Temporal vs. Spectral Approach to Feature Extraction from Prehensile EMG Signals

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Abstract

There are generally two nonparametric approaches in feature extraction from temporal signals: temporal and spectral approach. Both approaches were used in classification of prehensile electromyographic (EMG) signals. The goal of this paper is to define and evaluate some successful methods in both approaches and to determine experimentally which method and approach is the most appropriate. The evaluation is based on classification of real EMGs with an ART-based classifier. The efficiency analysis is also provided. The results have shown that a less expensive temporal approach has strong advantages over the spectral methods.

1. Introduction

Feature extraction is an important step in process of pattern recognition, especially if the pattern is represented by a temporal or spatial signal like acoustic, geodetic, electromyographic signal or 2D image. In case of electromyographic signals (EMG), a pattern is represented by a temporal signal *s(t)* which typically looks like in Fig. 1. Normally the temporal signals are of limited (shorter) duration and are sampled and converted into digital format. In such situation it is more appropriate to represent a pattern as a finite time sequence $s[0], s[1], ..., s[N-1]$. Presenting this sequence directly to a classifier is impractical due to the large number of inputs and due to the randomness of the signal. Therefore, the sequence $s[n]$ must be mapped into a smaller-dimension vector $\mathbf{x} = (x_1, x_2, ..., x_D)$, $D \ll N$, called *feature vector*, which best characterizes the pattern and provides a stable classifier training and classification at a good hit rate.

There are generally two approaches to feature extraction: temporal and spectral approach. Both approaches can be classified as nonparametric approaches. There are also parametric approaches (like ARMA) which are out of scope of this paper[1]. Both approaches have been used in classification of EMG patterns [8],[7],[4]. Spectral approaches have gained a big popularity in the last two decades. A remarkable work on the classification of prehensile EMG patterns was done by Kristin Farry [4].

The goal of this work is to present some of the existing and successful feature extraction methods that belong to both temporal and spectral approaches, to add some new methods, then to perform their comparative analysis. The evaluation of the methods will be done on prehensile EMG patterns [15] -[17], briefly described in section 4. The goodness of feature extraction will be quantified with the classification hit rate, obtained by an ART-based classifier developed at SDSU [18], [19]. We believe that the results presented here can help to decide which approach and which method for feature extraction is the most appropriate for classification of prehensile EMG patterns.

2. Spectral Approach

For the reason which will be obvious later, we start with the feature extraction methods that belong to spectral approach.

2. 1. Periodogram

A traditional way to characterize the spectral properties of a time sequence $s[n]$ is through its power spectral density (PSD) function *P(f)*. If the available observations of $s[n]$ constitute a truncated sequence $s[0], s[1], ..., s[N-1]$ then *P(f)* can only be estimated through some estimator. The simplest and oldest estimator of PSD is the periodogram:

$$\hat{P}(f) = \frac{1}{N}\left|\hat{S}(f)\right|^2 = \frac{1}{N}\left|\sum_{n=0}^{N-1} s[n]e^{-j2\pi fn}\right|^2. \qquad (1)$$

In order to decrease the spectral leakage caused by truncation, the sequence is often windowed, i.e. $s[n]$ is replaced by $s[n]w[n]$ where $w[n]$ is some time windowing function, for example the popular Hamming window.

2. 2. Spectral Magnitude Averages

Since the estimated PSD, $\hat{P}(f)$, is itself a random function, it is convenient to define the spectral-based features as some averaged values of $\hat{P}(f)$. A simple choice is the spectral magnitude averages defined over L equidistant frequency intervals:

$$\hat{P}_m = \frac{1}{f_m - f_{m-1}} \int_{f_{m-1}}^{f_m} \hat{P}(f)df, \quad m = 1, 2, ..., L. \qquad (2)$$

These averages help reduce the effect of a considerable variance of periodograms.

[1] In a previous work ARMA was considered and later abandoned due to its demand for longer time sequences.

