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A Brief Review of Strategies Used for EMG Signal Classification

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***Abstract*— This article presents a brief review of machine learning/classification strategies for the classification of EMG signals in the context of Myoelectric controlled prosthesis. It focuses on certain parameters adopted for machine learning such as selecting the size of windows and frequency range adopted for different filters, the filters of three domains including time domain, frequency domain and time-frequency domain, and the classifiers commonly used and that of different statistical tests performed for evaluating the significant difference between the EMG and performance of features and classifiers. Also, the comparative analysis of different EMG related studies has been done in this article. The paper would contribute to selecting the parameters before evaluating the results using machine learning. The criteria for selection of the papers to present the review is set by looking at the frequently used features and classifiers that have been used by the researchers for EMG signals analysis in the past 2 decades.**

Keywords*— *EMG; features; surface electrodes; males and females.

I. Introduction

The human muscles produce an electrical signal called Electromyography or EMG, produced by the nerve cells which control the contraction of these muscles; hence, helping in evaluating their performance. The signal could be a graph, sound, or numerical value to helping in diagnosing the muscle and nerve dysfunction [1]. This acquired EMG signal needs to be detected, decomposed, processed, and classified. The EMG signal can be acquired via invasive and non-invasive electrodes [2]. Surface EMG has been used to evaluate the muscle fatigue [3], assess abnormal patterns of muscle disorder [4], information about human locomotion [5] stroke and upper extremity nerve injuries [6], upper and lower limb muscles such as gluteus maximus, gluteus medius, tensor faciae latae, biceps femoris, semitendinosus, vastus medialis obliquus, vastus lateralis [9], rectus femoris, tibialis anterior, peroneus longus, soleus, gastrocnemius medialis and lateralis muscles [7], human lower limb (hip, knee and ankle) flexion extension joint angles [8], abdominal muscles [10], human machine interaction and control of hand prosthetics [11] [12]. The raw EMG collected from the human muscles is usually contaminated either due to Electroencephalography or ECG interference, background spikes, Gaussian noise, motion artifact or powerline interference [19]. Myoelectric signals are used in various medical applications such as assistive devices, teleoperation of robots, haptic devices, and virtual reality etc. These signals are used in myoelectric controlled prosthesis such as prosthetic hands which are aimed to assist the amputee in performing his daily routine activities [13]. Pattern recognition techniques show significant results with the use of surface EMG (sEMG) for myoelectric controlled prosthesis [14] [15] and the results of sEMG are compared with that of intramuscular EMG where sEMG either outperformed the iEMG or no significant difference was found between the two techniques [16] [17] [18]. It typically consists of feature extraction and feature classification of segmented data in signal processing to command to motor controller [13]. For classification, the classifiers such as Artificial neural network (ANN), Linear discriminant analysis (ANN), support vector machine (SVM), self-organizing map (SOP) and fuzzy classifiers are being used [31].

Pattern recognition generally involves the steps illustrated in Fig.1.

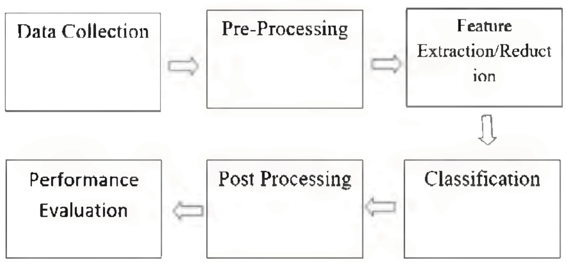

Fig.1 Steps for Pattern Recognition [34]

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II. METHODOLOGY

This paper briefly reviews the methodology adopted for the collection of EMG signals of males and females for their different muscles by performing different movements with the help of both surface and intramuscular electrodes to compare their performance. Also, the performance of features and classifiers has been compared.

