Scientific Research and Essays Vol. 6(23), pp. 4975-4983, 16 October, 2011
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE11.852
ISSN 1992-2248 ©2011 Academic Journals

Full Length Research Paper

An economic distant fetal electrocardiogram monitoring system

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Accepted 20 September, 2011

Fetal electrocardiogram (FECG) signal contains potentially precise information that could assist clinicians in making more appropriate and timely decisions during pregnancy period and labour. Fetal condition may change abruptly during the pregnancy period. Therefore, continuous FECG monitoring will ease the fetal well-being. This paper describes an implementation of an economical real time distant fetal electrocardiogram (ECG) monitoring system. A new algorithm using adaptive linear network (ADALINE) has been developed to extract fetal ECG from composite ECG (maternal and fetal ECG). A graphical user interface (GUI) program is written in matlab to detect the changes in extracted fetal ECG by different values of momentum, learning rate and initial weights used in the network. The total system comprises of an acquisition and a networking part. The acquisition part acquires ECG signal through electrodes and then amplifies the weak ECG signal by an amplifier and filter out noises. The networking part is in the form of a Java based client/server pair application. This part is utilizing Internet protocols (IP), commercial software and low cost component to transmit ECG data to physicians for monitoring, diagnosis and patients care at a significantly low cost, regardless of patient's location.

Key words: Fetal electrocardiogram (FECG), annotated electrocardiogram (AECG), fetal heart rate (FHR), QRS, neural network, adaptive linear network (ADALINE).

INTRODUCTION

Fetal heart rate (FHR) monitoring is a routine for obtaining significant information about the fetal condition during pregnancy and labour. The characteristics of the fetal electrocardiogram (FECG), such as heart rate, waveform, and dynamic behaviour, are convenient in determining the fetal life, fetal development, fetal maturity, and existence of fetal distress or congenital heart disease. The FHR may change as the fetus responds to conditions in the uterus. An abnormal FHR or pattern may mean that the fetus is not getting enough oxygen or there are other problems. Sometimes an abnormal pattern also may mean that an emergency or cesarean delivery is needed. During pregnancy, the motivation for monitoring the fetal is to recognize pathologic conditions, typically asphyxia, with sufficient warning to enable intervention by the clinician. Therefore, FHR carries a significant importance of clinical perspectives (Hassan et al., 2009).

The fetal electrocardiogram (ECG) signal is a recording of the fetal heart's electrical activity and provides valuable clinical information as to the heart performance. During the last 20 years, QRS detection has been one of the most frequently addressed tasks in ECG signal processing (Hassan et al., 2009; Poli, 1995). However, the reliability of the fetal QRS detection has been in question when the signal is accompanied by maternal signal and various sources of noise contamination such as baseline drifts, motion artifacts and muscular activity.

Fetal signal reside within abdominal ECG of pregnant woman, together with the maternal signal. Maternal signal is the dominating ECG in the abdominal ECG but easily susceptible to noise corruption due to its weaker

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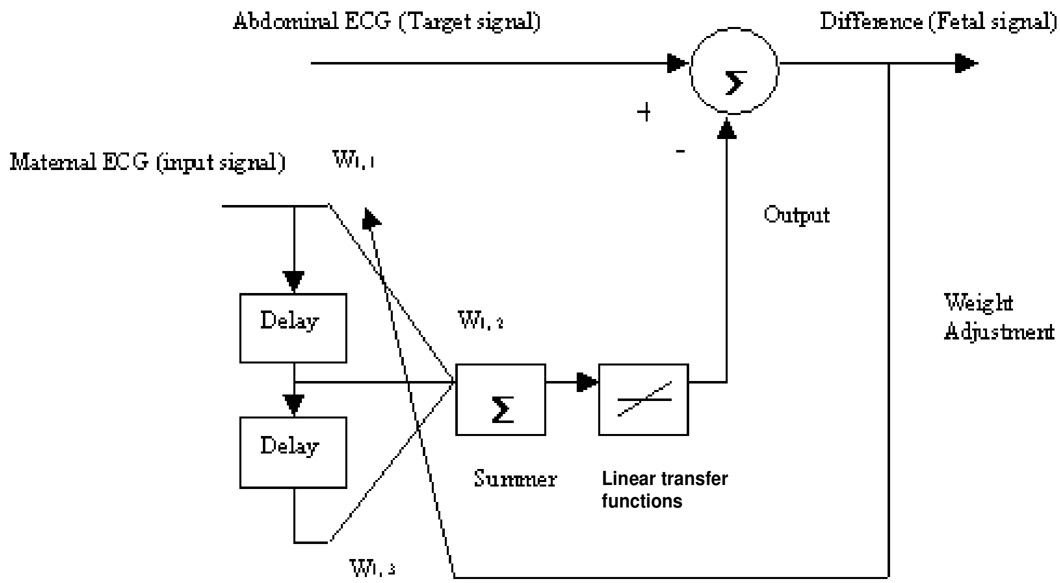

