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Real-Time EMG Signal Frequency Identification ⋆,⋆⋆,⋆⋆⋆

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Abstract: The paper deals with a method for real-time frequency analysis of the electromyogram. The method has been proposed for usage in control systems of advanced robotics for different applications. The method includes robust real-time frequency estimation with preliminary usage of bandwidth filters. The method is easy to program and requires no additional resources. The paper presents an example of experimental approbation of proposed method.

1. INTRODUCTION

Fast development of information and computer technologies led to appearance of new types of devices. It has also started evolving new control approaches. In fact, movement, mind and body control has become top priority domains of control devices development. This paper describes two EMG classification methods.

EMG is a biopotential electric research method of human being skin surface that contracts muscle fibers. With the help of received EMG signal one can classify performed movements and use them as source of control signals for different devices. Particularly, applications of this type of control for rehabilitation of patients with diseases of the muscles and locomotion systems are attractive (Borgul et al. [2012]; Matrone et al. [2011]; Fraiwan et al. [2011]; Majdalawieh et al. [2003]; Zimenko, Borgul and Margun [2013]).

Today, using of EMG as a source of control signal is not so widespread because of the high level of noise and complex nonstationary signal form. In addition, necessity of classification in a real time mode drastically complicates the application of EMG signals, and this circumstance becomes a difficult task in case of high computational complexity of most existing methods of classification.

The classification is based on features for each type of movement. These features may be computed in several domains, such as time domain, frequency domain, time-frequency and time-scale representations (Herle and Man [2009]; Parker et al. [2006]).

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Time-frequency domain features show better performance than other-domain features in case of assessing transient properties of a signal. The central concept of most of the methods is a decomposition of a signal into time-frequency atoms:

$$y(t) = \sum_{i=1}^{k} c_i \beta_i(t), \tag{1}$$

where $\beta_i(t)$ are the so called basis functions and c_i a corresponding coefficients.

The abundance of articles proves the importance of time-frequency domain features (actually, more than 50 articles have been published over the recent five years, for example (Yuan et al. [2009]; Yunfeng and Krishnan [2009]; Jasper and Othman [2010])). However, it is important to observe that the information provided by most methods is limited by the size of analysis window.

This paper deals with development for methods of signal classification in a real time mode for further application of control signal source for different types of devices, for example, exoskeletons, active prostheses, etc. First method is based on a robust harmonic frequency identification of signal using cascade reduction. The second one based on main robust frequency estimation method.

Section 2 is dedicated to research of EMG signals and their location within frequency characteristics by means of spectral analysis. Section 3 describes a method for the identification of robust frequency harmonic signal. Section 4 is devoted to the experimental validation of the proposed method. Section 5 contains the interpretation for research results.

Fig. 1. Nine-channel amplifier Neurobelt

2. PROBLEM STATEMENT

A series of experiments has been directed to search for EMG signal features. EMG signals reading has been conducted based on the reference scheme. The first electrode was fixed on the forearm. The second one was placed on the shoulder for reference comparison. The data has been received from the electrodes with nine-channel amplifier Neurobelt (Fig. 1). This device designed for continuous recording of electrophysiological signals with high resolution in the frequency band from 0 through 350 Hz. The data was transmitted to PC for processing. The experiments have been performed on five healthy men with the age varying from 19 to 24 years. Subjects performed three types of motion: wrist flexion, rotating clockwise and rotating counterclockwise.

After signal reception and spectral analysis had been completed a certain number of features have been found:

1) each type of movements had its own specific spectral characteristic;

2) frequencies containing main part of signal energy were quite close to the same type of movement;

3) most of the signals energy have been detected in two - three signal harmonics.

Based on the average spectral characteristics of many times repeated movements (Fig. 2–4) one can conclude that first harmonic is the same for all types of motion. Other harmonics has frequencies depending on the type of movement. Based on this, a set of bandwidth filters have been chosen with values varying from 12 through 20 Hz. Thus, in the further processing of the signal there was only area with one or two different harmonics for each of the movements: 15.6 Hz for wrist flexion, 13.7 and 17.57 Hz were registered when rotating clockwise, 13.7 Hz when rotating counterclockwise.

