Suppression of Impulse Noise using Adaptive Filters

Shankar Gupta, Ramchandra Manthalkar, Suhas Gajre

Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded, Maharashtra, India

Abstract

The electrical activity of muscles is usually modeled using Gaussian probability distribution function. Such assumption is not always true, because real-life muscle noise has impulse character as well. Adaptive threshold technique is one important step in the detection of QRS Complexes. However, presence of impulse noise may trigger false positives. The proposed system uses adaptive filters to suppress impulse noise in ECG signal and avoid the false positives. It was observed that despite the noise, the algorithm identifies the system and adjusts coefficients accordingly. Significant improvement in Signal-to-Noise ratio is achieved after suppressing impulse noise.

1. Introduction

The adaptive algorithm used to suppress impulse noise is based on a system identification application with impulse noise contribution. In this algorithm, $x(n)$ is the stimulus signal, which is applied to the unknown system and the adaptive filter. The output of the unknown system, $d(n)$ or desired signal, is corrupted by impulse noise and contaminated with Gaussian noise, not correlated to the adaptive system input $x(n)$. Weights are updated using delta learning rule. The updated weights are effectively reducing the impulse noise when a simulated impulse noise is added to the ECG signal. The brief theory of system identification technique is given for illustrating the algorithm. Detailed algorithm of suppression of impulse noise is described. The results of our experimentation are demonstrated by plotting the ECG with impulse noise (added by using simulation) and after suppression of impulse noise. The performance of our method is validated by computing SNR. This work will suppress the noise in the ECG signal, retaining the original information content of the signal.

2. Noise in ECG

The commonly encountered noise in ECG are power line interference, electrode pop or contacted noise, patient-electrode motion artifacts, electromyographic noise(EMG), baseline drift, data collecting device noise, electrosurgical noise, quantization noise and aliasing, and signal processing artifacts[1]. Though gaussianity is considered for the simulation of real world noise, the reality is different. The switching transient in power, accidental pulses in telephone lines contribute to impulse noise. Such phenomena occur in biomedical engineering in diathermia, while using surgical devices, in electrocardiology (muscle noise), when a system is switched from one mode to another. The impulses in such systems can be characterized by α stable distributions[2-3]. For electrocardiogram signal processing suppression of impulse noise is carried out by using nonlinear M-filters, namely, median and myriad filters.

The impulse noise in ECG can be characterized by a class of symmetric α stable distributions. A typical characteristic function is given by

$$\phi(t) = abs(\exp(j\mu t - \gamma|t|^{\alpha})) \tag{1}$$

where α is the characteristic exponent restricted in the range ($0 < \alpha \leq 2$), μ is real valued location parameter. The dispersion around the location parameter is given by γ. γ greater than zero determines the spread of density around its location parameter. The characteristic exponent α controls the heaviness of the distribution tails. If a stable random variable is absorbed the larger the value of α, the less likely it is to observe values of the random variable far from its central location. The noise can be added to ECG signal by sampling $\phi(t)$.

2.1. Modeling impulse noise in ECG

The muscle noise occurs as the result of superposition of large number of action potentials which form in the muscles. The EMG signal is non- stationary and non-linear in nature. The Electrical activity due to muscle contraction lasts around 50 ms between dc and 10,000 Hz with an average amplitude of 10 percent full scale deflection (FSD), the peak-to-peak ECG amplitude. For the modeling of muscle noise several methods were proposed. Muscle noise can be modeled as spikes which are assumed to be an impulse response of a second order linear system. The most frequent used model of a muscle noise is the white Gaussian noise. Classical statistical-physical models for impulse interference are based on the filtered impulse mechanism[2]. One can observe some number of samples for which values are significantly far from the average value of the samples while analyzing EMG signal. Such samples can be seen as spikes with large value. In this situation the α - stable distribution can be used as a proper model for the muscle noise. α stable random variables arise in the physical world as the effects of a large number of independent contributing factors. Significant, gains in performance can be obtained if the noise suppression algorithm is based on more appropriate statistical-physical models for impulse interference.

3. Model for suppression of impulse noise

The adaptive system identification is primarily responsible for determining a discrete estimation of the transfer function for an unknown digital or analog system. The same input $x(n)$ is applied to both the adaptive filter and the unknown system from which the outputs are compared as shown in Figure 1. The output of the adaptive filter $y(n)$ is subtracted from the output of the unknown system resulting in a desired signal $d(n)$. The resulting difference is an error signal $e(n)$ is used to manipulate the filter coefficients of the adaptive system trending towards an error signal of zero. In this case, the adaptive algorithm used to adjust the coefficients of the FIR filter has the task of continually tracking the statistical variations in the system.