Figure 1. Adaptive linear neural network filter architecture.

amplitude (Costa and Moraes, 2000; Hasan et al., 2009). Maternal ECG needs to be filtered out from abdominal ECG of pregnant woman, before that fetal ECG can be fed into QRS detection network. QRS complex detection is important so that RR-interval can be extracted for monitoring of fetal condition.

Recent research shows that the nonlinear domain can be modeled more accurately with artificial intelligence technologies (Hasan et al., 2007). Some approaches like fuzzy logic and moving averaged have been proposed to extract fetal ECG from abdominal ECG of pregnant woman (Azad et al., 1998; Park et al., 1992). Among different artificial intelligence tools, neural networks are increasingly applied to detect and extract fetal ECG (Hasan et al., 2009; Rodrigues et al. 2001; Hasan et al., 2008). Neural network is chosen mainly because it is adaptive to the nonlinear and time-varying features of ECG signal. It can be trained to recognize the normal waveform and filter out the unnecessary artifacts.

Insufficient emergency medical care supports for stillbirth is very common in developing and less developing countries. The regular check-up of the FECG is an earliest prevention of this occurrence. However, due to the insufficient medical doctors and unavailability of doctors in many places, a remote monitoring system could be a better solution for regular check-up of the FECG. There are very few researches on remote FECG monitoring (Fanelli et al., 2010; Karvounic et al., 2011; Rauf et al., 2011). Most of the present researches, remote FECG monitoring is accomplished using expensive portable devices (Fanelli et al., 2010; Karvounic et al., 2011; Rauf et al., 2011). Therefore, this research employed a new technique of simple and easy solution of remote FECG monitoring.

MATERIALS AND METHODS

Adaptive linear network approach

A new algorithm has been developed to extract FECG from the abdominal ECG using adaptive linear neural network filter, which has linear transfer function (Widrow and Stearns, 1985). The block diagram of adaptive linear neural network filter architecture is shown in Figure 1. However, linear networks that are adjusted at each time step based on new input and target vectors can find weights and biases, which minimize the network's sum-squared error for recent input and target vectors. The characteristic of the network that enables fetal extraction is due to the correlation between maternal ECG signals with the abdominal ECG signal. It makes the input signal (noisy maternal ECG) as closely as possible to the target signal (abdominal signal), thus the error between the maternal signal and abdominal signal would be the fetal signal (Reaz and Wei, 2004).

The maternal ECG, which is the signal to be predicted, enters into the network through tapped delay line. The value that enters the network is the current value. The two outputs of the tapped delay lines are actually the previous values of the ECG. The three values are multiplied with three weights value. Three weighted values enter a summer and linear transfer function. Since the target is abdominal ECG of pregnant woman, the network changes the weight on each time step to minimize the error. If the error is zero, then the network output is exactly equal to target ECG.

Hardware setup for ECG data acquisition

Hardware design of AECG data acquisition system is done on a stage-by-stage basis. The first stage is a simple AECG sensing,

