Comparative Analysis of EMG Signal Features in Time-domain and Frequency-domain using MYO Gesture Control

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ABSTRACT
Feature extraction is a pronounced method to infer the information utility which is concealed in electromyography (EMG) signal to study the characteristic properties and behavior of signal. This study gives a comparative analysis of thirteen complete and most up-to-date EMG feature signals in Time-domain and Frequency-domain. Particularly, the EMG signals are obtained from a device MYO gesture control on an embedded system. For this purpose, four healthy male volunteers are considered to perform four different hand movements based on stationary, double tap, single finger movement and finger spread. To be a successful classification of these EMG features in both domains, we prefer attribute selected classifier as it gives the better performance and higher rate of accuracy i.e. 93.8%. The experimental results prove that features in time-domain are superfluity and redundant while features in frequency-domain (measured by statistical parameters of EMG power spectral density) show the ultimate dominance and signal characterization. The findings of this study are highly beneficial for further use in order to predict the behavior of EMG in pattern recognition and in classification of EMG signals for assistive devices or in powered human arm prosthetics.

CCS Concepts
• Computing methodologies~Machine learning approaches • Computing methodologies~Classification and regression trees

Keywords
EMG; MYO gesture control; MUAPs; Features; Time-domain; Frequency-domain; PSD; Classification;

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1. INTRODUCTION
The Electromyography (EMG) signal is the electrical illustration of neuromuscular activity linked with muscles contraction. It is extremely complex signal which is influenced by the physiological and anatomical properties of muscles, the action of peripheral nervous system and the characteristic approach of instrumentation used to detect it. A neuron acquires the wealth of coincide information from another neuron through its connection to dendritic tree. It integrates this information at summing area near the axon hillock engendering the action potentials whenever an electric gateway is reached. Action potential transmits actively through axon with minimal attenuation. The action potential can travel up to 100 m/s for myelinated axons having larger diameter. The action potential totally relies on the muscle's diameter, distance between muscle and detection site and the properties of sensors or electrodes use for detection.

In past, myoelectric control systems have been utilizing to power any upper-limb assistive devices or prosthetic arms by conducting classified EMG signals. Mostly available literature on EMG pattern focus on enhancing the classification accuracy and its usability to control assistive devices or any upper-limb prosthesis. Classification and feature extraction of Electromyography (EMG) signals is a challenging process especially in case of forearm muscle due to different hand movements. Feature extraction from Electromyography (EMG) signal is a well-known technique used to acquire useful information encoded in raw EMG signal which is further deliberately use to control prosthetic hand movement, diagnose muscle diseases and pattern recognition. The characteristics of EMG signals are recognizing by using features in both domains as Time-domain and Frequency-domain. Time-domain (TD) feature extraction is a technique to extract the useful information in sequence data points encoded in EMG signal over specific time interval while Frequency-domain (FD) features are extracted using spectral analysis and power spectral density (PSD) of EMG signal.

To achieve an effective method of machine learning for classification of EMG signals through de-noising, feature extraction and classifier, Ercan Gokgoz et al [1] presents a framework of classification using (MSPCA) multiscale principle component analysis for de-noising, decision tree for classification and (DWT) discrete wavelet transform for feature extraction. This framework classifies the EMG signal as normal, myopathic and ALS automatically with C4.5, CART and Random forest decision tree classifiers. Derya Karabulut et al [2] evaluated the time-domain features of EMG signals to estimate the external forces applied to human hands. These time-domain features are consisting of integrated EMG (IEMG), root mean square (RMS) and wave form length (WL). Time-domain EMG features were extracted to classify using artificial neural networks (ANN) to predict the external forces. EMG data acquired from different muscle locations and simulated algorithm was used for interpretation of signals to estimate the parameters. First of all, different arm movements were analyzed then statistical approaches were applied to investigate the relationship between force and muscle. Muscle-gesture computer interface (MGCI) with MYO armband is used to power the five-fingered robotic hand movement. The MGCI basically consists of three parts: (a) MYO armband with user (b) muscle- gesture interface (c) The Robotic hand. The (MGCI) recognizes the hand or wrist motion under supervision of three steps as segmentation, feature extraction and classification by Guan-Chun Luh et al [5].

