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Locally-adaptive Myriad Filtration of One-dimensional Complex Signal

Nataliya Tulyakova[1*], Tatyana Neycheva[2], Oleksandr Trofymchuk[3], Oleksandr Stryzhak[3]

[1]*Institute of Applied Physics*
The National Academy of Sciences of Ukraine
58 Petropavlivska Str., 40000 Sumy, Ukraine
E-mail: nataliyatulyakova@gmail.com

[2]*Department of Analysis and Processing of Biomedical Signals and Data*
Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences
105 Acad. Georgi Bonchev Str., 1113 Sofia, Bulgaria
E-mail: tatiana@biomed.bas.bg

[3]*Institute of Telecommunications and Global Information Space*
The National Academy of Sciences of Ukraine
Chokolivskiy Bulv., 186 Kyiv, Ukraine
E-mails: itelua@kv.ukrtel.net, sae953@gmail.com

[*]*Corresponding author*

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Abstract: *Locally-adaptive algorithms of myriad filtering are proposed with adaptation of a sample myriad linearity parameter K, depending upon local estimates of a signal, and with "hard" switching of sliding window length settings and a coefficient which influences on the parameter K. Statistical estimates of the filters quality are obtained using a criterion of a minimum mean-square error for a model of one-dimensional complex signal that includes different elementary segments under conditions of additive Gaussian noise with zero mean and different variances and possible spikes presence. Improvement of integral and local performance indicators is shown in comparison to the highly effective non-linear locally-adaptive algorithms for the considered test signal. Having a complex signal of high efficiency, one of the proposed algorithms provides nearly optimal noise suppression at the segments of linear change of a signal; other algorithm provides higher quality of step edge preservation and the best noise suppression on a const signal. Better efficiency in cases of low and high noise levels is achieved by preliminary noise level estimation through comparison of locally-adaptive parameter and thresholds. It is shown that, in order to ensure better spikes removal, it is expedient to pre-process the signal by robust myriad filter with small window length. The considered adaptive nonlinear filters have possibility to be implemented in a real time mode.*

Keywords: *Locally-adaptive myriad filtering, One-dimensional complex signals, Minimum mean square error criterion, Statistical estimates of filter efficiency.*

Introduction

In many practical situations enhancement of digital signal processing quality is more desirable in complex conditions of noise variance increasing and presence of mixed additive and impulse noises. There are many signals, biomedical, in particular, with different and a priori unknown behavior of an information component. To provide high effectiveness of filtration for such signals in complex noisy conditions and stable operation of processing algorithm when the signal changing is unknown, it is necessary to use adaptive filters. If the information process contains step edges and other discontinuous transitions and possible spikes at various points of digital signal sequence, the use of adaptive nonlinear robust processing algorithms, in particular, locally-adaptive nonlinear filters is reasonable.

Locally-adaptive nonlinear stable (robust) filters are designed for the necessary balance in contradictory requirements to algorithms of filtration which are to ensure a high degree of noise suppression, to remove impulsive spikes and to minimize the dynamic errors introduced by filtration [4, 17, 18]. Most nonlinear filters, as well as the linear ones, are model-oriented, i.e. they are optimal or highly efficient for certain models of signals and known probability density functions (PDF) of noise [4, 22]. For a nonlinear filter of high nonlinearity, the dynamic properties are usually high: it preserves step edges, piecewise functions, etc. and removes spikes. Nonlinear filter of low nonlinearity better suppresses noise on signal segments approximated by linear and polynomial functions and introduces small errors while processing polynomial curves [4]. Adaptive use of the advantages of nonlinear filters depending on the type of processing signal is important for filtering processes which have different elementary segments. To handle such processes, particularly in electrocardiograms, adaptive approximating filters are applied that change the processing algorithm parameters depending on the high-frequency or low-frequency nature of the signal [5, 6, 8-12]. However, as most linear filters, they are not suitable for processing abrupt changes in the signal like step edge and other discontinuities and incapable to remove spikes [4, 22].

The basic idea of locally-adaptive non-linear filtering is to estimate the local signal-to-noise situation by so-called “local activity indicators” (LAI) calculated for the i-th position of a sliding window and to process the vicinity of the current i-th input signal sample with a more suitable filter. There are nonlinear locally-adaptive filters with “soft” and “hard” switching of parameters. Adaptive filters with “soft” switching are filters which adaptable parameters can take any possible values. In such algorithms, LAIs are usually a part of an analytic expression describing the output signal. Adaptive filters with “hard” switching are adaptive nonlinear filters which parameters take fixed values: for example, change of the window length, type and parameters of the nonlinear filter for local signal processing [17, 18].

For the design of locally-adaptive myriad filters (LAMFs), it is a good reason to use “soft” and “hard” switching simultaneously [23-26, 28-30]. For “soft” switching, an adaptive formula for a signal-dependent change of a sample myriad linearity parameter K [3, 14, 20, 23] is proposed. For “hard” switching, sliding window length and the tuning coefficient influencing on K are chosen from number of relevant values. The choice is based on the current LAI estimates of local signal-to-noise situation

Thus, locally-adaptive myriad filtering makes it possible to achieve a high degree of Gaussian noise suppression by adjusting the parameter K to a linear mode and by increasing the window length. Minimum errors while processing abrupt changes of the signal are achieved by setting the high nonlinearity properties of the myriad filter because it has small values of K and window length. Due to LAIs which determine the local signal-to-noise situation for adjusting the filter type and its parameters [17, 18, 23], it is possible to obtain a stable operation of the processing algorithm for different and a priori unknown signal behavior and non-stationary noise variance that is important for many practical applications. Parallel calculations allow implementation of the adaptive myriad filtering in a real-time mode.

The goal of the current study is to investigate the locally-adaptive myriad filtration on one-dimensional complex test signal which includes different elementary segments standard for a variety of practical situations under different noisy conditions. Comparison between the different LAMFs, applied on the simulated test signals could help the choice of more relevant adaptive filtering algorithm.

Methods

Locally-adaptive myriad filters

A sample myriad is an optimal *M*-estimate of location of the Cauchy PDF [7, 13-16], which is defined as:

$$\hat{\beta} \triangleq myriad\{x_1,\ x_2, ..., x_i, x_N; K\ \} = \arg\min_{\beta} \sum_{i=1}^{N} \log\ [K^2 + (x_i - \beta)^2]\ , \quad (1)$$

where x_i is the data sample within the sliding window; N is sliding window length; K is a linearity parameter of a myriad estimator, $K > 0$.

The parameter K controls the performance of the myriad filter. Small values of K set high nonlinear performance of the myriad filter at which it has high dynamic and robust properties (can successfully preserve abrupt changes in a signal and remove impulsive spikes) and for large K, myriad filtration tends to linear averaging [2, 7, 13, 14, 16, 19].

Three LAMFs are proposed in this work. LAIs are calculated and compared with the given thresholds for each *i*-th position of the sliding window, where *i* is index of central element in the window. As a result, one of the adaptive myriad filters (AMF) with parameters more suitable for processing the vicinity of *i*-th current sample is switched.

The output signal of the AMF can be described as follows:

$$y_i^{AMF} = myriad\{x_1, x_2, ..., x_i, ..., x_N, K_{ai}\}, \quad (2)$$

where K_{ai} is the adaptable linearity parameter K calculated for the *i*-th sliding window.

The adaptation of the linearity parameter K_{ai} of AMF is carried out by the formulas:

$$K_{ai} = bK_i \text{ or } K_{ai} = bK_i^f\ ,\ K_i = \max_{k \neq j} |\, x_k - x_j \,||_{k,j=1}^{N}, \quad (3)$$

where b is a fixed coefficient; K_i is local estimate of signal scale; K_i^f is pre-filtered value of K_i; N is sliding window length.

