Compression of an ECG Signal Using Mixed Transforms

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ABSTRACT

Electrocardiogram (ECG) is an important physiological signal for cardiac disease diagnosis. With the increasing use of modern electrocardiogram monitoring devices that generate vast amount of data requiring huge storage capacity. In order to decrease storage costs or make ECG signals suitable and ready for transmission through common communication channels, the ECG data volume must be reduced. So an effective data compression method is required. This paper presents an efficient technique for the compression of ECG signals. In this technique, different transforms have been used to compress the ECG signals. At first, a 1-D ECG data was segmented and aligned to a 2-D data array, then 2-D mixed transform was implemented to compress the ECG data in the 2-D form. The compression algorithms were implemented and tested using multiwavelet, wavelet and slantlet transforms to form the proposed method based on mixed transforms. Then vector quantization technique was employed to extract the mixed transform coefficients. Some selected records from MIT/BIH arrhythmia database were tested contrastively and the performance of the proposed methods was analyzed and evaluated using MATLAB package. Simulation results showed that the proposed methods gave a high compression ratio (CR) for the ECG signals comparing with other available methods. For example, the compression of one record (record 100) yielded CR of 24.4 associated with percent root mean square difference (PRD) of 2.56% was achieved.

Key words: ECG Compression, Wavelet, Multiwavelet and Slantlet Transforms, Vector Quantization

ضغط اشارة تخطيط القلب باستخدام التحويلات الخليطة

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الخلاصة

اشاره تخطيط القلب (ECG) تستخدم على نطاق واسع في تشخيص وعلاج امراض القلب. هذه الاشارة عادة تراقب بشكل مستمر , وهذا سيؤدي الى كميات كبيره من البيانات يحتاج تخزينها او نقلها .لذلك يتطلب وسيله فعاله لضغط هذه البيانات .

في هذا البحث تحويلات مختلفة لضغط اشارات تخطيط القلب تم أستخدامها . في البداية يتم تحويل اشارات تخطيط القلب اشارات ذات بعد واحد الى اشارات ذات بعدين , ثم بعد ذلك يتم ضغط عذه الاشارات بأستخدام خليط من التحويلات .طريقة الضغط تم تنفيذها باستخدام التحويات multiwavelet وWavelet و slantet حيث تم تشكيل طرق مختلفة اعتمادها على خلط مختلف لهذه التحويات .ثم بعد ذلك تم استخدام VQ لتشفير المعاملات الناتجة من التحويلات المختلطة .

تم أختيار اشارات تخطيط القلب من قاعدة البيانات (Mit-BHI arrhythmia database) وتم تحليل اداء الطرق المقترحة وتقيمها من خلال استخدام برنامج MATLAB.بينت نتائج المحاكاة ان الطرق المقترحة تعطي نسب ضغط عالية لاشارات تخطيط

القلب بالمقارنه مع الطرق الاخرى المتوفرة .على سبيل المثال، ضغط اشاره تخطيط قلب واحده (record 100) باستخدام الطريقه المقترحه اعطت نسبه ضغط تساوي 24,4 مه نسبه خطا تساوي 2,56 % .

1. INTRODUCTION

ECG is widely used in the diagnosis and treatment of cardiac disease. ECG signals usually continuously monitored and this will lead large amount of data needs to be stored or transmitted. ECG compression becomes mandatory to efficiently store and retrieve this data from medical database, **Polania, et al., 2011**. Compression of ECG is necessary for efficient storage and transmission of the digitized ECG signals. A typical ECG monitoring device generates a large amount of data in the continuous long-term (12-24 hours) ambulatory monitoring tasks. For good diagnostic quality, up to 12 different streams of data may be obtained from various sensors placed on the patient's body, **Hossain, et al., 2008**. Thus, efficient ECG data compression to dramatically reduce the data storage capacity is a necessary solution. On the other hand, it makes possible to transmit ECG data over a telephone line from one cardiac doctor to another to get opinions, **Wang, et al., 2008**.

