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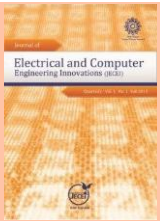
Journal of Electrical and Computer Engineering Innovations

JECEI, Vol. 4, No. 2, 2016

Regular Paper



Adaptive-Filtering-Based Algorithm for Impulsive Noise Cancellation from ECG Signal

Azam Khalili[1,*], Amir Rastegarnia[1], Vahid Vahidpour[1], and Md Kafiul Islam[2]

[1] Department of Electrical Engineering, Malayer University, Malayer, Iran.

[2] Department of Electrical and Electronic Engineering, Independent University, Bangladesh.

[*]Corresponding Author's Information: khalili@malayeru.ac.ir

ARTICLE INFO

ARTICLE HISTORY:
Received 03 January 2017
Revised 09 March 2017
Accepted 19 March 2017

KEYWORDS:
Adaptive filtering
Impulsive noise
Maximum correntropy
ECG signal
Noise cancellation

ABSTRACT

Suppression of noise and artifacts is a necessary step in biomedical data processing. Adaptive filtering is known as a useful method to overcome this problem. Among various contaminants, there are some situations such as electrical activities of muscles contribute to impulsive noise. This paper deals with modeling real-life muscle noise with α-stable probability distribution and adaptive filtering noise cancellation assessment with maximum correntropy criterion (MCC) as adaptive technique. Based on our test on some data of MIT-BIH arrhythmia and EMBC databases, we achieve an improved signal to noise ratio (SNR) in any electrocardiogram (ECG) signal corrupted by impulsive noise. The worst achieved improvement based on setting the best parameter values using trial and error for both filter and utilized algorithm is 9.5 dB with correlation coefficient value of 0.93. The SNR improvement on the whole utilized database records is 11.03 dB on average. The proposed algorithm is applied to the records from MIT-BIH arrhythmia and EMBC databases to remove the impulsive noise. A computer simulation is used to create and add it to the ECG signals. Simulation results are also provided to support the discussions.

1. Introduction

Due to significant technological advances in signal processing, system enhancements of biomedical signal analysis has become a major research field. Among the biomedical signals, electrocardiogram (ECG) acquires the most studied type for decades. Work on ECG signals has become a significant tool to diagnose for cardiac disorders [1]. Each segment of this biomedical signal type carries various types of important information for the clinician analyzing the patients' heart condition. For instance, the amplitude and occurrence of the P wave, and the duration of the Q wave, R wave and S wave (QRS) morphography are indicative of the cardiac muscles mass condition [2]. Loss of amplitude indicates muscle damage whereas increased amplitude indicates abnormal heart rates [3]. Thus it is crucial to estimate the parameters of the ECG signal like [4] RR-interval, QRS-length, PR-interval, and the elevation/depression of ST-segment with precise. Moreover, the recorded ECG signal is often perturbed by some artifacts with components within the frequency band of interest and contaminated with similar ECG signal characteristics. Consequently, ECG signal characteristics are highly susceptible to artifacts and extracting valuable and morphological features in order to signal enhancement in ECG analysis is become crucial [5, 6]. In other word, the ECG waveform can not be analyzed unless the ECG data is improved. Furthermore, maximizing the signal-to-noise (SNR) ratio is the primary objective of the ECG signal enhancement without elimination the valuable clinical information contained within the signal. To do so, digital signal processing technique is utilized to provide this information precisely and swiftly.

TABLE 1
LIST OF COMMON BIOSIGNAL CONTAMINANT

Type	Contaminant
Measurement	Motion artifact Skin stretch reflex
Instrumentation	Baseline wander Amplifier saturation Analog-to-digital converter over-ranging Poor electrode contact (including electrode lift)
Interference	Power line interference RF interference Unwanted physiological biosignals (e.g., cross talk)

Therefore, it is required to extract the valuable information from noisy ECG signals, so it would be readily accessible through diagnosis.

