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SIMULATION OF THE ELECTRICAL SIGNAL OF THE MUSCLES TO OBTAIN THE ELECTROMIOSIGNAL SPECTRUM

The object of research is the process of skeletal muscle contraction under the influence of natural electrical impulses of the nervous system or under the conditions of external electrical stimulation. The subject of research is models that describe electrical processes in muscles during contraction. The work is aimed at building an analytical model of the skeletal muscle electrical signal, which makes it possible to calculate the spectral density of this signal for further analysis.

Research methods are methods of mathematical modeling, theory of random processes and signals, methods of spectral analysis, methods of mathematical analysis.

The model of the electrical signal of the muscle as the sum of random impulse signals corresponding to the signals of motor units is studied in the work. In this regard, a signal is analyzed, which, in contrast to the Gaussian process, is formed by summing a limited number of pulse signals. It is shown that the voltage distribution law of such a signal is expressed by the sum of Gaussian functions. In the course of the study, the structure of the electromyographic signal spectrum was obtained, presented as a sum of periodic pulses shifted in time relative to each other. The relationship between the statistical properties of a random phase difference and the type of signal power spectrum has been analytically established. The obtained theoretical relations make it possible to calculate the spectral density of the electromyographic signal depending on the number of motor units and various phase shifts between them, as well as depending on the chosen law of distribution of random variables. The results of a numerical experiment are presented for a different number of motor units and different ranges of time shifts in the case of a distribution of gauss of the probability density. The results obtained can be used in assessing the degree of dysfunction of skeletal muscles in various injuries (for example, in trauma, atrophy, etc.), as well as in choosing the optimal individual parameters of electrical stimulation during rehabilitation procedures or training processes for increasing muscle mass in athletes.

Keywords: *skeletal muscle, motor unit, mathematical modeling of an electrical signal, spectral density, electromyographic signal, electrical stimulation.*

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1. Introduction

Estimation of motor activity by the level of bioelectrical potentials of muscles during superficial abduction is widely used in biomechanical and medical research. In this case, both the degree of muscle tension and the nature of their regulation, deviation from the norm and the degree of damage are determined. Muscle electrical signal (MES) modeling explains and refines the results of experimental studies that reflect information about the motor activity of the muscle contained in the signal [1, 2]. Signal modeling also makes it possible to reveal features of a noisy signal. The signal level during surface recording in case of damage and atrophy of muscle tissue or cicatricial damage to the skin can be 2–10 μV, while external interference can be a few Volts [3, 4].

Therefore, when building an electrical stimulation system, it is important to simulate the signal, which reflects the process of its formation, and makes it possible to divide the MES into components associated with natural and induced muscle contraction. Such a division makes it possible to evaluate the electrical stimulation effect, which determines muscle contraction, and to determine the most effective conditions and modes of electrical stimulation.

Thus, the process of skeletal muscle contraction under the influence of natural electrical impulses of the nervous system or under the conditions of external electrical stimulation is chosen as *the object of research*. *The aim of research* is to build an analytical model of the electrical signal of the skeletal muscle, which makes it possible to calculate the spectral density of this signal for further analysis.

2. Research methodology

2.1. Simulation signal «motor unit». The term «motor unit» was proposed by E. R. Liddell and C. S. Sherrington to refer to a group of muscle fibers innervated by the terminals (branches) of a single axon [5]. Currently, a motor unit (MU) is understood as an elementary functional unit of a muscle, which includes a motor neuron and the muscle fibers innervated by it [1, 5].

In the muscle, the axon of the motor neuron branches into many branches, each of which innervates the muscle fiber. One motor neuron innervates a fairly large number of muscle fibers (from a few to several thousand), while each muscle fiber is innervated by only one motor neuron [5].

It has been established that muscle fibers belonging to the same MU are dispersed throughout the muscle, that is, they belong to different muscle bundles. Such a distribution of muscle fibers of each MU ensures uniform muscle contraction, when only a MU part is «turned on» to work. One MU is made up of muscle fibers that have the same properties. By activating different MUs, the central nervous system controls the activity of the entire muscle.

