International Journal of Computational Research and Development (IJCRD)
Impact Factor: 4.775, ISSN (Online): 2456 - 3137
(www.dvpublication.com) Volume 1, Issue 2, 2016

FETAL HEART RATE DEDUCTION AND DATA COMPRESSION USING GENETIC ALGORITHM

V. Sakunthalamani* & S. Gowsalya**

* PG Scholar, Maharaja Prithvi Engineering College, Avinashi, Tamilnadu
** Assistant Professor & HOD, Department of Electronics and Communication Engineering, Maharaja Prithvi Engineering College, Avinashi, Tamilnadu

Cite This Article: V. Sakunthalamani & S. Gowsalya, "Fetal Heart Rate Deduction and Data Compression Using Genetic Algorithm", International Journal of Computational Research and Development, Volume 1, Issue 2, Page Number 120-124, 2016.

Abstract:

This project propose a new heart rate detection and separation framework for the fetal ECG extraction which uses genetic algorithm and wavelet signal analysis technique. Also combined technique for the detection of QRS complex and its compression in a wireless wearable ECG monitoring device with minimum complexity using which different Arrhythmias are detected. Linear Predictive coding is the common technique used for QRS detection and compression scheme. Arrhythmia detection is done using wavelet transform and SVM classifier. Detection of QRS waveforms in wearable device helps in the analysis of cardiac health of the patient. Lossless data compression of detected waveforms helps in saving the bandwidth of the channel when it needs to be send to other end. Heart rate is calculated from QRS detection section and a compression ratio of 2.27x is obtained when tested with MIT/BIH Arrhythmia database. 84.14% of Arrhythmia detection accuracy is obtained. Reduced overall complexity and good performance makes the proposed technique suitable for the wearable ECG devices.

Key Words: Compression, Electrocardiogram & QRS Detection

Introduction:

The fetal psychological condition depends on the heart rate, which is most related to the mothers cardiogram signal. The Electro Cardiogram represents the electrical activity of the heart which is shown as the heart beat. The ECG records the electrical activity of the heart, where each heart beat is displayed as a series of electrical waves characterized by peaks and valleys. The ECG signal provides us two kinds of information, the duration of the electrical wave crossing the heart which in turn decides whether the electrical activity is normal or irregular and the amount of electrical activity passing through the heart muscle which enables to find whether the parts of the heart is proper or not. Wavelet transform is a signal processing technique used in various applications - to decompose, filter, feature extraction etc…. Wavelet transform has a huge impact in biomedical systems for signal processing. For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content, on the other hand, imparts flavor or nuance. To gain a better appreciation of this process, it is performed with a one-stage discrete wavelet transform of a signal. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components.

Analysis of Wave:

In wavelet analysis, a signal is split into an approximation and a detail. The approximation is then itself split into a second-level approximation and detail, and the process is repeated. The transformed signal provides information about the time and the frequency. Using this approximated information low frequency data could be identified, which is more important in cardiac disease prediction. The fetal electrocardiogram (FECG) is used for the calculation of the fetal cardiac frequency and in the prediction of the fetal acidosis. An FECG provides information about the fetal well being and the physiological state of the fetus. Genetic algorithm is a common methodology using which the range of values can be fit into a specific function and evaluated using an another function. Using genetic algorithm the electrocardiogram signal can be evaluated as whether the signal can be assigned to mother cardiogram or fetal cardiogram. The genetic algorithm can be applied for the separation of signals of Electrocardiogram as mother and fetal.

Main Features of ECG:

