Analyze the Efficiency of Blind Signal Extraction Algorithms in a Background of Impulse Noise Based on the Maximization of the Absolute Value of the Kurtosis.

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Abstract:

In this paper, analyzed the efficiency of algorithms of blind pulse signal extraction in a background of impulse noise based on the maximization of the absolute value of the kurtosis. Synthesized blind separation algorithms with fixed point and it is considered in combination with the gradient. The convergence of these algorithms is shown for zero and nonzero initial conditions. A lemma and two theorems are formulated Allowing to prove the blind allocation of the signal and to determine the number of decisions with regard to signal extraction. Modeling established that the fixed point algorithm based on the maximization of the absolute kurtosis value is more efficient and allows to separate the pulse desire signal with the signal-to-noise ratio of 30 dB more than the gradient algorithm with the same objective function. Computer modeling of AbsoKurt and AbsoKurtFP algorithms Carried out in Simulink using Matlab programing.

Key words: Fixed-point algorithm, Hesse matrix, Blind signal separation, Convergence rate, Kurtosis.

الخلاصة

في هذا البحث، تم تحليل كفاءة خوارزميات استخلاص إشارة النبض العمياء في خلفية ضوضاء النبض على أساس تعظيم القيمة المطلقة للتفرطح .توليف خوارزميات الاستخلاص العمياء مع نقطة ثابتة وتدرس في تركيبة مع التدرج .ويظهر التقارب بين هذه الخوارزميات للشروط الاولية الصفرية وغير الصفرية. يتم صياغة برهان ليمي ومبرهنتين للسماح باثبات تخصيص أعمى للإشارة وتحديد عدد القرارات فيما يتعلق باستخلاص الإشارة .وقد أثبتت النمذجة أن خوارزمية النقطة الثابتة القائمة على تعظيم قيمة التفرطح المطلق هي أكثر كفاءة وتسمح بفصل إشارة النبضية المطلوبه بحيث ان نسبة الإشارة إلى الضوضاء تبلغ30 ديسيبل أكثر من خوارزمية التدرج التي لها نفس الوظيفة والهدف. ان المحاكاة لخوارزمية تعظيم قيمة التفرطح المطلق و خوارزمية النقطه الثابتة القائمة على تعظيم قيمة التفرطح المطلق تم تنفيذها باساخدام برنامج ماتلاب.

الكلمات المفتاحية: خوارزمية النقطة الثابتة، مصفوفة هيس، فصل الإشارة ألعمياء، معدل التقارب، التفرطح.

Introduction

The problem of blind signal extraction is solved as an estimation of one or several interesting signals with special statistical properties, and the remaining (noise) signals should be ignored. This problem can be formulated differently, as the identification of the corresponding vector hj of the mixing matrix H, and their inversions wj, which are the rows of the separating matrix W, assuming only the statistical independence of the primary sources and the linear independence of the columns of the matrix H (Cichocki and S.Amari, 2002;Yong Xiang *et.al.*,2015). Blind signal Extraction has a wide range of applications for the separation of digital streams on the background of impulse noise in multi-antenna systems such as (MIMO)**(** Rémi *et.al.*,2010**;** Sriyananda *et.al.*,2016**).**

As a rule, blind allocation of signals occurs through a multistage artificial neural network (ANN). The number of cascades is determined by the number of useful signals allocated. If a mixture of one signal and one interference acts in the channel, then it is sufficient to apply a single-stage neural network (Fig. 1).

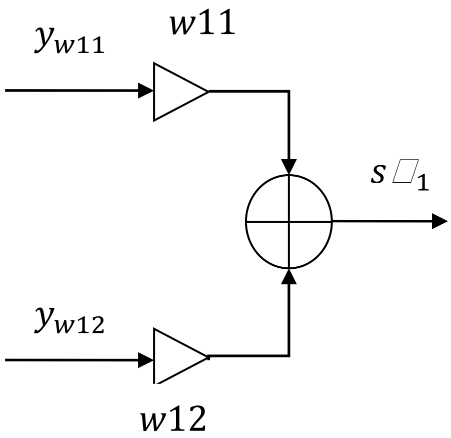

Fig. 1. Single-stage neural network

Suppose that at the inputs of the neural network are mixing the signal and the noise y_{w11} and y_{w12}, received by the receiving, detecting device (antennas). Since This procedure must be performed before the Signal extraction in order of the mixing matrix H to be orthogonal. Then the estimate of $s□_1$ at the output of the ANN (see Figure 1) can be expressed as:

$$s\hat{}_1 = W_1^T y_{w1} = \sum_{i=1}^{2} w_{1i} y_{w1i} \qquad (1)$$

If we assume that the signal and the noise are mutually independent and have specific statistical properties (for example, non-Gaussian), in this case to separate the desired signal $\boldsymbol{\hat{s}_1}$ Kurtosis maximization criterion is used *(*Cichocki and Amari, 2002).

We can observe that gradient algorithm of the Absokurt type (based on the maximization of the absolute kurtosis) (Hyvarinen ***et.al.,*** 2001), KuicNet (based on the maximization of the normalized Kurtosis) (Douglas ***et.al.,***1998) and Fixed Point (FP) - FastICA type algorithm (based on the maximization of the normal kurtosis) (Hyvarinen ***et.al.,***2001). Modeling these algorithms performed in order to separate:

1) Gauss-Markov process with a certain bandwidth in the background of non-Gaussian noise (continuous narrow-band, continuous broadband and pulse broadband),
2) Pulse processing with a Poisson distribution of different intensities on the background of wideband Gaussian noise.

