Розв'язана задача обробки імпульсних сигналів. Запропоновано адаптивний метод розкладання суперпозицій невідомих імпульсних сигналів. Розроблений метод не вимагає апріорної інформації про форму елементарних імпульсів, стійкий до впливу вимірювальних шумів. Представлені результати чисельного моделювання та реальної перевірки на прикладі сейсмічного зображення. Результати експериментів показали, що запропонований метод дозволяє ідентифікувати місцезнаходження елементарних імпульсів

Ключові слова: імпульс, модель, сигнал, суперпозиція, спектр, ехо-імпульсне зображення, вимірювальний шум

Решена задача обработки импульсных сигналов. Предложен адаптивный метод разложения суперпозиций неизвестных импульсных сигналов. Разработанный метод не требует априорной информации о форме элементарных импульсов, устойчив к влиянию измерительных шумов. Представлены результаты численного моделирования и реальной проверки на примере сейсмического изображения. Результаты экспериментов показали, что предложенный метод позволяет идентифицировать местоположение элементарных импульсов

Ключевые слова: импульс, модель, сигнал, суперпозиция, спектр, эхо-импульсное изображение, измерительный шум

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DEVELOPMENT OF THE METHOD FOR DECOMPOSITION OF SUPERPOSITIONS OF UNKNOWN PULSED SIGNALS USING THE SECOND-ORDER ADAPTIVE SPECTRAL ANALYSIS

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1. Introduction

A large number of problems in the field of ultrasonic diagnosis [1], reflective seismology [2], radiolocation [3], and spectroscopy [4] are related to the analysis of superpositions of pulse signals in the form:

$$s(t)=\sum_{i=1}^{L} a_i g_i(t-t_i)+n(t), \tag{1}$$

where $s(t)$ is the superposition of a signal; L is the number of measurements discrete steps of a signal $s(t)$; $g_i(t)$ represents some elementary impulse with a_i amplitude and t_i time delay; $n(t)$ is the measurement noise.

If a noise level is small and resolution capability of a recording system is sufficient to provide a visual analysis of s(t) superposition, then the estimation of its parameters L, a_i, t_i is usually not a significant problem. Typically, problems arise in situations where resolution capability is not enough to perform visual analysis due to overlapping of elementary impulses [5]. Therefore, it is actual to develop a new method for decomposition of superpositions of signals to solve image processing problems of insufficient resolution or problems of signals with overlapping impulses.

2. Literature review and problem statement

Let us assume that a form of an elementary impulse is known and identical for all signals in the expression (1). Then we can solve the problem of estimation of $s(t)$ superposition parameters using the reverse filtering method [5], which implies passing of $s(t)$ superposition through $f(t)$ filter whose spectral characteristic $F(t)$ is inverse to a spectral characteristic of spectrum of $G(f)$ elementary pulse, that is

$$F(f)=\frac{1}{G(f)}. \tag{2}$$

Such a variant of solution is quite acceptable if the level of measurement noise $n(t)$ is negligible. Since the method of reverse filtration belongs to the class of reverse incorrect problems [6], it is necessary to use regularized solutions $F(t)_{\text{reg}}$ in the presence of significant noise. They take the form:

$$F(f)_{reg}=\frac{G^{*}(f)}{\left|G(f)\right|^{2}+\gamma(f)}, \quad (3)$$

where $G^{*}(f)$ is the complex conjugation $G(f)$; $y(f)$ is the regularizing function, its optimal choice is possible with the known spectral characteristics of a signal and an interference $N(f)$ only.