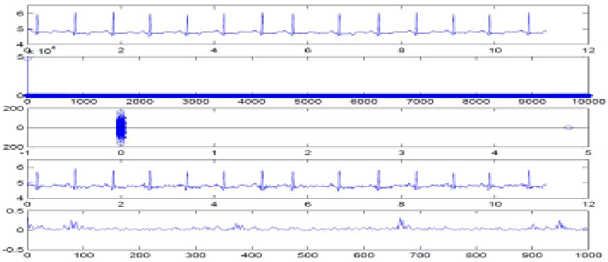
Health Care spending is increasingly becoming the major contributor of expenditure in many countries. U.S. alone spends roughly 18% of its GDP on healthcare. Cardiovascular diseases are one of the leading causes of the overall expenditure. These expenses are expected to skyrocket in the coming years due to an aging population, as a result of increasing life expectancies. The quality of life in this scenario can be improved by focusing on prevention and early detection of diseases. This can be achieved by proactive and long-term monitoring of individual's cardiovascular health using low-cost wearable electrocardiogram (ECG) sensor devices. The main features of the ECG, i.e., the P, Q, R, S, and T points, give information about the cardiac health of the person. A wearable ECG sensor can be used to acquire, process, and wirelessly transmit ECG signal to a monitoring center. The main challenge involved in the development of the sensor is to make the device low profile, unobtrusive, easy to use with long battery life for continuous usage. A high level of integration with inbuilt signal acquisition and data conversion is required to minimize the size, cost, and power consumption of such a sensor. The major source of power consumption in sucha system is the wireless transceiver, and hence, it is desirable to carry out preliminary ECG analysis tasks like QRS detection and RR interval estimation locally. This allows the transmission to be triggered only when it is deemed necessary based on cardiac rhythm analysis. Further, the large quantity of ECG data obtained by round the clock monitoring may need to be either stored locally in a flash device or transmitted wirelessly to a monitoring gateway for further analysis. The transmission of data incurs high power consumption, and the use of a local storage increases the device cost. The cost is further affected by the need for an on-chip SRAM which is typically used to interface the ECG chip with a microcontroller to support burst transfer. Although lossy compression techniques provide higher compression ratios (CR) and focus on lossless schemes so as to prevent the possibility of losing any patient information of potential diagnostic value. Also, it is worth noting that lossy compression techniques have not been approved by medical regulatory bodies in most countries and hence cannot be used in commercial devices. Most of the existing literature on lossless ECG compression predominantly focuses on achieving higher R. However, in the context of wireless sensors and ambulatory devices, the energy and memory savings obtained from the compression should be higher than what is consumed by the compressor itself.QRS detection is not a new topic. A comprehensive review of existing approaches can be found in. However, most of the reported approaches are aimed at increasing the accuracy of detection by using complex signal-processing techniques. For ambulatory devices and sensors, another very important figure of merit is the power consumption, and hence, the overall complexity should be low. In recent years, several QRS detection algorithms with low-power implementations have been reported for wireless sensors. Also several discrete or integrated lossy and lossless ECG compression implementations have been reported. It can be noted that using two distinct approaches for QRS detection and data compression will results higher overall system complexity. Till now, there are no reports on joint approaches for QRS detection and lossless data compression. The central idea of the proposed algorithm is to use a single technique for processing of QRS detection and data compression, instead of using two distinct approaches. The algorithm lowers the average computational complexity per task by sharing the computational load among two operations. This is done using a shared adaptive linear predictor for performing both ECG beat detection and lossless data compression. In addition, a novel fixed-length data coding-packaging technique for convenient representation of the signal entropy is presented.

Existing System:

FFT Compression Algorithm:

- ✓ Separate the ECG components into three components x, y, z.
- ✓ Find the frequency and time between two samples.
- ✓ Find the FFT of ECG signal and check for FFT coefficients (before compression) =0, increment the counter A if it is between +25 to-25 and assign to Index=0.
- ✓ Check for FFT coefficients (after compression) =0, increment the Counter B.
- ✓ Calculate inverse FFT and plot decompression, error.
- ✓ Calculate the compression ratio CR and PRD.

The original ECG signal record 100 which are selected from MIT-BIH arrhythmia database and its recorded.



Discrete Sine Transform (DST):

Discrete sine transform (DST) is a Fourier-relate transform similar to the discrete Fourier transform (DFT), but using a purely real matrix. It is equivalent to the imaginary parts of a DFT of roughly twice the length, operating on real datawith odd symmetry (since the Fourier transform of a real and odd function is imaginary and odd), where in some variants the input and/or output data are shifted by half a sample. Like any Fourier-related transform, discrete sine transforms (DSTs) express a function or a signal in terms of a sum of sinusoids with different frequencies and amplitudes. Like the discrete Fourier transforms (DFT), a DST operates on a function at a finite number of discrete data points. The obvious distinction between a DST and a DFT is that the former uses only sine functions, while the latter uses both cosines and sines (in the form of complex exponentials). However, this visible difference is merely a consequence of a deeper distinction: a DST implies different boundary conditions than the DFT or other related transforms.