Locally-adaptive myriad filter based on Z-parameters

One of the LAMFs switches the output signals between three AMF. One AMF has high dynamic properties due to high nonlinearity as a result of small values of K and small window length. This is a "detail preserving" component of LAMF. The other AMF is "noise suppressive" component of LAMF which has properties close to linear filter due to increase of parameter K and window length. An intermediate component of LAMF is AMF with medium properties. This LAMF uses LAIs referred to as Z-parameters [17, 18], which are defined as:

$$Z_i = \sum_{j=-(N-1)/2}^{(N-1)/2} \left(y_{i-j}^f - x_{i-j} \right) / \sum_{j=-(N-1)/2}^{(N-1)/2} |\, y_{i-j}^f - x_{i-j} \,|,$$

$$Q_{Z_i} = Z_i^{(p)} - Z_i^{(q)},\ p - q \approx (N-1)/2\,,\ p + q \approx N + 1, \quad (4)$$

where y_{i-j}^{f}, x_{i-j} are pre-filtered and input samples of a signal for calculation of the Z-parameter, respectively; Q_{Z_i} is quasi-range of a Z-parameter, where $Z_i^{(q)}$, $Z_i^{(p)}$ are q-th and p-th order statistics of the sorted set $\left(Z^{(1)} \le Z^{(2)} \le \ldots \le Z^{(N)}\right)$; N is sliding window length of a preliminary filter for calculation of a Z-parameter which is usually used as an intermediate component of this locally-adaptive filters [17, 18, 26].

The output of the considered three-component LAMF denoted as AMZ is defined as:

$$y_i^{AMZ} = \begin{cases} y_i^{AMF\,(N_3, b_3)}, if\ Z_i^f < Z_1^t; \\ y_i^{AMF\,(N_2, b_2)}, if\ (Z_i^f \ge Z_1^t) \wedge (Z_i^f < Z_2^t); \\ y_i^{AMF\,(N_1, b_1)}, if\ (Z_i^f \ge Z_2^t) \vee (Q_{Z_i}^f > Z_2^t); \end{cases} \quad (5)$$

where $y_i^{AMF(N_j, b_j)}$, $j = 1, \ldots, 3$, is output of j-th AMF (Eq. 2) with the given parameters of window length N_j and tuning coefficient b_j, $N_3 > N_2 > N_1$, $b_3 > b_2 > b_1$; Z_i^f, $Q_{Z_i}^f$ are LAIs pre-filtered by a median filter; $Z_1^t \approx 0.2$, $Z_2^t \approx 0.4$ are thresholds.

Locally-adaptive myriad filter based on Hampel threshold parameters

Another proposed LAMF uses adaptive "hard" switching of the outputs between two AMF. In one case, AMF with small window length and nonlinear properties due to small coefficient b is used. In another case, AMF with large window length and the linear filtering mode set by large coefficient b is applied. LAIs used in this LAMF are similar to the threshold parameters of Hampel decision based filter [21] which are described by formulas:

$$r_i = | x_i - m_i |,\ th_i = t\, S_i^{Mad},$$

$$S_i^{Mad} = 1.4826 \text{ median}\{| x_1 - m_i |, | x_2 - m_i |, \ldots, | x_N - m_i |\}, \quad (6)$$

where x_i, m_i are the central element and the sample median (*Med*) of the input samples $\{x_j\}_{j=1}^{N}$ within a sliding window with length N; t is a fixed threshold; S_i^{Mad} is median absolute deviation (*Mad*) that is a local estimate of a signal scale, where 1.4826 is a coefficient used for Gaussian PDF [16].

The output of this two-component LAMF denoted as AMH is described as:

$$y_i^{AMH} = \begin{cases} y_i^{AMF\,(N_1, b_1)},\ if\ r_i^f \le th_i^f; \\ y_i^{AMF\,(N_2, b_2)},\ else, \end{cases} \quad (7)$$

where $y_i^{AMF(N_1, b_1)}$, $y_i^{AMF(N_2, b_2)}$ are outputs of AMF (Eq. 2) with window lengths $N_1 < N_2$ and coefficients $b_1 < b_2$; $r_i^f = \text{mean}\{r_1, r_2, ..., r_i, ..., r_{N_3}\}$, $th_i^f = \text{mean}\{th_1, th_2, ..., th_i, ..., th_{N_4}\}$ are LAIs r_i, th_i smoothed by an averaging filter with window lengths N_3, N_4, respectively.

Locally-adaptive myriad filter based on Hampel threshold parameters with noise-dependent parameters set

The parameters (window lengths and values of coefficient b) of the "detail preserving" and "noise suppression" component AMFs for LAMFs AMZ and AMH are pre-set and remain unchanged during processing. In this case the appropriate parameters are chosen for the certain noisy conditions. If the noise level changes significantly, it is preferable to use the sets of component filters which are automatically switched depending on previously estimated noise level. Such adaptive nonlinear filter can use the comparison of the LAI r_i^f or th_i^f (Eq. 6) with given thresholds in order to estimate noise dispersion. The estimation is performed at the part of slow signal alteration when $r_i^f > th_i^f$. Flag variables which define the cases of low, middle and high noise levels can be used:

$$\begin{cases} ln = "yes", mn = "no", hn = "no", if\ (r_i^f > th_i^f) \wedge (r_i^f < \eta_1), \\ mn = "yes", ln = "no", hn = "no", if\ (r_i^f > th_i^f) \wedge (\eta_1 \ge r_i^f < \eta_2), \\ hn = "yes", ln = "no", mn = "no", if\ (r_i^f > th_i^f) \wedge (r_i^f > \eta_2); \end{cases} \tag{8}$$

where *ln*, *mn*, *hn* are Boolean variables which correspond to cases of low, middle and high noise levels, respectively; η_1, η_2 are threshold values.

Therefore, the output of the LAMF with noise-dependent parameters set, denoted as AMH′, can be described as

$$y_i^{AMH'} = \begin{cases} \begin{cases} y_i^{AMF(N_{11},b_{11})}, if\ (ln = "yes") \wedge (r_i^f \le th_i^f), \\ y_i^{AMF(N_{12},b_{12})}, if\ (ln = "yes") \wedge (r_i^f > th_i^f); \end{cases} \\ \begin{cases} y_i^{AMF(N_{21},b_{21})}, if\ (mn = "yes") \wedge (r_i^f \le th_i^f), \\ y_i^{AMF(N_{22},b_{22})}, if\ (mn = "yes") \wedge (r_i^f > th_i^f); \end{cases} \\ \begin{cases} y_i^{AMF(N_{31},b_{31})}, if\ (hn = "yes") \wedge (r_i^f \le th_i^f), \\ y_i^{AMF(N_{32},b_{32})}, if\ (hn = "yes") \wedge (r_i^f > th_i^f); \end{cases} \end{cases} \tag{9}$$

where $y_i^{AMF(N_{11},b_{11})}$, $y_i^{AMF(N_{12},b_{12})}$ is set of filters applied in case of "low noise", $N_{11} < N_{12}$, $b_{11} < b_{12}$; $y_i^{AMF(N_{21},b_{21})}$, $y_i^{AMF(N_{22},b_{22})}$ are component filters applied in case of "middle noise", $N_{21} < N_{22}$, $b_{21} < b_{22}$; $y_i^{AMF(N_{31},b_{31})}$, $y_i^{AMF(N_{32},b_{32})}$ are filters applied in case of "high noise", $N_{31} < N_{32}$, $b_{31} < b_{32}$.

Signal model. Criteria of effectiveness

The signal model of one-dimensional sampled data sequence can be described as:

$$x_i = \begin{cases} s_i + n_{ai}, \text{ with probability } 1 - P_{sp}, \\ s_i + n_{ai} + n_{spi}, \text{ with probability } P_{sp}; \end{cases} \tag{10}$$

where s_i is true signal value of the *i*-th sample; n_{ai} is zero mean Gaussian additive noise with the variance σ_a^2; $n_{spi} >> 3\sigma_a^2$ is amplitude of spikes which occur with probability P_{sp}.

The one-dimensional complex test signal (Fig. 1) consists of different elementary segments such as a constant level (*x*-axis indices from 10 to 40), a step edge (*x*-axis indices 40-60), piecewise linear segments (*x*-axis indices 90-110, 190-210), linearly increasing and decreasing parts (*x*-axis indices 110-140, 160-190), a peak-like maximum (*x*-axis indices 140-160), a piecewise function consisting of a constant level and a polynomial curve (*x*-axis indices 240-260), a parabolic maximum (*x*-axis indices 265-285).

The motivations behind the complex model of one-dimensional test signal (Fig. 1) are that it has to contain:

- Segments that can be met in practice and preservation of which is important in processing of denoised signal. In this sense, step edge, piecewise linear segments, both types of extrema and other points of discontinues are important.
- Constant value segments that allow characterizing maximal noise suppression efficiency.
- Signal increasing-decreasing segments that allow analyzing noise reduction depending upon derivative. Besides, the used test signal provides an opportunity to detect filter's shortcomings, i.e. types of segments for which a given filter performs poorly.