The simulation results revealed the following weaknesses in the algorithms used. In the FastICA algorithm, the initial conditions and small value kurtosis of the extracted process greatly slow down convergence, and if the process has a negative kurtosis, then FastICA generally ceases to function. In turn, the KuicNet algorithm requires a priori data on the kurtosis sign.

The best in practical terms are based on the maximization algorithm absolute kurtosis (AbsoKurt), not only invariant to the sign, but also to the absolute value of the kurtosis. This algorithm can be used even under more difficult conditions, for example, when a pulse signal is allocated on the background of impulse noise. The algorithm is the following (Hyvarinen ***et.al.,***2001):

$$\boldsymbol{w_1^+(n+1) = w_1(n) + \mu sign\{k_4(\hat{s}_1(n)\}\hat{s}_1^3(n) y_{w1}(n)},$$

$$\boldsymbol{w_1}(\boldsymbol{n}+\mathbf{1}) = \frac{\boldsymbol{w_1^+}(\boldsymbol{n}+\mathbf{1})}{\|\boldsymbol{w_1^+}(\boldsymbol{n}+\mathbf{1})\|}, \qquad (\mathbf{2})$$

Where $\boldsymbol{k_4}(\boldsymbol{\hat{s}_1}(\boldsymbol{n})) -$ Kurtosis of the allocated signal.

However, a disadvantage of gradient algorithms is the need to select the coefficient μ, which affects the rate of convergence.

1. Statement of the Problem

It is necessary to synthesize the FP algorithm based on the maximization of the absolute value of the kurtosis, which has all the advantages of the AbsoKurt algorithm (call it AbsoKurtFP), but does not use the μ coefficient.

For this we consider the functional:

$$J(w_1) = \frac{1}{4}\ |\ k_4(\hat{s}_1)|_{\|w\|^2=1} \qquad (3)$$

Taking into account the functional (3), we find the derivative of the Lagrange function with respect to w1:

$$\frac{\partial \mathrm{L}(\mathrm{w}_1, l)}{\partial \mathrm{w}_1} = \frac{1}{4}\frac{\partial|\ k_4(\hat{s}_1)|}{\partial \mathrm{w}_1} - 2l\mathrm{w}_1 = \frac{1}{4}\frac{\partial|E\{(w_1^T y_{w1})^4\} - 3\|\mathrm{w}_1\|^4|}{\partial \mathrm{w}_1} - 2l\mathrm{w}_1\bigg|_{l=\frac{\boldsymbol{k_4}(\hat{s}_1)}{2}}$$

$$= sign\{\ k_4(\hat{s}_1)\}\left(E\{\hat{s}_1^{\mathbf{3}}\ \ y_{w1}\} - \left(K_4^{S_1} + 3\|\mathrm{w}_1\|^2\right)\mathrm{w}_1\right). \qquad (4)$$

Where $E\{\ldots\} -$ Averaging operator; $sign\{\ldots\} -$ Sign function; $l -$ Lagrange multiplier.

Let the mixing matrix H after orthogonalization have the following form:

$$H = \begin{bmatrix} \sqrt{1-k^2} & -k \\ k & \sqrt{1-k^2} \end{bmatrix} \qquad (5)$$

Where k and $\sqrt{1-k^2}$ $-$ The standard deviation of random processes in mixing channels (k < 1).

Then from (4) for the positive Lagrange multiplier $l^* = {k_4^{s_1}}/{2}$ There are two stationary points:

$$w_1^* = \begin{pmatrix} \sqrt{1-k^2} \\ k \end{pmatrix}, w_1^* = \begin{pmatrix} -\sqrt{1-k^2} \\ -k \end{pmatrix}. \qquad (6)$$

Both stationary points are saddle points, since the Hessian (the determinant of the Hesse matrix) is negative *(* Aramanovich, 1965*)*, and they are global maxima, since Satisfy the Kuhn–Tucker conditions (Roberto *et.al.*,2012):

$$\frac{\partial \mathrm{L}(\mathrm{w}_1, l^*)}{\mathrm{w}_1}\bigg|_{w_1^*} = 0. \qquad (7)$$

$$l^*\frac{\partial \mathrm{L}(w_1^*, l)}{\partial l} = 0. \qquad (8)$$

2. Blind signal extraction by a neural network

Thus, for the functional (3), the number of global maxima is equal to twice the number of non-Gaussian independent processes in the mixture.

We generalize these conclusions in several theorems and the lemma and proof. that it is possible to separate a pulsed process acting in the background of impulse noise, that is, when the processes in the mixture have only a non-Gaussian distribution.

Lemma. When imposing a restriction on the norm of the weighting factor $\|\mathrm{w}_1\|^2 = 1$ the dispersion of the signal at the output of the ANN is unity.

Let $y_{w1} -$ A vector of a mixture of processes at the input of a neural network, then:

$$E\{\hat{s}_i^2\} = E\{(w_1^T y_{w1})^2\} = E\{w_1^T y_{w1} y_{w1}^T w_1\} = \|\mathrm{w}_1\|^2 = 1$$

Theorem 1. Let the mixing matrix H be orthogonal, i.e. $\mathrm{HH}^{\mathrm{T}} = \mathrm{I}$, and all m signals in the mixture are independent, then all solutions w1 with respect to the maximization of the kurtosis with restriction $\|\mathrm{w}_1\|^2 = 1$ can express $\mathrm{w}_1 = \pm \mathrm{He}$, where $e -$ A vector of dimension m having only one unit element with position number i equal to the number of the allocated signal in the mixture.

Proof.

