An Intelligent Adaptive Noise Cancellation System for the Extraction of Fetal ElectroCardioGram

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Abstract: - The continuous monitoring of fetal heart condition during pregnancy is of great medical importance. Electro Cardio Gram (ECG) is used to record changes in the heart, thus can diagnose any malfunctioning in the heart. The obtained fetal ECG (FECG) signal is severely contaminated by maternal cardiogram (MECG), power line interference, base line-wander etc. The low Signal to noise Ratio of fetal ECG makes it difficult to analyze it effectively. This paper describes the bio-medical application of adaptive noise cancelling techniques for filtering of the obtained noisy ECG using biologically inspired algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

Key-Words: - Fetal ECG, Adaptive Noise Cancellation, Genetic Algorithm (GA), Particle Swarm Optimization (PSO).

1 Introduction

The ECG of a person describes the electrical activity of the heart. It is an important tool for the physician for identifying abnormalities in the heart activity. The detection of an external fetal electrocardiogram (FECG) using abdominal leads, in clinical practice, is still a somewhat troublesome technique. There is no prior guarantee that the next recording will be successful. So, the reliability of the detection of FECG has been a question when the signal is accompanied by maternal signal and various sources of noise contamination such as motion artefacts and muscular activity.

2 Problem Description

The extraction of fetal ECG from the recordings of electrodes on the mother's body is fundamentally equivalent to that of adult ECG extraction, but, there are more difficulties that arise. The FECG is generated from a very small heart, which is a very low voltage signal i.e. the amplitude of the signal is very low. Noise from any activity affects the signal due to its low voltage. Another interfering source is the maternal ECG (MECG) which can be 5-1000 times higher in its intensity than the FECG. There is no possibility to obtain only FECG from the mother. In all cases where the FECG is observed, the MECG is higher in magnitude. So the elimination of the MECG from the recorded signal is very important. Furthermore, it is known that the ECG signal energy at the abdominal leads, extracted in the latest gestation months, contains information about the fetus ECG (FECG), though the signal energy is typical small relative to that of MECG. By comparing the chest and abdominal composite signals, a method may be devised for extracting information about the FECG from the composite signal.

Elimination of MECG by classical filtering techniques is not satisfying in most cases as the spectra of the wanted signal and the disturbances mainly overlap. So Intelligent adaptive noise cancellation techniques were applied which yields better results.

The most convenient acquisition of FECG is by means of surface, abdominal electrodes, a technique first reported in 1906 as shown in Figure 1. However as mentioned above, it is strongly contaminated by maternal ECG and other noises.
The system of adaptive filtering as shown in figure 2 consists of a Finite Impulse Response Filter whose weights will be updated by the learning algorithm based on the error signal (desired signal). Here the noisy abdominal signal is given as input and a thoracic electrode output signal is given at reference input.

3 Adaptive Noise Cancellation

The error signal obtained finally corresponds to the fetal heart beat signal but corrupted with residual noises which are in turn eliminated by filtering them adaptively. Various algorithms can be tested and the most efficient algorithm can be used. Some of the algorithms are discussed below.

3.1 Least Mean Square Algorithm

This algorithm was introduced by Widrow and Hoff in 1960 and widely used in practice because of its simplicity, computational efficiency, and good performance under a variety of operating conditions. The instantaneous error at any time-step 'k' can be represented as 

\[ e(k) = \sum w(k) x(k) + \mu e(k) \]

Where \( \mu \) is called Step-size or Convergence factor.

4 Genetic Algorithm

The Standard Genetic Algorithm (SGA) is inspired by Charles Darwin’s theory of evolution. Typically Genetic Algorithm maintains a population of candidate solutions for problem at hand and makes it evolve by iteratively applying a set of stochastic operations. This algorithm is a search technique used in computing to find approximate solutions to optimization and search problems. The SGA can be represented as a flow chart as shown in figure below.
Applied to FECG problem, at first the weight vector is initialized to a random set of weights (population initialization) and trained using the algorithm as shown in the block diagram.

Usually the probability of cross-over is kept high (more than 0.8) and the probability of mutation low (less than 0.2).

The evaluation function is often referred as fitness function. Here we use SGA as one of the algorithm for optimizing the weight vector for the adaptive linear combiner.

5 Particle Swarm Optimization

PSO is population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling etc.

The Swarm of particles indicates estimates of multiple parameters involved in the problem. We can begin with initializing a random swarm of particles like in SGA. During each iteration fitness of the particle is evaluated with the help of fitness function (Mean Square Error in our problem).

The algorithm progressively replaces most fit parameters of each particle i.e. pbest. Pbest is the best position of the particle itself.

There exist another best position gbest which is the global best i.e. the best position in the swarm. Each particle has the influence of these two bests in their trajectories. The parameters of each particle are updated with the following equations

\[ v_i(t+1) = w \cdot v_i(t) + c_1 \cdot \text{rand} \cdot (p_{best}(t) - x_i(t)) \]
\[ + \quad c_2 \cdot \text{rand} \cdot (g_{best}(t) - x_i(t)) \]

Position updation
\[ p = p + v \]

Where
- \( p \) - instantaneous position of the particle
- \( v \) - instantaneous velocity of the particle
- \( p_{best} \) - positional best of the particle
- \( g_{best} \) - global best position of the swarm of particles

\( W \) – Inertial weight factor
\( C_1, C_2 \) – acceleration coefficients

The trajectory of the particle is dependent on three factors: its previous position, pbest and gbest. Greater the strain of the particle in searching food, smaller is the acceleration coefficients. The inertial weight factor \( w \) signifies the importance of the particle’s previous position in further search.

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gbest to reach food early. If gbest has less number of values then the particles will reach the food early. The algorithm comes to an end when all the particles converge at that gbest i.e. food position. In our problem i.e. attaining minimum possible value for steady state error signal. The block diagram of PSO can be shown like this:

![Block Diagram of PSO](image)

6 SIMULATIONS AND RESULTS

The shape of the ECG of mother below is simulated assuming a 4000 Hz sampling rate. The heart rate for this signal is approximately 89 beats per minute, and the peak voltage of the signal is 3.5 millivolts.

![Maternal Heartbeat Signal](image)

![Fetal Heartbeat Signal](image)

The heart of a fetus beats noticeably faster than that of its mother, with rates ranging from 120 to 160 beats per minute. The fetal ECG signal generated corresponds to a heart rate of 139 beats per minute and a peak voltage of 0.25 millivolts.

![Abdominal Electrode Signal](image)

The signal obtained from the abdominal electrode is a noisy signal and is shown below. This is to be filtered and given as input to the adaptive noise canceller.

![Thoracic Electrode Signal](image)

The filtered signal from the abdominal electrode signal is obtained. This contains much noise in addition to the fetal heartbeat which is to be filtered.
by adaptive noise canceller trained by various algorithms.

The signal obtained by PSO is very much similar to the desired FECG. QRS detection is also very good compared to that obtained by various other algorithms.

7 CONCLUSIONS

Here in this paper we compared biologically inspired computational techniques with the conventional Least Mean Square algorithm. From simulations and results we can conclude that Particle Swarm Optimization based adaptive noise cancellation technique is performing better and hence preferred over the other techniques. Further scope can be carried by the implementation of the above discussed technique on FPGA.

REFERENCES