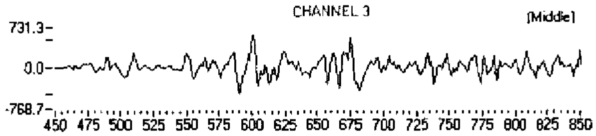

Fig. 1. Raw EMG signal recorded while the subject was grasping a large spherical object

2. 3. Spectral Moments

An alternative possibility to extract the features from a PSD estimate are the spectral moments:

$$M_m = \int_0^W f^m \hat{P}(f)df, \quad m = 0,1,...,L, \tag{3}$$

where W is bandwidth of the spectrum. As will be shown later, the spectral moments have given much better results in the case of classification of prehensile EMG patterns than the magnitude averages.

The most important spectral moments are the first three moments. These moments can be used to express some important characteristic of the PSD in a more "human friendly" form:

Energy:

$$E = M_o = \int_0^W \hat{P}(f)df \tag{4}$$

Central frequency (spectral center of gravity):

$$f_c = \frac{\int_0^W \hat{P}(f)f\,df}{\int_0^W \hat{P}(f)df} = \frac{M_1}{M_o}, \tag{5}$$

Variance of central frequency:

$$\sigma_f^2 = \frac{1}{M_o}\int_0^W \hat{P}(f)(f-f_c)^2 df = \frac{M_2}{M_o} - \left(\frac{M_1}{M_o}\right)^2. \tag{6}$$

2. 4. Thompson Transform

If the observed time sequence is too short, the periodogram becomes ineffective due to increased bias and variance. This can be seen if we express the true (untruncated) sequence through Cramer spectral representation:

$$s[n] = \int_{-1/2}^{1/2} e^{j2\pi fn} dZ(f), \tag{7}$$

where $dZ(f)$ is infinitesimal random complex amplitude of sinusoids, which has zero mean, $\mathcal{E}[dZ(f)] = 0$, and variance equal to true PSD, $\mathcal{E}[|dZ(f)|^2] = P(f)df$. The integral (7) is known as Fourier-Stiltjes integral. The discrete Fourier transform of the truncated sequence can be now written:

$$\hat{S}(f) = \sum_{n=0}^{N-1} s[n]e^{-j2\pi fn} = \int_{-1/2}^{1/2} \sum_{n=0}^{N-1} e^{j2\pi(u-f)} dZ(u). \tag{8}$$

The sum in the right hand side of (8) is known as Dirichlet kernel function

$$\mathcal{D}_N(x) = \sum_{n=0}^{N-1} e^{-j2\pi nx} = e^{-j\pi x(N-1)} \frac{\sin(N\pi x)}{\sin(\pi x)}. \tag{9}$$

After substituting (9) into (8) the latter becomes:

$$\hat{S}(f) = \int_{-1/2}^{1/2} D_N(f-u)dZ(u). \tag{10}$$

This equation clearly shows that the estimated spectrum $\hat{S}(f)$ is a convoluted (smeared) version of the true spectrum due to truncation of the time sequence. In order to make a best estimate of the true spectrum, the integral equation (10) has to be solved, which is an ill-posed inversion problem. Thompson [13] has offered a solution which is based on the spectral decomposition of the Dirichlet kernel function. The Thompson's estimator of PSD (the multitaper method) can be summarized as follows:

$$\hat{P}(f) = \frac{\sum_{k=0}^{K-1} \lambda_k \hat{P}_k(f)}{\sum_{k=0}^{K-1} \lambda_k}, \quad \hat{P}_k(f) = \left|\sum_{n=0}^{N-1} s[n]v_k[n]e^{-j2\pi fn}\right|^2, \tag{11}$$

where λ_k and $\mathbf{v}_k = (v_k[0], v_k[1], ..., v_k[N-1])^T$, $k = 1,2,...,K$, are eigenvalues and associated orthonormal eigenvectors of the Dirichlet-Toeplitz matrix $\mathbf{D} = [d_{ij}]_N$ with elements:

$$d_{ij} = \frac{\sin(2\pi(i-j))}{\pi(i-j)}. \tag{12}$$

The sequences $v_k[n]$ are proposed by Slepian [12] end are called *discrete prolate spheroidal sequences* (DPSS). ($v_k[n]$ and λ_k depend on parameters N and W, which are dropped for simplicity.) Interesting property of these sequences is that they have a maximum concentration of energy within the band limit W among all other possible time sequences [12]. The sum in (11) is limited to K terms that correspond to K largest eigenvalues of $\mathbf{D}$. The first four Slepian sequences are shown in Fig. 2. It should be noted that only the first sequence resembles the usual windowing functions, while others don't. They can even have negative values.

