# Sampling frequency and pass-band frequency effects on Neuromuscular Signals (EMG) Recognition

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*Abstract:* - This paper treats the effects of EMG signal sampling frequency and the pass-band frequency on neuromuscular signal recognition which are of a great importance. It improves the optimisation of the choice of those parameter values that guarantees the best performance. The considered EMG signal sampling frequency and pass-band frequency have a significant importance in viewpoint of the extracted information from this signal. It will be shown that this information depends on both sampling and pass-band frequency values. The signal information do not have the same pass-band frequency location and also do not have the same sampling frequency value for all the features, but these parameters are then self depending on the type of the feature. In this case the classification of the EMG signals is done by using only the beginning part of the signal, which is equal in our case to 256ms. The classification is done using two intelligent computational methods: Radial Basis Function network (*RBF*) and Fuzzy Subtractive Clustering network (*FSC*). Each method has been applied using four different values of spread and radius values corresponding to *RBF* and *FSC* respectively.

*Key-Words:* - Electromyography (EMG) Signals, Pattern Recognition, Feature Extraction, Intelligent Classification Methods, Sampling Frequency Effect, Pass-band frequency effect

## 1 Introduction

Surface muscle activity signals cannot be analyzed 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. Pattern recognition is used to describe the distribution of samples in feature-space and to relate each input sample to its group distribution. A sample is represented with a point in the feature-space; its feature values are the corresponding coordinates. The classification problem may be divided into three steps: signal analysis, feature extraction and finally classification. A variety of different intelligent computational methods are available for the classification task; the selection of a classification method is based on the complexity of the task. A set of complex measurements is classified by comparing their features with the known features of previous measurements. With help of myoelectric signals exploitation, amputee persons can have a chance to improve their life with myoelectric prostheses, which are able to function with the amputee's muscle movements. The EMG signal has been used as a tool to provide advanced man-machine interfaces [1], rehabilitation of the handicapped people, functional electrical stimulation devices (*FES*) [2] and control commands for limb prosthesis [3].

## 2 Experimentation and signal analysis

Three types of finger movements to be classified are selected: thumb-, pointer- as well as middle-finger. 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. The placement of EMG surface electrodes on muscle groups is very important to get the information that characterise each movement. From the input feature space, the classifier must be able to classify these three output classes exploiting the EMG signals measurements.

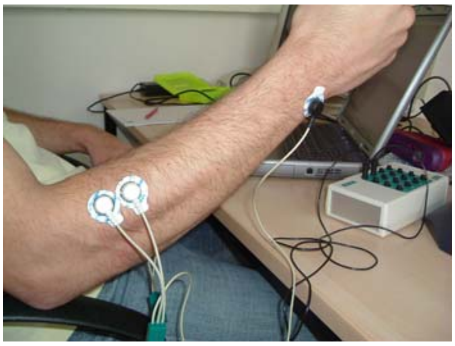

*Fig. 1: EMG training and test patterns recorded using two pairs of electrodes in Max Planck Institute laboratory in Magdeburg, Germany.*

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 1 kHz, 2 kHz and 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, 44 single contraction periods are separated from the corresponding sets of continuous movements. Initial transient part, 256ms, of each single contraction period is extracted from the signal by determined noise threshold level.

## 3 Pass-band filters design

Filters play a vital role in data acquisition and processing systems to remove unwanted selected frequencies from an incoming EMG signal and minimise artefacts, conducted disturbances and emitted disturbances. EMG signal offers a great deal of useful information depending on its band frequency. The motivations of signal filtering are the removing of unwanted components corrupting the signal of interest as shown on figure 2.