Based on the detected features of the signal let's suggest a classification algorithm that looks in the following way:

1) separation of the signal by bandwidth filters;

2) frequency identification of each filtered output signal;

3) in case the identified frequencies with sufficient accuracy coincide with the fundamental components of the studied

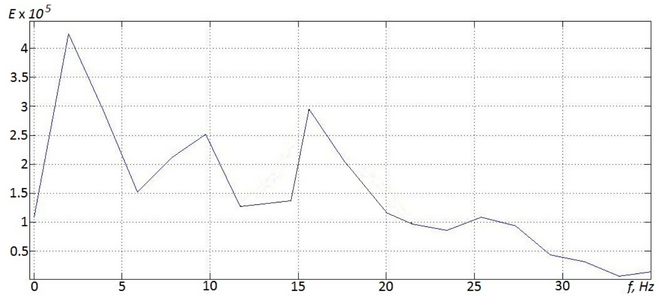

Fig. 2. Spectral density for flexion

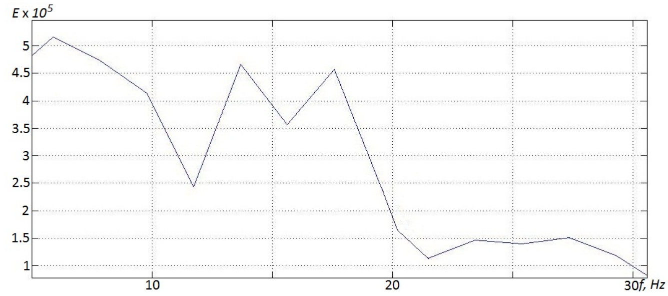

Fig. 3. Spectral density when rotating clockwise

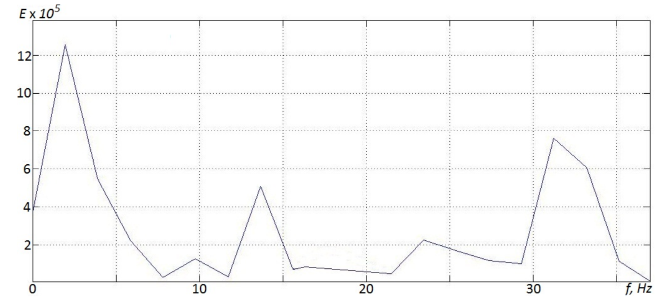

Fig. 4. Spectral density when rotating counterclockwise

movements, one may state that this movement has been actually performed.

Thus, EMG signal classification is becoming an issue of harmonic signals frequency estimation. In the next section a method of frequency real-time identification is described.

3. IDENTIFICATION ALGORITHMS

In this section the EMG frequency identification is described. Let's present (1) in the following form (Zimenko, Margun and Kremlev [2013]):

$$y(t) = \sum_{i=1}^{k} \sigma_i \sin(\omega_i t + \phi_i), \qquad (2)$$

where σ_i is an amplitude and ϕ_i is an initial phase of the i-th harmonic.

Each movement has its own unique set of harmonics. Therefore, identifying the frequency of the signal one can determine what kind of movement has been performed by a human being. Let us introduce here a brief description of the method of identification multiharmonic signal proposed in Aranovskii et al. [2010].

It is known that for generation of a signal $y(t)$ there is a way to use differential equation (Aranovskii et al. [2006])

$$(p^2-\theta_1)(p^2-\theta_2)\cdots(p^2-\theta_k)y(t)=0, \tag{3}$$

where $\theta_i=-\omega_i^2, i=\overline{1,k}$ are constant parameters.

Rewrite (3):

$$p^{2k}y(t)=\bar{\theta}_1 p^{2k-2}y(t)+\cdots+\bar{\theta}_{k-1}p^2y(t)+\bar{\theta}_k y(t), \tag{4}$$

where:

$$\begin{cases} \bar{\theta}_1=\theta_1+\theta_2+\cdots+\theta_k, \\ \bar{\theta}_2=-\theta_1\theta_2-\theta_1\theta_3-\cdots-\theta_{k-1}\theta_k, \\ \vdots \\ \bar{\theta}_k=(-1)^{k+1}\theta_1\theta_2\cdots\theta_1. \end{cases} \tag{5}$$

Tranforming to Laplace images in equation (4) we yield:

$$\begin{aligned} s^{2k}\bar{\triangle}(s)=\bar{\theta}_1 s^{2k-2}\bar{\triangle}(s)+\cdots+\bar{\theta}_{k-1}s^2\bar{\triangle}(s) \\ +\bar{\theta}_k\bar{\triangle}(s)+D(s), \end{aligned} \tag{6}$$

where s is a complex variable, $\bar{\triangle}(s)=\mathcal{L}\{y(t)\}$ is a Laplace image of function $y(t)$, and the polynomial $D(s)$ denotes sum of all terms containing initial conditions.

