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Methods and means of processing discrete information in networks with a high level of noise

Abstract: *The article is devoted to increasing the efficiency of digital signal processing in the conditions of high level of interference, for which the efficiency and reliability of the transmission of information have a priority over the speed of transmission and the amount of CP resources used. The authors provide readers with the improvement of current methods in order to increase the performance of information transmitting in difficult conditions environment. The method of determining the decomposition coefficients, which uses the replacement of the biorthogonal coefficients of the wavelet decomposition with the approximation sum using a series of quasi-random delta sequences, is used in the work, which is used to eliminate the Gibbs effect in signal processing. The method for evaluating the spectrum of the signal for an adaptive threshold method, which uses a multi-window average estimation of the logarithmic spectrum of the signal, is improved. A method of the fast median filtration which processes the finite quantities of date vector with splitting an original data vector onto some parts has been developed. The method of parallel fast wavelet transform is improved, which uses the partition of the data vector into blocks for processing data using a local wavelet transform in the diagonal sequence. The theoretical researches and modeling demonstrate the significant efficiency of the newly proposed and improved methods.*

Keywords: signal processing, signal filtering, denoising methods, wavelet filtering, adaptive threshold filtering.

Introduction

The constant increase of computer technologies and systems has the form of geometrical progression and the creation of highly efficient and reliable methods for the data transmitting and receiving are the key factors of computer systems developing. A very important role play computer networks which are designed for working in the high level of interference. In industrial probabilities, the transmission of information has a priority over speed, and often it is necessary to ensure the result of the transmission of information under all conditions.

In Wi-Fi networks, with the probability of error 0.1 causes than more than 40% of the information is lost. The father increase of the mistake probability makes transmission impossible. According to the Wi-Fi and WiMAX network standards a signal-noise ratio should be no less than 57 dB. In the CAN C 2.0 based networks when the failure counter indicator’s value of concrete nod reaches 256 the transition to the Bas Off mode take place. This mode provides the information transmitting not in the pre-duplex, but in simplex mode. There are many methods for data analysis, but in high-level interference conditions the traditional methods have the low performance and the needy of the known methods improvement still exists [1].

The specificity of the high level interference environment computer networks is the impossibility to provide the probable information transmitting by the connection channels which leads to the decrease system work deterioration in general and impossibility of such work in particular.

The classical information processing methods do not always provide the appropriate result. The system work efficiency and reliability depends on the quality of the information processing more than on the main processor modules. According to this in the high level interference environment computer networks the main attention should be applied to the increasing of information processing efficiency upto the possibly high level of error-free information reception and processing probability [2].

The specificity of the computer networks is regulated by the international standards which define the mandatory and recommended dictates of the hardware construction and the possible condition of the work environment. For example, in the case of xDSL technology a signal-noise ratio must be 10:1 or 21.3 dB and the mistake probability should not cross the 10^{-7} ratio. If this condition is not met (in industrial conditions, the signal/noise ratio may be less than 10:1), then the equipment operates in the unusual mode, and the probable transmission of information cannot be guaranteed. For systems in aviation, the probability of a mistake should be 10^{-19}, on the vehicle systems – not more than 10^{-12} [3].

The construction of industrial radio networks has a big potential because of providing the high speed information transmitting and the sparing of wireline’s means. But the radio networks are sensitive to interferences, and therefore require high-performance methods for providing constant communication. The known signal processing methods in the presence of the high level interferences very often are not efficient enough or require the significant hardware and resource means spending. So, the necessity of the known methods improvement and development of new methods and is present.

The main content of article

Thresholding method based on the quasypositive delta-sequences. The main signal processing methods can be divided onto two parts. The methods from the first part use the orthogonal functions, from the second one use the digital filters. Among orthogonal methods the most popular are the methods which apply the Fourier function and provide the full information about the frequency localization of a signal, but do not give information about the time localization. This shortcoming gives a start to the development of the Fourier window transformation method. This method evaluates the signal spectrum and noise to process this signals with the applying the adaptive threshold methods which efficiency directly depends on the accuracy of the spectrum value. In addition to the Fourier orthogonal basis, Walsh, Haar, Hartley bases and wavelets are also used. In case of frequency-time localization, the wavelet functions are the most accurate among all orthogonal bases functions.

According to this, wavelet transformation has a potential. The complicated calculation of the wavelet transferring and the limitation of the wavelet functions leads to signal distortion in the end of transferring - the Gibb's effect [4].

There are the known methods of the flaws correction which are applied to the other orthogonal functions. Also there are the wavelet transformation methods which only partially solve the problem. The fast wavelet transformation does not decrease the operation's complicity significantly.

For wavelet transformation, there are methods that partially solve the problem. Among the known digital filtration methods the median filtration shows the best results but this method is time consumption method because of the non-linear filter [4].

