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Locally-adaptive Myriad Filters for Processing ECG Signals in Real Time

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Abstract: *The locally adaptive myriad filters to suppress noise in electrocardiographic (ECG) signals in almost in real time are proposed. Statistical estimates of efficiency according to integral values of such criteria as mean square error (MSE) and signal-to-noise ratio (SNR) for the test ECG signals sampled at 400 Hz embedded in additive Gaussian noise with different values of variance are obtained. Comparative analysis of adaptive filters is carried out. High efficiency of ECG filtering and high quality of signal preservation are demonstrated. It is shown that locally adaptive myriad filters provide higher degree of suppressing additive Gaussian noise with possibility of real time implementation.*

Keywords: *Electrocardiogram filtering in real time, Locally adaptive myriad filters, Statistical estimates of efficiency.*

Introduction

Several noises are always accompanying the electrocardiographic (ECG) recordings: mains interference, electromyographic (EMG) noise, and baseline wander (drift) of the signal. The EMG noise is due to muscle strain and its dominant energy is located in the 20-400 Hz range. The EMG spectra is totally overlapping the ECG spectra thus making impossible the automatic analysis of the ECG. Filtering of the EMG noise causes distortions of the high-frequency components of the ECG, violating their diagnostically significant morphological parameters. In a study of the sources of variation in the *QT* readings [19] the authors argue that most of the low-pass filtering procedures effect on shifting outward the *Q* and *T* marks. For that reason, the recommendations from 1967 of the American Heart Association [20] for low-pass filtering of not less than 35 Hz cutoff were changed to 150 Hz for adolescents and adults and to 250 Hz for children [12].

Two highly effective methods for noise suppression have been suggested [11, 15,], based on orthogonal discrete cosine and wavelet transform, but at a high computation cost. Simple and highly effective algorithm for dynamic approximation have been described [4-6, 8] but this filters were not implemented in real time. The approximation is based on the [18] simplified last square procedure, applied dynamically in respect of the frequency spectra of the ECG waves. Despite the fact that the modern computer technology is allowing implementation of complex digital signal processing algorithms, some portable devices and ECG monitors are of limited resources and require filtering algorithms of high-speed performance and real time applicability.

A well-reasoned selection, among the digital filters for high frequency noise suppression in biomedical signals, is filtering with nonlinear stability, not only because of the non-Gaussian nature of the noise, but also due to the high dynamic properties (preservation of the signal waveform) of the nonlinear filters [3]. There are flexible algorithms, which at a certain parameter's settings, provide significant non-linearity properties to preserve discontinuities and abrupt changes of the signal and to remove outliers. One example of such filter is based on a sample myriad estimator. Depending on a value of the linearity parameter *K*, the myriad estimator in one marginal case has more robustness than a median filter and is optimal for Cauchy distribution which describes impulsive noise. In the other marginal case, the myriad estimator tends to a sample average and has linear properties, not worse than those of the averaging filter according to the degree of suppression of the Gaussian noise [9, 10]. The ability to change the myriad estimator properties, depending on the parameter *K*, was the basis for the development of adaptive myriad filtering algorithms, in particular for ECG processing [16]. In work [2], a locally-adaptive myriad filter that changes the linearity parameter *K* depending on the local adaptation parameters calculated in current *i*-th position of sliding window has been suggested. However, length of the sliding window of the adaptive filter should be selected based on a balance between efficient noise suppression and reduction of distortions introduced by the processing. For not a large window, the adaptive myriad filter is implemented in real time [2], but the use of a window of fixed size for ECG is not favourable, since high-frequency *QRS* complex requires processing with small windows applied; and the window length should be enlarged in order to suppress noise enough in the low-frequency *P*-, *T*-waves. In this connection, locally-adaptive myriad filters with dynamically varying window length and estimating of myriad linearity parameter *K* are proposed and their efficiency with respect to other adaptive algorithms is presented.

Locally-adaptive myriad filters

A sample myriad is a robust *M*-estimator of location of the Cauchy distribution with scaling factor $K > 0$ [9, 10], which is defined as:

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

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

In order to adjust the linearity parameter *K* of myriad filter for each *i*-th position of the sliding window, directly proportional dependency can be used:

$$K_a = bK_i, \; K_i = \max_{k \neq j} |x_k - x_j| \, |_{k,j=1}^{N}, \quad (2)$$

where *b* is a fixed coefficient.

The output signal of the adaptive myriad filter, denoted as AMF, can be described as follows:

$$y_i^{AMF} = myriad\{x_1, x_2, ..., x_i, ..., x_N, K_a\}, \quad (3)$$

where K_a is the linearity parameter calculated for the *i*-th sliding window.

The locally adaptive filter (LAF) is suggested for processing the neighbourhood of the current *i*-th sample of input signal. In one case the LAF applies AMF with a small window length and with nonlinear properties, and in another it uses AMF with a large window length and setting the properties to linearity mode by increasing the coefficient *b* (2). Thus, the local adaptation is controlled by choosing the more appropriate AMF sliding window length and by adaptation

of the linearity parameter K_a for an i-th position of AMF sliding window by choosing the appropriate coefficient b and calculating parameter K_i that estimates signal scale (2).
For adaptive hard switching of the outputs between two AMF, preliminary smoothed adaptation parameters similar to threshold parameters of Hampel filter [17] can be used. The output of the proposed myriad LAF, denoted as AMH, is defined as:

$$y_i^{AMH} = \begin{cases} y_i^{AMF(N_1, b_1)}, & if\ r_i^f \le th_i^f; \\ y_i^{AMF(N_2, b_2)}, & otherwise, \end{cases} \tag{4}$$

where $y_i^{AMF(N_1,b_1)}$, $y_i^{AMF(N_2,b_2)}$ are the outputs of AMF (3) with tuning parameters: window lengths $N_1 < N_2$ and coefficients $b_1 < b_2$; $r_i^f = mean\{r_1, r_2,..., r_i,..., r_{N_2}\}$ are values of the $r_i = | x_i - m_i |$ smoothed by averaging filter, where x_i is a central sample of the input set of the samples $\{x_j\}_{j=1}^{N_2}$ within the sliding window with length N_2, m_i is the sample median; $th_i^f = mean\{th_1,\ th_2,..., th_i,..., th_{N_2}\}$ are the smoothed values of the threshold parameters $th_i = t\, S_i^{Mad}$, where $S_i^{Mad} = 1.4826\, median\{| x_1 - m_i |, | x_2 - m_i |,\ \ldots,\ | x_{N_2} - m_i |\}$ are the local estimates of the signal scale, where 1.4826 is the coefficient for the Gaussian distribution, $\{x_j\}_{j=1}^{N_2}$ is the set of input samples, m_i is the set's median; t is a fixed threshold.