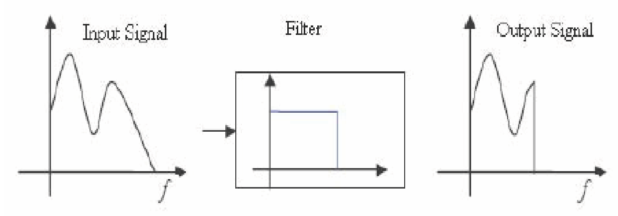


*Fig .2: Filter effect on signal's spectre.*

The objective is then to build a new signal from the raw signal by exclusion of the disturbances. A digital filter is just a filter that operates on digital signals represented inside a computer. There is a variety of available software for design of digital filters. The effective use of a filter design algorithm requires an understanding of its parameters designing, which requires also some understanding of filter theory [4]. Filtering it's a computation which takes one sequence of numbers of input signal and produces a new sequence of numbers of filtered output signal. The digital filter design methods fall into two main categories:

1) Finite Impulse Response (FIR) filter design.

2) Infinite Impulse Response (IIR) filter design.

For FIR filters, the current output y(n) is calculated solely from the current and previous input values:

$$y(n) = x(n), x(n-1), x(n-2), \ldots \quad (1)$$

These filter types are called non-recursive, because this filters usually require no feedback. In this case the impulse response of *FIR* filter is of finite duration. The *IIR* filters are commonly implemented using a feedback (recursive) structure. The word recursive means "running back", and refers to the fact that previously-calculated output values go back into the calculation of the latest output. The expression for a recursive filter therefore contains not only terms of input values: x(n), x(n−1), x(n−2), . . ., but also terms of output values: y(n−1), y(n−2), . . .. In this case the impulse response of IIR filter is theoretically not of finite duration and continues forever. Generally, to design a given frequency response characteristic, recursive filter requires fewer terms to be evaluated by the processor than the equivalent non-recursive filter. In *MATLAB* toolbox, the filtering process is performed by the filter function: $y$ = filter ($b$, $a$, $x$). This function uses an infinite impulse response (*IIR*) or finite impulse response (*FIR*) filter; where: $x$ is the input signal, $y$ the output signal, and where $b$ and $a$ are the coefficients. The optimum filter type is chosen on the basis of implementation complexity and magnitude response. In this paper the 6$^{th}$ order *IIR Butterworth* filter is chosen. This filter is applied for the following four pass-band frequencies: 30-300Hz, 10-300Hz, 30-500Hz and 10-500Hz.

## 4 Signal analysis and feature extraction

Extraction of features contained in time-frequency domain need the use of spectrum analysis. Although frequency domain representations such as the power spectrum of a signal often show useful information, they don't show how the frequency content of a signal evolves over time. Time-Frequency Analysis (*TFA*) can identify the frequency content of a signal and how that content evolves over time. There are a number of different methods available for Time Frequency Analysis. The Short Time Fourier Transform (*STFT*), which is used in this work, is a form of local Fourier analysis that treats time and frequency simultaneously, figure 3, and is the simplest TFA method and the easiest method to avoid computing-complexity. Theoretically it should be possible to recognize finger movements directly from the sampled EMG signals. However, because of the large variability of these signals, it is necessary to perform some form of feature extraction that would overcome this variability. Relevant features lead to high and accurate classification rates.

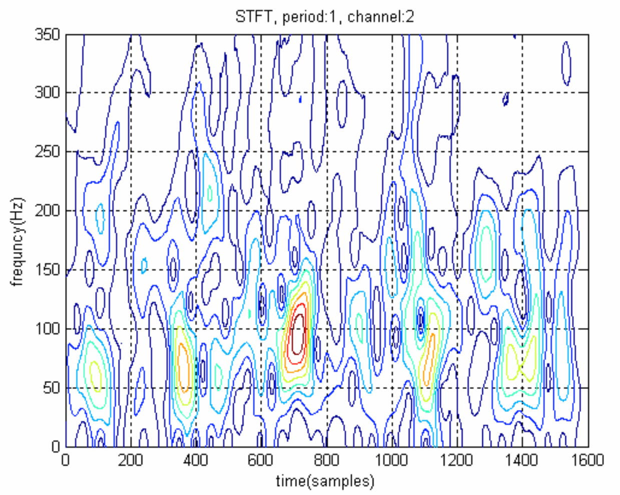


*Fig. 3: Contour presentation for the EMG signal analysis using STFT method.*

The basic spectral parameters, momentary frequency, Blake Hannaford, are used as features. The extracted features are: moments of frequency $M_n$. The definition of this feature is given in the following equation:

