2016 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS), 22 October 2016, Shah Alam, Malaysia

Feature Extraction of Surface Electromyography (sEMG) and Signal Processing Technique in Wavelet Transform: A Review

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***Abstract*— Electromyography (EMG) is used to measure and keep information of the electrical activity that produced by muscles during contract and relax. The electrical activity is detected with the help of EMG electrodes. This review paper will focus on usage of common EMG signal recording techniques which is surface electromyography (sEMG). During sEMG recording, there are some recognized noises and motion artifact which will affect sEMG signal. Hence, several of signal processing had been implemented to remove the noises and acquired the important signals which contain useful information. sEMG feature extraction is highlighted part in signal processing which extract features in sEMG signal. In this paper, several of sEMG feature extraction that applied any of three main domains which are time domain (TD), frequency domain (FD) and time-frequency domain (TFD) had been analyzed and studied to determine the good feature extraction method.**

***Index Terms*—Electromyography (EMG), surface electromyography (sEMG) signal, signal processing, feature extraction method, time domain (TD), frequency domain (FD), time-frequency domain (TFD).**

I. Introduction

This paper will review about surface electromyography (sEMG) in signal processing that widely uses in clinical application, engineering and researcher. Electromyography (EMG) is collective electrical signal acquired from skeletal muscle and includes the signals which have contains useful information from muscle contraction. Besides that, EMG also is a technique to measures and keeps information of the electrical signal produced from a small electrical currents during muscle contraction and also known as myoelectric signal [1]. The myoelectric signal that generated can be detected by using EMG electrodes. Generally, EMG electrodes can divide by two main types which are surface skin electrodes and inserted muscle electrodes. This paper discussed on surface electromyography (sEMG) electrode which is non-invasive technique. It is easy to implement and more convenient to use especially in engineering application and researcher. Indeed it is can be applied without any medical certificate [2]. The used of non-invasive was stated out by Surface EMG for non-invasive Assessment of Muscles (SENIAM) project which is recommended in European Activities on sEMG [3].

sEMG is a one of the techniques which electrodes are placed on the desired skin surface to record the present of information in muscle unit action potential (MUAP) [4]. Basically, surface electrodes can be divided into two types which mainly used that are gelled electrodes and dry electrodes. A gelled electrode is containing substance interface between electrodes and skin that known as electrolytic substance. Substances of silver-silver chloride (Ag-AgCI) is the suitable combination of metallic part and silver chloride (AgCI) layer which lets the current acquired from the muscle to move freely through the electrolyte and electrode [5]. In additional, there a few preparations that need be highlighted before placed the gelled EMG electrodes on the human skin which are the skin must be shaving off any hair and exfoliating and finally cleaning by 70% Isopropyl Alcohol. That will help to reduce unnecessary of noise and to acquire the best signal while EMG signal recording. On the other hand, dry EMG electrodes will measure the EMG signals by directly with human skin without any chemical interface such as electrolytic gel. Commonly, dry electrodes along with garments conductive yams that consisted of metal coated filaments provide a comfort wearing when stitching into it [6].

According that shows the EMG signal is quite sensitive and easily affected. Thus, combination of the numerous noise signal and artifact might have affected the original EMG signal with certain losses. Furthermore, noise can also originate from the electrode used. The features of the sEMG signal also might affected due to internal structure in human body like skin formation, velocity of blood flow, thickness of fatty tissue and muscle type [7], [8]. Hence, it is important to know sources of noises that recognized affect sEMG signal and this can be categorized into four types that are inherent noise, ambient noise, movement artifact, cross talk and internal noise [9], [10]:

1) Inherent Noise

Inherent noise is obtained from electronics equipment which is each electronic equipment produces noise.

2) Ambient Noise

Ambient noise is the source of noise where generated by electromagnetic radiation such as television transmission, electrical-power wires and radio.

3) Movement Artifact

The movement of the wire used that connect electrodes with amplifier circuit.

4) Cross talk

Unwanted signal that generated from active muscle that near to desired skeletal muscle (target muscle).

5) Internal noise

It most related with human body structure which involved the depth and location of the muscle fiber between surface electrodes and active muscle, the amount of excess body fat that will increase the distance or separation between surface electrodes and active muscle fiber.