We assume that the form of an elementary pulse is unknown, and we assume that it is the same for all signals in a superposition (1). Then a partial solution is possible using a method of cepstral analysis [7], based on the calculation of the reverse Fourier transform from the logarithm of an energy spectrum of the analyzed superposition:

$$z(t)=\int\log\left|S(f)\right|^{2}e^{j2\pi ft}\mathrm{d}f. \quad (4)$$

As for the method of cepstral analysis, it is necessary to note the following:

1) it is less sensitive to a level of measuring noise compared to the method of reverse filtering;

2) nonlinearity of a logarithmic operation increases time resolution capability of $z(t)$ dependence. However, the same nonlinearity leads to the emergence of numerous false peaks (artifacts). It complicates an unambiguous analysis and interpretation of $z(t)$ dependence radically;

3) it follows from statements 1 and 2 that analysis of a superposition of pulsed signals based on the specified method is, as a rule, limited by the case of superposition of two signals only. At the same time, their amplitudes should differ by several times, since the cepstral analysis is unsuitable for the estimation of a superposition of signals with approximately the same amplitude.

A practical application of the method of cepstral analysis seems very limited in many cases and is difficult due to the facts mentioned above.

Practical tasks on image processing in seismic exploration and ultrasonic medical diagnosis [8] relate to problems of decomposition of superpositions of pulse signals where a number of elementary pulses reaches hundreds [9]. And a form of elementary impulses is not only unknown, but, as a rule, is unequal. The level of measuring and structural noise can be compared with amplitudes of useful signals in such tasks. The estimation of a form of elementary impulses and their amplitudes is not so important under such conditions while the very fact of detection is important.

There is at present a sufficiently large number of propositions for different methods to process pulsed signals. Thus, paper [10] proposes a method of adaptive filtering of signals. A wavelet analysis is the base of a method for restoring echo impulse signals, proposed in [11]. However, we can use methods [10, 11] to reconstruct medical images only. Studies [12–17] propose methods of numerical analysis of signals of various forms [12], which make it possible to code the diversity of signals [13], to estimate parameters of unknown distributions [14], to detect a selected region based on a global contrast [15], to segment images based on algorithm of fuzzy C-averages [16], to estimate generative models [17]. However, the proposed methods allow solving a small class of highly specialized problems and they are difficult to apply in practice.

The methods proposed in papers [18–23] make it possible to perform image processing and analysis for solving specific practical problems, in particular, problems concerning the necessity of robust detection of watermarks [18] and hashing of lexicographic images [19]. In addition, we can use such methods for segmentation of images [20], improvement of blurred images [21], processing of x-rays [22] and low contrast [23, 24]. Papers [25–30] present methods for modeling complex dependences based on computational intelligence [25], associative rules [26], negative selection [27], neural-fuzzy networks [28], agent technologies [29], stochastic search [30]. The methods proposed in [25–30] make it possible to process data presented in various formats efficiently: usual samples of multidimensional data [25, 28–30], transaction databases [26], samples containing missing values [26, 27]. However, the methods proposed in papers [25–30] do not allow solving the problems associated with processing data presented in the form of time series effectively. Articles [31–33] propose information technologies, which realize methods [25–30]. Despite high efficiency in processing of large-volume of multidimensional data, such methods do not solve the problems of signal processing and time series [34] effectively enough. In addition, existing software tools [12] for analysis of echo-pulse images are very slow.

The specified disadvantages in existing methods and information technologies necessitate development of new methods and means for the decomposition of superpositions of pulse signals. The signals have unknown and different forms under conditions of significant measuring and structural noises. New methods should make it possible to solve various practical tasks on image processing and analysis.

3. The aim and objectives of the study

The aim of present study is to create a method for the decomposition of superpositions of pulse signals of unknown and different forms under conditions of significant measuring and structural noise.

To accomplish the aim, the following tasks have been set:

– proposition of an approach for the decomposition of superpositions of unknown impulse signals;

– experimental testing of suitability of the proposed approach to the intended application;

– analysis of results of the conducted experiments on the investigation of the efficiency of decomposition method for superpositions of unknown impulse signals.

4. Development of method for the decomposition of superpositions of unknown pulse signals by the adaptive spectral analysis of the second order

For the purpose of decomposition of superpositions of unknown impulse signals, it seems reasonable to decompose expression $s(t)$ (1) by increasing resolution capability of the spectral analysis. An idea of extrapolation of the estimated informative characteristics beyond the measurement interval underlies the approach to decomposition of signals. It provides an increase in its potential resolution capability.