We write the Lagrange equation for the functional $k_4(\hat{s}_1)$:

$\mathrm{L}(\mathrm{w}_1, l) = \frac{1}{4}(E\{(w_1^T y_{w1})^4\} - 3\|\mathrm{w}_1\|^4) - l(\|\mathrm{w}_1\|^2 - 1)$, which derivative with respect to w is equal to:

$$\frac{\partial \mathrm{L}(\mathrm{w}_1, l)}{\partial \mathrm{w}_1} = E\{\hat{s}_i^3 \; y_{w1}\} - \left(K_4^{S_i} + 3\|\mathrm{w}_1\|^2\right)\mathrm{w}_1 = 0 \qquad (10)$$

Where $S_i -$ Allocated useful signal with kurtosis $K_4^{S_i}$.

Equating the derivative to zero, we find the vector w_1 taking into account its normalization:

$$w_1 = \pm \frac{E\{\hat{s}_i^3 \; y_{w1}\}}{K_4^{S_i} + 3}. \qquad (11)$$

Represent the vector $y_{w1} = \mathrm{Hs}$, Where s $-$ is the vector of mixed independent processes with unit variance and zero mathematical expectation, and substituting it into (11), Assuming that the estimate of $\hat{s}_i$ at the output is equal to S_i:

$$w_1 = \pm \frac{E\{s_i^3 \; y_{w1}\}}{K_4^{S_i} + 3} = \pm \frac{E\{s_i^3 Hs\}}{K_4^{S_i} + 3} = \pm \frac{HE\{s_i^3 (S_1 \dots S_i \dots S_m)^T\}}{K_4^{S_i} + 3}$$

$$= \pm \frac{HE\left\{\left(s_i^3 S_1 \dots s_i^4 \dots s_i^3 S_m\right)^T\right\}}{K_4^{S_i} + 3} = \pm \frac{H\left(0 \dots m_4^{S_i} \dots 0\right)^T}{K_4^{S_i} + 3}, \qquad (12)$$

Where $m_4^{S_i} -$ The 4th order moment of the signal S_1.

Taking into account Lemma 1, 4th order moment of the allocated signal $m_4^{S_i} = K_4^{S_i} + 3$,

Then (12) can be written:

$$w_1 = \pm H \begin{pmatrix} 0 & \dots & \underbrace{1}_{i\_position} & \dots 0 \end{pmatrix}^T, \tag{13}$$

Which was to be proved.

Theorem 1 implies that the number of solutions w with respect to maximizing kurtosis is equal to 2m, where m - Number of non-Gaussian processes in the mixture.

Theorem 2. If the mixing matrix H is orthogonal and all the signals in the mixture are independent, and the vector w_1 is the solution with respect to the maximization of the kurtosis, then the selection of the signal at the output of the neural network, taking into account the limitations $\|w_1\|^2 = 1$ will accurate within a sign.

Proof.

Using Theorem 1, we prove the statement by writing the expression for the signal at the output of the neural network:

$$\hat{s} = w_1^T y_{w1} = \pm H^T e^T H s = \pm s \begin{pmatrix} 0 & \dots & \underbrace{1}_{i\_position} & \dots 0 \end{pmatrix}^T = \pm s_i, \tag{14}$$

Where $s^T = (s_1 \;\; s_2 \dots s_{m-1} \;\; s_m \;)^T$; The one in the vector *e* standing at the position with the number i equal to the number of the signal extracted.

Therefore, if the signal and the noise are non-Gaussian, then the number of maxima increases by a factor of 2, compared with the extraction non-Gaussian process (compensation) on the background of the Gaussian.

3. Synthesis Algorithm AbsoKurtFP

Will use (as in the AbsoKurt algorithm) the function (3), which gradient, taking into account the normalization of the weighting factor, is equal to:

$$\frac{\partial J(w_1)}{\partial w_1} = \frac{1}{4}\frac{\partial |\, k_4(\hat{s}_1)|}{\partial w_1}\bigg|_{\|w_1\|^2=1} = sign\{\, k_4(\hat{s}_1)\} E\{\hat{s}_1^3 y_{w1}\}. \tag{15}$$

Then the algorithm that maximizes the absolute kurtosis can be represented as follows:

$$w_1^+(n+1) = \beta E\{\hat{s}_1^3 \;\; y_{w1}\};$$

$$\boldsymbol{w_1(n+1)} = \frac{w_1^+(n+1)}{\|w_1^+(n+1)\|}, \tag{16}$$

Where $\boldsymbol{\beta = sign\{\, k_4(\hat{s}_1)\}}$.

A block diagram illustrating the implementation of the algorithm (16) is shown in Fig. 2.