The DST Compression Algorithm:

Separate the ECG components into three components x, y, z.

- ✓ Find the frequency and time between two samples.
- ✓ Find the DST of ECG signal and check for DST
- ✓ Coefficients (before compression) =0, increment the counter A if it is between +15 to-15 and assign to Index=0.
- ✓ Check for DST coefficients (after compression) = 0, increment the Counter B.
- ✓ Calculate inverse DST and plot decompression, error.
- ✓ Calculate the compression ratio CR and PRD.

Discrete Cosine Transform-II (DCT-II):

The most common variant of discrete cosine transform is the type-II DCT. The DCT-II is typically defined as a real, orthogonal (unitary), linear transformation by the following equation. DCT-II can be viewed as special case of the discrete Fourier transform (DFT) with real inputs of certain symmetry. This viewpoint is fruitful because it means that any FFT algorithm for the DFT leads immediately to a corresponding fast algorithm for the DCT-II simply by discarding the redundant operations.

DCT-II Compression Algorithm:

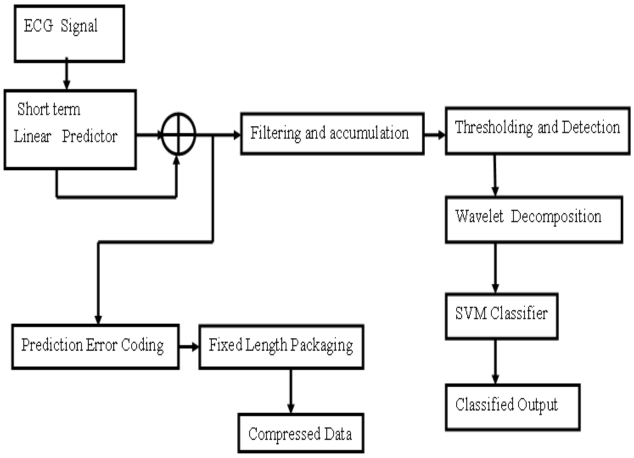
Partition of data sequence x in Nb consecutive blocks bi, i =0, 1, ¼.., Nb- 1, each one with Lb samples.

- ✓ DCT computation for each block.
- ✓ Quantization of the DCT coefficients.
- ✓ Lossless encoding of the quantized DCT coefficients.

The original ECG signal record 100 which are selected from MIT-BIH arrhythmia database and its reconstructed waveform when compressed by DCT-II.

Proposed Method:

The proposed method in Fig.4.1 has four stages: In the first stage the signal is transformed using wavelet transform to boost the signals, in the second stage we extract the features of the electrocardiogram signal, and in the third stage the boosted signals are applied with GA functions to evaluate the signal with the signals of the mother. Finally the fetal ECG is separated from mothers and combined to present the complete fetal ECG.

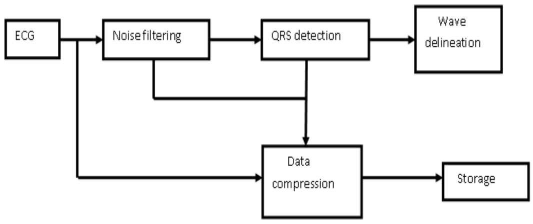


The proposed method has five stages:

- ✓ In the first stage the signal is transformed using wavelet transform to boost the signals,
- ✓ In the second stage we extract the features of the electrocardiogram signal,
- ✓ In the third stage the boosted signals are applied with Feature Extraction calculations to evaluate the signal with the signals of the mother.
- ✓ In the Fourth stage**,** the fetal ECG is separated from mothers and combined to present the complete fetal ECG.
- ✓ Finally compressed the signals and calculate the Compression ratio and SNR and PSNR measures.