The MU size is the number of muscle fibers innervated by one motor neuron. To find this indicator, the number of muscle fibers in the skeletal muscle and the number of motor neurons that innervate these muscle fibers are determined. Sometimes in the literature, the MU size is called the innervation ratio or the innervation coefficient [5].

Every time a motor neuron fires, it sends action potentials to all the muscle fibers it innervates. Therefore, the lower the coefficient of innervation, the more perfect the control of the nervous system over the muscle fibers. According to the coefficient of innervation, one can judge the number of branches necessary for the axon of the motor neuron to innervate all the fibers included in the MU.

The construction of the motor unit signal (MUS) model and MES is based on the hypothesis of the practical admissibility of using the superposition principle for muscle fiber signals. An analysis of the process of formation of a potential difference on the electrodes shows that with the help of rather small needle electrodes located near the muscle fiber (MF), it is possible to record the signal of individual MFs [6, 7].

Signal modeling makes it possible to reveal the features of a signal in comparison with noise, in particular, the ways of possible separation of a signal against the background of sinusoidal and noise interference using the amplitude limitation of a small voltage or registration by maximum peaks [8–10].

The MUS pulse U_D is formed as a result of the synchronous action of n_v signal pulses MF (MFS) U_v. It is conditional to consider the shift of impulses t_v MFS as a realization of a random function that has a certain distribution law $\omega(t_v)$, then:

$$U_D = \overset{o}{U}_D + \tilde{U}_D, \qquad (1)$$

where $\overset{o}{U}_D$ – denotes the mathematical expectation; $\tilde{U}_D$ – corresponding deviation of the MFS pulses.

Assuming that $\omega(t_v)$ and $\omega[U_v(t)]$ at a fixed t for synchronized MFS pulses are close to normal distribution laws. And also taking into account that the convolution of the function corresponding to pulses of the same polarity approaches the Gaussian function, in the case of a three-phase pulse, let's obtain an approximate expression for U_D and, accordingly, for $\overset{o}{U}_D$:

$$\overset{o}{U}_D = n_v\left(-d_1 e^{-\frac{t^2}{C_1^2}} + d_2 e^{-\frac{(t-t_1)^2}{C_2^2}} - d_3 e^{-\frac{(t-t_2)^2}{C_3^2}}\right), \qquad (2)$$

where d_1, d_2, d_3, C_1, C_2, C_3 – coefficients depending on the specific value of the phases in the MFS pulse U_v and the synchronization degree of the MFS pulses (Fig. 1).

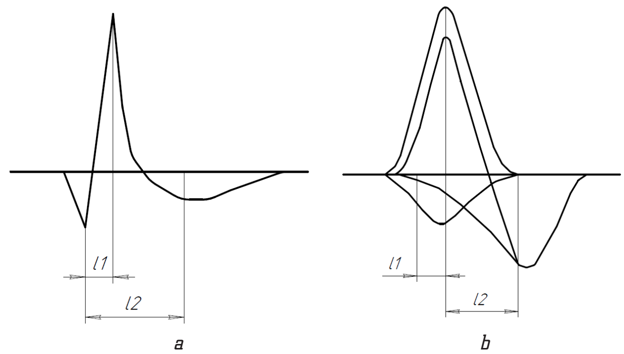

Fig. 1. Impulses: *a* – muscle fiber signal; *b* – formation of the MU signal when applying Gaussian functions

Another approximation of the signal U_D is also possible. MFS pulses are converted into pulses of the same polarity by integrating two-phase and double integrating three-phase pulses.

The dependence of voltage on time for the action potential of an individual MU is a definite function of $f(t)$ [11]. The form of this function is usually established by experimental-invasive methods. The electromyographic signal of one MU $U(t)$, taken by the skin method, is the sum of individual action potentials shifted relative to each other by time τ_n:

$$U_1(t) = \sum_{n=1}^{N} f(t-\tau_n), \qquad (3)$$

where N – the total number of individual MU pulses generated during electromyogram recording.