Compression methods have gained an importance in recent year in many medical areas like telemedicine and health monitoring. Many ECG data compression methods have been proposed to achieve a high compression ratio (CR) result and preserve clinical information. These methods can be categorized into time-domain, and transform-domain groups. Recently, a wavelet-based approach attracted much attention of researchers due to both its simplicity and high-compression performance, **Ku, et al., 2010**.

There are different ways of merging two or more transforms to form a mixed transforms. The proposed mixed transforms consists of two transforms in cascading form to be used to enhance compressing performance. Different schemes of applying wavelet, multiwavelet, and slantlet transforms are implemented. The results are obtained through simulation by MATLAB package in this work.

This paper is organized as follows: ECG compression techniques are explained in section II. The standard quantitative measurements that used for ECG are presented in section III. Section IV describes the proposed compression algorithms. Simulation results and comparisons with other compression algorithm in the literature are presented in section V. Finally the conclusion is given in section VI.

2. ECG COMPRESSION TECHNIQUES

The main goal of any compression technique is to achieve maximum data volume reduction while preserving the significant features, **Khalaj, and Naimi, 2009**. A compression algorithm takes an input X and generates a representation XC that hopefully requires fewer bits. There is a reconstruction algorithm that operates on the compressed representation XC to generate the reconstructed presentation Y.

2.1 Discrete Wavelet Transform

Wavelets are mathematical functions that provide the time-frequency representation. It cuts up data into different frequency components, and then study each component with a resolution matched to its scale. Most interesting dissimilarities between wavelet and Fourier transforms is that individual wavelet functions are localized in space, Fourier sine and cosine functions are not,

Graps, 1995. In discrete wavelet transform (DWT) the scale and translate parameters are chosen such that the resulting wavelet set forms an orthogonal set, i.e. the inner product of the individual wavelets ψ (j,k) is equal to zero. To this end, dilation factors are chosen to be powers of 2. For DWT, the set of dilation and translation of the mother wavelet is defined as, **Cohen, and Jelena, 1996.**

$$\psi_{j,k}(t) = 2^{j/2}\psi\left(2^{j}t - k\right) \tag{1}$$

Where j is the scaling factor and k is the translation factor. It is obvious that the dilation factor is a power of 2. Forward and inverse transforms are then calculated using the following equations, **Cohen, and Jelena, 1996**.

$$C_{\tau,s} = \int_{-\infty}^{+\infty} \mathrm{f(t)}\ \psi\ j,k\ (t)\ d(t) \tag{2}$$

$$f(t) = \sum_{j,k} C_{j,k}\ \psi_{\ j,k}(t) \tag{3}$$

For efficient decorrelation of the data, an analysis wavelet set ψ (j,k) should be chosen which matches the features of the data well. This together with orthogonally of the wavelet set will result in a series of sparse coefficients in the transform domain, which obviously will reduce the amount of bits needed to encode it, **Zafarifar, 2002**. A typical 2-D DWT, used in image compression, it generates the hierarchical pyramid structure shown in **Fig.1**.

2.2 Multiwavelet Transform

Multiwavelet has been introduced as a more powerful multi-scale analysis tool. A scalar wavelet system is based on a single scaling function and mother wavelet. On the other hand, a multiwavelet uses several scaling functions and mother wavelets, **Strela, and Heller, 1999**. Multiwavelets, namely, vector-valued wavelet functions, are a new addition to the classical wavelet theory that has revealed to be successful in practical applications, such as signal and image compression. In fact, multiwavelets possess several advantages in comparison to scalar wavelets, since a multiwavelet system can simultaneously provide perfect reconstruction while preserving orthogonality, symmetry, a high order of approximation (vanishing moments), etc. Nevertheless, multiwavelets differ from scalar wavelet systems in requiring two or more input streams to the multiwavelet filter bank, **Liang, et al., 1996.**

The multiwavelet idea originates from the generalization of scalar wavelets; instead of one scaling function and one wavelet, multiple scaling functions and wavelets are used (see **Fig. 2**). This leads to more degree of freedom in constructing wavelets. Therefore, opposed to scalar wavelets, properties such as compact support, orthogonality, symmetry, vanishing moments, short support can be gathered simultaneously in multiwavelets, which are fundamental in signal process. The increase in the degree of freedom in multiwavelets is obtained at the expense of replacing scalars with matrices, scalar functions with vector functions and single mattresses with a block of matrices. Also, prefiltering is an essential task which should be performed for any use of multiwavelet in the signal processing, **Al-Sammaraie, 2011**. Many types of multiwavelet such as Geronimo-Hardin-Massopust (GHM) and Chui-Lian (CL) multiwavelets have been developed, **Xia, et al., 1996**.