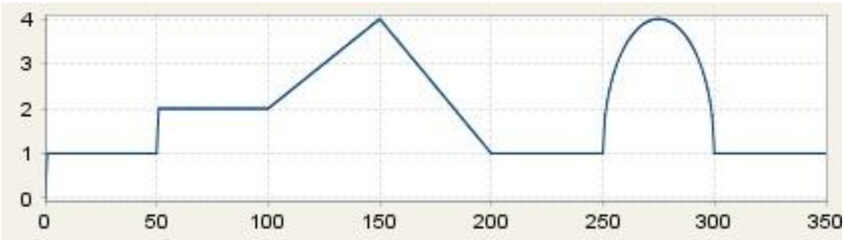


Fig. 1 A complex model of a one-dimensional test signal

To obtain statistical estimates of filtration efficiency, the criterion of minimum of mean square error (MSE) [4] is used and calculated as

$$\chi_{i_1-i_2} = \sum_{j=1}^{N_R} \left(\sum_{i=i_1}^{i_2} [y_i^f - s_i]^2 / [i_2 - i_1 + 1] \right) / N_R, \tag{11}$$

where y_i^f is output of the evaluated filter; s_i is true signal value of the i-th sample; i_1, i_2 are the indices of samples which define the signal segment for filter efficiency evaluation; N_R is number of the input signal realizations for statistical averaging.

Parameter settings for considered algorithms

Effectiveness of nonlinear robust filters is usually evaluated by numerical simulations since analytical description of their properties is too complicated. The numerical simulation algorithm consists of generating a test signal, generating and adding noise, filtering, calculating and saving filter performance indicators, repeating these steps a predetermined number of times, and calculating the average filter quality indicators [4].

Let us analyze the effectiveness of proposed LAMFs AMZ (Eq. 5) and AMH (Eq. 7), AMH′ (Eq. 9). The parameters of these algorithms are chosen by numerical simulations according to criterion of minimum MSE (Eq. 11) for the whole one-dimensional signal for medium level of Gaussian noise (σ_a^2 = 0.01) for the considered LAMFs (except for LAMF AMH′ which parameters are matched for low, middle and high noise levels).

For LAMF AMZ (Eq. 5), the parameters are as follows: N_1 = 7, b_1 = 0.3, N_2 = 13, b_2 = 0.5, N_3 = 17, b_3 = 1. AMF (Eq. 2) with parameters N = 15, b = 1 is used as a preliminary filter for calculating Z-parameters (Eq. 4). Because of the noisiness of Z-parameters [17, 18, 26], their values are processed by a median filter with window length N = 5.

For LAMF AMH (Eq. 7), the following parameters are selected: N_1 = 7, b_1 = 0.5, N_2 = 17, b_2 = 1, t = 0.6, for Med_i and Mad_i estimates the preliminary window with length N = 17 is used, LAIs r_i, th_i are smoothed by the averaging filters with windows N_3 = 21, N_4 = 15. For this LAMF, the filtering of adaptable parameter K_{ai} (Eq. 3) by AMF (Eq. 2) with parameters N = 17, b = 0.5 is used.

For modified LAMF AMH′ (Eq. 9), the parameters are as follows: N_{11} = 5, b_{11} = 0.5; N_{12} = 15, b_{12} = 1; N_{21} = 7, b_{21} = 0.5; N_{22} = 17, b_{22} = 1; N_{31} = 9, b_{31} = 0.5; N_{32} = 17, b_{32} = 1; the adaptable linearity parameter K_{ai} is processed by AMF with parameters N = 25, b = 1 in case of low and middle noise level and by AMF with parameters N = 21, b = 1 in case of high noise level; η_1 = 0.13, η_2 = 0.4 are the thresholds for noise level estimation; LAIs r_i, th_i are smoothed by averaging filters with window lengths N_3 = 21, N_4 = 15.

Note that suitable parameters of algorithms AMZ and AMH, AMH′ may differ for other signals. Also, the sign for comparison of filtered threshold parameters of Hampel filter [22] r_i^f, th_i^f in (Eq. 7), (Eq. 9) may be inverse. It is recommended to analyze the plots of LAIs r_i^f, th_i^f to choose better parameters of averaging filters for LAIs and to set thresholds.

Proposed LAMFs are compared to a nonlinear locally-adaptive filter with Z-parameters [17, 18], denoted as AZ, and LAMF based on LAI quasi-range Q_i [3] denoted as AMQ. These adaptive filters are highly effective for the given complex model of one-dimensional signal [3, 17, 18, 24, 26].

The algorithm AZ switches the outputs of median filter with small window and α-trimmed filters with middle and large window lengths [17, 18]. For algorithm AZ [17, 18], median filter with window N_1 = 5 is used as a component with high dynamic properties and α-trimmed filters with window lengths N_2 = 9, N_3 = 13 and trimmed parameters [αN_2 = 2], [αN_3 = 3], respectively, are used as intermediate and noise-suppressing components. The intermediate component of AZ is used as a preliminary filter for calculation of Z-parameters. The computational cost of algorithm AZ is not high because it uses simple operations of sorting, determination of a sample median, α-trimming and averaging. Its advantages are also high dynamic properties for low noise level [17, 18, 24, 26].

In the algorithm AMQ [3] the linearity parameter of the sample myriad is adaptively changed according to the formula:

$$K_{ai} = bQ_i^f, \quad (12)$$

where b is a fixed coefficient, Q_i^f is a filtered value of the quasi-range $Q_i = X^{(p)} - X^{(q)}$. It is calculated for each i-th sliding window as the difference between the p-th and the q-th order statistics of the sorted set of input samples $\left(X^{(1)} \le X^{(2)} \le ... \le X^{(N)}\right)$ within a sliding window with length N, $p - q = N + 1$.

For LAMF AMQ [3], the middle values of window length N = 9 and coefficient b = 0.7 are chosen. For filtering the sampled sequence of quasi-range Q_i median filter with window N = 9 is applied. This LAMF does not use “hard” switching of parameters; therefore its computational cost is less than that of LAMFs AMZ (Eq. 5) and AMH (Eq. 7), AMH′ (Eq. 9). The advantages of AMQ are the high quality of processing step edge and spikes removal [3, 24, 26]. To calculate a sample myriad for LAMFs AMQ, AMZ, AMH the algorithm of minimization of myriad cost function based on numerical Newton technique [1] is used because of its good preserving step edge and high robustness [2, 27].

For not very low probability of spikes, in order to ensure better spike removal, it is expedient to use a preliminary robust myriad filter with small window $N = 5$ (corresponding algorithms AZ, AMQ, AMZ, AMH, AMH′ are denoted as AZ_{pr}, AMQ_{pr}, AMZ_{pr}, AMH_{pr}, AMH'_{pr}). Parameter $K = 0.35$ of the preliminary myriad filter is chosen by numerical simulations.

Results and discussions

Testing and comparison of LAMFs

The efficiency of the suggested LAMFs AMZ (Eq. 5), AMH (Eq. 7), AMH′ (Eq. 9) and adaptive algorithms AZ [17, 18] and AMQ [3] used for comparison are analyzed on the basis of the statistical estimates of the MSE (Eq. 11) (Table 1), where $\chi_{i_1-i_2}$ is MSE calculated for the signal segment with indices from i_1 to i_2, χ_t is integrated MSE calculated for an entire complex one-dimensional test signal (Fig. 1). To obtain stable statistical estimates of the filter quality, in case of spikes absence, the number of realizations for averaging operation is $N_R = 200$, and in case of the spikes presence, it is $N_R = 500$.

As can be seen from the results of numerical simulations (Table 1), LAMFs AMZ (Eq. 5) and AMH (Eq. 7), AMH′ (Eq. 9) have high quality processing efficiency for all considered elementary segments of the complex test signal. They have the best integrated performance indicators for entire test signal at wide range of Gaussian noise level and in possible spikes presence.

For not very low probability of spikes presence, the integral efficiency indicators of the LAMFs AMZ (Eq. 5) and AMH (Eq. 7), AMH′ (Eq. 9) are also higher as compared to those of algorithms AZ and AMQ. The advantage, however, is less observable here in comparison with the similar cases of spikes absence (Table 1, cases 8-12). The use of a preliminary myriad filter [1] with a small window length and adjusted linearity parameter K significantly improves the robustness of corresponding nonlinear adaptive algorithms AZ_{pr}, AMQ_{pr}, AMZ_{pr}, AMH_{pr} (Table 1, cases 8-9).

