WHITE NOISE BASED MODELING OF SURFACE MYOELECTRIC SIGNALS DURING CYCLIC DYNAMIC CONTRACTIONS

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Abstract: Surface myoelectric signals recorded during fatiguing cyclic dynamic contractions are non-stationary signals with variable spectral parameters. In attempt to extract the essentials of their change and assess different time-frequency analysis methods many models have been developed. White noise based modeling is frequently used method. Accordingly, we developed model that allows control over power spectrum and signal amplitude. Synthesized signals were analyzed by continuous wavelet transform. The analysis show, that in general, white noise based models of cyclic dynamic contractions result in signals with high variability of modeled spectral parameters and therefore, are not suitable for assessment of different time-frequency analysis methods.

Introduction

The surface electromyographic (SEMG) signal of the skeletal muscle recorded during cyclic dynamic contractions is non-stationary signal that can be analysed by time-frequency analysis methods [1-4]. Different models of non-stationary SEMG signals have been developed to prove accuracy and reliability of analysis methods [5-8].

It is hardly feasible to develop common SEMG signal model that would comply with all types of SEMG signals and contain all possible (SEMG) characteristics. Therefore, models are developed and used to solve particular problems. Depending on the problem, the model needs to contain certain characteristics [9,10].

All SEMG signal models can be divided into two main types: models of SEMG as a stochastic process (stochastic models) and motor unit based models. The second type is highly demanding for modeling SEMG signals during cyclic dynamic contractions because of the complex and variable anatomical and physiological parameters that influence the SEMG signal [7].

The SEMG signal recorded by bipolar electrodes reflects the electrical activity throughout a wide cross-section of the underlying muscle or group of muscles [11]. The signal is the summation of contributions from many motor units. The potentials from the different motor units occur at random times to produce a noise-like pattern. Due to the irregular nature of motor unit discharges and the different shapes of the motor unit action potentials, the SEMG signal may be considered as a band-limited stochastic process with Gaussian distribution and zero mean [8,12].

The signal is usually analysed in terms of its intensity and power spectrum, using variables such as the average rectified value, the root-mean-square value and the mean or median frequency (MDF) of the power spectral density [13-15]. These variables are referred to as global SEMG variables because they reflect the overall state of the muscle. This leads us to models of SEMG as a stochastic process that allow global SEMG variables to be related to underlying physiological and anatomical parameters in the muscle [5].

None of developed stochastic models does adequately simulate the change in the spectrum of the SEMG during cyclic dynamic contractions [5,6,12]. The common problem of stochastic models is insufficient control over global variables. This will be demonstrated in this paper.

Herein, the method will be presented that takes into the account not only the change in the amplitude [6] but also the change in the spectrum of SEMG during cyclic dynamic contractions [2, 4].

Materials and Methods

In order to design model it is necessary to extract the essentials of real measured SEMG signal. Thus, finding out properties of signal and detecting variables to be modeled [9].

Measurement: In this work we used surface myoelectric signals recorded in our previous studies [4]. Ten subjects performed voluntary cyclic dynamic left knee extension that resembles to natural movement during exercise on rehabilitation equipment. The range of the shaft angle was form 110° (flexion) to 180° (extension).

The load for the cyclic contractions was adjusted to the half of the maximum voluntary dynamic left-knee extension. Each subject was free to select the cycle frequency. Number of cycles varied from subject to subject depending upon individual exhaustion.

Surface myoelectric signals were recorded from three quadriceps muscles: *m. rectus femoris, m. vastus lateralis and m. vastus medialis*.

Previous studies showed that this type of signals can be properly analysed by time-frequency methods [4,8,14] where median frequency is proven to be the best choice among global variables [4,16,17] for monitoring the spectral change of the SEMG signal.

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Figure 1 shows typical normalized measured SEMG signal, U, and the change of median frequency, MDF, during fatiguing cyclic dynamic contractions. The regression line that fits maximum values of MDF per contraction in a least square sense shows downward trend of median frequency.

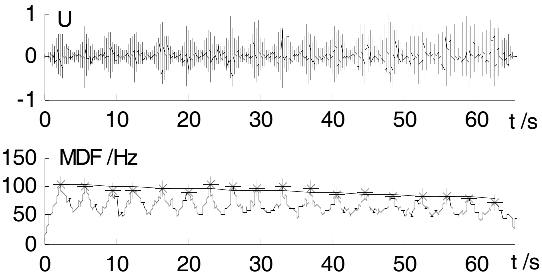

Figure 1: Normalized measured SEMG signal, U, and the change of median frequency, MDF, during cyclic dynamic contractions

Stochastic model: Two variables were chosen to be modeled: median frequency and amplitude. It is worthwhile noting that the shape of power spectral density defines median frequency. The shape can be very simple, defined by band-pass Butterworth filter [8] or very complex, defined by cascade of filters [5]. We chose band-pass Butterworth filter in order to simplify synthesis process.

