Заключение. Предложен новый тип городского общественного транспорта – информационный. Данный вид транспорта способен без помех со стороны других транспортных средств функционировать в насыщенной улично-дорожной среде и перевозить большое количество пассажиров, сравнимое с метро.

Предлагаемый тип транспорта является системой, в которой информационные процессы (сбор информации, обработка информации, принятие решений) выполняются постоянно и составляют основу информационной транспортной системы. Нарушение любого из этих процессов делает систему неработоспособной. Единичным транспортным средством системы является автономный электрокар (без водителя) вместимостью до 50 человек (инфобус).

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GLUSHCHENKO T.A., KASYANIK V.V., PROLISKY E.E., SHUTS V.N. Infobus – a new type of intellectual transport for passenger intercity transportation

A new type of urban public transport has been proposed - information. This type of transport is capable without interference from the other vehicles to operate in a bustling street environment and to transport large numbers of passengers comparable to the metro. The proposed type of transport is a system in which information processes (data collection, information processing, decision-making) are carried out continuously and form the basis of the information transport systems.

УДК 681.325

Lagun I., Nakonechnyi A.

SELECTION OF WAVELET BASIS FOR THE EFFECTIVENESS PROCESSING OF SIGNALS

Introduction. Currently, the wavelet theory is used to analyze a broad range of non-periodic, non-stationary types of signals in various application areas of science and technology, as it allows obtaining more comprehensive information about the signal.

The effectiveness of signal representations in wavelet domain and their analysis essentially depend on the choice of basis functions used during transform. The optimal choice of features enables the required accuracy of approximation of informative signals in a time-frequency domain. Wavelet transform allows compact representation of the energy of the signal in a small number of significant non-zero coefficients and thus, achieves a high speed of transformation with minimum required memory. Optimal selection of basis wavelet functions is important for signal denoising, and in many cases, determines the required number of signal decomposition levels and the thresholding methods.

1. The fundamental properties of wavelets. The theory of wavelet transform allows usage of different types of mother wavelets for signal processing. In most cases, during the selection of a parent wavelet, the following characteristics are taken into account: size of the support, the number of zero moments, and smoothness of basis functions [1]:

– compact support. It was established that the support size affects the approximation error of signals in the time-frequency domain, especially for finite functions. The smaller support size, the smaller error occurs during function decomposition. Dependence of the number of wavelet coefficients on a support size is also important. In order to minimize the quantity of coefficients with large amplitude is necessary to use the function with the smallest support size [2];

– some zero moments. The size of the support of functions and the number of zero moments are independent variables. Thus, there is trade-off between the number of zero moments and the size of support. Given this, while selecting the basis functions, we need to take into account the following: if the signal has some isolated features and is smooth between these features, you must use the basis functions of a large number of zero moments. This allows receiving of a large number of small wavelet coefficients on a small scale. However, if the number of features increases, it is advisable to reduce the size of the support by reducing the number of zero moments [1, 2];

– the smoothness of wavelet functions. It is known that the number of zero moments and smoothness of basis functions are interdependent, but the nature of such relationship may be different depending on the type of wavelets considered family. For smooth functions, the best approximation of a high-frequency component is provided by a large number of zero moments, but not regularity of wavelet [2, 3]. Also, it is important to consider that the result of the approximation depends not only on the smoothness and the number of zero moments in the basis functions but also on the structure of the signal. Also, it is important to remember that the result of the approximation depends not only on the smoothness and the number of zero moments in the basis functions, but also on the structure of the signal [3];

– orthogonality. An important feature of wavelet functions is orthogonality. Orthogonal basis functions allow effective approximation of certain types of signals using a small number of coefficients. Each orthogonal wavelet coefficient contains an information about the relevant part of the signal and has no redundancy in this representation [4, 5].

More than one parent wavelet exists that have similar properties.

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Moreover, these properties provide only the basic mathematical description of wavelets, which does not always allow definition of explicit recommendations on their practical application for the analysis and processing of certain types of signals. Therefore, various approaches have been developed to find the optimal wavelets, based on different criterions [6, 7].

2. Criteria for selection of basis functions. The main purpose of the signal analysis is to maximize the value of useful information extracted from an input signal, through its transformation and processing. Moreover, analysis of any signal involves finding the areas, in which behaviour of a signal is characterized by regularity, or a set of features. It is known, that the energy of the signal energy is one of the main parameters that characterizes the real signals.

$$E_1 = \int_{-\infty}^{\infty} S^2(t)\,dt\,, \qquad (1)$$

where E_1 – is the energy of the signal $S(t)$.