To implement the multiwavelet transform, a new filter bank structure is required where the lowpass and highpass filter banks are matrices rather than scalars. That is, the GHM two scaling and wavelet functions satisfy the following two-scale dilation equations, **Liang, et al., 1996**.

$$\begin{bmatrix} \phi_1(t) \\ \phi_2(t) \end{bmatrix} = \sqrt{2}\sum_k H_k \begin{bmatrix} \phi_1(2t-k) \\ \phi_2(2t-k) \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} \psi_1(t) \\ \psi_2(t) \end{bmatrix} = \sqrt{2}\sum_k G_k \begin{bmatrix} \psi_1(2t-k) \\ \psi_2(2t-k) \end{bmatrix} \tag{5}$$

The (2×2) matrix filters in the multiwavelet filter bank require vector inputs. Thus, a 1-D input signal must be transformed into two 1-D signals.

This transformation is called pre-processing. For some multiwavelet, the pre-processing must be accompanied by an appropriate pre-filtering operation that depends on the spectral characteristics of the multiwavelet filters, **Xia, 1998**.

2.3 Slantlet Transform

Slantlet transform (SLT) has been recently proposed as an improvement over the usual DWT. The SLT is an equivalent form of the DWT implementation but provides better time-localization due to the shorter supports of component filters. The SLT filters are essentially piecewise linear filters, have desirable properties of orthogonality and two vanishing moments, have an octave-band characteristic, can exactly provide a scale dilation factor of 2, provides a multiresolution decomposition. The SLT filter-bank is implemented in the form of a parallel structure, employing different filters for each scale whereas DWT is usually implemented in the form of an iterated filter-bank, utilizing a tree structure. SLT can exactly provide a scale dilation factor of 2 and is less frequent selective due to shorter supports of the component filters whereas DWT filters can approximately provide a scale dilation factor of 2 and provide short windows at high frequencies and long windows at low frequencies, **Kummar, and Muttoo, 2010**.

The usual iterated DWT filter-bank and its equivalent form are shown in **Fig.3**. The slantlet filter-bank is based on the equivalent structure that is occupied by different filters that are not products. With this extra degree of freedom obtained by giving up the product form, filters of shorter length are designed to satisfy orthogonality and zero moment conditions, **Selenick, 1999**.

For the two-channel case, the shortest filters for filter-bank is orthogonal and has K zero moments are well known filters described by Daubechies. For K = 2 zeros moments, filters H(z) and F(z) are of length 4. For this system, the iterated filters in Fig.4 are of length 10 and 4. Without the constraint that the filters are products, an orthogonal filter-bank with K = 2 zeros moments can be obtained where the filter lengths are 8 and 4, as shown in **Fig.4**. That is a reduction by two samples, which is a difference that grows with the number of stages. This reduction in length, while maintaining desirable orthogonality and moment properties, is possible because these filters are not constrained by the product form arising in the case of iterated filter-banks, **Selenick, 1999.**

2.4 Vector Quantization

Vector quantization (VQ) is used for both image and sound compression. In practice, VQ is commonly used to compress data that have been digitized from an analog source, such as sampled sound and scanned images. Vector quantization is based on two facts, **Cosman, et al., 1996**.

- The compression methods that compress strings, rather than individual symbols can, in principle, produce better results.
- Adjacent data items in an image (i.e., pixels) and digitized sound (i.e., samples) are correlated. There is a good chance that the nearest neighbors of a pixel P will have the same values as P or very similar values. Also consecutive sound samples rarely differ much.

