International Journal of Scientific Research & Engineering Trends
Volume 9, Issue 3, May-Jun-2023, ISSN (Online): 2395-566X

Review on Inversion of Short-Time Fourier Transform Magnitude in EMG signal by using MATLAB modelling

Tanmay Gupta, Assistant Professor Hemant Amhia
Jabalpur Engineering College
College in Jabalpur, Madhya Pradesh

Abstract- Electromyography (EMG) signal is the type of biomedical signal, which is obtained from the neuromuscular activities. Typically, an electromyogram instrument is used to capture the EMG signals. These signals are used to monitor medical abnormalities, activation level, and also to analyze the biomechanics of any animal movements. In this current work, we provide a short review of EMG signal acquisition and processing techniques. We found that the average efficiency to capture EMG signals with the current technologies is around 70 %. Once the signal is captured, the signal processing algorithms applied decides the recognition accuracy, with which signals are decoded for their corresponding purpose (e.g. moving robotic arm, speech recognition, gait analysis, etc). The recognition accuracy can go as high as 99.8 %. The accuracy with which the EMG signal is decoded has already crossed 99 %, and with the upcoming deep learning technology, there is a scope of improvement to design hardware, that can efficiently capture EMG signals.

Keywords – EMG, · Electromyogram, sEMG.

I. INTRODUCTION

The EMG signals are highly complex and non-linear signal. These signals are widely used in clinical trials for the diagnosis of neurological and neuromuscular problems [1]. Because of the complexity of EMG signals many times even experienced researchers are fail to provide enough information about these signals. EMG signals involve a great deal of information about the nervous system with anatomical and psychological properties of muscles. It is a record of electrical potentials generated by muscles cell [4]. The changes in the voltage difference between electrodes are sensed and amplified before it is transmitted to a computer program to display the tracing of the voltage potential recordings [2].

There are numerous neuromuscular disorders that influence the spinal cord, nerves or muscles. Early finding and diagnosis of these diseases by clinical examination is crucial for their management as well as their anticipation through prenatal diagnosis and genetic counseling. This information's are also valuable in research, which may lead to the understanding of the nature and eventual treatment of these diseases [4]. In the previous literatures Fast Fourier Transform (FFT) was used for analysis of EMG signals, but FFT suffers from large noise sensitivity [5]. Parametric power spectrum methods such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution [5]. Since, EMG signals are non-stationary; the parametric methods are not suitable for frequency decomposition of these signals. Another method is Short Time Fourier Transform (STFT) which provides resolution in short window of time for all frequencies. FFT, AR, STFT do not have time and frequency resolution at same time [7]. To extract the features of EMG signals and to overcome the problems of STFT, AR, FFT, a power-full tool that is Wavelet Transform can be applied to extract the wavelet coefficients of discrete time signals. This procedure makes use of multi-rate signal-processing techniques [4,13]. Artificial Neural Networks (ANN) has been used in great number of medical diagnostic decision support system applications because of the belief that these have great predictive power.

The measurement of muscle signal from electromyography (EMG) is able to assist SOCSO in diagnose MSDs problem from earlier. Electromyography (EMG) is the analytical study of electrical activity produced by skeletal muscles [2]. It will measure the electrical potential between the surface skins to muscle contraction that represent neuromuscular activities and easier to use in research on physiology. EMG signalcan be captured by two types of electrodes which are surface (non-invasive) and intramuscular fine wire(invasive) [8], [1].

Intramuscular fine wire is used to record EMG signal from deep muscle, however, is requires needle insertion into the muscle that need clinical assistant and cause pain to the subject. On the contrary, surface EMG electrode is easy to apply and free from pain [1]. EMG signal is described by its amplitude and frequency. The signals are complicated and non-stationary signal with highly complex time and frequency characteristics [1-10]. The amplitude of EMG signal is normally in the range of 0-10 millivolts(peak-to-peak) or 0-1.5 millivolts (root mean square) and the frequency is from 0- 500 Hz.

