accuracy for discriminate analysis based on TD features using SVM (Alkan & Guany, 2012). Limb motions were analyzed using EMG pattern by Tsai et al. to study isometric muscle contractions using an SVM classifier based on the TD feature analysis to reflect 90% recognition strength (Tsai, Hsieh, Luh, & Lin, 2014). Recently, researchers had combined used TD and FD features and proposed their work to demonstrate a combined TFD based feature analysis of EMG signals. This could achieve an accuracy of 90.66 (Sui, Wan & Zhang, 2019), 95% (Too et al., 2018), and more than 95% (Too, Abdullah, Saad, Ali & Musa, 2018).

3.2 Classification Involving Feature Reduction Approaches

The high-dimensional feature data can be reduced in size using a feature reduction technique. In 2016, Khushaba had focused its research on the dynamic features of the signal to address the challenges of the classification accuracy adjoining EMG signals. They implemented a wavelet transform to reduce feature size and results in recognition accuracy of 91% while implementing an SVM classifier.

Table 1: *Popular Dimensionality Reduction Techniques*

References	Techniques
Ghosh et al., 2020	Cosine Similarity
Too et al., 2018	Principal Component Analysis
Al-Faiza and Ali, 2018	Principal Component Analysis
Khushaba, 2016	Wavelet transform
Rodriguez et al., 2014	Cosine Similarity
Majidnezhad and Kheidorov, 2013	GA based reduction

Later, Too et al. had proposed the implementation of Principal Component Analysis (PCA) for the classification of 17 wrists and hand movement by analysing EMG signal patterns. The sample data was collected from the NinaPro database on which DWT feature extraction was applied to identify FD

features. This was followed by the implementation of PCA and SVM based classification. It was established that SVM based EMG classification reached the highest accuracy of 95%, followed by 71.3% for amputee samples (Too et al., 2018). PCA was also implemented by Al-Faiza & Ali while analyzing the robotic hand based on EMG signals of the amputee subjects (Al-Faiza & Ali, 2018). Table 1 summarizes the popular techniques used by various researchers to reduce the dimension of the features of the signal to reduce the computational cost and the processing time. It is found that cosine similarity has proved to be very efficient as a reductional technique and has been implemented for the size reduction of big data in various analytical studies (Ghosh et al., 2020).

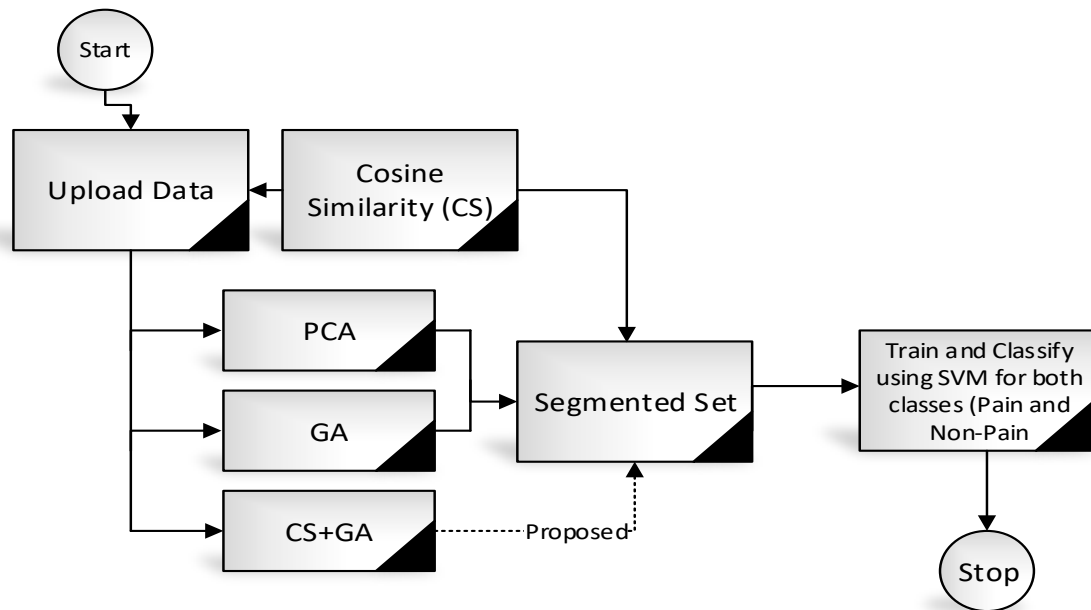


Figure 5: Proposed Segmentation Architecture

Though GA is an old natural computing-based selection method but the proposed work combined cosine similarity along with the GA to enhance the other existing selection algorithm. Wavelet transformation divides the data directly into the frequency domain, but if the data is already in the frequency domain, it does not provide relevant extracted features. To validate the selection approach, the designed architecture is shown in Figure 5. For the entire selection algorithm, two classes, namely pain and non-pain data, were segmented, trained, and classified. The training and classification algorithm is defined as follows.

