AN APPLICATION OF THE SIMPLE ADAPTIVE M-FILTER IN PROCESSING OF ECG SIGNALS

T.Pander*

* School of Pharmacy and Division of Laboratory Medicine, Medical University of Silesia, Katowice, Poland

tpander@slam.katowice.pl

Abstract: The adaptive methods are very often applied in the digital signal processing domain. The optimal solution of applying the adaptive filtering is the Wiener filter. The application of traditional adaptive methods in the presence of an impulsive type of noise can lead to incorrect operation of such systems. By replacing the traditional square function as the cost function with another function, one can to increase the level of robust for an outlier data. The main aim of this paper is to present the simple, adaptive robust filter with the Huber function as the cost function. Effectiveness of such filter is investigated during the filtration of the high resolution ECG signals in the presence of an impulsive noise.

Introduction

The biomedical signals are commonly recorded with noise. Many different kinds of noise exist in biomedical environment. Because there exists many different type of biomedical signals, the electrocardiogram (ECG) signal was chosen. This signal is well known for a long time and it is well described in a literature. The most often noises which arise in ECG signal processing are: baseline wander, motion artifacts, 50 Hz power line interferences and, the most difficult to suppress, is a waveform of an electrical activity of muscles (the electromyographic signal). This "natural" distortion is usually modeled with a white Gaussian noise. Such approach is justified with Central Limit Theory. But this assumption can lead to too optimistic conclusions. The muscle noise shows frequently an impulsive nature and it means that the Gaussian model may fail.

Linear filtering techniques are often used in applications of a digital signal processing. The reduction of a noise is a first step of each biomedical signal processing system. The precision of all afterward operations which are made on the signals, depends on the quality of noise-reduction methods [12].

The traditional methods of filtering are very sensitive to the presence of outliers caused by spike artifacts, bursts of noise or other [10, 12, 18]. The performances of systems developed under the assumption of Gaussian noise can be severely degraded by the non-Gaussian noise due to potent deviation from normality in the tails. Consequently, it is not possible to design optimal filters, and even systems based on generalized likelihood ratio (GLR) principles can perform very poorly [9]. The performance of conventional linear adaptive filters in the presence of an impulsive noise deteriorate significantly. The theory of a Wiener filter describes the behavior of the least-squares (LS) and the least-mean-squares (LMS) adaptive filters. If processing signals are stationary, then the coefficients of "optimal" Wiener filter are constant. But the real signals are often non-stationary and that is a reason, which makes in practice difficult to apply Wiener filter equations or it is impossible.

The most common method of removing the outliers in signal is the manual spike detection. Although practically successful, this method requires human supervision and its manual nature makes it especially time consuming when using multiple channels [14].

Then only the robust methods can suppress such an impulsive noise. An example of robust methods are an application of nonlinear filtration methods. The most often applied nonlinear filter is the median filter. The median filter is very attractive for this purpose, but also can remove from signal fine details [5]. Second well-known non-linear filter is the myriad filter. This approach based on M-filters has one disadvantage which depends on computational complexity for real-time signal processing applications [5].

The main aim of this work is to present adaptive filter, which is based on recursive method and the computational effort is small, so the filter can be applied in real-time signal processing applications. In order to protect output of the filter against outliers, the M-function (Huber function) is applied. The reference filters are the median filter, Savitzky-Golay filter and RLS filter.

The paper is organized as follows. In next section, the principle of M-estimators are briefly reviewed. The proposed simple, adaptive M-filter is then derived in next section and after it the symmetric α-stable distribution used to model the impulsive noise is shortly presented. Finally, results of investigations and conclusions are drawn in last section.

The basic theory of the M-estimators

One of the popular robust method is the method based on M-estimators. The principle of M-estimators can be formulated in the following way. Given a set of N data

ISSN: 1727-1983 © 2005 IFMBE

samples $x_1, x_2, \dots, x_N$, where $x_i = \beta + v_i$ and $1 \leq i \leq N$. The problem is to estimate the location parameter β under noise component v_i. The location parameter for the Gaussian distribution is a sample mean. The other location parameters are a median and a mode. These parameters identify the position of the probability density function (pdf) on the real line of data samples. The distribution of v_i in not assumed to be exactly known. The only basic assumption is that $v_1, \dots, v_N$ obey a symmetric, independent, identical distribution (symmetric i.i.d.) [6, 13].