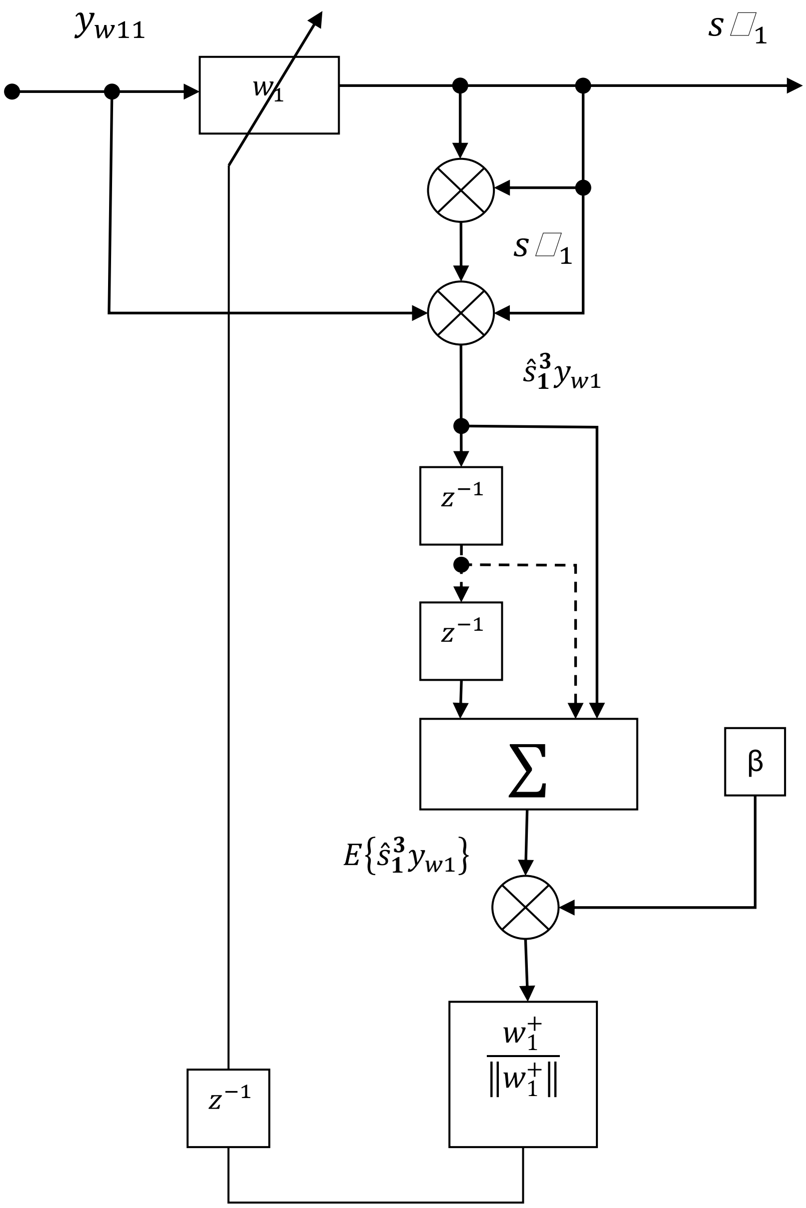

Fig. 2. Structural diagram illustrating the operation of the AbsoKurtFP algorithm

Let us prove and compare the convergence of the algorithms AbsoKurt and AbsoKurtFP for the separation of a pulse signal in the background of impulse noise and show the influence of the initial conditions on the rate of convergence.

4. Convergence of the AbsoKurtFP algorithm

We expand the gradient of the functional in a Taylor series to close of the solution w_1^*, corresponding to the maximum of the function:

$$\frac{\partial J(w_1)}{\partial w_1} = \left.\frac{\partial J(w_1)}{\partial w_1}\right|_{w_1=w_1^*} + (w_1 - w_1^*)\left.\frac{\partial^2 J(w_1)}{\partial w_1}\right|_{w_1=w_1^*} = (w_1 - w_1^*)HM(w_1^*). \quad (17)$$

Where HM − Hesse Matrix

Using the rule of finding the weight coefficients in (Hyvarinen *et.al.*, 2001), taking into account expression (16), we obtain:

$$w_1(n+1) = \frac{\frac{\partial J(w_1)}{\partial w_1}}{\left\|\frac{\partial J(w_1)}{\partial w_1}\right\|} = \frac{HM(w_1^*)(w_1(n)-w_1^*)}{\|HM(w_1^*)(w_1(n)-w_1^*)\|}. \tag{18}$$

The solution of the Lagrange equation with maximization of the functional $J(\mathrm{w}_1)$ yields two Lagrange multipliers $l_1^* = {k_4^{S_1}}/{2}, l_2^* = {k_4^{S_2}}/{2}$ And four values of the vector
$w_1^* = \pm\begin{pmatrix}\sqrt{1-k^2} \\ k\end{pmatrix}$, $w_1^* = \pm\left(\frac{-k}{\sqrt{1-k^2}}\right)$.

When allocating s_1 and s_2 Hesse matrices expresse:

$$HM^{S_1}(w_1^*) = K_4^{S_1}\begin{bmatrix} 2-3k^2 & 3k\sqrt{1-k^2} \\ 3k\sqrt{1-k^2} & 3k^2-1 \end{bmatrix}, \tag{19}$$

$$HM^{S_2}(w_1^*) = K_4^{S_2}\begin{bmatrix} 3k^2-1 & -3k\sqrt{1-k^2} \\ -3k\sqrt{1-k^2} & 2-3k^2 \end{bmatrix}. \tag{20}$$

Let the initial conditions - zero, then:

$$w_1(1)\frac{HM(w_1^*)(-w_1^*)}{\|HM(w_1^*)(-w_1^*)\|} = \frac{2K_4^{S_i}}{2K_4^{S_i}}(-w_1^*) = (-w_1^*). \tag{21}$$

The vector converges in one iteration to the true value accurate within a sign, which does not contradict Theorems 1 and 2.

Let us assume the initial conditions (IC) – Non-zero and $\mathrm{w}_1(0) = (0 \quad 1)^{\mathrm{T}}$. Changing of the error vector module $\Delta e(i) = 0.5|\mathrm{w}_1(i) - w_1^*|$ From iteration to iteration, found in an iterative way, is shown in Fig. 3.