According to the assumption, we know nothing about forms of elementary pulses $g_i(t)$ (i=1,..., L). Therefore, a key problem is a choice of such an informative characteristic, which has the following features. Such a characteristic should be related to the position on a time axis of each particular pulse, it should be independent of its form and to be resistant to an influence of intense interference.

Let us consider this question on the example of a superposition of two pulse signals of unknown and unequal form (5):

$$s(t)=a_1 g_1(t-t_1)+a_2 g_2(t-t_2). \quad (5)$$

In the spectral domain, we should write expression (5) as

$$S(f)=a_1 G_1(f)e^{-j2\pi f t_1}+a_2 G_2(f)e^{-j2\pi f t_2}. \quad (6)$$

From the analysis of expression (6) it follows that a position of each elementary pulse is encoded by a complex harmonic in a spectral domain. Its frequency does not depend either on a form or an amplitude of the impulse. The period of the harmonic is reversely proportional to a delay value t_i. The influence of the function $G(f)$ has little effect on harmonic components due to an insignificant influence of attenuation and scattering effects of high-frequency components of a probe impulse spectrum. It gives possibility to develop a stable adaptive method of decomposition of superpositions of unknown impulse signals in a spectral domain.

It may seem that the solution to the problem is possible on the basis of application of a direct Fourier transform to the dependence of type (6), since its application seems most natural for the evaluation of harmonic components. However, the approach will not produce positive results in the presence of overlapping pulses in a superposition of signals because the direct Fourier transform, as a linear transformation, does not lead to an increase in resolution capability in comparison with the original superposition of the analyzed signals $s(t)$ [5].

The theoretical basis of the new approach, which makes it possible to increase time resolution capability of the analysis, is the fact that an expression of form

$$S(f)=\sum_{i=1}^{L} a_i e^{-j2\pi f t_i}+N(f) \quad (7)$$

can look as a discrete linear prediction model [8]:

$$\hat{S}(f_n)=\sum_{i=1}^{2L} p_i S(f_{n-i}), \quad (8)$$

where p_i are the coefficients of a linear prediction model, calculation of which is possible on the basis of known methods [9].

Expression (8) is a model for prediction of a spectral characteristic by one spectral counting forward. The following expression characterizes an integral error of the prediction:

$$E(f)=S(f)-\hat{S}(f), \quad (9)$$

which makes it possible to keep away to a large degree from an influence of a structural noise.

A characteristic feature of using a linear prediction model (8) is the possibility of implementation of an adaptive procedure for neutralization of an influence of multiple re-reflections (if there are any) by the selection of a meaningful order of a linear prediction model Q=2L. In experiments, we used the Burg algorithm to calculate coefficients of linear prediction [9], which provides a higher resolution capability of spectral analysis by minimization of an influence of edge effects at the boundaries of spectral domains.

The question of a possible influence of $G_i(f)$ on the estimates of superposition parameters (not taken into account in the framework of model (7)) is not simple, since, according to the initial assumption, the form of elementary pulses is unknown to us. However, the mentioned factor is not significant enough as confirmed by the results of experimental studies [9]. Artifacts in the form of false spectral peaks may appear during performing a "perceptive" analysis, especially when analyzing noisy superpositions.

The representation of expression (7) in the form of linear prediction model (8) does not, however, solve the task on increasing resolution capability of visual analysis of superpositions of overlapping signals because we must carry out an analysis in the time domain, and not in the spectral domain. This stage proceeds based on the algorithm of adaptive parametric spectral analysis (second-order spectral analysis) [9] applied to the Fourier spectral characteristic $S(f)$. Thus, we find a spectrum of a spectrum, due to which a reverse transition occurs from a spectral domain to a time domain of interpretation of superposition parameters of impulse signals.

