DETECTION OF FETAL ECG WITH IIR ADAPTIVE FILTERING AND GENETIC ALGORITHMS

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ABSTRACT

The continuous monitoring of fetal heart condition during pregnancy and labor is of great clinical importance. The cardiac electrical activity of the fetus (FECG) may be recorded by means of surface abdominal electrodes. The signal is severely contaminated by the maternal cardiac signal (MECG). FECG enhancement is usually performed by FIR adaptive filtering. A new IIR FECG enhancement system is suggested and evaluated. In order to avoid convergence into local extremum, the system employs genetic algorithm (GA). Two architectures are considered. The first is a combination of adaptive filter and GA where the GA is recruited whenever the adaptive filter is suspected of reaching a local extremum . The second is an independent GA search. The hybrid IIR-GA was shown to be superior to the conventional FIR adaptive filtering.

1. INTRODUCTION

Monitoring fetal heart condition from early pregnancy to delivery is clinically important. In an experiment involving over 13,000 women, it has been shown that monitoring fetal heart rate [1] can halve the incidence of neonatal seizures (which has close correlation with long term handicap). The monitoring also plays an important role in decision for operative intervention. There are basically two ways of non-invasively performing the monitoring – electrically and by means of ultrasound. In recent years ultrasonic techniques have become popular for monitoring fetal heart rate (FHR). The method however is of mechanical origin and will thus contain no electrophysiological information.

Monitoring the electrical activity of the fetal heart may be done by means of scalp electrodes. The electrodes are attached to the fetal scalp by clips and are considered non-invasive to the fetus. The signal thus acquired is a high quality signal, it can however be used as continuous monitoring only during delivery and with some inconvenience.

The most convenient acquisition of FECG is by means of surface, abdominal electrodes, a technique first reported in 1906. The signal thus acquired is however weak and strongly contaminated by maternal ECG. Figure 1 shows a short recording of abdominal and chest electrodes. In the abdominal electrode the maternal ECG may be ten times stronger than the fetal ECG. In addition, 50 (60) Hz power line interference and muscle activity (EMG) interference further contaminate the signal. Several single lead methods for FECG enhancement were suggested. The original LMS method was suggested by Widrow [2] [3] to eliminate power line and maternal interference. In LMS methods, the maternal chest ECG is used as a reference signal. It is assumed that the contaminating maternal ECG is correlated with the chest MECG. The desired abdomonal MECG is estimated by means of adaptive FIR filter. Since then a variety of methods have been suggested in the literature to solve the enhancement problem. Auto-correlation and cross-correlation methods were used by Van Bemmel [4], spatial filtering using multiple electrodes recordings was used in [5] and [6]. Multiple electrodes Singular Value Decomposition (SVD) was suggested by Vanderschoot et al. [7], and single-channel SVD by Kanjilal et al. [8]. Other methods such as nonlinear state space projections [9] , matched filtering [10] or source separation [11], have recently been reported. This work examines the possibility of employing IIR adaptive filtering with Genetic Algorithms (GA), to eliminate MECG and other interference from a single lead abdominal electrode.

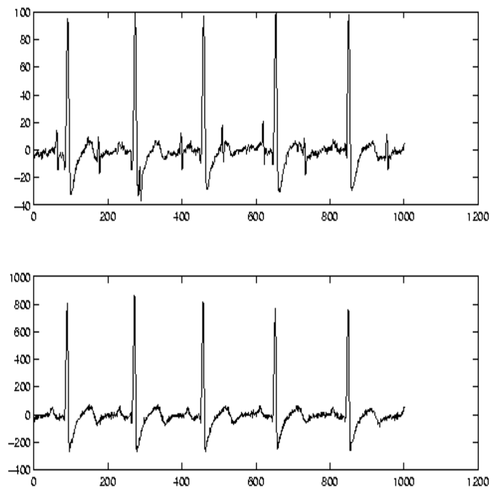

Figure 1: Upper Trace: abdominal electrode, fetal and maternal ECG. Lower Trace: Chest electrode, maternal ECG.

