Statistical Analysis of EMG-Based Features for Different Hand Movements

C. N. Savithri and E. Priya

Abstract The electrical activity of the muscles is analyzed by surface Electromyography (sEMG). EMG signals are the essential source of control for upper limb prosthetics and orthotics and also find numerous applications in biomedical engineering and rehabilitation fields. This work focuses on the analysis of sEMG signals acquired for three different hand actions using Analysis of Variance (ANOVA) for understanding the variability of features. A single-channel sEMG amplifier is designed and signals are recorded for three different hand movements from normal subjects. Empirical Mode Decomposition (EMD) is applied to denoise the signal from artifacts. Features are extracted in time, spectral, and wavelet domain. The prominent features are selected using fuzzy entropy measure. ANOVA on prominent features shows a linear relationship between features and different hand movements and therefore these prominent features can be used to activate the prosthetic hand.

1 Introduction

Modern technology has broadened the choice of sEMG signal in clinical diagnosis, biomedical engineering, and applications [1, 2]. The characteristics of hand movement owing to muscle contraction can be obtained from sEMG signal which is a manifestation of electrical potential in time-varying form. Single-channel acquisition with surface electrodes is used to record sEMG signals as an alternative of multichannel system [3]. The random nature of sEMG signal makes it unsuitable to extract the inherent properties from solitary feature and does not permit to use these signals directly in prosthetic applications. Various sources of noise disturbing the sEMG signal are electrode noise, electrode, and cable motion artifact, power

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line interference [4–7]. Several techniques are used for the removal of these types of noise. Filtering is a significant preprocessing technique that removes noise from the acquired signal. Few techniques include baseline wander correction accomplished by a combination of EEMD and morphological filtering [8], and canonical correlation analysis followed by morphological filtering for removal of additive white Gaussian noise [9]. The optimal window length is 150–250 ms to extract significant features from sEMG signal [10, 11]. It is imperative to extract feature vector from the input data so that it enhances the further processing stages probably a controller to actuate the prosthetic hand [12].

In this work, one-channel sEMG amplifier is developed to acquire sEMG signals for three different hand movements. Preprocessing step involves noise removal by Empirical Mode Decomposition (EMD) technique. Features in time, spectral and wavelet domain are extracted from preprocessed signal. Fuzzy entropy based feature reduction method is attempted to identify the best feature among different hand actions. The relationship between features and hand action is analyzed by Analysis of Variance (ANOVA) to get a good insight feature set and hand actions and to identify prominent features that will drive the controller of prosthetic hand.

2 Methodology

2.1 EMG Signal Acquisition

A one-channel sEMG acquisition system is designed and sEMG signal is recorded from thirteen normal subjects for three hand actions namely closed fist, spherical grasp, and point. The subjects are requested to perform one category of all hand action five times in each trial with a rest–motion–rest pattern. The muscle fatigue and mental stress to subjects are avoided by relaxing them for a minute between every hand motion.

The block diagram of one-channel sEMG amplifier developed is shown in Fig. 1. Three disposable disc surface electrodes are used one of which is a reference electrode placed over the wrist and a pair of signal electrodes on flexor digitorum superficialis muscle. Low-frequency noise and artifacts due to movements are filtered by 12 Hz RC high pass filter. A high pass filter at the second stage brings the signal to TTL level with an additional gain of 20.

The offset problems are resolved by bias adjustment that changes the reference level of the amplified signal. The sEMG signals are sampled by Analog to Digital Converter (ADC) of 10 bits resolution.

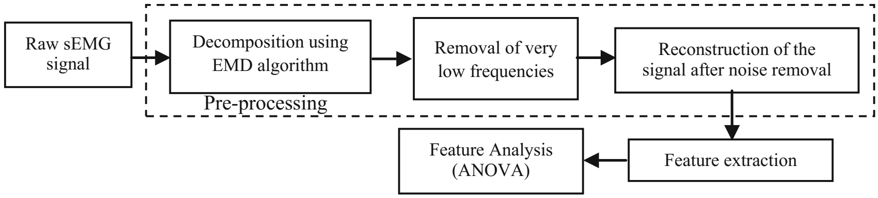

Fig. 1 Functional block diagram of sEMG signal processing

2.2 EMG Signal Preprocessing

The frequency components less than 10 Hz are eliminated by decomposition procedure and within 20–500 Hz are restored. EMD algorithm is applied as sEMG signals are nonstationary and nonlinear signals. EMD is a purely data-driven, signal-dependent procedure and makes no assumptions about the input signal [13].