The transition occurs based on the application of expression [9]

$$\hat{s}(t)=\frac{\sigma^2}{\left[1-\sum_{i=1}^{Q} p_i e^{-j2\pi i \Delta f t}\right]^2}, \quad (10)$$

where we consider σ^2 as a variance of a linear prediction error for a given order of model Q; $\Delta f=f_k-f_{k-1}$ is the value, which characterizes discreteness of $S(f)$ spectral characteristic arising due to the finite value of a time interval for recording of $s(t)$ superposition. It follows from expression (10) that selection of an order of the linear prediction model Q should be made until a prediction error approaches white noise. A distinctive feature of model (10) is the fact that construction of a parametric model of $S(f)$ dependence provides potential possibility for extrapolation of $S(f)$ dependence beyond the measurement frequency boundaries indirectly. In addition, model (10) provides for a possibility of increasing resolution capability of the analysis of superpositions in a time domain (an additional factor for increasing the resolution capability is a compensation of an influence of side spectral lobes characteristic for all Fourier spectroscopy methods).

A distinctive feature of the analysis of superpositions of signals based on expression (10) is the fact that there is a reflection of poles of a denominator of expression (10) and not physical amplitudes. Moreover, the poles are related to the presence of precisely the harmonic components in $S(f)$ spectral characteristic.

Thus, the method of decomposition of superpositions of unknown impulse signals by adaptive second order spectral analysis includes the following steps:

– transition from the time domain of initial measurements to the spectral domain using the direct Fourier transform (first-order spectral analysis);

– calculation of a linear prediction model for the spectral domain. The order of a linear prediction model determines a significant number of displayed impulses that will be detected in a subsequent stage;

– inverse transition from the spectral domain to the time domain using a nonlinear parametric spectral analysis (second-order spectral analysis). We can use a synthesized model of linear prediction of a spectral characteristic of the analyzed pulse superposition as a basis for such a transition.

5. Experiments and results of studying the method of decomposition of superpositions of unknown pulse signals

We carried out verification of the developed method based on the analysis of a noisy superposition of two different impulse signals of the form (we made no assumptions about their form) shown in Fig. 1, *a*.

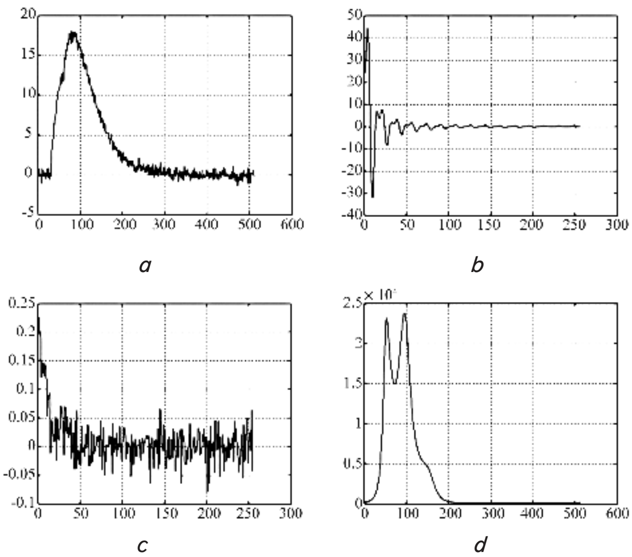


Fig. 1. Decomposition of a superposition of two unknown pulse signals (horizontal axis – time (ms), vertical axis – amplitude (mV)): *a* – original; *b* – real part of a spectral characteristic of a noiseless superposition; *c* – result of cepstral analysis; *d* – result of the proposed method

It follows from Fig. 1, *a* that it is not directly possible to estimate neither a number of elementary pulses in the signal under consideration, nor their relative time location on the basis of visual analysis of the original superposition $s(t)$. Fig. 1, *b* shows a real part of a spectral characteristic of a noiseless superposition of two signals. Fig. 1 shows clearly a superposition of two harmonics in the spectral domain corresponding to two different time delays (an amplitude modulation is conditioned by the influence of spectral characteristics of elementary pulses themselves, as follows from the expression (6)).

