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FPGA BASED FETAL ECG DENOISING AND EXTRACTION FORMEDICAL DIAGNOSIS

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ABSTRACT

In present days, several types of developments are carried towards the medical application. There are many methods to process the ECG signal. The accurate value of ECG signal is obtained by processing P, Q, R, and S signal from ECG output. Electrocardiogram is used to provide the information about heart beat condition. Analysis of the ECG waveform is used to identify whether the heart beat rate is normal and abnormalities. Measuring ECG during pregnancy period main problem is differentiating the mom's and fetus heart beat rate. The fetus heart beat is the important parameter to identify whether it contains any disease or not. To rectify this problem a novel method is proposed here to fetal extraction based on FPGA by using the Adaptive filtering method. The Adaptive filtering method removes the low power noises from the input ECG (fetal and maternal) after signal is passed through the feature extraction part. The feature extraction is used to separate the ECG signal into fetal and maternal without noise. The output shows that the baby condition is normal or abnormal and it shows whether the fetal contain any disease or not. The proposed design is simulated and comparison parameters are obtained in Quartus II 9.1.

Keywords: ECG Signal, Fetal Electrocardiogram (FECG), fetal heart rate (FHR), Feature Identification, DWT, ECG Clustering.

I.INTRODUCTION

The Fetal Electrocardiogram (FECG), which is a part of the Electrocardiogram (ECG), simulates the electrical activity of the fetal heart inside the mother belly. FECG produces such significant information about the physiological state of a fetus heart conditions during the pregnancy duration. Therefore, an early detection of any problem before delivery increases the effectiveness of the treatment. The obtained FECG signals are a collection of low power sources and noise. This noise at the received fetal signals is the amplitude of mother ECG as a high amplitudes signal in comparison with fetus. Numerous methods and approaches have been proposed and used for detecting of the FECG signal; such as adaptive filtering,

wavelet analysis, and blind source separation (BSS), independent component analysis (ICA). Normally, pregnant women are required to frequently visit hospitals to monitor the health of fetuses and conduct the test of fetal's heart beat rate, and dynamic behaviors.

The monitoring of the fetal cardiac activity using Doppler methods is a standard examination used, together with sonogram, for evaluating fetus health. Fetal monitoring is often performed in medical centers, and the analysis of the cardiac tracks is simply performed by eye inspecting the recordings. This means that the recognition relies on the experience of the doctors, with a possible low level of reliability. These considerations lead to the need of a portable system that can autonomously extract and identify the FECG in real-time, eventually storing it in a local memory or sending to a dock-unit through a Wi-Fi connection. This allows a continuous monitoring, not always possible with the traditional systems. Moreover, recent advances in the field of "textile wearable devices" make possible to develop a wearable unit that can acquire and examine the signals and send them to a remote diagnostic center. The acquired ECG signal is the result of the superimposition of electrical activities corresponding to maternal and fetal hearts. In addition, there are noisy contributions due to electrodes, maternal breath and involuntary movements. Noise can be reduced using a suitable filtering stage, so the system must be able to separate the FECG from the maternal one.

The heart rate is an important parameter, which is defined as the time between two consecutive R peaks; the inverse of the heart rate is called cardiac frequency. This frequency, in an adult, is typically in the range[60–100]beats per minute(bpm),while the fetal one is in the range [110–150] bpm. For what concerns fetal cardiac frequency, fast modifications of this frequency are considered normal, but their absence or a frequency out of the previous mentioned range are considered indicators of possible anomalies. Moreover, FECG is correlated with the maternal body response. For example, accelerations of the cardiac frequency with respect to uterine contractions (UC) rates is an indicator of non-correct abdominal venous circulation. Nowadays, fetal cardiac monitoring is mainly conducted in an invasive form and could happen only during labor. In this case an electrode is placed on the fetus head, but it is an extremely delicate procedure. For what concerns noninvasive techniques, the most common exploit ultrasound Doppler acquisition and feto scope, but, unfortunately, they do not allow a continuous monitoring. The ECG signal can also be acquired using surface electrodes positioned on the mother's abdomen. As said before, the electrodes acquire, together with the FECG, the maternal ECG and noise. Wearable ECG processing platform includes signal sensing, acquisition, local processing, recording and transmission. All of these components have to be designed to fit on an integrated system fulfilling the stringent power and area requirement. Signal sensing utilizes electrodes to pick the signals from the human body while acquisition is achieved through amplifier and analog to digital converter. Analyzing the acquired ECG signal requires efficient algorithms in order to extract vital features from ECG.