The improvement of signal processing can be accomplished by applying the method of determining the coefficients of decomposition to a partial sum under biorthogonal wavelet decomposition

$$Q_m f = \sum_{n\in Z}\tilde{b}_{m,n}\phi_{m,n} = \sum_{n\in Z}\tilde{b}_{0,n}\phi_{0,n} + \sum_{k=0}^{m-1}\sum_{n\in Z}\tilde{a}_{k,n}\psi_{k,n} \qquad (1)$$

where $\tilde{b}_{m,n} = \int_{-\infty}^{\infty} f(x)\tilde{\phi}_{m,n}(x)dx$, $\tilde{a}_{m,n} = \int_{-\infty}^{\infty} f(x)\tilde{\psi}_{m,n}(x)dx$, $\delta_m(x,y) = \sum_{n\in Z}\tilde{\phi}(y-n)\phi(x-n)$

$$Q_m^r f = r_m Q_0 f + \sum_{k=1}^{m}(r^{m-k} - r^{m-k+1})Q_k f$$

In the general case, using (1) we can approximate any function including Heaviside function [5]

$$(Q_m^r h)(x) = \int_{-\infty}^{\infty}\delta_m^r(x,y)h(y)dy, \qquad (2)$$

where $h = \begin{cases} 0, \text{if } x \le 0, \\ 1, \text{if } x \ge 0 \end{cases}$ – the Heviside function.

If $\delta_m(x,y) = \sum_{n\in Z}\tilde{\phi}(y-n)\phi(x-n)$, that expression (2) can has the next form

$$\delta_m^r(x,y) = r_m\delta_0(x,y) + \sum_{k=1}^{m}(r^{m-k} - r^{m-k+1})\delta_k(x,y). \qquad (3)$$

To approximate the Heviside function we should work with the continuous function H_r. This function is close to the Heviside function with a large number of members of the sum.

$$H_r(x) = \lim_{m\to\infty}(Q_m^r h)(2^{-m}x) \qquad (4)$$

Multiwindow spectrum estimation. The multiwindow function of the spectrum assessment in the case of window *I* is

$$\hat{S}^{MT}[i,k] = \frac{1}{L}\sum_{l=1}^{L}\hat{s}_l^{MT}[i,k] \qquad (5)$$

where $i \in Z$, $\hat{s}_l^{MT}[i,k] = \left|\sum_{m=0}^{N-1} a_l(m)x_i(m)\, e^{-jkm}\right|^2$, $k=0,1,\dots,N-1$.

The probability distribution function for the multiwindow estimation of the spectrum, that is $\hat{S}^{MT}(k)$, to the real spectrum, $S(k)$, can be approximated as

$$\upsilon(k) \equiv \frac{\hat{S}^{MT}(k)}{S(k)} \sim \frac{\chi^2_{2L}}{2L} \tag{6}$$

where χ^2_{2L}- distribution with a degree of freedom of $2L$ [6].

The logarithm of the multi-window evaluation of the spectrum gives an expression.

$$\log \hat{S}^{MT}(k) = \log S(k) + \log v(k). \tag{7}$$

If L value is 5 and more, the distribution log $v(k)$ can be approximated as a normal distribution with mathematical expectations $\psi(L)$ - log L and a dispersion $\psi'(L)$, where $\psi'(L)$ indicate diagram-function, and $\psi'(L)$ means three gamma –function. Thus, a random variable

$$\eta(k)\equiv\log(v(k))-\psi(L)+\log(L) \tag{8}$$

will be approximated by Gaussian, distributed between zero mathematical expectations and dispersion ψ '(L). The function Z (k) is defined as

$$Z(k)=\log \hat{S}^{MT}(k)-\psi(L)+\log(L)\ . \tag{9}$$

$Z(k)$ can be rewritten as

$$Z(k)=log\ S(k)+\eta(k). \tag{10}$$

The main multi-window spectrum of the signal $S_x(k)$ [7] can then be estimated by subtracting the spectra [8], that is $S_x(k) = S_y(k) - S_n(k)$. Therefore, the logarithmic multi-channel estimation of the spectrum of the noisy signal for a certain frequency can be written as

$$z = \log\ (t + q). \tag{11}$$

A simulation of the z distribution for different values of the test signal q was performed. In fig. 1 shows the received z distribution for values q = 0.05, 0.15, 0.25. Smooth lines produce results based on the theoretical data from the equation. Points are simulation results. From the figure it can be seen that the dispersion of the distribution σ_z^2 increases with decreasing q. This result can be explained by the fact that the logarithmic transformation compresses signals of high amplitude in higher ratio than signals with small amplitude [8].