For signal compression, VQ divides the signal into small blocks of pixels, typically 2×2 or 4×4. Each block is considered a vector. The encoder maintains a list (called a codebook) of vectors and compresses each block by writing to the compressed stream a pointer to the block in the codebook. The decoder has the easy task of reading pointers, following each pointer to a block in the codebook, and joining the block to the image so far (see **Fig.5**). Vector quantization is thus an asymmetric compression method.

An improved algorithm of VQ, codebook generation approaches such as the LBG algorithm has been developed. LBG algorithm designing a codebook that best represents the set of input vectors is very-hard. That means that it requires an exhaustive search for the best possible codewords in space, and the search increases exponentially as the number of codewords increases, therefore, we resort to suboptimal codebook design schemes, and the first one that comes to mind is the simplest. It is named LBG algorithm for Linde-Buzo-Gray and also it is known as K-means clustering.

The LGB algorithm is in fact designed to iteratively improve a given initial codebook. The design of a codebook with N-codewords can be stated as follows, **Bardekar, and Tijare, 2011**:-

1. Determine the number of codewords, N, or the size of the codebook .
2. Select N codewords at random, and let that be the initial codebook. The initial codewords can be randomly chosen from the set of input vectors .
3. Use the Euclidean distance to measure cluster size the vectors around each codeword. This is done by taking each input vector and finding the Euclidean distance between it and each codeword. The input vector belongs to the cluster of the codeword that yields the minimum distance .

Compute the new set of codewords. This is done by obtaining the average of each cluster. Add the component of each vector and divide by the number of vectors in the cluster, **Bardekar, and Tijare, 2011**.

$$y_i = \frac{1}{m} \sum_{j=1}^{m} x_{ij} \tag{6}$$

Where i is the component of each vector (x, y, z, directions) and m is the number of vectors in the cluster.

Repeat steps 1, 2 and 3 until either the codewords do not change or the change in the codewords is small.

This algorithm is by far the most popular, and that is due to its simplicity. Although it is locally optimal, yet it is very slow. The reason it is slow is because for each iteration, determining each cluster requires that each input vector be compared with all the codewords in the codebook.

3. PROPOSED METHOD

3.1 2-D ECG Construction

In the ECG signal, there are two kinds of dependencies, which are the dependencies in a single ECG cycle (interbeat dependencies) and the dependencies across ECG cycles (intrabeat dependencies), **Rezazadeh, et al., 2005**. Because of the intrabeat and interbeat correlations of ECG signals, 2-D ECG signal compression algorithms have better performance. An efficient compression scheme needs to exploit both dependencies to achieve maximum compression and minimum errors. The 1-D ECG sequence is treated to produce a two dimensional matrix. To map 1-D ECG signal to 2-D arrays, at first, the peak of QRS complex should be detected to identify each heartbeat period (which is named the R-R interval). In this array, each row contains one or more periods of ECG beat, so the interbeat dependencies can be seen in each row and intrabeat dependencies can be seen in each column of the matrix. Then, the original 1-D ECG signal is cut at nth samples. In order to period irregularity of ECG signals that presents a challenge to the 2-D matrix construction, resampling and normalizing are applied to the time duration of each cycle and set it to a constant number, i.e. 256 samples are in each cycle . After the 2-D array is produced, the amplitude should be normalized by scaling the value of the array from 0 to 255. Now, there is a grayscale image and a 2-D ECG signal. These processes are named cut and align (C&A), **Mohammadpour, and Mollaei, 2009**. **Fig.6** and **Fig.7** show the 1-D and 2-D ECG signals, respectively.

3.2 The Proposed Mixed Transform

Mainly it consists of applying the multiwavelet, wavelet and slantlet transforms in a cascaded manner to the ECG signal. This mixed transform is implemented by applying MWT first, this in turn introduced the four approximation subbands (L1L1, L1L2, L2L1 and L2L2), then wavelet and slantlet transforms and VQ algorithm are applied in different procedure.

The description of the procedure used in the compression process for this mixed transforms schemes, are as follows:

Step.1 Apply the MWT to the ECG signal which results four square bands as shown in **Fig.2**. The four square bands results are splits and each is processed individually.