1.1 Fetal heart rate (FHR)

Fetal heart rate (FHR) monitoring is one of the possible solution to test fetal well-being and to diagnose possible abnormalities. Fetal monitoring during pregnancy stage enables the physician to diagnose and recognize the pathologic condition especially asphyxia. The electrocardiogram (ECG) is the simplest noninvasive diagnostic method for various heart diseases.

Fetal ECG (FECG) signal reflects the electrical activity of the fetal heart and provides valuable information of its physiological state. Non-invasive FECG has been used to obtain valuable clinical information about the fetal condition during pregnancy by using skin electrodes placed on the maternal abdomen. However, abdominal ECG (AECG) is always corrupted with power line interference, maternal ECG (MECG) and electromyogram (EMG) where as FECG signal is corrupted by the gestational age, position of the electrodes and the skin impedance.

we have investigated the detection of another group of arrhythmias, which might not be critically life threatening but still need attention and therapy to avoid deterioration. An essential step toward detecting and classifying arrhythmias is the classification of heartbeats, given that heart rhythm category can be determined by the recognition of classes of consecutive heartbeats. Beat-by- beat human-based examination can be very time-consuming and tedious to be practical in many scenarios. Besides, automatic ECG analysis is significant in long-term online monitoring of cardiac activity for timely detection of abnormal heart conditions, in which case the human monitoring and interpretation is unable to satisfy real-time diagnosis requirements.

Most cardiac defects have some manifestation in the morphology of cardiac electrical signals, which are recorded by electrocardiography and are believed to contain much more information as compared with conventional sonographic methods. However, no signal processing technique has been able to reliably deliver an undistorted FECG signal from electrodes placed on the maternal abdomen because of the low signal-to-noise ratio (SNR) of the FECG recorded from the maternal body surface. The application of fetal electrocardiography has therefore been almost completely limited to heart-beat analysis and invasive ECG recordings.

Every year, one of hundred babies born with a few heart defects. This is occurs because of genetic disease, environmental condition like mistreatment of drugs. Heart monitoring is necessary before birth of baby. Hence, Fetal ECG (FECG) signals are essential to observe the heart situation of the fetus, hence any abnormalities detected then it can be solved and observed by doctors. Monitoring FECG is a diagnosis method to observe abnormalities in fetus. During pregnancy stage doctors can easily diagnosis and proper decision can be taken. This is the simplest way to analyse different heart disorder. Hyejung Kim [1] described a mixed-signal ECG processing platform with an 12-bit ADC architecture that can adapt its sampling rate according to the input signals rate of change. Can Ye [2] proposed a new approach for heartbeat classification based on a combination of morphological and dynamic features. Wavelet transform and ICA are applied separately to each heartbeat to extract morphological features. In addition, RR interval information is computed to provide dynamic features.

Shengkai Yang and HaibinShen [3] an automatic heartbeat Classification method based on discrete wavelet transform (DWT) and kernel principal component analysis (KPCA) is proposed. Tobias Schumacher [4] presented an accelerator for k-th nearest neighbor thinning, a run time intensive algorithmic kernel used in recent multi-objective optimizers.

Fahad Bin Muslim [5] focused on using an HLS based methodology to implement a widely used clustering algorithm. E. Tortia [6] described Monitoring the fetal cardiac activity during pregnancy is of crucial importance for evaluating fetus health.

Jaeyoung Kim&PinakiMazumder, [7] described an energy-efficient hardware architecture of a self-organizing map (SOM) for ECG clustering wass proposed. TemesghenTekeste [8] presented an ultra-low power Electrocardiography (ECG) feature extraction engine.

In this paper, Section II describes the existing method analysis, Section III describes proposed method and Section IV describes the Implementation results.