Results of filtering by LAMF AMZ

Due to the adaptation of the linearity parameter K, LAMF AMZ (Eq. 5) overcomes the drawback of a standard myriad filter, which involves low efficiency of noise suppression on the linearly increasing and decreasing segments depending upon the signal scale [2, 3]. LAMF AMZ almost optimally suppresses noise for these signals (Table 1). In cases of increasing noise variance and spikes absence, this LAMF provides the best efficiency for the entire test signal (Table 1, cases 4-6). In comparison with the basic algorithm AZ, LAMF AMZ is significantly efficient on linearly changing segments of the test signal (Table 1). LAMF AMZ improves the integrated MSE of AZ in the range from middle to high levels of Gaussian noise by $\left(\chi_t^{AZ} - \chi_t^{AMZ}\right)/\chi_t^{AZ}$ = 21-28 % (Table 1, cases 4-6).

Results of filtering by LAMF AMH

LAMF AMH (Eq. 7) and its modification AMH′ (Eq. 9) effectively preserves a step edge while simultaneously suppressing noise in its vicinity and provides the best efficiency of noise suppression on the segment of a constant signal in all simulated cases (Table 1). These LAMFs also have high dynamical properties while processing piecewise linear and parabolic segments of the complex test signal, as can be seen in the cases from low to middle levels of noise (Table 1, cases 1-3, cases 8-9). In comparison with algorithm AZ LAMFs AMH and AMH′ preserve the step edge more effectively and have the highest degree of noise suppression on the segment of const signal (Table 1). According to the integral MSE, in cases of spikes absence, LAMF AMH improves efficiency of AZ by 16-22 % (Table 1, cases 4-7).

Results of filtering by LAMF AMH′

The LAMF AMH′ (Eq. 9) has better effectiveness than AMH at a connection point of a constant signal and a polynomial curve (*x*-axis indices 240-260) for all considered cases (Table 1) and also has the best local performance indicators for this elementary signal in cases of noise dispersion increase (Table 1, cases 3-7). Smaller windows N_{ij} and coefficient b_{ij} in case of low noise level and larger ones in case of high noise level have made LAMF AMH′ more dynamical (Table 1, cases 1-2) and noise suppressive (Table 1, cases 6-7).

Analysis of signals plots

The illustration of the output signals for low (Fig. 2), middle (Fig. 3) and high (Fig. 4) levels of Gaussian noise of the considered nonlinear adaptive algorithms confirms the numerical simulation results. As can be seen from the case of the not low probability of impulse noise (Fig. 5), nonlinear adaptive algorithms AZ_{pr}, AMQ_{pr}, AMZ_{pr}, AMH_{pr}, AMH'_{pr} remove spikes without significant signal distortions, which is also confirmed by the high efficiency indicators of these algorithms in spikes presence (Table 1, cases 8-12).

The behavior of the local adaptation parameters of the LAMFs AMZ (Eq. 5) and AMH (Eq. 7), AMH′ (Eq. 9) in cases of low ($\sigma_a^2 = 0.0006$) and high ($\sigma_a^2 = 0.06$) levels of noise is shown in Figs. 6-7. The change of sliding window length N is similar to the change of the coefficient b for the corresponding LAMF (not shown).

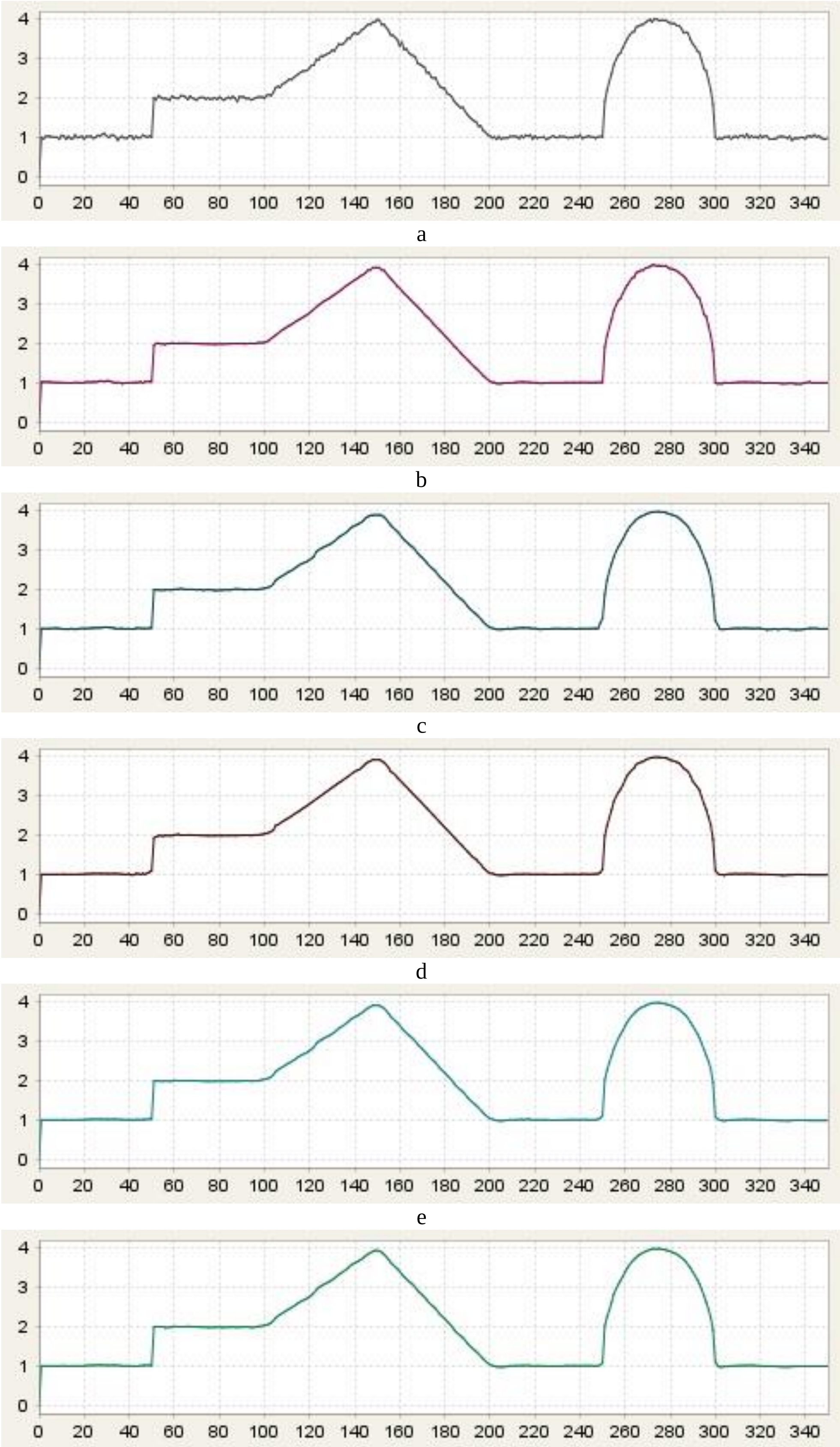
As can be seen from the plots of the local adaptation parameters (Figs. 6-7), LAMFs AMZ, AMH, AMH′ correctly switch the coefficient b (similarly window length N) to small values in the neighborhoods of a step edge (*x*-axis indices 40-60), piecewise linear functions (*x*-axis indices 90-110, 140-160, 190-210), a connection point of a constant level and a polynomial curve (*x*-axis indices 240-260). This allows adjustment of the myriad filtration to the nonlinear mode with high robustness and, therefore, preservation such transitions. Setting of a small window length in LAMFs AMZ and AMH, AMH′ also better preserves a polynomial extremum (*x*-axis indices 265-285) for low level of noise (Fig. 6). While processing this elementary segment in case of high level of noise (Fig. 7), LAMF AMZ sets a middle window length, and LAMFs AMH, AMH′ set a large window. As a result, the noise is well-smoothed. For LAMF AMZ, there are few errors in hard switching to a middle window length on the segments of the linear signal which do not decrease in processing quality essentially. For LAMFs AMH, AMH′ switching errors are less. However, in contrast with AMH and AMH′, on the linearly changing segments (*x*-axis indices 110-140, 160-190) the LAMF AMZ correctly sets large window length and a linear mode of myriad filtration, thus noise is strongly suppressed, which is an advantage of this algorithm.