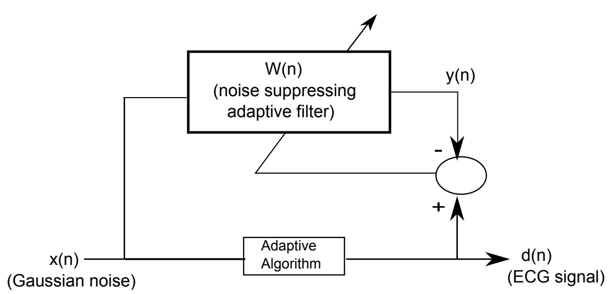

Figure 1. System Identification

At time n, the estimation error is non-zero,implying that the model deviates from the unknown system. In an attempt to account for the deviation, the estimation error $e(n)$ is used as the input to an adaptive control algorithm, whereby it controls the corrections applied to the individual tap weights set of values for use on the next iteration. Thus at time $n + 1$, a new filter output is produced, and with it a new value for the estimation error. The operation described is then repeated. This process is continued for a sufficiently large number of iterations, until the deviation of the model from the unknown dynamic system, measured by the estimation error $e(n)$, becomes sufficiently small in some statistical sense, mean-square error in this case.

After a number of iterations of this process are performed , and if the system is designed correctly, the adaptive filter's transfer function will converge to, or near to, the unknown system's transfer function. For this configuration, the error signal does not have to go to zero, although convergence to zero is the ideal situation, to closely approximate the given system. There will, however, be a difference between adaptive filter transfer function and the unknown system transfer function if the error is nonzero and the magnitude of that difference will be directly related to the magnitude of the error signal.

When the adaptive model has enough flexibility to match the dynamic response of the W(n), its output will perfectly match that of the unknown system except for noise W(n)(noise in unknown model)[4-5]. The noise is generally uncorrelated with the system model. If the adaptive model is an adaptive linear combiner whose weights are adjusted to minimize mean-square error, then the least-squares solution will be unaffected by the presence of the noise in model. The least-squares solution will be determined primarily by the impulse response of the system to be modeled. It is significantly affected by the statistical or spectral character of the input signal.

4. Suppression of impulse noise in ECG

Adaptive filters are based on minimization of a certain cost function. The most widely cost function is the mean square error. This cost function implicitly assumes the error produce by the adaptive system to be Gaussian. In many real world problems the noise encountered is more impulse then that predicted by a Gaussian distribution. An obvious option is to use a different cost function. A well known alternative, based on robust statistics is the use of a convex combination of cost functions of the form $J(n) = E(|e(n)|^r)$, where r is a parameter and n denotes discrete time. The main drawback of this type of function is the choice of the optimal values of r.

We have chosen the cost function

$$J(n) = \frac{log[cosh(\beta \cdot e(n))]}{\beta} \quad (2)$$

where β controls the concavity in the cost function about the origin and the sensitivity to large outliers in the value of e(n)[6].

Considering a length L FIR filter with coefficients

$$\mathbf{w}(n) = [w_1(n), w_2(n), ..., w_L(n)]^T \quad (3)$$

where $(.)^T$ denotes transposition. the input vector at instant n

$$\mathbf{x}(n) = [x(n), x(n-1), ..., x(n-L+1)]^T \quad (4)$$

The error signal is given by

$$e(n) = d(n) - \mathbf{w}^T(n)x(n) \quad (5)$$

By using delta learning rule for updating the coefficients

$$w_{n+1} = w_n + \mu \cdot tanh[\beta \cdot e(n)] \cdot x_n \quad (6)$$

where μ is the learning rate.