Application of the method of cepstral analysis [1, 9] (Fig. 1, *c*), as a rule, used to solve problems of such class, does not yield any positive results due to the influence of noise factors. Using the proposed method of parametric spectral analysis (the order of a model is four, Fig. 1, *d*) made it possible to identify the presence and location of elementary pulses (but not their amplitudes) unambiguously. A distinctive feature of the analysis of superposition of signals based on expression (10) is that such an approach "genetically" takes into account the fact of the existence of uncorrelated noise of measurements. This is explained by the fact that the method becomes unstable in a general case (a numerator of expression (10) tends to be close (or equal) to zero).

Let us consider the proposed method on the example in Fig. 2 to investigate the effectiveness of its use to solve problems on the elimination of signal re-reflections in layered structures characterized by noiseless superpositions of band pulse signals. Fig. 2, *a* shows a noiseless superposition of band pulse signals corresponding to the presence of multiple re-reflections inside a plane-layered structure, and Fig. 2, *b* shows its noisy copy. Fig. 2, *c, d* show the results of identification of re-reflections in a noisy superposition with the proposed method.

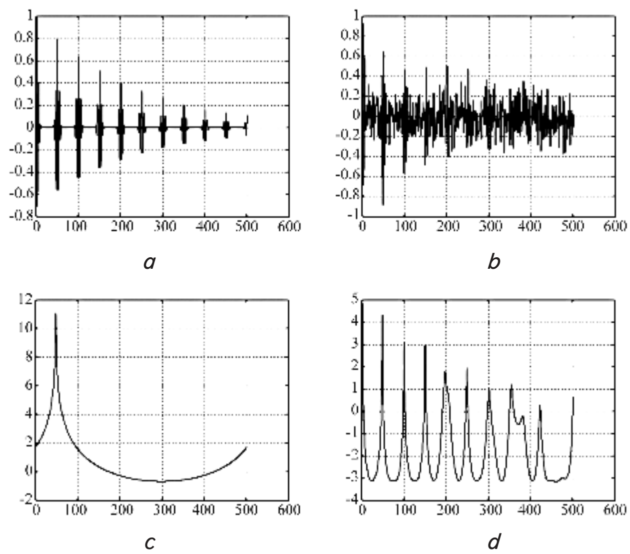


Fig. 2. Analysis of a reverberation band pulse sequence (horizontal axis – time (ms), vertical axis – amplitude (mV)): *a* – noiseless pulse sequence; *b* – noisy pulse sequence; *c* – isolation of the first re-reflection corresponding to the lower boundary of single-layered plane-layered structure (an order of a linear prediction model is 2); *d* – isolation of all re-reflections in a noisy superposition (an order of a linear prediction model is 12)

As we can see from Fig. 2, the proposed method makes it possible to identify re-reflections of a noisy superposition effectively. However, the characteristic feature of the example is in the following. In this case, the problem is not an increase in resolution capability of the analysis, but a need to neutralize a parasitic effect of multiple re-reflections of a probing impulse inside the layer under investigation.

6. Discussion of results of studying the method of decomposition of superpositions of unknown pulse signals

Fig. 3, *a* shows a seismic image of a section of the earth's surface.

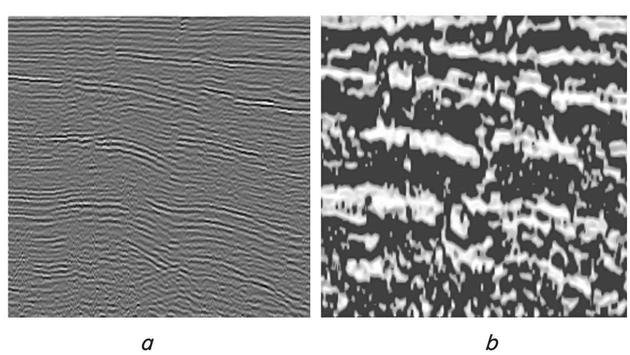
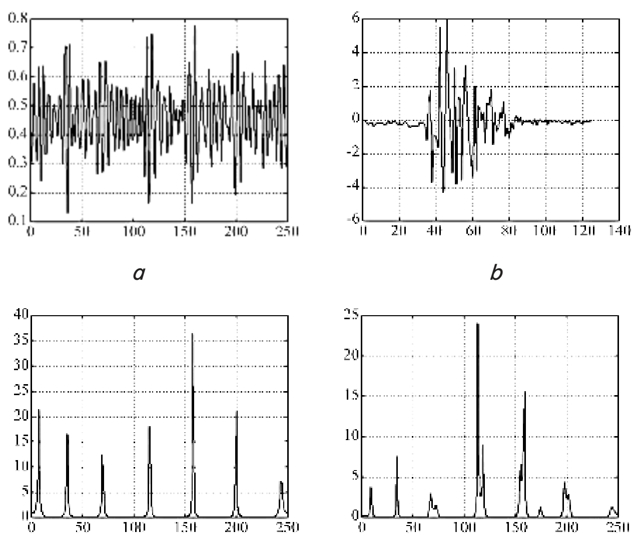