In this paper, we proposed the methodology of classification and feature extraction of Electromyography (EMG) signal using MYO armband. For this purpose, we acquire raw EMG data from forearm muscle through MYO gesture control. Four healthy male subjects were participated in this experiment to perform four different hand gestures including stationary, double tap, single-finger and finger-spread hand movement as shown in Figure 1 & Figure 2. From these different hand gestures, we extract our features in both Time-domain and Frequency-domain to analyze the characteristics of our EMG signal. Time-domain features show the statistical analysis and information carried in EMG signal over specific time interval while Frequency-domain features involve the measurement and variables which explain the different aspect of frequency spectrum in EMG signal. For normal distribution of EMG spectrum, the median frequency and mean frequency will be the same while any deviation from normal spectrum will show the opposite values of both median and mean frequencies. After feature extraction in both domains we classify our EMG signal under supervision of Neural Network (NN), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM) and attribute selected classifier in WEKA. The recognition utility of these features shows a very high rate of accuracy as in case of attribute selected classifier.

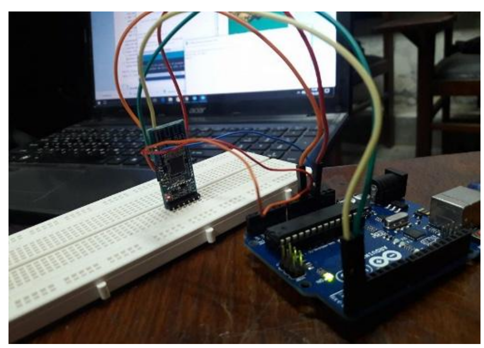
2. BACKGROUND AND RELATED WORKS

The geometric characteristics of hand describe the hand posture depends upon the finger locations, center of palm location and wrist positions. To localize and extract each finger, an algorithm of weighted radial projection seeks with its origin at wrist position. The system used in this approach can not only evaluate the features of extensional fingers but also the flexional fingers with rate of high accuracy. For this approach, Yimin Zhou et al [6] proposed a novel method in real time for recognition of hand gesture. The comparison of unsupervised approach of Principle Component Analysis (PCA) and supervised approach of common spatial pattern was taken in account to identify the best classification strategy. A set of low density surface EMG sensors was used on forearm muscle to acquire the EMG data. Results show that the first approach of unsupervised PCA has the accuracy of 88.8% and the second approach of supervised methodology of CSP shows the rate of accuracy higher than PCA with 89.3% of F. Riillo et al [7]. Angkoon Phinyomark et al [8] presents the complete study of thirty-seven features with their properties. For this experiment, six upper-hand movements (hand open, hand close, wrist flexion, wrist extension, forearm pronation, forearm supination) were performed to test the behavior. The results are verified on behalf of scatterplot of different features, classifiers and statistical analysis which shows that time domain features are more redundant than the features of frequency domain. The features of (TD) can further be assemble into four types as energy and complexity, model of prediction, dependence on time and frequency according to mathematical property.

Angkoon Phinyomark et al [9] measure the response for fifty features including Time-domain (TD) and Frequency-domain (FD) to differentiate the ten upper hand motions using EMG data. The results of this study place the sample entropy at top position of accuracy than other features as compared to (LDA) and a robust classifier. The best robust feature in single set is SampEn (sample entropy) and in multiple set SampEn+CC+RMS+WL is the best robust feature. While Time-Domain have better performance than Frequency-Domain. Abdulhamit Subasi et al [10] proposed different methods of feature extraction for understanding motor unit action potential (MUP) morphology. The (MUPs) in EMG signals have a consequential source of information to aces the neuromuscular disorders. Needle electrode was used to record the EMG data from a contracted muscle to investigate its neuromuscular disorder. For classification of EMG signals soft computing techniques had been adopted that will categorize the EMG signals into normal, myopathic and neurogenic automatically. Cemil Altın et al [11] give a comparison of features in Time domain and Frequency domain using EMG data acquisition.

3. PROPOSED METHODOLOGY

The EMG data used in this study are carried out from four healthy male subjects performing 4-different hand gestures. For this purpose, we adopt a simple approach of getting EMG data from MYO through an embedded microcontroller. Data acquisition is being carried through 8 channel MYO armband via HM-10 Bluetooth module on an embedded controller as shown in Figure 1. The gain of EMG signals is used to extract its features in both Time-domain and Frequency-domain. Feature extraction is a well-known approach to transfigure raw input data in to a reduced set of features which contain the useful information of signal. Time-domain features are habitually faster and to execute more feasibly because they don't need any transformation. Features in time-domain are extensively use in the field of biomedical engineering, medical researches and practices. Time-domain features have better classification performance and less computational complexity than features in Frequency-domain. Frequency-domain represent the statistical properties of power spectral density in EMG signal.