The M-estimate or maximum likelihood-type estimator (MLE), was originally proposed to improve robustness of statistical estimators subject to small deviations mentioned above. The M-estimate of $\hat{\beta}$ is defined as the minimum of a global energy function:

$$\hat{\beta} = \arg\min_{\beta} \sum_{i=1}^{N} \rho(x_i - \beta) \quad (1)$$

The $\rho(\cdot)$ is called the penalty or the cost function. An M-estimator of location is defined as the parameter $\hat{\beta}$ that minimizes the expression in (1). The behavior of the M-estimator is completely characterized by the shape of ρ function [2, 5, 13].

The $\rho(z)$ is a function of a single variable $z \equiv (x_i - \beta)$. Let the function $\psi(z)$ is the derivative of $\rho(z)$, e.g.:

$$\psi(z) = \frac{d\rho(z)}{dz} \quad (2)$$

The $\psi(z)$ function, known as the influence function, is some odd, continuous, and sign-preserving function [11, 16]. The $\psi(z)$ measures the influence of a data set on the value of the parameter estimate. In addition also the weight function can be defined as:

$$\phi(z) = \frac{\psi(z)}{z} \quad (3)$$

In order to minimize equation (1) it is necessary to solve the following equation:

$$0 = \sum_{i=1}^{N} \psi(x_i - \beta) \quad (4)$$

The last expression is the useful in presentation of different kind of M-estimators.

Special cases of the $\rho(z)$ and $\psi(z)$ functions:

- the errors are normally distributed then $\rho(z) = \frac{1}{2}z^2$ and $\psi(z) = z$. These last dependence leads to the sample mean and the associated M-estimator is the least squares estimator. The $\psi(z)$ function is linear and it means, that the influence of a data on the estimate increases linearly with the size of its error, which confirms the non-robustness of the least-squares estimator [20].

- the errors are distributed as a double or two-sided exponential $\rho(z) = |z|$ and $\psi(z) = sgn(z)$. This expression denotes the sample median.

- the errors are distributed as a Cauchy distribution and then $\rho(z) = \log[K^2 + z^2]$ and $\psi(z) = \frac{2z}{K^2+z^2}$ where $K > 0$. This expression is the base of the sample myriad with a linear parameter K, which tune properties of this estimator. For properties of myriad filters see [5, 8].

These functions in cases mentioned above determine the robust property of the M-estimators. This general idea, that the weight given individual point should first increase with deviation, then decrease, inspires some other prescriptions for the ψ function which do not especially correspond to standard, text book probability distributions [17].

The generalized form of M-estimator is the following. If the cost function $\rho(\mathbf{x}, \beta)$ is chosen as:

$$\rho(\mathbf{x}, \beta) = -\log f(\mathbf{x}, \beta) \quad (5)$$

then the M-estimate gives the ordinary maximum likelihood estimate, where $\mathbf{x}$ is the observed random variable with probability density function (pdf) $f(\mathbf{x})$, and β is the parameter to be estimated. In practical situations, the underlying *pdf* of the noises are difficult to estimate, and $\rho(\mathbf{x}, \beta)$ is usually chosen as a fixed function of $\mathbf{x}$ only, that is, $\rho(x)$.

In this paper as the M-estimator, as the cost function ρ the Huber function is applied. The Huber objective function is a hybrid of the L_1 and L_2 norms. The ρ function is given by [7, 15, 20]:

$$\rho(z) = \begin{cases} \frac{z^2}{2}, & |z| \leq k; \\ k|z| - \frac{k^2}{2}, & |z| > k. \end{cases} \quad (6)$$

where k is the cutoff value. The ρ function is not strictly convex. The influence function ψ, is an odd function and is given by:

$$\psi(z) = \begin{cases} z, & |z| \leq k; \\ k \cdot sgn(z), & |z| > k. \end{cases} \quad (7)$$

The weight function ϕ for the Huber function has the following form:

$$\phi(z) = \begin{cases} 1, & |z| \leq k; \\ k \cdot sgn(z)/z, & |z| > k. \end{cases} \quad (8)$$