In general, ECG contaminants can be classified into the common categories listed in Table I. Among these, two most noteworthy contaminants encountered through biomedical signal acquisition are power line interference (PLI) and baseline wandering (BW). They can have a severely effect on ECG signal analysis. Except for these two noises, other noises may be broad-band. PLI arises from a narrow-band noise with a bandwidth of less than 1 Hz centered at 60 Hz (or 50 Hz). Generally, ECG signal acquisition hardware can suppress the power line interference. However, suppression of baseline wandering and other wideband artifacts are not achieved simply by hardware equipment. In preference to hardware equipment, the mathematical techniques of the digital signal processing are more influential and attainable for non-real time ECG signal processing.

A. Literature Review

In order for artifact and noise suppression purposes, the use of various algorithms to analyze the ECG data has drawn increasing attention in the last three decades. These methods attempt to improve the SNR for preferable interpretation and classification. Projecting out the noise and artifacts from ECG signals and representing noise and artifacts as independent components are the basic idea of using Independent component analysis (ICA) methods [7], [8]. A method for suppression of noise and artifacts in ECG recordings based on combined principal component analysis (PCA) and different version of ICA (fICA, sICA, and cICA) is discussed in [9]. Wavelet filtering (WF), leads to good performance of detection algorithm even in the presence of severe high and low frequency noise, has been utilized as denoising technique in some approaches [10], [11].

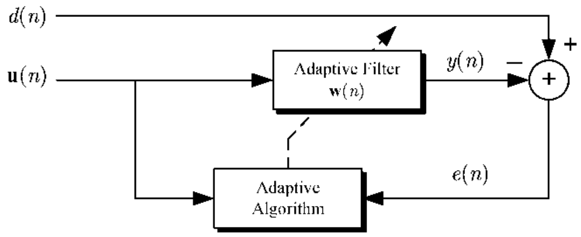


Figure 1: Diagram of an adaptive filter.

Moreover, there exist some denoising methods from ECG signal based on Wavelet Wiener filtering (WWF) in literature [12], [13]. In [14], a Kalman filter with adaptive noise covariance estimation has been proposed. This filter, which is derived using a Bayesian framework, uses the actual ECG data as basis and infers whether this ECG data is corrupted by noise or dynamic variations, in contrast to filters uses parametric function to model ECG for filtering [15]. In [16], ECG waveform is completely simulated mathematically with model parameters and an adaptive noise canceller (ANC) is presented to remove the added noise. Then, different adaptive algorithms, such as LMS and NLMS, are performed to evaluate the noise cancelation performance.

In [17], a new method of myriad filter output computation based on least square approximation is proposed. Results demonstrate effective performance in suppression of muscle (impulsive) noise in ECG signal. Suppression of impulsive noise using M-filters and application of the alpha-stable distribution as a model of muscle noise in ECG signals is proposed in [18]. The ability of suppression impulsive noise based on an adaptive filter has been discussed in [19].

B. Our Contributions

In biomedical signal processing, adaptive techniques prove extremely useful in noise interference removal, notably in the case of non-stationary processes. Adaptive filters are able to modify their parameters based on the input signal, either no prior information is available or signal or noise is non-stationary. In the former case, an adaptive filter requires an initial period for learning and adaptation. After learning and adaptation, the filter, tracking non-stationary changes in signal and noise, is supposed to act optimally.

Noise cancelling is a variation of optimal filtering that utilizes a supplementary reference input extracted from one or more sensors located at point(s) in the noise field where the signal power is weak or unnoticeable. This input is filtered and subtracted from a primary input comprises both signal and noise. Consequently, the primary noise is attenuated or removed by cancellation. Fig.1 indicates a typical adaptive noise cancellation system (ANC). In summary, the adaptive noise cancellation is composed of two separate inputs, desired input signal $d(n) = s(n) + v(n)$, corrupted by noise, and a reference input (vector) $\mathbf{u}(n)$ contains noise related in some way to that in the main input but does not contain anything related to the signal. The reference input is passed through the adaptive filter and the output $y(n)$ is produced as a close replica as of $v(n)$.

