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Real-Time Replication of Arm Movements Using Surface EMG Signals

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Abstract

In this paper, a real time application to replicate nine arm movements is proposed. The two important joints that are controlled are wrist and elbow. Electromyogram signals are recorded for four wrist positions and five elbow positions. These signals are enhanced and features pertaining to muscle movements are extracted. Dimension of these feature sets is reduced to obtain the optimal set of features. These feature sets are given as input to the classifier. Performance evaluation of Support Vector Machine (SVM), K-Nearest Neighbors, Random Forest and Relevant Vector Machine (RVM) classifiers, in recognizing different wrist and elbow positions, is discussed. As per the results, the best overall accuracy of 93.3% was obtained from SVM with radial basis function (RBF) kernel, in classifying both the wrist and elbow positions. Although, RVM as a classifier yielded the same accuracy in recognizing wrist positions, it resulted in the lowest accuracy of 88.67% in recognizing elbow positions. Therefore, SVM-RBF fared better in identifying the arm movements. Furthermore, these arm movements are used to control the actuators.

Keywords: Electromyogram; Wrist movement; Elbow movement; SVM; RVM.

1. Introduction

The muscle attached to the bone is called the skeletal muscle. The contraction of this muscle is responsible for the movement of the limbs. This contraction leads to the generation of an electrical signal called electromyography (EMG) signal. Multiple strands called myofibrils present in the muscle are chemically activated by neurons which leads to the generation of charge whose motion in turn produces electromagnetic field. In a motor unit all the action

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potentials generated by myofibrils are combined together and hence this is termed as motor unit action potential (MUAP). Surface EMG electrodes collect several such MUAPs for each skeletal muscle. The physiology of the signal depends on the arm movement that led to its generation. This unique identity of each signal can be used to replicate specific arm movements in an orthotic arm using actuators.

An orthotic arm is a device which is capable of supporting movements of non-functional body parts. The functioning of wrist and elbow joints is essential for any arm movement. EMG signals produced by the arm can be tapped to replicate these movements using an orthotic arm and significant work has been done in this field. There are a few models available which replicate finger and the wrist movements. Some models also replicate movements of the knee joint[1,2,3]. EMG signals are constantly generated despite the loss of arm movements due to muscle disorders. These signals need to be collected in a systematic manner in order to avoid artefacts. Thorough understanding of signal acquisition techniques and the physiology of the signal are essential for the creation of an accurate dataset[4] and the need for adopting differential electrodes for acquiring low amplitude EMG signals. The exact position as well as the distance between the two electrodes also play an essential role in the process of signal acquisition. EMG signals are usually contaminated with unwanted artefacts. Efficient elimination of these artefacts such as ECG artefacts, ambient noise and motion artefacts becomes important[5]. Feature extraction involves the collection of the most useful information from a signal. The extraction of features irrelevant to EMG leads to inefficient learning and hence incorrect classification. This issue has been discussed in several works[6,7,8]. Here, a compilation of about 37 features are discussed. This feature set comprises of both time-domain (TD) and frequency-domain (FD) features which are most relevant to EMG signals. These features need to be reduced to obtain the smallest possible feature set which contributes the most to efficient learning. Principal Component Analysis (PCA) is one of the dimensionality reduction techniques used for the purpose. Recursive Feature Elimination (RFE) is also one such method. Significant research has been conducted to prove the importance of PCA in multi-class classification of EMG signals[9,10,11]. PCA helps in enhancing the classification accuracy and is hence crucial for efficient real-time replication. Upon obtaining the final feature set, the performance of various classifiers need to be tested against this vector. Traditional classifiers like, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forests (RF)[12,13,14] can be employed for classification and hence prediction of the desired arm movement, post feature extraction. Researchers have described the performance of neural networks, SVM and other algorithms for efficient classification of EMG[15,16]. Relevance vector machine (RVM) is yet another classification algorithm which overcomes some major disadvantages associated with SVM and also proved to provide best results[17].