When measuring with the skin method, the recorded signal is usually created by more than one motor unit. MU, located next to the electrodes, create for the latter some voltage of the same type as the signal (3), since they are controlled by one nerve fiber. However, due to various reasons, the registered complete signal will be a superposition of signals of type (3), randomly shifted relative to each other along the time axis by some value Δt_k, where the index k is the conditional number of the motor unit.

In the case of the same contribution of a certain number of K motor units, the recorded signal takes the form:

$$U(t) = \sum_{k=1}^{K} U_1(t-\Delta t_k) = \sum_{k=1}^{K}\sum_{n=1}^{N} f(t-\tau_n-\Delta t_k). \qquad (4)$$

2.2. The structure of the electromyosignal spectrum. It is known that from the properties of the Fourier transform follows the multiplicativity of the spectrum of the signal generated by one MU [12]. It is shown in [13] that also in the case of a signal of type (4), which takes into account the generation of signals by many motor units, the multiplicity of the spectrum is preserved and a new factor is added that describes the influence of interference of signals from many motor units.

Interference effects from the assembly of signals from different MUs in the spectrum appear only in the frequency range near zero. The frequency range is determined by the standard deviation $|\Delta\nu|<1/\sigma$. If the value of the dispersion is comparable to the characteristic period of the passage of impulses in one motor unit, then the interference effects may not appear at all in the full power spectrum averaged over the implementation. The spectral power of the signal in this case at almost all frequencies will be proportional to the number of motor units involved in its formation.

Complex spectral function [14] $A(w)$ of signal (4):

$$A(\omega)=A_0(\omega)\cdot A_1(\omega)\cdot A_2(\omega), \quad (5)$$

where

$$A_0(\omega)=\int_{-\infty}^{\infty} f(t)\cdot e^{-i\omega t}\mathrm{d}t, \quad (6)$$

$$A_1(\omega)=\sum_{n=1}^{N} e^{-i\omega\tau_n}, \quad (7)$$

$$A_2(\omega)=\sum_{k=1}^{K} e^{-i\omega\Delta t_k}, \quad (8)$$

where i – imaginary unit; $f(t)$ – original function.

When studying deterministic signals and random processes, their spectral representation in the form of a spectral density based on the Fourier transform is widely used.

If some process or signal $f(t)$ has a finite energy and is quadratic ally integrable, which is also typical for the electromyogram signal, then for a separate implementation, the Fourier transform can be defined as a random complex function of frequency:

$$F(\omega)=\int_{-\infty}^{\infty} f(t)e^{-iwt}\mathrm{d}t. \quad (9)$$

But for the description of the ensemble, this turns out to be practically useless. Therefore, some parameters of the spectrum should be discarded (phase spectrum) and a function should be constructed that characterizes the distribution of the energy of the process as a function of frequency. Then, according to the Parseval's theorem, the energy:

$$E=\int_{-\infty}^{\infty}|f(t)|^2 dt=\int_{-\infty}^{\infty}|F(\omega)|^2\mathrm{d}t. \quad (10)$$

The function $S_f(\omega)=|f(\omega)|^2$ characterizes the distribution of energy depending on the frequency and the spectral density of the implementation. Averaging such a function over all realizations gives the spectral density of the process [15].

The representation of the frequency composition of the process with the help of the spectral density is the most physical, since it is the values of the process energy that are measured by the instruments.

The spectral signal power $S(w)$ measured by the instrument is always a pair function and is defined as:

$$S(\omega)=|A(\omega)|^2=|A_0(\omega)|^2|A_1(\omega)|^2|A_2(\omega)|^2= \\ =S_0(\omega)S_1(\omega)S_2(\omega). \quad (11)$$

Let's consider how a random phase shift between different motor units affects the spectrum. This influence is fully described by the function $S_2(\omega)=|A_2(\omega)|^2$.

