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De-Noising of ECG Signal Using Adaptive Filters Based on Genetic Algorithm

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Abstract: ***Electrocardiography (ECG), which is measures the electrical activity of the heart, the shape of the ECG signal tells much about the patient's heart condition. Naturally the ECG signal gets distorted by different artifacts which must be removed otherwise it will convey an incorrect information regarding the patient's heart condition. Several simple and efficient sign based LMS and Normalized LMS adaptive filters, which are computationally superior having multiplier free weight update loops are used for cancellation of noise in ECG signals. We have Implementing genetic algorithm (GA) on adaptive noise cancellation (ANC) provides better performance than adaptive techniques used to enhance the ECG signal. In this work, fidelity parameters like signal to noise ratio (SNR), and mean square error (MSE) have to be computed.***

Keywords: Electrocardiograph, Adaptive filters, Genetic Algorithm

1. Introduction

Electrocardiogram (ECG) is a one of the most valuable technique that has been in used for throughout a century. The ECG is a biomedical signal, which records the electrical activity of time versus heart. The electrocardiogram (ECG) is a graphical representation of hearts functionality and is an important tool used for diagnosis of cardiac abnormalities [1]. The ECG waveform of a normal individual signal consists of P wave, T wave, U wave, QRS complex and ST segment [2]. The ECG signal taken from MIT-BIH Arrhythmia Database [3-4]. The MIT-BIH Arrhythmia Database contains different patient`s data of the ECG recordings. The MIT-BIH Arrhythmia Database obtained from some number of subjects collected by a mixed population of inpatients and outpatients studied by the MIT-BIH Arrhythmia Laboratory. The subjects were taken from, 21 women aged 30 to 80 years and 24 men aged 22 to 74 years. In clinical environment Artifacts that commonly appear in ECG signal during acquisition are elaborately discussed. Different modes of lead placement and the MIT-BIH arrhythmia database are also described. The strongest artifacts present in the ECG includes: power-line interference (PLI), baseline wander (BW), muscle artifacts (MA) and motion artifacts (EM). Among these noises, the power line interference and the baseline wandering (BW) are the most significant and can strongly affect ECG signal analysis. These noises strongly affect the ECG signal and degrade the signal quality, frequency resolution, produces large amplitude signals in ECG that can resemble PQRST waveforms. Remove of these noises in ECG signals is a better task for diagnosis [5-9]. The goal of ECG signal enhancement is to separate the quality signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation. Many approaches have been reported in the literature to address ECG enhancement using efficient sign based LMS and Normalized LMS adaptive filters [10]. We have used a Genetic algorithm is proposed to the ECG signal, it provides better performance than adaptive techniques and it is used to enhance the better quality of the ECG signal.

2. Adaptive Filters

In digital communications or digital signal processing has brought more attention to the adaptive least mean squares methods. Many digital signal processing applications requires linear filters and adaptive techniques in signal processing and analysis. A filter is designed and used to extract or enhance the desired information contained in a signal. In real time applications such as inverse system identification, channel equalization, noise cancellations, echo cancellation, signal prediction, the statistical properties of a signal and noise are usually unknown which leads to the development of adaptive filtering algorithms[11] such as Least Mean Square(LMS). An adaptive filter is a self-designing and time-varying system that uses a recursive algorithm continuously to adjust its tap weights for operation in an unknown environment. An adaptive filter is a filter with an associated adaptive algorithm for updating filter coefficients so that the filter can be operated in an unknown and changing environment. The adaptive algorithm determines filter characteristics by adjusting filter coefficients according to the signal conditions and performance criteria. Adaptive filtering finds practical applications in many diverse fields such as communications, radar, sonar, control, navigation, seismology, biomedical engineering and even in financial engineering.

3. Existing Method

A typical performance criterion is based on an error signal, which is the difference between the filter output signal and a given reference (or) desired signal. Figure 1 shows a typical structure of the adaptive filter, which consists of two basic functional blocks: (i) a digital filter to perform the desired filtering (ii) an adaptive algorithm to adjust the tap weights of the filter. The digital filter computes the output y(n) in response to the input signal x(n), and generates an error signal e(n) by comparing y(n) with the desired response d(n), which is also called the reference signal, as shown in Figure 1 The performance feedback signal e(n) (also called the error signal) is used by the adaptive algorithm to adjust the tap weights of the digital filter. An adaptive algorithm is a set of recursive equations used to adjust the weight vector **w**(n) automatically to minimize the error signal e(n) such that the weight vector converges iteratively to the optimum solutions.