Multiply (6) on $\frac{\lambda^{2k}}{(s+\lambda)^{2k}}$, where λ is a constant parameter, and consider an auxiliary filter:

$$\xi(s)=\frac{\lambda^{2k}}{(s+\lambda)^{2k}}\bar{\triangle}(s) \tag{7}$$

After inverse Laplace transformation for (6):

$$\xi^{(2k)}(t)=\bar{\theta}_1\xi^{(2k-2)}(t)+\cdots+\bar{\theta}_k\xi(t)+\varepsilon(t), \tag{8}$$

where $\varepsilon(t)=\mathcal{L}^{-1}\left\{\frac{D(s)}{(s+\lambda)^{2k}}\right\}$ is the exponential decaying term caused by nonzero initial conditions.

The term $\varepsilon(t)=\mathcal{L}^{-1}\left\{\frac{D(s)}{(s+\lambda)^{2k}}\right\}$ depend on the parameter λ, there is a way to accelerate convergence it to zero by increasing the parameter λ.

Neglecting term $\varepsilon(t)$ we have

$$\xi^{(2k)}=\Omega^T(t)\bar{\Theta}, \tag{9}$$

where $\Omega^T(t)=[\xi^{(2k-2)}(t)\ \ldots\ \xi^{(2)}(t)\ \xi(t)]$ is regressor, $\bar{\Theta}^T=[\bar{\theta}_1\ \ldots\ \bar{\theta}_{k-1}\ \bar{\theta}_k]$ is vector of unknown parameters.

Similarly to Bobtsov, Kolyubin and Pyrkin [2010] and taking into account that $\Omega(t)\xi^{(2k)}=\Omega(t)\Omega^T(t)\bar{\Theta}(t)$ parameter vector $\bar{\Theta}$ estimation are set in the following way:

$$\dot{\hat{\bar{\Theta}}}(t)=K\Omega(t)(\xi^{(2k)}-\Omega^T(t)\hat{\bar{\Theta}}(t)), \tag{10}$$

where $K=diag\{k_i>0\},\ i=\overline{1,k}$, and k_i is some parameter, the increase of that can speed up the convergence of $\hat{\bar{\theta}}_i$ to $\bar{\theta}_i$.

Since the frequency spectrum of the EMG varies rapidly when performing any movement, we use large values of k and λ (e.g. $\lambda>5$, $k>1000$) to define the frequencies.

Now consider the system presented in (5). Equations of the system (5) are Viet's formulas. Therefore parameters $\theta_i,\ i=\overline{1,k}$ are roots of $p^{2k}+\bar{\theta}_1p^{2k-2}+\cdots+\bar{\theta}_{k-1}p^2+\bar{\theta}_k$.

Based on the parameters $\bar{\theta}_i,\ i=\overline{1,k}$ we can unambiguously define roots $\theta_i,\ i=\overline{1,k}$.

Thus, we have the hybrid identification scheme of $\theta_i\ i=\overline{1,k}$. Frequencies of multiharmonic signal we yield from equation (3):

$$\hat{\omega}_i(t)=\sqrt{|\hat{\theta}_i(t)|},\ \ i=\overline{1,k} \tag{11}$$

Basic research of Pearson [1987] found that muscle EMG consists mainly of low-frequency vibrations. In order to use the method described above it is proposed to pass EMG signal through a bandwidth filter. This is done for two reasons:

1) select frequency area required for application in control system and movement identification;

2) avoid the effect of noise (e.g. the most frequent type of noise is 50 Hz coming from devices that operate from industrial power).

Selection of the bandwidth filter is based on preliminary spectrum analysis.

It should be noted that the method is sensitive to noise and external disturbances. Therefore modification has been developed. That modification provides robust main frequency estimation of noisy harmonic signal, with regard to lower amplitude signals and noise (Aranovskii et al. [2010]).