Adaptive, robust M-filter

Let $x(n)$ is a deterministic signal which is corrupted with noise $v(n)$, so that the observed signal is $y(n) = x(n) + v(n)$. The estimation of $x(n)$ is denoted as $\hat{x}(n)$. Let define estimation error as:

$$e(n) = y(n) - \hat{x}(n) \quad (9)$$

Traditionally, using the least squares estimator which minimizes the weighted squared sum of estimation error samples, the performance function J_{LS} has the following form:

$$J_{LS} = \sum_{i=0}^{n} \lambda^{n-i} (e(i))^2 \quad (10)$$

where $\lambda (0 < \lambda < 1)$ is the exponential weighting factor or simply, positive forgetting factor.

ISSN: 1727-1983

In the case of presence of an impulsive noise, to provide robust filtering, the performance function J has to used the proposed in above section robust M-function instead of a square function. Then the performance function J_M can be defined as:

$$J_M = \sum_{i=0}^{n} \lambda^{n-i} \rho(e(i)) \quad (11)$$

where: $\rho(\cdot)$ is the cost M-function, λ is forgetting factor (in this work $\lambda = 0.8$).

In order to minimize expression (11), the method from [3] is presented and using (4) the following equation has to be solved:

$$\sum_{i=0}^{n} \lambda^{n-i} \psi(e(i)) = 0 \quad (12)$$

From (3), the equation (12) can be written as:

$$\sum_{i=0}^{n} \lambda^{n-i} \phi(e(i)) e(i) = 0 \quad (13)$$

Let denote as $v(i) = \phi(e(i))$, and using (9)then

$$\sum_{i=0}^{n} \lambda^{n-i} v(i)(y(i) - \hat{x}_M(n)) = 0 \quad (14)$$

where $\hat{x}_M(n)$ is the M-estimate of $\hat{x}(n)$. Evolving (14) one gets:

$$\sum_{i=0}^{n} \lambda^{n-i} v(i) y(i) = \sum_{i=0}^{n} \lambda^{n-i} v(i) \hat{x}_M(n) \quad (15)$$

and finnaly:

$$\hat{x}_M(n) = \frac{\sum_{i=0}^{n} \lambda^{n-i} v(i) y(i)}{\sum_{i=0}^{n} \lambda^{n-i} v(i)} \quad (16)$$

The sequence $v(i)$ assumes knowledge of the optimum solution, e.g. $\hat{x}_M(n) = \hat{x}_{opt}(n)$ at time n and makes error sequence $e(i)$. It is not true and this is the reason that in the place of $v(i) = \phi(e(i))$ the sequence of $w(i) = \phi(\xi(i))$ is used where:

$$\xi(n) = y(n) - \hat{x}(n-1) \quad (17)$$

and denote the *a priori* estimation error.
Using (16) and (17) the estimation of $\hat{x}_M(n)$ at time n is defined as:

$$\hat{x}_M(n) = \frac{\sum_{i=0}^{n} \lambda^{n-i} w(i) y(i)}{\sum_{i=0}^{n} \lambda^{n-i} w(i)} \quad (18)$$

Let define auxiliary variable $S_M(n)$ defined as:

$$S_M(n) = \sum_{i=0}^{n} \lambda^{n-i} w(i) \quad (19)$$

The $S_M(n)$ can be calculated using the following recursive formula:

$$\begin{aligned} S_M(n) &= w(n) + \lambda \sum_{i=0}^{n-1} \lambda^{(n-1)-i} w(i) = \\ &= w(n) + \lambda S_M(n-1) \end{aligned} \quad (20)$$

Using (20), then the numerator in the right hand side of (18) can be modified and written as:

$$\begin{aligned} \sum_{i=0}^{n} \lambda^{n-i} w(i) y(i) &= w(n)y(n) + \lambda \sum_{i=0}^{n-1} \lambda^{(n-1)-i} w(i) y(i) \\ &= w(n)y(n) + \lambda S_M(n-1) \hat{x}_M(n-1) \end{aligned} \quad (21)$$

Finally, using (20) and (21) the estimation of $\hat{x}_M(n)$ at time n can be written as:

$$\hat{x}_M(n) = \frac{w(n)y(n) + \lambda S_M(n-1) \hat{x}_M(n-1)}{w(n) + \lambda S_M(n-1)} \quad (22)$$