Fig. 3. Echo-pulse seismic image (horizontal axis – spatial, vertical axis – time): *a* – the original; *b* – result of application of the new method (an order of a linear prediction model is equal to 14)

The visual analysis of Fig. 3 shows that the initial echo-pulse image has a large number of re-reflections within geological layers, which seriously complicates the allocation of their boundaries and, ultimately, the segmentation of the layers. The application of the proposed method of a linear prediction (Fig. 3, *b*) made it possible to neutralize the effect of parasitic re-reflections effectively and to identify a structure of geological layers clearly, which makes possible to improve the efficiency of visual analysis of seismograms.

The essence of the proposed method becomes clearer when considering amplitude (but not bright) graphs of individual seismic traces (Fig. 3, *a*). Fig. 4, *a* shows the seismic trace corresponding to the 120th column of the original seismogram (Fig. 3, *a*), it has numerous pulse re-reflections of unknown form. Fig. 4, *b* shows the real part of the Fourier spectrum of the seismic trace (first-order spectral analysis) used as input data for the linear prediction method. Fig. 4, *c, d* show the results of suppressing the effect of multiple re-reflections by the developed method with the transition from the frequency domain to the temporal one on the basis of adaptive second order spectral analysis. The orders of the linear prediction models are 16 and 26, respectively.



a *b* *c* *d*

Fig. 4. Amplitude charts of the results of analysis of the 120th seismic trace: *a* – seismic trace; *b* – real part of the Fourier spectrum of the seismic trace (first-order spectral analysis); *c, d* – result of application of the linear prediction method for the orders of the model equal to 16 and 26, respectively (second-order spectral analysis): the horizontal axes are temporary for "a, c, d", and the frequency axis for "b"

As follows from the results of analysis presented in Fig. 4, the proposed adaptive method of parametric spectral analysis of second order makes it possible to effectively neutralize the impact of multiple re-reflections under condition of optimal choice of the order of the linear prediction model (Fig. 4, *c*). This is explained by the fact that the splitting of spectral peaks begins with an excess order (Fig. 4, *d*). Since the real geological model of the probed area is not known, optimization of the selection of an order of a linear prediction model is possible only based on a degree of visual perception of the synthesized image, which, as the study results show, is not critical in practical terms. We should keep in mind that, in contrast to actual physical amplitudes (Fig. 4, *a*, vertical axis), the amplitudes in Fig. 4, *c, d* are not physical but mathematical. They show a degree of proximity of poles of expression (10) to a unit circle in the z-plane. Since such a mapping is essentially nonlinear, this circumstance makes it possible to increase reliability of separation of boundaries of low-contrast areas of echo-pulse images of the layered structures (Fig. 3, *a, b*).

Thus, the results of the experiments showed that we can use the proposed method effectively for decomposition of superpositions of impulse signals of unknown and different forms under conditions of meaningful measuring and structural noise. Practical application of the proposed method is possible in areas where impulse signal processing is required, for example, ultrasonic medical diagnosis, seismic imaging, and non-destructive testing. Further studies may consider the improvement of the proposed method by using wavelet transforms.