To calculate the spectral power, it is necessary to find the modulus of expression (8). Let's write:

$$A_2(\omega)=\sum_{k=1}^{K} e^{-i\omega\Delta t_k}= \\ =e^{-i\omega\Delta t_1}+e^{-i\omega\Delta t_2}+e^{-i\omega\Delta t_3}+e^{-i\omega\Delta t_4}+e^{-i\omega\Delta t_5}+\ldots . \quad (12)$$

Using the Euler formula for the connection of the complex component with trigonometric functions, let's obtain:

$$A_2(\omega)=\cos(\omega\Delta t_1)-i\sin(\omega\Delta t_1)+\cos(\omega\Delta t_2)- \\ -i\sin(\omega\Delta t_2)+\cos(\omega\Delta t_3)-i\sin(\omega\Delta t_3)+\cos(\omega\Delta t_4)- \\ -i\sin(\omega\Delta t_4)+\cos(\omega\Delta t_5)-i\sin(\omega\Delta t_5)+\ldots . \quad (13)$$

After a series of transformations, let's obtain:

$$A_2(\omega)=A_2^r(\omega)-iA_2^j(\omega), \quad (14)$$

where

$$A_2^r(\omega)=\cos(\omega\Delta t_1)+\cos(\omega\Delta t_2)+ \\ +\cos(\omega\Delta t_3)+\cos(\omega\Delta t_4)+\cos(\omega\Delta t_5)+\ldots, \quad (15)$$

$$A_2^j(\omega)=\sin(\omega\Delta t_1)+\sin(\omega\Delta t_2)+ \\ +\sin(\omega\Delta t_3)+\sin(\omega\Delta t_4)+\sin(\omega\Delta t_5)+\ldots . \quad (16)$$

The final modulus is:

$$|A_2(\omega)|=\sqrt{\left[A_2^r(\omega)\right]^2+\left[A_2^j(\omega)\right]^2}. \quad (17)$$

To calculate the modulus of expression (8), it is necessary to know the obvious form of the sequence Δt_k. This sequence is formed randomly, so it is necessary to decide on the type of statistics that the value of Δt_k obeys.

The probability $\mathrm{d}W(\Delta t_k)$ to get the value Δt_k in the interval $d(\Delta t_k)$ is determined by the probability density $p(\Delta t_k)$: $\mathrm{d}W(\Delta t_k)=p(\Delta t_k)d(\Delta t_k)$. If it is necessary to calculate the spectral function (8) of one realization, then it is necessary to set the probability density $p(\Delta t)$ and numerically simulate the sum (8) using an appropriate random number generator.

3. Research results and discussion

Figs. 2–4 show the results of numerical simulation $|A_2(w)|$ in the MatLab environment for the Gaussian distribution of the probability density $p(\Delta t)$ with standard deviation $\sigma=T_0/2$, that is, for a different number of motor units:

$$p(\Delta t)=\frac{1}{\sqrt{2\pi\sigma^2}}\cdot e\left(-\frac{\Delta t^2}{2\sigma^2}\right). \quad (18)$$

This study is limited to using only the Gaussian probability density distribution, as well as the number of MUs up to 100.

A possible development of the study is to determine the pulse repetition rate of individual MUs by the power spectrum of a surface electromyogram and increase the number of MUs to 1000.