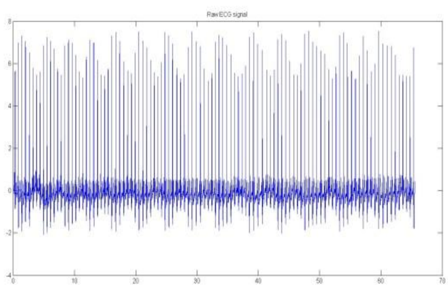
ECG Signal Processing:

These algorithms are frequently implemented to operate in sequential order, information on the occurrence time of a heartbeat, as produced by the QRS detector, is sometimes incorporated into the other algorithms to improve performance is shown in Fig.4.2. The complexity of each algorithm varies from application to application so that, for example, noise filtering performed in ambulatory monitoring is much more sophisticated than that required in resting ECG analysis. Once the information produced by the basic set of algorithms is available, a wide range of ECG applications exist where it is of interest to use signal processing for quantifying heart rhythm and beat morphology properties. The signal processing associated with two such applications—high-resolution ECG and T wave alternates are briefly described at the end of this article. The timing information produced by the QRS detector may be fed to the blocks for noise filtering and data compression (indicated by gray arrows) to improve their respective performance. The output of the upper branch is the conditioned ECG signal and related temporal information, including the occurrence time of each heartbeat and the onset and end of each wave.

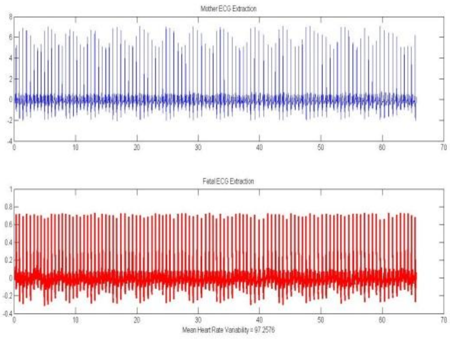


The algorithm composed of five compressing procedures and four reconstruction procedures. For compression, the first procedure is to obtain backward differences after 1/2 down-sampling of the ECG signal. The second procedure is to detect the peak of the differenced signal and classify it from the current peak to the previous peak and store the result. The third procedure is to obtain the DCT of the stored data. The fourth procedure is to filter the transformed data obtained in the previous procedure using a window filter, and the final procedure is to apply the Huffman coding algorithm. The data transmitted to a server or a base station from e-health devices are the data block coming out of the last compression procedure. The channel number can be added to the protocol header if e-health devices need to transmit multiple bio-signals. It also shows the reconstruction procedure, which is the reverse order of the compression procedure. The first reconstruction procedure applies the inverse Huffman coding algorithm to the compressed and transmitted data. The second procedure obtains the inverse discrete cosine transform. The third interpolates the recovered time signal during the previous procedure using Spline interpolation, and the final procedure is to reconstruct the original signal after calculating the inverse difference. ECG, which is an analog signal, is usually sampled at 200 Hz to 1 kHz depending on the purpose of applications. Usually, the sampled data are represented as a 2-byte data. In the proposed data compression algorithm, the acquired ECG signal is first down sampled by 1/2 and represented as 1-byte data after calculating the backward difference, decreasing its data size by 75%. The signed 1-byte data can be represented from –128 to +127 in decimal. ECG Data Compression is required to reduce the disk space required to store the data, as ECG is a continuous data taken for a very long interval of time. Also by compressing redundant data from the signal can be removed which actually takes considerably large area in memory. The need of signal transmission over telephone lines or antenna for remote analysis makes the compression and data reconstruction of the signal an important issue in signal processing. ECG is a graphic display of the electrical activity of the heart. Due to low cost and no invasion, ECG signal has been extended for heart disease diagnosis and ambulatory monitoring. For storage and transmission of large signal data, it is necessary to compress the ECG signal data. Data compression has its application in many fields and so as in the field of medical science. ECG is an important parameter that measures patient's health and reports abnormalities if any. This paper has done a survey of various kinds of ECG data compression techniques. Recently, numerous research and techniques have been developed for compression of the signal. These techniques are essential to a variety of application ranging from diagnostic to ambulatory ECG's. Thus, the need for ECG compression techniques is of great importance Many existing compression algorithms shown some success in electrocardiogram compression; however, algorithms that produce better compression ratios and less loss of data in the reconstructed signal are needed.