EMD decompose the signal into finite number of one-dimensional function called Intrinsic Mode Functions (IMFs). Sifting algorithm performs the iterative method to find the IMFs of any given signal $x(t)$. By computing minima and maxima from the signal envelope, the mean is calculated and is subtracted from the original signal to compute the IMFs. This iterative procedure is continued until the difference remains unchanged. The whole process is repeated until $x(t)$ has more than one extremum (neither a constant nor a trend). The de-noised signal is constructed with the lower order IMFs leaving the three higher order IMFs. The time, frequency, and wavelet domain features are extracted from the reconstructed signal.

2.3 Feature Extraction

Features are distinctive properties of signal that help in differentiating between the categories of signal patterns. The mathematical formulation [14] of the features is discussed in the next few paragraphs.

The Mean or the Average Value (MAV) of the signals is obtained by averaging the absolute value of the signals over the number of signals at any time instant. MAV aid in quantifying the muscle contraction levels and is given by

$$\mathrm{MAV} = \frac{1}{N}\sum_{k=1}^{N}|x_k| \tag{1}$$

where x_k is the kth sample in the analysis among N total samples.

Integral Absolute Value (IAV) is an indication of total muscular effort and is represented by

$$\mathrm{IAV} = \sum_{k=1}^{N} |x_k| = \mathrm{MAV} \times N \tag{2}$$

The power of sEMG signals is related to non-fatiguing contraction and other forces that act on muscles. This is analyzed using Root Mean Square (RMS) value and given by

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} x_k^2} \tag{3}$$

Waveform Length (WL) is the cumulative length of the EMG signal and is given by,

$$\mathrm{WL} = \sum_{k=1}^{N} |\Delta x_k| \quad \text{where } \Delta x_k = x_k - x_{k-1} \tag{4}$$

Muscle contraction state data can be obtained from Auto Regression (AR) coefficients. Generally, linear autoregressive time series are used in modeling individual EMG signals

$$x_k = \sum_{i=1}^{p} a_i x_{k-1} + e_k \tag{5}$$

where a_i presents autoregressive coefficients, p is the order of AR model, and e_k is the residual white noise. The frequency with which signal crosses zero is given by Zero Crossing (ZC), and it is linked to the original signal frequency. Low-level noise cutoff is achieved by incorporating a threshold ε.

$$\begin{aligned}&\{x_k > 0 \text{ and } x_{k+1} < 0\} \text{ or } \{x_k < 0 \text{ and } x_{k+1} > 0\} \text{ and}\\ &|x_k - x_{k+1}| \geq \varepsilon\end{aligned} \tag{6}$$

Signals can sometimes exceed the threshold. The frequency of the change of EMG signal is Wilson Amplitude (WA) and is indicative of muscle contraction level.

$$\mathrm{WA} = \sum_{i=1}^{N} f(|x_i - x_{i-1}|) \quad f(x) = \begin{cases} 1 \text{ if } x > \text{Threshold} \\ 0 \quad\; < \text{Threshold} \end{cases} \tag{7}$$

Wavelet transform finds numerous applications in bio-signal processing [15, 16]. Discrete Wavelet Transform (DWT) is performed to decompose the signal into four levels with coiflet (coif) as mother wavelet. Better performance analysis of EMG signal is obtained by decomposing the signal to four levels [17]. Relevant features are computed from the fourth level approximation coefficients.

2.4 Entropy-Based Feature Selection

Fuzzy entropy is used to express the mathematical values of the fuzziness of fuzzy sets. It is a measure of uncertainty or vagueness that exists for a given data set. The fuzzy entropy value $H(A)$ is computed with the similarity values $\mu(x_i)$.

$$H(A) = -\sum_{i=1}^{n} \mu_A(x_i) \log\mu_A(x_i) + (1 - \mu_A(x_i)) \log(1 - \mu_A(x_i)) \tag{8}$$

A high similarity is indicated by low fuzzy entropy value and a feature is eliminated from feature set that has highest entropy value [18]. Prominent features are computed by iterating the above procedure.