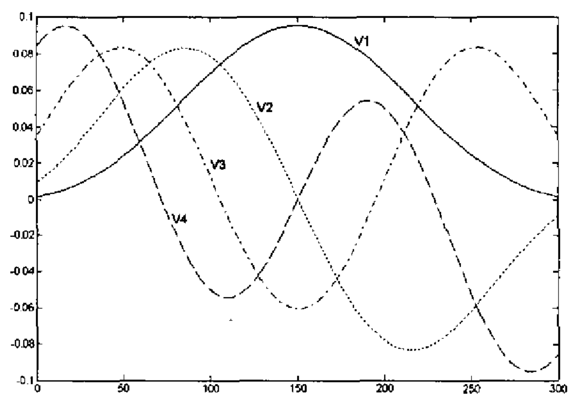

Fig. 2. Discrete prolate spheroidal sequences

Fig. 3. illustrates the effectiveness of Thompson transform applied to prehensile EMG signals. It can be seen that the latter approach has significantly reduced spectral leakage and variance.

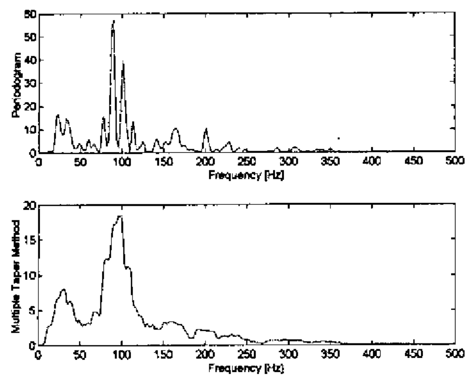

Fig. 3. Comparison of periodogram and Thompson transfom

It is known [12] that the largest values of eigenvalues λ_k are very close to 1 as long as the number of tappers doesn't exceed $K = 2NW$. In that case, the left part of eq. (11) can be simplified:

$$\hat{P}(f) = \frac{1}{K}\sum_{k=0}^{K-1}\hat{P}_k(f). \tag{13}$$

2. 5. Short Time Fourier Transform

The fact that the EMG signals have an inherent temporal structure was given attention and researched by Hanaford etal. [7]. They have used the short-time Fourier transform (STFT) to study the rapid head and wrist movement, and to show that the spectrum changes with time. The STFT can be expressed by using a windowing function which has shorter width than the entire sequence and which can be positioned arbitrarily along the time range of the sequence:

$$S(f,t) = \sum_{n=0}^{N-1} s[n]w[n-t]e^{-j2\pi f t}. \tag{14}$$

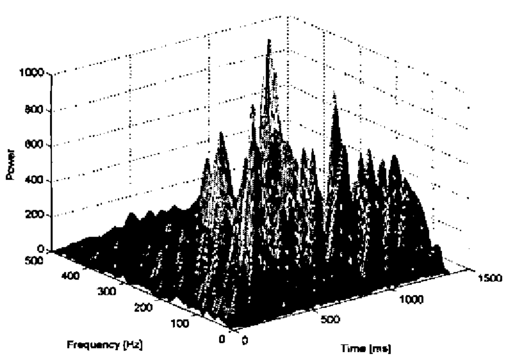

Fig. 4. Time-frequency plot of EMG signal

An example of the time-dependent PSD, $|S(f,t)|^2$, of a prehensile EMG signal used in our research is shown in Fig. 4.

The figure clearly indicates that the PSD changes with time. For practical reasons there can be defined several equally spaced window locations, which is equivalent to slicing the time sequence in several subsequences. En extensive experimental work has shown that the best results in classification of prehensile EMG patterns can be obtained with three 30% overlapping Hamming windows, as shown in Fig. 5. In this figure the total sequence length was $N = 200$, and the three spectra were: $S(f,n_i)$, $n_i = 40,\ 100,\ 160$. The spectral estimates for each window become:

$$\hat{S}_i(f) = \sum_{n=0}^{N-1} s[n]w[n-n_i]e^{-j2\pi f t},$$
$$\hat{P}_i(f) = \left|\hat{S}_i(f)\right|^2,\ i = 1,2,\ldots,J. \tag{15}$$

These functions can be used in further feature extraction procedure, either by using spectral magnitude averages, or spectral moments derived for each window.