Step.2 Apply the WT to the first approximation square which consists of four approximation subbands (L1L1, L1L2, L2L1, and L2L2) which in tern introduce four subbands (LL, LH, HL, and HH), then apply SLT to the three bands (LH, HL, and HH) and the results of SLT are treated by VQ.

Step.3 Apply SLT to the three details square remains from applying MWT in step 1, then the results of SLT are treated by VQ.

Fig.8 shows the proposed scheme of using the proposed mixed transforms on ECG signals.

4. PERFORMANCE MEASUREMENTS

Evaluation of lossy ECG encoders uses measurements related to the amplitude difference between the original and the reconstructed signal. The standard quantitative measurement is the percent root mean square difference (PRD), which is given by the following, **Lee, et al., 2012**:

$$PRD=\sqrt{\frac{\sum_{n=1}^{N}(x(n)-\tilde{x}(n))^2}{\sum_{n=1}^{N}(x(n))^2}}\times 100 \qquad (7)$$

Where $x(n)$ is the original signal, $\tilde{x}(n)$ is the reconstructed signal and n is the number of samples.

Since a lower PRD value indicates that the reconstruction approximates more closely to the original. However, qualitative evaluations are almost invariably used due to human beings better judgment of which details of the signal are important

The compression ratio (CR) is a measure of the amount of data size reduction achieved and it is calculated by, **Polania, et al., 201**1:

$$CR=\frac{uncompressed\ \text{size}}{compressed\ \text{size}}\ :1 \qquad (8)$$

5. RESULTS AND DISCUSSION

The proposed algorithm was tested and evaluated by using an actual data from the MIT-BIH arrhythmia database, **MIT-BIH**. This database includes different shapes of ECG signals arranged in different records. The records used are 100, 107, 109, and 117, which are different in shape of the ECG signals. Records 100 and 109 have a regular period of QRS compared with the other signals while records 107 and 117 have an almost regular QRS period.

The results of performing the compression algorithm for the proposed mixed transform using different types of records are given in the table 1.

This results show that each signal has a different CR than the other signals after applying the same algorithm. The variation in performance parameters depends on the shape and size of each ECG signal. For nearly the same values of CR, it is shown that records 100 and 109 have a lower PRD than records 107 and 117 at the all codebook sizes (256), (64), and (16). This difference in PRD is due to the regularity of QRS periods in records 100 and 109 compared with records 107 and 117 which have an almost regular QRS period.

The proposed algorithms are also compared to other ECG coders through their reports performance in the literature. In table 2, PRD and CR comparisons of different coding algorithms were shown. As the results show, the proposed schemes exhibits better performance than well-known methods such as those based on matrix completion, **Polania, et al., 2011**, wavelet transform, **Hossain et al., 2008**, and new efficient fractal, **Khalaj, and Naimi, 2009**.

Figures 9, 10, and 11 show samples of original, reconstructed and error signals for different types of ECG signals.

6. CONCLUSION

Difference transforms have been used in this paper, using MWT, WT, and SLT which are employed with the VQ algorithm in different distribution. This distribution was exploited by cascading manner. The work includes an ECG signal compression method using 2-D mixed transform. The following points are the summary of the important conclusions:

1. The proposed method offers a compression performance of ECG signal up to 27 with little effects will be noticed on the ECG quality.
2. The codebook size refers to the total numbers of code vectors in the codebook. As the size of codebook increase the quality of the reconstructed signal improves, but the compression ratio reduces. Therefore, there is a tradeoff between the quality of the reconstructed signal and the amount of compression achieved.
3. The compression performances of the proposed mixed transforms are different from one ECG signal to another depending on the regularity of the ECG signals. For records that have regular QRS-complex the PRD will be less than records that has irregular QRS-complex.