II. EMG DISEASES

An EMG is a clinical test used to find function of muscles and the nerves that control them. EMG signals studies are used to help in the diagnosis of disorders such as the muscular dystrophies and neuropathies. Nerve conduction studies that measure how well and how fast the nerves conduct. Neuromuscular diseases are a group of disorders which contain motor nuclei of the cranial nerves, anterior cells of the spinal cord, nerve roots and spinal nerves cause muscular weakness [14].

Neuropathies describe damage to the peripheral nervous system which transmits information from the brain and spinal cord to every other part of the body. Patient may experience temporary numbness, tingling, pricking sensations and sensitivity to touch or muscle weakness. Some others symptoms are burning pain, muscle wasting, paralysis or organ or gland dysfunction [9]. Myopathy is a muscle disease where muscle fibers are not working properly. Patient may experience muscle stiffness, cramp and spasm [9]. Some others symptoms are difficulty in speaking and breathing. Early diagnosis may cure these diseases. Therefore, EMG signal analysis is carried out to diagnosis these types of diseases in early stage.

However, these injuries can be prevented by taking appropriate steps to eliminate or reduce the exposure to the work-related risk factors that can minimize the risk of MSDs in the workplace and then the prevention can be simple and inexpensive by often making straightforward and basic changes can reduce MSD risks significantly [7]. Social Security Organisation (SOCSO) has classified occupational diseases into hearing impairment, musculoskeletal disorder, vibration disorder, skin diseases and occupational asthma [2], [8], [9].

Statistic of industrial accidents in Malaysia recorded 57,639 cases compared to 55,186for the previous year. Musculoskeletal disorder is one of the critical occupational injuries and disabilities. In2006, it showed an increment of 174% from 31 to 85 cases [10]. The effect of MSDs can be progressed from mild to severe disorder [10], [11]. There has been an increasing effort in recent years to investigate the causes of MSDs and to take action to prevent them. In order to prevent low back disorders we must first understand the concept and method that able to detect the symptoms that will contribute to MSDs problem. This literature review provides new insight on the critical literature and issues that have contributed to the results of previous research to being used as the guidance for the future researcher.

III. WAVELET ANALYSIS

A transform can be thought of as a remapping of a signal that provides more information than the original. The Fourier transform fits this definition quite well because the frequency information it provides often leads to new insights about the original signal. Fourier analysis provides a good description of the frequencies in a waveform, but not their timing. However, the inability of the Fourier transform to describe both time and frequency characteristics of the waveform led to a number of different approaches. None of these approaches was able to completely solve the time–frequency problem. Timing information is often of primary interest in many biomedical signals. A wide range of approaches have been developed to try to extract both time and frequency information from a waveform. Basically they can be divided into two groups: time–frequency methods and time–scale methods. The wavelet transform can be used as yet another way to describe the properties of a waveform that changes over time, but in this case the waveform is divided not into sections of time, but segments of scale [3].

The CWT has one serious problem: it is highly redundant (In its continuous form, it is actually infinitely redundant). The CWT provides an oversampling of the original waveform: many more coefficients are generated than are actually needed to uniquely specify the signal. This redundancy is usually not a problem in analysis applications such as described above, but will be costly if the application calls for recovery of the original signal. For recovery, all of the coefficients will be required and the computational effort could be excessive. In applications that require bilateral transformations, we would prefer a transform that produces the minimum number of coefficients required to recover accurately the original signal.

The discrete wavelet transform (DWT) achieves this parsimony by restricting the variation in translation and scale, usually to powers of 2. In the DWT, a new concept is introduced termed the scaling function, a function that facilitates computation of the DWT. To implement the DWT efficiently, the finest resolution is computed first. The computation then proceeds to coarser resolutions, but rather than start over on the original waveform, the computation uses a smoothed version of the fine resolution waveform. This smoothed version is obtained with the help of the scaling function. In fact, the scaling function is sometimes referred to as the smoothing function.