In Equation 6 the proposed cost function is noise-robust. The hyperbolic tangent saturates to ± 1 for extreme values. The contribution of the outliers in $e(n)$ to the coefficient updates is limited and easily controlled with β. This equation is easy for hardware implementation[7].

$$tanh(\beta \cdot x) = \begin{cases} sign(x), & \text{if } |x| > 1/\beta \\ -x \cdot |x| \cdot (\beta)^2 + 2\beta \cdot x, & \text{if } |x| \leq 1/\beta \end{cases} \quad (7)$$

The update of the coefficients is given by

$$w_{n+1} = \begin{cases} w_n + \mu sign[e(n)]x_n, & \text{if } |e(n)| > 1/\beta \\ w_n + \mu[2\beta - \beta^2|e(n)|]e(n) \cdot x_n, & \text{if } |e(n)| \leq 1/\beta \end{cases} \quad (8)$$

The value of β is modified iteratively according to the error in the learning process. The threshold to consider a pattern as outlier is taken as three standard deviations, since tanh(|3|)=|0.96|, i.e., a value close to unity, the parameter β can be obtained as follows:

$$\beta = \frac{3}{m + 3 \cdot \sigma} \quad (9)$$

where m is the mean value of the error signal and σ its standard deviation. This threshold for the outliers is modified, providing different levels of immunity to impulse noise.

The calculation process for updating coefficients requires the values of $e(n)$, β and μ. Most of the applications in adaptive filtering have zero mean signals. When the number of samples is high, the value of m can be rounded to zero. A fixed value for β is not necessary as it controls the outlier immunity. The standard deviation or its square(the variance) can used to estimate the value of β[7]. Thus, in equation (9) β can be approximated as $1/\sigma^2$. This simplifies the calculation of β.

5. Results and discussion

The proposed method is tested on ECG data obtained from MIT-BIH arrhythmia database (360 samples/s, 11-bit resolution) and University of Glasgow database (500 samples/s, 12-bit resolution)by adding simulated impulse noise. The order of the adaptive system affects the smallest error that the system can obtain. If there are insufficient coefficients in the adaptive system to model the unknown system, it is said to be under specified. This condition may cause the error to converge to a nonzero constant instead of zero which is undesirable. In contrast, if the adaptive filter is over specified, meaning that there are more coefficients than needed to model the unknown system, the error will converge to zero, but the number of iterations for converging will be more resulting in increased time for the filter to converge. By using trial and error we have fixed the FIR filter length to 9.

The algorithm presented in [8] is used to calculate the SNR improvement. The achievable improvement of the SNR of a noisy signal depends on the noise reduction method and on the SNR of the noise contained in the data. Let $s(n)$ is real valued, discrete time signal its empirical mean is defined as $\langle S \rangle = \frac{1}{L}\sum_{n=1}^{L} s(n)$. The power of $s(n)$ is defined as $P_s = \langle S^2 \rangle - \langle S \rangle^2$. Let the $d(n)$ is the signal corrupted by noise, then the SNR in $d(n)$ is defined as $SNR_d = 10log10(P_s/P_{s-d})$. If by a noise reduction algorithm from $d(n)$ is generated another signal $d'(n)$ supposed to be a better estimate of $s(n)$, the SNR improvement is defined as $SNR_{impr} = SNR_{d'} - SNR_d$. The representative SNR improvement values for two ECG signals from databases are given in the captions of respective signal plots.

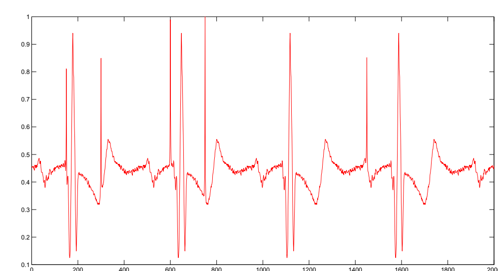

Figure 2. ECG signal corrupted with simulated impulse noise (1V1 of university of Glasgow database)

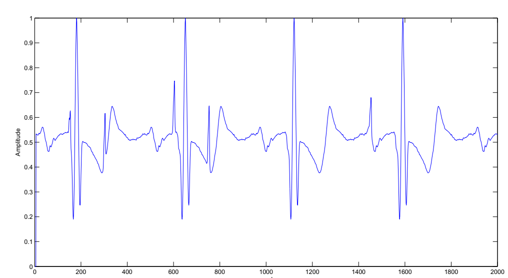

Figure 3. ECG signal(Figure 2) with suppressed noise. SNR_{impr} =48.3dB (mean)