It is expected that LAF AMH (4) can preserve ECG signal on fragments of its rapid changing due to high dynamic properties of AMF in the nonlinear mode and small length of the sliding window and can effectively suppress noise while processing fragments of the slow signal behaviour by adjusting the parameter K_a to a linear mode and increasing the window length. The more appropriate algorithm for calculation a sample myriad for the LAF (4) is the algorithm of minimization of myriad cost function based on a numerical Newton technique [1, 22] because in order to determine the accuracy of iterations can be use calculated MAD-estimates of data scale.

The myriad LAF which adaptively switches the output signals between three AMF components by comparing local activity indicators referred as Z-parameters [13, 14] to the given thresholds is considered [21-24]. The output of this LAF denoted as AMZ is defined as:

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

where $y_i^{AMF(N_j,b_j)}$, j = 1, 2, 3, is output of j-th AMF (3) with the window length N_j and the tuning coefficient b_j, $N_3 > N_2 > N_1$, $b_3 > b_2 > b_1$; Z_i^f, $Q_{Z_i}^f$ are pre-filtered by median filter values of local activity indicators $Z_i = \sum_{j=-(N-1)/2}^{(N-1)/2} (y_{i-j}^f - x_{i-j}) / \sum_{j=-(N-1)/2}^{(N-1)/2} | y_{i-j}^f - x_{i-j} |$, where y_{i-j}^f, x_{i-j} are pre-filtered and input samples for calculation of the Z-parameter, respectively ($N = N_2$); $Q_{Z_i} = Z_i^{(q)} - Z_i^{(p)}$ is quasirange of Z-parameter calculated as the difference between the q-th and p-th order statistics of the sorted set $\{Z^{(1)}, Z^{(2)}, \ldots,\ Z^{(N)}\}$, $q - p \approx (N-1)/2$; $Z_1^t \approx 0.2$, $Z_2^t \approx 0.4$ are the thresholds. The preliminary filter with the "middle" sliding window length N and "intermediate" dynamic and statistical properties is used to calculate the

Z-parameter. This filter is usually an intermediate component of LAFs based on Z-parameter [13, 14, 21, 23, 24].

For myriad LAF (5) in contrast to LAF (4), not two but three component filters are used. The use of an intermediate component can improve the dynamic properties of filtering. However, application of three-component's LAF requires more calculations which can essentially affect the processing time as the sampling rate and length of the window increases.

Criteria of effectiveness

The statistical estimates of filtering efficiency are evaluated using criteria of mean square error (MSE) and signal-to-noise ratio (SNR) averaged for a large number of input signal realizations [3]:

$$MSE = \sum_{j=1}^{N_R} [\sum_{i=1}^{I} (y_i^f - s_i)^2 / I\,] / N_R\,, \tag{6}$$

$$SNR = \sum_{j=1}^{N_R} 10\lg(p_s / p_n) / N_R\,, \tag{7}$$

where y_i^f is the output of the evaluated filter; s_i is the true signal value of the i-th sample; I is the signal's length; $p_s = \sum_{i=1}^{I} (s_i - \bar{s})^2 / I$ is the signal power; $\bar{s} = \sum_{i=1}^{I} s_i / I$ is the mean value of the signal; $p_n = \sum_{i=1}^{I} (y_i^f - s_i)^2 / I$ is the noise power; N_R is number of input signal realizations for statistical averaging.

State of the art

Effectiveness of nonlinear robust filters is usually evaluated by numerical simulations since analytical description of their properties is too complex [3]. Parameters of these filters can also be selected or specified by numerical simulations. In this case, for myriad LAF AMH (4) parameters for the test ECG are chosen in presence of medium level of the Gaussian noise (input SNR is 10 - 11 dB): $N_1 = 5$, $b_1 = 1$, $N_2 = 17$, $b_2 = 10$, $t = 0.5$. Similarly, for myriad LAF AMZ (5) the parameters are as follows: $N_1 = 5$, $b_1 = 1$, $N_2 = 13$, $b_2 = 5$, $N_3 = 17$, $b_3 = 10$. The intermediate component of LAF AMZ as a preliminary filter for calculating the Z-parameters has the parameters $N_2 = 13$, $b_2 = 5$. Due to the noisiness of Z-parameter [13, 14, 24] its values are processed by the median filter with window length $N = 5$. Note that for the other test signals suitable parameters of adaptive algorithms AMH and AMZ may differ.

Myriad LAF AMH and AMZ process the input signal within sliding windows with little delay of the current i-th sample of output signal in relation to the reference sample of the input signal, i.e. in almost in real time. The proposed myriad LAF processes the input signal by two or three component filters in parallel and in parallel calculates the parameters of local adaptation r_i^f, th_i^f (4), Z_i^f (5), which define the selection of the output signal of the more appropriate filter. Thus, for myriad LAF AMH, output delay in relation to the input sample can be N_2 samples where N_2 is the length of the sliding window used for calculation of the local adaptation parameters and the window length of the second LAF component (4). Since the sorted set $\{Z^{(1)}, Z^{(2)}, ..., Z^{(N)}\}$ is required for calculation of quasirange of the Z-parameter, the processing delay for AMZ is higher than that of AMH.

Myriad LAFs (4-5) were compared to the dynamic approximation algorithms [4, 6] that suppress sufficiently the noise in ECG with minimal distortion of high frequency content of the signal. These filters apply the optimal Savitzky and Golay (S&G) procedure within the approximation interval, which length is adaptively changed depending on the fast (*QRS* complex) or slow (*P*-, *T*-waves) behaviour of the ECG signal.