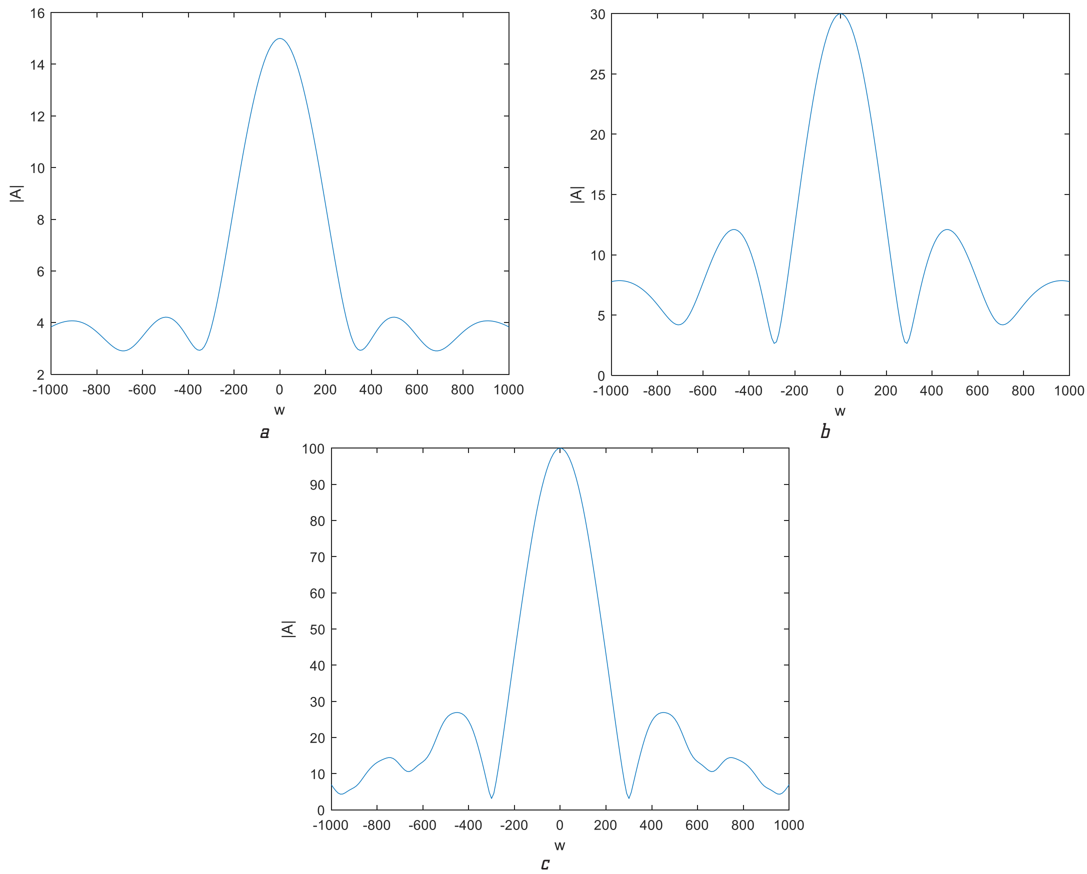

Fig. 2. Results of numerical simulation $|A_2(w)|$ for the Gaussian distribution of the probability density $p(\Delta t)$, due to a random phase shift in the range from –0.01 to 0.01 s, with the number of motor units: *a* – K=15; *b* – K=30; *c* – K=100