1. Algorithm Select and Classify (SAC)
2. Inputs:Raw_Data (RD) Output:Class_Accuracy (CA)
3. Initialize Selected_Data(SD)to empty
4. Foreach rd in RD

5. Apply selection algorithm
6. Check Fitness Function
7. If is satisfied →fitness function
8. Select row and attributes
9. Append row value to SD
10. End If
11. End For
12. Foreach sd in SD,
13. Initialize SVM
14. Kernel Type: Polynomial
15. Train SVM
16. Select random test data out of the sample
17. Classify
18. Evaluate Class_Accuracy
19. $Class_Accuracy = \frac{\text{Total number of classified samples}}{\text{Total number of samples present in the class.}}$

The results are illustrated in Table 2.

Table 2: Class Accuracy

Techniques	Class Pain: Accuracy	Class Non-Pain Accuracy
GA	0.412	0.4524
PCA	0.3214	0.3326
Cosine	0.42115	0.4315
GA+Cosine	0.42885	0.44225

The pictorial representation of the architecture is shown in Figure 6. As clear from Table 2, the class accuracy of the proposed selection architecture is more as compared to other existing architectures in the network.

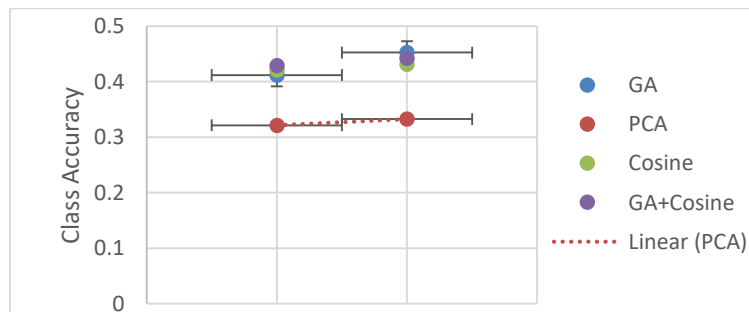


Figure 6: Pictorial Representation of the Architecture

3.3 Classification Involving Optimization Approaches

The EMG signals for the muscular activity involving the movement of the finger were analyzed by Purushothaman and Vikas. The work involved two swarm-based approaches, namely, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) for feature selection of EMG signals. SVM, LDA, and NB approaches were evaluated using FD feature metrics, namely, MAV and WL. The implementation proved to be 95% effective for the proposed combination (Purushothaman & Vikas, 2018). Sui and proposed a PSO-improved-SVM to identify 6-types of upper limb movements using EMG signal evaluation with the involvement of the Wavelet Packet Transform. The EMG based analysis resulted in a 90.66% recognition rate using RBF kernel in the proposed design (Sui et al., 2019). Subasi had taken advantage of PSO optimized SVM for biomedical applications as a diagnostics of neuromuscular dysfunction. The EMG features of both time and frequency domain were used for classification into diseased and normal samples of EMG. The technique PSO-SVM demonstrated a detection accuracy of around 96% (Subasi, 2013).

4. Results and Outcomes

The presented review is summarized under various categories, such as type of EMG sampling techniques used, feature domain considered for feature extraction of EMG signals, various machine learning approaches implemented for classification of EMG signals, additional feature decomposition and optimization approaches involved to improve the classification accuracy of proposed by various researchers. This study summarizes the existing work in the field of EMG signal classification presented in the last decade. Some of the important proposed work of authors is given in Table 3.

Table 3: *Performance Analysis of Some Existing EMG Classification Approaches*

Year	Authors	Feature Domain	Classifiers	Accuracy
2020	Abu et al.,	TD	ANN	80
2020	Asif et al.,	TD	CNN	92
2019	Sui, Wan & Zhang	TFD	SVM	90.66
2019	Too, Abdullah, Saad & Tee	TD	PB-PSO + KNN	93
2018	Ishii, Murooka & Tajima	TD	SVM	89.7
2018	Too et al.,	TFD	PCA - SVM	95
2017	Amirabdollahian & Walters	TD	SVM	94.9
2016	Khushaba et al.,	TD	DWT-SVM	91