In order to get the actual raw EMG signal, several approaches need to be done in analyzing the EMG signal. Thus, important to know the proper feature that can be extracting from the EMG signal. The wrong feature extraction used might affect the raw EMG signal [11]. For upcoming section, the feature extraction methods will be discussing throughout the research studied specially about the feature extraction methods chosen either time domain, frequency domain and time-frequency domain that will be describes.

II. sEMG Feature Extraction

sEMG feature extraction is the first stage and highlighted part in signal processing that functioning to remove the noise and get the important signal. Additionally, EMG signal is a non-stationary signal which is indicates into time domain and frequency domain. Basically, most attempts that had been utilized in many researches to extract features from sEMG signal can be categorized into three methods which is time domain, frequency domain and time-frequency domain. Thus, there will be many algorithm methods to extract the sEMG feature. The feature extraction algorithm used to eliminate undesired part and extract the useful data which is invisible in sEMG signal [12]. Hence, selection of features extraction vector needs to be carefully to achieve optimal classification EMG signals performance.

According that, time-frequency domain is more computability technique to extract the feature because of this method contains both time and frequency domain to analyze the signal. Therefore, it might have problems when time domain and frequency domain operated separately. The problems faced are EMG signal will be assumed as stationary signal in time domain method while frequency domain not able to access in time domain [13].

A. Time Domain Feature Extraction

Time domain presents the behaviour of the signal in time. Time domain features have been extensively used in biological system, engineering applications and researches. Many of researchers used time domain method in signal classification is due reduction in complexity that related with the feature extraction, low noise in environment, and easy to implementation especially the features of the raw EMG data is calculated in time series [14]. In the study carried out by among of the first consider that time domain features like Mean Absolute Value (MAV), Mean Absolute Value Slope (MAVS), Zero Crossings (ZC), Slope Sign Changes (SSC), and Waveform Length (WL) are the effectiveness of the simple features [15]. Additional methods had been utilized by other researcher for time domain feature extraction are including Integrated EMG (IEM), Modified Mean Absolute Value 1 (MMAV1), Modified Mean Absolute Value 2 (MMAV2), Simple Square Integral (SSI), Variance of EMG (VAR), Root Mean Square (RMS), Willison Amplitude (WAMP), and Histogram of EMG (HEMG) [16], [17].

B. Frequency Domain Feature Extraction

Frequency domain is one of the methods used to analyse the signal data obtained in frequency. In frequency domain analysis used transformation concept which it will convert a time domain function that obtained from raw EMG data to a frequency domain function. In additional, power spectral density (PSD) is a main analysis in frequency domain where its function is to measure the present of power signal in frequency domain [18], [19]. There are eleven frequency domain features had been carried out which are mean frequency (MNF), median frequency (MDF), peak frequency (PKF), mean power (MNP), total power (TTP), the 1st, 2nd, and 3rd spectral moments that known as (SM1), (SM2), and (SM3), frequency ratio (FR), power spectrum ratio (PSR), variance of central frequency (VCF) [12]. In the experimental results have shown that EMG features based on frequency domain are not suitable in classification of the EMG signal is due to classification accuracy of several frequency domain features are found approximation to the time domain features. This approved by the evaluation of thirty-seven time domain features and frequency domain features in that experimental study. Their feature space quality in term of class separability shows that are not suitable where the separability measurement (RES) for frequency domain features still cannot superior the time domain features [20].

C. Time-Frequency Domain Feature Extraction

Various signals analysis in many applications including biomedicine, multimedia, radar and industry preferred to deal with this time-frequency signal analysis method which can provide signal information in both time domain and frequency domain. Other than that, type of signal provided is a non-stationary signal where present of frequency components vary with time [21]. Therefore, this method is more suitable to implement in sEMG signal analysis which the type of sEMG signal is also is a non-stationary signal that contain various frequency components. A recent work had been exploited that the short-time Fourier Transform (STFT)-ranking feature was determined more satisfactory performance rather than other features tested which including frequency domain features and time domain features for motion pattern recognition in their research [22]. The result of the recognition accuracy for STFT-ranking feature is exceeding 90% which is superior to that other features when muscle contraction during training and validation phase are from the same type of participant. Moreover, the result of data distribution in their research also shows the feature data distribution using STFT-ranking feature are more separable compared with other features. Commonly, non-stationary signal can be analysed by time-frequency domain techniques such as short-time Fourier Transform (STFT), wavelet transform (WT), and wavelet packet transform (WPT) [23], [24].