In this case let us consider the following variable

$$\chi(t)=\hat{\theta}(t)-k_1\dot{\xi}(t)y(t), \tag{12}$$

or

$$\hat{\theta}(t)=\chi(t)+k_1\dot{\xi}(t)y(t), \tag{13}$$

where with $k=1$ following to (7) $\xi=\frac{\lambda}{s+\lambda}y(t)$. Differentiating equation (12) we yield:

$$\begin{aligned} \dot{\chi}(t) &= \dot{\hat{\theta}}(t)-k_1\ddot{\xi}(t)y(t)-k_1\dot{\xi}(t)(t) \\ &= k_1\dot{\xi}(t)(\dot{y}(t)-2\lambda\ddot{\xi}(t)-\lambda^2\dot{\xi}(t))-k_1\dot{\xi}^2\hat{\theta}(t) \\ &\quad -k_1\ddot{\xi}(t)y(t)-k_1\dot{\xi}(t)(t) \\ &= k_1\dot{\xi}(t)(-2\lambda\ddot{\xi}(t)-\lambda^2\dot{\xi}(t))-k_1\dot{\xi}^2(t)\hat{\theta}(t) \\ &\quad -k_1\ddot{\xi}(t)y(t). \end{aligned} \tag{14}$$

Equations (12) and (14) form realizable identification algorithm. Lets consider issue of robustness of this algorithm:

$$\begin{aligned} \dot{\chi}(t) &= k_1\dot{\xi}(t)(-2\lambda\ddot{\xi}(t)-\lambda^2\dot{\xi}(t))-k_1\dot{\xi}^2(t)\hat{\theta}(t) \\ &\quad -k_1\ddot{\xi}(t)y(t)-\bar{k}_2\hat{\theta}(t), \end{aligned} \tag{15}$$

where $k_2\geq 0$.

The modification of identification algorithm (14) assumes that outside bounded region in the state-space the derivative of Lyapunov function becomes negative. The main drawback is that a bias term is added to the parameter update equation, therefore zero residual error cannot be guaranteed when the disturbances are removed (Bobtsov [2008]). In this case we can use the following approach:

$$k_a=\bar{k}_a(\hat{\theta})=\begin{cases} 0, |\hat{\theta}|<\theta_0, \\ \left(\dfrac{|\hat{\theta}|}{\theta_0}\right), \theta_0\leq|\hat{\theta}|\leq 2\theta_0, \\ 1, |\hat{\theta}|>2\theta_0. \end{cases} \tag{16}$$

Examples of using the above methods are presented in Section 4.

4. SIMULATION RESULTS

To demonstrate the efficiency of the proposed method consider real-time classification of movements problem. Series of experiments have been made to verify operability of proposed method. EMG signals experiments conducted are similar to those presented in Section 2.

As was mentioned above based on the spectral characteristics (Fig. 2–4) we can conclude that most of the energy signals contain in two - three harmonics. First harmonic is the same for all types of movements. Other harmonics has frequencies depending on type of movement. Based on this we choose a bandwidth filter with a band varying 12 to 20 Hz. Thus, in the further processing of the signal the only area with one or two different harmonics for each of the movements: 15.6 Hz for wrist flexion, 13.7 and 17.57 Hz when rotating clockwise, 13.7 Hz when rotating counterclockwise.

Thus presenting (2) as a sum of two harmonics:

$$y(t) = A_1 \sin(\omega_1 t + \varphi_1) + A_2 \sin(\omega_2 t + \varphi_2), \tag{17}$$

where $A_1, \omega_1, \varphi_1, A_2, \omega_2, \varphi_2$ are unknown constant parameters.

According to (4), (5):

$$p^4 y(t) = \theta_1 p^2 y(t) + \theta_2 y(t), \tag{18}$$

where $\bar{\theta}_1 = -\omega_1^2 - \omega_2^2, \bar{\theta}_2 = -\omega_1^2\omega_2^2$ are unknown parameters to be identified.