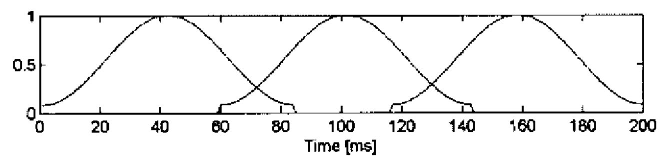

Fig. 5. Three overlapping Hamming windows

2. 6. Short Time Thompson Transform

The Thompson transform discussed in section *2* was motivated in the first place by the short time sequences. If we split an already short time sequence into even shorter ones, the usage of Thomson transform becomes even more justified. This fact was recognized by Farry etal. [4], who have used the short time Thomson transform (STTT) on prehensile EMG signals very successfully. The features extracted from the PSD were spectral magnitude averages. We have used spectral moments extracted from STTT-based PSDs, which have resulted in significantly better classification hit rates (see section 5).

3. Temporal Approach

In temporal approach the features are extracted directly from the temporal sequence $s[n]$. Hudgins [8] has realized that the deterministic structure of EMG can be exploited for the multifunctional prosthetic control from a single EMG channel. He characterized the time sequence by the following quantities: mean absolute value, mean absolute value slope, number of zero crossings, slope sign changes, and waveform length. Although Hudgins claimed a successful discrimination of various limb functions, the above temporal characterizations didn't help much in the hand motions, particularly in the discrimination of six synergetic grasp motions [10]. An exception was the first parameter, the mean absolute value, which can be loosely related to the signal's energy. As will be shown later, the energy of the signal plays a major role in a successful classification of prehensile motions.

An interesting attempt was made with a method which consisted in enveloping of the initial EMG burst with some known function, for example cosine or bell function. The parameters of the functions were estimated and used as features [5]. The initial EMG burst corresponds to the hand preshaping phase, which is most relevant to the grasp type. This method can be categorized as a parametric temporal approach, which however has offered a limited success.

A good classification hit rate was achieved in [15], where the raw EMG signals were first squared then processed with a FIR filter. The resulting smooth waveform has reflected the hand preshaping dynamics in a form of a high amplitude oscillation. The amplitude of this oscillation was extracted as a feature.

The problem with the latter two methods is that they are relatively complex and, they worked well only with sequences longer than 400 ms, which is not acceptable in real-time application. In the following subsections we consider a couple of methods that were used either for their simplicity, or for their good performance with shorter time sequences.

3. 1. Integral Square

This is the simplest method, it represents the signal's energy:

$$x = \int_0^{T_s} s(t)^2 dt = \sum_{n=0}^{N-1} s[n]^2, \tag{16}$$

where T_s is signal observation time , $N = T_s/\Delta t$, and Δt is sampling period (Δt = 1ms in our case). According to Parseval's theorem the energy can be defined either in time domain (16), or in frequency domain (4).

3. 2. Multiple Hamming Windows

The energy, i.e. the zero moment M_o can be computed with (4) for J windows:

$$M_{oi} = \int_0^W \hat{P}_i(f)df = \int_0^W \left|\hat{S}_i(f)\right|^2 df, \quad i=1,2,...,J \tag{17}$$

After applying the Parceval's theorem to (17) and taking into account (15) we can compute the spectral moment M_o entirely in time domain:

$$x_i = \sum_{n=0}^{N-1} \left(s[n]w[n-n_i]\right)^2, \quad i=1,2,...,J. \tag{18}$$

It is important to note that the computation of the spectral moment doesn't require derivation of the spectrum beforehand. In other words, an excessive FP operation like FFT can be entirely eliminated. The features here are based on the STFT; similar version can be obtained for STTT.

In order to emphasize the importance of the zero moment, we can analyze diagrams in Fig. 6. The last diagram shows the zero moment $M_0(t)$ computed for sliding window (14) for all four EMG channels, for a particular grasp motion. The former two diagrams show the central frequency (5) and variance of central frequency (6), based on moments $M_1(t)$ and $M_2(t)$ for the same grasp motion. If we imagine the smoothed version of these diagrams, we can easily conclude that the zero moment contains significantly more time structure than the other two moments. This will be confirmed later through experimental results.