2.5 Analysis of Variance (ANOVA)

ANOVA is a statistical tool for testing the hypothesis by measuring the variability within groups that has a baseline against which differences among group means can be compared [19]. The variability within groups (SSW) and between groups (SSB) is compared to determine if the group means are significantly different. The strength of the relationship between-group membership and the variable measured is quantified by a descriptive statistic parameter R^2. The $F -$ ratio (F) is the ratio of variance of the group means to mean of the within-group variances. It gives an insight to whether there exists a significant difference in variance between the means of two populations. The percentage variance for between-group variations is given by a parameter called critical value (f_{crit}). Thus, analysis of variance is performed to explore suitable relationship that exists between features and hand movements.

3 Results and Discussion

The sEMG amplifier picks up the raw sEMG signal for three movements with each action repeated five times. Figure 2 shows hand gestures for three different actions and Fig. 3a shows a typical waveform for closed fist. The "rest-motion-rest" movement and the offset shift in voltage are shown by single burst in Fig. 3a.

The sEMG signal is de-noised using EMD algorithm which resolves the signal into eleven IMFs. The preprocessed signal is obtained by reconstructing the signal omitting the three higher order IMFs and nullified offset as shown in Fig. 3b. The decomposition of the signal by EMD is shown in Fig. 3c. The computed features set of eight each from time; frequency and wavelet domain are shown in Table 1.

Fuzzy entropy measure selects the prominent features from the feature set presented in Table 1. Entropy values calculated after each iteration is listed in Table 1

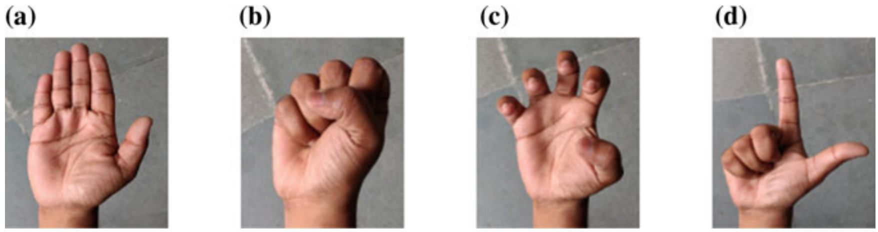

Fig. 2 Different hand gestures **a** rest, **b** closed fist, **c** spherical grasp and **d** point

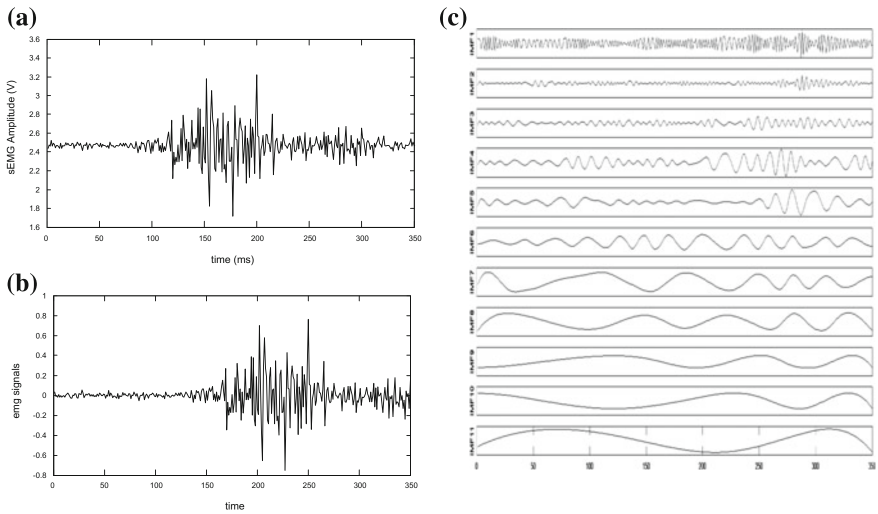

Fig. 3 Typical (**a**) raw (**b**) reconstructed sEMG signal for closed fist (**c**) corresponding IMFs of EMD

and the blank entry represents the elimination of the feature Drop in Power density ratio (DP) during first iteration. Actually, the feature with highest entropy value is removed as the impact of sEMG signal on that feature is very less and the process is repeated with remaining features. Finally, the features Zero Crossing (ZC), mean frequency (meanf) and WA qualify as prominent features in time, frequency and wavelet domain respectively which are used to control the prosthetic hand.

Relational interpretations between the features and hand actions are studied by calculating the statistical parameters of one way ANOVA. R^2 value is computed from the results of ANOVA which equals the between-group sum-of squares to total sum-of-squares. Higher value indicates a linear relationship with feature set and hand actions. Table 2 shows the R^2 values computed for all the 24 features together in time, spectral, and wavelet domain against each hand action.

