EMG FEATURE EVALUATION USING TRANSPARENT FUZZY SYSTEM FOR HAND AND FINGER MOVEMENTS IDENTIFICATION

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Abstract: Myoelectric signal (MES) is the electrical manifestation of muscular contraction. The transient part of the EMG signal, which is recorded at the surface of the skin of the forearm using only 2 channels, has been exploited to provide the recognition of 3 finger movements and hand closing. The objective of the paper is first to describe our identification procedure, based on Transparent (interpretability) Fuzzy System, which is used to compare the classification accuracy for some extracted features. An initial fuzzy rule system is generated using the statistic's trimmed mean method [01], in stat of clustering, which fulfils many criteria for transparency and semantic. The tuning of premise and consequents of zero-order Takagi Sogeno [02] fuzzy model is obtained with Gradient descent and Least squares Estimator respectively in a combined hybrid algorithm. Second is to show the evaluation of different time-frequency domain features corresponding to their rate classification for controlling of an artificial hand. Here, 3 EMG signal features have been extracted.

The presented method may be used for real time control applications regarding to its low computation costs, transparency and required only two EMG surface electrodes or channels.

Introduction

Surface muscle activity signals cannot be analysed using classical methods, since they are non-stationary and have complex time-frequency characteristics. It is considered that signals of muscle activity using surface EMG are divided into two types: transient signals EMG and steady-state signals EMG, the transient signals are more important and more favourable for the "on line" classification, although they are more difficult to handle. Transient signals, which are evolving in time in an unpredictable way require the notion of frequency analysis for each local time. Although frequency domain representations such as the power spectrum of a signal often show useful information, these representations don't show how the frequency content of a signal evolves over time.

A Surface EMG signal classification based on STFT transform is presented in this paper using pattern recognition, which describes the distribution of samples in sample-space and relates an input sample to the distribution. A sample is represented with a point in the sample space; its feature values are the corresponding coordinates. The EMG signal has been used as a tool to provide advanced man-machine interfaces [03], rehabilitation of the handicapped people, functional electrical stimulation devices (FES) [04] and control commands for limb prostheses [05]. The classification problem may be divided into three steps: signal presentation, feature extraction and pattern recognition.

Experimentation

Four types of finger and hand movements to be classified are selected: thumb, pointer, middle and hand close. The placement of EMG surface electrodes on muscle groups is important to have more information about each movement. Two EMG surface electrodes are placed on two muscle groups, palnaris longus (channel_1) and extensor digitorum (channel_2), the locations of electrodes on the subject's arm is given in figure 1 from the input feature space, the classifier must be able to classify the four output classes exploiting the EMG signals measurements.

Figure 1: EMG training and test patterns recorded using two pairs of electrodes in Max Planck Institute laboratory in Magdeburg, Germany.

For each channel the signal was acquired using a single bipolar surface electrode pair. A differential amplifier with an isolated input and signal gain of 2000 was used. The signal was sampled at a rate of 4 kHz using A/D board in an IBM PC/AT compatible microcomputer; this algorithm is developed with MATLAB 6 and is performed in a PC-based off-line process. The human subject was asked to produce a number of continuous movements, 34 single contraction periods are separated from the corresponding sets of continuous movements. Initial transient part (400 ms) of each single contraction period is extracted from the raw signal by determined threshold are analysed with Short time Fourier Transform (STFT), which gives a measure of both time and frequency information for small segments of a signal.

Trimmed mean clustering method TMC

An initial fuzzy rule base is derived from the n available input-output data pairs (X_{nf}, Y_n), the input Matrix $X_{nf} = [X_{ij}]$, where $i = 1,...,n$: number of measured samples and $j = 1,..., f$: number of features. Our TMC method of clustering, [06] for extracting initial fuzzy model from data set is based on a statistic's trimmed mean method [01] to obtain a set of initial rules and then applying optimisation algorithm to adapt the rule parameters. The aim of this method is to find the centres and the radius of different groups, for this task we calculate the mean value for each feature vector F_j and each class k without taking the outliers samples in consideration. $F_j = X_{ij}\ (i = 1,...n_k)$, The class $k = 1,..., K$, here n_k denotes the number of samples for the class k, and K the number of classes. The samples number for all classes $n = \sum_{k=1}^{K} n_k$, In short description of this method, the matrix X_{nf} is ordered from the smallest to largest value, deleting a selected number of samples from each end of the ordered list, and then averaging the remaining values figure 2. For this task we have to choose the trimming percentage β, which denotes the percentage of values deleted from each end of the ordered list.