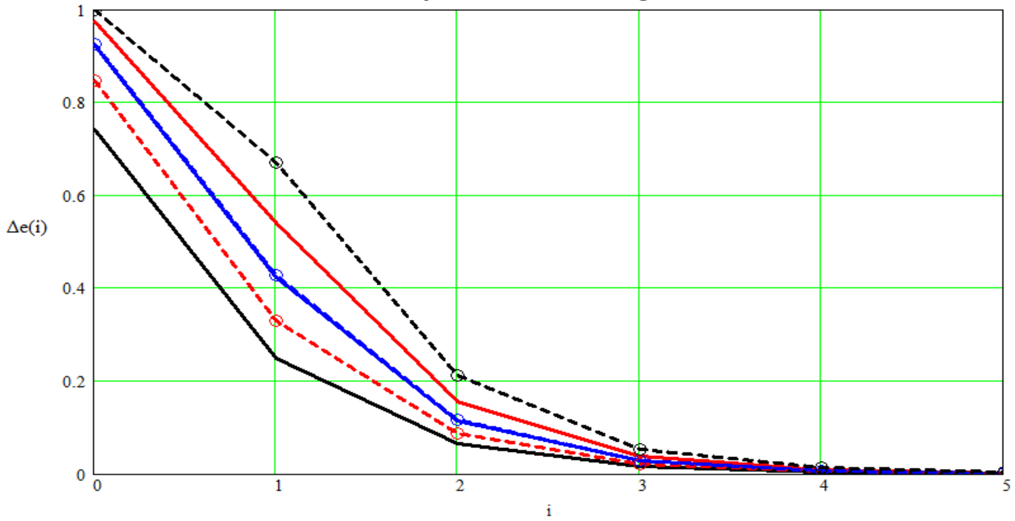

Fig. 3. The dependence of the error vector module at the allocation algorithm AbsoKurtFP processes s_1 (continuous) and s_1 (discontinuous with circles) from the iteration number at $K = 0.9$ (red), $k = 0.7$ (blue), $k = 0.1$ (black) with (IC) $(0, 1)$

Convergence is accomplished in 5 iterations and is not significantly dependent on other parameters$\left(K_4^{S_i}, k, s_i\right)$. At the same time, a slight difference of the curves due to the different on the location on the circle value of the vector w_1^* (for various signals), and its nearness to the initial conditions.

5. Convergence of the Algorithm AbsoKurt

We write the vector of weight coefficients taking into account (16) and (17):

$$w_1^+(n+1) = \mathrm{w}_1(n) + \mu HM(w_1^*)(\mathrm{w}_1(n) - w_1^*) = \left(I + \mu HM(w_1^*)\right)\mathrm{w}_1(n) - 2\mu K_4^{S_i} w_1^*; \tag{22}$$

$$w_1(n+1) = \frac{\left(I+\mu HM(w_1^*)\right)\mathrm{w}_1(n) - 2\mu K_4^{S_i} w_1^*}{\left\|\left(I+\mu HM(w_1^*)\right)\mathrm{w}_1(n) - 2\mu K_4^{S_i} w_1^*\right\|},$$

Where $I -$ is the identity matrix.

Under zero initial conditions, the convergence to the optimal solution accurate within a sign occurs in one step:

$$\mathrm{w}_1(1) = \frac{-2\mu K_4^{S_i} w_1^*}{\left\|-2\mu K_4^{S_i} w_1^*\right\|} = -w_1^*. \tag{23}$$

Under other initial conditions, for example $\mathrm{w}_1(0) = (0 \quad 1)^{\mathrm{T}}$, iteratively represent the dependence of the modulus of the error vector at the iteration number (Fig.4).When constructing the curves, the choice of the parameter μ = 0.01 implemented at random, Since With the chosen mathematical model, any values of μ do not lead to divergence of the algorithm.

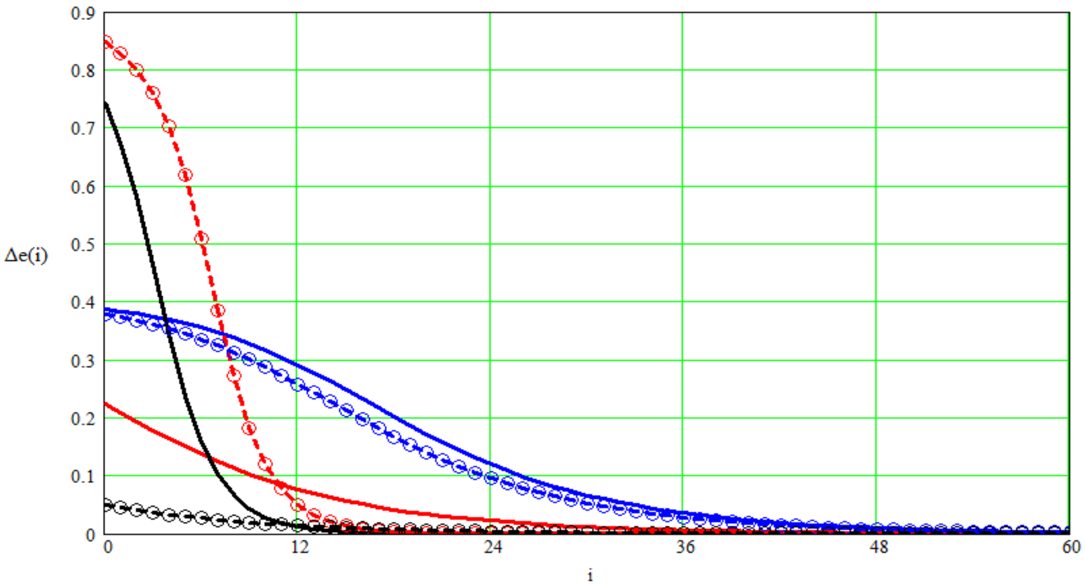

Fig. 4. The dependence of the error vector module at the allocation algorithm AbsoKurtFP processes s_1 (continuous) and s_1 (discontinuous with circles) from the iteration number at $K = 0.9$ (red), $k = 0.7$ (blue), $k = 0.1$ (black); kurtosis are equal to 10; $\mu = 0.01$ with (IC) $(0, 1)$