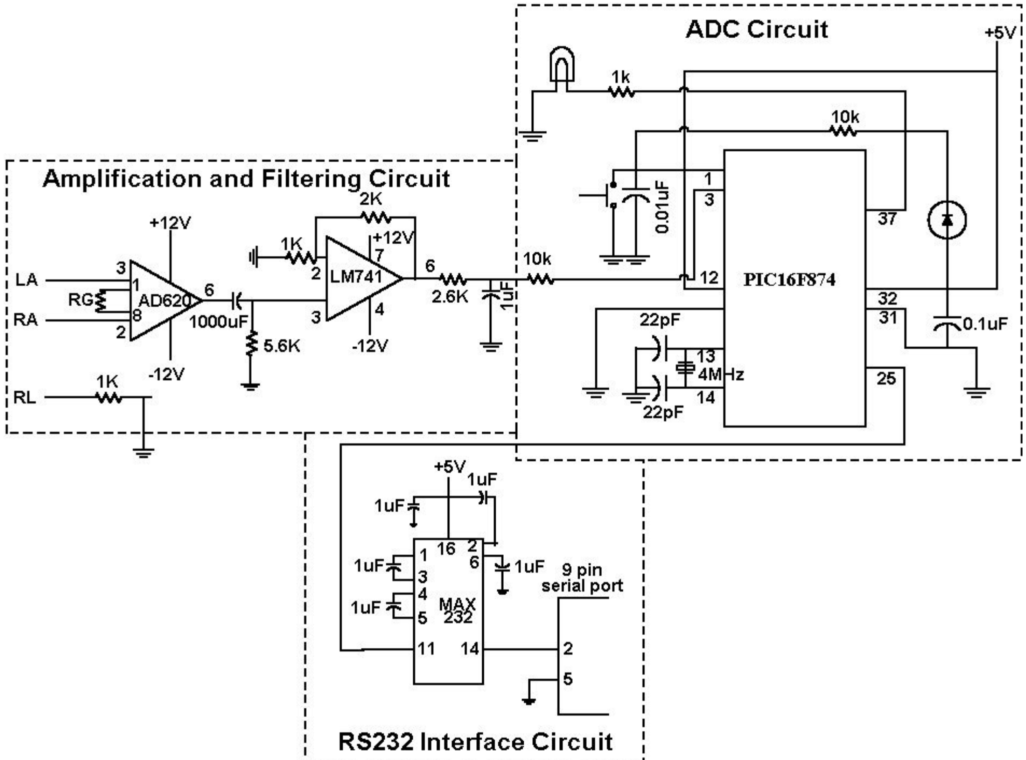

Figure 2. Schematic diagram of amplification and filtering stage.

using electrodes. Consequently, the output from AECG sensor (electrode) is fed into the second stage for signal amplification and filtering purposes. Next, the analog output from the second stage is fed into the third stage for analog to digital conversion. Finally, the digital output from ADC is sent to a PC via an RS232 interface circuit. Figure 2 shows the schematic diagram of the amplification and filtering circuit.

The AECG electrode used in this project is an Ag-AgCl electrode, also referred to as a ‘disposable floating electrode’. The electrodes are placed on patient’s right arm, left arm, and right leg (BIOPAC, 2002).

The AECG signal is very difficult to measure because it is very weak compared to the 50 Hz line interference from power supply and other noise sources. In order to get an amplified and filtered AECG signal, the AD620 instrumentation amplifier is used. The gain of AD620 is adjusted with a single external resistor. The external resistance value is chosen to be 200 Ω, in order to set the AD620 amplifier gain to 250.

The amplified and filtered AECG signal is fed into an ADC. In this paper, the PIC16F874 series microcontroller is chosen for the ADC circuit. The PIC is programmed to perform a 10bit analog to digital conversion. The coding process is divided into three stages. The first stage is to design a timing program. The second stage is to incorporate the concept of timing into the asynchronous transmission program. The final stage is the complete programming, which includes A/D conversion and transmission of result to a PC. After developing a complete set of code, the final step is to load the code into the PIC (also known as programming) using a customized IC programmer.

Before feeding the digitized AECG signal into the computer, the digitized AECG data is first fed into an RS232 driver circuit. This will convert the digitized AECG signal into an acceptable level. The output voltage is then sent to the PC's serial port where the AECG recorder is connected. A program that acts as an interface between RS232 driver and a PC is developed to monitor AECG data from the PIC microcontroller's ADC. The interface program takes the AECG data and stores it in the computer.

Network setup for remote monitoring

TCP/IP protocol is used to setup the network for control of remote AECG system. The software is developed using Java programming language, which is written with the objective of sending a patient’s AECG data and heart beat sound from a computer to another computer using TCP/IP.

The networking program is manifested in the form of a client/server pair application. The client application, known as a local patient monitoring system (LPMS), is installed in the patient’s terminal (PC) while the server application, known as remote patient monitoring system (RPMS), is installed in the physician’s terminal. A connection is established when a user in LPMS chooses a desired location to be connected. The desired locations are restricted to the predefined hospitals or clinics. Once the network has been successfully set up, user sends AECG data file as well as sound file to RPMS. Physicians at the remote location display the AECG graph and carry out analysis on the patient’s heart condition. The physician may also listen to the audio file (heart beat sounds) using a standalone audio player, which enables the sound clip to be played and looped, as desired. In addition, users from both ends can communicate with each other via a simple chat program that is