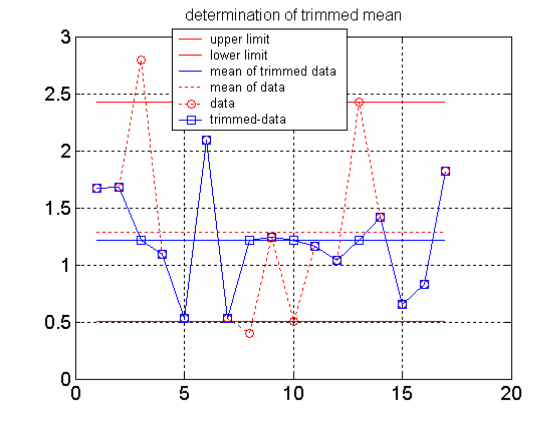

Figure 2: Mean of original data and mean of trimmed data.

The most authors, usually, use several Data clustering algorithms such as: K-Means, Fuzzy C-Means [7], Mountain Clustering method [8], and subtractive clustering [9], for extraction of the membership functions, which can find each region (class) in the input space. In this work the statistical trimmed mean [1] method is used.

EMG Signal Preprocessing

Surface muscle activity signals cannot be analysed using classical methods, since they are non-stationary and have complex time-frequency characteristics. EMG signals, figure 3, which are evolving in time in an unpredictable way (like a speech signal) require the notion of frequency analysis for each local time. Although frequency-domain representations such as the power spectrum of a signal often show useful information, these representations don't show how the frequency content of a signal evolves over time. Time-Frequency Analysis can identify not only the frequency content of a signal, but also how that content evolves over time.

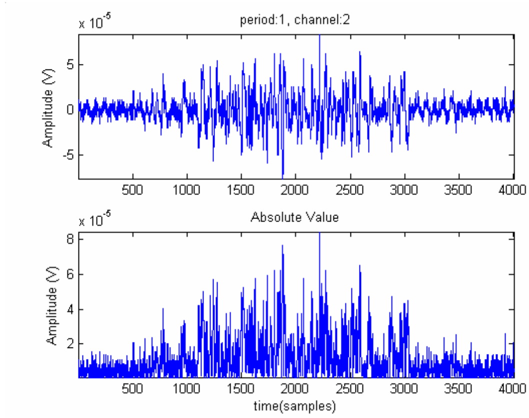

Figure 3: Measured raw EMG signal from channel_2 (extensor digitorum) muscle, and its absolute value.

There are a number of different methods available for Time Frequency Analysis. Each type shows a different time-frequency representation. The Short Time Fourier Transform (STFT), figure 4 and 5, which is used in this paper, is the simplest TFA method and the easiest to compute.

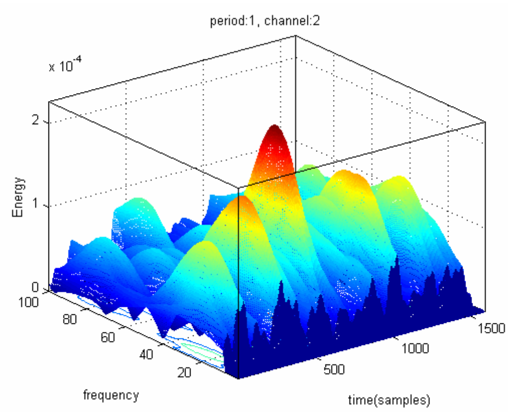

Figure 4: Thumb: 400 ms EMG Signal analyzed with STFT method.