Table 1. Statistical estimates of the filter efficiency according to criteria of MSE (ppm)

Filter	χ_t	χ_{10-40}	χ_{40-60}	χ_{90-110}	$\chi_{110-140}$	$\chi_{140-160}$	$\chi_{160-190}$	$\chi_{190-210}$	$\chi_{240-260}$	$\chi_{265-285}$
1) $\sigma_a^2 = 0.001$, $P_{sp} = 0.00$, $N_R = 200$										
None	998	1023	1025	978	950	986	1041	1024	958	992
AZ	**271**	127	355	251	140	**553**	152	316	**610**	351
AMQ	774	152	**160**	291	304	1237	312	323	4230	308
AMZ	446	76	999	284	**73**	906	**69**	369	1690	398
AMH	441	**65**	**262**	**243**	229	713	240	**291**	2104	**253**
AMH′	**342**	**69**	**213**	**226**	232	**425**	252	**265**	**1441**	**242**
2) $\sigma_a^2 = 0.003$, $P_{sp} = 0.00$, $N_R = 200$										
None	2994	3068	3074	2933	2849	2958	3122	3071	2873	2975
AZ	690	381	1053	608	401	979	440	750	**1599**	786
AMQ	1242	455	**498**	739	802	1766	882	837	5181	771
AMZ	794	219	1634	617	**202**	1379	**200**	797	2549	940
AMH	755	**195**	**623**	**582**	614	1100	675	**682**	2665	**651**
AMH′	**683**	**206**	**637**	**589**	676	**846**	722	**652**	**2002**	**677**
3) $\sigma_a^2 = 0.006$, $P_{sp} = 0.00$, $N_R = 200$										
None	5988	6135	6147	5866	5698	5917	6244	6142	5747	5950
AZ	1308	761	2643	1033	780	**1555**	861	1261	**3081**	1287
AMQ	1872	909	**1049**	1272	1390	2394	1634	1498	6400	1383
AMZ	**1263**	422	2548	**1023**	**387**	1847	**395**	1282	3783	1665
AMH	**1226**	**391**	**1214**	**1024**	1139	1629	1272	**1189**	3641	**1255**
AMH′	**1194**	413	**1315**	1094	1323	**1463**	1402	**1206**	**2901**	1346
4) $\sigma_a^2 = 0.01$, $P_{sp} = 0.00$, $N_R = 200$										
None	9980	10226	10245	9776	9497	9861	10406	10236	9578	9917
AZ	2204	1268	5855	1557	1270	2336	1451	1879	4930	**1923**
AMQ	2653	1515	**1875**	1900	2060	3087	2526	2262	7882	2139
AMZ	**1848**	692	3751	**1494**	**631**	2378	**655**	**1787**	5358	2585
AMH	**1857**	**652**	**2095**	1625	1810	**2301**	2027	1813	5073	2060
AMH′	**1883**	687	2260	1794	2182	**2275**	2291	1929	**4156**	2247
5) $\sigma_a^2 = 0.03$, $P_{sp} = 0.00$, $N_R = 200$										
None	29939	30677	30735	29329	28492	29583	31218	30708	28734	29752
AZ	6438	3752	20798	3993	3520	5357	4072	4503	14350	**4613**
AMQ	6376	4546	**8546**	4774	5034	6144	6254	5546	13889	5578
AMZ	**4647**	2018	12969	**3087**	**1837**	**5215**	**1973**	**3735**	11990	5633
AMH	**5030**	**1956**	**8955**	4027	4763	6668	5638	4809	**11186**	5799
AMH′	5060	**1931**	9683	4096	4926	6360	5251	4470	**10882**	5574
6) $\sigma_a^2 = 0.06$, $P_{sp} = 0.00$, $N_R = 200$										
None	59878	61354	61470	58658	56985	59167	62436	61416	57468	59503
AZ	11328	7477	31811	7445	6820	8953	8007	8250	24747	**8499**
AMQ	11898	9092	**21890**	9007	9289	10399	11173	10159	22049	10458
AMZ	**9059**	3989	36379	**5086**	**3654**	**8218**	**3903**	**6034**	20585	8533
AMH	9342	3906	24629	5931	7120	11165	10626	8337	**18808**	9773
AMH′	**9071**	**3728**	25395	5789	6566	10618	9496	7766	**18607**	9190
7) $\sigma_a^2 = 0.1$, $P_{sp} = 0.00$, $N_R = 200$										
None	99797	102257	102450	97763	94975	98611	104060	102360	95780	99172
AZ	17165	12401	42047	12080	11316	13809	12971	13585	34913	13672
AMQ	18834	15153	**35300**	14635	14920	16007	17515	16191	32058	16860
AMZ	13971	6610	53490	**7605**	**6048**	**11314**	**6517**	**8736**	33277	**12213**
AMH	14071	6511	**43111**	8284	8874	14531	15070	11195	**27522**	13932
AMH′	**13637**	**6319**	43496	8085	8367	13933	13702	10650	**26891**	13243

Table 1. Statistical estimates of the filter efficiency according to criteria of MSE (ppm) (*continuation*)

Filter	χ_t	χ_{10-40}	χ_{40-60}	χ_{90-110}	$\chi_{110-140}$	$\chi_{140-160}$	$\chi_{160-190}$	$\chi_{190-210}$	$\chi_{240-260}$	$\chi_{265-285}$
8) $\sigma_a^2 = 0.003$, $P_{sp} = 0.01$, $n_{sp} = 1.0$, $N_R = 500$										
None	12998	13574	11224	13018	12429	14726	11773	14613	12423	14002
AZ	1196	453	4101	737	564	1382	709	895	3405	816
AZ_{pr}	**1018**	437	2841	558	460	931	509	637	**3323**	632
AMQ	1644	454	2930	761	817	1858	983	879	6986	732
AMQ_{pr}	1530	343	**2166**	**560**	587	1563	646	**650**	7770	**551**
AMZ	1472	309	6442	1007	393	1485	631	1486	4318	853
AMZ_{pr}	1277	293	3405	565	**384**	1176	**418**	666	5455	605
AMH	1586	403	7704	985	630	1241	752	995	4620	658
AMH_{pr}	1295	**261**	**2256**	**540**	509	1214	543	**653**	6468	**539**
AMH′	1565	413	7008	1017	713	1032	829	1011	**3948**	828
AMH'_{pr}	1193	**257**	**2329**	**543**	503	**964**	554	**655**	5634	**542**
9) $\sigma_a^2 = 0.01$, $P_{sp} = 0.01$, $n_{sp} = 1.0$, $N_R = 500$										
None	19935	20527	18007	19945	19496	21843	18554	21657	19467	20946
AZ	2798	1481	8082	1895	1606	2954	1785	2272	7110	2051
AZ_{pr}	**2220**	1411	4375	1620	1468	**2198**	1522	1780	**5446**	1772
AMQ	3027	1515	4178	1988	2073	3334	2570	2323	9506	1958
AMQ_{pr}	2648	1114	**3159**	1610	1792	2783	1970	1761	9966	1584
AMZ	2562	870	8450	2016	**894**	2767	**1115**	2633	6952	2288
AMZ_{pr}	2282	928	4694	1564	1119	2475	1239	1753	7388	1783
AMH	2676	898	8799	2190	1833	2860	2036	2276	6807	1881
AMH_{pr}	2266	**846**	**3387**	**1524**	1616	2360	1697	**1685**	8370	**1512**
AMH′	2812	967	8901	2337	2178	2797	2220	2360	**6384**	2137
AMH'_{pr}	**2170**	827	**3558**	1536	1595	2125	1694	**1678**	7273	**1550**
10) $\sigma_a^2 = 0.01$, $P_{sp} = 0.03$, $n_{sp} = 1.0$, $N_R = 500$										
None	39945	41144	36340	37851	38959	41577	39797	43052	41595	40505
AZ_{pr}	3015	1727	6724	1812	1687	2554	1856	2071	**8618**	2136
AMQ_{pr}	3338	1260	**5826**	1820	2022	2936	2221	2043	12944	1655
AMZ_{pr}	2994	1190	6988	1747	**1272**	2661	**1396**	2043	10500	1875
AMH_{pr}	**2971**	**967**	**6078**	**1714**	1832	2535	1929	**1964**	11465	**1575**
AMH'_{pr}	**2907**	**943**	**6200**	1726	1818	**2469**	2024	**1965**	**10461**	**1651**
11) $\sigma_a^2 = 0.03$, $P_{sp} = 0.1$, $n_{sp} = 1.0$, $N_R = 500$										
None	129519	131771	128347	126106	131582	133284	128623	131746	127932	130284
AZ_{pr}	14408	11242	25418	9598	11225	14611	9894	12509	30448	10712
AMQ_{pr}	11348	6002	**21744**	7874	9078	**9298**	9134	**9364**	31028	**6938**
AMZ_{pr}	11526	6324	24987	**7324**	**7514**	11369	**6496**	9423	30553	7580
AMH_{pr}	**11037**	**4901**	24406	7851	9922	9600	9247	9578	30786	7461
AMH'_{pr}	11525	**4844**	25038	8115	10636	10356	9459	10539	**30007**	8502
12) $\sigma_a^2 = 0.06$, $P_{sp} = 0.3$, $n_{sp} = 1.0$, $N_R = 500$										
None	359755	365570	354770	358898	360030	366737	361104	352123	363535	355473
AZ_{pr}	117665	102360	146408	115721	106783	113205	106895	124124	156326	107923
AMQ_{pr}	97843	78575	**129604**	91183	85693	87609	92219	108811	152163	80953
AMZ_{pr}	93139	70018	139292	**86261**	**76112**	**85949**	**76648**	**100479**	158534	**69124**
AMH_{pr}	95107	70596	137474	88761	88608	90858	97872	108021	146933	81517
AMH'_{pr}	**93297**	**66414**	138177	86973	85831	87856	92391	104864	**144214**	79180