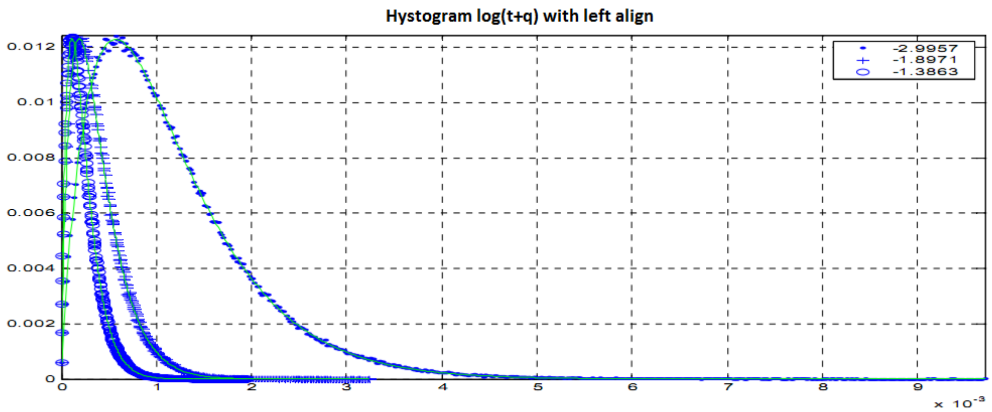

Fig. 1 – The logarithmical spectrum function $z = log(t + q)$

Fast median filter. The median filter is a sliding window, which usually covers an odd number of samples N of the analog signal $x(t)$. The output value of the filter y_j is the count for which there are (N-1)/2 counting with the value less or equal to him

$$\hat{y}_j = med\{\hat{x}_0, \hat{x}_1, ..., \hat{x}_j, ..., \hat{x}_{N-2}, \hat{x}_{N-1}\}\ . \tag{12}$$

For a median filter, it is possible to simply implement a fast processing algorithm based on the matrix gotten by the means of the threshold function of the saturation $F_{ij} = f(x_i - x_j)$, where

$$f(\Delta x)=\begin{cases}1, \Delta x \geq 0;\\ 0, \Delta x < 0.\end{cases} \quad (13)$$

In case of filter's aperture N = 5 for the first 5 values the matrix F_0 has the next form.

$$F_0=\begin{Vmatrix} f(x_0-x_0) & f(x_1-x_0) & f(x_2-x_0) & f(x_3-x_0) & f(x_4-x_0)\\ f(x_0-x_1) & f(x_1-x_1) & f(x_2-x_1) & f(x_3-x_1) & f(x_4-x_1)\\ f(x_0-x_2) & f(x_1-x_2) & f(x_2-x_2) & f(x_3-x_2) & f(x_4-x_2)\\ f(x_0-x_3) & f(x_1-x_3) & f(x_2-x_3) & f(x_3-x_3) & f(x_4-x_3)\\ f(x_0-x_4) & f(x_1-x_4) & f(x_2-x_4) & f(x_3-x_4) & f(x_4-x_4)\end{Vmatrix}. \quad (14)$$

This matrix describes the differences between neighboring counting. The values of these differences can be determined whether this point contains a random component, that is, interference. A shift in one position along a series of values gives the matrix F_1 where one should only nine values located in the selected area

$$F_1=\begin{Vmatrix} F_{11} & F_{21} & F_{31} & F_{41} & \vdots & F_{51}\\ F_{12} & F_{22} & F_{32} & F_{42} & \vdots & F_{52}\\ F_{13} & F_{23} & F_{33} & F_{43} & \vdots & F_{53}\\ F_{14} & F_{24} & F_{34} & F_{44} & \vdots & F_{54}\\ \cdots & \cdots & \cdots & \cdots & \cdots & \\ F_{15} & F_{25} & F_{35} & F_{45} & & F_{55}\end{Vmatrix} \quad (15)$$

The sum of the difference in values of F_{ij} in columns [10]

$$F_i=\sum_{j=0}^{N} F_{ij}=\sum_{j=0}^{N} f(x_i-x_j). \quad (16)$$

It is necessary to make the next steps in order to provide the fast processing of the values by the median filter:

- form the matrix F_0 for the first N registered values according to the choosed filter's aperture;
- calculate $F_{0.j}$ values for each of the columns of the F_0 matrix;
- select the necessary value from the first N registered values;
- define for F_n matrix $F_{(n+j)(n+N-1)}$ and $F_{(n+N-1)(n+j)}$ values in case of $0 \leq j < N$;
- remove the $F_{(n-1)(n+j)}$ and the $F_{(n+j)(n-1)}$ values from the $F_{n,j \pm 1}$ value.

- add $F_{(n+j)(n+N-1)}$) to the column F (n + j) of the matrix Fn.

The minimum number of counting, which is necessary to clean the informative signal with median filter, is $N-0.5 \cdot k_m$, where: $k_m \geq 1$ – coefficient of sampling rate of the signal [8].

Median filtering is simple enough to implement hardware on programmable devices. The block diagram for it is depicted in Fig. 2. Software implementation allows changing the aperture of the window depending on the signal parameters before the filter is started and during processing, that is, to implement an adaptive median filter [9].

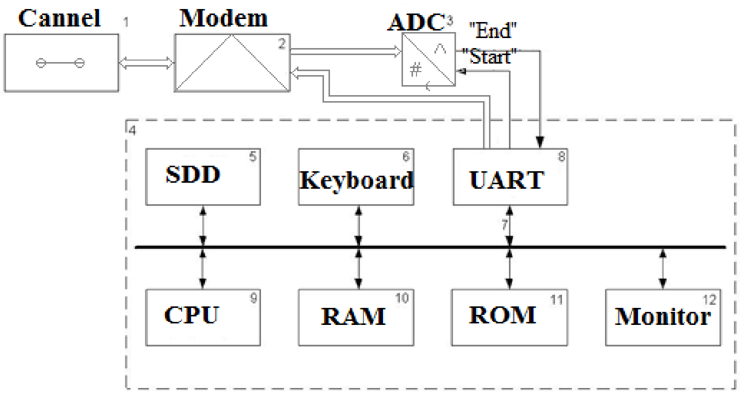

Fig. 2 – The structure of the device for the fast median filtration [9]

In order to estimate the work efficiency we should form a complicated discrete signal, expose it to white noises of the different amplitudes and process it by the median filter of the selected aperture.