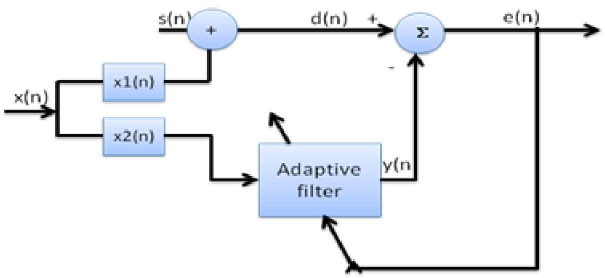

Figure 1: Block diagram of adaptive LMS filter

The adaptive filter algorithms used by us for noise reduction in ECG in this thesis are least mean square (LMS), Normalized least mean square (NLMS), sign data least mean square (SDLMS), sign error least mean square (SELMS) and sign-sign least mean square (SSLMS) algorithms[12-14].

3.1 LMS based adaptive filter

The least-mean-square (LMS) algorithm is the most widely used among various adaptive algorithms because of its simplicity and robustness. The LMS algorithm updates the weight vector as follows:

$$w(n+1) = w(n) + \mu x(n)e(n)$$
$$e(n) = d(n) - y(n)$$
$$y(n) = w(n)x(n)$$

where μ is the step size (or convergence factor) that determines the stability and the convergence rate of the algorithm. It adapts to the change in signal characteristics in order to minimize the error. In adaptive filters, the weight vectors are updated by an adaptive algorithm to minimize the cost function.

3.2 NLMS based adaptive filter

Normalized LMS (NLMS) algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter. This algorithm accounts the variation in the signal level at the filter output and selecting the normalized step size parameter that results in a stable as well as fast converging algorithm. The weight update relation for NLMS algorithm is as follows:

$$w(n+1) = w(n) + \frac{\mu}{[x(n).'x(n)]} * (e(n)x(n))$$

3.3 Sign based adaptive filter techniques

The sign function, as defined by the following equation, can simplify the standard LMS algorithm.

$$\operatorname{sgn}(e) = \begin{cases} 1 & e > 0 \\ 0 & e = 0 \\ -1 & e < 0 \end{cases}$$

Applying the sign function to the standard LMS algorithm returns the following three types of sign LMS algorithms.

3.3.1 Sign-error LMS algorithm

Applies the sign function to the error signal e(n). This algorithm updates the coefficients of an adaptive filter using the following equation:

$$w_i(n+1) = w_i(n) + \mu x(n)\operatorname{sgn}(e(n))$$

3.3.2 Sign-data LMS algorithm

Applies the sign function to the input signal vector μ. This algorithm updates the coefficients of an adaptive filter using the following equation:

$$w_i(n+1) = w_i(n) + \mu e(n)\operatorname{sgn}(x(n))$$

3.3.3 Sign-sign LMS algorithm

Applies the sign function to both e(n) and μ. This algorithm updates the coefficients of an adaptive filter using the following equation:

$$w_i(n+1) = w_i(n) + \mu \operatorname{sgn}(e(n))\operatorname{sgn}(x(n))$$

4. Proposed Method

4.1 Genetic algorithm:

Genetic algorithms are a type of optimization algorithm, meaning they are used to find the optimal solution(s) to a given computational problem that maximizes or minimizes a particular function. It is inspired by natural evolution, such as inheritance, mutation, selection and crossover. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population [17-18]. Genetic Algorithm used to solve many optimization problems in science and Engineering such as pattern recognition, robotics, biology, medicine and many other applications.GA has been emerged into optimum filter designs.GA optimizes are particularly effective when the goal is to find an approximate global minimum in a high dimension. Genetic Algorithm optimization methods have emerged as a powerful approach to solve the more difficult optimization problems [19-23]. Easy to understand Supports multi-objective optimization Good for noisy environment we always get answer and answer gets better with time Easy to exploit for precious or alternate solutions Flexible in forming building blocks for hybrid applications.

4.1.1 Genetic operators

The decision to make during implantation of genetic algorithm is the choices of genetic operators are to be used. The genetic operators are the most important features of GA and are described below.

