Expert Systems with Applications 39 (2012) 44–47

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Identification of EMG signals using discriminant analysis and SVM classifier

Ahmet Alkan *, Mücahid Günay

Kahramanmaras Sutcu Imam University, Department of Electrical & Electronics Engineering, Kahramanmaras, Turkey

ARTICLE INFO

Keywords:
EMG
Discriminant analysis
Cross validation
SVM

ABSTRACT

The electromyography (EMG) signal is a bioelectrical signal variation, generated in muscles during voluntary or involuntary muscle activities. The muscle activities such as contraction or relaxation are always controlled by the nervous system. The EMG signal is a complicated biomedical signal due to anatomical/physiological properties of the muscles and its noisy environment. In this paper, a classification technique is proposed to classify signals required for a prosperous arm prosthesis control by using surface EMG signals. This work uses recorded EMG signals generated by biceps and triceps muscles for four different movements. Each signal has one single pattern and it is essential to separate and classify these patterns properly. Discriminant analysis and support vector machine (SVM) classifier have been used to classify four different arm movement signals. Prior to classification, proper feature vectors are derived from the signal. The feature vectors are generated by using mean absolute value (MAV). These feature vectors are provided as inputs to the identification/classification system. Discriminant analysis using five different approaches, classification accuracy rates achieved from very good (98%) to poor (96%) by using 10-fold cross validation. SVM classifier gives a very good average accuracy rate (99%) for four movements with the classification error rate 1%. Correct classification rates of the applied techniques are very high which can be used to classify EMG signals for prosperous arm prosthesis control studies.

1. Introduction

Bioelectrical signals are usually taken to be electric currents produced by the sum of electrical potential differences across a specialized tissue or organ as a result of different electrochemical events happening in the body. EMG signal is one of the best-known bioelectrical signals which can be detected over the skin surface and are generated by the electrical activity of the muscle fibres during contraction or relaxation.

Each movement of muscles corresponds to a specific pattern of activation of several muscle fibres; therefore multi-channel EMG recordings can be used to identify the movement. Due to the complex nature of the signal, detailed analysis and classification is often difficult, especially if the EMG relates to movement (Kumar, Ma, & Burton, 2001).

For this purpose, different pattern recognition schemes, consisting of feature extraction and classification, have been applied (Parker, Englehart, & Hudgins 2004). This concept has been used for the development of myoelectric prosthesis control systems obtained by classification of EMG signals (Choi & Kim, 2007; Englehart, Hudgins, & Parker, 2001; Hu & Nenov, 2004; Kumar et al., 2001; Lucas, Gaufriau, Pascual, Doncarli, & Farina, 2008; Parker & Scott, 1986; Parker et al., 2004; Tscharner, 2000; Wojtczak, Amaral, Dias, Wolczowski, & Kurzynski 2009.

As in Lucas et al. (2008), the discrete wavelet transforms (DWT) based representation space is used for supervised classification of multi-channel surface electromyography signals with the aim of controlling myoelectric prostheses. They applied a support vector machine (SVM) approach to classify a multichannel representation space. They optimized the mother wavelet with the criterion of minimum classification error, as estimated from the learning signal set. Then the method was applied to the classification of six hand movements with recording of the surface EMG from eight locations over the forearm. For all subjects using the eight channels they reported a misclassification rate as (mean ± S.D.) 4.7 ± 3.7% with the proposed approach while it was 11.1 ± 10.0% without proposed technique. They stated that DWT and SVM can be implemented with fast algorithms and their method is suitable for real-time applications.

The success of a myoelectric control scheme depends largely on the classification accuracy. Englehart et al. (2001), proposed a novel approach that demonstrates greater accuracy than their previous work. They used wavelet-based feature set, reduced in dimension by principal components analysis. Further, it is exposed that four channels of myoelectric data increases the classification accuracy, as compared to one or two channels. They claimed that a robust online classifier is constructed, which produces class decisions on a continuous stream of data.

