DCAEOCS: Divide and Conquer Algorithm Based Electro Cardiac Signal Compression Scheme

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Abstract. The method of recording heart electrical activity over a period of time using electrodes implanted in the skin is referred to as electrocardiography (ECG). In constant patient monitoring, vast volumes of ECG data need to be treated. Therefore, when each time we need to track the patient’s heart condition, we have to store more details. It is very costly, however, to store, transfer and allocate bandwidth to this Meta data. Here, an effective compression technique has been applied to solve this problem in such a way that all the salient features that have been clinically needed can be preserved. We used the MIT-BIH ECG data database to validate the ECG.

Keywords: Compression, Electrocardiogram, ECG, Divide and Conquer Algorithm (DCA), MATLAB.

Introduction
The structured measure of the electrocardiogram (ECG) tests how the heart functions by monitoring the heart’s electrical activity. Persons with a heart-related condition are present with a long record of ECGs, which means a lot of storage space is required. There is consequently a structure provision together with the ECG inquiry, which involves the pressure of ECG signals. ECG pressure is an emerging technology for reducing numerical, multi-faceted data quality. Flag pressure and flag examination have request in numerous application territories particularly in biomedical zone. ECG signals are diverse for every individual. The identification of ECG architecture is a standout among the most reliable evidence techniques identifiable for coronary disease. The ECG is the basic instrument for tracking and diagnosing cardiovascular conditions by assessing the heart’s electrical motion. The cathodes connected to the body identify the electrical movement of the heart. From every terminal the ECG signals will record and store for a drawn out stretch of time. Preparing the ECG flag by using existing ECG library data contains ECG waveform parameters such as P wave, QRS complex and T wave.

The most important feature of the QRS complex is the electrical depolarization of the ventricle muscles in the heart. The length and stature of QRS offers the doctor a critical measure of knowledge so that he/she can certainly understand the state of the heart. A cardiovascular patient with the history of heart infections will dependably need to keep up a ton of ECG reports while going to a doctor for interview. We will likely outline a framework which includes pressure of ECG signals for ordering typical and strange classes of ECG signals. Digitizing the ECG flag will take care of the storage issue and it likewise gets to be practical when comes to sharing and finding [1].

1. Literature Survey
[1] The research paper suggests the development of a single-channel ECG amplifier which can produce a satisfactory reading of the ECG remaining signal. Construction and implementation of an electrical amplifier with DSP post-processing in MATLAB. A multichannel ECG amp to record the regular 12-lead
device may be extended. The site selection and site planning go hand in hand for the most detailed and accurate ECG outcomes. The sensitivity of the ECG is profoundly affected where and how the ECG electrodes are connected. In addition, the optical filtering is used to obtain better performance [1].

[2] Electrocardiography compression using Fast Fourier Transform. The ECG compression approach based on fast Fourier transformation was discussed in this article. The main concept is that QRS-complex signals from an ECG signal are calculated. The QRS complex is calculated by means of partial ECG signal the original ECG signal. It contributes to increased CR and less PRD. In order to increase therapeutic effectiveness, FFT methodology will require further investigations. This modern method in signal processing. In broad clinical trials, simultaneous diagnostic and prognostic sense of wavelet techniques in different areas of electrocardiology must be identified. [2].

[3] New technologies for ECG Signal Compression in an optimised way. We may implement new lossless compression methods with a high compressive ratio with many changes to this process. Digital ECG and ECG strip recording provides potentially better quality [3].

[4] Compression of the wavelet-based ECG signal by run length encoding. The simulation findings were obtained using the signal data chosen in this research paper from the MIT-BIH arrhythmia database. WT checked the reconstructed signal of the cardiologist. Both clinical information was stated to be retained in the restored signal by wavelet transformation. Increased CRs are often obtained without any distortion using run length coding in the method presented. As no zero trees exists, it is simple and easy to introduce coding and decoding. [4].

[5] Robust Algorithm for Heart Rate (HR) Identification as well as Heart Rate Variability Estimation, ACTA Physica Polonica. This research paper suggests that ARP should be used as a pattern for human biosignal recognition schemes that are readily preserved in medical databases. The HRV tool is a very powerful HRV frequency analysis framework when considering several approaches for PSD estimation and accurate PSD parameter computation for user-fixed analysis region [5].

[6] Suggested ECG Signal Efficient Lossless Compression Scheme. This research paper proposes for real-time implementations a robust lossless ECG data compression scheme. Compressed ECG information is provided as a text file [8].

[7] Suggested Telemedicine ECG Data Compression This research paper proposes for real-time implementations a robust lossless ECG data compression scheme. Compressed ECG information is provided as a text file [8]. The methods developed are very useful for telemedicine, particularly in telecardiology. Overall work performed can be seen as a constructive and important addition to successful healthcare systems for remotely located patients [9].