Let us explain the convergence in Fig. 5. When allocating the process s_1 parameter $k = 0.9$ corresponds to the location of the solution with respect to the vector w_1 is near to the initial conditions, so the error vector at zero iteration is minimal, at the same time, for s_2 parameter $k = 0.9$ is spaced by a large distance, which leads to a large initial error. However, the rate of convergence for the second process is higher due to the fact that the selection is produced accurately within the sign and the solution converges to a negative value of the vector that is closer to the selected initial conditions (for the first process all Conversely). Similar conclusions can also be expressed for the value $k = 0.1$.

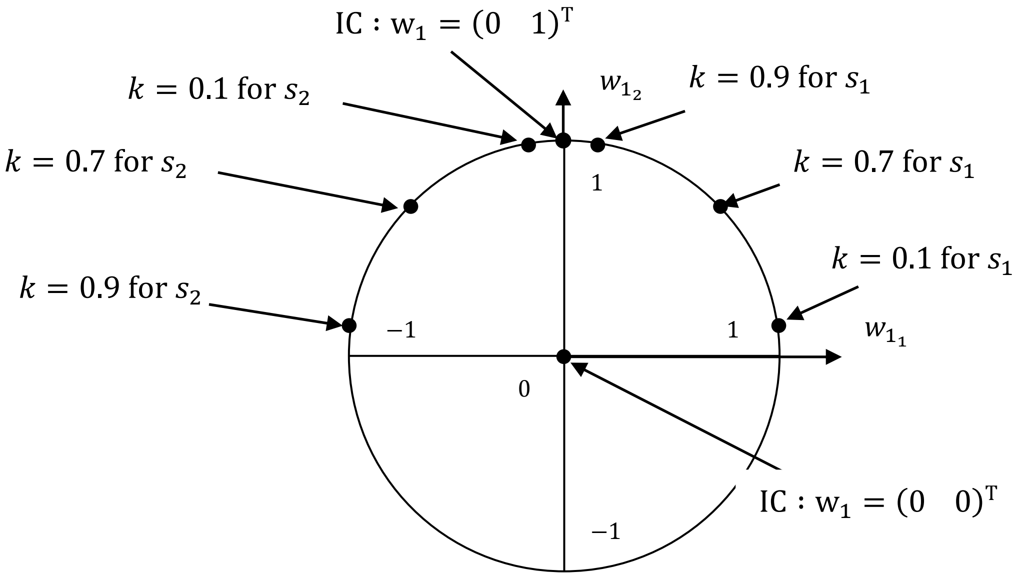

Fig. 5. Diagram of the arrangements of optimal solutions depending on the parameter k and the signal s_i

When the parameter k is close to $1/\sqrt{2}$, then if the kurtosis of the Hesse matrices is equal for both signals, they will also be equal, and the rate of convergence will be the same.

Thus, for both algorithms, the fastest convergence is established under zero initial conditions (per 1 step). For non-zero initial vectors, the rate of convergence decreases, in this case, in comparison with the algorithm AbsoKurt, the algorithm AbsoKurtFP several times faster converges to the optimal solution. The rate of convergence will depend on the location on the circle value of the optimal vector w_1^* (for different signals), and for the algorithm AbsoKurt in addition to the product the parameters $\mu K_4^{s_i}$.

6. Simulation

Computer modeling of AbsoKurt and AbsoKurtFP algorithms Carried out in Simulink (fig. 6).The implementation of the AbsoKurtFP algorithm is shown in Fig. 7, and the algorithm AbsoKurt - in fig. 8.

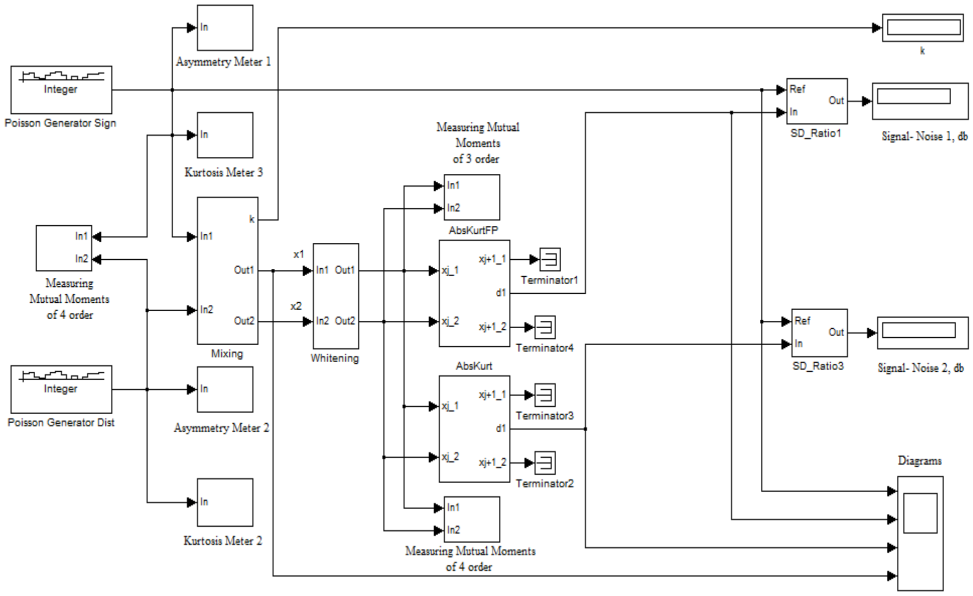

Fig. 6. Simulink of realizing the extraction of a pulse signal on the background of impulse noise.

