A Review on EMG Signal Classification and Applications

Evon Lim Wan Ting and Almon Chai
Swinburne University of Technology Sarawak Campus, Kuching, Malaysia
Email: evonlwt@hotmail.com, achai@swinburne.edu.my

Lim Phei Chin
Universiti Malaysia Sarawak, Kuching, Malaysia
Email: pclim@unimas.my

***Abstract*—Electromyography (EMG) signals are muscles signals that enable the identification of human movements without the need of complex human kinematics calculations. Researchers prefer EMG signals as input signals to control prosthetic arms and exoskeleton robots. However, the proper algorithm to classify human movements from raw EMG signals has been an interesting and challenging topic to researchers. Various studies have been carried out to produce EMG-based human movement classification that gives high accuracy and high reliability. In this paper, the methods used in EMG signal acquisition and processing are reviewed. The different types of feature extraction techniques preferred by researchers are also discussed, including some combination and comparison of feature extraction techniques. This paper also reviews the different types of classifiers favored by researchers to recognize human movements based on EMG signals. The current applications of EMG signals are also reviewed.**

***Index Terms*—classification, electromyography, feature extraction, human movement**

I. Introduction

When muscles are contracted, electrical currents are generated. These currents are known as Electromyography (EMG) signals. The evaluation of EMG signals allows analysis of neuromuscular activities, without the need of complex human kinematics calculations. Hence, EMG signals are widely used by researchers to study human motions or to analyse muscular disorders.

Over the years, EMG-based human movements classification had become an interesting and challenging topic to researchers. EMG signals can be collected from muscles via electrodes. There are two ways to acquire EMG signals from human muscles: (i) needle electrodes where EMG signals are acquired invasively and (ii) surface electrodes where EMG signals are acquired non-invasively. The non-invasive way is more preferred by researchers. The invasive way requires advice and guidance from professionals, and could be painful and uncomfortable since the needle needs to be inserted into the muscle [1]. A report regarding recommendations on surface EMG signals acquisition with the title "Surface EMG for Non-Invasive Assessment of Muscles (SENIAM)" is published and widely used by researchers [2]. The report provides recommendations regarding the type, shape, size, materials of electrodes, and also skin preparation, inter-electrode distance and the placement of electrodes.

EMG signals are weak and contaminated with noises. Noises are present in the signals even during the acquisition stage. Examples of noises that pollute the EMG signals are ambient noise, inherent noise, motion artifact and inherent instability [3]. The presence of noises affects the analysis of the EMG signals, and will have an impact on the accuracy in the classification of human movements. Proper signal amplification, processing and filtering are required before further analysis of the EMG signals can be carried out for pattern classification. Therefore, a lot of research studies has been carried out on topics regarding EMG signal processing, filtering and analysis that can lead to high accuracy in human movement classifications.

The focus of this paper will be on the reviewing of the different kinds of methodologies regarding EMG signal acquisition, processing, feature extracting and classification that are preferred by researchers over the past years. Besides, a review regarding the current applications of EMG signals is also discussed.

II. EMG Signal Acquisition

The placement of electrodes during EMG signals acquisition is an interesting topic. Two common types of electrode placement techniques are observed in research studies: dense sampling approach and precise anatomical positioning approach. For dense sampling approach, no specific muscle location is pointed out. Instead, electrodes are equivalently placed around the limb. For precise anatomical positioning approach, electrodes are positioned precisely at the main activity spot of those chosen muscles. The muscles are usually selected based on the movements of interest in which the research study aims to classify.

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It is observed that, for EMG-based classification related to hand gestures, researchers mostly preferred to use the dense sampling approach for EMG signal acquisition. In [4]-[6], the teams used an eight electrodes MYO armband for EMG signals acquisition. The MYO armband is placed at the forearm to collect EMG signals for the classification of hand gestures. In [4], 37 subjects participated in this study regarding the classification of seven varieties of hand gestures. The best classification accuracy achieved is 93% via k-Nearest Neighbor (kNN). The research study presented by [5] managed to classify three types of hand gestures with a recognition accuracy that is greater than 90%. In [6], the EMG signals are collected from 21 subjects to analyse the classification of one hand gesture. The average classification result is around 99%. The research study carried out by [7] acquired EMG signals through electrodes located at the lower elbow. The EMG signals collected are used to classify two hand gestures: grasp and release. The classification accuracy reported by the team is around 92% to 94%.