For dynamic approximation presented in works [6, 7], *Wing*-function with extremes inside high-frequency *QRS* complex was introduced to estimate the slope of the ECG signal. Smoothed *Wing*-function, its minimum and maximum values were used in the analytical expression which define the length n_i of approximation intervals for the application of the S&G algorithm, so that the processing interval was minimal inside the *QRS* complex and the maximal outside it. For processing of ECG registered with sampling rate 400 Hz, the length of approximation interval ranged from $n_{min} = 1$ to $n_{max} = 15$ [6]. The advantages of the dynamic approximation algorithm [6], denoted as DAW, are the simplicity and high efficiency of noise suppression, but this algorithm is not implemented in real time, because it is necessary to use the signal realization along ECG period in order to calculate the *Wing*-function, to smooth it, to search its minimum and maximum values.

For dynamic approximation algorithm described in work [4], the ratio of standard deviations of the residual noise outside and inside *QRS* was used for adaptive setting of the minimum length of approximation interval applied inside the *QRS* complex, and the constant maximum length of approximation interval n_{max} was applied outside *QRS*. In case of ECG signals sampled at 400 Hz, the minimum length of the approximation interval for processing the *QRS* complex was automatically adjusted between $n_{min} = 6$ to $n_{min} = 2$, depending on the noise level. To process the low frequency segments of the ECG signal the maximum length of approximation interval equals to $n_{max} = 15$ [4]. This dynamic approximation algorithm, denoted as DARN, has high dynamic and statistical properties [4, 24], but its implementation requires the segmentation of the ECG signal and adjusting the parameter n_{min}.

Results and discussions

A "clean" ECG signal recorded with the sampling rate 400 Hz (Fig. 1) is used as a model signal. Conditions for the additive Gaussian noise with zero mean and different variances σ_a^2 are simulated. The efficiency of the suggested myriad LAF AMH (4), AMZ (5) and dynamic approximation algorithms DAW [6] and DARN [4] are analyzed on the basis of the statistical estimates of the MSE (6) and SNR (7) (Table 1). A number of realizations for the statistical averaging operation is $N_R = 200$.

As can be seen from Table 1 (case 1-3) for low level of the additive Gaussian noise, the DARN dynamic approximation algorithm has the best effectiveness, providing high dynamic properties (minimal distortions of a signal). In case of low level of noise (the input SNR varying from 21.2 to 12 dB) DARN algorithm provides a reduction of MSE in 7.7-10 times and increase of SNR by 9-10 dB. The advantage of DARN is observable at very low level of noise (Table 1, case 1-2) and is lost as the noise variance increases. In cases of increasing noise variance, the best efficiency for the considered adaptive filters is provided by AMH (Table 1). In case of middle level of noise (Table 1, case 4-7, the input SNR belongs to the interval 12.2-9.2 dB), AMH MSE is decreased in 10-11.3 times and AMH SNR increases by 10.2-10.8 dB. In case of high level of noise (Table 1, case 8-10, the input SNR varying from 8.2 to 3.5 dB), the indicators of the efficiency of AMH are as follows: the AMH MSE decreases in 11.5-12.5 times, AMH SNR increases by 11-11.2 dB.

The illustrations of the output signals (Figs. 1-5) of the considered adaptive filters confirm the numerical simulation results (Table. 1). If a noise-free signal is processed (Fig. 1), the smallest distortions in *QRS*-complex area are produced by the algorithm DARN [4] due to

n_{min} tuning to minimal value. Since for LAF (4-5) the sliding window lengths of component filters are fixed, *QRS*-complex processing by the myriad LAF leads to more distortions with some smoothing of *Q*, *R*, and *S* peaks. The algorithm DAW preserves amplitude of *R*-peak but distorts *Q* and *S*-waves. In the case of low level of noise (Fig. 2), the considered adaptive filters demonstrate high quality of preserving signal component. In the cases of middle (Fig. 3) and high (Fig. 4) levels of Gaussian noise, the LAFs provide better quality of filtering.