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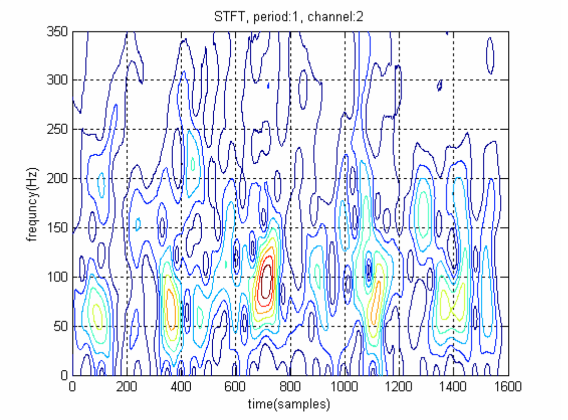

Figure 5: Contour presentation for the same above signal of figure 4.

EMG features extraction

After EMG signal pre-processing operation using spectrum analysis based on short-time Fourier transform (STFT), which is a form of local Fourier analysis that treats time and frequency simultaneously, it is possible to exploit and to quantify the behaviour of dynamic information present in these EMG signals and to design characteristic vectors, which can perform some relevant features that lead to high and accurate classification rates of these different classes of movements.
The functions of central frequency 'Cent_freq', standard deviation 'Std_dev' and Moment of order 2 'M2' [10] are used as features. The definition of each function is given below:

$$M_n(t) = \sum_k \omega_k^n \left| STFT(t,k) \right| \;, \quad \text{n = 1, 2, 3} \qquad (1)$$

$$Cent\_freq = \frac{M_1}{M_0} \qquad (2)$$

$$Std\_dev = \sqrt{\frac{M_2}{M_0} - \left(\frac{M_1}{M_0}\right)^2} \qquad (4)$$

M_n: is the moment of the frequency distribution at time t, n: order, ω : frequency.
W : Windows size.

For the two channels we prepare some EMG training and test data, from raw EMG signal, each class has 17 training and 17 test patterns. The four classes labelled 1, 2, 3 and 4 have 68 train-samples and 68 test-samples. The distribution of all samples in two-dimensional space Channel-1 and channel-2, in the case of standard deviation feature, is showed in figure 6.

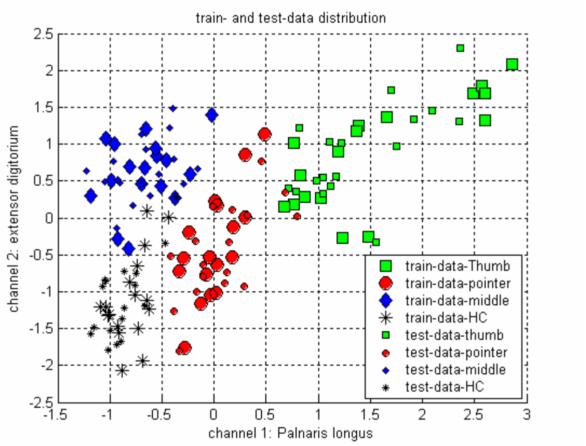

Figure 6: train and test data distribution of feature Std_dev for all four classes.

Initial fuzzy trimmed mean clustering (FTMC)

Since all training and test data are prepared, we estimate the accuracy of fuzzy trimmed mean clustering (FTMC) model [6] according to trimming percentage β = 0.9. The derived clusters for this β value using training data were anticipated to classify the samples of test data. In the case of standard deviation feature we trace the clusters (ellipses), figure 7, derived from TMC algorithm for the training samples of each class In 2-D space (two channels), corresponding to the four classes: thumb, pointer, middle and hand close movements.

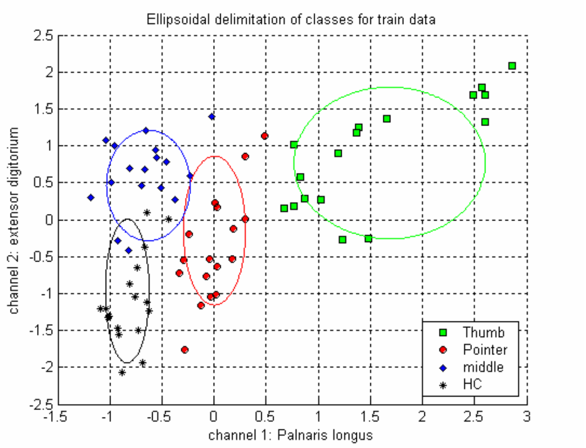

Figure 7: clusters derived from TMC algorithm for training samples.