$$M_n(t) = \sum_k W_k^n |STFT(t,k)|,\ n = 1,2,... \quad (2)$$

where: $M_n$ is the $n$-th moment of the frequency distribution at time $t$, $n=1,\ 2\ and\ 3$ represents the orders of our three features and $w$ represents the frequency.

With two channels of measurement, 44 EMG signals are recorded for each movement class. The three classes, labelled 1, 2 and 3 give 132 feature samples.

## 5 Intelligent computational methods of classification

Classification procedure deals with the building of models that can correctly predict the right classes basing on some extracted characteristics (features). These methods are generally used for classification of complex systems like EMG signals. There are many algorithms which belong to intelligent computational classification methods. Two methods among them are introduced in this paper to classify our three hand movement classes. These methods belong to neuro-fuzzy intelligent computational methods. The first method, which belongs to supervised methods, is Radial Basis Function (*RBF*) network. And the second method, which belongs to unsupervised methods, is Fuzzy Subtractive Clustering (*FSC*) network.

### 5.1 Radial Basis Function (*RBF*) classification method

The Network shown on figure 4, is a one hidden layer Neural Network with several forms of radial basis activation functions, like Gaussian function. We use the method, which creates neurons one at a time. The input vector is used to create a new neuron for every iteration step. The error of the new network is checked, and if it is not low enough the next neuron is added. This procedure is repeated until the error goal is met, or the maximum number of neurons is reached.

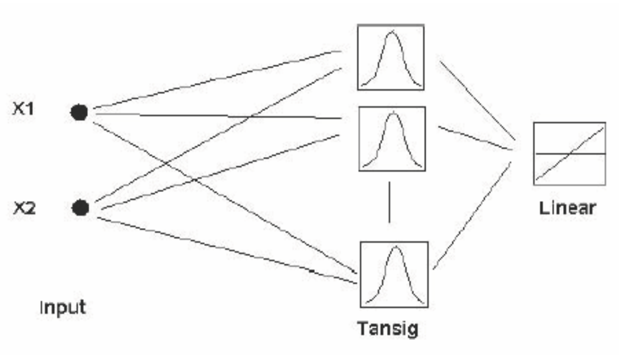


*Fig. 4: Architecture of RBF network*

### 5.2 Fuzzy Subtractive Clustering (FSC) classification method

The goal of fuzzy subtractive clustering method is to extract a set of fuzzy rules, which describe the distribution of different classes in the input space data. The initial set of linguistic rules can be given by several data clustering algorithms. The subtractive clustering algorithm [5] which has been proposed by Chiu, estimates the number of clusters and the cluster centres in a set of data. The clusters obtained, with iterative optimisation-based clustering methods fuzzy c-means (fcm), are used to initialise the fuzzy sets, for model identification method *ANFIS*. As initial model the first order *Takagi-Sugeno* (*T. S.*) model is used. The advantage of using this method (subtractive clustering algorithm) is that the number of clusters is not required to be specified. This method allows a scatter partition of the input space:

$$X_{nf} = [X_{ij}] \text{ in } C_k \text{ classes,} \qquad (3)$$

where $i=1,2,\ldots,n$, $n$-number of measured samples, $j=1,2,\ldots,f$, $f$ - number of features, and $k=1,2,\ldots,K$, $K$ is the number of classes.
Each feature vector is designed as $F_j$, where:

$$F_j = X_{ij} \ (i = 1,\ldots n_k)$$

where: $n_k$ denotes the number of samples for the class $C_k$. The number of samples for all classes is given by:

$$n = \sum_{k=1}^{K} n_k$$

# 6 Results

## 6.1 Classification performance with *RBF*-based approach

### 6.1.1 Case of 10-500 Hz pass-band filter

RBF classification method it applied for the group of three features ($M_0$, $M_1$ and $M_2$) filtered in frequency band 10-500 Hz (figure 5). If the first frequency sampling value 1 kHz is considered, the classification performance for the first feature $M_0$ increases with the spread value between 70% and 83%. For the second feature $M_1$ the classification performance gets its max value of 79% with the spread value equal to 1.2 and 0.4. The third feature $M_2$ reaches its max classification accuracy equal to 81% with the spread value of 1.2. Generally these performances of classification with three features are limited between 70% and 83%. If we make a comparison with the two following sampling frequencies, 2 kHz and 4 kHz, these results are obviously bad. For the second sampling frequency, 2kHz, the results of classification are more better in which the lowest classification accuracy is equal to 75%, this classification accuracy is obtained with the feature $M_2$ and for spread value equal to 0.4 of RBF classifier. The highest classification accuracy, 99%, is reached with the feature $M_1$ and for spread values, 1.2 and 1.4. Globally classification accuracy in this case, $F_s$ = 2 kHz, is better than for the first sampling frequency value of 1 kHz. The third sampling frequency, 4 kHz, gives the best classification performances. The worst classification result in this case and for all our three features is equal to 83%.

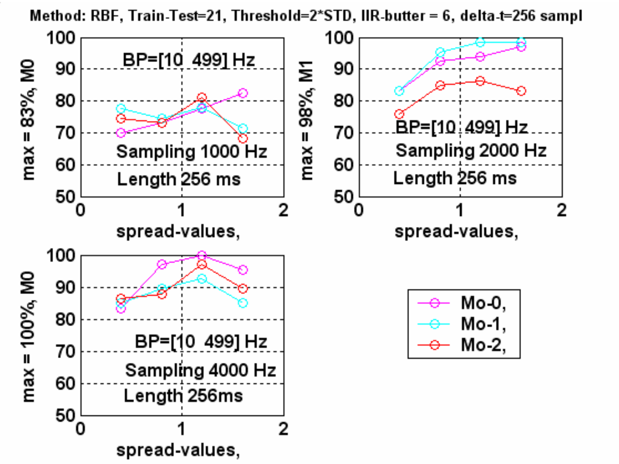


*Fig. 5: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz. In each case three features $M_0$, $M_1$ and $M_2$ are classified with RBF method for four different spread values: 0.4, 0.8, 1.2 and 1.6.*

### 6.1.2 Case of 30-500 Hz pass-band filter

In this case the band frequency is reduced from the low frequency side. The frequencies in the range of 10-30Hz have been removed. The consequence of this operation is a decrease in classification performances for all three sampling frequencies comparatively with the results in section 6.1.1 (figure 6). But the effect of sampling frequency is the same like in section 6.1.1. The increase of the sampling frequency increases the classification performance. This conclusion in the pass band frequency of 10-500 Hz is true.

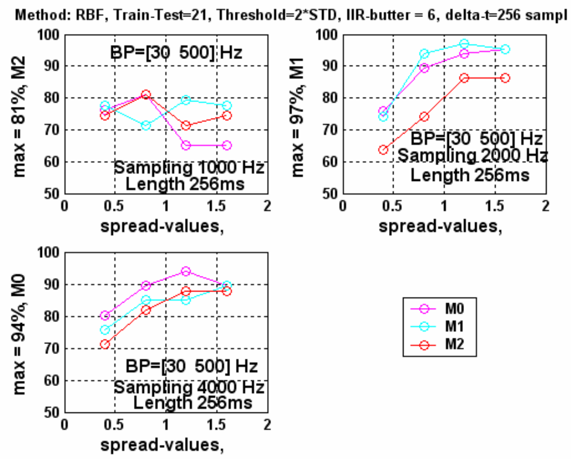


*Fig. 6: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz in case of 30-500Hz pass band filter. For each sampling frequency three features $M_0$, $M_1$ and $M_2$ are classified with RBF method for four different spread values: 0.4, 0.8, 1.2 and 1.6.*