4.1.2 Fitness Function:

The fitness function is defined over the genetic representation and measures the quality of the represented solution. A fitness function is a particular type of objective function that is used to summarize, as a single figure of merit, how close a given design solution is to achieving the set aims. The scaling function converts raw fitness scores returned by the fitness function to values in a range that is suitable for the selection function. The fitness function is the function you want to optimize. For standard optimization algorithms, this is known as the objective function. The toolbox software tries to find the minimum of the fitness function. Write the fitness function as a file or anonymous function, and pass it as a function handle input argument to the main genetic algorithm function. The fitness function is usually an objective or cost function but anything will suffice as long as it can successfully quantify the quality of all possible phenotype solutions. The fitness function is dependent on the environment and application of the system that is undergoing the genetic search process and it is the only connection between the physical problem being optimized and the genetic algorithm itself.

4.1.3 Reproduction:

Reproduction options control how the genetic algorithm creates the next generation. The options are Elite count. The number of individuals with the best fitness values in the current generation that are guaranteed to survive to the next generation. These individuals are called elite children. The default value of Elite count is 2. When Elite count is at least 1, the best fitness value can only decrease from one generation to the next. This is what you want to happen, since the genetic algorithm minimizes the fitness function. Setting Elite count to a high value causes the fittest individuals to dominate the population, which can make the search less effective.

4.1.4 Crossover:

Crossover combines two individuals, or parents, to form a new individual, or child, for the next generation. Crossover recombines genetic material from selected individuals to form one or more offspring where some of the useful traits of the parents are preserved. The goal is to generate new chromosomes that are more fit than their ancestors, thereby contributing to the overall convergence of the population.

4.1.5 Mutation

Mutation plays a secondary role in genetic algorithms. Mutation functions make small random changes in the individuals in the population. Mutation is treated as supporting operator for the purpose of restoring lost genetic population. Mutation takes place with a certain probability, thus genetic content of a particular individual gets changed and a new generation is produced. After selection and crossover, you now have a new population full of individuals. Some are directly copied, and others are produced by crossover. In order to ensure that the individuals are not all exactly the same, you allow for a small chance of mutation. You loop through all the alleles of all the individuals, and if that allele is selected for mutation, you can either change it by a small amount or replace it with a new value. Mutation is fairly simple. You just change the selected alleles based on what you feel is necessary and move on. Mutation is, however, vital to ensuring genetic diversity within the population.

5. Design of Adaptive Filters by Using Genetic Algorithm

Step 1: By multiplying the desired transfer function with windows, we can get transfer function of FIR low pass filter i.e.

$$h(n) = h_d(n) * w(n)$$

where w(n) is represents Transfer function of following windows

1)Bartlett window
2)Hanning window
3)Hamming window
4)Kaiser window

Step 2: now h(n) is compared with $h_i(n)$ the ideal response of LPF to get error function for GA.
Step3: now applying GA to obtain best individuals as filter coefficients which minimizes the error function.

6. Simulation Results and Implementations

The simulation results are obtained by MATLAB and the simulation parameters are;

Cutoff frequency of LPF: 0.1π
Order of the filter: 25
GA parameters are
Population type: double vector
Population size: 20
Initial range :(0-1)
Scaling function: Rank
Selection function: stochastic function
Elite count: 2
Crossover fraction: 0.8
Mutation function: Gaussian function

Migration fraction: 0.2
No: of generations: 100

Table 1: Performance contrast of various algorithms for remove the base line noise and power line noise

S. No	Type of Noise In ECG	Type of Algorithm	SNR	MSE
1	Base Line Noise	LMS	21.5572	4.9544e-04
		GA_LMS	21.7397	2.2928e-04
		NLMS	22.6992	0.0080
		GA_NLMS	22.7257	0.0086
2	Power Line Noise	LMS	19.1898	0.0011
		GA_LMS	20.1724	5.2598e-04
		NLMS	22.6992	0.0080
		GA_NLMS	27.7228	0.0169

The responses of adaptive filter with combined LMS algorithms and Genetic algorithm for removal of base line and power line noises are shown from figure1 to figure 8.