The results of the calculations of the dependence of the probability of pulse noise removal on the probability of p_χ for the median filters with different apertures are shown in Fig. 3. The results obtained show the high efficiency of the use of filters of this type.

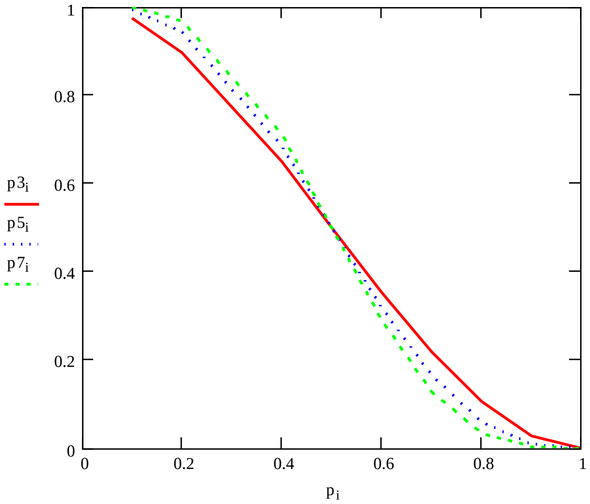

Fig. 3 – Dependence probability of pulse noise removal p_N from the probability p_χ for median filters with apertures N = 3, 5, 7

Paralelling computing for fast wavelet transformation. We can reduce the implementation of the fast wavelet transformation to the next mathematical form

$$X(W^{\lambda_N})^T. \tag{17}$$

For a matrix of M lines, the number of operations with a floating point will be

$$F_{MFWT}(N,M) = 4DMN(1-\frac{1}{2^{\lambda}N}) \cdot \tag{18}$$

The recurrent formula has a next form

$$c_{m,n}^{i+1} = \sum_{l=0}^{D-1} a_l c_{m\langle l+2n\rangle_{s_i}}^{i}, \tag{19}$$

$$d_{m,n}^{i+1} = \sum_{l=0}^{D-1} b_l c_{m\langle l+2n\rangle_{s_i}}^{i}, \tag{20}$$

where i=0, 1, ..., λ_N-1, m=0, 1, ..., M-1, n=0, 1, ..., S_{i+1}-1.

The execution time of one step for multiple fast wavelet transforms [10] is $S_i(t_s+2DMt_v)$ and the full execution time for this case

$$T_{MFWT} = \sum_{i=0}^{\lambda_N-1}\frac{N}{2^i}(t_s+2MDt_v) = 2N(1-\frac{1}{2^{\lambda}N})(t_s+2MDt_v) \cdot \tag{21}$$

Performance can be calculated as

$$R_{MFWT} = \frac{F_{MFWT}}{T_{MFWT}} = \frac{2MD}{t_s+2MDt_v}. \tag{22}$$

During the processing the initial data in a sequential algorithm, the data distribution in the form of the results of each stage of the transformation equally between the processors leads to a poor balance of load. In case of two processors distribution the first one performs the processing of 1 to 8 bits for each three stages, and the second one processes only 9 - 16 bits during the first stage, after which no further processing is required. To provide a well-balanced load between the two processors, each of them should be equally involved in all three stages [11]. The sequence of the 16 bits processing of the wavelet transformation in case of the two processors system and the two stages transformation is showed on the fig. 4.

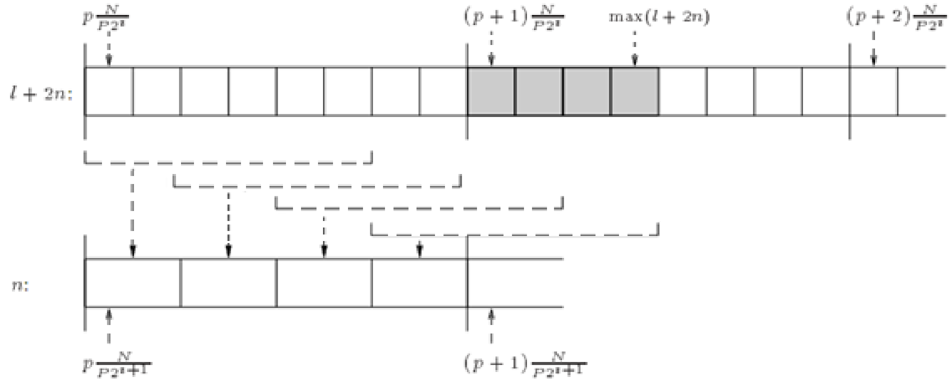

Fig. 4 – Distribution of data vector between two processors for two stages of fast wavelet transformation

Avoiding of the mutual connections between processors and arranging the intermediate results and the final vector of transformation we can get a well-balanced load.