To conclude, the algorithm of adaptive, robust M-estimation can be formulated as [3]:
Initialisation: $S_M(0) = 0$ and $\hat{x}_M(0) = 0$
Basic recursion: $\forall n = 1, 2, \ldots$
1. using the weighted function ϕ of robust M-function calculate $w(n)$ as:

$$w(n) = \phi(y(n) - \hat{x}_M(n-1)) \quad (23)$$

2. estimation of $\hat{x}_M(n)$ according to eq. (22),
3. estimation of $S_M(n)$ according to eq. (20),
4. goto step 1.

The proposed filter for purpose of this paper is applied as the predictor of the first order.

In this work the Huber M-function is applied (see (6), (7) and (8))with cutoff value k. The choice of cutoff value k in significantly determines on the proposed algorithm. In this case, the cutoff value k can be chosen as [2]:

$$k = 2.576 \cdot \hat{\sigma}(n) \quad (24)$$

where $\hat{\sigma}^2(n)$ is estimated variance of the "impulse-free" estimation error. To estimate $\hat{\sigma}^2(n)$ the following formula can be used [2]:

$$\hat{\sigma}^2(n) = \lambda_\sigma \hat{\sigma}^2(n-1) + (1 - \lambda_\sigma) c_1 med(A_e(n)) \quad (25)$$

where $A_e(n) = \{e^2(n), \ldots, e^2(n - N_w + 1)\}$, $med(\cdot)$ denotes the sample median operation, N_w is the length of the estimation window ($N_w = 21$), λ_σ is the forgetting factor (in this work $\lambda_\sigma = 0.65$) and $c_1 = 1.483(1 + 5/(N_w - 1))$ is a finite sample correction factor.

The α-stable distributions

In the real world of signals and noises there exist many of them, which don't reveal the gaussianity, for example switching transients in power, accidental pulses in telephone lines and many others. In biomedical engineering, such phenomena occur in diathermia, when using surgical devices, or in electrocardiology (muscle noise), when a system is switched from one mode to another. Such signals can be characterized by their impulsiveness. These impulsive features can be well characterized using the α-stable distributions [18, 19]. In this work the symmetric α-stable distribution is applied.

A class of symmetric α-stable distributions (SαS) can be characterized by their distribution having a characteristic function

$$\varphi(t) = \exp(j\mu t - \gamma |t|^\alpha) \quad (26)$$

 ISSN: 1727-1983

where α is the characteristic exponent restricted in the range $0 < \alpha \leq 2$, μ is the real-valued location parameter, γ is the dispersion of the distribution ($\gamma > 0$), it determines the spread of the density around its location parameter [18]. The most important parameter of α-stable distributions is the characteristic exponent, because α controls the heaviness of the distribution tails [18].

For the estimation of the α-stable distributions parameters several methods have been proposed, see [4, 18, 19]. In this paper, the method described in [4] is used. Estimation in the $\log|S\alpha S|$-process characterizes low computational complexity, and the estimators are a closed form expression. Let $Y = \log|X|$, where X denotes random variable of the $S\alpha S$ distribution. The first and second moment of Y can be determined as:

$$E(Y) = C_e\left(\frac{1}{\alpha} - 1\right) + \frac{1}{\alpha}\log(\gamma) \tag{27}$$

$$Var(Y) = E\{[Y - E(Y)]^2\} = \frac{\pi^2}{6}\left(\frac{1}{\alpha^2} + \frac{1}{2}\right) \tag{28}$$

where: C_e=0.57721566... is Euler constant, $E(\cdot)$ is the expected value operator.
From (28) the characteristic exponent α is calculated and from (27) the dispersion γ is obtained.

Filtering procedure and simulation results

The M-filters presented in previous section were evaluated through a computer simulation procedure involving the ECG cycles filtering corrupted by simulated artificial α-stable noise and a muscle noise. The five ECG cycles were randomly chosen from the existing database. The ECG signal is sampled 2000 time per second and is of length $L = 1560$.