Since the real signals are finite, the integral expression (1) is determined and a result is a number:

$$E_1 = \int_{0}^{T} S^2(t)\,dt\,, \qquad (2)$$

where T – is the period of the signal.
Spectral energy is defined as:

$$E_2(\omega) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \left|S(\omega)\right|^2 d\omega\,. \qquad (3)$$

If you limit the domain of the integral by frequency band within which the maximum energy is transmitted signal, the integral (3) is defined in this frequency domain [8, 9].

It is known that Parseval theorem allows linking energy signal in time and frequency domain [3]:

$$\frac{1}{2\pi}\int_{-\omega_m}^{\omega_m} \left|S(\omega)\right|^2 d\omega = (1-\xi)E_1\,, \qquad (4)$$

where ξ – is the a value that determines energy loss outside the spectral bands for digital signals:

$$\sum_n \left|s(n)\right|^2 = \frac{1}{N}\sum_k \left|S(k)\right|^2\,, \qquad (5)$$

where N – is the number of discrete signal samples, $s(n)$ – discrete signal, $S(k)$ – the range of the sampled signal.

Thus, according to Parseval's theorem, the connection signal energy and the energy of its wavelet coefficients represented as:

$$E_S = \sum_n \left|s(n)\right|^2\,, \qquad (6)$$

$$E_C = \sum_m \sum_n \left|C_{n,m}\right|^2\,, \qquad (7)$$

$$\sum_n \left|s(n)\right|^2 = \sum_m \sum_n \left|C_{m,n}\right|^2\,, \qquad (8)$$

where E_s – the energy of the signal in the time space, E_C – energy signal in wavelet space, $C_{m,n}$ – coefficients of discrete wavelet transform.

During the decomposition of a signal using the wavelet transform, signal power can be divided into multiple levels of decomposition in different ways.

Moreover, the higher the energy derived from the test signal on fewer levels of conversion, the more effective will be the wavelet transform of the signal. This distribution will depend both on the characteristics of the signal, and the selected basis function. Given this, the energy distribution of the signal can be used as a criterion for selecting the wavelet base [10–12].

It is also important to note that a spectral energy distribution of wavelet coefficients plays a significant role in the wavelet based signal analysis and processing. The quantitative measure of the energy distribution is Shannon entropy [13].

$$H = -\sum_n p_n \cdot \log p_n\,, \qquad (9)$$

where $p_n = \dfrac{\left|C_{n,m}\right|^2}{E_C}$ – is the probability distribution of the wavelet coefficients. The lower value is Shannon entropy, the higher one – the concentration of power.

Thus, the criterion for evaluating the effectiveness of basis wavelet can be determined by the ratio between energy and Shannon entropy (Energy to Shannon Entropy ratio – EER).

$$EER = \frac{E_C}{H}\,. \qquad (10)$$

In general, the wavelet transform determines the similarity between the analyzed signal and scalable version of the wavelet base. To determine the degree of similarity of the two signals, the notion of correlation is employed. Several publications [14, 15] proposed to use the correlation coefficient as a criterion for selecting the wavelet base.

$$\rho(s,\psi) = \frac{COV_{S\psi}}{\sigma_S \cdot \sigma_\psi}\,, \qquad (11)$$

where $\rho(s,\psi)$ – is the coefficient of correlation between the analyzed signal and the wavelet base, $COV_{S\psi}$ – mutual covariance sequences, σ_S and σ_ψ – the standard deviation sequences.

The absolute value of $\rho(s,\psi)$ can vary from 0 to 1. The greater the similarity between the signal and basis wavelet, the greater will be approaching to 1 correlation coefficient. Basis wavelet that provides maximum correlation with the analyzed signal will be most appropriate for further processing of the signal.

If the correlation describes only a linear relationship of variables, the information describes any relationship. The wavelet transform is mainly used for the analysis and processing of signals that have some uncertainty information so appropriate will use the entropy. The ratio of the energy to the Shannon entropy, which is defined by (10), evaluates the energy content of wavelet coefficients. To get their information content and compare it with the information content of the signal, it is proposed to use such information criteria as joint entropy, conditional entropy, and mutual information.

Common entropy of the signal and its wavelet coefficients $H(S,C)$ allows determining the overall information content of these sequences [16]

$$H(S,C) = -\sum_{s\in S}\sum_{c\in C} p(s,c)\cdot \ln p(s,c)\,, \qquad (12)$$

where $p(s,c)$ – is the common chance of distribution of the signal and its wavelet coefficients.