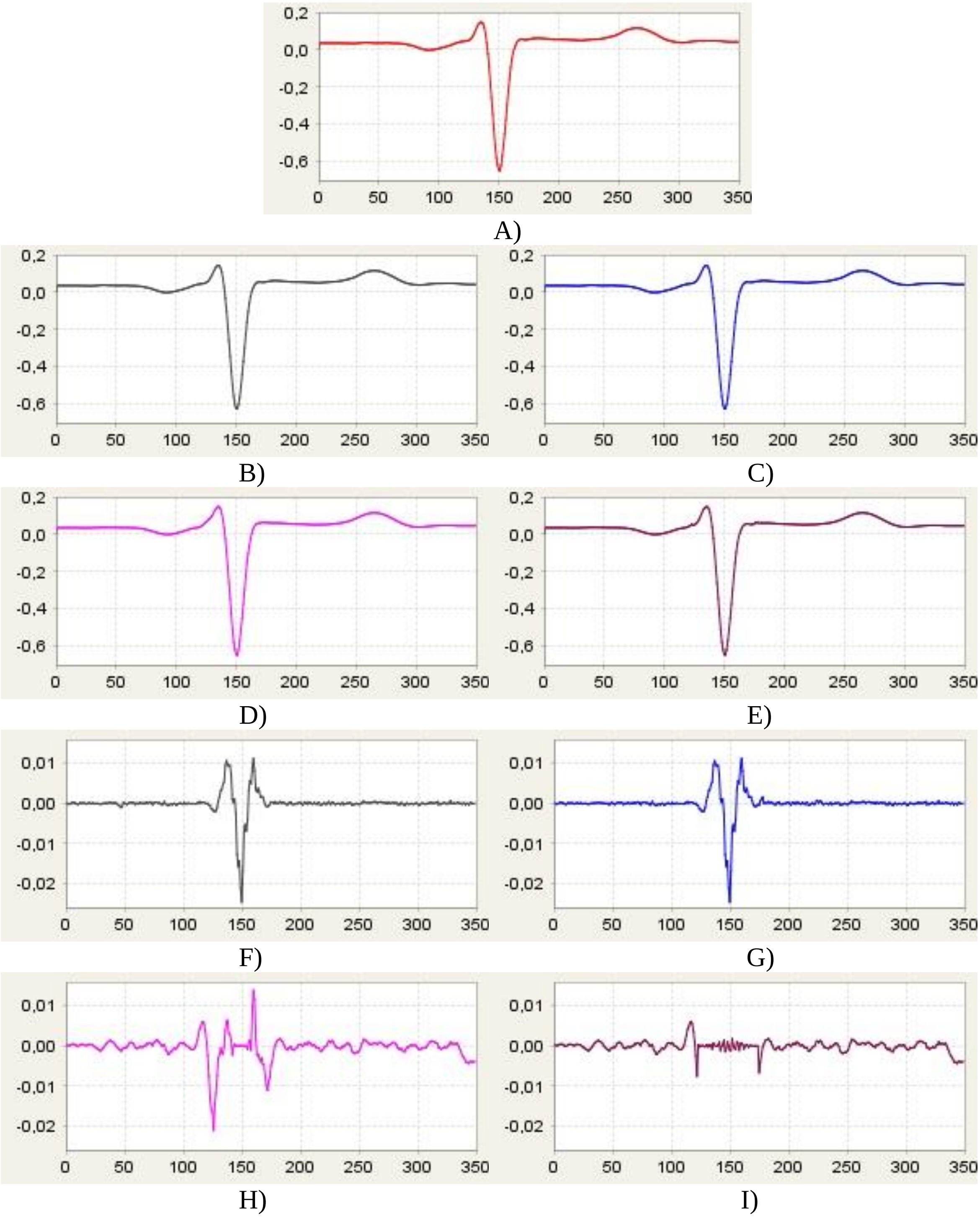
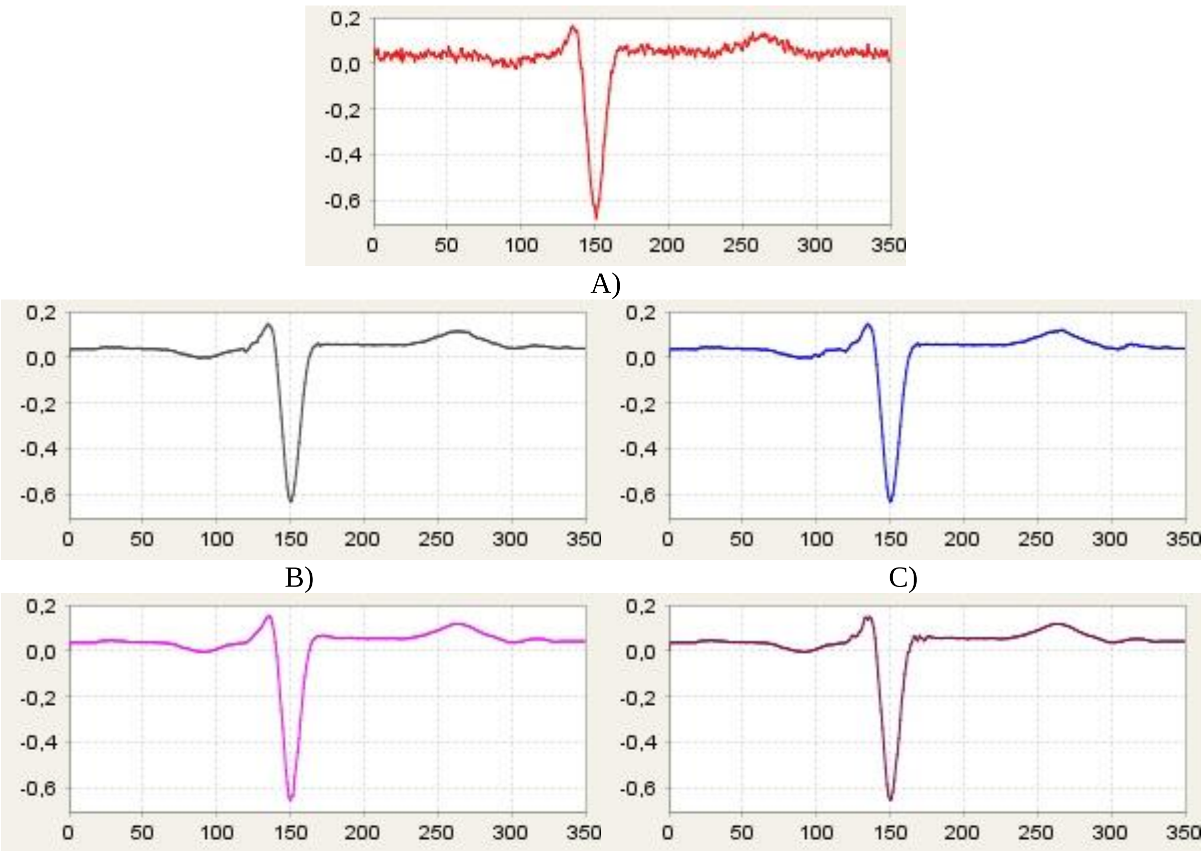


Fig. 1 Signal distortions: A) “clean” ECG signal; B) output of AMH; C) output of AMZ; D) output of DAW; E) output of DARN; F) signal distortions of AMH; G) signal distortions of AMZ; H) signal distortions of DAW; I) signal distortions of DARN.

Table 1. Statistical estimates of the efficiency according to MSE (ppm) and SNR (dB) criteria

Filter	**MSE**	**SNR**	**MSE**	**SNR**	**MSE**	**SNR**	**MSE**	**SNR**	**MSE**	**SNR**
1) σ_a^2 = 0.0001; N_R = 200			2) σ_a^2 = 0.0003		3) σ_a^2 = 0.0006		4) σ_a^2 = 0.0008		5) σ_a^2 = 0.001	
None	100	21.23	299	16.46	599	13.45	798	12.20	998	11.23
AMH	22	27.93	40	25.48	64	23.38	**80**	**22.42**	**96**	**21.66**
AMZ	21	28,21	40	25.43	67	23.20	85	22.19	102	21.39
DAW	21	28.18	43	24.98	77	22.47	100	21.34	123	20.44
DARN	**13**	**30.16**	**34**	**26.19**	**63**	**23.47**	83	22.30	102	21.38
6) σ_a^2 = 0.0014			7) σ_a^2 = 0.0016		8) σ_a^2 = 0.002		9) σ_a^2 = 0.003		10) σ_a^2 = 0.006	
None	1397	9.77	1597	9.19	1996	8.22	2994	6.46	5988	3.45
AMH	**127**	**20.44**	**142**	**19.94**	**173**	**19.09**	**249**	**17.51**	**480**	**14.66**
AMZ	136	20.14	153	19.63	187	18.77	270	17.18	517	14.36
DAW	169	19.06	193	18.48	240	17.53	361	15.77	735	12.68
DARN	141	19.99	161	19.43	200	18.48	297	16.76	589	13.79



A)

B)

C)

D)

E)

Fig. 2 Processing of the test ECG signal with low level of the additive Gaussian noise: A) noisy signal (σ_a^2 = 0.0002); B) output of AMH; C) output of AMZ; D) output of DAW; E) output of DARN.