2. GENETIC ALGORITHMS

Genetic algorithms (GA) are directed random search methods used in optimization problems. Searching a multi-modal surface for a global optimum, may be performed by a random search. A set of N hypothesized solutions is randomly chosen. Each one of the solutions is evaluated and the best is kept. Another set is chosen and the process is repeated. The convergence of such random search is slow. In order to improve the convergence rate, methods for directing the search have been developed. In gradient search methods, the gradient of the surface is estimated and the hypothesized solution is lead against the gradient. GA methods provide directed search that is based on genetics and evolutionary rules [13] [14]. The simple GA includes the following steps:

- *Survival of the fittest:* Evaluate current solution population (current generation) according to a fitness function. Retain the best N solutions. The rest of the solutions are killed. The search is terminated when a good solution is found, or when successive generations provide the same population.
- *Mating :* according to some mating rules, select pairs of solutions for "mating". The mating is performed by the parent solutions exchange parts, in order to generate offspring. The type of exchange is controlled by a random variable called the crossover rate.
- *Mutation:* perform random changes in solutions. The type of change is controlled by a random variable called the mutation rate.
- Return to *Survival of the fittest.*

Various strategies for survival rules, for mating and for mutation that improve the performance of the simple GA have been suggested. In general GAs converge slowly and require relatively heavy computations. GAs have the advantage of seeking for the global optimum in multi-modal surfaces.

3. IIR ADAPTIVE FILTERING

IIR adaptive filtering differs from the conventional FIR filtering in that the adaptive filter is, in general, an ARMA filter. An ARMA filter has the advantage that it may better describe the reference transformation. Algorithms for the adaptation of both zeroes and poles are available [12]. The main disadvantage of the IIR filter is that the error surface is not quadratic (as is the case in FIR adaptive filtering) but a multi-modal surface. Gradient based search algorithms, such as the LMS, may converge to local minima . The adaptive ARMA filter may be implemented as a transversal filter, in which case the coefficients of the nominator and denominator of the transfer function are to be adapted. It may also be implemented as an ARMA lattice filter [15], in which case the reflection coefficients and MA coefficients are to be adapted. The stability of the lattice representation is easy to check and also its poles are represented by the reflection coefficients which are in some sense, decoupled .

4. HYBRID IIR-GA ADAPTIVE FILTERING

A hybrid system for adaptive filtering consisting of an LMS adaptation rule combined with GA was suggested [16]. In this scheme a conventional IIR adaptive filter is used. Whenever the estimated gradient possesses a low value, it is assumed that a local minimum has been reached. The GA is then activated. Let us denote the current solution (the parameters of the estimated adapted filter) $\hat{\theta}$, we generate a population of N new solutions $\hat{\theta}_i$ by perturbing $\hat{\theta}$

$$\hat{\theta}_i = \hat{\theta} + \varepsilon_i D\,; \quad i = 1,2,..,N \tag{1}$$

where ε_i is a random number uniformly distributed in the range $[-1,1]$ and D is a limit on the size of the perturbation. The population of N+1 solutions (the original plus N offspring) are evaluated by means of a fitness function. The best solution is used as the adapted filter for the next LMS iteration. The perturbation idea used in the hybrid algorithm is similar, in principle to simulated annealing methods. Figure 2 shows the block diagram of the hybrid system.