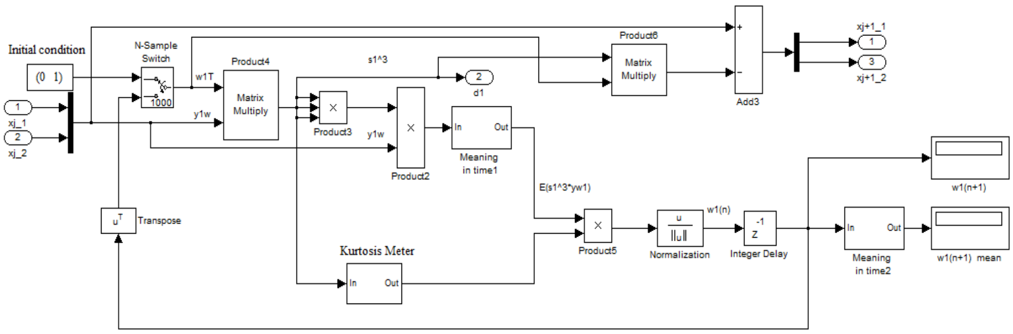

Fig. 7. The algorithm AbsoKurtFP

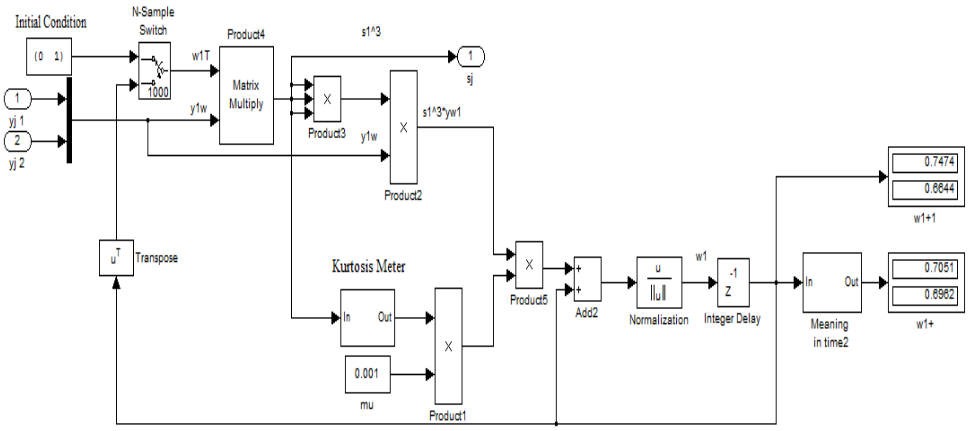

Fig. 8. The algorithm AbsoKurt

The Poisson process with different intensity parameters (different values of kurtosis, respectively) was used as the signal and the noise. Mixtures in two channels after whitening can be expressed in vector-matrix form:

$$\begin{bmatrix} y_{w1_1} \\ y_{w1_2} \end{bmatrix} = \begin{bmatrix} \sqrt{1-k^2} & -k \\ k & \sqrt{1-k^2} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \end{bmatrix}. \tag{24}$$

The values of k correspond to the signal to noise ratios at the input of the detector:

k	0.9	0.8	0.7	0.5	0.3	0.1
η_1, db	–4.1	–2.5	–1.1	0.2	1.3	2.5
η_2, db	4.1	2.5	1.1	–0.2	–1.3	–2.5

Computer modeling of the convergence process of the AbsoKurt algorithm was performed with averaging $E\{\hat{s}_1^3 y_{w1}\}$ in order to approximate the proposed model of convergence to practical results. In this case, the Hesse matrix is formed by formulas (19) and (20) Before the algorithm starts extraction of the impulse signal.

The results are shown in Fig. 9, 10 confirm the correctness the choice of mathematical models of convergence for two algorithms (formulas 18 and 22).