II.THEORETICALBACKGROUND

2.1 Fetus ECG

The FECG describes the electrical physiological activity of a fetal heart. It contains important indications about the health and condition of the fetus [9]. The fetal ECG extraction is an interesting and challenging problem in biomedical engineering. Therefore, many approaches have been proposed to get the FECG such as Adaptive Neuron Fuzzy Interface System (ANFIS) to cancel the Mother ECG (MECG).

2.2 FECG Extraction

The FECG extraction has a vital role in medical diagnosis during pregnancy using electrodes placed on the maternal abdomen and chest. The abdominal is a composite signal, consisting of the contributions from maternal electrocardiogram (MECG) and the FECG, while the chest contains MECG only [10]. No current standards exist for electrode location, but concentric circles on the abdomen, covering all available angles will provide the maximal coverage.

2.3 Wireless FECG Monitoring System

The core of wireless fetal ECG monitoring system is the design of wireless monitoring terminals. These terminals are used to transmit information for medical evaluation and take the suitable medical decisions to ensure the safety of the fetus during pregnancy. Therefore, the FECG is became an important branch in telemedicine. Recent research papers have been included: In [11] simple and portable emergency medical care for fetal ECG monitoring system was implemented.

2.4 Discrete Wavelet Transform

The wavelet transform, which is a powerful tool for time varying signal analysis, provides a time-frequency representation of the signal. The time-domain characteristics are retained while the frequency analysis is performed using WT. DWT is widely used in time-varying signal processing for its simplicity, efficiency and non-redundancy.

Daubechies wavelet of order 8 has exhibited outstanding performance on heartbeat feature extraction. In agreement with, the four-level decomposition were applied using db8 wavelet, and the detail coefficients at level 3 and level 4 and the approximation coefficients at level 4 were retained. These 114 coefficients constituted the morphological characteristics of the heartbeat.

III.PROPOSED METHODOLOGY

The ECG is a track representing the heart's electrical activity. A typical ECG record shows a cardiac cycle which is made up of three parts: the P wave (related to the atrial depolarization), the QRS complex (related to ventricles depolarization) and the T wave (related to new ventricle polarization). The heart rate is an important parameter, which is defined as the time between two consecutive R peaks; the inverse of the heart rate is called cardiac frequency. This frequency, in an adult, is typically in the range [60–100] beats per minute (bpm), while the fetal one is in the range [110–150] bpm. For what concerns fetal cardiac frequency, fast modifications of this frequency are considered normal, but their absence or a frequency out of the previous mentioned range are considered indicators of possible anomalies. Moreover, FECG is correlated with the maternal body response. For example, accelerations of the cardiac frequency with respect to uterine contractions (UC) rates is an indicator of non-correct abdominal venous circulation. Nowadays, fetal cardiac monitoring is mainly conducted in an invasive form and could happen only during labor.

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3.1 Feature signals creation

This phase exploits a series of FIR filters for highlighting the peaks related to the QRS complex. We decided, according to [12], to use first order derivative filter, second order derivative filter, Multiplication of Background Difference

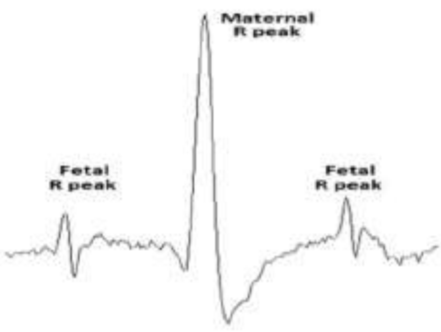

Fig 3.1.1 Superimposition of FECG, maternal ECG and noise.

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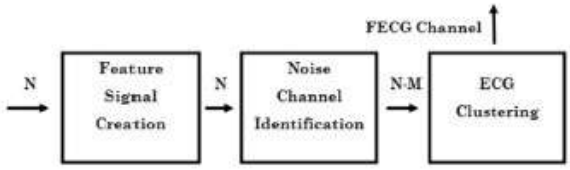

Fig 3.1.2 Block diagram of the Proposed Methodology

(MOBD) filter, weighted moving average filter. The first order derivative filter is a high-pass filter and is used for highlighting the fast amplitude variations, which typically occur in QRS events.

$$y[n] = x[n+1] - x[n-1] \quad [1]$$
$$y[n] = 2x[n+2] + x[n+1] \quad [2]$$
$$y[n] = x[n] - x[n-1] \quad [3]$$

where x denotes the input sample vector.