The conditional entropy $H(C\,|\,S)$ – is the average amount of information contained in the wavelet coefficients if the statistical correlation of the signal [16]

$$H(C\,|\,S) = -\sum_{s\in S} p(s)\sum_{c\in C} p(c\,|\,s)\cdot \ln p(c\,|\,s)\,, \qquad (13)$$

where $p(c\,|\,s) = \dfrac{p(s,c)}{p(s)}$ – the conditional probability of distribution of wavelet coefficients relative to signal distribution, $p(s)$ – chance of distribution of the signal.

Mutual information $I(S;C)$ – number of information in the wavelet coefficients of signal [11]

$$I(S;C)=-\sum_{s\in S}\sum_{c\in C}p(s,c)\cdot\ln\frac{p(s,c)}{p(s)p(c)}=$$
$$=-\sum_{s\in S}\sum_{c\in C}p(s,c)\cdot\ln p(s,c)-$$
$$-\sum_{s\in S}\sum_{c\in C}p(s,c)\cdot\ln\big(p(s)p(c)\big)=-H(S,C)-\sum_{s\in S}p(s)\ln p(s)-$$
$$-\sum_{s\in S}p(c)\ln p(c)=-H(S,C)+H(S)+H(C) \tag{14}$$

where $p(c)$ – the probability distribution of the wavelet coefficients, $H(S)$ – entropy signal, $H(C)$ – entropy wavelet coefficients.

Another characteristic of the theory of information is Kullback-Leibler divergence or relative entropy, which is a measure of the distance between two probability distributions defined on the same alphabet. In contrast, mutual information is a measure of the distance of two variables within a distribution of relative entropy determines the distance between the distributions [16]:

$$D(S\,||\,C)=\sum_{i\in S,C}p(S_i)\ln\frac{p(S_i)}{p(C_i)}. \tag{15}$$

If one distribution should be similar to another, the relative entropy allows determining this similarity with fairly high accuracy. If $p(s)=p(c)$, then $D(S\,||\,C)=0$.

Thus, taking into account the need to ensure the maximum mutual information and the minimum relative entropy, a criterion for evaluating the effectiveness of selected basis wavelet can be determined using the ratio (Mutual information to relative entropy ratio – IER):

$$IER=\frac{I(S,C)}{D(S\,||\,C)}. \tag{16}$$

The basis wavelet, which ensures the maximum relation of the mutual information to the relative entropy test signal, would be most appropriate for further processing of the signal.

Therefore, [17–19] consider the possibility of applying principles of the theory of information for a quantitative comparison between different types of dependencies such as signals and corresponding coefficients of the wavelet transform.

3. Analysis of the efficiency criteria for selection of basis functions for different types of signals. The following families of orthogonal functions are selected for further studied: Daubechies with the compact support (db1 ... db20), Coiflets (coif1 ... coif5), Symlets (sym1 ... sym20), and the test signals from Matlab package: bumps, blocks, doppler, heavy sine, trsin, wcantor [20]. Test signals are shown in Fig. 1.

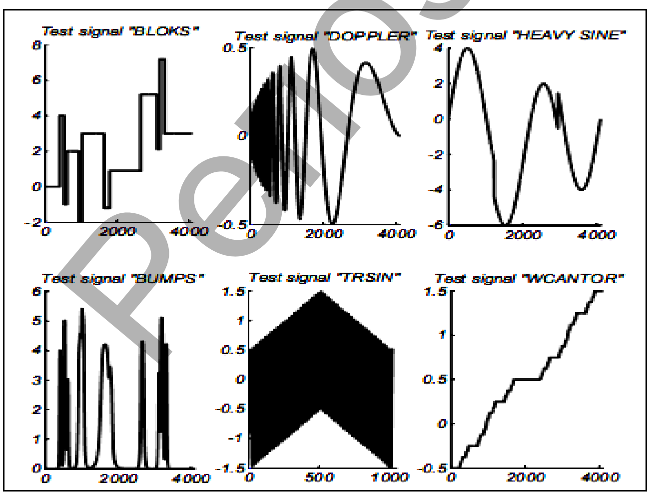


Figure 1 – The test signals to evaluate the effectiveness of criteria for selection of basis wavelet

Each test signal and selected basis functions were tested using Matlab. Fig. 2 shows the examples of results for some of the signals as a dependencies values for each criterion, calculated according to expression (10), (11) and (16) of the basis wavelet.