This paper proposes one such model of an orthotic arm in which EMG signals of the desired arm movement are acquired in real-time from a subject and hence subjected to noise removal, feature set formation, detection of arm movement and finally, replication using actuators. It also compiles the performance of various classifiers which provided superior results in categorizing these EMG signals, in real-time. The model proposed is capable of replicating nine unique and essential arm movements, of the wrist and elbow joints, and can hence help patients overcome the ill-effects of neuromuscular disorders. The novelty also lies in the application of RVM for recognizing different arm movements.

2. Methodology

EMG signals were acquired for a duration of five seconds. These signals were subject to pre-processing for the elimination of artefacts. Different TD and FD features were collected which was followed by dimensionality reduction to retain the most relevant features. These features were fed to machine learning algorithms, namely, SVM, KNN, RF and RVM. The test signal was classified using the algorithm which provided the best results and this prediction is used to control the servo motors of the orthotic arm. This system has been developed in several stages. In this section all these stages are explained in detail.

2.1. Data acquisition

Thirty healthy subjects (15 boys and 15 girls, aged 18-22) with no injuries in the upper limb were selected to participate for data acquisition and informed consent was taken from them. The signals were recorded from the right hand for a duration of five seconds. The EMG signals were acquired using three muscle sensors interfaced with Arduino. Among these two are differential electrodes and one is used as reference. The differential electrodes were placed along the Flexor Carpi Radialis, which is responsible for flexion at wrist for the hand movements and along Brachialis Muscle which is responsible for flexion of elbow for forearm movements. The sampling rate of the signal was the same as that of the Arduino i.e. 9620 Hz. The EMG signals were acquired for four positions of the wrist and five positions of the elbow.

2.2. Signal preprocessing

EMG signal is a biomedical signal which is highly sensitive and hence easily affected by various noise sources. This noise can be due to the hardware used for data acquisition, movement of the electrode, the electrical activity of the heart and the environment[5]. It is essential to eliminate this disturbance before extracting features to ensure higher precision during classification. The raw EMG signal has a high DC value. Hence its mean is subtracted from the original signal. EMG signals usually range from 20 to 450 Hz. Therefore, the signal is filtered from 20 to 450 Hz to remove the movement artefacts and the other noise components in the signals. This is carried out by a Butterworth bandpass filter of order five, followed by bandstop filter of order three to eliminate electrocardiographic (ECG) artefacts in the frequency band of 49 to 52 Hz.

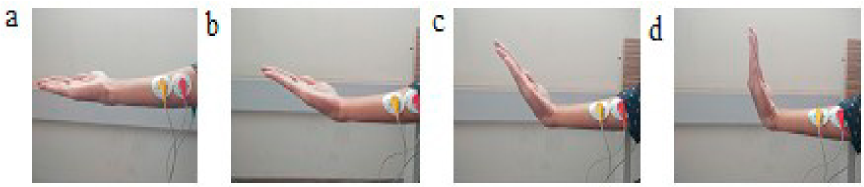

Fig. 1. Wrist positions (a) 0^{o}; (b) 30^{o}; (c) 60^{o}; (d) 90^{o}.

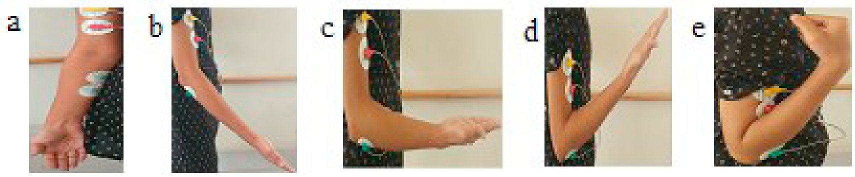

Fig. 2. Elbow positions (a) -90o; (b) -45o; (c) 0o; (d) 45o; (e) 90o.

2.3. Feature extraction and selection

Feature extraction involves the collection of useful information from the acquired EMG data, to form a feature vector. From all the signals pertaining to different wrist and elbow positions, seven TD and five FD features were extracted [6]. These seven TD features are; Mean Absolute Value (MAV), Variance (VAR), Standard Deviation (SD), Root Mean Square (RMS), Integrated EMG (IEMG), Log Detector (LD), Modified MAV (MAV1), extracted based on the time varying signal amplitude. The five FD features are; Power Spectral Entropy (PSE), Mean Frequency (MNF), Median Frequency (MDF), Total Power (TTP) and Mean Power (MNP), containing the power spectrum density (PSD) of the signals. Table. 1 summarizes the mathematical relation and the medical significance of these TD and FD features. Finally, the feature set obtained is, Fs = {MAV, VAR, SD, RMS, IEMG, LD, MAV1, PSE, MNF, MDF, TTP, MNP}.