Choi and Kim (2007) investigated to design an assistive real-time system for the upper limb disabled to access a computer via

* Corresponding author.
E-mail addresses: aalkan@ksu.edu.tr (A. Alkan), mucahidgunay@gmail.com (M. Günay).

0957-4174/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2011.06.043

residual muscle activities without standard computer interfaces. For this idea, EMG signals from muscles in the lower arm were recorded and filtered using signal statistics such as mean and variance. In order to control movement and clicking of a cursor from the obtained signals, they classified six patterns, applying a supervised multi-layer neural network trained by a back propagation algorithm. Also, they developed an on-screen keyboard, making it possible to enter Roman and Korean letters on the computer. It is reported that using this computer interface, the user can browse the Internet and read/send e-mail.

Tscharner (2000), developed a time-frequency analysis of the intensities in time series for the analysis of surface myoelectric signals. The author proposed an intensity analysis which uses a filter bank of non-linearly scaled wavelets with specified time-resolution to extract time-frequency representations of the signal. To approximate the power of the signal in time domain, certain procedures were developed to calculate intensity. It is reported that the method resolves events within the EMG signal.

Hu and Nenov (2004), compared the performance of two feature extraction methods for multichannel EMG based arm movement classification. They used a scalar autoregressive model (sAR) for each channel and a multivariate AR model (mAR) which models all channels as a whole. Leave-one-out cross-validation was adopted for evaluating the classification performance using a parametric statistical classifier. They processed a total of 216 EMG segments obtained from repeated 18 performances by three normal subjects. It is reported that mAR model based feature set achieved a better classification accuracy than sAR did for each configuration.

Artificial neural networks are used to classify EMG signals to control multifunction prosthesis. Finger motions discrimination is taken as the key problem in Wojtczak et al. (2009). The EMG signal classification system was established using the linear neural network. It is reported that the experimental results show a promising performance in classification of motions based on bio-signal patterns.

Multi-channel surface electromyography (SEMG) provides information on motion detection of flexion and extension of fingers, wrist, forearm, and arm. A portable hand motion classifier (HMC) is developed to identify hand motion from the SEMG signals with an electrode configuration system (ECS) and recognition using grey relational analysis (GRA) based classifier in Dua, Hung, Shyu, and Chen (2010). They reported that the ECS consists of seven active electrodes place around the forearm to acquire the multichannel SEMG signals of corresponding muscle groups and the GRA-based classifier could be further recommend to implement in prosthesis control, robotic manipulator or hand motion classification applications.

2. Materials and methods

2.1. Material

In this study, four upper arm movements were designed. They included elbow flexion (EF), elbow extension (EE), forearm pronation (FP) and forearm supination (FS). For each movement there are 100 patterns and each of the patterns has 512 points. First 256 points obtained from biceps and the last 256 points from triceps muscles. Sampling frequency of the acquisition system is 1000 Hz (Englehart & Hudgins, 2003; Kocyigit & Korurek, 2005). A sample EMG pattern can be seen in Fig. 1.

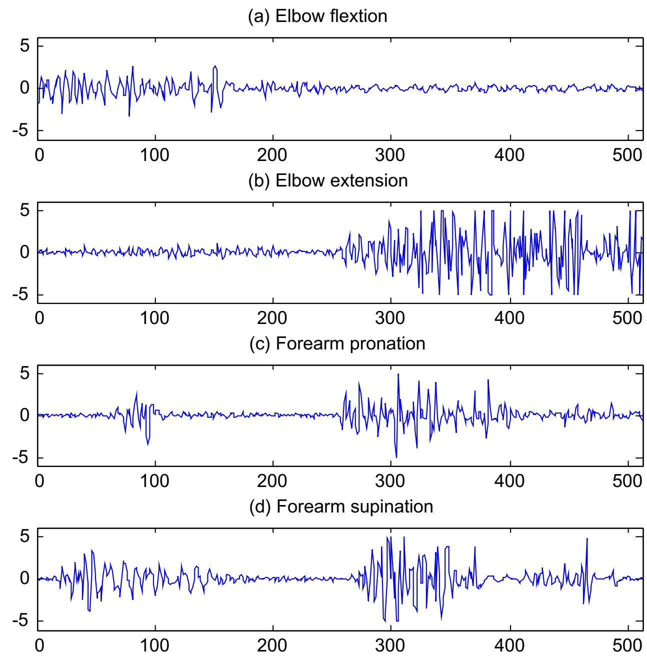

Fig. 1. A sample EMG data from four different arm movements.