a

b

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Fig. 2 Processing of the complex test signal with low level of the additive Gaussian noise: a) noisy signal ($\sigma_a^2 = 0.001$); b) output of AZ; c) output of AMQ; d) output of AMZ; e) output of AMH; f) output of AMH′.

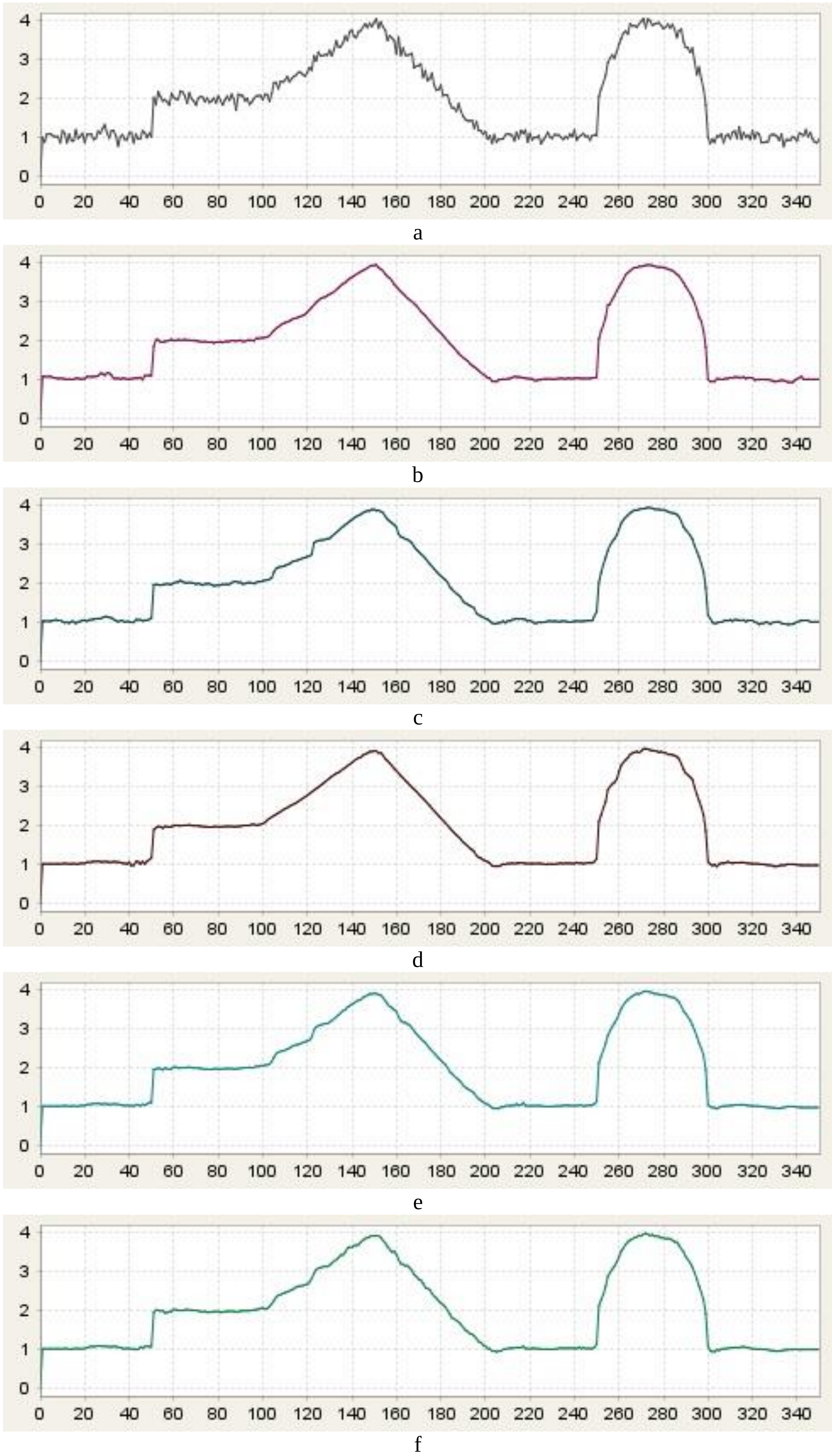
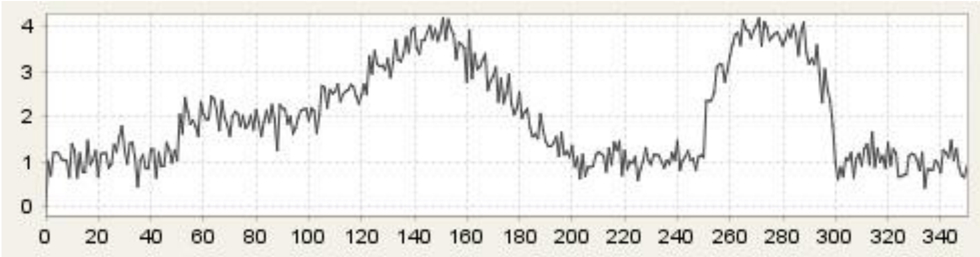


Fig. 3 Processing of the complex test signal with middle level of the additive Gaussian noise: a) noisy signal (σ_a^2 = 0.01); b) output of AZ; c) output of AMQ; d) output of AMZ; e) output of AMH; f) output of AMH′.



a

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c

d

e

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Fig. 4 Processing of the complex test signal with high level of the additive Gaussian noise: a) noisy signal (σ_a^2 = 0.06); b) output of AZ; c) output of AMQ; d) output of AMZ; e) output of AMH; f) output of AMH′.