2016	Geethanjali et al.,	TD	SVM	92.8
2014	Tsai et al.,	TFD	SVM	90
2013	Balbinot & Favieiro	TD	ANFIS	86
2013	Ibrahim, Ahsan & Khalifa	TD	ANN	88.4
2012	Phinyomark et al.	TD	LDA	91.64
2011	Ahsan, Ibrahimy & Khalifa	TD	ANN	89.2

It represents the year wise summary of various classification approaches that either focused on the Time Domain features (Asif et al.,2020; Ishii, Murooka & Tajima, 2018; Amirabdollahian & Walters, 2017; Ibrahim, Ahsan & Khalifa, 2013; Balbinot & Favieiro, 2013; Ahsan, Ibrahimy & Khalifa, 2011) or combination of Frequency-Time Domain features. However, Frequency domain-based signal analysis has not been found to be a common means for studying features of EMG signals due to computationally being very costly. It is also concluded that author to improve the classification accuracies, few researchers also involved feature reduction to minimize the computational cost of ECG signal classification. For instance, Khushaba et al., 2016 had implemented wavelet decomposition with machine learning SVM classifier to demonstrate classification accuracy of 91%; however, Too et al., 2018 demonstrated that involvement of PCA for reduction of feature size could result in better classification accuracy of 95% by implementing the same classifier.

4.1 Sampling Techniques

Surface EMG has been more popular among the subjects as compared to intra-muscular sampling as being the non-invasive and painless application of electrodes. However, the quality analysis could only be achieved with intra-muscular EMG sampling to obtain better performance and instrumental results, as reflected by Figure 7.

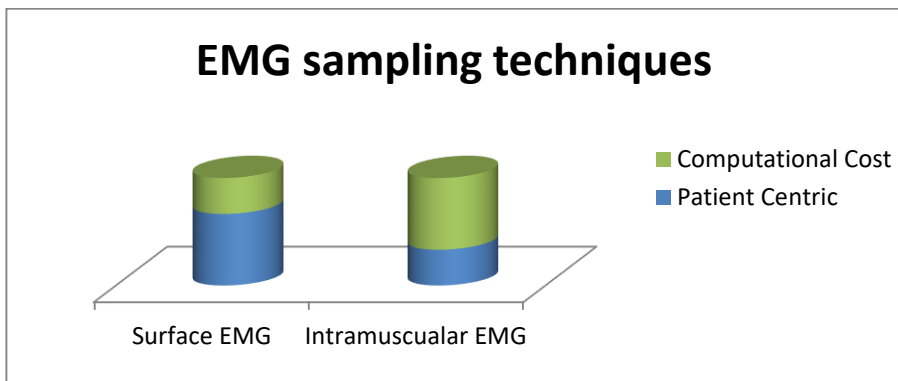


Figure 7: EMG Sampling Techniques

4.2 Practical Applications

The review of the existing approaches shows that most of the researchers have used EMG based signal analysis for two types of studies, namely pattern recognition and classification. Patterns Recognition of the EMG signals to analyze the effect on the muscular activity due to the involvement of some stress, involvement of prosthesis, artificial limb, etc.