3.2 Noise channels identification

The feature signals obtained using the filtering stage are the inputs of the noise channel identification stage. This phase is needed for sending a limited number of channels to the clustering stage, accelerating the classification phase, to avoid working on signals with no clinical interest. For each channel, a suitable threshold is computed as function of the maximum amplitude, to exclude uninteresting signals. This is done to remove the baseline noise. In our implementation, this threshold has been set to 30% of the maximum value, so we can remove the baseline noise without removing plausible QRS peaks.

After that another first order derivative filter, like the one described in the previous section, is applied, for highlighting the transactions from positive to negative derivative of each channel. Those transactions are defined as the turning points (TP), related to the number of QRS events of each signal. The number of the detected turning points is used to evaluate if a channel should be sent to the clustering stage or not.

3.3 Clustering

We chose to test different clustering techniques in order to improve the performance. Instead of using the Pearson correlation index for evaluating the distance between two clusters, we used a single linking cluster working on the number of turning points. We also adopted a K-means clustering method, testing two different ways of partitioning data. The first one uses only the number of turning points as parameter to perform the partitioning, while the second one uses also the standard deviation between all the turning points distance and the average between the distances. Those values are computed by the previous noise channel identification stage.

We tested four clustering algorithms (agglomerative clustering from [13], single linking clustering and the two K-means clustering described before) with our dataset and we found that the best accuracy is obtained using the K-means method based only on the number of the turning points (accuracy of 100%).

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IV. IMPLEMENTATION AND RESULTS

4.1 Implementation of Noise Cancellation unit

It is obvious that one of the most critical steps in ECG digital signal processing is noise filtering because ECG signals are noisily affected by many different sources. Those noises can be reduced by many low pass FIR Filter in VHDL to reduce high- frequency noise and power-line interference.

The FIR filter is basically implemented by using D-Flip-Flops, signed multipliers and adders. A basic block includes one N- bit register, one multiplier, and one adder. The VHDL generate statement is used to generate the full design using the basic block. The DWT based Noise Cancellation unit is shown in Fig 3.

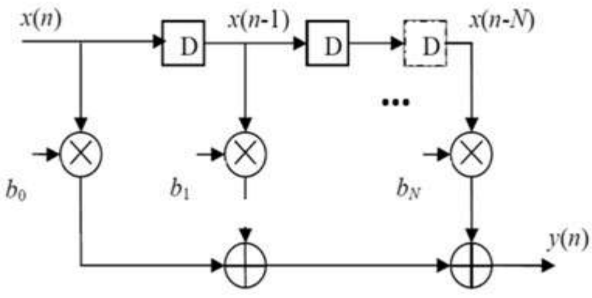

Fig 4.1.1 DWT Based Noise Cancellation unit

The input of the Noise Cancellation unit is discrete wavelet transform odd and even terms. It was removed noise in DWT. It can be performed as the multi resolution signal analysis in the time-scale plane. Taking the properties of scaling and shifting, a signal can be expressed as the combinations of the wavelets with different resolution. In other words, the DWT has excellent spatial and spectral locality properties and can decompose a signal into components in different frequency bands. The Denoising unit was implemented in Quartus II software for different nm technology and the corresponding power and time were measured and tabulated in the Table 1.

FPGA Platform	Power (mW)	Time (nS)
Cyclone II	248.37	59.728
Cyclone III	118.14	49.107
Stratix II	774.11	39.428
Stratix III	456.84	29.282

Table 4.1.2 Power and Time analysis of Noise Cancellation unit

The RTL View and Simulation Waveform of the Noise Cancellation unit are shown in Fig 4 and 5 respectively.