For studies related to movement of a specific finger or the joint of the upper limb, it is spotted that the precise anatomical positioning approach is more preferred by researchers. In [8], EMG signals are collected from the extensor digitorum communis to study the classification regarding the extension of three fingers: index, middle and ring. The classification rate reported in the study is more than 90%. In [9], EMG signals are gathered from the biceps to study the classification of elbow joint. The highest classification accuracy achieved by the team is around 96.4%. Similarly, the authors of [10] acquired EMG signals from the biceps to evaluate the classification of elbow joint flexion to control a prosthetic arm. In another study regarding the classification of wrist joint movements, the authors selected the flexor carpi radialis, flexor carpi ulnaris, extensor carpi ulnaris and extensor long thumb muscles for the classification of wrist flexion, extension, abduction and adduction [11]. In [12], palmaris longus and extensor digitorum are chosen to classify the flexion of the thumb, pointer finger, middle finger and hand grasp. The highest classification rate achieved in the study is around 92.64%. However, there are also cases where the precise anatomical positioning approach is used to acquire EMG signals for gesture or posture based classification. In [13], the flexor carpi radialis muscle is selected for EMG signal acquisition for the classification of eight hand postures. The classification accuracy achieved is around 81.2%. In another study, EMG signals are collected from the flexor carpi ulnaris and extensor carpi radialis, longus and brevis to classify three hand gestures [14].

III. EMG Signal Conditioning and Processing

Raw EMG signal is naturally weak and contaminated with noise. Noises exist even during the signal acquisition stage. Raw EMG signal has an amplitude that is around 0 to 10 mV [15]. EMG signal has frequency that is between 10 and 500 Hz. According to [16], the main energy of EMG signal stands between 50 and 150 Hz. One of the common methods to remove noises from EMG signals is through signal amplification and filtering. However, proper care should be taken into consideration during the amplification and filtering process to reduce signal distortion in order to prevent the removal of useful information from the signal.

Researchers often prefer to use an instrumentation amplifier with a large Common Mode Rejection Ratio (CMRR) to remove the background noises from EMG signals. These background noises are common mode signals that reach the electrodes simultaneously and hence can be rejected via instrumentation amplifier. Although the elimination of common mode noises is performed at the amplification stage, EMG signals can also be polluted with noises caused by motion artifacts, power lines as well as those at the electrode-skin junction. Therefore, signal filtering is required. The frequencies of these noises are lower than 20 Hz. Hence, a band-pass filter to remove frequency components that are lower than 20 Hz and higher than 500 Hz are recommended [17], [18]. However, it is also discovered that several research studies proposed band-pass filter with different band-pass frequencies. The use of the notch filter to eliminate power line noise at 50 Hz is also commonly seen in research studies [14], [19].

The study conducted to analyse the capability of Support Vector Machine (SVM) and k-Nearest Neighbor (kNN) to recognize the three types of hand gestures utilized a 15 Hz to 500 Hz band-pass filter and a notch filter for signal filtering at 50 Hz [14]. The authors of [20]-[22] applied a 10 Hz to 500 Hz band-pass filter for the removal of unwanted noises from the EMG signals. The study on angle estimation of wrist movement via EMG signals described in [11] utilized the Bessel type filter in the EMG module to remove noises that are outside the ranges of 25 Hz and 500 Hz before rectification is performed to the signal. In [23], an EMG sensor is developed, where a band pass filter is utilized to filter unwanted signals outside the range of 90Hz to 450 Hz. Besides, a notch filter is also applied to reject common mode noise.

IV. Feature Extraction and Classification

The extraction of features is an important step in EMG signal classification. Hence, it is important to select the correct method to extract useful information from the processed EMG signals so as to increase the classification accuracy of EMG signals. There are numerous kinds of feature extraction techniques that have been used or proposed by researchers over the years. These feature extraction methods that are widely preferred by researchers are sorted into three categories: time domain, frequency domain as well as both time and frequency domain.