IV. LITERATURE REVIEW

Jiaqi Xue et al. Electromyography (EMG) can reveal the state of muscle activity in advance, therefore, it has been widely used in human–machine interaction (HMI) to predict human intention. Force estimation from EMG signals is acknowledged as an important research topic in HMI. In order to develop a simple and smooth HMI system, it is necessary to estimate the dynamic force effectively and smoothly from a small number of EMG electrodes. In this paper, we have proposed an EMG-based dynamic force reconstruction scheme applied in HMI system. A deep neural prediction network using one-dimensional convolutional structure has been proposed to learn the complex EMG features automatically from three-channel EMG signals. This model was applied in our interactive system to estimate dynamic force and reconstruct it on a robotic gripper for precise EMG-based robot control. Our proposed model outperformed the two-dimensional convolutional neural network (CNN) method and feature-based linear regression. And it can meet the requirement of online interaction. The offline and online tests have shown good estimation performance with 0.99 and 0.83, respectively. The average prediction speed has reached 115.5 μs per sample. The system has avoided tedious feature extraction process and has demonstrated dynamic recognition in real time which can further advance various prosthesis and assistive robotic applications in the future.

Abdulkerim Darendeli et al. Changes in movement capabilities after an injury to the ankle may impose adaptations in the peripheral and central nervous system. The purpose of our study was to compare the electromyogram (EMG) profile of ankle stabilizer muscles and stride-time variation during treadmill running in individuals with and without chronic ankle instability (CAI). Recreationally active individuals with (n = 12) and without (n = 15) CAI ran on a treadmill at two speeds.

EMG activity of four shank muscles as well as tibial acceleration data were recorded during the running trials. EMG amplitude, timing of EMG peaks, and variation in stride-time were analyzed from 30 consecutive stride cycles. EMG data were time-normalized to stride duration and amplitude was normalized relative to the appropriate maximal voluntary contraction (MVC) task. Individuals with CAI had similar EMG amplitudes and peak timing, but an altered order of peak EMG activity in ankle stabilizer muscles, a significantly greater EMG amplitude for PL with an increase in speed, and a greater stride-time variability during treadmill running compared with individuals who had no history of ankle sprains. The results of our study indicate that individuals with CAI exhibit altered activation strategies for ankle stabilizer muscles when running on a treadmill.

Matteo Beretta-Piccoli et al. The fractal dimension (FD) of the surface electromyographic (EMG) signal has been reported to be influenced by changes in the firing rate and synchronization of motor units. The purpose of this study was to validate these relations during experimental signals. Thirteen healthy subjects (12 men and 1 woman) performed an isometric knee extension at 5 % of their maximal voluntary contraction for 300 s. Intramuscular and surface EMG signal were recorded concurrently from the vastus medialis obliquus. Synchronization and firing rate were calculated from the decomposed intramuscular EMG signal, while FD was estimated using the box-counting method. The first and last 50 s of contractions were considered during the correlation analyses.FD was negatively related to the level of motor unit synchronization ($r_s = -0.30$; $p < 0.05$) and positively correlated with firing rate ($r_s = 0.25$; $p < 0.01$) when all data were pooled. FD was correlated with firing rate only during the initial 50 s of contraction ($r_s = 0.52$; $p < 0.001$).
FD of the sEMG signal is a parameter mostly related to the firing rate when fatigue does not develop and may be considered as an index of performance fatigability during sustained or at the end of prolonged contractions at very low forces. Indeed, FD cannot be considered as an exclusive index of motor unit synchronization during fatiguing contractions, but rather as largely related to central factors.

Juan Pablo Vásconez et al. Hand gesture recognition (HGR) based on electromyography signals (EMGs) has been one of the most relevant research topics in the human–machine interfaces field in recent years. The HGR systems are aimed at identifying the moment in which a hand gesture was performed as well as the gesture category.