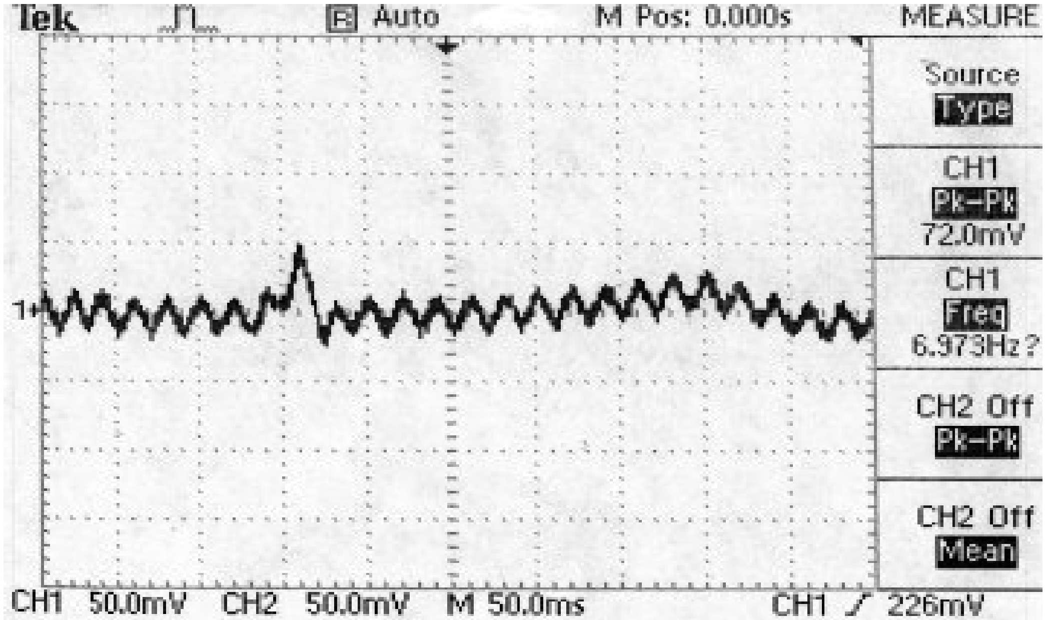

Figure 3. The amplified ECG signal from the instrumentation amplifier (AD620) without filtering.

incorporated in both LPMS and RPMS. Finally, RPMS has a patient's medical information database that enables patient's data entry to be created, updated and retrieved. The interface for both LPMS and RPMS provides similar features except for the database feature, which is only available at RPMS.

RESULTS

ECG data acquisition

A test is carried out on each part of the developed ECG data acquisition hardware setup to view how one affects the other. Figure 3 shows the output ECG signal from the instrumentation amplifier (AD620) without filtering.

Figure 4 shows the output ECG signal from the instrumentation amplifier after feeding it into a high pass filter with a corner frequency of 0.03Hz.

Figure 5 shows the output from the analogue circuit with the low pass filter with corner frequency 50 Hz, which is the ECG signal passed into the PIC microcontroller.

Local patient monitoring

When testing on the LPMS program, the connection part of the program is first tested. After selecting the location that it wants to be connected, the 'connect' button is clicked. Once the connection to the RPMS is successful, the user notifies through the message in the dialog session. Message 'Connection established' and 'Dialog session established' is sent to the user at the LPMS. With this notification, the user starts to send the ECG file or the heart beat sounds of the patient to the RPMS, to display and view a patient's ECG waveform or to have a chat session with the physician at the other terminal in the network. The graphical interface of the program is shown in Figure 6 where all tasks are performed together.

Remote patient monitoring

To test the RPMS program, it is executed together with the LPMS program. Thus, when the user in the LPMS initiate a transmission of either an ECG or audio file, user at the RPMS is prompted a message box requesting its permission to download the received file. When the message box is pop up, user at the RPMS decides either to save the file or terminates the file. Once a file save is complete, the user can view the ECG data using the plot graph features in the program. User at the RPMS can also play the received audio file using the standalone audio player. The graphical interface of the RPMS is as shown in Figure 7.