A. Data Collection

The EMG in [20] was collected with the help of shimmer EMG electrodes and dynamometer for prolonged isometric contraction of biceps brachii performed by 20 right-handed(10 males and females) to study the effects of EMG on gender basis. In [21], 40 subjects performed 4 hand gestures such as press, left, right and circling to design an RC car. NeXus-10™ with Myoscan-Pro™ EMG sensor and a pair of electrodes were used to collect the EMG from four different muscles i.e. Flexor carpi radialis & Palmaris longus (wrist) & flexor digitorum superficialis (finger). J. Craig Garrison et.al evaluated the difference in EMG of lower limb muscles of males and females such as gluteus medius, lateral hamstrings, vastus lateralis & rectus femoris during landing of 16 soccer players consisting 8 males and females. Their EMG was collected using double-differential EMG electrodes (Motion Lab Systems MA-300-16, Baton Rouge, La) [22]. In [23], 20 normal subjects (10 males and females) performed six upper limb movements i.e. hand close (HC), hand open (HO), hand pronation (HP), hand supination (HS), hand flexion (HF) and hand extension (HE). The EMG was collected from their upper limb muscles including flexor carpi radialis, extensor carpi radialis muscles, extensor carpi radialis longus and extensor carpi ulnaris for evaluating the best performance of features for males and females. Ten healthy and 6 amputees (only men) performed 11 hand movements such as hand rest (HR), hand open, hand close, hand extension, hand flexion, hand supination, hand pronation, pointer, agree, side grip (SG) and fine grip (FG) and their EMG was collected using both surface and intramuscular electrodes. The purpose of the study was to compare the EMG obtained from surface and intramuscular EMG and that of performance of two classifiers [24]. In [25], forearm EMG of four datasets (31 healthy & 9 trans radial amputees) was evaluated to study the effects of sampling rates on classifying the hand and finger movements. In protocol, the last EMG dataset was divided into 3 exercises. Exercise A consisted of 12 basic movements of fingers (flexions & extensions), exercise B had 8 isometric & isotonic hand configuration & 9 basic movements of wrist (adduction and abduction, flexion and extension and pronation and supination), while exercise C consisted of 23 grasping and functional movements. Yosra Saidane, and Sofia Ben Jebara took EMG of 15 subjects (8 males & 7 females) who performed isometric contractions to compare the premotor activity and transition step for their muscle i.e. flexor digitorum superficialis (FDS) [26]. In [27], EMG analysis of two motions i.e. flexion extension and adduction abduction with maximum clench at various angles for dominant and non-dominant hands for 16 subjects was evaluated for their muscles i.e. flexor carpi radialis, flexor digitorum superficialis, extensor carpi ulnaris and extensor digitorum communis. In [28], the authors compared the EMG activity between male and female athletes during the flat bench press from four of their muscles i.e. pectoralis major (PM), the anterior deltoid (AD), the lateral head of the triceps brachii (TBlat) and the long head of the triceps brachii (TBlong). Lauren H. Smith and Levi J. Hargrove took four able bodied subjects to determine whether the use of intramuscular EMG improved pattern classification of simultaneous hand movements compared to surface EMG and took EMG from their muscles i.e. pronator teres, supinator, flexor carpi radialis, extensor carpi radialis longus, flexor digitorum profundus, and extensor digitorum [29]. In [30], EMG of ten males and females was compared during prostration by applying Ag/AgCl surface electrodes to the lower limb muscles i.e. gastrocnemius and tibialis anterior. Zia Ur Rehman et.al in [31], five healthy and two amputee subjects performed 11 hand movements for one and two consecutive days. The EMG was recorded using the surface electrodes from their forearm muscles. The movements included HO, HC, HF, HE, HP, HS, SG, FG, agree, pointer and rest to compare performance of SSAE Vs LDA. In [32], MYO arm band was used to collect the surface EMG of 7 healthy subjects who performed 6 basic hand motions including rest. The muscles selected for EMG recording included extensor carpi radialis, extensor digitorum, extensor carpi ulnaris, flexor carpi radialis, palmaris longus, and flexor digitorum superficialis muscles to compare performance of LDA and SSAE with CNN. In [34], two surface EMG electrodes were used to collect data from the forearm muscles of 6 males and 2 females to discriminate between the individual and combined finger movements. Ten healthy and 8 amputee subjects performed 11 hand motions i.e. HO, HC, WF, WE, PRO, SUP, SG, FG, Agree, Pointer and HR. Their EMG was recorded using both surface electrodes made up of Ag/AgCl and intramuscular electrodes made up of Teflon36 coated stainless steel and were analyzed using certain features to compare the performance of classifiers [52]. In [50], 5 healthy subjects performed 10 movements with the surface electrodes placed on their biceps and triceps to assess the performance of classifiers for given features. Although the already proposed time domain features showed good performance in movement classification of upper limb, yet the newly proposed three features i.e. ASS, ASM and MSR achieved classification accuracies 6.49% higher than that of old features [48].