a) Short-time Fourier Transform

STFT is the oldest analysis technique in area of time-frequency analysis that generated by transformation of a longer time signal which proposed to break into a shorter segment of same span and followed by applying the Fourier Transform to each shorter segment [25], [26]. Hence, the time interval for this process is shorter compared to be entire signal length. The function of the STFT method analysis is used in various signal representation which to determine phase content and frequency of a signal obtained as it changes along time [27]. The STFT is express as

$$STFT\left(t_{fix,}f\right) = \int_{-\infty}^{\infty} x(\tau)\omega(\tau - t_{fix})e^{-j2\pi f\tau}dt \qquad (1)$$

$$t_{fix} = t_s(N_{fix}) \qquad (2)$$

where w(τ) is the window function, t_s is the sampling rate, N_{fix} is fixed window length and t_{fix} is a fixed time delay.

b) Wavelet Transform

Recently, wavelet is best method has been used for the signal analysis in biomedical, engineering and researcher application. Wavelet analysis is alike with Fourier analysis in term of breakdown a signal into its basic parts of analysis and both are linear process that produce a data structure that contain log_2n segments of various length. Other similarities for both signal analysis methods are matrices equation characteristic included in the transforms. The signal acquired in fourier transform only will divided the signal into a series of sine and cosine signal of different frequencies while wavelet transform (WT) is more complicated method that uses basis function that called wavelets, mother wavelet and analysing wavelets [28]. Many researchers attempt to use a WT in signal analysing for acquired best features that represents raw EMG signal. WT is an effective measurable tool to analyse a highly fluctuated signal like EMG signal where WT had good performance in visualization of neuropathy and myopathy activities compared to STFT [29]. A quite similar work where compared two methods had been used in spectral analysed which are WT and STFT [30].

Wavelet transform method consists of two categories which are discrete wavelet transform (DWT) and continuous wavelet transform (CWT). CWT displays the distribution of signal amplitude and phase into two variables which are time and scale. The two variables are discretized and used to break a time function into a small wave which is called wavelet. Basically, the efficiency of the feature extraction might have disturbed by a large amount of data produced in CWT analysis. The redundancy of CWT can be solved by scale and translate in DWT method. However, the researchers attempt to use CWT as feature extraction method since it has shown better than previous method which is STFT. According that, the accuracy and reliability of the CWT method was compared with STFT, Wigner-Viller distribution (WVD), and Choi-Williams distribution (CWD) on stimulate and real myoelectric signals recorded from healthy subjects [31]. The result for that work shows the CWT is better statistical performance than STFT, WVD and CWD where the CWT has the lowest variance and relative errors all cases while the STFT had higher relative errors rather than others. A quite similar by other researcher work which is compare the STFT analysis with CWT analysis in EMG signal analysis [32]. The findings show that the CWT is less variability and larger accuracy in EMG signals analysis compared to the STFT.

DWT was widely used in among of researchers and defined as a one of the method in time-frequency domain which is powerful tool that can decomposes non-stationary signal into orthonormal time series with different frequency bands [33]. The DWT method was selected as a feature extraction method in this study because of an effectiveness processing of the signal in time-frequency domain and its concentration on real-time applications. A recent work was utilized DWT have two set of functions that are scaling and wavelet function which are interrelated with high-pass filters and low-pass filters, whereby each step combines two filter and two down sampling [34]. It is required to obtain successful of signal brake down into different frequency bands. In other paper work was analysed the influence of feature selection from four feature sets and determined the most appropriate feature in time-frequency domain [35]. As a result, DWT used as feature in time-frequency domain was selected as feature vector because of highest average accuracy rate is 94.833% that obtained compared with other features.

There are two important selections must be conducted and considered which are wavelet function or mother wavelet and depth of decomposition. A previous works was informed that the right selection wavelet function is required to ensure the perfect reconstruction and performs a better signal analysis where its depends on best correlation with sEMG signal [36]. Mother wavelet selection is the key role of capability of the transformation to construct a feature set through DWT [37]. Where different mother wavelet such as morlet wavelet, daubechies wavelet, coiflet wavelet, biorthogonal wavelet and symlets wavelet will have different time-frequency characteristic and it also can affect the performance of wavelet transform. Thus, these mother wavelets need to evaluate for obtain the best mother wavelet performance. It is followed by find maximum depth of decomposition to obtain the desired level in wavelet decomposition. The maximum depth of decomposition can be express as

$$J = log_2^N \qquad (3)$$

where J is known as the maximum depth of decomposition and N is the signal length of samples.