The results of the experiments showed that application of the method in the processing of seismic signals is associated with limitations of the depth of measurement (the method is effective in studying the depth of a surface up to 200 meters and if structures of generating layers have sufficient contrast). The ways to solve this problem and the direction of development of further research can be the modification of the proposed method by using models based on neural networks and wavelet transforms.

7. Conclusions

1. We developed an approach for the decomposition of superpositions of unknown pulse signals. The basis of the developed approach is a consistent use of various methods of spectral analysis, which increases sensitivity of visual analysis of echo-pulse images.

2. We performed experiments to investigate suitability of the proposed approach to the intended application. We solved the tasks on the elimination of signal re-reflections in layered structures characterized by noiseless superpositions of band pulse signals. The proposed method makes it possible to unambiguously identify the presence and location of elementary pulses.

3. We analyzed results of the experiments conducted. Based on the results of analysis, we established that the proposed method makes it possible to improve the signal-to-noise ratio of an image by 3 times, as well as to increase resolution capability in processing signals and images without using *a priori* information about the form of elementary pulses. The method is resistant to the influence of measuring noise. Neutralization of the effect of parasitic reflections occurs due to the optimization of selection of an order of a linear prediction model of Fourier spectral characteristics of the analyzed seismic traces.

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RECURRENT NETWORK AS A TOOL FOR CALIBRATION IN AUTOMATED SYSTEMS AND INTERACTIVE SIMULATORS

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Побудовано метод автокалібрування та корегування значень вектору магнітної індукції, що є придатним до застосування в умовах обмежених обчислювальних ресурсів мікроконтроллерів та SoC-систем автоматизованих систем та інтерактивних тренажерів. Досліджено працездатність алгоритмів калібрування і обробки периферійної інформації, що реалізують систему, та залежність величини похибки вимірювання від властивостей датчика та апаратних особливостей

Ключові слова: метод автокалібрування, корегування, структура рекурентної мережі, SoC-системи, інтерактивні тренажери

Построен метод автокалибровки и корректировки значений вектора магнитной индукции, который пригоден для применения в условиях ограниченных вычислительных ресурсов микроконтроллеров и SoC-систем Предложена структура рекуррентной сети автоматизированных систем и интерактивных тренажеров. Исследована работоспособность алгоритмов калибровки и обработки периферийной информации, которая реализует систему и зависимость величины ошибки измерения от свойств датчика и аппаратных особенностей

Ключевые слова: метод автокалибровки, коррекция, структура рекуррентной сети, SoC-системы, интерактивные тренажеры

1. Introduction

It is common knowledge that the conditions of functioning of primary transducers of physical quantities, sensors, measuring instruments, controllers and other elements of automated production and automated work places of training simulators are unpredictably different from the ideal ones [1–10]. A wide range of levels, such as vibration, noise, humidity, temperature, as well as a change in parameters of technological process over a wide range, is characteristic of the mining, shipbuilding, machine-building, casting, rolling and other machining industries. Such changes in technological parameters and influences exerted by the external working environment significantly affect the accuracy of measuring a controlled magnitude [11–13]. Each of the factors that causes the error, typically under laboratory conditions, can be measured and separately taken into consideration in the results of measurements. However, under actual industrial conditions it appears impossible to take them all into account at the same time [11]. Given the impact of the specified factors, the results of measurement by each sensor, along with a predictable systematic error of the measured magnitude, include an additional random error, predetermined by a change in the modes of its operation [4–11]. The sensors that are built on the Hall effect, as well as other semiconductor sensors, have a pronounced temperature dependence and the non-linearity of characteristics [12]. These are only two of the factors among all that determine the accuracy of measurement by a given type of sensors. With regard to a rather high price related to an increase in the accuracy of measurements by improving the structural solutions and the overall circuitry, it is an important task to search for methods that imply less cost [13–17]. One of such methods for the adjustment of sensors' characteristics is the recurrent artificial neural-network (RANN) method that has been gaining traction recently [1]. The main areas of application of neural networks include the approximation of functions, associative memory, data compression, recognition and classification,