(a) Hardware Interfacing

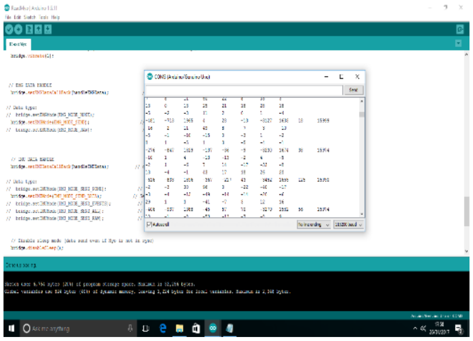


Figure 1: (b) Data extraction from MYO

Thirteen features of Time and frequency domain has been proposed in this paper. These features have been analyzing linearly and non-linearly with specific parameters. To estimate the power and attributes, we take the power spectral density (PSD) of EMG signal.

Figure 2: 4-Hand gesture movement

3.1 Time-domain Features

Mean Absolute Value (MAV) is a very well-known feature used in evaluation of EMG signals. It is same as integrated EMG feature used in the detection of surface EMG signal. It is also known as average rectified value (ARV), Integral of absolute value (IAV) or average absolute value (AAV). MAV is basically a reckon of summation absolute value and measurement of level contraction in EMG signal. It perceives the mean of EMG amplitude over length of signal.

$$\text{mean}(\mu) = \frac{1}{N}\sum_{n=1}^{N} x_n \qquad \textbf{(1)}$$

Variance of EMG signal (VAR) is another statistical power tool used to measure EMG signal. Variance is measured as the expectation of average square deviation of random variable from their mean. Variance is also defining as the measure of power density of an EMG signal.

$$\text{var} = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \mu)^2 \qquad \textbf{(2)}$$

Standard Deviation (SD) is a Time-domain statistical approach to measure the dispersion of data from its mean. It is measure as the square root of variance by estimating the variation among data points to its mean. If data are outlying from its mean, then it shows the higher deviation with in the data set.

$$\text{std}(\sigma) = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x_n - \mu)^2} \qquad \textbf{(3)}$$

Skewness is defined as a measurement of symmetry of signal for both cases, more precise symmetery or lack of symmetry on either side of centre point or it may be simply defined as the estimation of third order cumulative.

$$skew = \frac{\frac{1}{N}\sum_{n=1}^{N}(X_n - \mu)^3}{\sigma^3} \qquad \textbf{(4)}$$

Kurtosis is defined as the measure of probabilty distribution of random variables or the estimation of fourth order cumulative.

$$kurt = \frac{\frac{1}{N}\sum_{n=1}^{N}(X_n - \mu)^4}{\sigma^4} \qquad \textbf{(5)}$$

Standard Error (SE) is defined as a standard deviation from its sampling distribution of a signal.

$$\text{SE}_{\bar{x}} = \frac{s}{\sqrt{n}} \qquad \textbf{(6)}$$

Mean absolute deviation (MAD) is a statistical approach to find the average interval among each data value of a data set from its mean. It is used to find the variations in data set.

$$\text{MAD} = \frac{1}{N}\sum_{n=1}^{N}|x_n - ORT| \qquad \textbf{(7)}$$

3.2 Frequency-domain Features

Mean Frequency is an average frequency of the spectrum which is defined as the sum of the product (SOP) of EMG power spectrum and frequency, divided by sum of spectrogram intensity.

$$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j \qquad \textbf{(8)}$$

Median frequency splits the spectrum in to two regions with same amplitudes on both sides. Its spectrum is calculated first as the summation of the intensity of whole signal divided by 2 and then cumulative intensity of selected frequency should exceed the calculated value of previous step.

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \qquad \textbf{(9)}$$

Power Bandwidth is basically the frequency range or upper frequency limit of a signal for which the rated output power can manage to atleast half of the full rated power without any distortion.

Total Harmonic Distortion (THD) is defined as the sum of power of all harmonic components to the power of fundamental frequency. Total harmonic distortion (THD) is in fact the estimation of harmonic distortion present in signal.

Signal-to-Noise Ratio (SNR) is defined as a ratio of signal power to noise power. It is quoted for electrical signals and often expressed in decibels.