[10] The novel ECG classification system was suggested. Proposed an improved ICA system is added during the extraction process. In the system 3 fragments of the heartbeat (P wave, QRS interval, segment ST) are retrieved. These three vectors first construct the single lead function. During this time, a multilead feature is generated by 12 vectors with single lead. Finally, the Vector Support Machine (SVM) can be used for several and two classification experiments. The studies are performed at the same time with all available data in the MIT-BIH Arrhythmia Database and total of 2500 functional data obtained from around 500 individuals. The final average accuracy of test results is 98.18%, the average sensitivity is 98.68%. [10] The ECG approach was proposed for printing using the ECG beat grouping Concept Components Analysis & Vector Support Machines. PCA and SVM were subsequently created to establish a classifier model for using ECG imprints on paper. With LIBSVM, based on the MIT-BIH arrhythmia database used for SVM training and assessment, the performance of this classifier is 99.6367 percent. Erik Zellmer et al (2009) presented a highly [11].

2. Methodology
Heart illnesses are the real sympathy toward many individuals. Therefore, it is usually important to find heart-related symptoms and counteractive behaviour of the same. The electrocardiogram (ECG) flag is the standard measure to diagnose the heart problem. The use of partition and winning calculations for the wavelength ECG examination was demonstrated in this experiment. Persons with a heart condition have a comprehensive record of ECGs for predictive a purpose, which means that a lot of stock is required. The additional memory problem can be overcome by creating such a system with pressure and reproduction capability.

The Walsh-Hadamard Discrete Transformation (WHT) is now an orthogonal transformation that breaks down the symbol into the Walsh functions, a sequence of rectangular orthogonal waveforms. Just +1 or -1 is used for the Hadamard transformation. The DWHT pair for an x(t) length signal is expressed as follows, respectively:

\[ y_n = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x_i W \cdot (n, i), n = 1, 2, \ldots, N - 1 \tag{1} \]

\[ x_i = \sum_{d=0}^{N-1} y_n W \cdot (n, i), i = 1, 2, \ldots, N - 1 \tag{2} \]

Where the initial signals are x(n) and y(n). The WHT is used to define non linear, multiplexing and coding of communications, conceptual architecture and interpretation and to address non linear differential equations. in numerous applications, such as philtres, power spectrum analysis, voice recognition and bio-medical signals. A divided and conquered algorithm (DCA) works by breaking down a problem by splitting into two or more same or similar sub-problems, until they become sufficiently easy to solve directly. The solutions to the sub-problems are merged in order to solve the original problem. Fast Walsh hadamard is a DCA that breaks the size N of WHTs into two smaller N/2 WHTs. This implementation is accompanied by the recursive description \( 2N \times 2N \) matrix of Hadamard.

\[ H_N = \frac{1}{\sqrt{2}} \begin{bmatrix} I_{N-1} & H_{N-1} \\ I_{N-1} & H_{N-1} \end{bmatrix} \tag{3} \]

The normalisation factors may be grouped or even ignored for each point. In computerising the above FWHT, the ordered sequence, which is also called Walsh, is easily transformed by Walsh – Hadamard (FWHT\(_w\)) and then the output is rearranged.

**Algorithm:**

\[ \text{Input } ECG = 0 \]
\[ \text{Compressed ECG} = Y \]
\[ \text{Reconstructed ECG} = R \]

Step 1: Read an input ECG signal ‘O’ from MIT-BIH database.
Step 2: Replicate it to create more data ‘Or’.
Step 3: Add some random noise to the ‘Or’ with a variance of 0.1 to get the ‘X’.
Step 4: Now apply DCA to the ‘X’ to get the Walsh hadamard coefficients with lesser number of coefficients.
Step 5: Consider only first 1024 coefficients out of 4096, which has most of signal energy and store it in Y.
Step 6: Now, reconstruct the ECG data using Y by applying inverse DCA.
Step 7: Finally, compare the ‘O’ and ‘R’ to observe the compression of ECG data, in which the storage memory has been reduced from 32,678 bytes to 8200 bytes.

2.1. Walsh Transform (WT)
One dimensional signal:
This transformation varies somewhat from the transformations that you would see so far. Suppose we have a position, \( f(x), x=0, \ldots, N-1 \) where \( N = 2^n \) and its Walsh transform \( W(u) \).

In binary representation, we require bits to display the values of the independent variables. Therefore, we should write about the binary representation as,

\[
202110 \quad (x_b x_b x_b x_b x_b x_b x_b x_b) = (x_b x_b x_b x_b x_b x_b x_b)
\]

Example:
If \( f(x), x=0, \ldots, 7, (8 \text{ samples}) \) then \( n=3 \) and for \( x=6 \),

\[
6 = (110) \Rightarrow b_0(6)=1, b_1(6)=1, b_2(6)=0
\]

We define now the 1-D Walsh transform as

\[
W(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) \prod_{j=0}^{n-1} (-1)^{b_j(x) b_{j+1}(u)}
\]

(4)

A symmetrical matrix with orthogonal rows and 4 columns is the array generated by the Walsh kernels. Therefore, the Walsh transformation is structure and its components are formed. The square waves have structure. The related square wave “frequency” increases with the increasing vector (which represents their transform index).