After introducing auxiliary filter $\xi(s) = \frac{\lambda^4}{(s+\lambda)^4}$ we yield:

$$\begin{aligned} z(t) = \xi^{(4)}(t) = \frac{\lambda^4 s^4}{(s+\lambda)^4} y(t), \quad \varsigma_1(t) = \xi^{(2)}(t) \\ = \frac{\lambda^4 s^2}{(s+\lambda)^4} y(t), \quad \varsigma_2(t) = \xi(t) = \frac{\lambda^4}{(s+\lambda)^4} y(t). \end{aligned} \tag{19}$$

Then using (18) and (19) for model (17) the equation (9) will look like:

$$z(t) = \bar{\theta}_1 \varsigma_1(t) + \bar{\theta}_2 \varsigma_2(t) + \varepsilon(t) = \varsigma^T \theta, \tag{20}$$

where $\bar{\theta} = \mathrm{col}\left\{\bar{\theta}_1, \bar{\theta}_2\right\}, \varsigma = \mathrm{col}\left\{\varsigma_1, \varsigma_2\right\}$.

Similarly to (10) and neglecting $\varepsilon(t)$ we can use an algorithm of identification that has the following look:

$$\dot{\hat{\bar{\theta}}} = -k\varsigma\varsigma^T \hat{\bar{\theta}} + k\varsigma z, \tag{21}$$

where $\hat{\bar{\theta}}$ is an estimate of the vector $\bar{\theta}$ and $k > 0$ is some coefficient either chosen during a synthesis or is set during the operation.

In the scalar case the increase of $k > 0$ implies increasing of the convergence speed. But generally it is not the case. The solution to this problem can be found using a hybrid scheme of parameters setting based on the method of cascade reduction (Pyrkin et al. [2013]). Let's transform (20)applying this method. For this, multiply (20) by ς_1 and integrate the yielded equation:

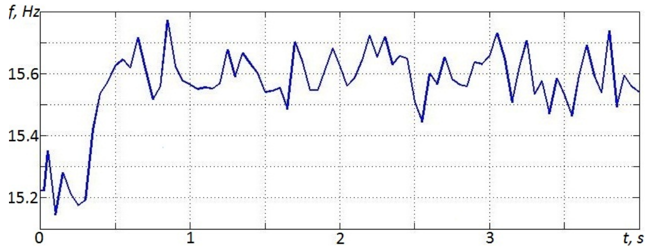

Fig. 5. Transients of estimates of the frequency ω_1 of wrist flexion

$$\begin{gathered} \varsigma_1 = \bar{\theta}_1 \varsigma_1^2 + \bar{\theta}_2 \varsigma_2 \varsigma_1, \\ \int_0^t z\varsigma_1 d\tau = \bar{\theta}_1 \int_0^t \varsigma_1^2 d\tau + \bar{\theta}_2 \int_0^t \varsigma_2 \varsigma_1 d\tau. \end{gathered} \tag{22}$$

Denote $\gamma_1 = \int_0^t z\varsigma_1 d\tau, \gamma_2 = \int_0^t \varsigma_1^2 d\tau$ and $\gamma_3 = \int_0^t \varsigma_2\varsigma_1 d\tau$. First we consistently divide the relation relation above by ξ_2. Next we integrate it having the following:

$$\dot{\gamma}_1 \gamma_2^{-1} - \gamma_1 \dot{\gamma}_2 \gamma_2^{-2} = \theta_2 \left(\dot{\gamma}_3 \gamma_2^{-1} - \xi_3 \dot{\gamma}_2 \gamma_2^{-2}\right) \tag{23}$$

or

$$\dot{\gamma}_1 \gamma_2 - \gamma_1 \dot{\gamma}_2 = \theta_2 \left(\dot{\gamma}_3 \gamma_2 - \gamma_3 \dot{\gamma}_2\right). \tag{24}$$

Denote $\bar{z}(t) = \dot{\gamma}_1\gamma_2 - \gamma_1\dot{\gamma}_2$ and $\bar{\varsigma}_2 = \dot{\gamma}_3\gamma_2 - \gamma_3\dot{\gamma}_2$. Then the equation (24) will look like the following:

$$\bar{z}(t) = \bar{\theta}_2 \bar{\varsigma}_2. \tag{25}$$

Out of (25) it is easy to get the identification algorithm of parameter $\bar{\theta}_2$:

$$\dot{\hat{\bar{\theta}}}_2 = -k_2 \bar{\varsigma}_2^2 \hat{\bar{\theta}}_2 + k_2 \bar{\varsigma}_2 \bar{z}, \tag{26}$$