### 6.1.3 Case of 10-300 Hz pass-band filter

In this case the band frequency is reduced from the high frequency side. The frequencies in the range of 300-500Hz have been removed. The consequence of this operation doesn't confirm the conclusion found in the above section 6.1.2. In this case the sampling frequency of 4 kHz gives less classification accuracy than in the case of sampling frequency of 2 kHz (figure 7).

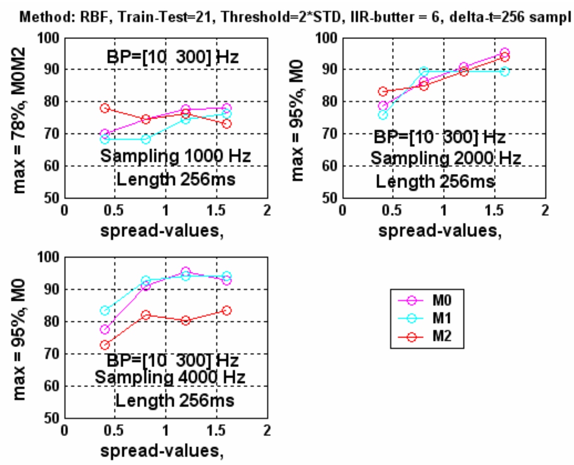


*Fig. 7: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz in case of 10-300Hz pass band filter. For each sampling frequency three features $M_0$, $M_1$ and $M_2$ are classified with RBF method for four different spread values: 0.4, 0.8, 1.2 and 1.6.*

### 6.1.4 Case of 30-300 Hz pass-band filter

In this case the band frequency is reduced from the high frequency side and low frequency side. The frequencies in the range of 300-500Hz and 10-30Hz have been removed. The consequence of this operation is the same like in section 6.1.3. The sampling frequency of 4 kHz gives less classification accuracy than in the case of sampling frequency of 2 kHz (figure 8).

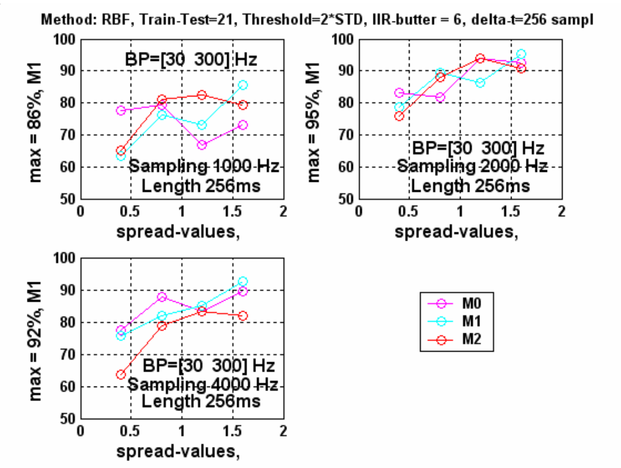


*Fig. 8: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz in case of 30-300Hz pass band filter. For each sampling frequency three features $M_0$, $M_1$ and $M_2$ are classified with RBF method for four different spread values: 0.4, 0.8, 1.2 and 1.6.*

## 6.2 Classification performance with *FSC*-based approach

### 6.2.1 Case of 10-500 Hz pass-band filter

In this case, three sampling frequencies 1 kHz, 2 kHz and 4 kHz are applied. In each case three features $M_0$, $M_1$ and $M_2$ are classified with FSC method for four different radius values: 0.2, 0.4, 0.6 and 0.8. From the results shown in figure 9, and using the same procedure, see above study section 6.1.1, it's clear that the effect of these three sampling frequencies: 1 kHz, 2 kHz and 4 kHz is the same like with *RBF* classification method in section 6.1.1. These classification results with *FSC* method confirm the idea that the effect of the increasing in sampling frequency is positive in case of band frequency equal to 10-500Hz. The best results are occurred using 4 kHz sampling frequency. In this case classification accuracy, for all three features, is limited between 89% and 98%.