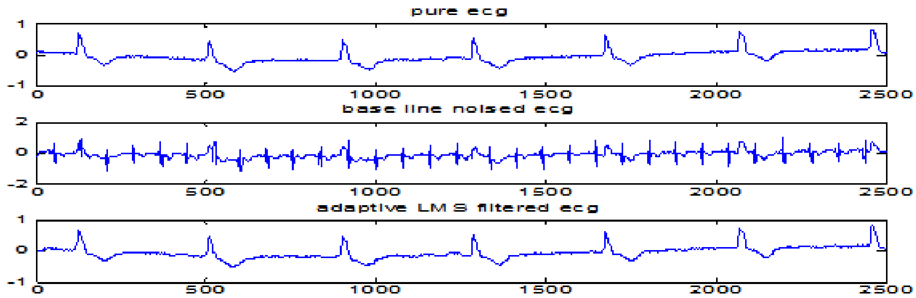

Figure 1: Removal of base line noise by using LMS algorithm

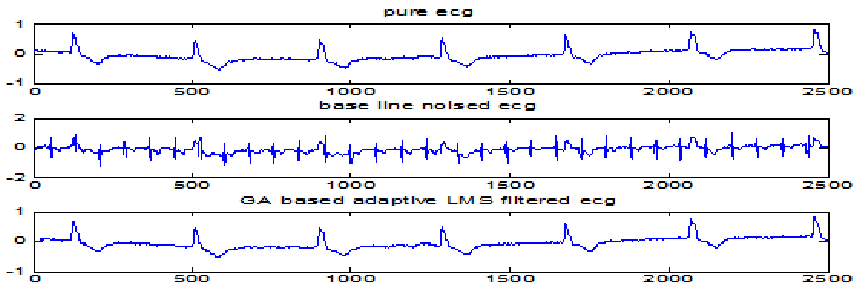

Figure 2: Removal of base line noise by using GA_LMS algorithm

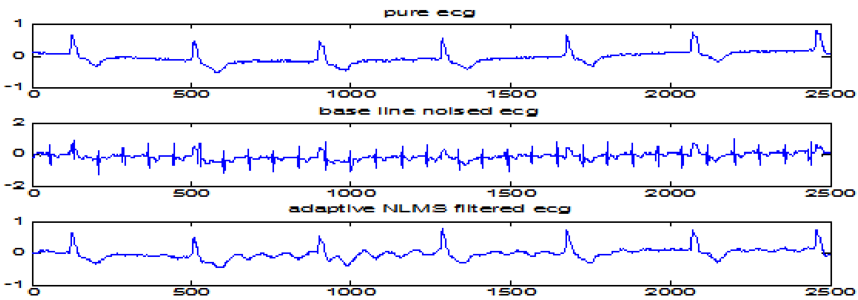

Figure 3: Removal of base line noise by using NLMS algorithm

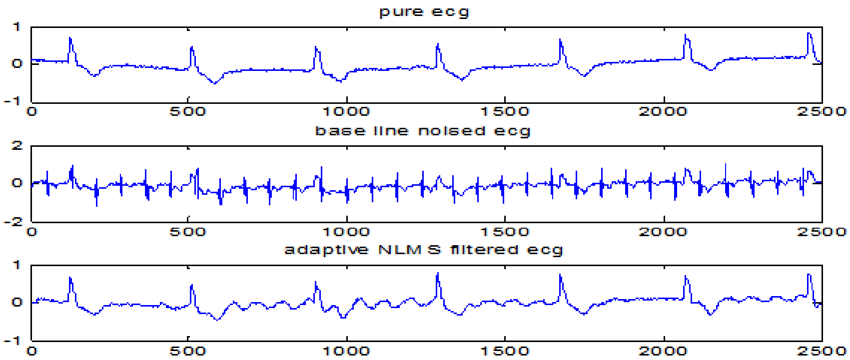

Figure 4: Removal of base line noise by using GA_NLMS algorithm

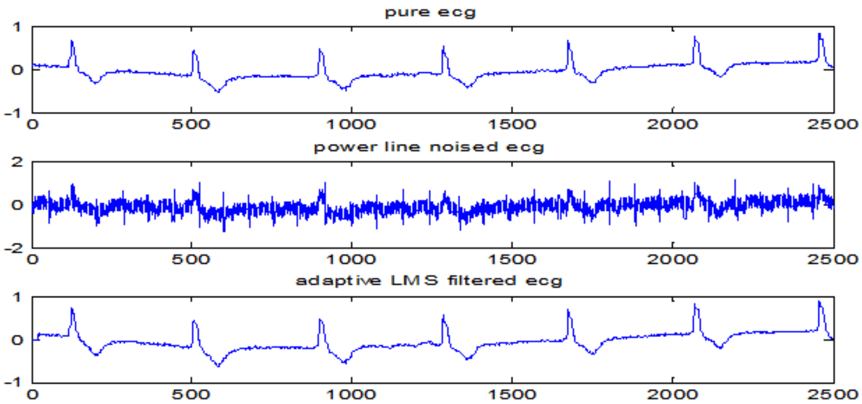

Figure 5: Removal of power line noise by using LMS algorithm

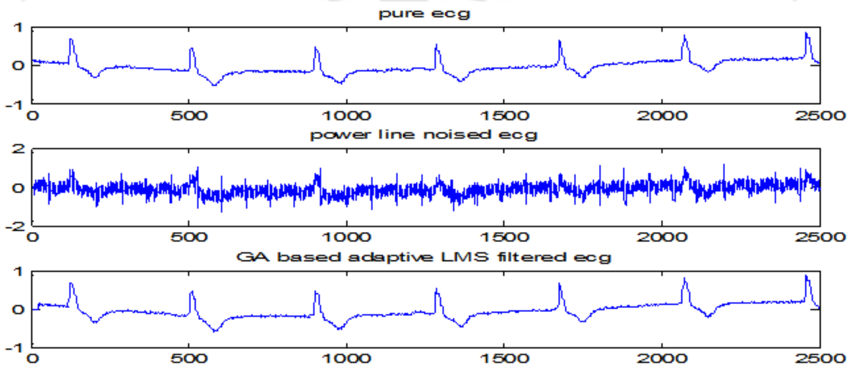

Figure 6: Removal of power line noise by using GA_LMS algorithm

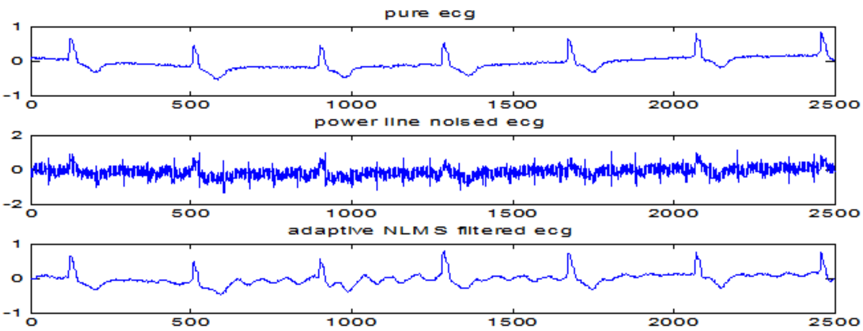

Figure 7: Removal of power line noise by using NLMS algorithm

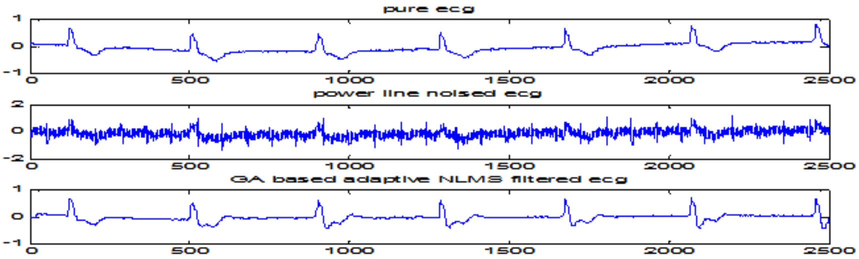

Figure 8: Removal of power line noise by using GA_ NLMS algorithm

7. Conclusion

In this paper the problem of noise canceller from ECG signal using Genetic Algorithm based LMS and NLMS adaptive filters are proposed and tested on real signals with different artifacts obtained from MIT-BIH database. Among the two algorithms the NLMS performs better than the LMS. And genetic algorithm (GA) even gives better results for both algorithms which are presented in Table-1. From the simulation results it is clear that these two adaptive algorithms combined with GA removes non-stationary noise effectively which are shown in terms of responses from Fig:1 to Fig:8. Hence the proposed GA_LMS and GA_NLMS are more suitable for wireless biotelemetry ECG systems. Genetic algorithms can still achieve good results even in cases in which the function has several local minima or maxima.

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