To minimize the error between $v(n)$ and $y(n)$ during this process, the filter readjusts its coefficient continuously. Therefore, the filter $\mathbf{w}(n)$ requires dynamic adaptation to perform the successful interference noise removal from the polluted signal of interest $d(n)$. Here, $\mathbf{w}(n)$ may be an m-point Finite Impulse Response (FIR) filter with real values. Then, the output $y(n)$ is subtracted from the desired input to form the system output $e(n)$, which is the denoised signal. This process is run in a recursive manner to obtain the noise free signal which is supposed to be equal or alike to primary signal $s(n)$.

An adaptive procedure relies on an objective function or cost function to optimize under a certain criterion. For instance, the Least Mean Squares (LMS) adaptive algorithm is a popular adaptation technique which minimizes the mean squared error (MSE) between the desired signal and the filter output. The MSE-based adaptive algorithms may perform poorly for non-Gaussian situations signals, especially when the data are corrupted by impulsive noises. To address this issue, one possible way is to move beyond mean squared error, and consider techniques which exploit higher order moments of the error.

In this paper, we employ maximum correntropy criterion (MCC)-based algorithm to express a cost function defined further as JMCC. Therefore, the optimization criterion is the minimization of such objective function JMCC. The MCC has recently been applied to adaptive filtering algorithms to improve the tracking performance in impulsive interference [20], [21], while MSE-based algorithms perform poorly [22]. Compared with conventional minimum mean square error (MMSE) criterion-based adaptive filtering algorithm, the MCC-based algorithm shows a better robustness against impulsive interference [23].

Here in, we consider the problem of noise suppression in the ECG signal, under the noise cancellation setup conditions of adaptive filtering. The adaptive algorithm is based on MCC. More specifically, the main objective of this paper is to model the ECG signal with α-stable distribution and then suppress this noise using adaptive filtering. An additional aim of this paper is to present the effect of MCC-based algorithm on suppression of impulsive noise in biomedical signal. It is worth noting that for the system to be reliable, following properties should be ensured:

- Maximizing signal-to-noise ratio without removing clinical information contained within signal.
- Strictly accurate estimation of important ECG signal morphological parameters.
- False ECG wave shapes are not created.
- Implementing and maintaining diagnostic information practically, reliably and safely by the technique.

The rest of the paper is organized as follows. Section 2 defines noise model. Brief overview of α-stable distribution is presented. The MCC algorithm is presented in Section 3. In Section 4, the utilized database is explained. The simulation results and discussion are given in Section 5. The conclusion is drawn in Section 6.

2. Impulsive Noise Model

According to the central limit theorem, Gaussian distribution could be considered for all real applications, when enough samples from a distribution are available. This issue is underlined in the signal processing field where Gaussian distribution is utilized to model the random noise in a signal [24]. However, a wide variety of signals found in practice arise non-Gaussian impulsive behavior [25]. This impulsive phenomenon exhibits in high peaks in small time durations. Atmospheric radio noise, telephone lines noise, office equipments noise, and multi-user interference in mobile communication systems are some typical examples of impulsive noise. Furthermore, in biomedical engineering, while using surgical device, and in electrocardiology, i.e. muscle noise, some situations occur where it contributes to impulsive noise. As mentioned above, the Gaussian model could not be considered to model such cases. Several non-Gaussian impulsive noise models [26], [27] exist in literature. The α-stable family has been shown to be an accurate statistical-physical model for non-Gaussian impulsive interference.

As there is no closed-form of the probability density function (PDF) for α-stable distribution, its characteristic function rather describes it. So, t denotes a α-stable distributed random variable, if we have

$$\varphi(t) = \exp\{j\delta t - \gamma\left|t\right|^{\alpha}\left[1 + j\beta\,\mathrm{sgn}(t)\rho(t,\alpha)\right]\} \quad (1)$$

where

$$\rho(t,\alpha) = \begin{cases} \dfrac{2}{\pi}\log\left|t\right|, & \alpha = 1 \\ \tan\dfrac{\pi\alpha}{2}, & \alpha \neq 1 \end{cases} \quad (2)$$

The characteristic exponent, $0 < \alpha \leq 2$, describes the degree of impulsiveness (Fig. 2).