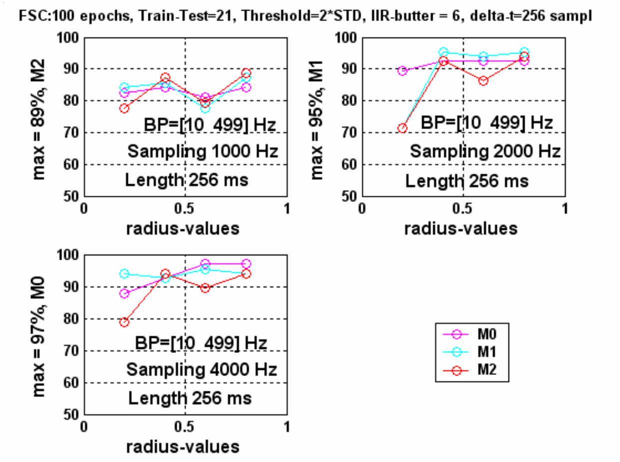


*Fig. 9: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz in case of 10-500Hz pass band filter. For each sampling frequency three features $M_0$, $M_1$ and $M_2$ are classified with FSC method for four different radius values: 0.2, 0.4, 0.6 and 0.8.*

### 6.2.2 Case of 30-500 Hz pass-band filter

In this case the band frequency is reduced from the low frequency side. The frequencies in the range of 10-30Hz have been removed.

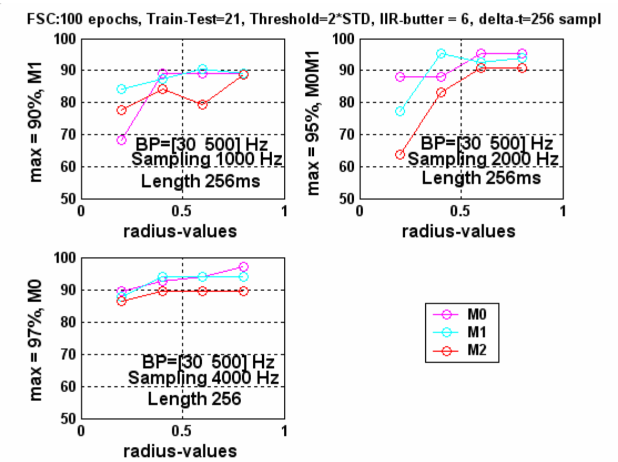


*Fig. 10: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz in case of 30-500Hz pass band filter. For each sampling frequency three features $M_0$, $M_1$ and $M_2$ are classified with FSC method for four different radius values: 0.2, 0.4, 0.6 and 0.8.*

The consequence of this operation is a small decrease in classification performances for all three sampling frequencies comparatively with the results in section 6.2.1 (figure 10). But the effect of sampling frequency is the same like in section 6.2.1. The increasing in sampling frequency increases the classification performances. This conclusion in the pass band frequency of 10-500 Hz is true.

### 6.2.3 Case of 10-300 Hz pass-band filter

In this case the band frequency is reduced from the high frequency side. The frequencies in the range of 300-500Hz have been removed. The consequence of this operation doesn't confirm the conclusion found in the above section 6.2.2. In this case the sampling frequency of 4 kHz gives less classification accuracy than in the case of sampling frequency of 2 kHz(figure 11).