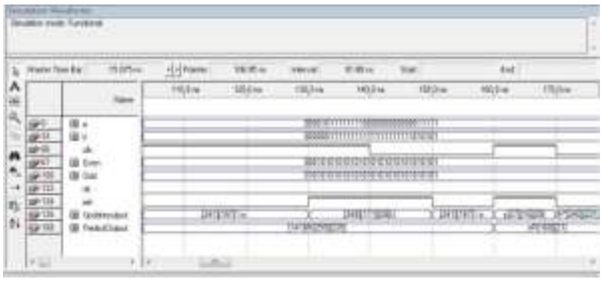

Fig 4.1.3 Simulation Waveform of the Noise Cancellation unit

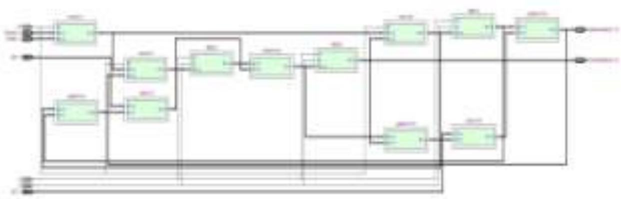

Fig 4.1.4 RTL View of the Noise Cancellation unit

4.2Implementation of ECG Clustering unit

TheECGClusteringunitwasimplementedinQuartusIIsoftwarefordifferentnmtechnologyandthecorrespondingpower and time were measured and tabulated in the Table 2.

FPGA Platform	Power (mW)	Time (nS)
Cyclone II	247.54	54.790
Cyclone III	146.41	46.071
Stratix II	302.89	35.369
Stratix III	458.32	28.951

Table 4.2.1 Power and Time analysis of ECG Clustering unit

The RTL View and Simulation Waveform of the ECG Clustering unit are shown in Fig 6 and 7 respectively.

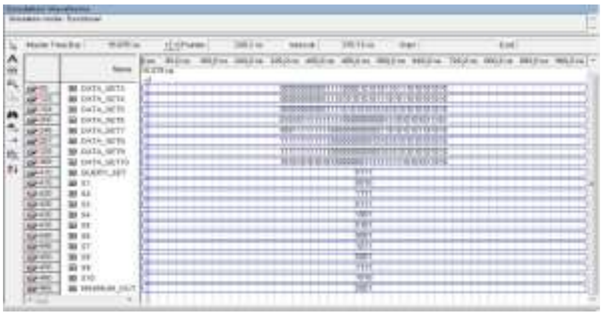

Fig 4.2.2 Simulation Waveform Of The ECG Clustering Unit

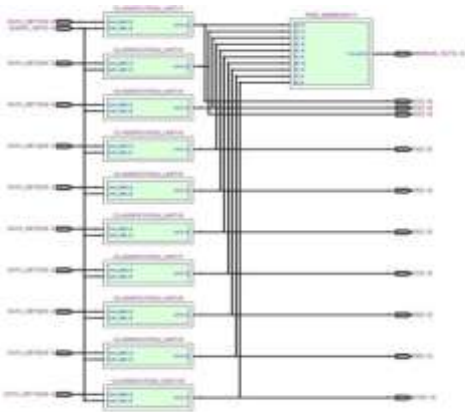

Fig 4.2.3RTL View Of TheEcg Clustering Unit

V.CONCLUSION

In this paper, we present a novel architecture for FECG extraction and identification. A suitable dataset, made up of both synthetic and in vivo signals, has been correctly classified by the system. Estimated power consumption is compatible with the Constraints given by a portable device, overall large to this project. The proposed architecture out performs the elaboration times of the other works in literature who implement similar algorithms for successfully separating the tracks. Moreover, the resource usage is compliant with the implementation of future algorithms on the same FPGA. For example, it is possible to improve the system by adding diagnostic functions, such as morphological analysis of the fetal track, which canal so be performed in real- time. At last, it is possible to add a cryptography function forprotecting data before transmission, since those data are strictly personal. Another possibility is to use a smaller FPGA, such as an Altera Cyclone V, which is equipped with less logic resources.

This device has a lower power consumption than the one considered by us. This choice will further reduce the power consumption of our system. However, this device is suitable for housing only ours System, without the possibility to expand its functions with the features described above.

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