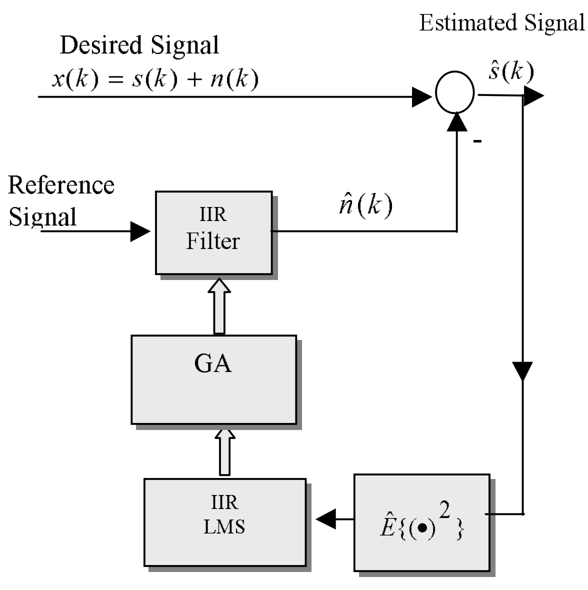

Figure 2: The Hybrid IIR-GA adaptive Filter

5. EXPERIMENTS

In order to evaluate the various architectures for FECG enhancement, two types of experiments were performed. Simulation studies were performed assuming linear, low pass ARMA relations between chest MECG and abdominal MECG.

Real data was then used to demonstrate the enhancement operation in real measurement.

5.1 Simulation Studies

The simulation studies used two real (chest) ECG signal, one with the higher rate was used to simulate FECG and the other – the reference abdominal MECG. The FECG was attenuated to have an R wave of about five times less the reference MECG. The chest MECG was generated from the reference MECG by the ARMA transformation

$$H(z) = \frac{0.05 - 0.4z^{-1}}{1 - 1.1314z^{-1} + 0.25z^{-2}} \qquad (2)$$

The simulation setup is shown in figure 3.

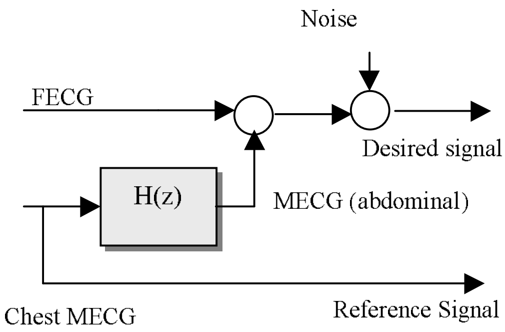

Figure 3: Simulation Setup.

Figure 4 shows a sample of the signals used in the simulation experiments. Note the abdominal MECG is a transformed version of the chest (reference) MECG. In some experiments white noise was added to the desired signal (SNR of 20db).

Four adaptive configurations were evaluated:

- The conventional FIR LMS adaptive filtering (order of filter was 20 and $\mu = 5*10^{-5}$)
- IIR LMS (Transversal of order 3, $\mu = 4*10^{-5}$)
- Hybrid IIR+GA (Transversal of order 3, $\mu = 1*10^{-6}$, N=50, D=0.5)
- GA (N=100, Mutation rate=0.05, Crossover rate=0.8)

The convergence of the (transversal IIR and the hybrid configuration is shown in figure 5. The two algorithms are the same until the GA is activated for the first time. The solution

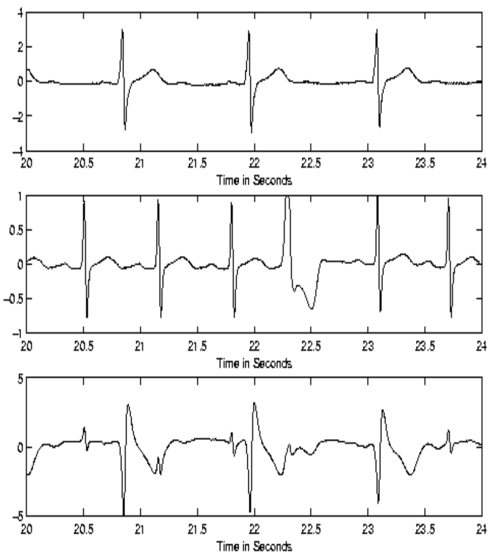

Figure 4: *Upper Trace*: Reference signal (Chest MECG); *Middle Trace*: FECG (not to scale); *Lower Trace*: Abdominal Signal (FECG+MECG)

found by the GA speeds up the convergence into a better steady state solution.