For example for \( u=0 \) we see that,

\[
(u_b)_0 = (b_{n-1}(u)b_{n-2}(u) \ldots b_0(u)) = (00 \ldots 0)_2 \quad \text{and hence, } \quad b_{n-1-i}(u) = 0, \quad \text{for any } i.
\]

Thus, \( T(0,x)=1 \) and

\[
W(0) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) \quad \text{We see that the first element of the Walsh Transform as is the case with the Fourier transform in the mean of the initial function (DC value).}
\]

The opposite transformation of Walsh is defined as follows. The inverse transformation of Walsh is defined as follows for two-dimensional signals.

Two dimensional signals:
That the Walsh Transform was defined as follows for two-dimensional signals.

\[
W(u,v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \prod_{j=0}^{n-1} (-1)^{b_j(x) b_{j+1}(u)}
\]

(6)

The inverse transformation of Walsh is defined as follows for two-dimensional signals.

\[
f(x,y) = \frac{1}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} W(u,v) \prod_{j=0}^{n-1} (-1)^{b_j(x) b_{j+1}(u)}
\]

(7)

2.2. Hadamard Transform (HT)
In a similar form as the Walsh transform, the 2-D Hadamard transform is defined as follows.

Forward,

\[
H(u,v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \prod_{j=0}^{n-1} (-1)^{h_j(x) h_{j+1}(u)}
\]

(8)

Properties of the Hadamard Transform:
The Hadamard transformation varies only in the order of the fundamental functions from the Walsh transformation. By using a simple modification of the FFT, a simple calculation does not allow the order of basic Hadamard transform functions. The Hadamard Transform is an expanded variant of the ordered Hadamard Transform, A Fast Hadamard Transform (FHT) algorithm can be used to do this. The significant property of a transformation of Hadamard is that, let it represent that the matrix of order, the recursive relationship is expressed as follows:
\[ H_{2N} = \begin{bmatrix} H_N & H_N \\ H_N & -H_N \end{bmatrix} \]

3. Results and Discussions

This project deals with the experimental analysis of proposed DCA algorithm to compress the ECG signal data which have been done in MATLAB environment. MATLAB is a high-quality technical language used to build algorithms for signal processing. It has many advantages over conventional programming languages such as C, C++, JAVA, FORTAN, COBALT, VHDL and VERILOG.

![Figure 2. Input ECG signal](image)

![Figure 3. Coefficients after applying DCA scheme](image)

![Figure 4. Comparison of original and reconstructed signal using DCA scheme](image)

We have considered MIT-BIH ECG database for testing the proposed algorithm. Original ECG signal data has been shown in Figure 2. Output of DCA scheme has been shown in Figure 3, where the most of the signal energy has been sequenced in coefficients less than 1100.

In Figure 4 it has shown that the reconstructed signal compared with the original signal after applying inverse DCA scheme by considering only 1024 coefficients, which indicates that the signal will be compressed almost 4 times to the original ECG signal data that means the compression ratio is 4:1.
4. Conclusion and Future Works

With a reduced number of computations using the DCA scheme, an optimised scheme for compression electro cardiac signal data has been introduced. Proposed scheme performed excellent simulation results over conventional compression schemes in terms of storage in number of bytes. Although for ECG classifications the combined features of morphological S-transform-based features with time characteristics work considerably, these characteristics cannot classify few super ventricular (S) and natural (N) groups correctly. The QRS complex associated with the premature atrial beat of class S is natural and morphologically similar to class N. Therefore, one might assume that one would use a complementary function set to differentiate premature a trial and normal beat correctly. To boost the classification efficiency, an effective transformation technique can be applied to the extracted feature vectors. In order to minimise the computational burden the transformed function vector should be linearly labelled and include the features decorated.

Significant differences in regular and irregular ECG signals among various patients also contribute to cardiac disease misclassification. The creation of an unattended classifier for the ECG beat classification is a potential alternative. An unregulated classifier does not include class foreknowledge nor does it include training data set for the ECG beats classification. In the analysis of the potential disease in people along with ECG signal analysis, analysis of other biosignals, such as electromyogram (EMG), electacephalograms (EEG) is also important. EMG diagnostes muscle or nerve defects within muscles and EEG can be used for the diagnosis of neurological disorder and disease such as epilepsy, tumour, cerebrovascular injury, and trauma-related ischemia. Further investigations will also be carried out to identify a potential disease based on the study of these biosignals. That the open question of study is the elimination of the foetal ECG signals from the composite maternal ECG signal. The maternal ECG signal is higher than the foetal ECG signal. For the fetal ECG signal, the background noise of muscle activity and fetal movement makes the identification capacity difficult. It is also of scientific interest to study the derived foetal ECG signal for automated cardiac abnormality identification.

5. References

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