The median frequency of a model is periodic and simulates the change found in the SEMG signal during cyclic dynamic contractions. The signal

$$x[i] = \begin{cases} \left| f_{gk} \sin\left(\frac{\pi}{T_{SR}} t[i] \right) \right| & , x[i] > 20,\ i = 1,2,3...N \\ 20 & , x[i] \le 20,\ i = 1,2,3...N \end{cases} \tag{1}$$

is added to linearly decreasing component with aim to mimic downward trend of median frequency. f_{gk} is a constant equal to 40 Hz and N is the total number of signal samples. The period of sinusoidal component, T_{SR}, is equal to 3.514 s. Duration of the signal is 65 s. Both values were chosen from one of the measured SEMG signals. The sampling frequency is assumed to be the same as for measured SEMG signals, 1000 Hz.

The modeled change of power spectrum median frequency is

$$f_{med}[i] = x[i] - \frac{f_0 - f_z}{\Delta T} t[i] + \left(f_0 - f_{gk} \right),\ i = 1,2,3...N \tag{2}$$

where x is a periodic component given by (1). N is the total number of elements within vectors. Frequencies f_0 and f_z were set to 110 Hz and 100 Hz, respectively.

From equation (2) the slope of the regression line was calculated: -9.23 Hz/min.

Figure 2 shows graphically median frequency calculated from equation (2).

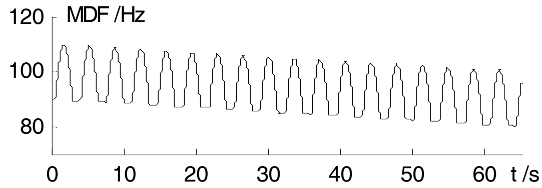

Figure 2: Modeled median frequency

The simulated SEMG signals were generated by passing the Gaussian white noise sequences through a sharp Butterworth band-pass filter with an order of four. To avoid artefacts in the signal in the transition region between steps, final values of the filter states were used in the next step as initial state condition. Changing the cutoff frequencies of Butterworth filter and thus changing the shape of the power density spectrum, MDF variations were synthesized [14].

During fatiguing contractions the frequency content of SEMG signal gradually shifts towards lower frequencies. To a large extent frequency shift can be explained as a compression of the power spectrum, i.e. the form of the spectrum does not change, but only the scale factor of the frequency axis changes [17,18].

The compression of the power spectrum was embedded in filter cutoff frequencies by simple change of low cutoff frequency,

$$f_L = \frac{2L}{L+H} f_{med}, \tag{3}$$

and high cutoff frequency,

$$f_H = \frac{2H}{L+H} f_{med}. \tag{4}$$

Since the frequency content of SEMG signal is typically below 500 Hz with dominant energy in the 50-150 Hz range [2, 11] the parameters L and H were set to 90 and 200, respectively.

Afterwards, the signal was amplitude modulated to ensure pattern similar to the SEMG recorded during dynamic contractions. The frequency and the phase of the modulating signal were carefully selected so that maximums of signal amplitude and median frequency correspond in time within each contraction.

In measured SEMG signals, amplitude is increasing toward the end of exercise due to fatigue. Although the amplitude is indeed dependent on fatigue, it is a second order effect [11]. In addition, an examination of the effects of amplitude modulation on modeled SEMG signals revealed that changes in variance created in this way do not significantly affect characteristic frequency data to obscure an effect of fatigue [6]. These were the reasons why amplitude modulation was done with constant amplitude modulating signal.

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Since the developed method uses stochastic signal for modeling, ensembles of 33 physical realizations were synthesized for different sequence lengths (SL), ranging from 32 to 56 samples. The number of samples needed for proper spectral definition defines lowest sequence length [19]. The smaller the sequence length is, the better precision in change of median frequency of synthesised SEMG signal can be obtained.

Analysis: Continuous wavelet transform (5) was applied on synthesized signals.

$$WT_x^{\psi} = \int x(t)\left(\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)\right)dt \; . \qquad (5)$$

$\psi^*()$ is Wavelet function set derived from a base wavelet function, s is scale and τ is shift. As the base wavelet function we chose Daubechies wavelet order of 10 [20].

In order to improve accuracy of the spectral estimates wavelet shrinkage was applied. The method was first introduced in order to overcome the difficulties with the traditional windowing approaches since it has near-optimal mean square error (MSE) and near ideal spatial adaptation [21].