Figure 6 shows an example of the enhanced FECG in each one of the above configurations. The examples suggest that the IIR+GA configuration best estimates the FECG. Traces of MECG interference may be observed in the IIR+GA estimation, these are however considerably smaller than the interference in other configurations.

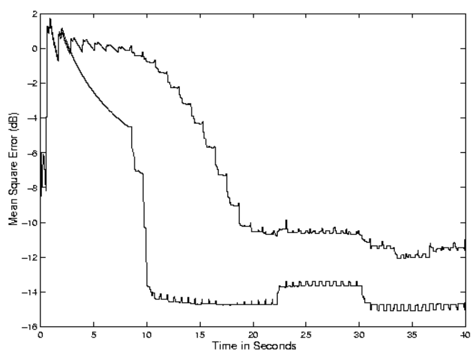

Figure 5: Convergence of the IIR LMS (upper trace) and the hybrid IIR+GA (lower trace) algorithms.

5.2 Real Data experiments

Real data was recorded from the chest and abdomen of a pregnant woman. An examples of the enhanced signals are shown in figure 7.

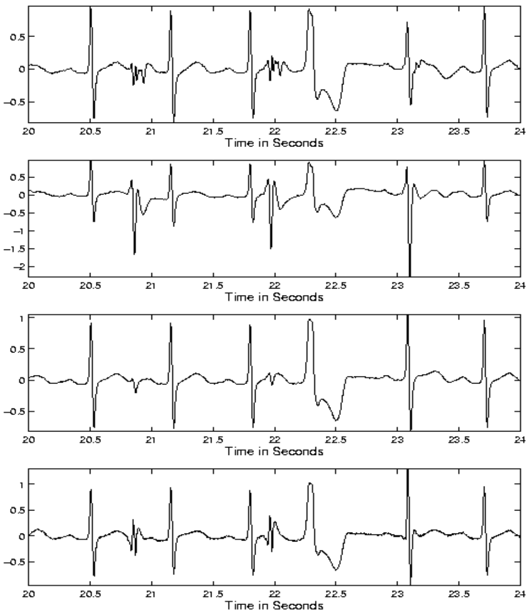

Figure 6: The enhanced FECG in (top down): FIR LMS; IIR transversal LMS; Hybrid IIR+GA; and GA. (the correct FECG is shown in figure 4).

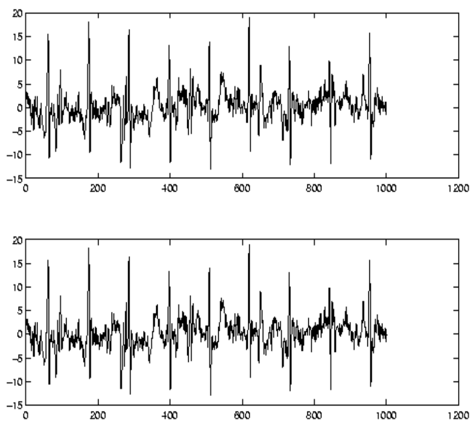

Figure 7: Real Data: *Upper Trace*: FECG Enhanced by FIR LMS; *Lower Trace*: FECG enhanced by IIR+GA. The unprocessed abdominal ECG is shown in figure 1

6. SUMMARY

Several algorithms for FECG enhancement were presented. Simulation results suggest the IIR+GA algorithm is the best one. Experiments with real data however fail to show significant differences between the conventional FIR LMS and the IIR+GA algorithm. This may be explained by assuming the body transfer function, in the low frequency range of the ECG, behaves like a simple low order low pass filter so that a low order FIR adaptive filter is sufficient. Further research is underway to evaluate this assumptions.

7. REFERENCES

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