Results:



This is the raw ECG signal obtained from the perspective report from the hospital. This signal contains around 60,000 samples and this is to be applied to the filters for removing the unwanted noises. Identified P-wave and QRS-wave are grouped to form the electrocardiogram wave of the fetal and separated from mother ECG. All identified wave forms of the fetal is joined to form the complete wave form to analyze the condition of the fetal for medical investigations.



QRS wave will have a large value of e(n) comparing to the other parts of ECG. With further processing on e(n), QRS complex can be extracted . Also linear predictive coding is a main part of lossless compression techniques. Hence predictors can be jointly used to detect and compress the ECG signal thereby reducing the complexity.

Conclusion:

A novel scheme for joint QRS detection and lossless data compression aimed at wearable ECG devices and for arrhythmia detection. It uses a linear predictor in both detection and compression section and therefore the complexity is less. The algorithm enables the sharing of computational load among multiple critical functions needed in a wearable sensor. It uses a lossless mode of compression since the data preservation is very important. A compression ratio of 2.276x is obtained. Arrhythmia detected from obtained QRS complex using wavelet decomposition and SVM classifier. The outputs of the extracted signal were recorded on MATLAB. Finally, the fetal ECG signal is extracted and heartbeat of the signal is calculated. The algorithm based on Adaptive Noise Canceller (ANC) is proposed and implemented successfully. The performance of the algorithm has been verified successfully on MATLAB and the algorithm is found to be highly efficient. It is found after successful implementation that fetal ECG (FECG) signal can be successfully extracted by using Least Mean Square (LMS) algorithm for tap-weight vectors. The LMS algorithm is implemented by MATLAB codes and hence the LMS algorithm implements ANC successfully.

References:

1. Can Ye , Miguel Tavares Coimbra and Vijaya Kumar(2010),‘Arrhythmia Detection and Classification using Morphological and Dynamic Features of ECG Signals’,32nd Annual International Conference of the IEEE EMBS Buenos Aires, Argentina.
2. ChuaE. and FangW.(2011),‘Mixed bio-signal lossless data compressor for portable brain-heartmonitoring systems’, IEEE Trans. Consum. Electron, Vol. 57, no. 1, pp. 267–273.
3. DeepuC.J.and Yong Lian (2015), ‘A Joint QRS Detection and Data Compression Scheme for Wearable Sensors”, IEEE Transactions Biomed. Eng., vol. 62, no.1.
4. Jacaranda Ghosh-Dastidar J. (2003) ‘An efficient test vector compression scheme using selective Huffman coding’, IEEE Trans. Comput.-Aided Des. Integr. Circuits Syst., vol. 22, no. 6, pp. 797–806.
5. Kohler B. U, Hennig C. and Orglmeister R (2002),‘The principles of software QRS detection’, IEEE Eng. Med. Biol. Mag., vol. 21, no. 1. pp. 42–57.
6. MoodyG.B. and MarkG.R .(2001), ’The impact of the MIT-BIH Arrhythmia database’, IEEE Eng. Med. Biol. Mag., vol. 20, no. 3. pp. 45–50.
7. Nallathambi G. and Principe J. (2013), ‘Integrate and fire pulse train automaton for QRS detection’, IEEE Trans. Biomed. Eng., vol. 61, no. 2, pp. 317–326.
8. RiglerS, Bishop W. and KenningsA (2007), ‘FPGA-based lossless data compression using Huffman and LZ77 algorithms’, in Proc. Can. Conf. Electron. Comput. Eng., pp. 1235–1238.
9. Schafer R. W (2012), ‘Vector Machine Based on Wavelet Multi resolution Analysis’, The 11th International conference on Information Sciences, Signal Processing and their Applications.
10. Winokur E. S, Delano M. K. and Sodini C. G (2013), ‘A wearable cardiac monitor for long-term data acquisition and analysis’, IEEE Trans. Biomed. Eng., vol. 60, no. 1, pp. 189–192.
11. Zhang D. R, Deepu C. J. and Lia Y.(2011), ‘A wireless ECG plaster for real-time cardiac health monitoring in boy sensor networks’, in Proc. IEEE Biomed. Circuits Syst. Conf, pp. 205–208.