The parameters of each cluster will be used to generate the initial FTMC input-sets, for this task the generalized bell membership function is chosen.
TMC-based input fuzzy sets initialisation for train data gives us the following partition of our input space, figure 8.

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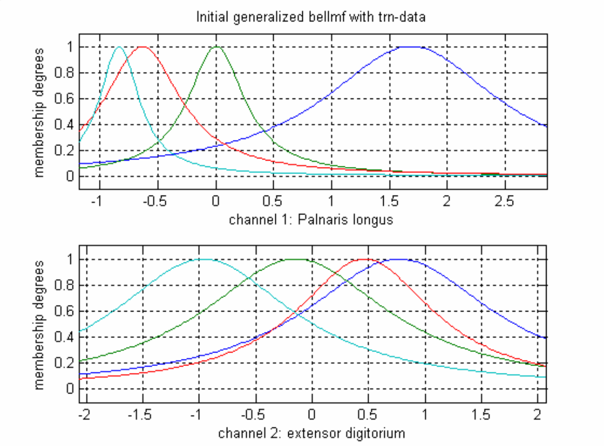


Figure 8: Input FTMC sets initialisation for train data.

The output Z_n of this model use the following classification rules:

$$\text{Class}_k = \begin{cases} 1 & if \quad Z_k < 1{,}5 \\ 2 & if \quad 1{,}5 \le Z_k < 2{,}5 \\ 3 & if \quad 2.5 \le Z_k < 3{,}5 \\ 4 & if \quad Z_k \ge 3.5 \end{cases} \tag{6}$$

FTMC model adaptation and results

After application of FTMC model and generating the initial scatter partitioning of input space, the following adaptation method is applied to perform, this initial FTMC model:

a) Optimisation of the premise parameters (membership functions parameters) with Gradient Descent (GD)
b) Optimisation of the linear parameters (Consequence parameters) with linear Least Squares Estimator (LSE).

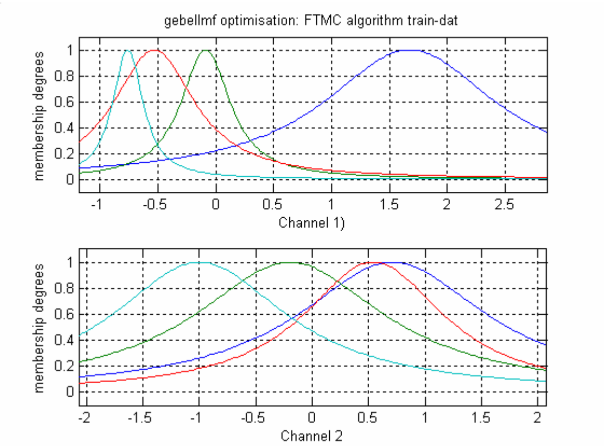


Figure 9: Input FTMC sets optimisation for train data in case of std-dev feature.

Our initial FTMC identification algorithm described above can find a good starting point in proximity of the global minimum, hence the farther application of a few epochs, only 4 epochs, with GD will not have a big effect on overlap of the membership functions. Hence the input-space partition with this method fulfils many criteria for transparency properties [11].

The initial FTMC model, figure 8, with four rules, in the case of standard deviation feature, which describe 4 classes with singleton consequents, has average classification accuracy of 85.294 % giving 10 misclassifications on the test data. After optimisation, figure 9, on both antecedents and consequents parameters using GD and LSE respectively, we obtain after 4 epochs the classification accuracy of 88.235 % giving 8 samples misclassification on the data test figure 10, 11.