2.2. Methods

2.2.1. Pre-processing

Pre-processing or feature extraction is very important issue in many signal processing applications because of the very complex natures of the biomedical signals. As in the case of many bioelectrical signals surface myoelectric signals are routinely pre-processed using different techniques to reduce noise and highlight for the analysis. For this aim, some popular techniques such as time domain features, spectral analysis, zero crossing and turns counting, root mean square, integral of RMS and wavelet analysis are used (Ma, Kumar, & Pah, 2001).

In this study a time domain feature extraction method, namely, mean absolute value (MAV) is used. Absolute values of the individual patterns are used to elaborate the features of the signals (Englehart & Hudgins, 2003). Then these patterns are windowed and average values of the each window are used as the feature values. Using the variable m to represent window index, x_k to represent the EMG data point at time k, and L to represent classification window length the estimate of mean absolute value is given by:

$$\overline{X}_m = \frac{1}{L}\sum_{k=1}^{L}|x_k| \tag{1}$$

Window length is the single parameter affecting the output of pre-processing method (MAV). The output of MAV has influenced indirectly upon the success of classification because of being applied as an input to the classifiers. That is why, it is so important to define the window length. Different window lengths are tried and regarding to the classification accuracy, it is decided to use 32 samples as an optimum window length for the data. Thus, 512 points are reduced to 16 points by calculating absolute value and then taking the average of each of the windows. So, for each pattern, instead of 512 values 16 values can be used for further processing system. The EMG classification/analysis steps can be seen in Fig. 2. Also, a sample pre-processed EMG signal from four arm movements are shown in Fig. 3.

2.2.2. Discriminant analysis

Discriminant analysis is a well-known statistical classification technique which uses training data to estimate the parameters of discriminant functions of the predictor variables. Discriminant functions determine boundaries in predictor space between

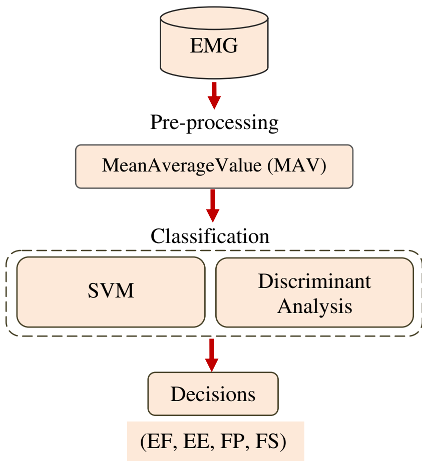

Fig. 2. EMG classification steps.

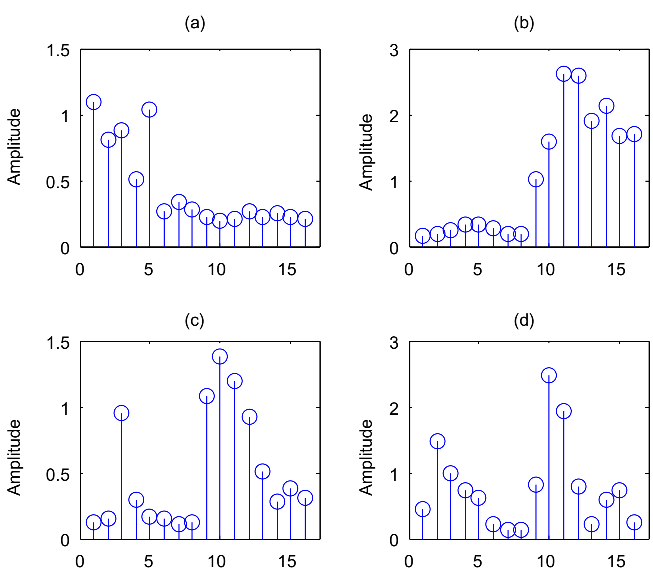

Fig. 3. A sample pre-processed EMG signal from four arm movements: (a) Elbow flexion. (b) Elbow extension. (c) Forearm pronation. (d) Forearm supination.