Although the statistical properties of EMG signal are always changing over the time, time domain features are still more preferred by researchers. This is because when compared to frequency domain features, computation of time domain features are less complex [24]. Among the well-known types of time domain extraction methods that are preferred by researchers are Mean Absolute Value (MAV), Simple Square Integral (SSI), Root Mean Square (RMS), Waveform Length (WL), Zero Crossing (ZC), Auto-Regressive Coefficients (AR), Mean Absolute Value Slope (MAVS), Integrated Absolute Value (IAV), Variance (VAR), Signal Length (SL), Difference of Mean Absolute Value (DMAV) and Integrated EMG (IEMG). Fast Fourier Transform (FFT) is one type of technique that converts EMG signals into the frequency domain [25]. Features of the frequency domain have been commonly obtained according to the statistical parameters of the Power Spectral Density (PSD). Examples of frequency domain features are Mean Frequency (MNF), Median Frequency (MDF), Peak Frequency (PKF), Mean Power (MNP), Power Spectrum Ratio (PSR) and Frequency Ratio (FR).

Human movements can be classified via recognition of EMG patterns that are formed from features extracted from processed EMG signals. Most of the EMG based research studies preferred classifiers that can be trained with sample patterns. Among the common classifiers preferred by researchers are k-Nearest Neighbor (kNN), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Deep Neural Network (DNN), and Support Vector Machine (SVM).

In [10], a trans-humeral patient has successfully controlled the flexion of the elbow joint of a prosthetic arm based on RMS features extracted according to the EMG data collected via the biceps muscle. [26] combined the AR model and ANN in their methodology to classify six kinds of finger movements. EMG signals are collected from four subjects. The classification rate achieved by the proposed system is more than 77% for each subject. [27] used the wavelet transform technique to extract features from EMG signals to classify five finger movements via a DNN. The proposed method led to an average of 96.7% recognition rate. In another study, valuable features are obtained through EMG data collected from four subjects via Discrete Wavelet Transform (DWT) to classify three kinds of hand movements. The average classification rate of the experiment is reported to be 93.25% [28]. The study carried out by [21] applied ANN to classify six types of forearm movements based on EMG feature patterns extracted from Hilbert Huang Transform. Subject-specific ANN are trained and tested individually using EMG samples from the same subject, collected from both the right and left hand. The overall average accuracy of the EMG data acquired from the right hand (86.2%) is slightly higher in comparison to the left hand (85.8%). Nevertheless, no evaluation of data among any individual has been carried out in the study.

There are also various studies that utilized multiple time domain features for EMG classification. The study conducted by [29] applied five types of time domain features, namely MAV, SSC, RMS, SL and ZC, to classify the flexion and extension of the elbow joint, pronation and supination. The authors managed to classify the four movements of eight subjects with an average accuracy of 91.78% via ANN. The study conducted by [30] described the control of a bionic hand via four types of hand poses identification. The team extracted four features (WL, SSC, MAV and ZC) from the EMG signals of 13 subjects. The team managed to achieve 80% and 94% accuracy from the classification of WL and MAV features via kNN for offline and online experiment respectively. However, the classification result of this study is subject-specific as the EMG samples utilized in both training and testing are from the same subject.

Besides, there are also research studies that utilized multiple features for classification, but at the same time, utilized Principal Component Analysis (PCA) to lessen the feature to improve recognition rate. [13] extracted 16 time domain features from the EMG data collected from 15 subjects, aimed to classify eight types of hand postures. PCA is applied to reduce the 16 features into three principal components. The team managed to achieve 81.2% classification rate via ANN. [5] presented a sensor-assisted EMG data acquiring system that aimed to classify three hand gestures. A total of 48 features are produced during signal processing. Similarly, PCA is applied to select 14 features for classification. The maximum average classification achieved via SVM is more than 90%. The authors in [31] assessed the performance of two classifiers, namely Linear Discriminant Analysis (LDA) and Multinomial Logistic Regression (MLR) to recognize eight types of upper limb movements that are related to the shoulder joint. A total of 26 time domain features and 10 frequency domain features are extracted from the EMG signals to form a feature vector with a dimension of 288. Then, PCA is performed for feature reduction. It is reported that the LDA and MLR managed to achieve classification accuracy of 88.8% and 91.8% respectively.

In [20], various features are combined into groups to identify the best combination of feature groups that can enhance the performance of the EMG based classifier to manipulate the prosthetic hand in real-time. Five feature groups are formed from nine time domain features to classify six hand movements. The team concluded that the feature group with MAV, SSC, ZC and WL is the best combination when classification is done with Simple Logistic Regression (SLR) classifier, where 91.1% of accuracy is achieved for healthy subjects and 73.2% is achieved for trans-radial amputees.