The general procedure of wavelet shrinkage can be implemented in two steps. First, shrinking the empirical wavelet coefficients by tresholding (all wavelet coefficients of magnitude less than the threshold are set to zero) and second, inverting the tresholded coefficients. The universal threshold was used with threshold rescaling using a level-dependent estimation of the noise level [21].

The power density function or scalogram was estimated (6) in the frequency range 0 to 500 Hz.

$$SCAL(\tau, s) = \left|WT_x^{\psi}(\tau, s)\right|^2 \; . \qquad (6)$$

For each time moment in scalogram the median scale was calculated (7)

$$\int_0^{MDS} SCAL(s)ds = \int_{MDS}^{SN} SCAL(s)ds = \frac{1}{2}\int_0^{SN} SCAL(s)ds \; , \qquad (7)$$

where SN is a scale value that corresponds to Nyquist frequency, i.e. 500 Hz. The SCAL(s) denotes scalogram and MDS denotes median scale. Based on the scalogram, median frequency was estimated for all signals [14] and filtered with moving average finite impulse response (FIR) filter. The length of moving average filter was very high, 200 samples. That implies strong averaging of MDF signal.

After filtering, for each realization a slope of regression line that fits maximum median frequency values was calculated. The method considers the maximum median frequency values (which correspond to maximal extension) during each contraction. The slope is also referred to as numerical fatigue index for dynamic contractions [4].

For all ensembles mean value of fatigue index, k [Hz/min], is calculated.

Results

Figure 3 shows typical synthesized SEMG signal (U) based on defined stochastic model and resulting median scale (MDS), filtered median frequency (MDF) and the regression line.

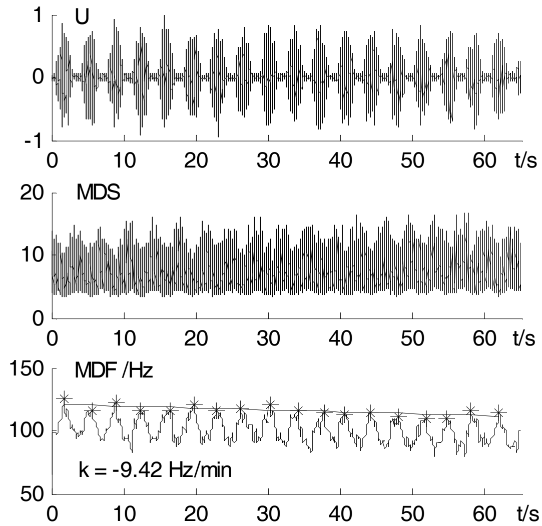

Figure 3: Synthesized SEMG signal (U), median scale (MDS) and filtered median frequency (MDF)

Deviation of the mean value of all slopes belonging to one ensemble, defined by sequence length (SL), was relatively high, as shown in Figure 4.

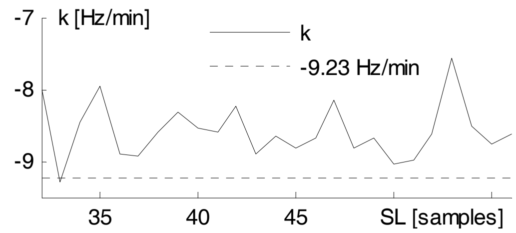

Figure 4: The mean value of slopes for different sequence lengths

Discussion

The SEMG signal measured during cyclic dynamic contractions is non-stationary. The envelope of signal amplitude and the change of median frequency are mutually related in sense that both variables reach their maximal values in almost the same time instant.

The proposed stochastic model takes into account not only the relationship of amplitude and median frequency but also change in power spectral density due to muscle fatigue. The model does not produce signal with typical power spectral density shape - for simplicity Butterworth filter was chosen to shape power spectral density. Nevertheless, proposed modeling is a good representative of white noise based modeling of SEMG signals during cyclic dynamic contractions [5, 7, 8].

Physical realisations belonging to one ensemble were evaluated by means of mean fatigue index calculated from fatigue index of all realizations within particular ensemble.

The results of the study showed high deviation of modeled fatigue index from initially defined value. Figure 4 shows independent variations of mean fatigue index with different sequence lengths.

Moreover, high variability of mean fatigue index implies high variability of underlying median frequency. The same conclusion can be expanded to any global spectral parameter.

Conclusions

Proposed stochastic model for synthesis of surface myoelectrical signal during cyclic dynamic contractions showed that models based on white noise filtering result in signals with high variability of modeled spectral parameters.

Therefore, it is not possible to generate one SEMG signal or ensemble, based on white noise modeling, suitable for assessment of analysis methods in case when SEMG signal during cyclic dynamic contractions is modeled.

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