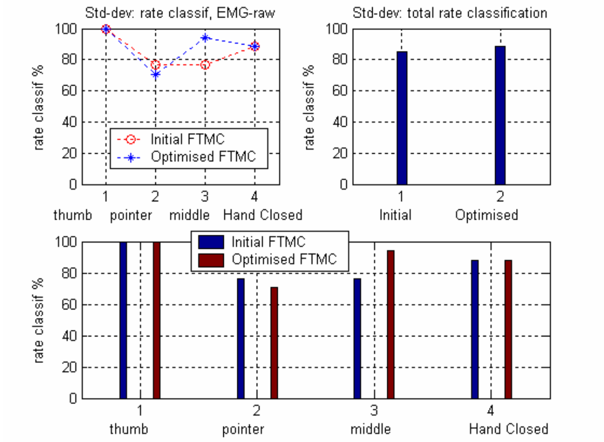


Figure 10: Average classification accuracy and classification accuracy for each class with initial and optimised FTMC model

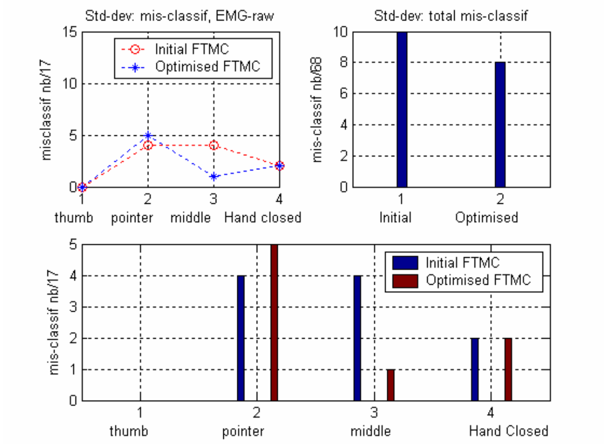
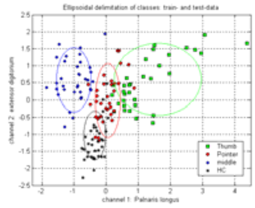


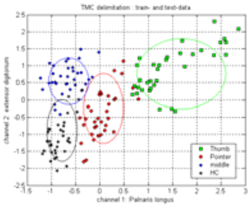
Figure 11: Average misclassification and misclassification for each class with initial and optimised FTMC model in case of std-dev feature.

Classification accuracy comparison of all features

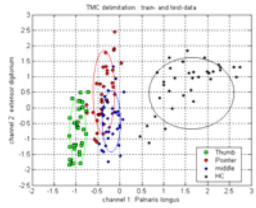
In this study we used three features, which have been extracted from time-frequency analysis using STFT method. The distribution of these features is presented in following figure 12. The ellipses that delimit the different groups are calculated with help of TMC algorithm described above.



Cent-freq feature distribution



Std-dev feature distribution



M2 feature distribution.
Figures :12-1, 12-2 and 12-3.

To resume the results obtained with the features extracted using time-frequency analysis, we present for all these features their classification rate for initial and optimised FTMC model identification in figure 13.

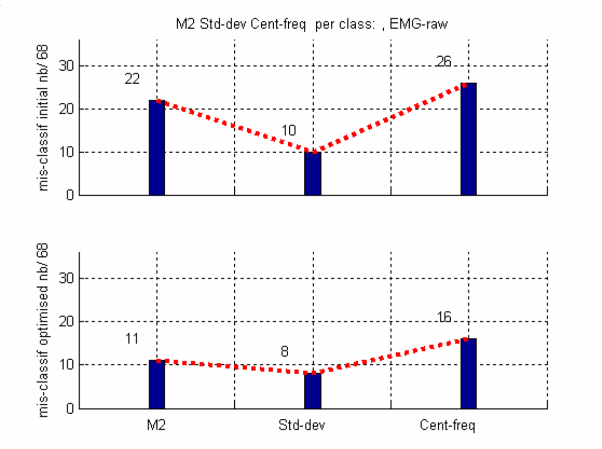


Figure 13: Average misclassification for each class with initial and optimised FTMC identification model.

Conclusions

This work was done concerning the classification of 3 fingers movements and hand closing using transient EMG signals recorded through only two surface electrodes on forearm muscles. The classification accuracies of three extracted time-frequency features using STFT method are compared with help of our Fuzzy Trimmed Mean Clustering (FTMC) algorithm. This algorithm, which fulfils simplicity and interpretability, has been trained during only 4 epochs for every feature. The results of classification obtained; 8, 11 and 16 misclassifications from 68 samples; were very satisfying if we consider the only two channels of surface electrodes used in this study and only 4 epochs of optimisations. Our ongoing work is focused on online case.

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