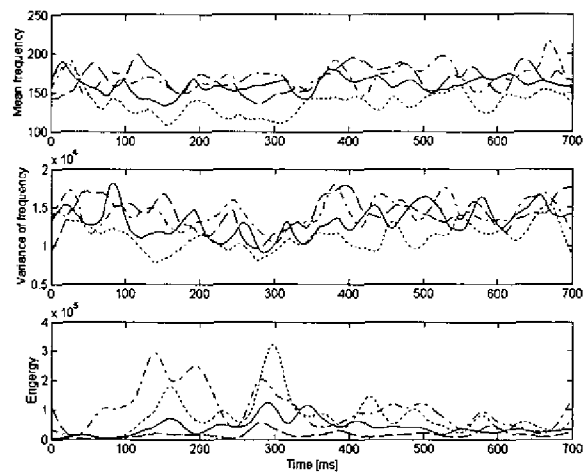

Fig. 6. Time dependency of mean frequency, variation of frequency and energy for four EMG channels

3. 3. Multiple Trapezoidal Windows

In spectral estimation with periodogram, the Hamming window is used to decrease the spectral leakage caused by the truncated time sequence. However, in computing the signal's energy in time domain, the spectral leakage is not an issue. As a matter of fact, the Hamming windows even destroy the energy information at the beginning and at the end of each window, even if the windows are overlapped. Therefore we heuristically introduce windows that preserve energy, like windows with the trapezoidal shape, as shown in Fig. 7. The trapezoidal windowing functions have the amplitudes adjusted so that the area of each window is equal to one. As will be shown later, these windows offered much better classification hit rates than the Hamming windows.

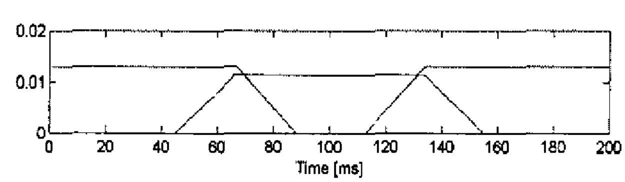

Fig. 7. Three overlapping trapezoidal windows

4. Prehensile Motion and EMG Patterns

A great deal of pattern recognition research at SDSU has been motivated by the idea of the new generation prosthetic hand, which is based on a multifingered, multifunctional prosthetic device instead of a classical single degree of freedom gripper. However, while the electromyographic (EMG) control of single DOF devices was an easy task, it is much more difficult to interface a human limb with a multiple DOF device. This problem was addressed by several researchers [4], [6], [9], [14] with a goal to control the individual finger joints from real-time EMG signals.

The research at SDSU has focused on the *synergetic control* of groups of finger joints that correspond to the basic prehensile motions, rather than on controlling the individual fingers [15]-[17]. According to Schlesinger [11], there are five basic types of hand grasps: *cylindrical* grasp, *spherical* grasp, *precision (pinch)* grasp, *lateral (key)* grasp, and *hook* grasp. The four–channel raw EMG signals are recorded from several subjects, for the first four grasp types from the Schlesinger classification (see Fig. 8). In addition, cylindrical and spherical grasps were subdivided into small and large cylindrical grasp, and in small and large spherical grasp respectively, which made six grasp types altogether. The experiments in this work were performed for the two cases: four and six grasp types. The latter case is more difficult for classification since there is a considerable overlapping between the grasps with smaller and larger apertures.

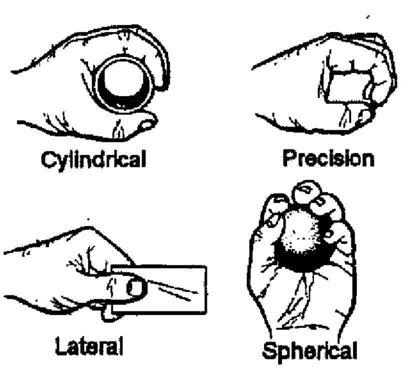

Fig. 8. Four grasp types

5. Experimental Results

The feature extraction methods discussed above were used on a database of EMGs recorded from a subject with healthy hand. The subject was repeatedly performing six types of hand motions by grasping various objects: small cylinder, large cylinder, small ball, large ball, small object, and a key mounted on a vertical fixture. There were 173 grasp recordings evenly distributed across the six grasp types.