Zahra Taghizadeh et al. EMG signals have played a pivotal role as a fundamental component of myriad modern prostheses to control prostheses' movements as well as identifying individual and combined hand or finger gestures. Despite a great deal of interest in these signals, the non-stationary nature of biological EMG signals has led to complications in EMG applications. Stationary signals have been analyzed plainly by time domain approaches like Fourier Transform, while non-stationary signals analysis is not satisfactory to be carried out with such method as it is not capable to illustrate the incidence time of various frequency components, besides, extracting both time and frequency information is essential.

Ronald H. Gabel et al. Ensemble averaged EMG profiles generated for leg muscles during gait have been used to clinically assess disease or injury. Several of the methods that have been reported for conditioning gait EMG signals were compared using data collected from clinically normal subjects walking on a treadmill. Specifically investigated were the effects of filtering and the quantity of data averaged upon several statistical tests that measure the variability of, or differences between, EMG profiles. Our results suggest that the variance ratio (VR) provides a reasonable test of data variability because of its modest sensitivity to both the degree of filtering and the amount of data averaged. They also suggest that of the comparison statistics: Pearson's *r*, the Kolmogorov-Smirnov *T* test and the ANOVA *F* ratio, the *T* test was the most reliable in detecting differences between given profiles for all test conditions. However, recognition of this ability of the *T* test must be tempered by the knowledge that while obvious EMG signal differences did exist, observable functional differences in gait did not.

G Olmo et al. During a sustained muscular contraction, variations in the myoelectric signal parameters can be noticed, before a force decrease is observed. This phenomenon is known as localized muscular fatigue, and always preceedes the true physical tiredness. In particular, for the electrically elicited contraction, the signal variations are essentially due to two different phenomena: a *time stretching*, that can be interpreted as the occurrence of a scaling factor, due to either an enlargement of the depolarized area or a decrease of the conduction velocity; a *shape variation*, which takes into account all those phenomena that are not due to a time stretching, and could be associated to a change in the recruited muscular fibers activity (for example, a different distribution of the conduction velocity).

Rahul Dubey et al. Muscle activity decreases due to various conditions like age factors and muscle diseases namely, amyotrophic lateral sclerosis (ALS) and myopathy. Electromyogram (EMG) signals are regularly explored by specialists to analyze the irregularity of muscles. Manual investigation of EMG signals is a tedious task for medical practitioners.

Yazan Ali et al. Jarrah Electromyogram (EMG) based pattern recognition (PR) strategies have been well investigated and applied as viable control strategies for upper limb prostheses. Transhumeral amputees often do not have enough residual muscles to produce high-quality signals needed to control the device adequately, so EMG-PR based prostheses for above-elbow amputees have not yet gained widespread acceptance in clinical and commercial settings. The limited acquired signal from these amputees often contains noises that make it challenging to accurately decode their limb movement intent.

S. Karlsson et al. This paper describes a prototype system that uses an advanced data acquisition processor in combination with a personal computer (PC) to analyse surface electromyogram (EMG) signals on-line and in real-time.

Vineet Gupta et al. Nonlinear analysis techniques are necessary to understand the complexity of the EMG. The purpose of the present study was to determine the fractal dimension of surface EMO obtained from the biceps brachii of normal subjects during isokinetic flexion-extension of the arm. The measurements were obtained with different loading conditions on the arm and for various rates of flexion-extension. Fractal dimensions of the surface EMG signals were calculated for each of these conditions. ANOVA results showed statistically significant differences between the fractal dimensions calculated for different loading conditions and rates of flexion-extension (P <- 0.005). Linear regression analysis showed a correlation coefficient of 0.99 between the fractal dimension and the load, and a correlation coefficient of 0.98 between the fractal dimension and the rate of flexion-extension. The results of the study show that the fractal dimension can be used along with other parameters to characterize the EMG signal.