An ECG cycles are corrupted by the simulated α-stable noise with the known value of α and generalized SNR (GSNR) defined as:

$$GSNR = \log_{10}\frac{\sigma_s^2}{a\gamma} \tag{29}$$

where σ_s^2 is the variance of a clean signal signal, γ is the dispersion of an impulsive noise calculated as is described in [4], a is a scaling factor. When the characteristic exponent of $S\alpha S$ equals $\alpha = 2$, then standard SNR definition can be obtained. In the same way the ECG cycles are disturbed with the muscle noise.

In order to evaluate a performance of non-linear filtering the normalized mean square error (NMSE) factor is introduced and NSME is defined as:

$$NMSE = \frac{\sum_{i=1}^{L}[x_M(i) - s(i)]^2}{\sum_{i=1}^{L}[s(i)]^2}100\% \tag{30}$$

where: $x_M(i)$ is output of the M-filter, $s(i)$ is the deterministic part of a signal, without a noise, L is the signal length. The NMSE factor is the distortion measure of a signal after filtering procedure.

The algorithm presented in [1] is used to calculate the SNR improvement. The achievable improvement of the SNR of a noisy time series depends on the noise reduction method and on the SNR of the noise contained in the date. Let $s(n)$ is a real valued, time-discrete signal and its empirical mean is defined as:

$$\langle S\rangle = \frac{1}{L}\sum_{i}^{L} s(i) \tag{31}$$

The power of $s(n)$ is defined as $P_s = \langle S^2\rangle - \langle S\rangle^2$. Let the $x(n)$ is the signal corrupted by noise, then the SNR in $x(n)$ is defined as:

$$SNR_x = 10\log_{10}(\frac{P_s}{P_{s-x}}) \tag{32}$$

If by a noise reduction algorithm from $x(n)$ is generated another signal $x_M(n)$ supposed to be a better estimate of $s(n)$, the SNR improvement is defined as:

$$SNR_{impr} = SNR_{x_M} - SNR_x \tag{33}$$

The results are grouped into two categories. The first group of results are obtained for one value of GSNR, i.e. 10 dB for artificial, simulated impulsive noise. For each value of α (in the range from 1.5 to 2 with step 0.1), 200 different realizations of an impulsive noise were generated with known value of GSNR and added to clean cycle of ECG. The second group of results are obtained for the muscle noise. The muscle noise (200 different realizations of length 1560 samples, randomly chosen from the set of 5000000 samples) were added to a clean cycle of ECG signal at different, known levels of GSNR (10 dB, 15 dB, 20 dB, 30 dB, 40 dB). After filtering procedure, results were averaged separately for both this groups. The tables present mean values of NMSE factor and SNR_{impr}. The Savitzky-Golay filter, RLS filter and median filter are the reference filters.

Discussion and conclusions

The illustration of artificial impulsive noise added to the ECG cycle is plotted in Fig. 1. An example of the signal shape after filtering is presented in Fig. 2.

The artificial impulsive noise

This example shows the effectiveness of proposed filter when ECG cycle is corrupted with an impulsive noise modeled by the symmetric α-stable distributions. The results are presented in Table 1 and 2.

Nearly in the whole range of changing the characteristic exponent the best results are obtained for the median filter, except for $\alpha = 2$ (Gaussian distribution of noise). Then the best is common RLS filter. Good results are also obtained when $\alpha \leq 1.8$ for proposed filter. In the range of changing α results obtained by the proposed filter are nearly the same, mean value of NMSE equals 2.4%. When the distribution of noise is similar to the

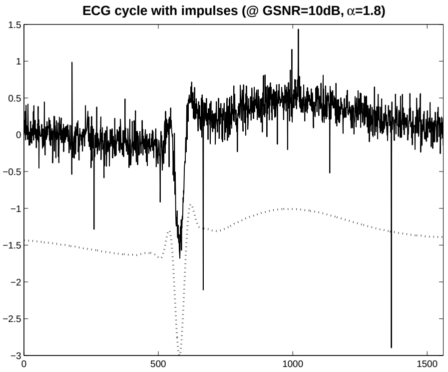

Figure 1: The ECG cycle disturbed with artificial impulsive noise (solid line) and clean signal (dotted line).