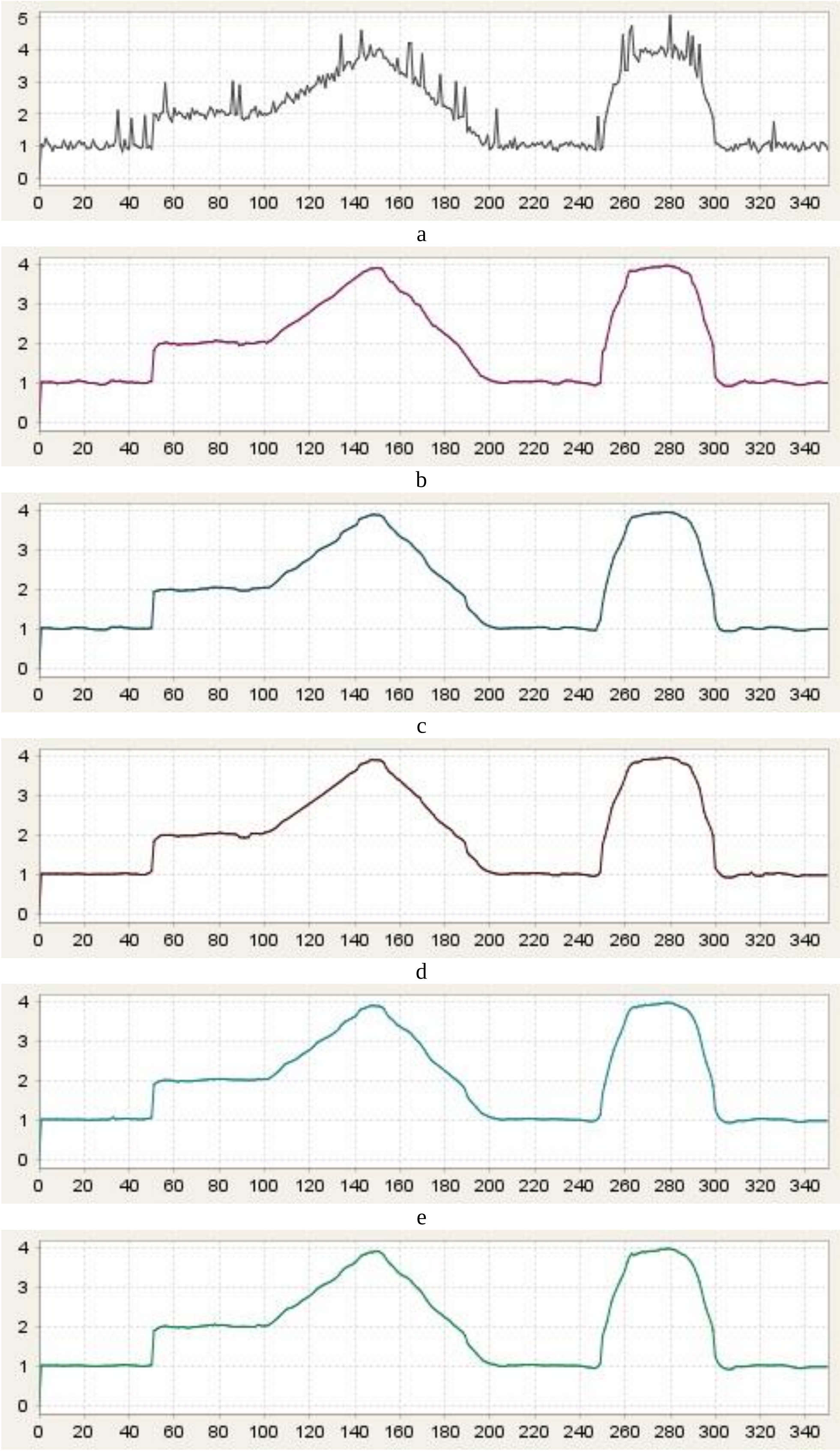
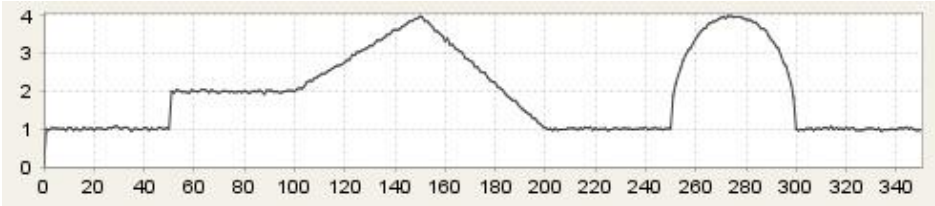
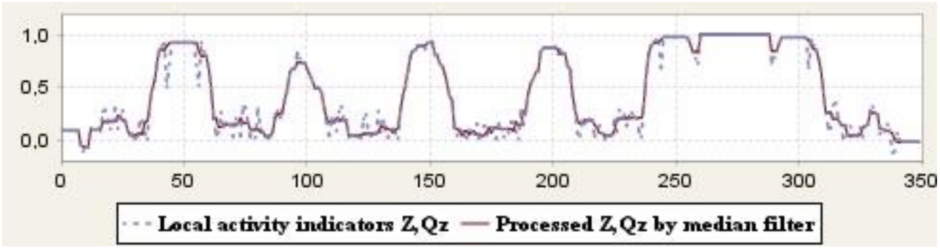


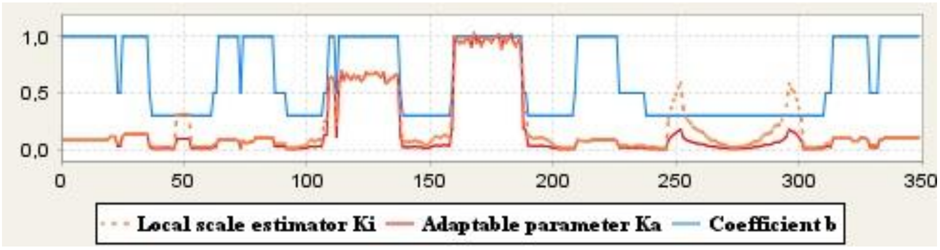
Fig. 5 Processing of the complex test signal with additive Gaussian and impulse noises: a) noisy signal ($\sigma_a^2 = 0.01$, $P_{sp} = 0.06$, $n_{sp} = 1$); b) output of AZ_{pr}; c) output of AMQ_{pr}; d) output of AMZ_{pr}; e) output of AMH_{pr}; f) output of AMH'_{pr}.



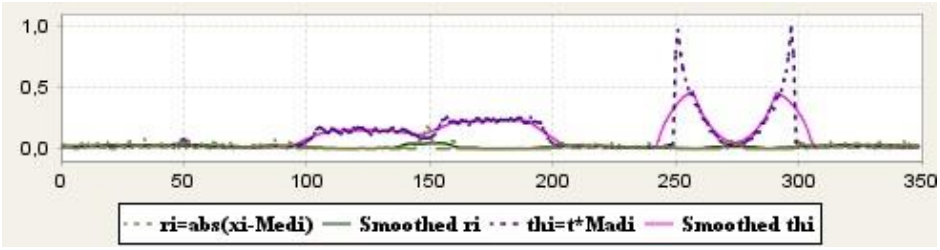
a



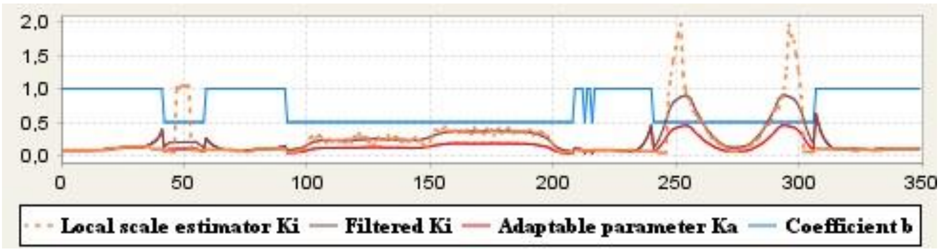
b



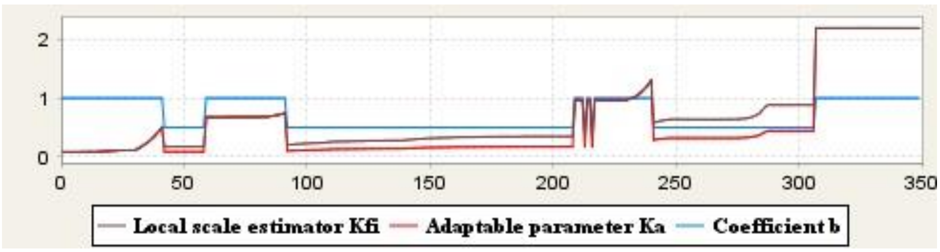
c



d



e



f

Fig. 6 Local adaptation in case of low noise level: a) input signal; b) LAI $Z_i \vee Q_{Z\,i}$, its filtered values; c) local scale estimator K_i, linearity parameter K_{ai}, coefficient b of AMZ; d) threshold parameters r_i, th_i, its smoothed values; e) local scale estimator K_i, its filtered values, linearity parameter K_{ai}, coefficient b of AMH; f) local scale estimator K_i^f, linearity parameter K_{ai}, coefficient b of AMH′.