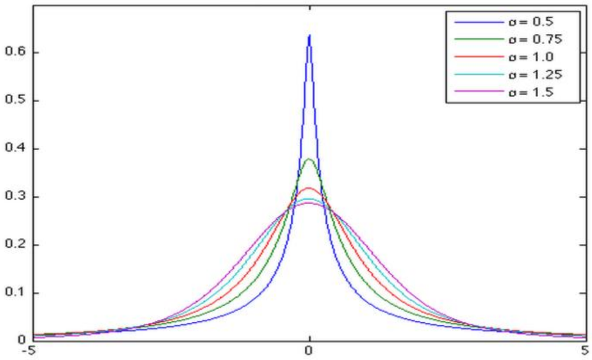


Figure 2: The probability density function of a symmetric α-stable distribution for different values of α (β=0, γ=1 and δ=0).

The smaller the α, the more impulses frequently occur. The dispersion parameter, $\gamma > 0$, describes the spread of distribution around its location parameter δ which is represented by mean as $1 < \alpha \leq 2$ and median as $0 < \alpha \leq 1$, and the index of skewness, $-1 \leq \beta \leq 1$, determines the distribution symmetry.

3. PROPOSED ALGORITHM

Consider the desired signal $d(n)$ to be expressed as

$$d(n) = \mathbf{u}(n)^T \mathbf{w}_o + v(n) \tag{3}$$

where $\mathbf{w}_o \in \mathbb{R}^M$ is an unknown parameter to be estimated, $\mathbf{u}(n) = [u(n), \cdots, u(n-m+1)]^T$ is the input vector, and $v(n)$ is the impulsive noise. Moreover, the error signal is defined as

$$e(n) = d(n) - \mathbf{w}^T(n)\mathbf{u}(n) \tag{4}$$

where $\mathbf{w}(n)$ denotes the weight vector of the adaptive filter. A more robust solution in non-Gaussian interference (i.e. impulsive case) [28]-[31] has recently been successfully proposed by the MCC-based adaptive algorithm [28-33]. Given two random variables X and Y, the correntropy is defined as

$$V(X,Y) = \mathrm{E}\left[\kappa(X,Y)\right] = \int \kappa(x,y) dF_{X,Y}(x,y) \tag{5}$$

where $\kappa(\cdot\,,\cdot)$ is a shift-invariant Mercer kernel, and $F_{X,Y}(x,y)$ denotes the joint distribution function of (x,y). The Gaussian kernel is the most widely used kernel in correntropy

$$\kappa(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\zeta^2}{2\sigma^2}\right) \tag{6}$$

where $\zeta = x - y$, and $\sigma > 0$ is the kernel width.

Using the MCC-based algorithm we can express the following cost function:

$$J_{MCC} = \mathrm{E}\left[\exp\left(-\frac{e^2(i)}{2\sigma^2}\right)\right] \tag{7}$$

Maximizing (8) leads to the optimal weight vector of the filter. Using the stochastic gradient based adaptive algorithm, the MCC-based algorithm can be derived as [20], [32].

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \eta \;\; \exp\left(-\frac{e^2(n)}{2\sigma^2}\right) e(n)\mathbf{u}(n) \tag{8}$$

where $\eta > 0$ is the step-size. Although (9) is more robust against impulsive interference, it still exists the performance trade-off problem like traditional adaptive algorithm. The appropriate selection of kernel width, σ, can be found in [33]. Fixed kernel width leads to controlling the tracking performance of (9) by the step-size η [32].

4. DATA DESCRIPTION

The proposed method is tested on ECG data obtained from MIT-BIH arrhythmia database [34]. These recordings were obtained from inpatients and outpatients intended to serve as a representative sample of the variety of waveforms and artifact that an arrhythmia detector might encounter in routine clinical use. Segments selected in this way were excluded only if neither of two ECG signals was of adequate quality for analysis by human experts. Two-channel ambulatory ECG recordings were obtained by placing the electrodes on the chest. The upper signal is modified limb lead II (MLII) and the lower is usually a modified V1 (both electrodes are placed on the chest). The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV (±5 mV). Sample values thus range from 0 to 2047 inclusive with value of 1024 corresponding to zero volts. The 11-bit samples were originally recorded in 8 bit first in a different format. Besides MIT-BIH arrhythmia database, another database has been utilized on our proposed method [35]. These three-channel of the 12 bits resolution clean ECG signal were collected from derivations II, V5 and V6, from healthy subjects with a duration of 30 minutes each at 250 samples per second. Fig. 3 shows one example of pure noise (simulated noise), clean ECG, and a combination of both noise and clean ECG from the former database.