The residual noise retained after application of the myriad LAF AMH is less than for the filters AMZ, DAW (Figs. 3-4). It is more observable on the high-frequency *QRS*-complex.

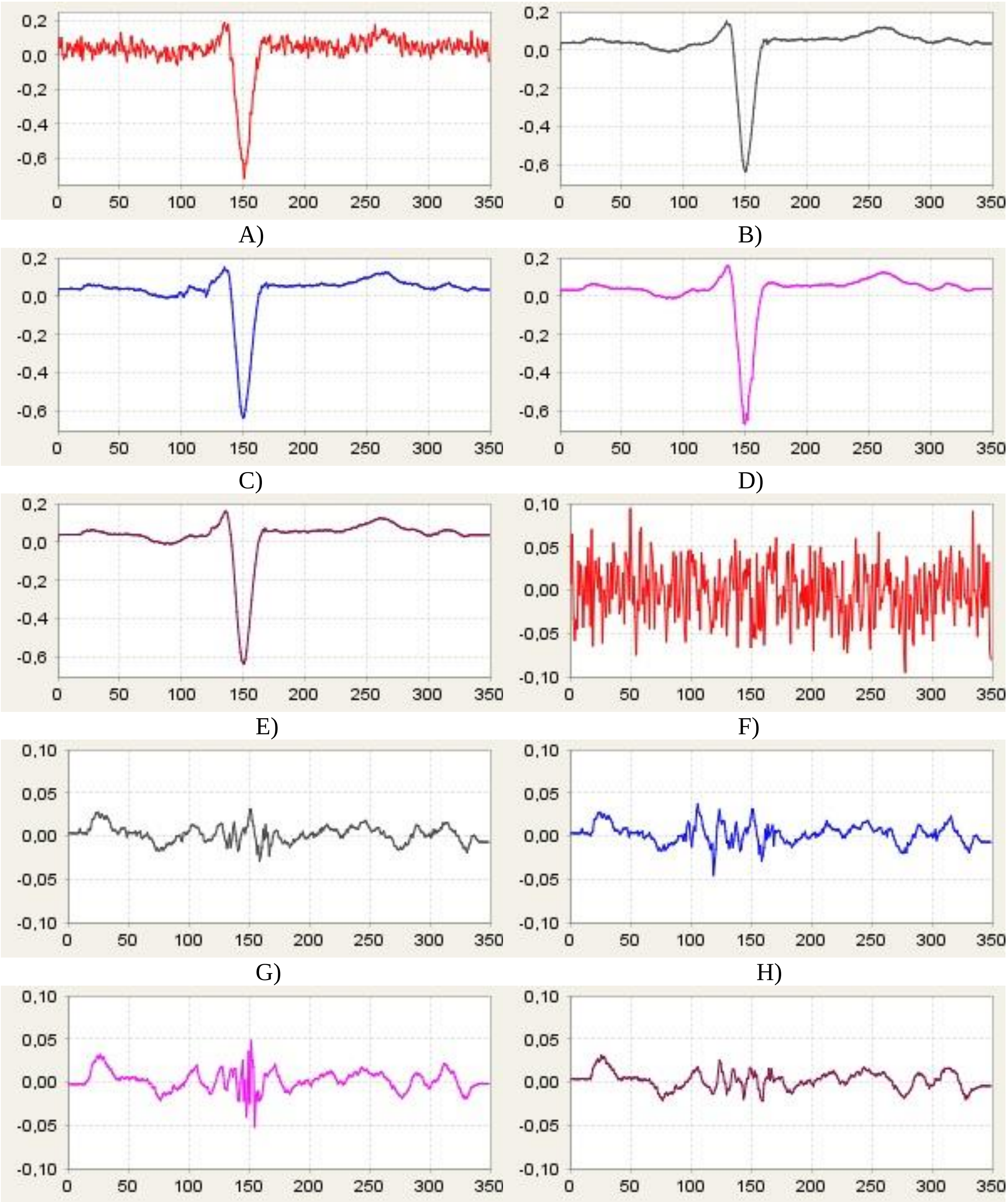


Fig. 3 Processing of the test ECG with middle level of the additive Gaussian noise: A) noisy signal ($\sigma_a^2 = 0.0012$); B) output of AMH; C) output of AMZ; D) output of DAW; E) output of DARN; F) noise; F) residual noise after AMH; G) residual noise after AMZ; I) residual noise after DAW; J) residual noise after DARN.

Minimal distortions of the signal amplitudes and high effective suppression of EMG noise in ECG by the considered filters are can be seen (Fig. 5). The algorithm DARN and the LAFs (4-5) better preserve *QRS*-complex since the algorithm DAW slightly expands the *Q*-wave.