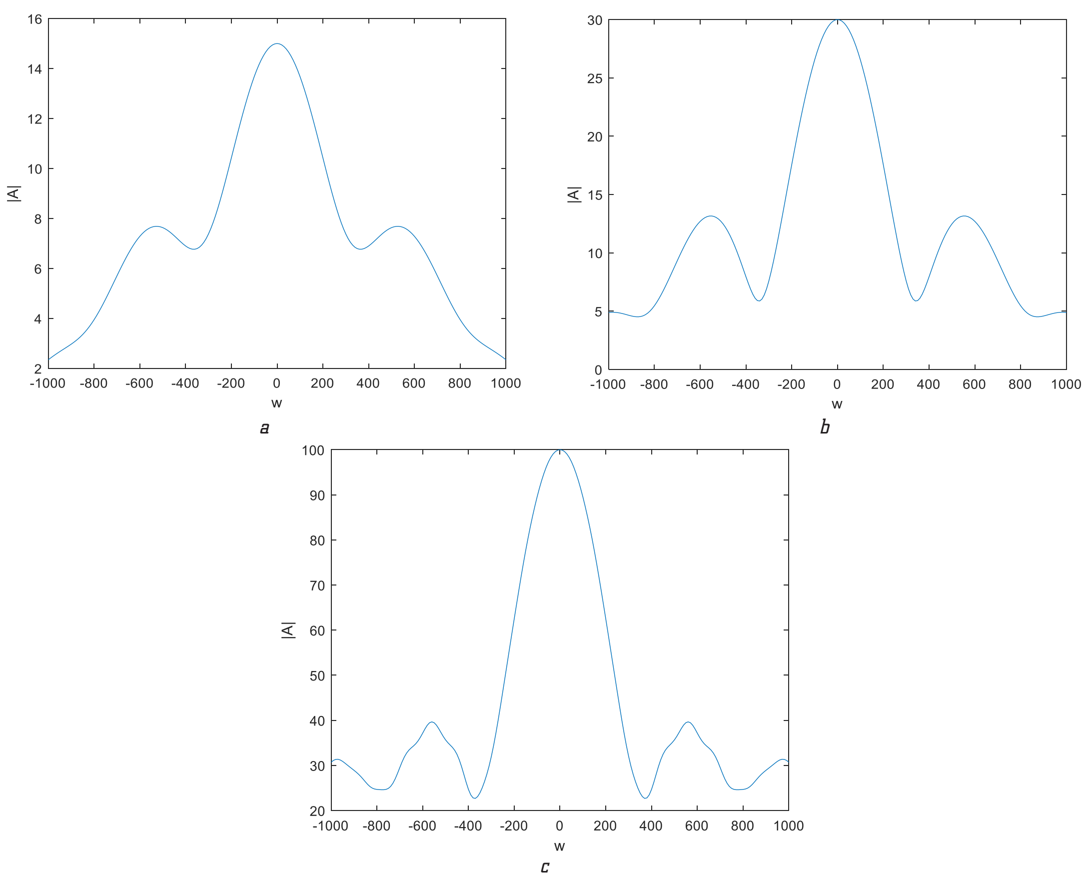

Fig. 3. Results of numerical simulation $|A_2(w)|$ for the Gaussian distribution of the probability density $p(\Delta t)$, due to a random phase shift in the range from –0.005 to 0.01 s, with the number of motor units: *a* – K=15; *b* – K=30; *c* – K=100