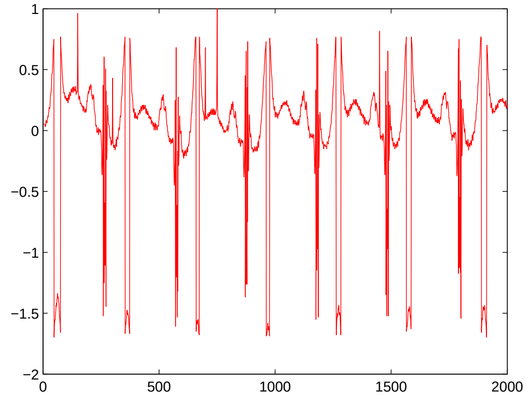

Figure 4. ECG Signal corrupted with simulated impulse noise modeled (103 of MIT-BIH arrhythmia database)

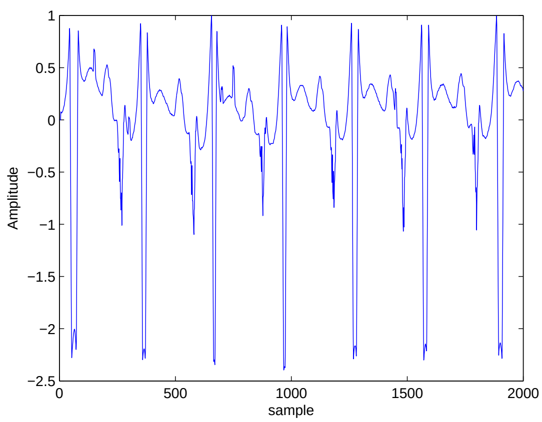

Figure 5. ECG signal(Figure 4) with suppressed noise. SNR_{impr}=29.2dB (mean)

The R wave is detected in ECG by setting upper threshold level and lower threshold level. The reduction of impulse noise is such that the possibility of false R detection is drastically reduced.

The trend today is implementation of successful DSP algorithms on FPGA platform to exploit the advantage of reconfiguration. Modern FPGAs contain many resources that support DSP applications such as embedded multipliers, multiply accumulate units, intellectual property cores for specific functions. This algorithm can be modified for effective hardware implementation on ECG machines.

6. Conclusion

The simulated impulse noise in ECG is suppressed using Adaptive Filters. The impulse is considered as outlier and a parameter is adaptively computed to reduce its effect in signal corruption. The threshold for outliers is modified which provides different levels of immunity to impulse noise. This noise suppression algorithm can be applied in real time ECG analysis system to increase accuracy and efficiency using hardware implementation.

References

[1] Clifford G, McSharry P. Advanced Methods and Tools for ECG Data Analysis. London: Artech House, 2006.

[2] Tsihrintzis G, Nikias C. Fast estimation of the parameters of alpha-stable impulsive interference. IEEE Trans Sig Proc 1996;44(6):1492-1503.

[3] Pander T. A suppression of an impulsive noise in ecg signal processing. In Proc 26th Ann Int Conf IEEE EMBS vol 1 2004;596-599.

[4] Haykin S, Adaptive Filter Theory. Pearson, 2002.

[5] Widrow B, Stearns S. Adaptive Signal Processing. Englewood Cliffs, NJ: Prentice-Hall, 1985.

[6] Soria-Olivas E, Martn-Guerrero JD, Serrano-Lpez AJ, Calpe-Maravilla J, Chambers J. Steady-state and tracking analysis of a robust adaptive filter with low computational cost. Signal Processing 2007;87(1):210-215.

[7] Rosado-Muñoz A, Bataller-Mompean M, Soria-Olivas E, Scarante C, Guerrero-Martinez J. FPGA implementation of an adaptive filter robust to impulsive noise: two approaches. IEEE Trans Industrial Electronics 2011;58(3):860-870.

[8] Brocker J, Parlitz U, Ogorzalek M. Nonlinear noise reduction. Proc IEEE 2002;90(5):898918. ISSN 0018-9219.

Acknowledgments

The work was supported by funds from All India Council for Technical Education (AICTE), New Delhi under Research Promotion Scheme Grant Number 8023/RID/RPS-86/2011-12. We thank Prof. Peter W. MacFarlane of University of Glasgow, Scotland for providing ECG database for our research work.

References

Address for correspondence:

Ramchandra R Manthalkar
Department of Electronics and Telecommunication
Shri Guru Gobind Singhji Institute of Engineering and Technology, Nanded-431606, Maharashtra, INDIA
Phone: +91-9423373690 Email: rrmanthalkar@sggs.ac.in, rmanthalkar@yahoo.com