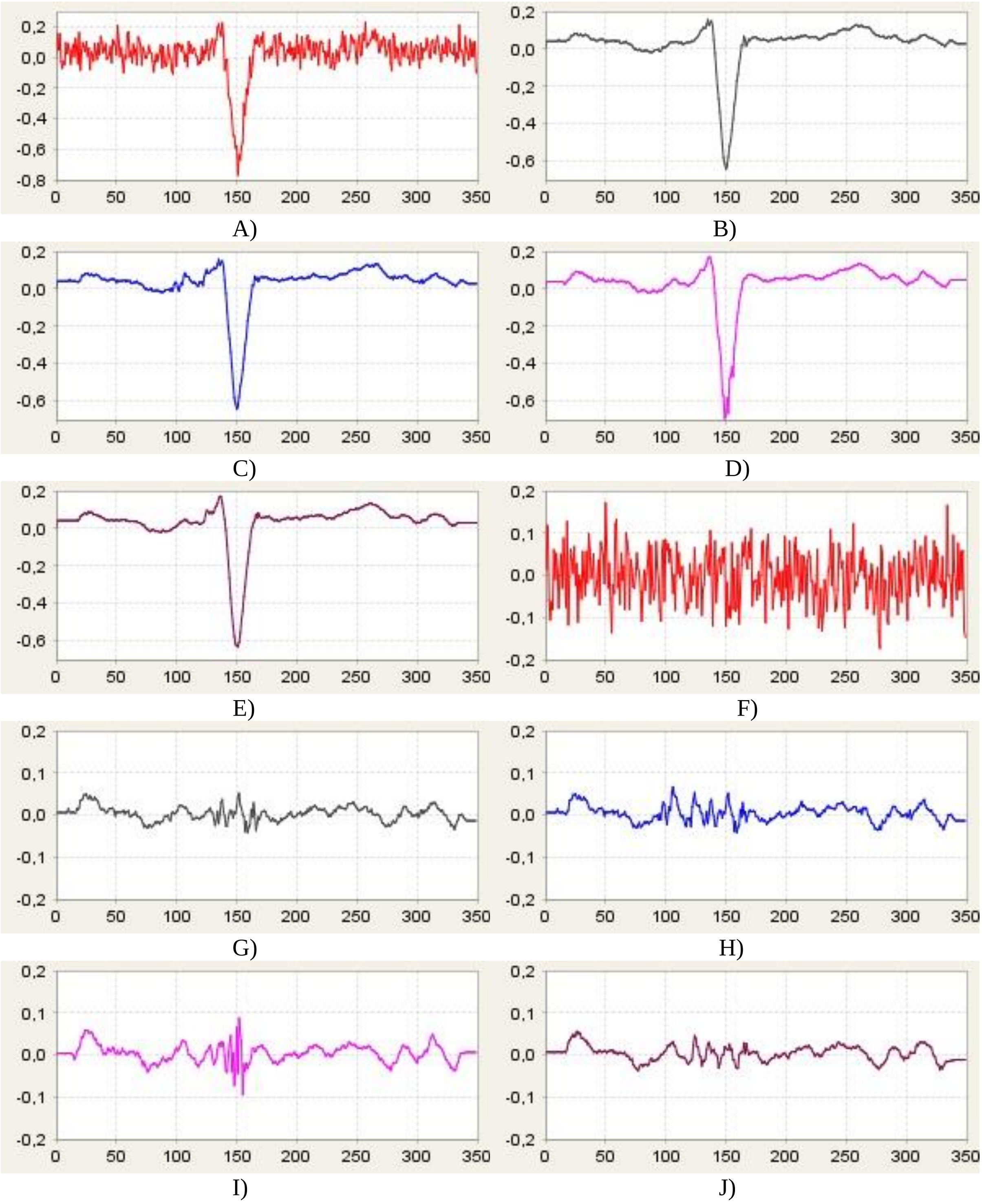


Fig. 4 Processing of the test ECG with high level of the additive Gaussian noise:
A) noisy signal (σ_a^2 = 0.004); B) output of AMH; C) output of AMZ; D) output of DAW;
E) output of DARN; F) noise; F) residual noise after AMH; G) residual noise after AMZ;
I) residual noise after DAW; J) residual noise after DARN.

The behavior of the local adaptation parameters of the myriad LAFs (4-5) in Figs. 6-7 shows mainly correct hard-switching. The use of "incorrect" component filters due to noisiness of local adaptation parameters does not lead to essential decrease of processing quality (Figs. 2-4).