The feature set obtained cannot be directly supplied to a classifier, as it can also contain some redundant features which do not contribute to the classification accuracy. Hence, it is essential to retain only those features which contribute the most. Dimensionality reduction techniques such as RFE and PCA can help obtain the best feature vector. Using PCA, the data was projected onto a lower dimensional space. It is used to overcome feature redundancy in a dataset. Since the dataset obtained is of lower dimension, this approach helps in reducing the space and time complexity. RFE, a feature selection process helps in selecting a subset of the features. This was done by constructing a model repeatedly and selecting the best feature based on the performance and saving it. The whole process is repeated for the remaining features. The features are given ranks based on their relevance and the features that contribute the most in detecting the target arm movement were assessed based on the model accuracy.

2.4. Classification

Supervised machine learning algorithms perform the task of identification of the arm movement which needs to be replicated. Upon successful prediction of the same, the result are to be shared with the actuators to perform the replication action accordingly. Hence, the selection of an efficient classifier plays a crucial role for real-time replication.

Table 1. Mathematical relation and medical significance of the extracted features.

	Feature Extracted	Mathematical Relation	Medical Significance
1	MAV	$MAV(\mu) = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$	It gives an estimate of the muscle contractile force.
2	VAR	$VAR = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\mu)^2$	High value at rest indicates a muscle disorder.
3	SD	$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}x_i^2}$	Used to measure threshold level of muscle contraction activity.
4	RMS	$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N}x_n^2}$	Used to quantify the electrical signal in the motor unit during contraction.
5	IEMG	$IEMG = \sum_{i=1}^{N}\lvert x_i\rvert$	Like variance, a high value at rest indicates a muscle disorder.
6	LD	$LD = e^{\frac{1}{N}\sum_{i=1}^{N}\log(\lvert x_i\rvert)}$	Provides an estimate of the muscle contractile force.
7	MAV1	$MAV1 = \frac{1}{N}\sum_{i=1}^{N}w_i\lvert x_i\rvert$, $w_i\begin{cases}1 & for\ i = 0.25N\ to\ 0.75N\\0.5 & Otherwise\end{cases}$	Similar to mean, provides an estimate of the muscle contractile force.
8	PSE	$PSE = -\sum_{i=1}^{n}p_i\ln p_i$	Describes the EMG signal variability
9	MNF	$MNF = \sum_{j=1}^{M}f_jP_j / \sum_{j=1}^{M}P_j$	To assess muscle fatigue in surface EMG signal.
10	MDF	$\sum_{j=1}^{MDF}P_j = \sum_{MDF}^{M}P_j = \frac{1}{N}\sum_{j=1}^{M}P_j$	Also, to assess muscle fatigue.
11	TTP	$TTP = \sum_{j=1}^{M}P_j$	As a frequency domain feature, it is used for measuring the strain in the muscle.
12	MNP	$MNP = \sum_{j=1}^{M}P_j/M$	Used for assessing the fatigue and tension in the muscle.

The performance of the four machine learning algorithms, namely, SVM, KNN, RF and RVM12,13,14,17 was studied and hyperparameters associated with these algorithms were varied to obtain the best performance. This was measured using mainly three performance metrics, namely, accuracy, precision and recall. The two main hyperparameters associated with SVM are cost function, denoted by ‘c’ and ‘gamma’. Cost function represents the trade-off between simplicity and precision and was set to one while classifying wrist positions using linear as well as RBF kernels. In case of elbow positions' detection, c set to value of 0.1 was used with SVM-linear classifier. Whereas gamma, which represents the influence of the support vector on a far-away data point, and was set to 0.1 for SVM-RBF. The hyperparameters associated with KNN and RF are 'K' and 'N-estimators', respectively. Here, K represent the number of neighbouring points in KNN, and N-estimators represents the number of decision trees in RF. For classifying wrist positions K=9 and N-estimators=30 were used, whereas, for elbow positions, K was set to three and N-estimators remained unchanged.