Table 1 lists the basis wavelets, which achieves the best value for each criterion.

Table 1 – Baseline wavelets for processing of various signals

Test signal	Energy to Shannon Entropy ratio	Mutual information to relative entropy ratio	Correlation coefficient
"blocks"	sym20	db19	db1, sym1
"bumps"	all exept db1 and sym1	db20	db3
"doppler"	db19, db20	sym14, coif1	coif1
"heavy sine"	sym11	coif1	db1
"trsin"	sym20	db19	coif1
"wcantor"	sym20	coif1	db1

Overall, the following conclusions can be made:

– for the signals "blocks" and "wcantor" with a stepped shape, the most efficient wavelet basis function of the criterion Energy to Shannon Entropy is a function of the family Symlets order 20;
– for the signals "doppler" and "trsin", containing high-frequency harmonic components, the most effective basis wavelet criterion for Energy to Shannon Entropy is functions of families Daubechies and Symlets of order 19 and 20.
– for the signals "trsin", which has a triangular distribution, the most efficient wavelet basis function of the criterion Correlation coefficient is a function of the family Coiflets, order 1.
– for the signals "doppler" and "heavy sine", with a harmonic distribution, the most efficient wavelet basis function of the criterion Mutual information to relative entropy ratio is a function of the family Coiflets, order 1.

However, based on the results presented in Table 1, an observation can be made that there is no unique correspondences between the types of test signals and basis wavelets for each criterion studied there. Therefore, to determine the effectiveness of each of the criteria, further research of basis wavelets from Table 1 has been conducted.

Within the scope of further research, a noise has been added to each of the test signals, followed by a noise reduction step.

For each of the recovered signals, the values of signal/noise ratio, mean square error, and the correlation coefficient between the analyzed signal S and its de-noised version $\tilde{S}$, have been calculated according to the equations:

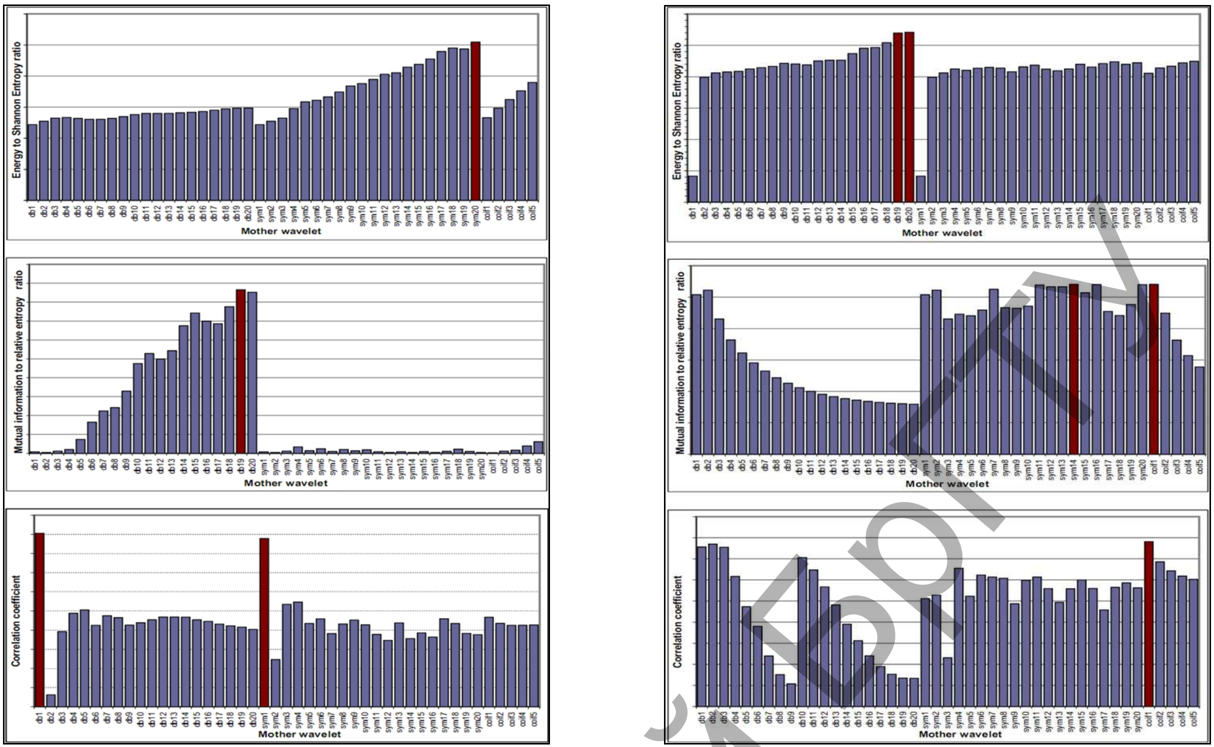
$$SNR=10\cdot\log_{10}\left(\frac{\sum_{i=1}^{N}S_i^2}{\sum_{i=1}^{N}\left|s_i-\tilde{s}_i\right|^2}\right), \tag{17}$$