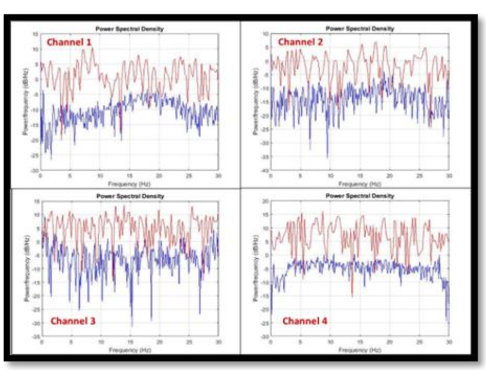
$$\mathrm{SNR_{dB}} = 10\log_{10}\left(\frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}}\right) \qquad \textbf{(10)}$$

Power spectral Density (PSD) of a signal indicates the preseance of power in signal as a function of frequency, per unit frequency. PSD is often expessed in watts per hertz (W/Hz). The PSD of a signal is basically the average of the Fourier transform magnitude squared, over a wide-range time interval.

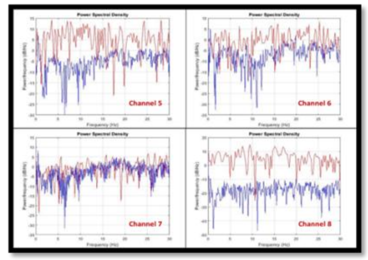
$$S_x(f) = \lim_{T\to\infty} E\left\{\frac{1}{2T}\left|\int_{-T}^{T} x(t)e^{-j2\pi ft}dt\right|^2\right\} \qquad \textbf{(11)}$$

4. RESULTS AND DISCUSSION

This section explains the behavior and classification results of used classifier in extracting features of EMG signal in Time-domain and Frequency-domain. As we mentioned above that for this study four healthy male volunteers took part in performing four different hand-movemets. These hand-movements were relatively based on stationary, Double tap, single finger movement and fingers spread as shown in Figure 2. The EMG signals of these hand-movements were further extracted and used to generate feature extraction in Time-domain and Frequency-domain. Analysis based on feature extraction of electromyogram (EMG) signals becomes an utmost criterion before interpretation. As the EMG signal depend upon time and force with amplitude variations, so the normalization of EMG signal is necessary to define its characteristic properties and features in both domain. Subsequently, before extracting features from signal the frequency-domain parameter power spectral density (PSD) is determined and analyzed; for a given signal. The power spectral density of a EMG signal shows the power (energy per unit time) falling within given frequency limits. The power spectral density (PSD) of 8-channel EMG signals for 4-hand gesture shows the strength and disorderly action potentials of EMG signal with increasing rates and amplitude overlaps at 60Hz frequency in Figure 3 and Figure 4.



(a)



(b)

Figure 3: PSD of EMG signals (Stationary Vs Double Tap)

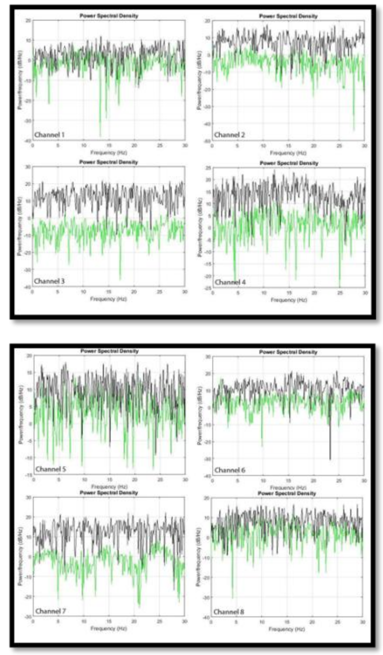


Figure 4: PSD of EMG signals (Single finger mov. Vs Finger spread)

There is no activation in muscle's action potentials at rest position while on contraction of musles it acquire more and more action potentials. That's why in Figure 3 we can see the more strength and saturation of double tap signals (in blue) than stationary EMG signal (in red). Similarly in case of single finger movement and finger spread, the muscle fibers produce more MUAP's as contraction level of muscles increases. Figure 4 explains the PSD of more contracted gestures of single finger movement (in green) and finger spread (in black) with high disorder of actions potentials and variying amplitudes that show the strength and saturation of EMG signals. In comparision of 4-gesture hand movement we can see the more strength and alignment of 8-channel EMG signals in case of Figure 4 as it shows the more contraction of muscles.