The feature set provides direct measurement of force involved while performing various hand actions. It is observed that there exists a significant difference between all features across domain and hand action. In all cases, the F (9.71) is larger than

Table 1 Feature set and their corresponding fuzzy entropy measure

Time domain		Frequency domain		Wavelet domain	
Feature	Entropy value	Feature	Entropy value	Feature	Entropy value
feat_MAV	22.22	DP	–	feat_RMS	24.69
feat_RMS	17.30	**meanf**	**15.42**	feat_WL	24.41
feat_IAV	21.56	medianf	17.15	feat_ZC	23.26
feat_SSC	20.85	SM0	23.63	feat_ar1	17.99
feat_WL	19.19	SM1	23.29	feat_ar2	17.19
feat_ZC	**16.42**	SM2	23.05	feat_aac	24.21
feat_ar1	18.64	OHM	24.63	feat_aav	24.18
feat_ar2	16.75	SM	25.49	**feat_WA**	**10.98**

Table 2 R^2 values for hand actions and features across different domain

Hand actions	Time domain features	Frequency domain features	Wavelet domain features
Closed fist + Spherical grasp + Point	0.60	0.56	0.63

Table 3 R^2 values for all hand actions and all features across different domain

Hand actions	Time domain features	Frequency domain features	Wavelet domain features
Closed fist	0.727	0.575	0.737
Spherical grasp	0.676	0.676	0.731
Point	0.518	0.471	0.534

the critical value f_{crit} (1.99), which implies means are significantly different. Hence, there is significant difference between the groups (SSB) than within groups (SSW) and p-values are found to be less than 0.05. Subsequently, the null hypothesis of equal means is rejected and the test statistic is significant at this level. Thus, the relationship between feature set and hand actions are not linear.

In search of feature set with higher linear relationship, next analysis of variance is computed considering all features for three actions separately for time; spectral and wavelet domain. Table 3 shows R^2 values for three hand actions separately and all features across different domains.

It is observed again that there is a significant difference in SSB than SSW. In this case also, the F is larger than the critical value f_{crit}, which implies means are significantly different. The p-values are found to be less than 0.05. Subsequently, the null hypothesis of equal means is rejected and the test statistic is significant at this level too. Thus, the relationship between features and hand actions is not linear.

The next analysis of variance is computed for the prominent feature selected by fuzzy entropy measure for three actions in time, spectral and wavelet domain. It is

Table 4 ANOVA results for feature WA for all hand action in wavelet domain

Source of variation	SS	Df	MS	F	P-value	f_{crit}
SSB	0.0026	2	0.0013	0.0168	0.983	6.16
SSW	2.791704	36	0.077			
Total	2.794304	38				

observed from Table 1 that among ZC, meanf and WA, the most significant feature is WA as the entropy value is the least and hence ANOVA is performed for WA.

It is observed that F is lesser than critical value f_{crit} (6.16) also, the p-value is large ($p > 0.005$) for the three prominent features and hence the null hypothesis is not rejected, i.e., this feature satisfies the null hypothesis. The R^2 computed through one way ANOVA is 0.91 for ZC, 0.83 in for meanf and 0.99 for WA indicating a linear relationship between the features and hand actions. Table 4 shows ANOVA results for WA in wavelet domain and it exhibits higher linear relationship among the three significant features. This indicates that muscle contraction is linear with hand action that is being performed.

4 Conclusion

This work presents an analysis based on fuzzy entropy measure and ANOVA for the exhaustive feature set derived from the acquired de-noised sEMG signal. The features ZC in time domain, meanf in frequency domain, and WA in wavelet domain are identified as effective features based on the fuzzy entropy measure. It is observed from ANOVA results when exhaustive feature set is considered the relationship is not linear between features and hand actions. This is due to the fact that variance between groups is very less leading to small R^2 value. Hence, an exhaustive feature set cannot be used to actuate controller that drives prosthetic arm as it increases the computational load and may increase the time of response. The variability between group increases as feature dimensionality reduces. ANOVA is very promising as it reveals a linear relationship between prominent features selected by fuzzy entropy measure and the hand movements. As a future work, it is planned to design a controller using these effective features for the control action of prosthetic hand, as they show linear relationship with hand movements.

Declaration Authors have taken the consent from the concerned authority to use the materials, etc., in the paper. Authors will be solely responsible if any issues arise in future with regard to this.

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