various classes. The resulting classifier discriminates among the classes (the categorical levels of the response) based on the predictor data. The details of the discriminant analysis classifier can be found in Cao and Sanders (1996).

The feature vectors are provided to the discriminant analysis classifier which is so simple to implement and much faster to train. The performances of the following five different types of Discriminant analysis classifiers have been investigated in the identification of surface myoelectric records to identify the movement.

Linear discriminant function fits a multivariate normal density to each group, with a pooled estimate of the covariance matrix. Diagonal linear discriminant function is similar to linear discriminant function except the estimate of covariance matrix being diagonal, not pooled. This diagonal covariance matrix is estimated by taking only the diagonal of the estimated sample (pooled) covariance matrix, and ignoring the rest. Quadratic discriminant function fits multivariate normal densities with covariance estimates stratified by group. Diagonal quadratic discriminant function is similar to quadratic discriminant function except the estimate of covariance matrix being diagonal. Mahalanobis discriminant function uses Mahalanobis distances with stratified covariance estimates.

For all of these classifiers, the underlying analysis is based on the evaluation of discriminant functions; therefore a general name, discriminant analysis, is used for this type of classifier design.

2.2.3. Cross validation (CV)

CV is a method that divides the data set into two groups as 'training' and 'sample' for supervised learning. K–fold CV firstly obtains k subsets having equal number of members from the data set and members are randomly shared by the subsets. For one classification process, each of the subsets is used as a training set and all of the other subsets as a sample set. So, the resultant prediction accuracy rate is calculated by the average of k prediction accuracy rates (Bollen & Gu, 2006).

2.2.4. SVM classifier

Vapnik has presented a new computational method called support vector machine. His theory has been advanced between years 1995–1998 (Qian, Mao, Xiang, & Wang, 2010). SVM takes the input data as an n-dimensional feature space. Then an $(n-1)$ dimensional hyperplane separates the space into two parts. n-dimensional input data x_i $(i = 1, 2, \ldots, l)$ is labelled as $y_i = 1$ for class 1 and as $y_i = -1$ for class 2 by y_i matrix. A hyperplane can be defined for linearly separable data.

$$f(x) = \omega \cdot x + b = \sum_{i=1}^{n} \omega_i x_i + b = 0 \tag{2}$$

Sgn $(f(x))$ is the decision function. In Eq. (2), ω is an n-dimensional vector and b is a scalar. These determine the position of the hyperplane that completely separates the space has to obey the limits:

$$y_i(x_i \cdot \omega + b) - 1 \geqslant 0 \Longleftrightarrow \begin{cases} f(x_i) = x_i \cdot \omega + b \geqslant 1 & y_i = +1 \\ f(x_i) = x_i \cdot \omega + b \leqslant -1 & y_i = -1 \end{cases} \tag{3}$$

The hyperplane that creates maximum limit is called an optimal hyperplane. In the equation below, ξ_i is the independent variable and C is the error penalty. The minimized solution of the hyperplane is as followed:

$$\phi(\omega, \xi) = 1/2(\omega \cdot \omega) + C\left(\sum_{i=1}^{l} \xi_i\right) \tag{4}$$

depending on

$$y_i[(x_i \cdot \omega) + b] \geqslant 1 - \xi_i, \quad i = 1, 2, \ldots, l \tag{5}$$

ξ_i measures the distance between the limit and the sample x_i on the other side of the limit. This calculation can be simplified as followed:

$$V(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j Ker(x_i . x_j) \tag{6}$$

depending on

$$\sum_{i=1}^{l} y_i \alpha_i = 0, \quad C \geqslant \alpha \geqslant 0, i = 1, 2, \ldots, l \tag{7}$$

The function $Ker(x_i\, x_j)$ is called as kernel function returns the dot product of the feature space maps of the original data points. Details of the method can be found in the literature (Wang, Yuan, Liu, Yu, & Li, 2009).