Fetal ECG extraction

A graphical user interface (GUI) program was written in matlab to detect the changes in extracted fetal ECG by different values of momentum, learning rate and initial

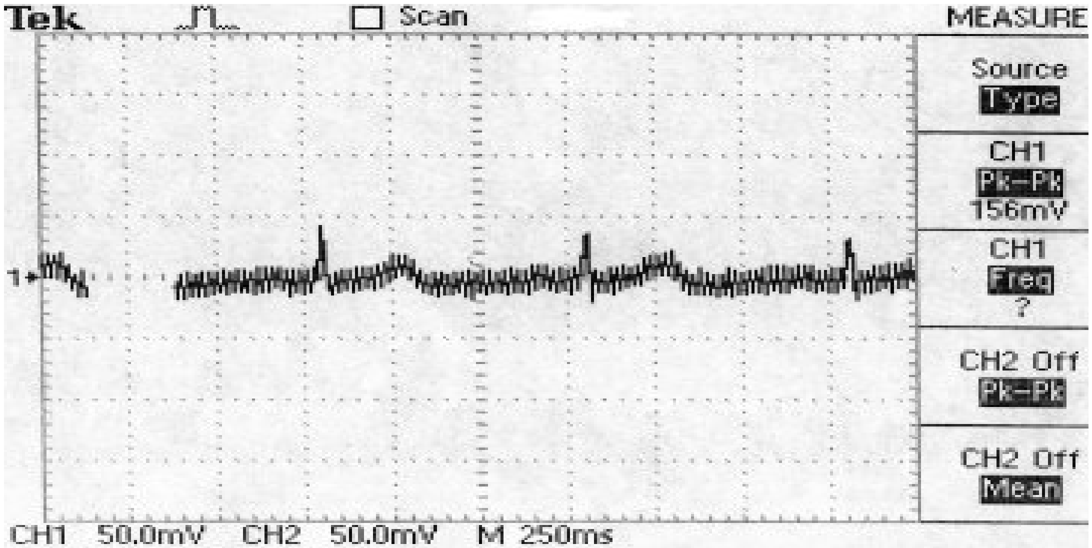

Figure 4. The amplified ECG signal from the instrumentation amplifier after feeding it into a high pass filter.

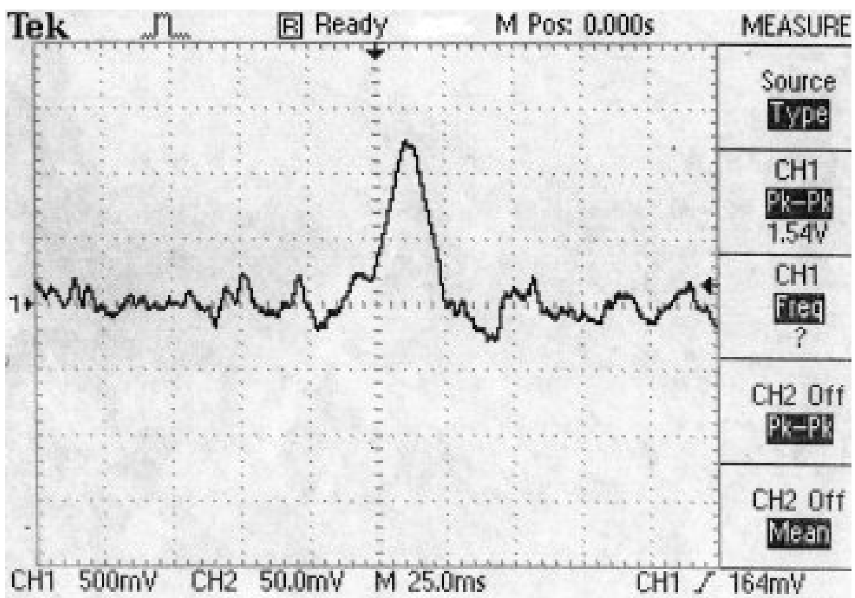

Figure 5. The output from the analogue circuit with the low pass filter.

weights used in the network. Three signals were shown in the program. They were target signal (the abdominal ECG of pregnant woman), output or the signal estimated from network (which was close to maternal ECG), and the difference between these two signals (which was the fetal signal). Three radio buttons were used to choose which signal to display.

First, a smooth and noise free signal was used to extract the fetal ECG. At the second step, noisy signal was fed into the network. The same learning rate, momentum and initial weights were used to compare the difference between smooth signals and noisy signals. Since the input was noisy, the estimated signal was also quite noisy. When the noise was too high, the amplitude was almost equivalent to amplitude of fetal ECG. To get a better signal for detecting QRS complex, the fetal ECG was raised to the power of two thus the peaks was larger than the noise. The difference between the noisy target