$$MSE=\frac{1}{N}\sum_{i=1}^{N}(s_i-\tilde{s}_i)^2, \tag{18}$$

$$Cr=\frac{\sum_{i=1}^{N}(s_i-\bar{s})(\tilde{s}_i-\bar{\tilde{s}})}{\sqrt{\sum_{i=1}^{N}(s_i-\bar{s})^2\sum_{i=1}^{N}(\tilde{s}_i-\bar{\tilde{s}})^2}}. \tag{19}$$

As a result of research, the set of values is obtained: signal/noise ratio (SNR), mean square error (MSE) and the correlation coefficient for the most effective basis functions defined by each of the of criteria for all test signals. The results of experiments are presented in Table 2.

Based on the obtained results, the efficiency of application of each of wavelet functions determined according to the corresponding criteria, can be estimated. Fig. 3. shows the diagrams of the distribution of values SNR, MSE and correlation coefficient Cr, as results of signal de-noising for the wavelets, defined by a corresponding criteria.

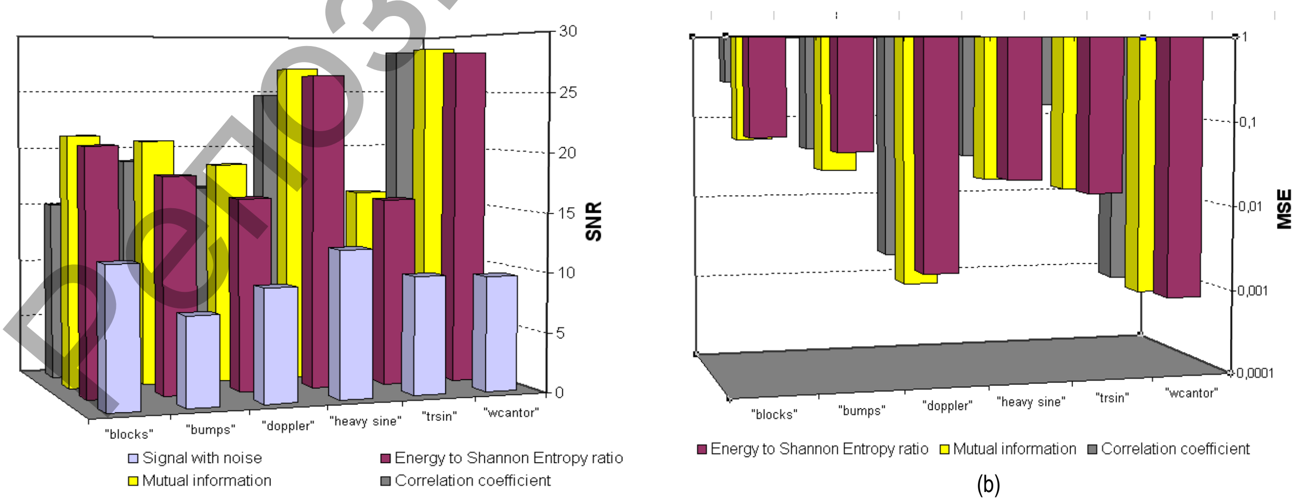


(a) (b)

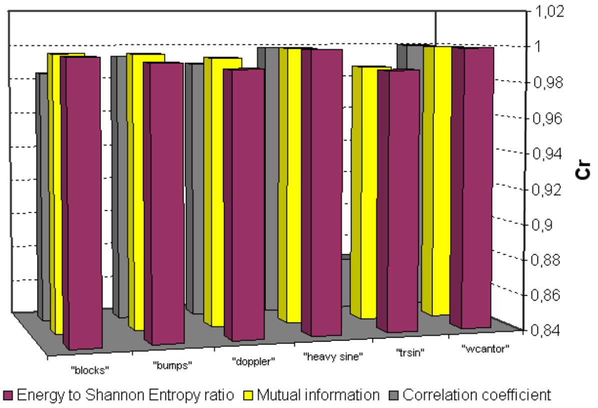
Figure 2 – Dependencies of criteria's values Energy to Shannon Entropy ratio, Mutual information to relative entropy ratio and Correlation coefficient on forty five basis functions orthogonal families of Daubechies, Symlets and Coiflets for signals: (a) "blocks" and (b) "doppler"