3. Results

Using the classify routine of discriminant analysis; five different types of discriminant analysis classifiers are implemented. In performance analysis of different types of classifiers one needs to

Table 1
Classification results: Training (resubstitution) and 10-fold error rates for different types of classifiers based on the discriminant analysis and SVM.

Classifiers	Methods	Correction rates (%)	Error rates (%)
Discriminant analysis	Linear	97.75	2.25
	Diaglinear	97.25	2.75
	Quadratic	97.75	2.25
	Diagquadratic	98.00	2.00
	Mahalanobis	96.00	4.00
SVM		99.00	1.00

report prediction/classification error and/or accuracy rate. (The classification accuracy is 1– classification error rate).

The issue of assessment of prediction error of a classifier also deserves much attention. The experimental classification error is the ratio of wrong decisions to the total number of cases studied. The true error rate is statistically defined as the error rate of a classifier on an asymptotically large number of new cases that converge in the limit to the actual population distribution. During training, underlying parameters of a classifier are adjusted using the information contained in the training samples. The prediction accuracy can initially be evaluated by testing the classifier back on the training set and noting the resultant training or re-substitution error. This type of assessment of classifier performance, based on training error, is instrumental during the design phase.

If the training set contains too many outliers or excessive training is done, the generalizability performance of the classifier will be poor. Therefore, while evaluating prediction accuracy of classification methods, it is important not to use the training error only (Asyali, Colak, Demirkaya, & Inan, 2006). In general, the training error rates tend to be biased optimistically, i.e., the true error rate is almost invariably higher than the training error rate. If there are plenty of training samples available, one can partition the overall training set into two sets and use one for training and the other for testing. If the classifier is designed based on a small training set, the generalizability performance of the classifier will be poor again.

After the pre-processing step, features are applied to classification system to classify EMG signals related to four upper arm movements. In this study for discriminant analysis 10-fold CV is used. Table 1 reports the 10-fold CV error rates for the five different types of discriminant analysis classifiers.

The same features are applied to a SVM classifier to compare the classification results of all methods with the same pre-processing technique. In the SVM classifier, the overall data set is randomly divided into two equal subsets, selecting the half of the data for training and the other half for testing.

4. Discussion

In this study we have proposed a surface EMG signal classification system which uses five discriminant functions and a SVM classifier. The variability of accurate classification of discriminant analysis classifiers is from very good (98%) to poor (96%). If the classification results are examined, one can see that all five discriminant analysis methods give less than 5% classification error rates. Between these five methods, diagonal quadratic discriminant function gives the best classification error rate (2%). The error rates of linear and quadratic discriminant functions are 2.25%. Diagonal linear and Mahalanobis discriminant functions have error rates 2.75% and 4% respectively.

A discriminant analysis classifier is a graceful method using the probability distributions. However, the computational complexity is high when the dimension of features becomes large even for a Gaussian probability density function. This often reduces the practical application of discriminant analysis classifiers. On the other hand, a SVM classifier minimizes the generalization error on the test set under the structural risk minimization (SRM) principle (Bollen & Gu, 2006).

This can be seen in Table 1 that SVM classifier gives a very good average accuracy rate (99%) for four movements with the classification error rate 1%. Since misclassified patterns are generally same, data set plays important role for classification errors. Correct classification rates of the applied techniques are very high which can be used to classify EMG signals prosperous arm prosthesis control studies.

Acknowledgements

This study is supported by the Scientific Research Project Management Department of Kahramanmaras Sutcu Imam University with the project "Identification and Classification of EMG signals for Arm Prosthesis", Project number: 2010/5-8 YLS.