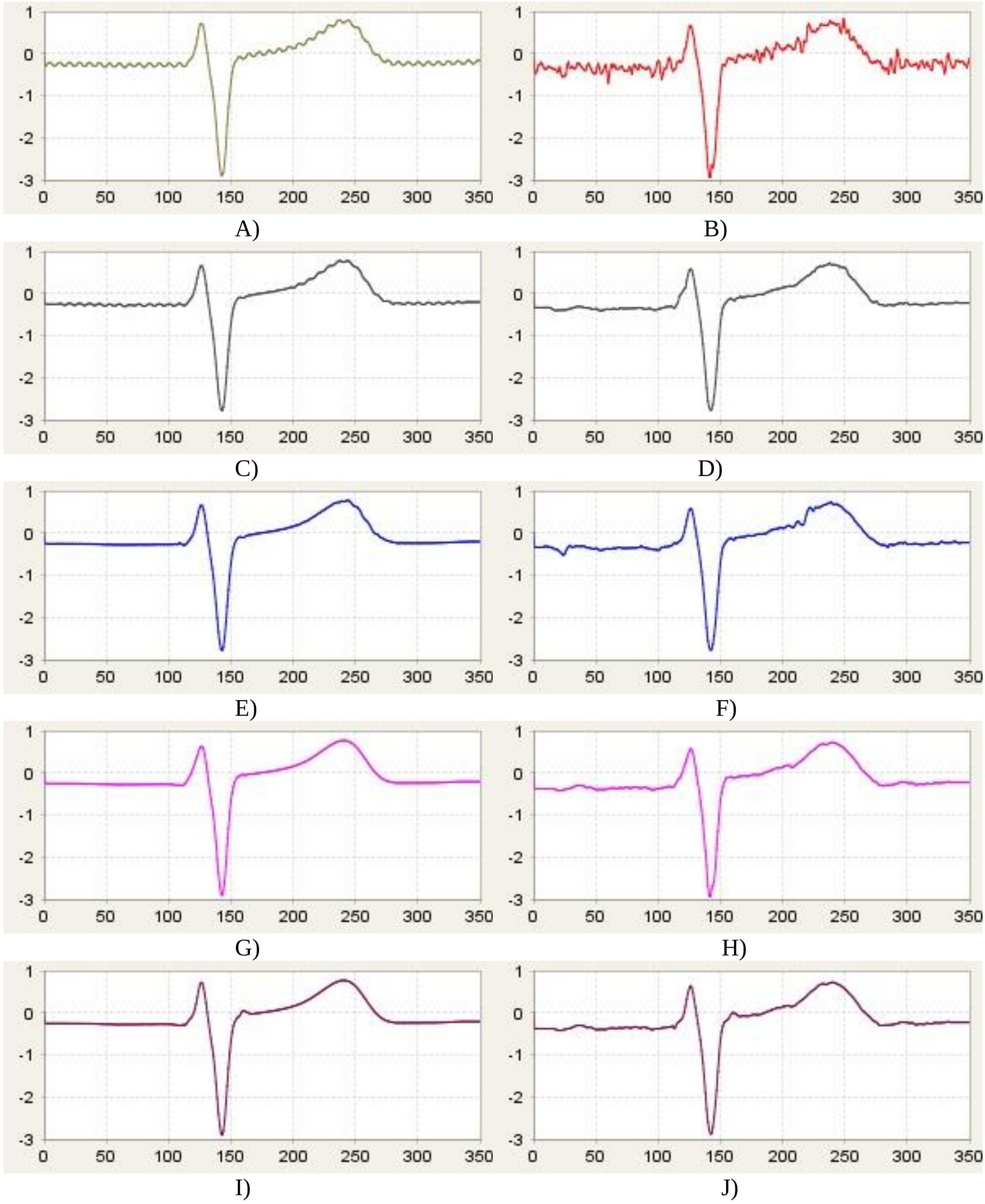


Fig. 5 Processing of the test ECG: A) ECG with power line interference; B) ECG corrupted by EMG noise; C, D) outputs of AMH in case of absence and presence of EMG noise, respectively; E, F) outputs of AMZ in case of absence and presence of EMG noise; G, H) outputs of DAW in case of absence and presence of EMG noise; I, J) outputs of DARN in case of absence and presence of EMG noise.

As can be seen from Fig. 6, small values of linearity parameter K_a (2) that determine nonlinear mode of myriad operation and small values of scanning window size for LAFs correspond correctly to high-frequency fragment of *QRS* complex and neighborhoods of *T*-wave start and end where one needs to use a processing algorithm with high dynamic properties.

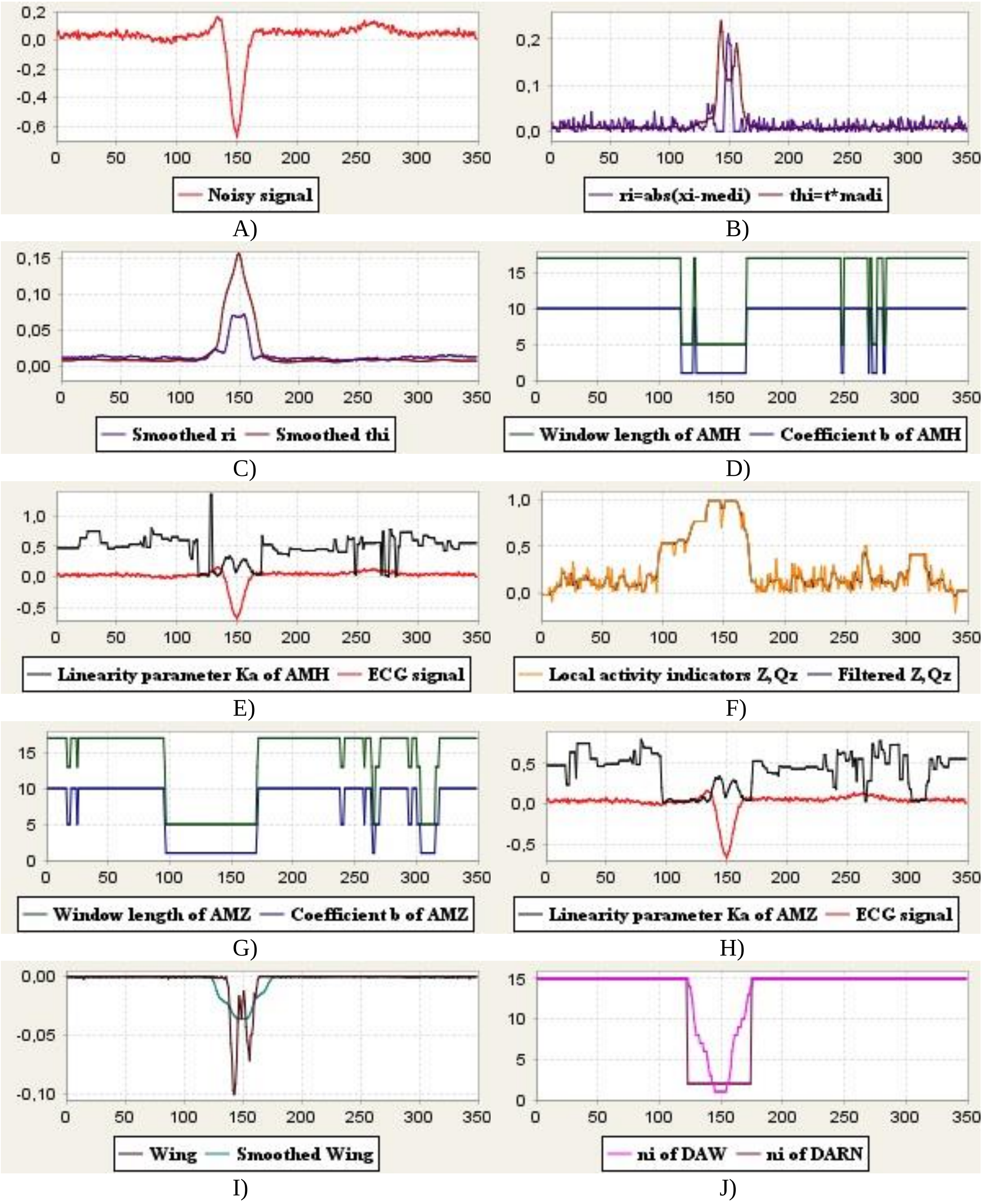


Fig. 6 Illustration of the local adaptation in case of low level of Gaussian noise: A) test signal; B) local adaptation parameters r_i, th_i of LAF AMH; C) smoothed r_i, th_i; D) adaptable parameters of window length and of coefficient *b* of LAF AMH; E) adaptable linearity parameter K_a of AMH; F) local activity indicators Z_i, Q_{Zi} of LAF AMZ; G) adaptable parameters of window length and of coefficient *b* of LAF AMZ; H) adaptable linearity parameter K_a of AMZ; I) *Wing*-function; J) approximation intervals of DAW and of DARN.