where $k_2 > 0$ is some parameter, the increase of it can speed up the convergence of $\hat{\bar{\theta}}_2$ to $\bar{\theta}_2$. Neglecting term $\varepsilon(t)$ in the equation (20), to identification of the parameter $\bar{\theta}_1$ we use an algorithm in the following form:

$$\dot{\hat{\bar{\theta}}}_1 = -k_1 \varsigma_1^2 \hat{\bar{\theta}}_1 + k_1 \varsigma_1 z', \tag{27}$$

where $z' = z - \hat{\bar{\theta}}_2 \varsigma_2$ and $k_1 > 0$ is a parameter, the increase of it, as in the previous case, allows to increase the speed of convergence of $\hat{\bar{\theta}}_1$ to $\bar{\theta}_1$.

Thus, we have the hybrid identification scheme of $\bar{\theta}_1 = -\omega_1^2 - \omega_2^2$ and $\bar{\theta}_2 = \omega_1^2\omega_2^2$ that involves the reduced model (25) and parametric setting with algorithms (26) and (27). Resolving the quadratic equation, it is easy to obtain estimation of the frequencies of the original signal's harmonics from the estimation for $\hat{\bar{\theta}}_1$ and $\hat{\bar{\theta}}_2$.

Write the equations of the frequencies explicitly:

$$\omega_1 = \sqrt{\frac{\bar{\theta}_1 + \sqrt{|\bar{\theta}_1^2 - 4\bar{\theta}_2^2|}}{2}}, \tag{28}$$

$$\omega_2 = \sqrt{|\bar{\theta}_1 - \omega_1^2|}. \tag{29}$$

Taking into account that $f = \frac{\omega}{2\pi}$, graphs (Fig. 5–10) have been obtained.

Similar series of experiments was performed for the modified method of robust estimation to identify fundamental

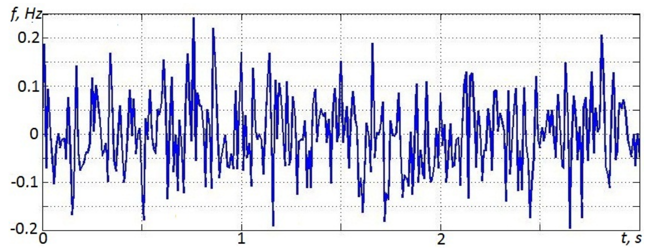

Fig. 6. Transients of estimates of the frequency ω_2 of wrist flexion

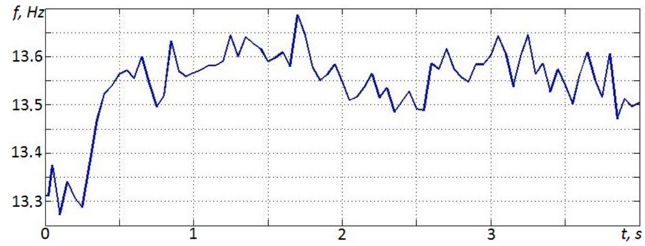

Fig. 7. Transients of estimates of the frequency ω_1 when rotating clockwise

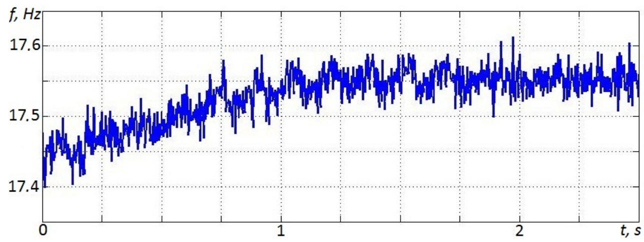

Fig. 8. Transients of estimates of the frequency ω_2 when rotating clockwise

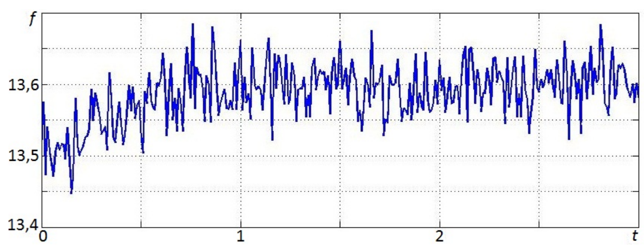

Fig. 9. Transients of estimates of the frequency ω_1 when rotating counterclockwise