Jun-Yao Wang et al. To explore the influence of the fusion of different features on recognition, this paper took the electromyogram (EMG) signals of rectus femoris under different motions (walk, step, ramp, squat, and sitting) as signals, linear features (time-domain features (variance (VAR) and root mean square (RMS)), frequency-domain features (mean frequency (MF) and mean power frequency (MPF)), and nonlinear features (**EMD**) of the signals were extracted. Two feature fusion algorithms, the series splicing method and complex vector method, were designed, which were verified by a double hidden layer error back propagation (BP) neural network.

Mahsa Barfi, Hamidreza Karami et al. Robotic or prosthetic organs are designed to have the maximum similarity to human organs. This paper aims to improve robotic hand control via an adaptive Fuzzy-PI controller using EMG signals. The data is collected from the FDS and FPL muscles of the forearm of five individuals who performed eight movements. Then, appropriate filters are used to eliminate the noise of the signals, and MAV, VAR, and SE features are extracted. Based on MAV and VAR, classification is carried out using DA, KNN, and SVM. With an average accuracy, specificity, and sensitivity of 90.69%, 94.64%, and 62.10%, SVM is a better choice for movement detection.

Aiping Liu et al. In this paper, we propose modeling the activity coordination network between lumbar muscles using surface electromyography (sEMG) signals and performing the network analysis to compare the lumbar muscle coordination patterns between patients with low back pain (LBP) and healthy control subjects. Ten healthy subjects and eleven LBP patients were asked to perform flexion–extension task, and the sEMG signals were recorded. Both the subject-level and the group-level PC_{fdr} algorithms are applied to learn the sEMG coordination networks with the error-rate being controlled..

Haoyu Zhang et al. As an efficient means of Amyotrophic Lateral Sclerosis (ALS) diagnosis in clinical practice, needle Electromyography (EMG) is often used to sample data from different muscle parts for ALS diagnosis. Although EMG signals from different muscle parts have different effects on the diagnosis of ALS, there are common features of neurogenic injury for cross-muscle parts.

Serial Number	Author name	Year	Methodology
1	Xue, J., & Lai, K. W. C	2023	Convolutional neural network (CNN) method
2	Darendeli, A., Ertan, H., Cuğ, M., Wikstrom,	2023	maximal voluntary

	E., & Enoka, R. M.		contraction (MVC) task
3	Beretta-Piccoli, M., Cescon, C., Vistarini, A., Pisegna, C., Vannini, B., Zampella, C., ... & D'Antona, G.	2023	correlation analyses
4	Vásconez, J. P., López, L. I. B., Caraguay, Á. L. V., & Benalcázar, M. E.	2023	Reinforcement learning (RL)
5	Taghizadeh, Z., Rashidi, S., & Shalbaf, A.	2021	Fractional Fourier Transform

V. CONCLUSIONS

This paper provides a brief introduction of the wavelet transform in EMG signals processing. For EMG signal processing; the WT is an alternative to other to other time frequency representations. WT has the advantage of being linear, yielding a multiresolution representation. Crossterms do not affect WT when dealing with multicomponent signals. We see that a major drawback of SFT is that stationary signal is assumed. The Electrocardiogram signal is a good example of a weak bio signal since its amplitude is commonly under a microvolt, and it is commonly contaminated by noise with amplitude on the order of millivolts. Conventional Wavelet Denoising (WD) has been demonstrated to be an effective algorithm for a wide range of signal processing, when the signal-to-noise ratio (SNR) of the signal being denoised is relatively high. Thus, Wavelet denoising methods is expected to offer a powerful compliment to conventional filtering techniques like notch filters and frequency domain filtering methods, which will be very efficient for sEMG signal analysis. Finally, we conclude that wavelet is a powerful tool that is used for the frequency analysis of the EMG signals.

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