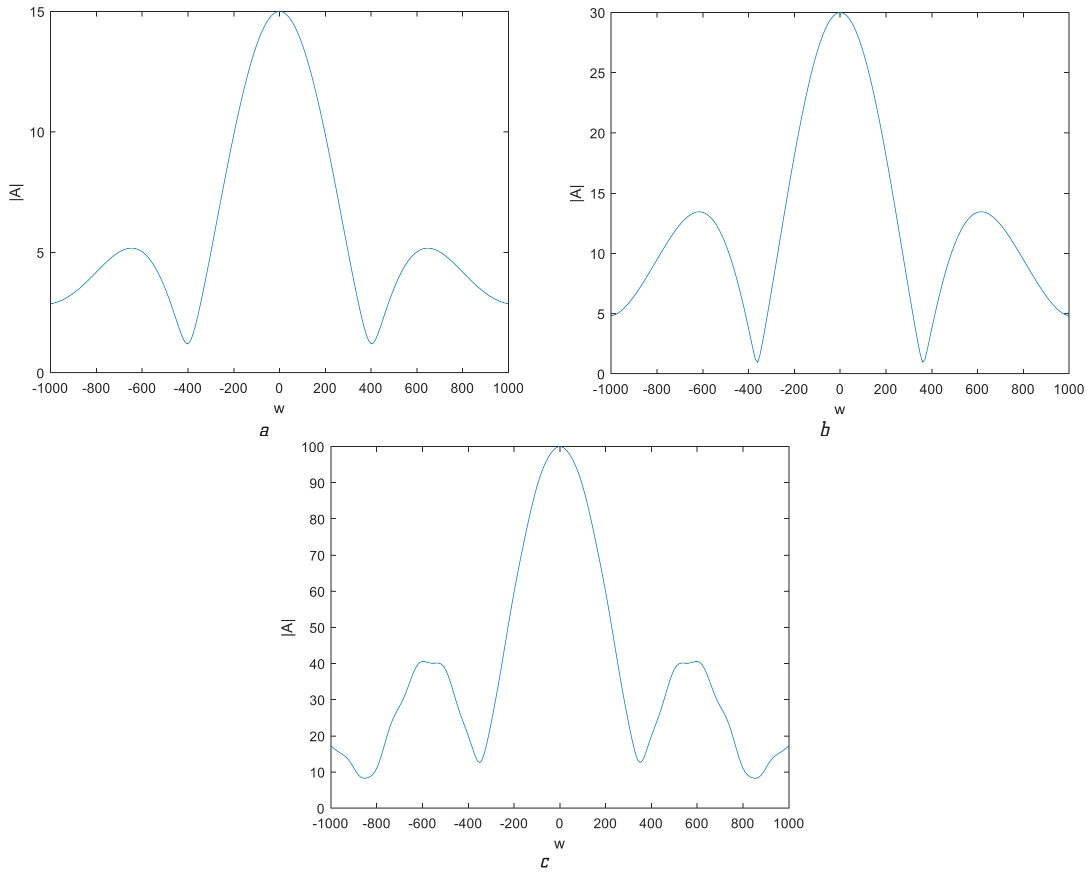

Fig. 4. Results of numerical simulation $|A_2(w)|$ for the Gaussian distribution of the probability density $p(\Delta t)$, due to a random phase shift in the range from –0.01 to 0.005 s, with the number of motor units: *a* – $K=15$; *b* – $K=30$; *c* – $K=100$

4. Conclusions

A model of the electrical signal of a muscle as a sum of random impulse signals corresponding to the signals of motor units has been studied. The signal is analyzed, which, in contrast to the Gaussian process, is formed by the sum of a limited number of pulse signals. It is shown that the voltage distribution law of such a signal is expressed by the sum of Gaussian functions. An analysis of the MES model, which includes typical MUS pulses, shows that this distribution law extends to the approximate expression of the MES. The study was carried out for the MU amount of 15, 30 and 100 in the phase shift range from –0.01 to 0.01 s.

The spectral frequency properties of the MES are determined by the shape of the MUS pulses. In some cases, a second maximum is possible in the frequency spectrum, corresponding to the frequency response of the muscle fiber signal impulse. MU synchronization reduces the frequency of peaks. The spectral properties are shifted towards low frequencies. The distinctive features of the signal are increased in comparison with a noise signal having a similar power spectrum.

The MUS impulse is determined by the average shape of the impulses, forms its MFS and the law of distribution of the moment of their impact, approximately corresponds to the sum of impulses of different polarity. These expressions for the MUS determine the amplitude frequency spectrum of the MUS and, accordingly, the MES. These conclusions are consistent with the data of experimental studies of natural MES.

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COST ESTIMATION OF PHOTOPOLYMER RESIN FOR 3D EXPOSURE OF CIRCUIT BOARDS

The research object in the work is the printed circuit boards (PCB) production technological process using the additive technology of photopolymer 3D printing. The existing problem is that the manufacturing process of single-sided and double-sided PCBs, simple in technology, from the third to the fifth accuracy class, requires the use of a large amount of consumables and technological equipment. In turn, this affects the cost of the product. The research subject is models and methods for manufacturing PCB using photopolymer 3D printing.

In order to reduce the cost of materials: film or aerosol photoresist, as well as reduce the number of technological operations, applying photoresist and for the manufacture of PCBs stencils, it is proposed to use photopolymer 3D printing technologies for the manufacture of PCBs. The paper analyzes the costs of Plexiwire Resin Basic Orange Transparen photopolymer resin for the manufacture of single-sided PCBs and calculates the cost of the consumable (resin) compared to the costs of dry film photoresist. 60 % cost of consumables (photopolymer resin) compared to dry film photoresist for making single-sided PCBs. The work is aimed at determining the dependence of the geometric dimensions of the PCBs topology and the consumption of photopolymer resin on the technological parameters of photopolymer exposure. A regression correlation model of the dependence of resin consumption on exposure parameters has been developed and correlation coefficients have been calculated. It has been established that with an increase in the exposure time of the photopolymer resin, the consumption of the photopolymer resin increases and the deviation of the geometric dimensions of the PCBs topology increases, which in turn negatively affects the quality of the product. Therefore, using the obtained regression model, it is possible to calculate the influence of parameters on the PCB topology and reduce the deviation of conductor sizes and resin consumption.

Keywords: *circuit boards, photolithography, photopolymer exposure, additive technology, DLP, LCD, photo masks.*

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1. Introduction

The rapid development of modern technologies has led to the fourth industrial revolution (Industry 4.0) [1–3]. Industry 4.0 is based on advanced research in the fields of artificial intelligence, robotics, cloud computing, additive technologies, etc. This allowed to improve significantly technological production processes by developing