DWT is a technique to transforms the signal of interest into multiresolution or multifrequency subsets of coefficients [38]. Initial step in DWT technique is the original sEMG known as (S) is throughout high-pass filter and low-pass filters. At first level, filtered raw sEMG signal was processed by wavelet function or mother wavelet to obtain detailed coefficient subset (cD1) and an approximation coefficient subset (cA1). Then, data was processed for various levels until the chosen final level. The chosen final level is determined by the maximum depth of decomposition. Next, it will proceed to reconstruction for wavelet coefficient subset of all the wavelet components at the final decomposition level which to estimate an effective sEMG components by using inverse DWT (IDWT). For example, the wavelet coefficient subset is (cD1-cDx, cAx) and the reconstructed sEMG signal will be (D1-Dx, Ax). Then, it can be used as the features of the hand motions. The DWT decomposition tree and procedure of this method can referred in Fig. 1 and Fig. 2.

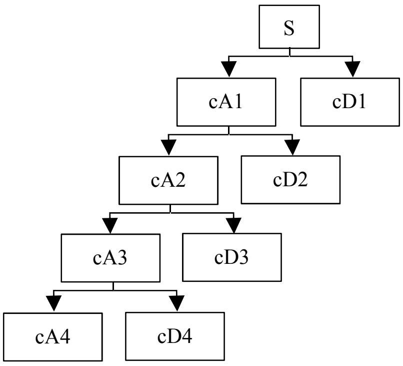

Fig. 1. The Discrete Wavelet Transform decomposition tree in level 4.

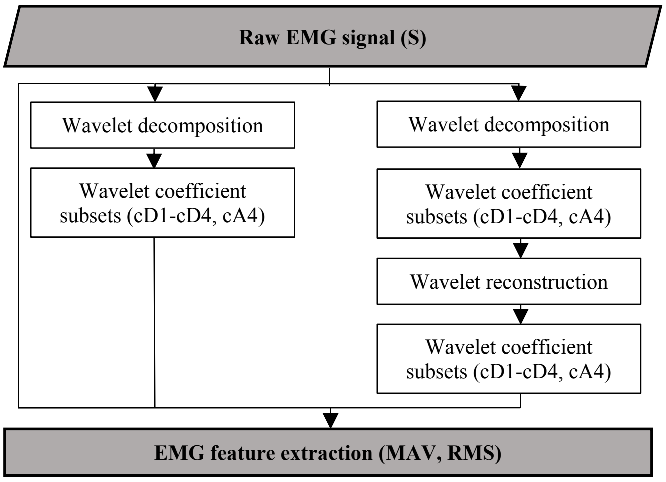

Fig. 2. The procedure of EMG features extraction.

After the feature extraction of sEMG signal procedure was completed, each wavelet coefficient subsets need to evaluate their class separability performance. A maximum separation between classes and minimum of variation shows the best quality class separability. Basically, there two statistical measurements will be used for evaluation criteria which are scatter graph and RES index [4]. The RES index is the ratio between Euclidean Distance (ED) and Standard Deviation (SD):

$$RES = \frac{ED}{\bar{\sigma}} \quad (4)$$

The better class separability performance is obtained from the higher result of RES index value. The ED equation is defined as:

$$ED = \sqrt{(a_{ch1} - b_{ch1})^2 + (a_{ch2} - b_{ch2})^2} \quad (5)$$

where a and b is known as feature mean of two motions with two muscles, ch1 is flexor capri radilis muscle and ch2 is extensor capri radialis muscle. The SD equation is shown as below:

$$SD = \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_1 - \bar{x})^2} \quad (6)$$

where N is known as number of samples, x_1 is the mean absolute value (MAV) features and x-bar is the mean of the MAV features. The MAV of sEMG signal is used as representative features to complete this evaluation for obtain the best performance level in selected mother wavelet.