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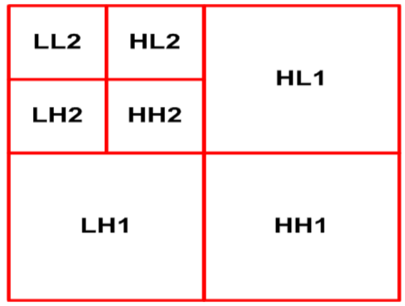


Figure1. Pyramid structure of wavelet decomposition**.**

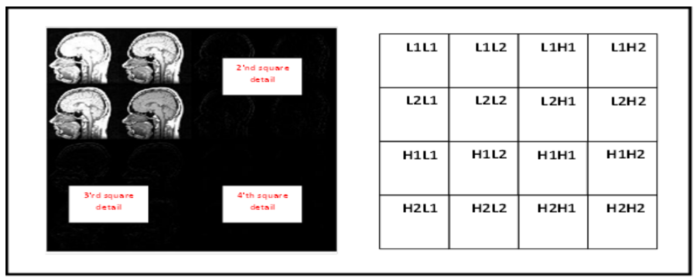


Figure 2. Resultant multiwavelet transform bands.

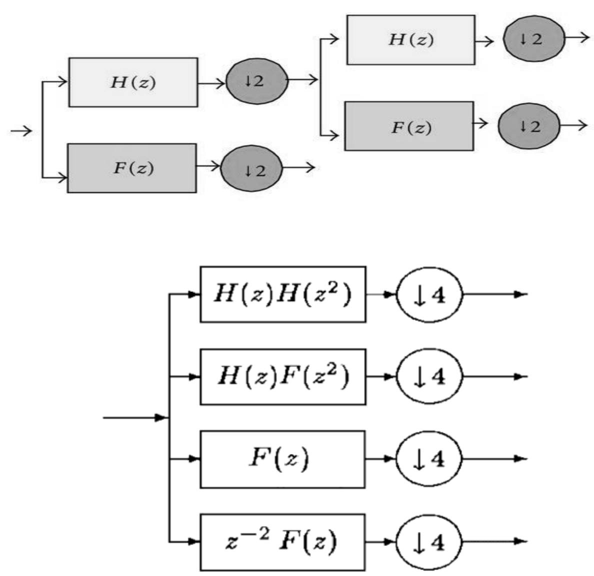


Figure 3. Two-scale filter bank and an equivalent structure.

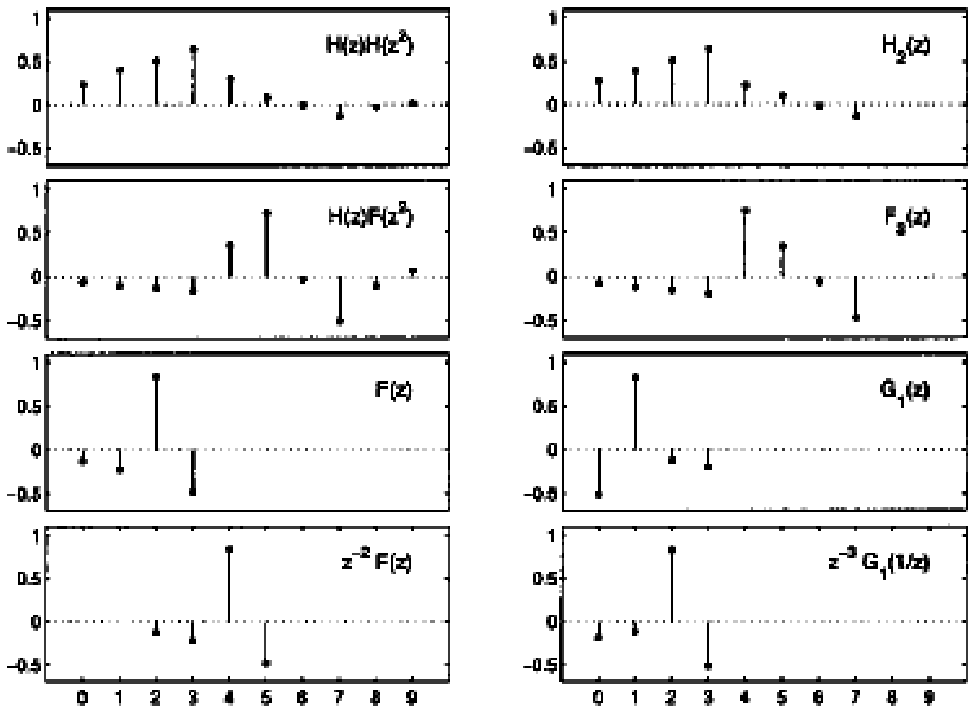


Figure 4. Comparison of two-scale iterated D2 filter bank (left-hand side) and two-scale slantlet filter bank (right-hand side).