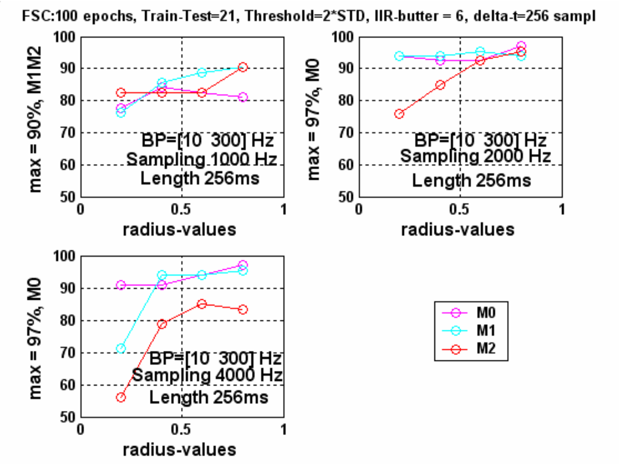


*Fig. 11: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz in case of 10-300Hz pass band filter. For each sampling frequency three features $M_0$, $M_1$ and $M_2$ are classified with FSC method for four different radius values: 0.2, 0.4, 0.6 and 0.8.*

### 6.2.4 Case of 30-300 Hz pass-band filter

In this case the band frequency is reduced from the high frequency side and low frequency side. The frequencies in the range of 300-500Hz and 10-30Hz have been removed. The consequence of this operation is the same like in section 6.2.3. The sampling frequency of 4 kHz gives less classification accuracy than in the case of sampling frequency of 2 kHz (figure 12).

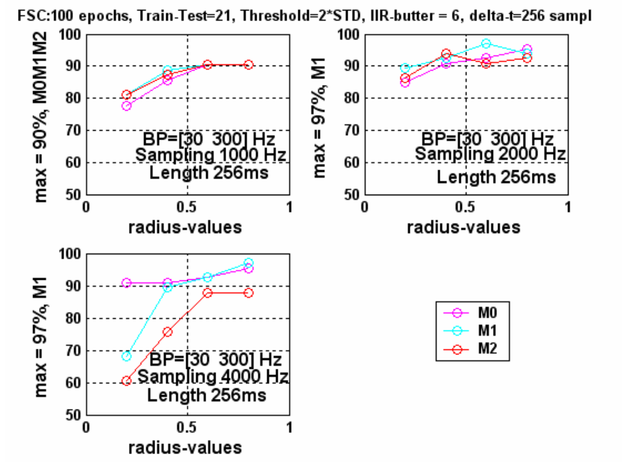


*Fig. 12: Classification accuracy corresponding to three sampling frequencies, 1 kHz, 2 kHz and 4 kHz in case of 30-300Hz pass band filter. For each sampling frequency three features $M_0$, $M_1$ and $M_2$ are classified with FSC method for four different radius values: 0.2, 0.4, 0.6 and 0.8.*

## 7 Conclusion

Forearm EMG signals has been acquired using three sampling frequencies: 1 kHz, 2 kHz and 4 kHz. Acquired signal is filtered with four different pass band frequencies: 10-500 Hz, 10-300 Hz, 30-500Hz and 30-300Hz and for each sampling frequency these four band frequencies are applied. In each case three features $M_0$, $M_1$, and $M_2$ are extracted and classified with RBF and FSC classification methods. There are applied four different spread values: 0.4, 0.8, 1.2 and 1.6 corresponding to RBF classification method and four different radius values: 0.2, 0.4, 0.6 and 0.8 corresponding to FSC classification method. The acquired results are gained using both methods, RBF and FSC; and with three different features, ($M_0$, $M_1$ and $M_2$), in case of band frequencies 10-500Hz and 30-500Hz have been shown that the effect of sampling frequency is positive and monotone with the classification accuracy. The interpretation of these results can be seen in the signal information which is dependent on sampling frequency. If the sampling frequency is increased we get more significant signal information. However this conclusion can not be generalised for all band frequencies. For the two other band frequencies 10-300Hz and

30-300Hz the classification performance is poorer when using 4 kHz sampling frequency, than when using 2 kHz sampling frequency. From this study we came to the conclusion that we have to take in consideration these two parameters Sampling frequency and band frequency together, when we deal with EMG signals.

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