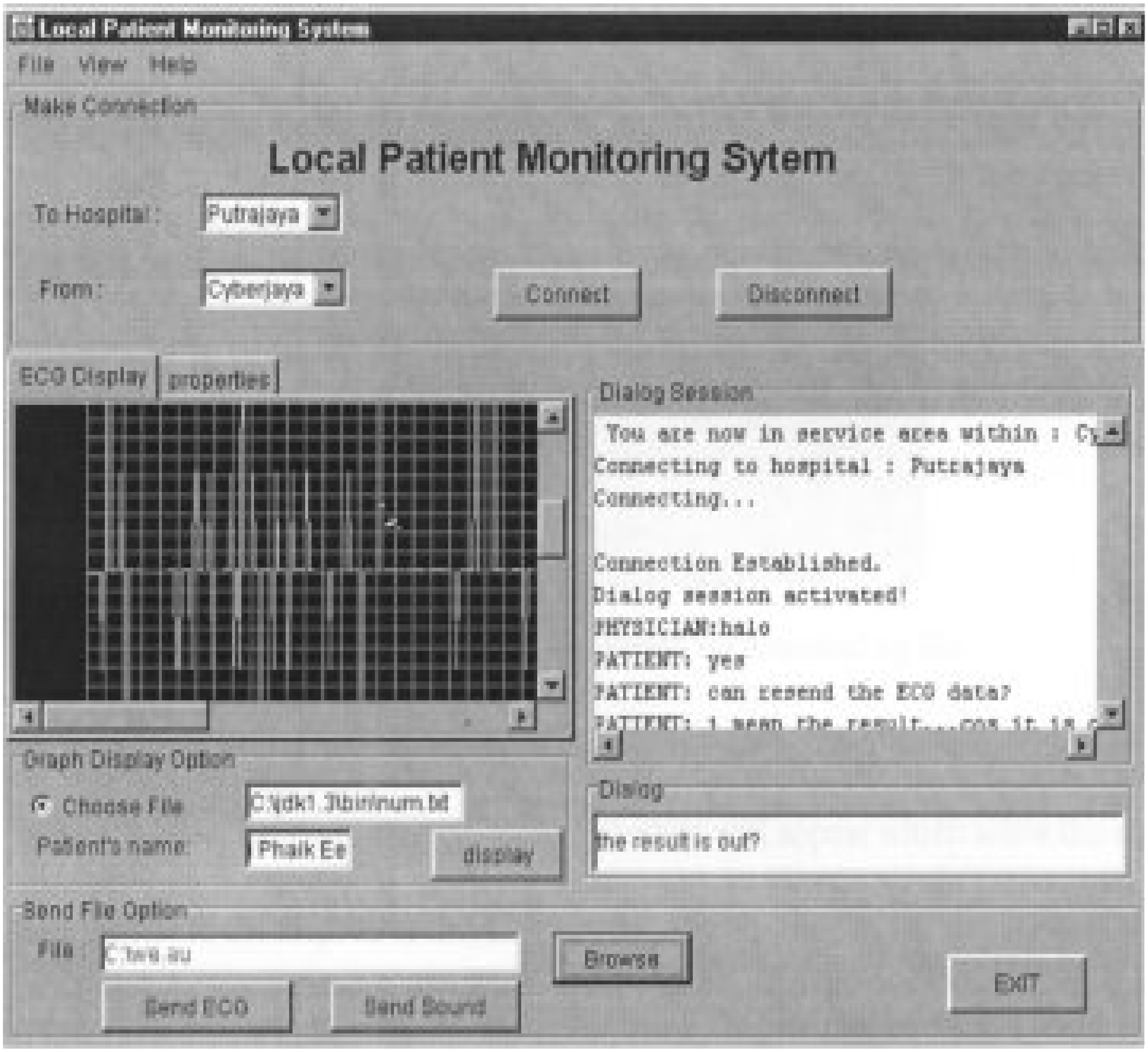

Figure 6. Graphical user interface for using features at LPMS.

signals and the estimated signals are shown in Figure 8. The estimated and the difference signal are shown in Figure 9 when learning rate was high.

DISCUSSION

During the ECG data acquisition, we have used instrumentation amplifier (AD620), which has the common mode noise rejection ratio feature. Therefore, the 50Hz or 60 Hz line interface is reduced. However, there is still noise overridden on the ECG waveform. These noises are due to the remaining 50Hz interference and the electrical activity of the active muscle and white noise. To reduce the noise further, we have used a high pass filter, which contributed to the huge reduction of low noise frequency while measuring the ECG signal from human's body. While placing the ECG signal into the PIC microcontroller, we have used few analog circuitry with the low pass filter. Due to this arrangement, peak R-wave was clearly noticed in Figure 5. The 60 Hz power line interference in the ECG signal was also greatly reduced