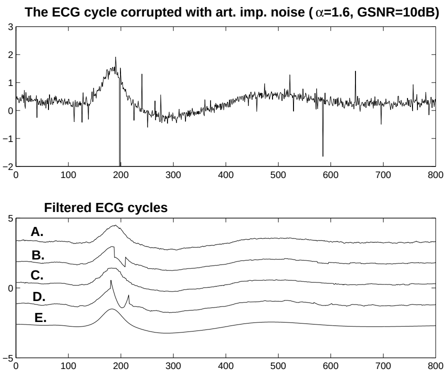

Figure 2: ECG cycle noisy (upper plot) and after filtering (lower plot: A - presented filter, B - RLS filter, C - Median filter, D - Savitzky-Golay filter, E - clean signal.).

Gaussian distribution ($\alpha \geq 1.9$) the reference filters lead to better results (smaller value of NMSE factor).

The same situation is during compering results for SNR improvement. The best results are obtained for the median filter, only for $\alpha = 2$ the Savitzky-Golay filter leads to the best improvement. The proposed filter leads to worse results than the median filter, but for $1.5 \leq \alpha \leq 1.7$ the proposed filter is better than other reference filters.

The muscle noise

This example shows the effectiveness of proposed filter when ECG cycle is corrupted with the muscle noise. The results are presented in Table 3 and 4. The results obtained under these conditions are different than previous. The best results are obtained for reference filters (the RLS filter and the Savitzky-Golay filter) for the highest value of GSNR. These filters introduce the smallest distortions (lower values of NMSE) in the filtered signal. The value of NMSE factor for the proposed filter it nearly two times greater than for the smallest value obtained with one of the reference filters. When GSNR is lower, all used filters lead to nearly the same results, but the proposed filter leads to a little worse results (higher value of NMSE and smaller SNR improvement). The proposed filter doesn't offer good the SNR improvement. Better SNR improvement offers the reference filters than the proposed filter.

Table 1: The evaluation of the NMSE factor for the proposed filter (MLOC), the RLS filter, the median filter and the Savitzky-Golay filter (sgol) for GSNR=10 dB. ECG signal is disturbed with noise modeled with α-stable distribution

average NMSE [%]				
α	MLOC	RLS N=21	med N=21	sgol order=2, N=35
1.5	2.63	179.95	1.25	210.40
1.6	2.48	12.13	1.23	14.61
1.7	2.47	30.62	1.24	35.22
1.8	2.41	2.09	1.24	2.51
1.9	2.29	1.38	1.21	1.64
2.0	2.12	0.80	1.15	0.91

Table 2: The evaluation of the SNR_{impr} factor for the proposed filter (MLOC), the RLS filter, the median filter and the Savitzky-Golay filter (sgol) for GSNR=10 dB. ECG signal is disturbed with noise modeled with α-stable distribution

average SNR_{impr}				
α	MLOC	RLS N=21	med N=21	sgol order=2, N=35
1.5	18.47	12.88	21.66	11.95
1.6	15.79	12.90	18.84	11.93
1.7	13.21	12.83	16.20	12.01
1.8	11.22	12.72	14.12	11.93
1.9	9.78	12.65	12.56	11.95
2.0	8.15	12.48	10.82	11.91

Table 3: The evaluation of the NMSE factor for the proposed filter (MLOC), the RLS filter, the median filter and the Savitzky-Golay filter (sgol) for the muscle noise

average NMSE [%]				
GSNR	MLOC	RLS N=21	med N=21	sgol order=2, N=35
10	9.32	5.90	6.01	7.58
15	3.70	2.02	2.12	2.58
20	2.00	0.97	0.98	1.16
30	0.70	0.14	0.09	0.07
40	0.66	0.10	0.02	0.01

Conclusions

The present filter offers a useful and robust approach to suppress the different kind of an strictly impulsive

ISSN: 1727-1983 © 2005 IFMBE

Table 4: The evaluation of the SNR_{impr} factor for the proposed filter (MLOC), the RLS filter, the median filter and the Savitzky-Golay filter (sgol) for the ECG cycles disturbed with the muscle noise.

average SNR_{impr}				
GSNR	MLOC	RLS N=21	med N=21	sgol order=2, N=35
10	2.43	5.57	5.29	4.79
15	0.99	4.99	4.86	4.72
20	-1.33	3.89	4.20	4.64
30	-9.56	-1.77	1.33	3.84
40	-18.67	-10.00	-4.28	1.15

noise. The results obtained for artificial impulsive noise, when $\alpha \leq 1.7$ show the advantage of the proposed filter in the field of the smallest distortions introduced to filtered signal and good SNR improvement. The second advantage of the proposed filter is a small computation effort. Worse results obtained for the muscle noise can be caused the fact that a level of impulsiveness in the muscle noise is not so high (equivalent of the characteristic exponent $\alpha \geq 1.8$) and higher contribution of Gaussian distribution.