If the noise is level high, the probability of incorrect switching for AMH is less than for AMZ (Fig. 7). However, the algorithm AMZ (5) correctly switches window size to N_1 = 5 and

N_2 = 13 for processing parabolic wave. This provides smaller distortions due to filtering for this fragment of ECG. Besides, the thresholds for LAF AMZ are obtained by analytical way [19, 20] whereas the threshold parameter t for LAF AMH is tuned for the signal heuristically.

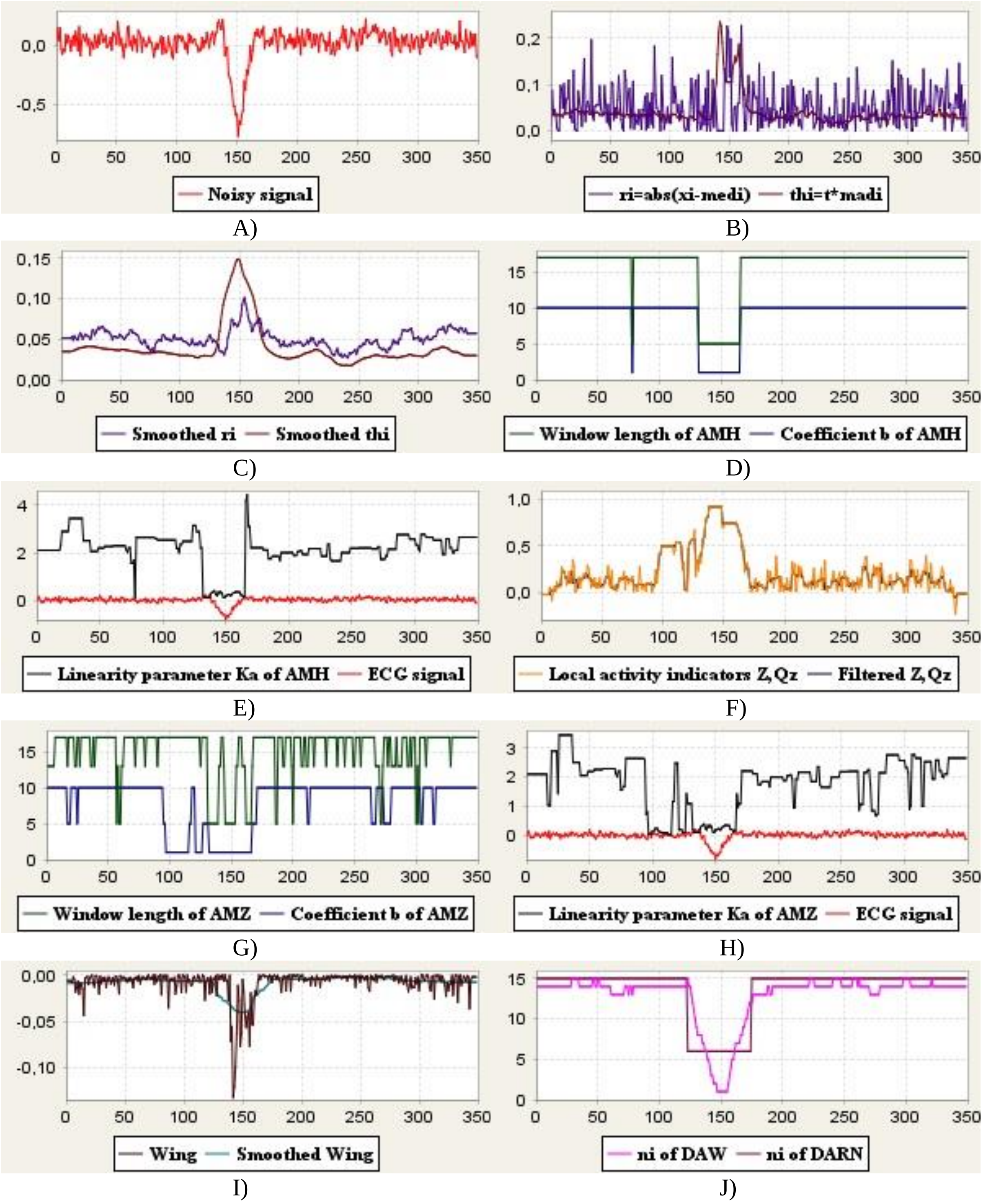


Fig. 7 Illustration of the local adaptation in case of high level of Gaussian noise: A) test signal; B) local adaptation parameters r_i, th_i of LAF AMH; C) smoothed r_i, th_i; D) adaptable parameters of window length and of coefficient b of LAF AMH; E) adaptable linearity parameter K_a of AMH; F) local activity indicators Z_i, Q_{Zi} of LAF AMZ; G) adaptable parameters of window length and of coefficient b of LAF AMZ; H) adaptable linearity parameter K_a of AMZ; I) *Wing*-function; J) approximation intervals of DAW and of DARN.

Conclusions

The locally adaptive myriad filters with variable window length and coefficient used for adaptive calculation of myriad linearity parameter K depending upon local estimates of signal properties are proposed. High efficiency of locally-adaptive myriad filters is demonstrated with the statistical estimates of filters efficiency according to MSE and SNR criteria for the test ECG sampled with 400 Hz for different levels of the additive Gaussian noise. Locally adaptive myriad filters are more efficient in suppression of noise as compared to highly effective dynamic approximation algorithms which are not implemented in real-time. Locally adaptive myriad filters do not require any preliminary procedures for estimating noise variance, detection of the *QRS* complexes, do not require adjusting the filter parameters and have fast algorithm implementations which allow process the signal in a real time mode.

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