Fig. 2 Subject performinghand movement

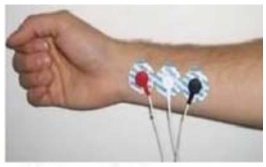

Fig. 3 Position of Surface electrodes on muscles [21]

Fig. 4 Basic hand movements [20]

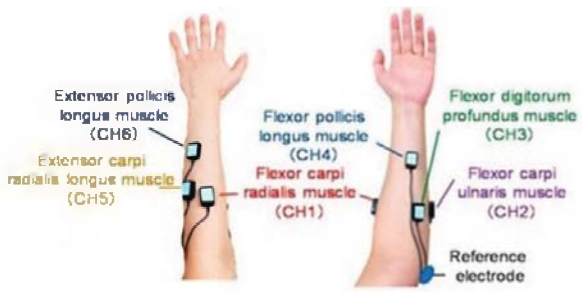

Fig.5 Surface Electrodes Used on Forearm Muscles [33]

. Fig. 5 shows the placement of surface electrodes on the forearm muscles of subject. Six channels' electrodes are placed on the forearm muscles i.e. Channel 1 (Flexor Carpi Radialis), Channel 2 (Flexor Carpi Ulnaris), Channel 3 (Flexor Digitorum Profundus), Channel 4 (Flexor Pollicis Longus), Channel 5 (Extensor Carpi Radialis Longus), and Channel 6 (Extensor Pollis Longus).

B. *EMG filtering*

The 6 channels raw EMG obtained with surface electrodes for different hand movements is shown in Fig.6. It usually contains noise which is removed with different types of desired filters. The noise could either be coming from the electric leads or the electric device. Therefore, to make sure that the proper EMG 6 channels is collected from recording device, the factors contributing to noise must be eliminated. Table I shows the filters type with the frequency range selected for the EMG signals in different studies.

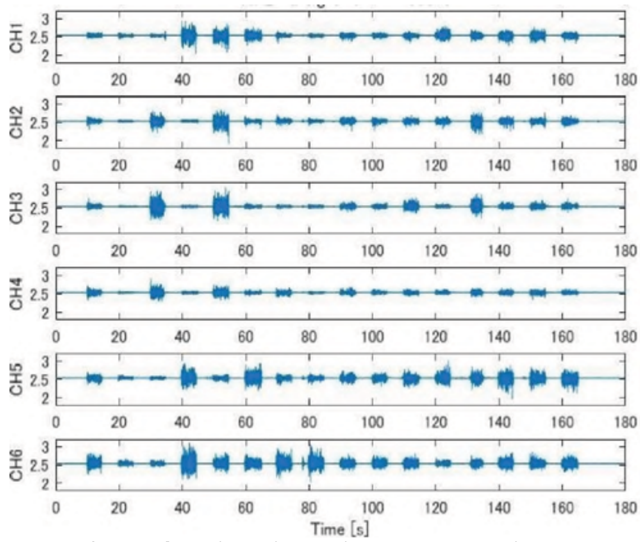

Fig.6 Surface Electrodes Used on Forearm Muscles [33]