To conclude, the proposed filter can effectively suppress the impulsive noise in biomedical signals.

References

[1] BROCKER J., PARLITZ U., and OGORZALEK M. Nonlinear noise reduction. *Proceedings of the IEEE*, 90:898–918, 2002.

[2] CHAN S. and ZOU Y. A recursive least m-estimate algorithm for robust adaptive filtering in impulsive noise: fast algorithm and convergence performance analysis. *IEEE Trans. on Signal Processing*, 52:975–991, 2004.

[3] GEORGIADIS A.T. Adaptive equalisation for impulsive noise environments. *The Univeristy of Edinburgh, PhD thesis*, September 2000.

[4] GEORGIOU P.G., TSAKALIDES P., and KYRIAKAKIS CH. Alpha-stable modeling of noise and robust time-delay estimation in the presence of impulsive noise. *IEEE Trans. on Multimedia*, 1:291–301, 1999.

[5] GONZALEZ J.G. and ARCE G.R. Statistically-efficient filtering in impulsive environments: weighted myriad filters. *EURASIP Journal on Applied Signal Processing*, 1:4–20, 2002.

[6] HONG X. and CHEN S. M-estimator and d-optimality model construction using orthogonal forward regression. *IEEE Trans. on Systmes, Man and Cybernetics*, 35:1–7, 2005.

[7] HUBER P.J. *Robust Statistics*. Wiley-Interscience, 1981.

[8] KALLURI S. and ARCE G.R. Fast algorithms for weighted myriad computation by fixed point search. *IEEE Trans. on Signal Processing*, 48:159–171, 2000.

[9] KIM S.R. and EFRON A. Adaptive robust impulse noise filtering. *IEEE Trans. on Signal Processing*, 43:1855–1866, 1995.

[10] LEE Y.H. and KASSAM S.A. Generalized median filtering and related nonlinear filtering techniques. *IEEE Trans. on Acoustics, Speech, and Signal Processing*, 33:672–683, 1985.

[11] LEE Y.H. and KASSAM S.A. Generalized median filtering and related nonlinear filtering techniques. *IEEE Trans. on Acoustics, Speech, and Signal Processing*, 33:672–683, 1985.

[12] LESKI J. Robust weighted averaging. *IEEE Trans. On Biomedical Engineering*, 49:796–804, 2002.

[13] LI S.Z. Robustizing robust m-estimation using deterministic anealing. *Pattern Recognition*, 29:159–166, 1996.

[14] NENADIC Z. and BURDICK J.W. Spike detection using the continuous wavelet transform. *IEEE Trans. on Biomedical Engineering*, 52:74–87, 2005.

[15] PETRUS P. Robust huber adaptive filter. *IEEE Trans. on Signal Processing*, 47:1129–1133, 1999.

[16] POULARIKAS A.D. *The Handbook of Formulas and Tables for Signal Processing*. CRC Press LLC, 1999.

[17] PRESS W.H., TEUKOLSKY S.A., VETTERLING W.T., and FLANNERY B.P. Numerical recipes in c: The art of scientific computing. http://www.nr.com.

[18] SHAO M. and NIKIAS CH.L. Signal processing with fractional lower order moments: stable processes and their applications. *Proceedings of IEEE*, 81:986–1009, 1993.

[19] TSIHRINTZIS G.A. and NIKIAS CH.L. Fast estimation of the parameters of alpha-stable impulsive interference. *IEEE Trans. on Signal Processing*, 44:1492–1503, 1996.

[20] ZHANG Z. Parameter estimation techniques: A tutorial with application to conic fitting. http://www-sop.inria.fr/robotvis/personnel/zzhang/Publis/Tutorial-Estim/node1.html.

ISSN: 1727-1983 © 2005 IFMBE