Performing computing and distributing the data vector is shown in Fig. 5

The calculation on the *p* processor needs *D*-2 elements of the processor *p*+1, *D*=6 and $N/(P2^i)$=8. The width of the line *D* indicates the size of the subvector filters which have different values *n*.

$$\lambda \le \log_2\left(\frac{N}{P}\right). \tag{23}$$

The values in (23) can be calculated during the absence of two processor's connections when *l*+2*n* elements are not sent to the other processors.

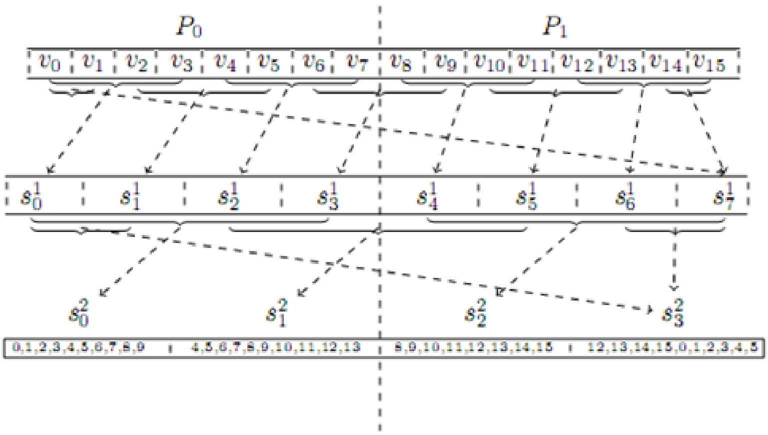

Fig. 5 – Distribution of data vector between processors for better balance of load [12]

The fig. 6 shows the scheme of data block dividing between 4 processors onto data subblocks when the fast local wavelet transformation is applied. In the first stage, the processing is carried out over the darkened blocks, on each next the local processing of the next diagonal blocks is performed by biasing one block. The block's quantity in the diagonal depends on the processes quantity. For each stage of transformation the data block processing takes place only in one diagonal. After the last stage of the transformation all results of the block processing will be summarized.

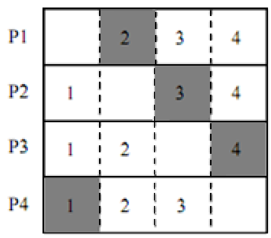

Fig. 6 – Diagonal processing of data

There are λ steps of the wavelet transformation, so the simple model for full time for data exchange between processors is

$$C_{MFWT} = \lambda(t_l + M(D-2)t_d). \quad (24)$$

C_{MFWT} increases linearly during the M increasing, but independently from processors quantity P and the value of the N parameter.

Combining the time calculation and the time of the data transferring expressions we can get the model which describes the full duration of the P processors executions when $P > 1$.

$$T^{P}_{MFWT}(N) = \frac{T^{0}_{MFWT}(N)}{P} + C_{MFWT}(N), \quad (25)$$

and performance for a parallel algorithm

$$R^{P}_{MFWT}(N) = \frac{F_{MFWT}(N)}{T^{P}_{MFWT}(N)}. \quad (26)$$

Combining expressions for performance (24), (25) and (26) gives a formula for increasing speed

$$S^{P}_{MFWT}(N) = \frac{T^{0}_{MFWT}(N)}{T^{P}_{MFWT}(N)} = \frac{P}{1 + P\dfrac{C_{MFWT}(N)}{T^{0}_{MFWT}(N)}}. \quad (27)$$

The efficiency of the parallel calculations we define as the increase of speed provided by the each additional processor

$$E^{P}_{MFWT}(N) = \frac{S^{P}_{MFWT}(N)}{P} = \frac{1}{1 + P\dfrac{C_{MFWT}(N)}{T^{0}_{MFWT}(N)}}. \quad (28)$$

According to (28), in case of constant N the increasing of processors quantities P the system efficiency drops.

Modelling experiments on the test signal

The coefficient decomposition defining method can eliminate the Gibbs effect so this method could be used for signal filtration. We can estimate the efficiency of his method by the purifying noised signal from adapted noise. We use a digitally provided signal like a test signal. This signal has smoothed fronts and recessions, which is characteristic for impulses after receiving from communication channels [13].

To the test signal was added white Gaussian noise with amplitude 0.05 V, that is, the signal/noise ratio would be h = 26 dB.

The parameter of the depth of transformation (or accuracy) was formed as r = 0.5. The processing of this noised signal was provided by the method of determining the coefficients of decomposition (through the use of numerical methods, since the test signal is also given numerically). By comparing the noise-cleared signal with the initial test signal to estimate the residual noise level, it can be argued that the signal-to-noise ratio increased to 33 dB. The test of the method was performed at a higher level of noise. A white Gaussian [14] amplitude of 0.2 V was added to the test signal, which means that the signal to noise ratio would be h = 14 dB. The parameter of the depth of transform (or accuracy) was given r = 0.4. By comparing the noise-cleared signal with the initial test signal to estimate the residual noise level, it can be argued that the signal-to-noise ratio increased to 23 dB.