TABLE I. FILTERS AND FREQUENCY RANGES

Type of Filter	Frequency Range (Hz)	Reference
Fourth order Butterworth bandpass filter	5-500	[20] [27] [38]
High and Low pass filter	10 and 500	[22]
Butterworth 3rd and 4th order Bandpass filter and 4th order notch filter	20-500	[31] [32] [24] [30] [34] [41]
Bandpass filter	4-450, 10-2000, 20-450, 20-500, 10-500, 5-450	[33],[29],[50] [34], [35],[30] [42] [48] [52],[43]
5th order Butterworth high pass filter and notch filter	5 and 50	[40]
Notch filter and 8th order Butterworth and elliptic Butterworth bandpass	60	[42] [43]
4th order zero lag Butterworth filter	20	[8]

Fig.7 shows the frequency response (from left) of the EMG signal from 0-500 Hz. The initial 0-19 Hz frequency range is removed by applying a bandpass filter of frequency range 20-500 Hz. The noise harmonics such as 50 Hz powerline interference and that of others are removed by applying narrow range notch filters.

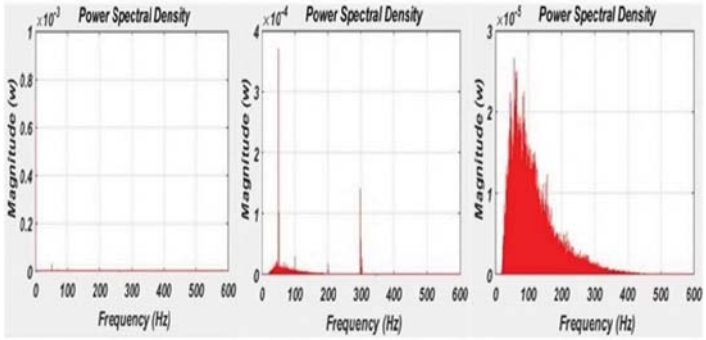

Fig.7 Filtered EMG after noise removed [31]

C. *Windows Selection*

The length of the windows selected for EMG analysis varies in different studies as shown in table II.

TABLE II. WINDOWS SIZE

	Size of Windows milliseconds (ms)	Reference
Windows Size	200 ms with a gap of 28.5 ms	[31]
	150 ms with a step of 25 ms, 50 ms	[32], [18]
	250 ms	[41] [29]
	250, 500, 750, 1000 and 2000 ms	[36]
	384 sample window size with 192 sample window increment	[37]
	250 ms with window shift of 25 ms	[39]
	Range of window length (50ms to 300ms) with the window increment of 25ms, 50ms, and 100ms	[40]
	250, 300, 500 and 1000 ms	[42]

D. *Features Selection*

Table III shows the time-domain features, table IV shows the frequency domain features while table V shows the time-frequency domain features proposed in research for EMGanalysis. Moreover, Table VI shows the comparative analysis of different studies related to machine learning carried out for EMG signals. The classifiers that showed better results include Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Stacked Sparse Auto Encoders (SSAE), and Artificial Neural Networks (ANN). For example, SSAE performed better than LDA for both iEMG and sEMG data of healthy and amputee subjects and showed robustness to between-day variability in signal features [24].

TABLE III. TIME DOMAIN FEATURES

Type	Features	Reference
Time Domain Features	Root Mean Square (RMS), SSAE-r and SSAE-f	[20] [25] [22] [27] [40], [32]
	Zero Crossing (ZC)	[18] [40] [13] [32] [47] [49]
	Slope Sign Change (SSC)	[18] [32] [31] [47] [49]
	Willison Amplitude (WAMP)	[40] [48]
	Mean Absolute Value (MAV)	[18] [31] [32] [25] [40] [13] [47] [49]
	Waveform Length (WL)	[18] [40] [24] [25] [31] [32] [47] [48] [49]
	Integrated Absolute Value (IAV) and Variance (VAR)	[13]

TABLE IV. FREQUENCY DOMAIN FEATURES

Type	Frequency	Reference
Frequency Domain Features	Median Frequency (MDF)	[25] [27]
	Power Spectral Density (PSD)	[44]
	Mean Frequency (MNF)	[27]
	Peak Frequency Power (PFK), Mean Frequency Power (MFP), Frequency Median (FMD), Frequency Mean (FMN), Modified Frequency Median (MFMD)	[40]
	Fast Fourier Transform (FFT)	[13]
	Frequency ratio (FR)	[50]
	Variance of Central Frequency (VCF), Total Power (TTP), Power Spectrum Ratio (PSR), Power Spectrum Deformation (PSD), Peak Frequency (PKF), Power Spectral Density Fractal dimension (PSDFD)	[51]
	Fundamental Frequency Region Length & Fourier Variance	[21]