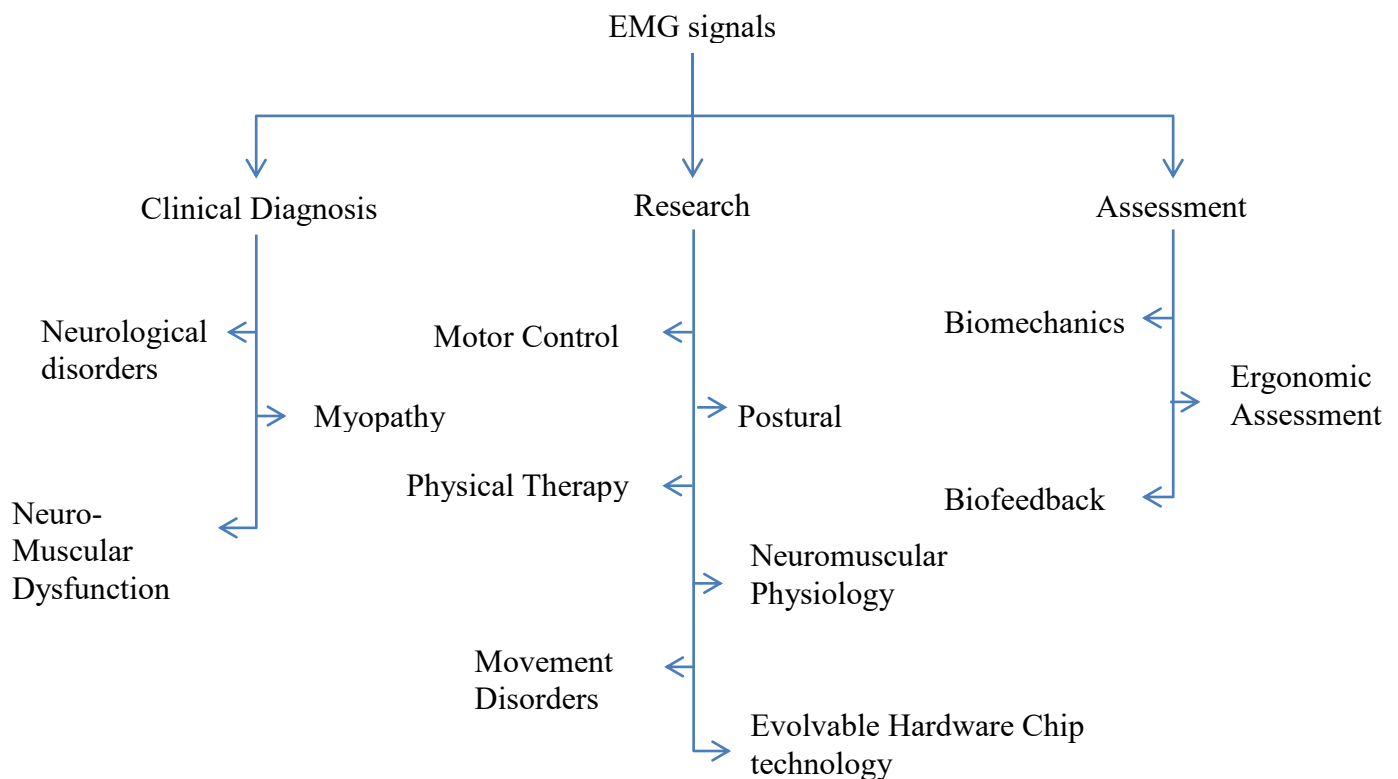


Figure 8: Applications of EMG Signal Analysis

Signal Classification of the myoelectric signals obtained EMG wave to analyze the myopathy or dysfunction in any muscle or group of muscles. As shown in Figure 8, it has numerous applications in neuro-muscular health analysis. However, EMG applications are not limited to clinical diagnostics while analyzing the neuro-muscular health of patients or subjects. Biometric-based assessment is getting popular where muscular health confers the biofeedback aiding in ergonomics studies. The survey reflected researches combining the human-computer interface has a wide range of applications in prosthetic control using hardware chip technology in addition to posture and locomotors disorders.

4.3 Classification Approaches

It has been observed that with time the trend in the implementation of computer Intelligence has also revolutionized itself. Figure 9 shows the type of techniques used by the scientific community over

the past 10 years for conducting EMG signal based research. There were different types of classifiers implemented by researchers with a thrust to achieve better EMG signal recognition and classification.