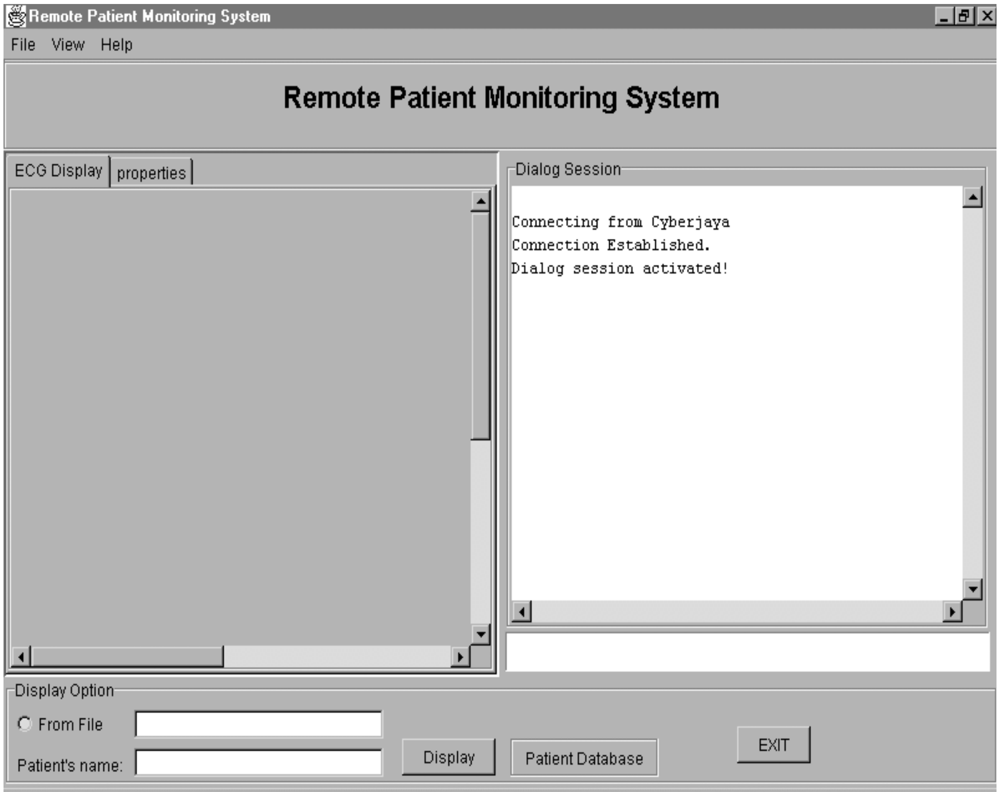

Figure 7. Graphical user interface for successful connection at RPMS.

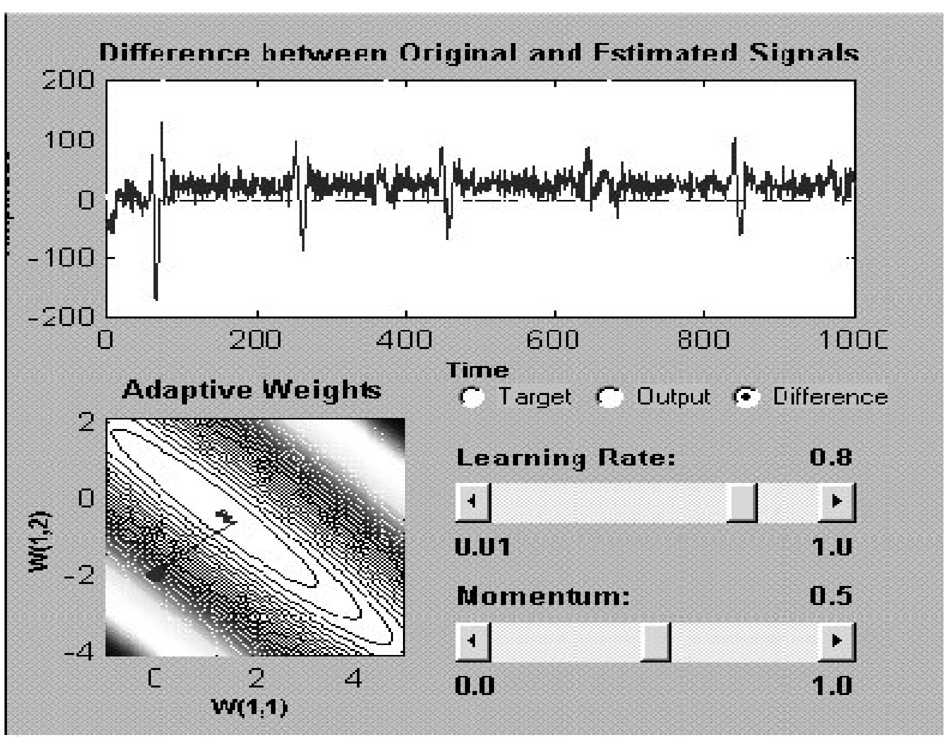

Figure 8. Difference signal (fetal ECG) of network in noisy environment.