There were three different EMG sequence lengths used in this experiment: 200ms, 300ms and 400ms sequences (the sampling period was 1 ms). The three sequences were obtained by truncating the same recording.

The feature extraction methods were as follows: zero moment only (M_o), zero and first moment (M_o and M_1), zero, first and second moment (M_o, M_1 and M_2), and spectral magnitude average (SMA), all for short-time Fourier transform (STFT) and for short-time Thompson transform (STTT). For temporal approach the feature extraction methods were: integral-square (IS), multiple Hamming windows (MHW), and multiple trapezoidal windows (MTW).

The evaluation of the feature extraction methods was based on the classification hit rates. The classifier used here was the Mahalanobis distance-based ARTMAP network (MART), developed at SDSU [17]-[19]. The experiments were performed on randomly generated training and test sets obtained by randomly splitting the entire data set, such that both sets contained an equal number of all grasp types. The experiment was repeated 100 times and the average hit rate was computed across all 100 independent experiments.

The results for spectral approach are shown in Fig. 9 and Fig. 10. In STFT are used three 30% overlapping Hamming windows ($J = 3$). In STTT are used three non-overlapping segments, and in each segment were used four Slepian sequences (DPSS). The choice of the number of segments, Slepian sequences and overlapping factor was decided experimentally, as a tradeoff between efficiency and good classification hit rate. The results are given for three different lengths of time sequences: 200ms (white bars), 300ms (grey bars), and 400ms (dark grey bars)

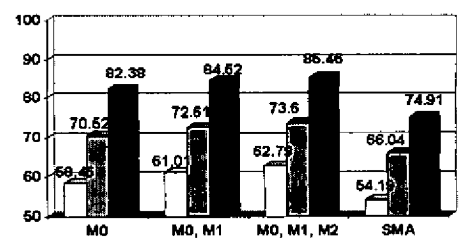

Fig. 9. Classification hit rates for STFT

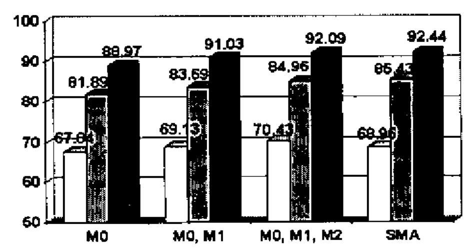

Fig. 10. Classification hit rates for STTT

The results can be summarized as follows:

(a) Usage of two and three spectral moments has scored slightly better hit rates than the usage of only M_0. The differences were between 3 and 5%[2]

(b) The spectral moments have shown significantly better results than the spectral magnitude averages (SMA), in case of STFT (over 11%). However, this was not true in the case of STTT. This can be explained by the smaller leakage and variance of STTT over STFT.

(c) STTT has performed much better than STFT (differences over 7 to 9%).

(d) Fig. 11 shows the performance of temporal methods. The simplest temporal method, IS, was inferior in comparison to any other temporal or spectral method.

(e) MHW scored better hit rates than IS (over 6%), while MTW was better than MWH (over 3%).

(f) The MTW performed better than the best STFT method (about 6% better).

(g) The MTW performed slightly worse than three moments of STTT (between 1 and 5%), but slightly better than the single moment STTT (about 2%). In other words, STTT has shown little advantage over MTW in terms of the classification hit rate. As shown below, the MTW has a significant advantage over STTT in terms of execution efficiency.

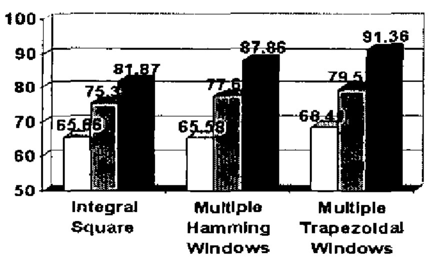

Fig. 11. Classification hit rates for temporal methods

The graphs in Fig. 9 to Fig. 11 show hit rates for the training and classification of six grasp types, which is more difficult than classification of four grasp types, because there is a considerable similarity between small and large cylindrical, and small and large spherical grasps. The results for four grasp types are shown in Fig. 12. As expected, the hit rates are much higher here: the trapezoidal feature extraction method has scored an average of 97.23% for 400ms sequences.