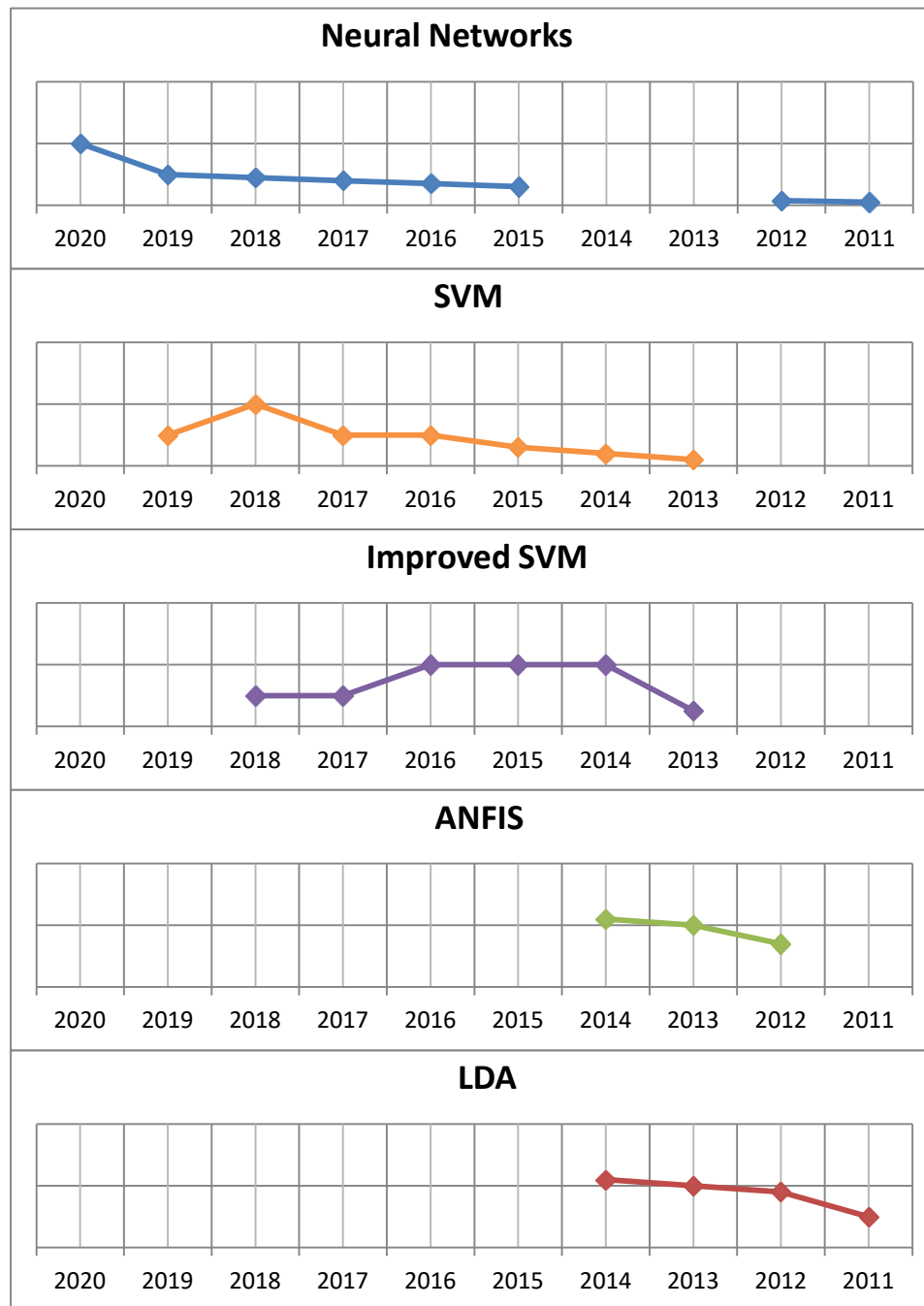


Figure 9: Popularity of Classifiers as EMG Signal Classification Approach

Some of the widely focused methods were Neural Networks (NN) majorly, Artificial Neural Networks (ANN), Artificial Neural Network Fuzzy Inference System (ANFIS) and Convolutional

Neural Networks (CNN), Support Vector Machines (SVM), Markov Model (MM) and Linear Discriminant Analysis (LDA). It has been observed from the survey that Neural Networks and its variants are in recent trend and used as machine learning classifiers to perform EMG signal classification. However, the years from 2013 to 2019 have been marked to be dominated by SVM, its variants while involving various nature-inspired optimization techniques to improve the overall classification strengths of EMG signals using SVM. The research before 2014 had majorly marked with Linear Discriminant Analysis (LDA) and the advent of some naïve neural network-based analysis of EMG signals. The evolution in the type of classifiers aimed at EMG signal classification is summarized in Figure 9. It means that the past decade has demonstrated the evolution in the various computational intelligence-based technologies with better classification accuracy with the involvement of feature reduction approaches.

5. Conclusion

EMG signals provide valuable information regarding muscular activity involving neuro-muscular health status in addition to prosthetics. Therefore, the present paper was aimed at proving a comprehensive idea about the available EMG signal classification techniques along with the information regarding its feature extraction and decomposition to offer a better EMG signal recognition design. The paper summarized that the last decade has seen the blooming of various computational intelligence techniques, particularly SVM, NN with improved classification accuracies achieved with the involvement of feature reduction and optimization approaches. It was also concluded that out of various feature reduction techniques, cosine similarity has proved to be very popular in the present scientific community with potential applications in vivid types of signal-based analysis. Based on the technical aspects, the paper evaluates and guides the researcher's community for the selection of the type of sampling methods, type of feature domains, reduction techniques, and the popular classifiers that could be implemented for practical applications of EMG signals. Hence, it can guide researchers focusing on EMG based analysis combining human-computer interface for future research.

In addition to reviewing existing EMG base work, the paper also proposes CS+GA as the best feature selection algorithm that could reduce overall processing time and computational cost. As such, in the near future, a significant improvement in EMG signal classification can be achieved when CS+GA based EMG features are passed to some classification approach leading to the deployment of more comprehensive applications.

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