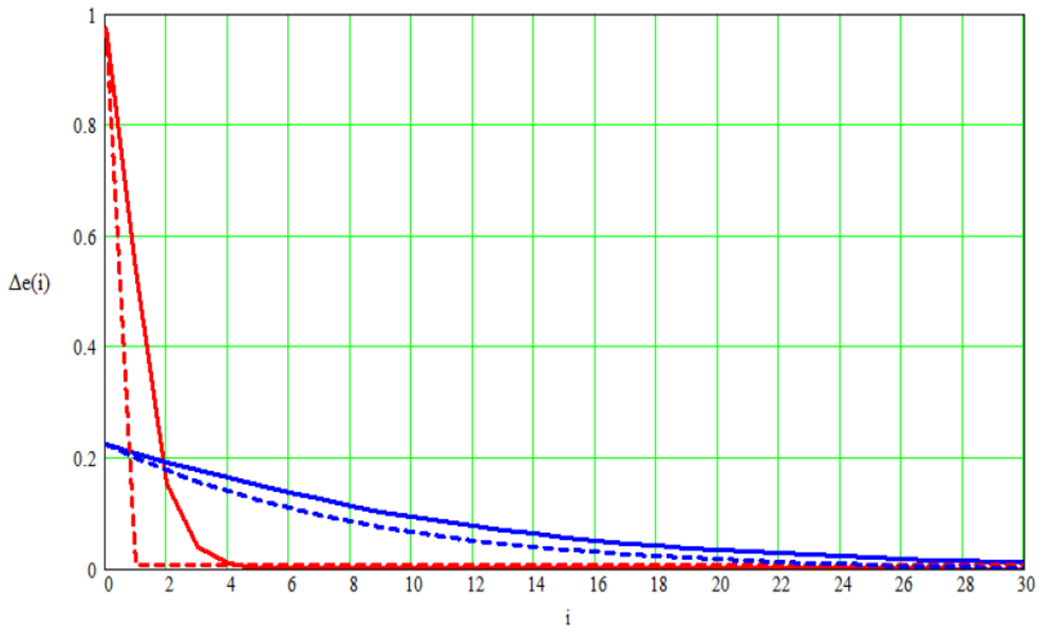

Fig. 9. Dependence of the modulus of the error vector when the signal is extraction by the algorithm AbsoKurt (continuous blue - simulation, dotted –theoretical) And AbsoKurtFP (continuous red - simulation, dotted–theoretical) from the iteration number at k = 0.9; The kurtosis of the signal is 10; The kurtosis of the noise is equal to 1; $\mu = 0.01$; The initial vector $(0, 1)$

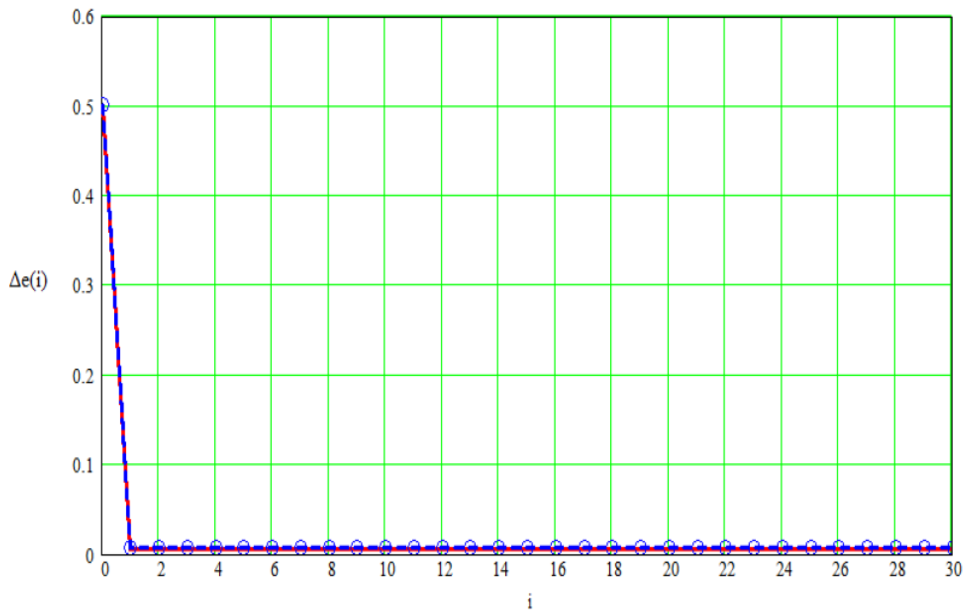

Fig. 10. The dependence of the modulus of the error vector when the signal is extraction by the algorithm AbsoKurt (continuous blue) and AbsoKurtFP (continuous red with circles) from the iteration number for $\boldsymbol{k} = \mathbf{0.9}$; The kurtosis of the signal is 10; The kurtosis of the noise is equal to 1; μ = 0.01; The initial vector $(\mathbf{0}, \mathbf{0})$.

The results of experiments of separation pulse signal on the background of impulse noise at zero initial conditions are shown in Tables 1 and 2.

Table 1 Dependences of the signal-to-noise ratio in the output of the ANN (q) at the signal-to-noise ratio in the detector by different algorithms blind extraction Poisson process (the kurtosis is 10) on the background of the Poisson process (the kurtosis is 0.1); μ = 0.01

k	0.9	0.8	0.7	0.5	0.3	0.1
$q_{AbsKurtFP}, db$	43.8	43.8	43.8	43.8	43.8	43.8
$q_{AbsKurt}, db$	13.6	13.6	13.6	13.6	13.6	13.6

Table 2 Dependences of the signal-to-noise ratio in the output of the ANN (q) at the parameter μ by using the algorithm AbsoKurt to extract the Poisson process (the kurtosis is 10) on the background of the Poisson process (kurtosis is 0.1) at k = 0.7

μ	10^{-2}	5.10^{-3}	10^{-3}	5.10^{-4}	10^{-4}	5.10^{-5}	10^{-5}
q, db	13.6	15.9	20.8	22.9	28.3	30.5	35.2

Conclusions

Analyzing the results of the simulation, we can illustrate the following.

First, the proposed mathematical models of convergence allowed us to verify that the fastest convergence of both AbsoKurt and AbsoKurtFP algorithms is observed under zero initial conditions, and also confirmed the results of the theorems formulated. The results illustrate the efficiency of both AbsoKurt and AbsoKurtFP algorithms for the separation of pulse signal on the background of impulse noise.

Secondly, the fastest converging and efficient algorithm is the AbsoKurtFP algorithm, Which is better than AbsoKurt with respect to the signal-to-noise ratio by 30 dB. This is explained that the replacement by the algorithm of AbsoKurt the procedure of gradient averaging at the current value of the gradient when the pulse signal is separated on the background of the impulse noise reduces the efficiency of its operation and in this case it is necessary to decrease the parameter μ, which leads to a slowing down of convergence.

These algorithms are applicable for the separation of digital streams on the background of impulse noise in multi-antenna systems such as (MIMO), widely used in cellular networks (standard LTE) and wireless (such as Wi-Fi) communications.

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