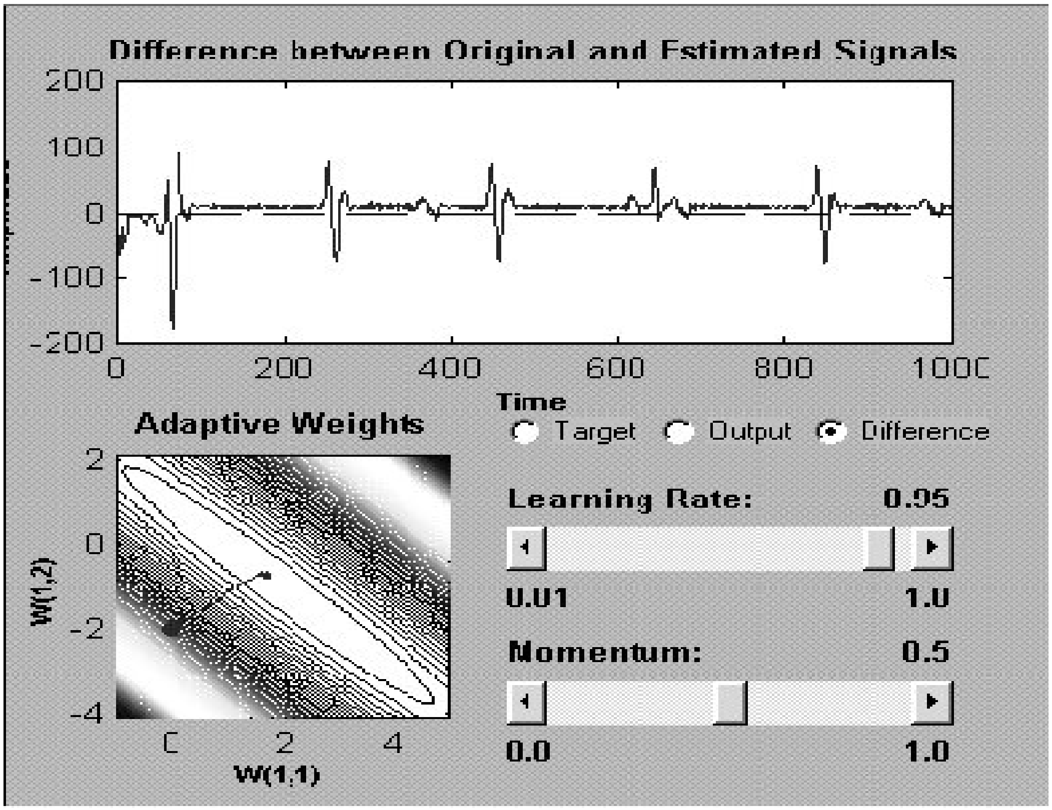

Figure 9. Difference signal (fetal ECG) when learning rate was high.

through the low pass filter.

Since not all the maternal ECG was estimated, the subtraction between the estimated ECG and target ECG will not produce the desired fetal ECG. Some parts of maternal ECG were still included. It shows that before 500 samples, the fetal ECG still consists of maternal ECG. Therefore, low learning rate value was not suitable. When high value of learning rate was used, the estimated signal was very close to maternal ECG because the input maternal ECG was closely correlated to the target abdominal ECG of pregnant woman.

The learning rate and momentum was affected in several ways on the fetal ECG extraction process. When high value of momentum was used, the global minimum error surface was missed out, causing the fetal ECG extracted incorrect. Another factor that affects the output of the network was the initial weights. The weights were randomized at small values at the beginning of the training. However, when the weights were too high, the network had difficulties adjusting the weight.

Conclusion

The proposed approach of using adaptive neural network to extract fetal ECG was successfully designed, implemented and tested. By using adaptive filter, desirable signal will not be filtered out, like in conventional filter method. Instead, it is subtracted out by comparison between input and target, which is a new and novel approach. The remote ECG monitoring system was also developed and tested successfully. The networking system enabled transfer of ECG and heart beat sound files, online chat, ECG display and also retrieves, update and create patient’s medical record database. Thus, fetal ECG extraction and the real time implementation of ECG data transfer are achieved.

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