5. Simulation Results and Discussions

In order to assess our MCC-based impulsive denoising technique performance, we have achieved some simulated scenarios on some the segments from the mentioned databases. The selected segments contain impulsive noise by adding simulated impulse noise. A segment of the record 101 from MIT-BIH arrhythmia database and another of the record D102 from second database are used to demonstrate the performance of the proposed method visually.

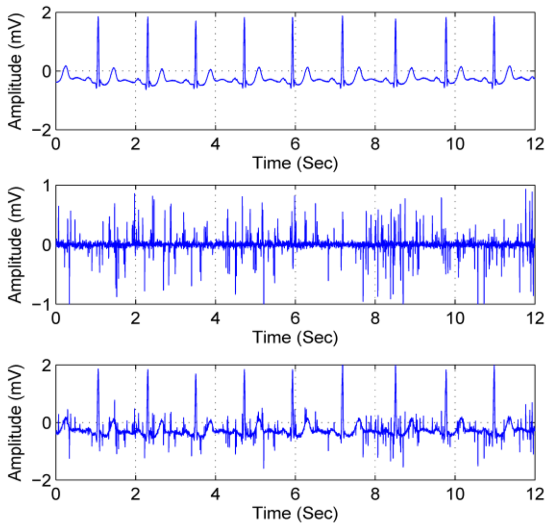


Figure 3: (a) Clean ECG signal (103 of MIT-BIH arrhythmia database), (b) simulated noise, (c) sum of both simulated noise and clean ECG signal.

Implementation of the above denoising technique and applying it to the mentioned records yielded promising results (Fig. 4 and Fig. 5). It is clearly visible that the proposed algorithm removes impulse noise efficiently.

In this paper, SNR improvement and correlation coefficient are two evaluation criteria to show the performance of the MCC-based adaptive algorithm. The signal to noise ratio is calculated by

$$\text{SNR} = 10\log_{10}\left(\frac{P_S}{P_N}\right) \tag{9}$$

where P_S and P_N denotes the power of the signal and noise respectively. Now, consider corrupted signal S with signal-to-noise ratio SNR_{in} in dB. If a noise reduction algorithm, utilized on S, leads to better signal-to-noise ratio denoted by SNR_{out} , the SNR improvement is defined as

$$\text{SNR}_I = \text{SNR}_{out} - \text{SNR}_{in} \tag{10}$$

Furthermore, to make sure the filtered output is similar to the original ECG signal, the correlation coefficient is computed. Table II shows the SNR improvement and correlation coefficient obtained for impulsive noise removal on 6 records from utilized database (101, 102, and 104 are of MIT-BIH arrhythmia and D104, D112, and D116 are of EMBC database). It should be noted that values close to 1 suggest that there is a positive linear relationship between the original and filtered ECG signal. To show the effect of kernel width σ and step size η parameters on SNR improvement, we organized another experiment. These situations are described in Fig. 6 and Fig. 7.

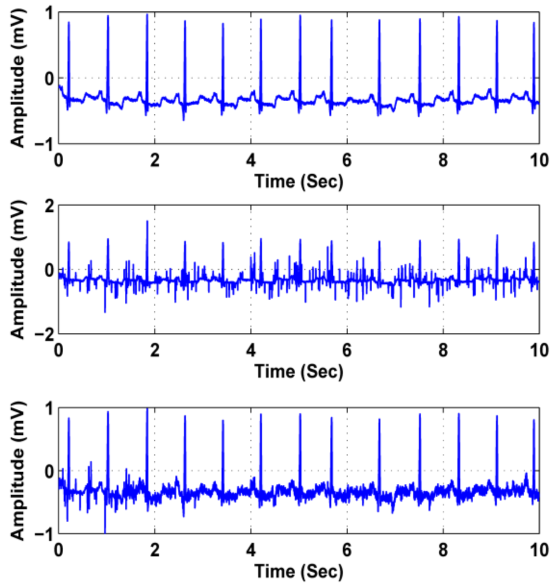


Figure 4: (a) Clean ECG signal (100 of MIT-BIH arrhythmia database), (b) corrupted ECG signal with simulated impulse noise, (c) ECG signal with suppressed noise.