On the basis of the obtained results it can be argued that the method of determining the decomposition coefficients can be effectively used as a filter. The disadvantage of this use is that, for small values of r, it often produces worse results than traditional filtration methods, and for large values of r, the execution time of the procedure will be greatly increased, which introduces limitations on its use of the method. In industrial networks with high levels of interference [15], where the reliability and efficiency of the transmission of information have priority over the speed of transmission and processing of signals, this method can be applied.

An estimation of the efficiency of the method of multiwindow estimation of the spectrum was performed by modeling in LabView on a virtual device. The effectiveness evaluation was determined by comparing the accuracy of the spectrum estimation using a different number of window functions on test signals whose spectra were previously known.

The test signals was the sequences of rectangular pulses and the sequences of the rectangular pulses influenced by the additive interference such as the white Gaussian noise which spectrum was previously known for this experiment.

In Fig. 7 shows the finding of the spectral signal estimation using the averaged estimation of two window functions. The window function is selected from the pop-up menu.

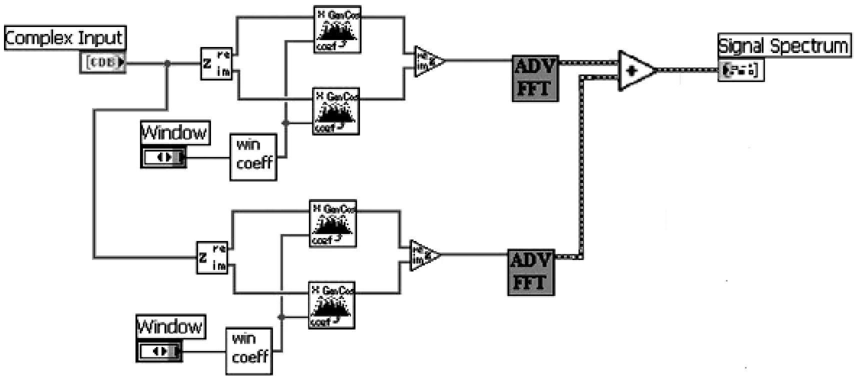

Fig. 7 – Converts a signal using two window functions for fast Fourier transform with averaging their estimation

The Fig. 8 shows that mean square deviation *z* is changing when *q* has changed in case of the window's range *q* from 2 to 6.

We have executed the efficiency comparison of the adapted threshold methods in case of the applying one window spectrum assessment and multi window spectrum assessment in order to provide a signal cleaning from a noise

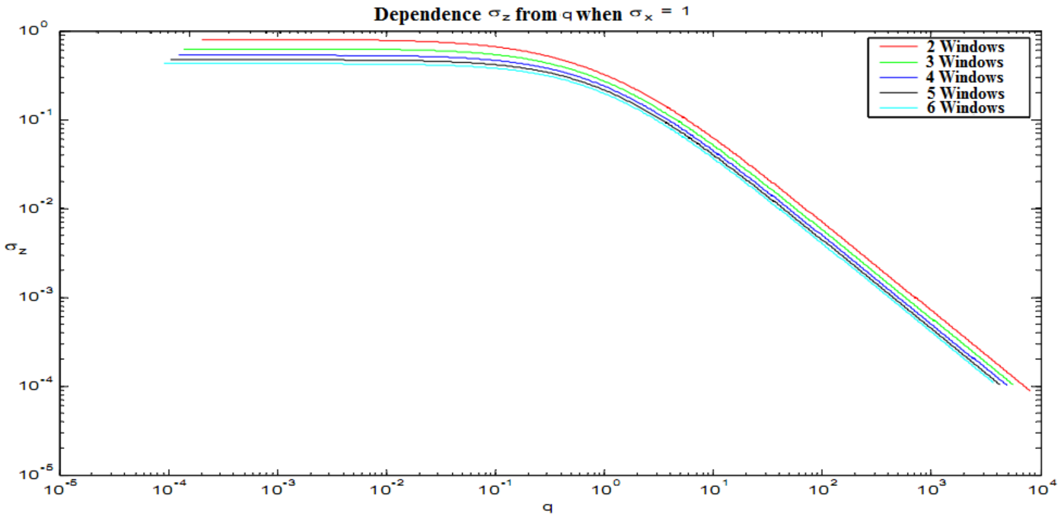

Fig. 8 – The ratio *q* to the mean square deviation σ_z of the function z=log(t+q)

A comparison of efficiency for an adaptive threshold method was performed using a one-window spectrum evaluation and a multi- window spectrum estimation to provide a signal cleaning from a noise.

The test signal in the form of two rectangular pulses was exposed to the white Gaussian noise with an amplitude of 0.2 V, so the signal-noise ratio was h = 14 dB. The noised signal was processed with the adapted threshold methods. The result of the treatment using the Henning window function for evaluating the spectrum for the adaptive threshold method gave an increase in the signal to noise ratio to h = 21 dB. The result of the treatment when used for the joint evaluation of the spectrum for the adaptive threshold method of the three window functions: the Henning window function, the sinus window function and the Kaiser-Bessel window function (β = 1) gave an increase of the signal-to-noise ratio to h = 28 dB [16].