Table 2 – The values of SNR, MSE, and correlation coefficient Cr for the results of signal denoising

Test signal with noise	SNR, dB (noise signal)	Energy to Shannon Entropy ratio			Mutual information to relative entropy ratio			Correlation coefficient		
		SNR, dB	MSE	Cr	SNR, dB	MSE	Cr	SNR, dB	MSE	Cr
"blocks"	12,2	15,23	0,076	0,9956	21,32	0,064	0,9964	15,15	0,286	0,9839
"bumps"	7,4	18,16	0,0498	0,9923	20,84	0,0267	0.9960	18,9	0,042	0.9936
"doppler"	9,4	16,18	0,0019	0,9884	18,74	0,0011	0,9935	16,45	0,0019	0,9890
"heavy sine"	12,25	26,37	0,0221	0,9988	26,98	0,0191	0,9989	24,7	0,0328	0,9983
"trsin"	9,9	15,85	0,0147	0,9871	16,14	0,0140	0,9878	5,05	0,1413	0,8693
"wcantor"	9,7	28,4	0,0008	0,9993	28,81	0,0007	0,9993	28,61	0,0008	0,9994



(a) (b)



(c)

Figure 3 – Comparison of: (a) SNR, (b) MSE and (c) the correlation coefficient Cr, estimated after signal denoising for the wavelets defined by each criterion.

Based in Fig. 3 values of statistical indicators the best results according to SNR and MSE were obtained with the use of wavelets determined by criterion Mutual information to relative entropy ratio. Estimation of the correlation coefficient for different criteria is the same. In general for signals of "blocks", "bumps" and "doppler" effective criterions Mutual information to relative entropy ratio. For signals of "heavy sine", "wcantor" and "vonkoch" all three criteria are equally effective for selecting wavelet base.

Conclusions. The article presents an analysis of the main criteria for choosing the optimal wavelet functions that are frequently used for processing of certain types of signals, such as biomedical signals, signals of partial discharge, vibration signals, and others. This set of criteria is based on the energy, entropy and correlation, named Energy to Shannon Entropy ratio, Mutual information to relative entropy ratio, and Correlation coefficient. The article discusses the possibility of applying these criteria to a wide range of signals, processing of which is mainly done by discrete wavelet transformation, and the processing efficiency of which significantly depends on the choice of basis wavelets.

The experiments carried out on Matlab test signals package ("bumps", "blocks", "doppler", "heavy sine", "trsin", "wcantor") with the family of orthogonal functions Daubechies (db1 ... db20) Coiflets (coif1 ... coif5), Symlets (sym1 ... sym20) allowed selection of the most effective basis wavelets that correspond to the maximum value for the criteria: Energy to Shannon Entropy ratio, Mutual information to relative entropy ratio and Correlation coefficient. In most of the cases, the differences between the estimated values of the criterion is insignificant. However, it has been observed that the choice of the most effective basis wavelets defined based on the criterion Mutual information to relative entropy ratio for all test signals is more clearly defined, contrary to the cases of the correlation and energy criteria.

It has been concluded that the best results according to SNR and MSE obtained using wavelets determined by the criterion of Mutual information to relative entropy ratio.

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LAGUN I.I., NAKONECHNYI A.I. Selection of wavelet Basis for The effectiveness Processing of signals

In article results of a research of the existing criteria of the choice of basic veyvlet-functions for the purpose of effective handling of signals are provided. The following criteria were researched: "Energy to Shannon Entropy ratio", "Mutual information to relative entropy ratio", "Correlation coefficient" and forty five basic functions of the orthogonal Daubechies, Symlets and Coiflets families. Pilot study was conducted for the most widespread types of the signals chosen from the database of a packet MATLAB. Basic functions which were determined by these to criteria as optimum for each type of a signal, were used for filtering noisy signals subsequently. Results of filtering were compared for each criterion by means of estimates: ratios signal / noise (SNR), a mean square error (MSE) and coefficient of correlation between the considered signal and the signal cleared of noise.