4.1 Classification of EMG features in Time-domain and Frequency-domain

Based on secure classification approaches of various classifiers the behavior of each set of time-domain (TD) and frequency-domain (FD) were tested. The classification based on attribute selected classifier shows the higher rate of accuracy as compared to previous approaches with 93.8% on platform of WEKA. The average classification results of all features in both time-domain and frequency-domain for 4-gesture hand movement are given in **Table 1**

Table 1: Classification results of EMG features

Time domain features			Frequency domain features	
Sr.	Feature	Performance	Feature	Performance
1.	Mean absolute value(MAV)	100%	Mean frequency	100%
2.	Variance	100%	Median frequency	100%
3.	Standard deviation (SD)	75%	Power Bandwidth	100%
4.	Skewness	100%	THD	100%
5.	Kurtosis	80%	SNR	100%
6.	Standard Error	100%		
7.	Mean absolute deviation (MAD)	75%		

To classify the thirteen features EMG data we used 10-fold cross validation approach in WEKA. For this purpose, we also trained our sample at ratio of 60% to train with ratio of 40% to test or to evaluate the remaining data. True positive class, precision, FC-Measure and ROC (Region of convergence) area as given in **Table 2**.

Table 2: Classification results of WEKA

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Mean (MAV)
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Sample Variance
	0.750	0.023	0.750	0.750	0.750	0.727	0.980	0.799	Standard Deviation
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Skewness
	1.000	0.023	0.800	1.000	0.889	0.884	0.989	0.800	Kurtosis
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Standard Error
	1.000	0.022	0.750	1.000	0.857	0.856	0.996	0.917	MAD
	0.000	0.000	0.000	0.000	0.000	0.000	0.989	0.500	MAD
	0.750	0.000	1.000	0.750	0.857	0.856	0.997	0.950	Mean Frequency
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Median Frequency
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Power Bandwidth
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	THD
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	SNR
Weighted Avg.	0.938	0.005	0.926	0.938	0.928	0.926	0.997	0.947	

4.2 Comparitive Analysis

As compared with previous studies we used more feasible, non invasive and cost effective approach to acquire EMG data using a band MYO gesture control rather to use electrodes with high signal to noise ratio. MYO gesture control has 8 channel EMG sensors with 9-axis inertial measurement unit to measure the EMG signals wirlessly through an embedded system. So in our case there's no resistance, low motion artifacts and no shuffeling of wires. Cemil Altın and Orhan Er study a biological EMG signal for different gestures. They filtered and classify the hand movement using the feature extraction methodology by extracting features in both wrist flexion and wrist extension cases. Classification was made using K Nearest Neighbor algorithm (KNN). The dataset involve in this study was derived by EMG signal acquisition tool. Overall 90 % accuracy was achieved by (KNN) algorithm purposed for signal classification. While we acquire the overall accuracy of 93.8% using attribute selected classifier in WEKA as shown in **Table 3.**

Table 3: Comparative Analysis

Time-domain Features				Frequency-domain features		
Sr.	Feature	Performance (By Cemil Altın and Orhan Er*)	Performance (In this study)	Feature	Performance (By Cemil Altın and Orhan Er*)	Performance (In this study)
1.	Mean Absolute Value (MAV)	91%	100%	Mean Frequency (MF)	65%	100%
2.	Variance	79%	100%	Median Frequency (MDF)	83%	100%
3.	Standard Deviation (SD)	81%	75%	Power Bandwidth	___	100%
4.	Skewness	72%	100%	THD	___	100%
5.	Kurtosis	74%	80%	SNR	35%	100%
6.	Standard Error (SE)	___	100%			
7.	Mean Absolute Deviation (MAD)	83%	75%			

5. Conclusions and Future work

In this study, thirteen different features of Time-domain and Frequency-domain from EMG signals are extracted and evaluated for 4-gesture hand movements. In this experiment, 4 healthy male volunteers take part to perform four different hand movements. Extracted features are further classified under supervision of various classifiers on WEKA to predict the behavior of gesture. It is concluded that attribute selected classifier is the best classifiers with higher performance and accuracy of 93.8% as compared to other classifiers. For this scope, attribute selected classifier is trained through 10 fold-cross validation approach with 60% training data and 40% test data to predict the features of four-class EMG signals in both domains (TD & FD). It is also analyzed that that features in frequency-domain shows the ultimate dominance and signal characterization as compared to the features in time-domain. The findings of this study are highly beneficial to predict the behavior of EMG in pattern recognition and to evaluate the relation between different feature vectors and motion patterns. The obtained results will proceed to contribute in process of classification of EMG signals for assistive devices or powered human arm prosthetics.

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