RVM[17] is a machine learning technique which is similar to SVM but is capable of giving probabilistic outputs, which is absent in SVMs. In this the learning functions and the relevant parameters play very important roles in improving the accuracy. For wrist movements' recognition 'n_iter', the number of iterations was set to 300 with RBF being the kernel. Whereas, for elbow movements, the use of sigmoid function yielded the best accuracies, with 'alpha=beta=1e-06'.

2.5. Replication

For the final stage of replication, an EMG signal was acquired from the subject for a duration of five seconds in real-time. The signal acquired was hence subject to pre-processing and feature extraction. The classifier trained using the reduced feature vector treats this signal as a test vector and hence classifies it into the appropriate wrist/elbow angle. A GUI was employed to decide if a wrist or elbow action is to be replicated. Upon successful classification of the arm position, the result was hence shared with the microcontroller to control the actuators for replication of the arm movement.

Upon successful classification, the label of the corresponding class is hence shared with the microcontroller which in turn controls the movement of the servo motors representing the wrist and elbow joints accordingly. The rotation of the shaft of the servo motor hence replicates the desired position of the orthotic arm[1].

3. Experimental Outcome

To measure the prediction accuracy of the classifiers, k-fold cross validation was employed. It involves formation of the train and test sets by dividing the dataset into '*K*' subsets. Here, '*K-1*' subsets form the train set and the one remaining set plays the role of a test set. Upon performing several trials, the most optimum results were obtained for K=15. Hence, the results summarized in this paper were obtained for fourteen train sets and one test set for every iteration. As explained under the section pertaining to feature extraction, it is the feature vector obtained using dimensionality reduction which was employed for the purpose of classification. PCA and RFE were the two techniques utilised for this purpose. Upon comparing the accuracies obtained using the resultant feature vectors, it was observed that the feature vector from RFE provided superior results. The best set of feature vectors obtained from RFE were: MAV, LD, MAV1, RMS and PSE in that order of priority for wrist angle classification. And, MAV, MAV1, RMS, LD and PSE in that order of priority for elbow angle classification. The performance of the four classifiers, SVM with linear and RBF kernels, KNN, RF and RVM, are compared in this work.

In Table. 2, the sensitivity (SN) and specificity (SP) obtained for all the four wrist positions, [0^o, 30^o, 60^o, 90^o], are presented along with the overall accuracy. SN and SP measure the proportion of correct identification of actual positives and actual negatives, respectively. These performance metrics along with accuracy help determine the efficiency of a classifier. In detecting the aforementioned wrist positions, the performance of SVM-RBF, KNN and RVM classifiers fared better with an accuracy of 93.3%, and was observed to be efficient for most positions. But the SN obtained for 60^o position was in the range of 73.3-83.3%, which was relatively lesser and that in turn reduced the overall accuracy.

Table 2. Outcome of all classifiers for the four WRIST angles

Classifier	Overall Accuracy	0^o		30^o		60^o		90^o	
		SN	SP	SN	SP	SN	SP	SN	SP
SVM-linear	92.5%	100%	100%	96.6%	93.3%	73.3%	98.8%	100%	97.7%
SVM-RBF	93.3%	100%	100%	100%	95.5%	73.3%	98.8%	96.6%	95.5%
KNN	93.3%	100%	100%	100%	95.5%	76.6%	98.8%	96.6%	96.6%
RF	92.5%	100%	100%	93.3%	97.7%	83.3%	95.5%	93.3%	96.6%
RVM	93.3%	96.6%	100%	100%	95.5%	80%	98.8%	96.6%	96.6%

In Table. 3, SN and SP values of all the five elbow positions, [-90^o, -45^o, 0^o, 45^o, 90^o], are presented. According to which SVM-RBF gave the best accuracy of 93.3%. However, relatively lesser SN values are obtained for 45^o position of the elbow joint, which reduced the overall accuracy.

A summary of the overall accuracies obtained for the four wrist positions and five elbow positions using different classifiers are presented in Table. 4, along with recorded optimal hyperparameters. The precision and recall values noted for the classifiers can also be found in the same. As per these results it can be observed that the novel RVM classifier's performance is on par with that of the SVM-RBF and KNN in predicting the wrist positions. In addition, RVM's precision percentage of 94% is slightly greater than 92.5% precision of SVM-RBF and KNN. These three classifier models fared better than the other classifiers. However, in case of detecting the five elbow positions SVM-RBF yielded the best accuracy of 93.3%.