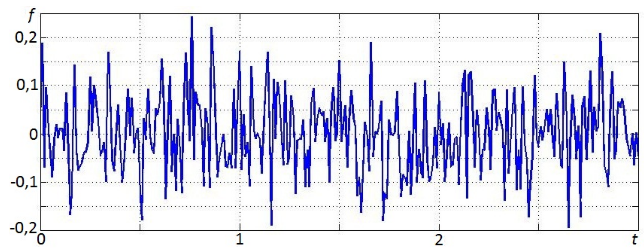

Fig. 10. Transients of estimates of the frequency ω_2 when rotating counterclockwise

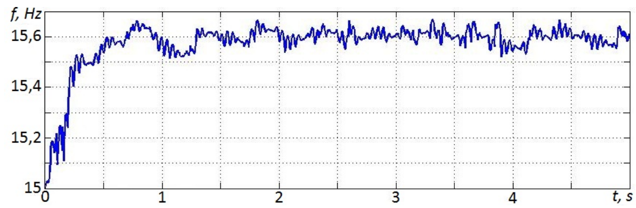

Fig. 11. Transients of estimates of the frequency ω_1 of wrist flexion based on the method of cascade reduction

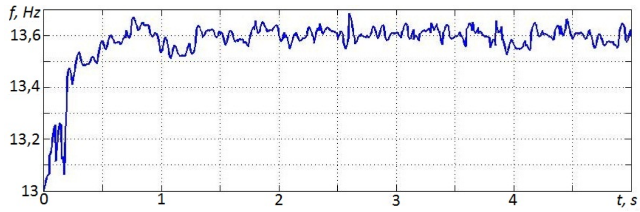

Fig. 12. Transients of estimates of the frequency ω_1 when rotating clockwise based on the method of cascade reduction

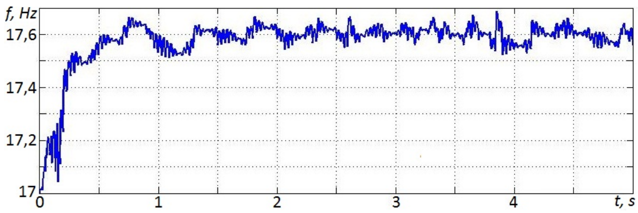

Fig. 13. Transients of estimates of the frequency ω_2 when rotating clockwise based on the method of cascade reduction

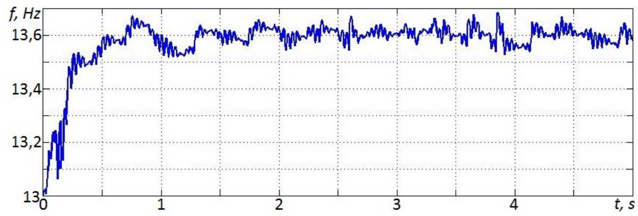

Fig. 14. Transients of estimates of the frequency ω_1 when rotating counterclockwise based on the method of cascade reduction

frequency of harmonic signal. The results indicate a higher accuracy of this approach compared with the previous one (Fig. 11–14).

Thus cascade reduction and robust main frequency estimation methods have been used for real-time identification of multiharmonic signal frequencies. The yielded results are in line with spectral analysis with high accuracy. The table below shows a comparison of performance for proposed methods. Thus, proposed methods based on data from EMG may be used for real-time classification of movements.

Comparison of methods			
Cascade reduction method			
Movement	Frequency	Identification time (s)	Average error (Hz)
Wrist flexion	f_1	0.61	0.11
Rotating clockwise	f_1	0.69	0.07
Rotating clockwise	f_2	1.05	0.11
Rotating counter-clockwise	f_1	0.6	0.071
Main frequency estimation method			
Movement	Frequency	Identification time (s)	Average error (Hz)
Wrist flexion	f_1	0.58	0.04
Rotating clockwise	f_1	0.59	0.044
Rotating clockwise	f_2	0.55	0.042
Rotating counter-clockwise	f_1	0.55	0.04

5. CONCLUSIONS

The method of classification of EMG signals as a source of control of different engineering devices has been developed. The spectral decomposition of the signal gives way to identify the frequency characteristics for use in classification.

Using the method of robust frequency identification and harmonic frequency bandwidth filters allows it's application even in very noisy measurements in real time mode. Experimental testing confirmed the performance of the proposed approach with a high degree of accuracy. The results are applicable in biomedical engineering and rehabilitation devices also.

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