[2] The standard deviations for all results presented here were in the neighborhood of 3%.

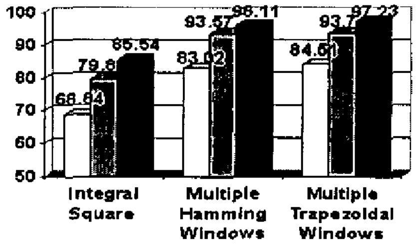

Fig. 12. Same as Fig. 11, only four objects were used instead of six objects.

In order to get a complete picture about the methods, we analyze other aspects, the efficiency. TABLE I shows the number of required floating point operations (basically additions and multiplications) needed for each algorithm for a single EMG channel. It is interesting to note that the temporal methods depend only on the sequence length (N) and the amount of overlap (P), while the number of window/segments (J) has no impact. The Spectral methods have an addition, the computation of the FFT on sequences of length N/K. The left part of the expressions covers windowing and computation of PDS from the spectrum.

TABLE I
Cost of various feature extraction methods per EMG channel

Method	*Number of FP operations*	
SI	$2N$	
MHW	$3(1+P)N$	
MTW	$3(1+P)N$	
STFT - SMA	$3(1+P)N$	+ J*FFT
STFT - moments	$(2+L)(1+P)N$	+ J *FFT
STTT - SMA	$(1+5K)N/2$	+ J *K*FFT
STTT - moments	$(2L+5K-1)N/2$	+ J *K*FFT

N - sequence length; L - number of moments;
J - number of windows; K - number of DPSS;
P - overlap in %/100;

The concrete results for N = 400, K = 4, J = 3, are shown in TABLE II. Again, results are given for a single EMG channel. The table shows the classification hit rates, the algorithm's efficiency in terms of the number of FP operations, and the resulting dimension of the feature vector.

TABLE II
Performance of various feature extraction methods

Method	*# of features*	*# of FP operations*	*Hit rate [%]*
SI	1	800	81.9
MHW	3	1,560	87.9
MTW	3	1,560	91.4
STFT - SMA	9	1,560 + 3*FFT	74.9
STFT - 1 moment	3	1,560 + 3*FFT	82.4
STFT - 2 moments	6	1,652 + 3*FFT	84.5
STFT - 3 moments	9	2,600 + 3*FFT	85.5
STTT - SMA	9	4,200 + 12*FFT	92.4
STTT - 1 moment	3	4,200 + 12*FFT	89.0
STTT - 2 moments	6	4,600 + 12*FFT	91.0
STTT - 3 moments	9	5,000 + 12*FFT	92.1

The table shows that the three-moment STTT is the most superior in terms of the hit rate, however it is also the most expensive algorithm in terms of the execution time. Moreover, the algorithm generates the 9-element feature vector per EMG channel. Dimensionality of the feature space has a heavy impact on the efficiency of the network training and on the classification after training. On the other hand, the multiple trapezoidal windowing (MTW) has hit rate which is slightly smaller (less than 1%) than the three-moment STTT, but doesn't require FFT. It also produces feature space whose dimensionality is three times smaller. At this point we can reconsider the value of the expensive spectral approach versus the simpler and inexpensive temporal approach, at least for the feature extraction of prehensile EMG patterns.

6. Conclusion

The central goal of this research was to reconsider the value of the expensive spectral approaches for feature extraction from the raw EMG signals used for recognition of prehensile motions. Several spectral methods were systematically compared with several temporal methods. To the group of temporal approaches were added two new methods: the multiple Hamming and the multiple trapezoidal windowing method. The later has proved experimentally to be very effective. All the methods were tried on real EMG data and the features extracted were used on an ART-based classifier. The experimental results were surprising: the inexpensive and simple multiple trapezoidal windowing, which is a temporal method, has offered much better time efficiency and lower dimension of the feature vector than the expensive method based on the short time Thompson transform, with just a slightly smaller classification hit rate.

Acknowledgement

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