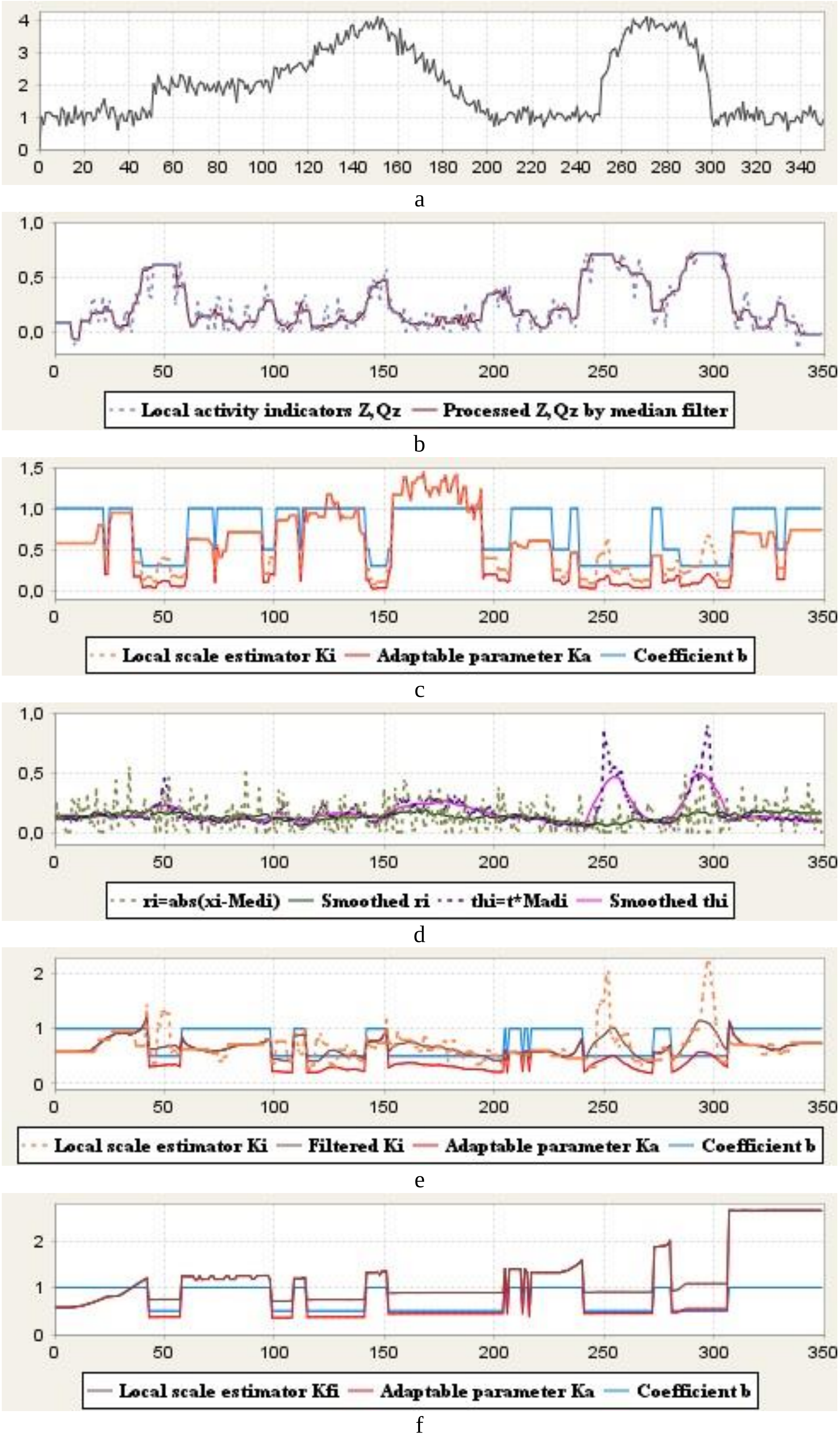


Fig. 7 Local adaptation in case of high noise level: a) input signal; b) LAI $Z_i \vee Q_{Z\,i}$, its filtered values; c) local scale estimator K_i, linearity parameter K_{ai}, coefficient b of AMZ; d) threshold parameters r_i, th_i, its smoothed values; e) local scale estimator K_i, its filtered values, linearity parameter K_{ai}, coefficient b of AMH; f) local scale estimator K_i^f, linearity parameter K_{ai}, coefficient b of AMH′.

The behaviors of the adaptable linearity parameter K_{ai} (Eq. 3) for low (Fig. 6) and high (Fig. 7) Gaussian noise levels are similar, but when noise dispersion is increased, the mean level of function of K_{ai} is higher, thus the myriad filtering has more linear properties, which allows better noise suppression. For high noise level (Fig. 7), a local maximum of the K_{ai} function occurs in the flat area of the polynomial maximum (*x*-axis indices 265-285), which also leads to better noise smoothing. The mean level of the K_{ai}^f function at the segments of a constant signal (*x*-axis indices 10-40) is higher for LAMF AMH′ in comparison to AMH, which causes better noise suppression with AMH′. LAMF AMH′ also has smaller values of K_{ai}^f in vicinity of the connection point of the constant and polynomial signals (*x*-axis indices 240-260) and respectively provides better dynamic properties for such signals.

Conclusion

We proposed algorithms for locally adaptive myriad filtering with adaptation of a sample myriad linearity parameter *K*, depending on signal scale local estimates, as well as with "hard" switching of the values set for the sliding window lengths and coefficients, which influence the parameter *K*. The proposed LAMFs are shown to preserve a step edge, piecewise functions and parabolic extremums effectively due to high dynamic properties for nonlinear mode of myriad filtering (small values of the linearity parameter *K*) and small length of the sliding window. LAMFs suppress noise effectively while processing the segments of linear behavior of signal and polynomial curves by adjusting the parameter *K* to a linear mode and by increasing the window length.

Having high efficiency for all segments of the considered complex signal, one of the proposed algorithms provides almost optimal noise suppression on the segment of linear change of the signal. Other algorithm provides higher quality of step-like and constant signal processing. In order to improve effectiveness of filtration in cases of low and high noise levels, the modified algorithm applies noise level estimation through comparison of a locally-adaptive parameter and thresholds. As a result of application of the proposed LAMFs, improvement of integral and local performance indicators is shown in comparison to the highly effective locally-adaptive algorithms [3, 17, 18]. In case of spikes presence, a significant enhancement of the processing quality is shown due to application of the preliminary robust myriad filtering.

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Nataliya Tulyakova, Ph.D.
E-mail: nataliyatulyakova@gmail.com

Nataliya Tulyakova graduated from Kharkiv Aviation Institute named after M. Ye. Zhukovsky, Faculty of Radioelectronic Systems of Flying Vehicles, with a M.Sc. degree in Biotechnical and Medical Devices and Systems (with highest honors). She received her Ph.D. degree in Biological and Medical Devices and Systems in Kharkiv National University of Radioelectronics. Her Ph.D. thesis was dedicated to design of nonlinear stable methods for removing mixed noise and physiological artifacts in biomedical signals. Her research work deals with digital signal/image processing.

Senior Assist. Prof. Tatyana Neycheva, Ph.D.
E-mail: tatiana@biomed.bas.bg

Tatyana Neycheva is a member of Department Processing and Analysis of Biomedical Data and Signals at the Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences, Sofia, Bulgaria. She defended her Ph.D. in 2003. She is a Senior Assistant Professor since 2003. Her interests are in the field of diagnostic interpretation of biomedical signals and data for autonomous cardiac control and its clinical application; non-invasive determination of physiological parameters with clinical application; new types of electrostimulation signals and defibrillation pulses; analysis of bioimpedance. Her publications are in the field of medical and biological engineering and computing or electronics.

Corr. Mem. Prof. Oleksandr Trofymchuk, Ph.D., D.Sc.
E-mail: itelua@kv.ukrtel.net

Oleksandr Mykolayovych Trofymchuk is a Corresponding Member of the National Academy of Sciences (NAS) of Ukraine, Doctor of Engineering, Professor, Laureate of State Prize of Ukraine in the field of science and technology (2005), awarded with Diploma of Merit by the Cabinet of Ministers of Ukraine (2005), awarded with Diploma of Merit by the Verkhovna Rada (Parliament) of Ukraine (2005), Honored worker of science and technology (2015), Laureate of State Prize of Ukraine in the field of education (2017). Author of more than 460 scientific works including 20 monographs and 2 educational books.

Assoc. Prof. Oleksandr Stryzhak, Ph.D., D.Sc.
E-mail: sae953@gmail.com

Stryzhak Oleksandr Yevheniiovych is a Doctor of Engineering, Associate Professor, Scientific Projects Supervisor. The sphere of his scientific interests encompasses the study and solving of contemporary problems, which arise during implementation of complex systemic analytical studies related to the processing of immense arrays of unstructured information that has significant number of interdisciplinary relationships and is created based on the use of various information technologies and standards. He made significant contribution to the development of new principles and further evolution of scientific fundamentals of the transdisciplinary modeling of complex systems and cognitive management of the knowledge systems. He proposed a new methodology for transdisciplinary research and systemic analysis of the processes of integration of informational resources found in different branches of knowledge during solving of complex applied tasks.