According that, there are some researchers attempt to use wavelet transform to analyse EMG signal for investigate the usefulness of EMG features extraction throughout multiple-decomposition of the EMG signal [39]. The researchers proposed that the suitable mother wavelet and decomposition level are the seventh order daubechies wavelet and the forth wavelet decomposition level because of the RES index of MAV feature from the reconstructed EMG signal D2 show that dB7 wavelet is the best mother wavelet. While the selected forth wavelet decomposition is because the four levels of wavelet decomposition show good performance compared to other levels [40]. The WT techniques was applied to enhance the performance of sEMG feature extraction in sEMG signal analysis [41]. Referring to that paper, the WT has many advantages compared with other features in time-frequency domain where it has variable window size is more flexible compared to STFT which only has a fixed window size. Moreover, the WT techniques able to provide the required low frequency component while in the STFT do not have.

c) Wavelet Packet Transform

Wavelet packet transform (WPT) is quite similar with WT technique that started from wavelet coefficients and reconstructed sEMG signal. However, the WPT is capable to split a signal into a detail and an approximation at the first level. Then, the approximation and detail acquired from the first level can able to more split into a new detail and approximation. As information, the WPT is produced a binary structure of subspaces by a set of bases [42]. The decomposition tree of WPT in third level is shown in Fig. 3 [43]. In paper work [44], have been described that the first level of the WPT is the time representation of the signal while the last level has good frequency resolution. Hence, the WPT technique shows a better performance and WPT able to extract more features of signal compared to WT.

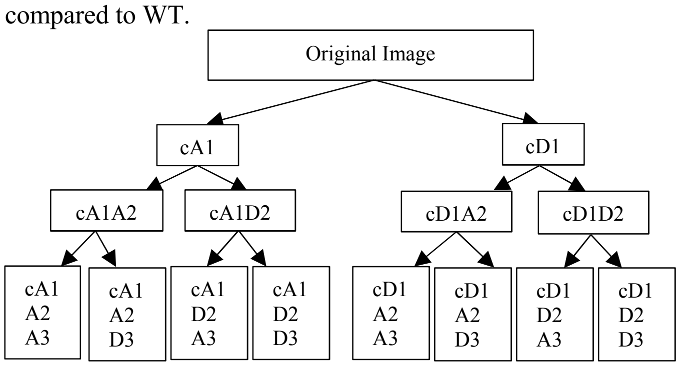

Fig. 3. The decomposition tree of WPT

III. Discussion

WT proved to be useful tool in signal analyzing of sEMG signal for various application concerning biomedical purpose diagnostic, rehabilitation for injured and surgery and sport science for performance improvement injury detection. The WT is an effective technique which is able to remove the baseline noise effectively from sEMG signals without altering signal information produced [45]. It is useful processing of the signal in time-frequency representation with the advantages of permits inspection of different waves at varying scales and resolution [46]. Concept of wavelet transform is used for both methods which are DWT and CWT. However, the both methods have a quite difference in how to scale and translate the signals. This paper proposed to use DWT which the helpful technique compared to CWT. The DWT offers adequate information for analysis and synthesis of the original signal. In low frequencies, it demonstrates good frequency resolution while in high frequencies, a good time resolution will be obtained [47]. Typically, the DWT generates a smaller signal than the original signal where it is considerably easier to implement compared to CWT. Other than that, the DWT provide perfect reconstruction of the signal and redundancy factor is less than CWT which contain the highly redundancy transform. Hence in future works, recommended to more study in extract the EMG feature by using WPT which a previous literature mentioned the method contain a much better performance in frequency resolution that can acquired for the decomposed signal compared to WT.

IV. Conclusion

A review according to the relevant literatures related to this research has been done. The important thing that needs to highlight in process of sEMG classification system is to choose the best feature extraction. The successful of the electromyogram classification system is most depends on the selected and extracted features quality. As mentioned in literatures, sEMG signal is very sensitive and easily affected. Hence, original or the raw sEMG signal easy to lose when various noise and artifact detected among EMG signals. Researchers need to use different type of feature extraction methods to find the best feature to extract the signals. Recently, the best feature extraction had been suggested in many researches is WT technique.

Acknowledgement

The support of Universiti Teknikal Malaysia Melaka (UTeM) and Ministry of Education (MOE) are greatly acknowledge. The research was funded by Research Acculturation Grant Scheme (RAGS) Grant No. RAGS/1/2015/TK05/FTK/03/B0012.

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