Comparison of classifiers to identify the optimal classifier is also one of the interesting areas in EMG signal classification. In [9], both kNN and SVM classifier are used to distinguish the flexion of the elbow joint. Four time domain features are obtained from the EMG signals collected from 10 subjects. The capability of the kNN (96.4%) is better in comparison to the SVM classifier (85%). Similarly, [4] analysed the performance of the kNN and SVM classifier in recognizing seven hand gestures of 37 participants. Both classifiers are used to classify feature patterns that are concatenated into a feature matrix. The classification accuracy of the kNN and SVM classifier is 93% and 83% respectively. However, the study conducted by [14] showed that the recognition ability of SVM is better than kNN. Seven EMG features collected from five subjects while performing three hand gestures are obtained via the time domain approach. The EMG features are analysed separately. The SVM classified all EMG features better than the kNN.

In [32], the authors compared four types of classifier and four types of feature extraction techniques to classify five hand movements via EMG signals acquired from six subjects. Four time domain features are extracted from the raw EMG signals via MAV, RMS, variance and SSI techniques. These EMG features are classified using the Support Vector Machine (SVM), Naïve Bayes (NB), k-Nearest Neighbor (k-NN) and Random Forest (RF). From the outcomes presented in the study, the combination of SVM with MAV and RF with RMS show the highest classification accuracy, which is around 98%.

The study conducted by [12] compared three types of classifier, namely ANN, Radial Basis Function (RBF) and Learning Vector Quantization (LVQ). The performances of these three classifiers are further studied in details. The ANN is tested with different number of hidden neurons; the RBF classifier with Gaussian function is tested with different spread values; while the LVQ classifier is evaluated by varying the number of competitive neurons. All three classifiers are trained to recognize five types of movements based on EMG signals collected via two electrodes channels from two selected muscles. The classification rate of the ANN with 10 hidden neurons is the highest, which is approximately 93%. The average classification accuracy achieved by the RBF classifier with 0.7 spread value is around 84%. The LVQ with 28 competitive neurons has the best recognition rate, where the classification rate achieved is 89%.

In the study of [8], an approach is introduced to improve the Back-Propagation (BP) algorithm of the ANN for the recognition of three finger movements. A correction factor is assigned to the hidden layer to enlarge the input sensitivity to speed up the time required for the training to escape the local minimum point. The proposed method is validated with EMG signals collected from one male and one female subject, where the AR model is used to extract features for classification. The experiment result shows that the classification rate attained via the improved BP neural network is greater than 90%, which is better than the classification rate of a normal BP neural network.

V. Applications of EMG Signals

Over the years, EMG signals have been applied in various applications, such as rehabilitation therapy, power-assist exoskeleton and prosthetic hand control, robotic manipulator control, personal authentication, automated diagnosis of neuromuscular diseases as well as ergonomics studies.

In rehabilitation, robot or exoskeleton has been introduced to help patients to carry out the required movement therapy. During the treatment, these robots or exoskeletons are designed to passively help the patients to move their limbs with the aid of actuators. In [33], a 7-DOF upper-limb exoskeleton, known as ETS-MARSE, is designed for passive rehabilitation therapy. The controller of the ETS-MARSE monitors the EMG signals of the wearer continuously during the therapy and offers help if the controller detects that the wearer is incapable of performing the necessary motion. The study conducted by [34] not only utilized EMG signals to control a robotic arm, but also implemented an Internet-of-Things system that enables real-time remote control applications such as switching on or off a light bulb, fan or electric heater via EMG-based hand gestures recognition.

Researchers have been using EMG signals in the diagnosis of neuromuscular diseases, including myopathy, DPN disorder and amyotrophic lateral sclerosis diseases. This method of diagnosis allows neuromuscular diseases to be done automatically and more accurately as compared to diagnosis through human eyes. In [35], the team proposed an automated diagnosis of myopathy through EMG data recognition. EMG data obtained from the biceps brachii are analysed via various feature extraction techniques and later classified via ANN classifier. The method introduced by the team is able to discriminate EMG signals among healthy subjects and myopathy patients, with an encouraging result, where 87% classification accuracy is achieved. A method on EMG-based automated diagnosis of amyotrophic lateral sclerosis diseases is proposed by [28]. The combination of continuous wavelet transform and SVM classifier is used to distinguish EMG signals between healthy and unhealthy subjects. The proposed method managed to distinguish 93.75% of the samples correctly.