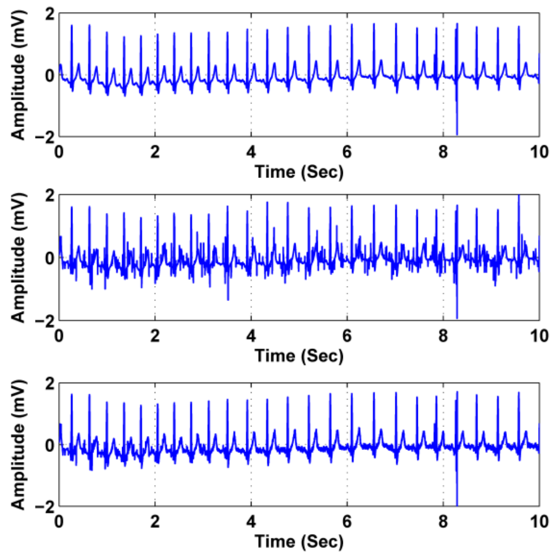


Figure 5: (a) Clean ECG signal (D102 of EMBC database), (b) corrupted ECG signal with simulated impulsive noise, (c) ECG signal with suppressed noise.

TABLE 2
SNR IMPROVEMENT AND CORRELATION COEFFICIENT FOR IMPULSIVE NOISE

Record	SNR Improvement (dB)	Correlation Coefficient
101	14.9660	0.9216
102	9.5582	0.9390
104	10.1046	0.9722
D104	9.7869	0.9743
D112	11.9998	0.9646
D116	9.7833	0.9433
Average	11.0331	0.9525

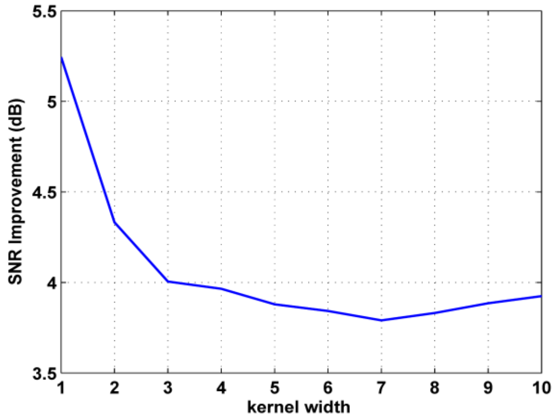


Figure 6: The SNR improvement under kernel width σ variations for a sample record.

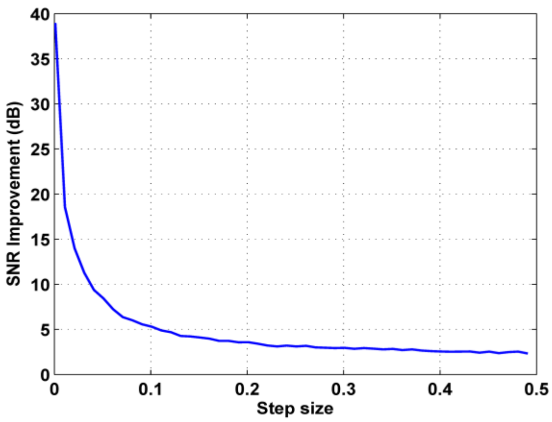


Figure 7: The SNR improvement under step size η variations for a sample record.

These graphs demonstrate the SNR improvement behavior under kernel width σ and step size η variations. Besides, Fig. 6 and Fig. 7 express the SNR improvement increases from 5.2 dB to 3.79 dB with increasing kernel width σ and decreases from 38.96 dB to 2.34 dB with increasing step size η, respectively. In other words, the smaller (larger) the η (σ), the more increasing (decreasing) SNR improvement. Fig. 8 shows the SNR improvements for different algorithms, including our proposed algorithm, the LMS algorithm and least-mean P-power (LMP) algorithm [36].