TABLE V. TIME FREQUENCY DOMAIN FEATURES

Type	Frequency	Reference
Time-Frequency Domain Features	Wavelet Transform (WT), Wavelet Packet Transform (WPT), Short Time Fourier Transform (STFT)	[53] [50]

TABLE VI. COMARATIVE ANALYSES OF DIFFERENT STUDIES

Sr. No.	Ref.	No. of Subjects	Recording Muscles	Sampling Rate	Selected Features	Classifiers
1	[24]	10	Flexor and extensor muscles	8kHz	Mean absolute value (MAV), waveform length (WL), zero crossing (ZC), and slope-sign change (SSC)	SSAE, LDA
2	[53]	5	Extensor Digitorum, Extensor Carpi Radialis Longus and Flexor Digitorum Superficialis	2kHz	MAV, WL, ZL, WAMP and SSC	Artificial Neural Networks (ANN)
3	[54]	20	Forearm muscles	2KHz	MAV, Correlation coefficient, Mean firing velocity, Waveform length, Skewness etc.	Artificial Neural Networks (ANN)
4	[55]	9	Forearm Muscles, Hand muscles	2KHz	Fusion of time domain descriptors (FTDD), Hudgins time domain descriptors, etc.	Convolution Neural Network (CNN), Long-Short term memory (LSTM) network
5	[56]	8	Forearm Muscles	200Hz	MAV, Short-term Fourier Transform	Support Vector machine, Convolution Neural Network (CNN)
6	[57]	-	Hand muscles	-	RMS, WL, Median Amplitude Spectrum, SampEn,	GRNN neural network.
7	[58]	9	Hand muscles	2KHz	Geometric mean, Precision and F1-score, Accuracy	K-NN, CVSM
8	[59]	5	Hand muscles	-	Dimension reduction Methods,	Principal Component Analysis (PCA), Diffusion Maps, K-NN

The common classifiers used, and the statistical tests performed for features evaluation are shown in table VII.

TABLE VII. FREQUENCY DOMAIN FEATURES

Classifiers	Reference	Statistical Tests	Reference
ANN, Naive Bayes (NB), Decision trees (TREE) (C4.5, (CART), REP, LAD)	[18][50] [49], [52], [12]	%MVC Vs time, CoV and ANOVA	[20] [52] [22] [16]
KNN, Bayes, CNN	[18][52],[21], [32]	MANOVA, Paired Samples T Tests	[22], [30]
LDA, SSAE	[51] [24] [31] [52] [16] [18] [49], [24][31]	Hudgin's & Du's	[51]
SVM	[25] [52][18] [40]	Boxplot	[26]
WPD	[52]	Kruskal-Wallis ANOVA	[28]
RF, Rotation Forests, RT, Quadratic Discriminant Anaysis (QDA), SEMG	[40], [12], [40], [50]	Classification error (CE), separability index (SI), scatter matrix separability criterion (SMSC)	[47]

III. RESULTS AND DISCUSSION

The results in these articles are obtained on the basis of features and classifiers selected for the EMG analysis of males and females. The performance of features is evaluated on the basis of classification accuracies of classifiers. Also, the significant difference between the features, classifiers and EMG of males and females has been evaluated by setting threshold value e.g. $p<0.05$ [24] [31] [32].

IV. CONCLUSION

This paper focuses on literature based on the comparison of EMG of males and females for their different muscles (upper and lower limb), the windows size and filters with a specific frequency range, the features of three domains i.e. time domain, frequency domain and time-frequency domain, generally proposed classifiers for obtaining classification accuracies for different features and types of statistical tests performed for obtaining significant difference between the EMG, features performance and classification accuracies for males and females.

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