Since the intention of human movements can be determined by analyzing the EMG data gathered from the muscles, researchers have been proposing and introducing approaches regarding the manipulation of human-assistive robotics, such as powered exoskeleton, prosthetic arm and bionic hand, via EMG signals. In [36], the team proposed the use of a 4-channel EMG signals to distinguish six types of hand gestures for the actuation of prosthetic drive. The classification outcomes of the EMG signals are used as control signals to trigger the DC motors designed to mimic the intended movements. The team of [10] reported the successful control of an artificial arm model developed to demonstrate elbow flexion after interpreting the intention of the amputee via EMG signal of the biceps muscle. An EMG-based upper-limb exoskeleton for power assist is developed in [37]. The team constructed an EMG-angle model via BPNN to recognize RMS features extracted from the EMG signals collected from four muscles. The results achieved by the team indicated that predicting the intention of the wearer through EMG signal analysis could manipulate the exoskeleton in real time.

Researchers have also proposed a EMG-based personal authentication. In [38], EMG signals are acquired from a proposed 2-channel EMG module to detect a specific hand gesture. A total of 100 samples are collected from 10 subjects. Five feature extraction techniques are used to extract useful patterns from the EMG samples. The usage of an ANN to recognize the EMG patterns is proposed in the methodology. The outcomes obtained via the proposed method proved the feasibility of EMG-based personal authentication, where a 95% recognition rate is achieved.

EMG signals are also used in ergonomics study. The authors in [39] conducted a study on the evaluation of occupational injuries based on EMG signals. Ten subjects are invited to participate in the study. The EMG signals from the biceps brachii are collected from the participants while performing a specific task that is suspected to cause Musculoskeletal Disorder (MSD). The team concluded from their study that the frequency domain features obtained from the EMG data are able to give more information, but time domain features perform better in classification. In another study, the posture comfort of the firefighter is assessed via EMG approach [40]. EMG signals are acquired while the firefighter performs certain postures that are common during firefighting activities to evaluate the comfort level of the postures. The research results can act as a reference on operating posture for firefighter to follow and practice to avoid discomfort during firefighting operations.

VI. Conclusion

The classification of EMG signals to predict human movements allows the control of the prosthetic arm and exoskeleton robot to be done based on the intention of the human operator. Current research studies focused more on selecting the appropriate feature extraction techniques and classifiers to improve classification accuracy. Various research studies have proposed the use of more than one feature extraction techniques. Researchers have also been finding appropriate combination of feature extraction approaches that could further enhance the classification accuracy. The types of classifiers that are most preferred by researchers are kNN, SVM and ANN. Comparison between the performances of different classifiers has been carried out in several studies.

From the studies reviewed, most of the studies only focus on classifying small amount of human movements. The number of subjects participating in the studies is also small. The number of EMG samples should be increased to enlarge the database that allows more comparison between subjects to be done so as to upsurge the reliability of the research outcomes. There are also studies without inter-subject comparison. Although the accuracy achieved is high, the suitability of the proposed algorithm for generic applications cannot be justified. Besides, the EMG data used in most research studies are not published. Researchers have proposed different methods, but these methods cannot be compared since the EMG data used in their studies are different. The amount of EMG data used in each study should be enlarged to increase the reliability of a proposed algorithm.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors have contributed equally to this work; all authors had approved the final version.

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Evon Lim Wan Ting received the Bachelor of Engineering in Robotics and Mechatronics from Swinburne University of Technology, Sarawak Campus, in 2014 and the Ph. D. degree in Engineering from Swinburne University of Technology in 2020. She is currently a post-doctoral research fellow with the School of Research, Swinburne University of Technology Sarawak Campus. Her research interest includes the analytics and optimization on classification and application of EMG signals related to movement control and manipulation of exoskeleton.

Almon Chai received his bachelor's degree in Electrical and Electronics engineering in 2000 and PhD in Manufacturing specializing in thermofluids in 2007. He is currently an academic with Faculty of Engineering, Computing and Science at Swinburne University of Technology Sarawak Campus. His research interest included computational techniques, simulation, human factors and ergonomics.

Lim Phei Chin is a lecturer at the Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak. She has been involved in various research projects since completing her PHD in Text and Data Mining in 2016. Her research interests are in image processing, statistical analysis, machine learning and recently ventured into web security.