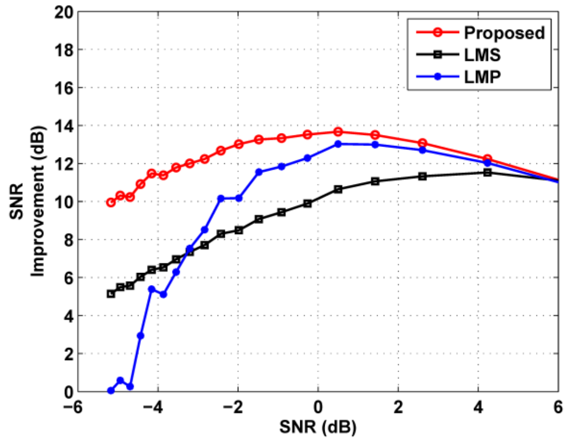


Figure 8: The effect of SNR variations on SNR improvement for a sample record.

As it is clear from Fig. 8, the proposed algorithm exhibits better performance, especially for low SNR values. Note that, as expected, for high SNRs, all algorithms provide similar performances.

6. CONCLUSIONS

This paper investigated the performance of the maximum correntropy criterion (MCC) based algorithm in suppression of impulsive noise types from ECG signals. Results indicated that using MCC-based algorithm as the adaptive algorithm with noise cancellation setup has a noticeable effect on denoising ECG signals. Moreover, the implementation of proposed algorithm was successfully accomplished, with results that have an extremely positive and favorable response.

It is evident from the results that the selection of suitable parameter values, such as filter length, step size, and kernel width, results in a positive effect on performance of the adaptive filter and the utilized adaptive algorithm. Based on our test on some data of MIT-BIH arrhythmia and EMBC databases, we achieve an improved SNR in any ECG signal corrupted by impulsive noise.

The worst achieved improvement based on setting the best parameter values using trial and error for both filter and utilized algorithm was 9.5582 dB with correlation coefficient value of 0.9390.

SNR improvement on the whole utilized database records (Table II) was 11.0331 dB on average.

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Biographies

Azam Khalili was born in Malayer, Iran. She received the Ph.D. degree in Electrical Engineering from the University of Tabriz, Tabriz, Iran, in 2011. In 2011, she joined the Department of Electrical Engineering, Malayer University, as Assistant Professor. Her current research interests are theory and methods for adaptive filtering, distributed adaptive estimation, as well as signal processing for communications. She is a Member of the IEEE.

Amir Rastegarnia was born in Urmia, Iran. He completed his Ph.D. degree in the electrical engineering at the University of Tabriz, Tabriz, Iran, in 2011. In 2011, he joined the Department of Electrical Engineering, Malayer University, as Assistant Professor. His current research interests are theory and methods for adaptive and statistical signal processing, distributed adaptive estimation, as well as signal processing for communications. He is a Member of the IEEE.

Vahid Vahidpour received the M.Sc. degree in Communication Engineering from Malayer University, Hamedan, Iran, in 2016. His research interests include underwater acoustic, distributed and adaptive signal processing and biomedical signal processing. Vahidpour is a student member of the IEEE.

Md Kafiul Islam was born in 1988 in Bangladesh where he is currently serving as an Assistant Professor at Dept. of Electrical and Electronic Engineering (EEE), Independent University, Bangladesh. Before that, he has received his Ph.D. degree from Dept. of Electrical and Computer Engineering (ECE), National University of Singapore in 2015. His B.Sc. in EEE was awarded in 2008 from Islamic University of Technology (IUT), Dhaka, Bangladesh. His research interests include biomedical signal processing and instrumentation, neural engineering, Brain-Computer Interface.

How to cite this paper:

A. Khalili , A. Rastegarnia, V. Vahidpour, and M. Kafiul Islam, "Adaptive-filtering-based algorithm for impulsive noise cancellation from ECG signal," Journal of Electrical and Computer Engineering Innovations, vol. 4. no. 2, pp. 169-176, 2016.

DOI: 10.22061/jecei.2017.619

URL: http:// jecei.srttu.edu/article_619.html