To evaluate the effectiveness of the median filter by modeling, LabView created a virtual device that generates test signals in the form of rectangular pulses, simulates the transmission of the channel by overlaying white noise, performs signal processing and then analyses them after all. The signal processing unit is a fast median filter, which can contain virtual software or hardware implementation. The Fig. 9 shows a diagram of a virtual device that generates and analyzes a pulse in the presence of interferences with the expected peak value exceeding 100% of the expected pulse amplitude, as in Fig. 10

The signal generated by this virtual device has the following pulse parameters: the amplitude is 5.0 V, the delay is 64, the duration is 32.

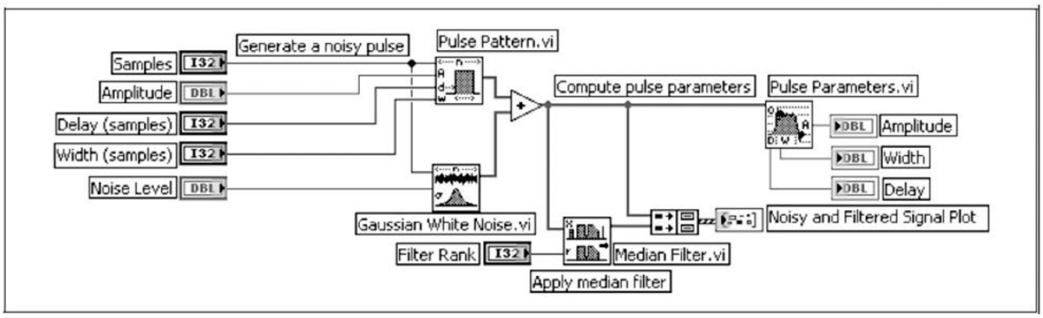

Fig. 9 – The scheme of the signal processing modeling with the use of a fast median filter

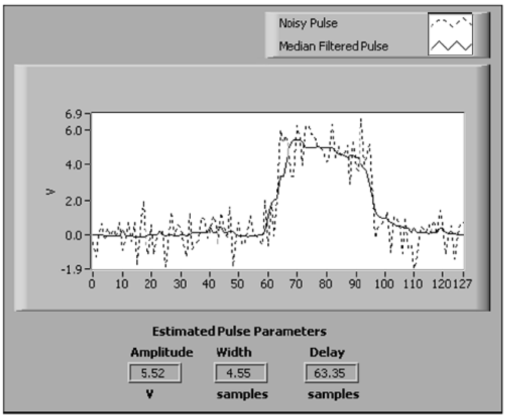

Fig. 10 – A noised rectangular pulse signal and a filtered one with the use of a fast median filter

The results of the experimental verification using the CAN simulation program using the developed methods in the form of Errors I and II, depending on the signal-to-noise ratio for the method of rapid median filtering, are shown in Fig. 11, for the method of determining the coefficients of expansion are shown in Fig. 12 and for the method of multi-window estimation of the spectrum are shown in Fig. 13.

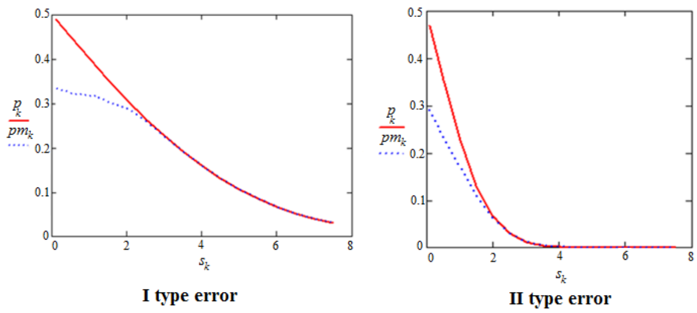

Fig. 11 – The probability of the 1st and 2nd type errors for the method of fast median filtering depending on the ratio of *s* signal/noise: *p* - the probability of errors without a median filter; *pm* is the probability of errors using the median filter

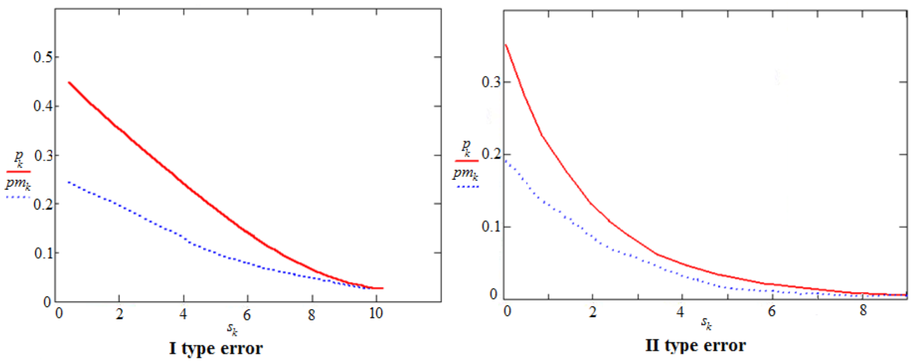

Fig. 12 – The probability of the 1st and 2nd type errors for the method of fast median filtering depending on the ratio of *s* signal/noise: *p* - the probability of errors without a median filter; *pm* is the probability of errors using the median filter