Table 3. Outcome of all classifiers for the five ELBOW angles

Classifier	Overall Accuracy	-90^o		-45^o		0^o		45^o		90^o	
		SN	SP	SN	SP	SN	SP	SN	SP	SN	SP
SVM-linear	92.7%	96.7%	99.16%	90%	98.3%	93.3%	95%	86.6%	98.3%	96.6%	100%
SVM-RBF	93.3%	96.7%	100%	93.3%	98.3%	93.3%	95%	86.6%	98.3%	96.6%	100%
KNN	92.7%	96.7%	100%	93.3%	98.3%	90%	95%	86.6%	97.5%	96.6%	100%
RF	92.7%	96.7%	100%	93.3%	98.3%	90%	95%	86.6%	97.5%	96.6%	100%
RVM	88.67%	96.6%	99.16%	90%	98.3%	86.6%	92.5%	73.3%	96.6%	96.6%	99.16%

Since, SVM-RBF gave the maximum accuracy in predicting both wrist and elbow joints, when compared to other classifiers, it was considered for the real-time replication of the arm movements. The replication of the four different wrist positions are shown in Fig. 3(a)-(d) and the five elbow positions, in Fig. 4(a)-(e).

Table 4. Overall outcome of all classifiers for WRIST and ELBOW positions and the hyperparameters.

Classifiers	WRIST Positions				ELBOW Positions			
	Parameters	*Accuracy*	*Precision*	*Recall*	*Parameters*	*Accuracy*	*Precision*	*Recall*
SVM-linear	C=1	92.5%	91.9%	92.5%	C=0.1	92.7%	92.7%	92.9%
SVM-RBF	C=1, gamma=0.1	93.3%	92.5%	93.3%	C=1, gamma=0.1	93.3%	93.8%	93.3%
KNN	K-neighbours=9	93.3%	92.5%	93.3%	K-neighbours=3	92.7%	94.4%	92.7%
RF	N-estimators=30	92.5%	90.9%	90.9%	N-estimators=30	92.7%	91.9%	91.3%
RVM	RBF n_iter = 300	93.33%	94%	93.53%	Sigmoid function alpha=1e-06, beta=1e-06	88.67%	89.8%	88.66%

Fig. 3. Actuator movement for different wrist positions (a) 0º; (b) 30º; (c) 60º; (d) 90º.

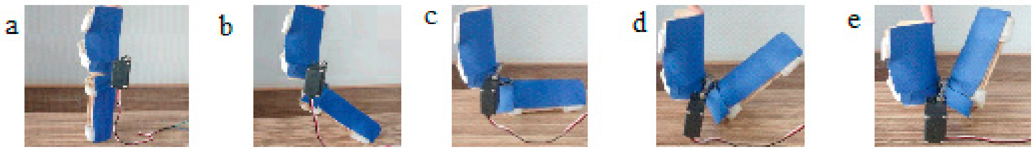

Fig. 4. Actuator movement for different elbow positions (a) -90o; (b) -45o; (c) 0o; (d) 45o; (e) 90o.

4. Conclusion

The orthotic arm proposed hence replicates the nine human arm movements in real-time. These nine movements include: four wrist and five elbow positions. The arm is controlled using the electromyography signals of the human arm which are collected in real-time, processed and hence classified to replicate the required position of the human arm. Based on the average accuracy of 93.3% obtained, it can be concluded that SVM-RBF is the best suited classifier when compared with SVM-linear, RVM, RF and KNN in the replication of the arm movements. Although, the RVM accuracy was same as that of SVM-RBF in classifying wrist positions, it failed to recognize elbow positions accurately and resulted in an overall accuracy of 88.67%.

The system developed acts as a support system for a damaged arm and hence serves its purpose of helping patients suffering from neuromuscular disorders overcome the ill-effects of these disorders. Since speed as well as accuracy are crucial for any real-time application, the aim is to make the orthotic arm more robust. Also, additional arm positions can be replicated in the future.

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