This study was presented at the 1st International Symposium on Computing in Science & Engineering (ISCSE 2010) June, 3-5, 2010, in Kusadasi, Aydın/Turkey.

References

Asyali, M. H., Colak, D., Demirkaya, O., & Inan, M. S. (2006). Gene expression profile classification: A review. *Current Bioinformatics, 1*(1), 55–73.
Bollen, M. H. J., & Gu, I. Y. H. (2006). Signal Processing of power quality disturbances. Springer, pp. 684–686.
Cao, J., & Sanders, D. B. (1996). Multivariate discriminant analysis of the electromyographic interference pattern: statistical approach to discrimination among controls, myopathies and neuropathies. *Medical and Biological Engineering and Computing, 34*(5), 369–374.
Choi, C., & Kim, J. (2007). A Real-time EMG-based Assistive Computer Interface for the Upper Limb Disabled. In *Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics*, Noordwijk, The Netherlands.
Dua, Y. C., Hung, C. L., Shyu, L. Y., & Chen, T. (2010). Portable hand motion classifier for multi-channel surface electromyography recognition using grey relational analysis. *Expert Systems with Applications, 37*, 4283–4291.
Englehart, K., & Hudgins, B. (2003). A robust, real-time control scheme for multifunction myoelectric control. *IEEE Transactions on Biomedical Engineering, 50*, 7.
Englehart, K., Hudgins, B., & Parker, P. A. (2001). A wavelet-based continuous classification scheme for multifunction myoelectric control. *IEEE Transactions On Biomedical Engineering, 48*.
Hu, X., & Nenov, V. (2004). Multivariate AR modeling of electromyography for the classification of upper arm movements. *Clinical Neurophysiology, 115*, 1276–1287.
Kocyigit, Y., & Korurek, M. (2005). EMG signal classification using wavelet transform and fuzzy logic classifier. *ITU dergisi/d mühendislik, 4*, 3.
Kumar, D. K., Ma, N., & Burton, P. (2001). Classification of dynamic multi-channel electromyography by neural network. *Electromyography and Clinical Neurophysiology, 41*(7), 401–408.
Lucas, M. F., Gaufriau, A., Pascual, S., Doncarli, C., & Farina, D. (2008). Multi-channel surface EMG classification using support vector machines and signal-based wavelet optimization. *Biomedical Signal Processing and Control, 3*, 169–174.
Ma, N., Kumar, D.K., & Pah, N. (2001). Classification of hand direction using multi-channel electromyography by neural network. In *Seventh Australian and New Zealand Intelligent Information Systems Conference, Perth, Western Australia*.
Parker, P. A., Englehart, K., & Hudgins, B. (2004). The control of upper limb prostheses. In R. Merletti & P. A. Parker (Eds.), *Electromyography: Physiology engineering and non-invasive applications*. Wiley-IEEE Press.
Parker, P. A., & Scott, R. N. (1986). Myoelectric control of prostheses. *Critical Reviews in Biomedical Engineering, 13*, 283–310.
Qian, H., Mao, Y., Xiang, W., & Wang, Z. (2010). Recognition of human activities using SVM multi-class classifier. *Pattern Recognition Letters, 31*, 100–111.
Tscharner, V. (2000). Intensity analysis in time-frequency space of surface myoelectric signals by wavelets of specified resolution. *Journal of Electromyography and Kinesiology, 10*, 433–445.
Wang, A., Yuan, W., Liu, J., Yu, Z., & Li, H. (2009). A novel pattern recognition algorithm: Combining ART network with SVM to reconstruct a multi-class classifier. *Computers and Mathematics with Applications, 57*, 1908–1914.
Wojtczak, P., Amaral, T. G., Dias, O. P., Wolczowski, A., & Kurzynski, M. (2009). Hand movement recognition based on biosignal analysis. *Engineering Applications of Artificial Intelligence, 22*, 608–615.