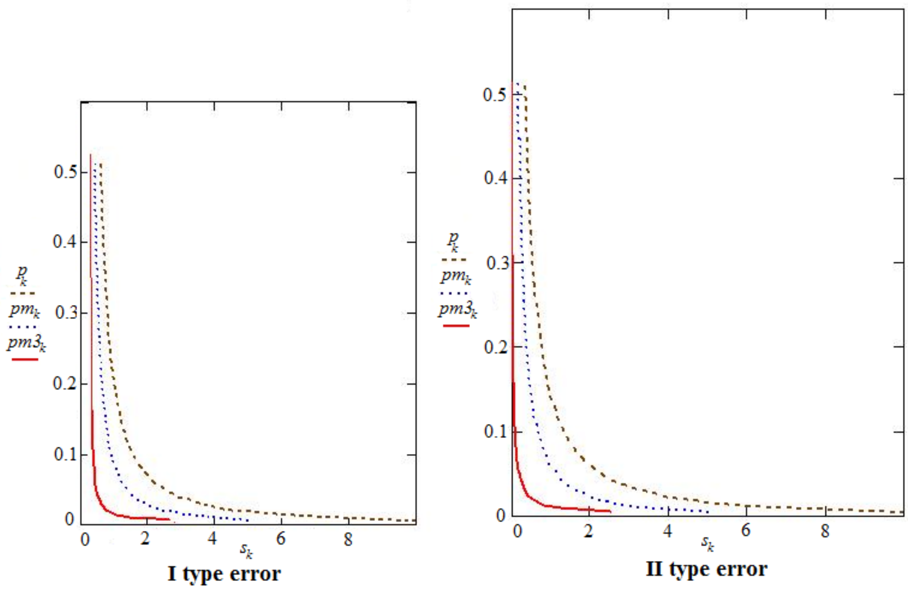

Fig. 13 – The probability of errors of the 1st and 2nd generations for the method of multi-window estimation of the decomposition spectrum depending on the ratio of s signal/noise: p - the probability of errors without using the method; *pm* is the probability of errors using a threshold method with a one-window estimation of the spectrum; *pm3* - probability of error using the probability error method using a threshold method with a three-window spectrum estimation

The performance and the processors quantities ratios were assessed in case of the diagonal data processing like a method of the fast wavelet transformation. This ratio is showed on the Fig. 14.

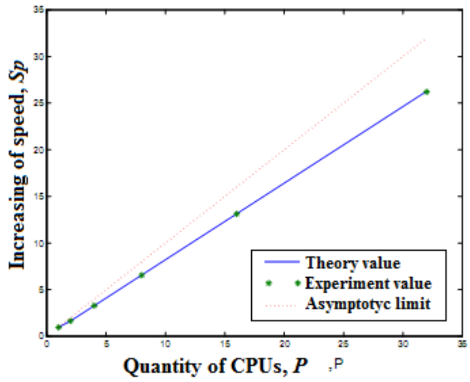

Fig. 14 – Comparison of the dependence of increasing the speed of the number of processors for various methods of fast wavelet transformation median filter impulse median filter

The theoretical limit of a performance increasing is a linage increasing with a constant ratio $S/P = 1$. The comparison was performed with $M = 512$, $N = 128$, $D = 12$. In case of Intel i5 the average parameters are t_d = 0.2 (mks), t_l = 200 (mks), t_f = 6 (ns). The fast wavelet transformation with the diagonal data processing $C_{MFWT}/T^{0}_{MFWT}(N)$ does not depend on *P*, so this ratio can be viewed like a constant value. When $P \to \infty$ this expression does not influence the increasing of performance on $S^{P}_{MFWT}(N)$, so the performance increasing graphic comes close to the $P/(1+P)$ curve. When $N \to \infty$ the performance increasing value can be reduced to the $1/(1+ \mathrm{O(P)})$, where :$C_{MFWT}/T^{0}_{MFWT}(N) \approx O(P)$.

Conclusions

In the article is developed the method of the fast median filtration which in contrast to currant existing methods operates with the finite quantities of the data by means of splitting of the data vector onto components which leads to log2N time consumption shrinking. The method of determining the decomposition coefficients, which uses the replacement of the biorthogonal at the wavelet decomposition with the approximation amount using a series of quasipositive delta sequences, and also for the elimination of the Gibbs effect and interferences in the processing of signals, which makes it possible to increase the efficiency of their processing and increase the signal/noise ratio from 14 up to 23 dB. The method of parallel fast wavelet transformation is improved, which, unlike existing ones, uses the partition of the data vector into blocks for processing data using a local wavelet transform in the diagonal sequence, which allows minimizing the number of requests to the data vector and reducing the time required for rapid wavelet transform to be 25-35 %. The method of window evaluation of the spectrum of the signal is improved, which unlike the existing method uses a multi-window averaged estimation of the logarithmic spectrum of the signal, which allows obtaining a precise 10-50 % estimation of the spectrum of the signal and increase the efficiency of the use of threshold methods of signal processing.

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