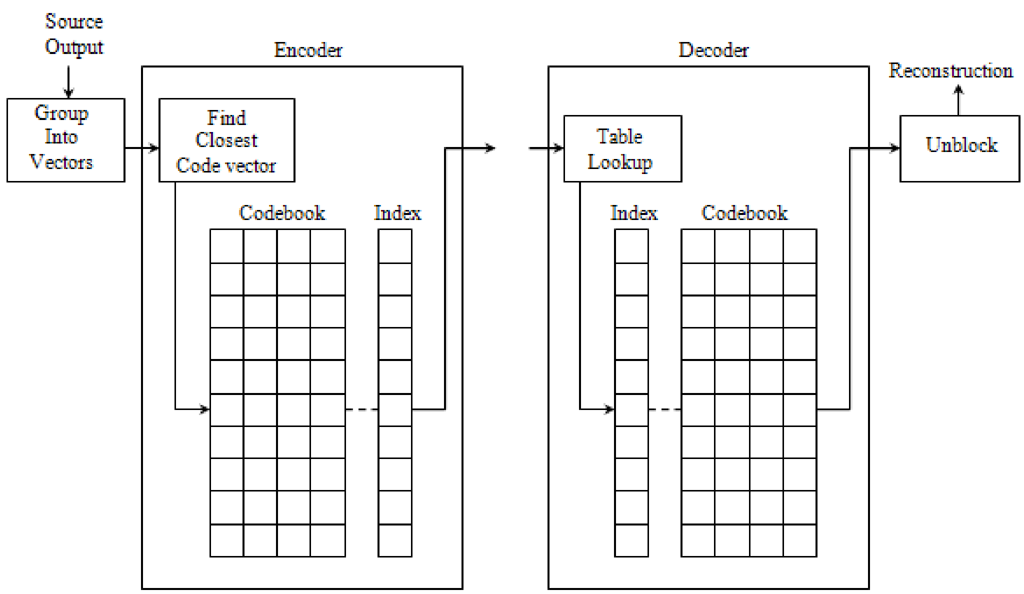
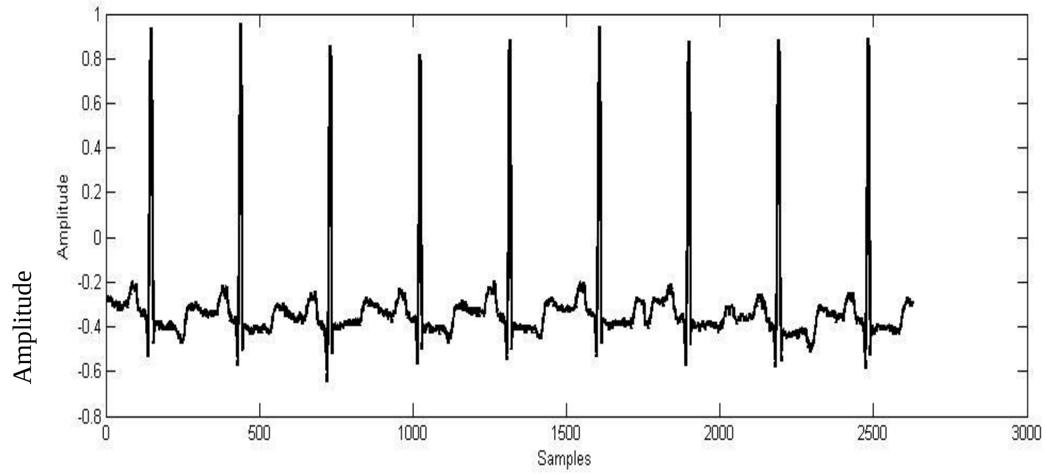


Figure 5. The encoder and decoder in a vector quantization.



Samples

Figure 6. Waveform of 1-D ECG signal.

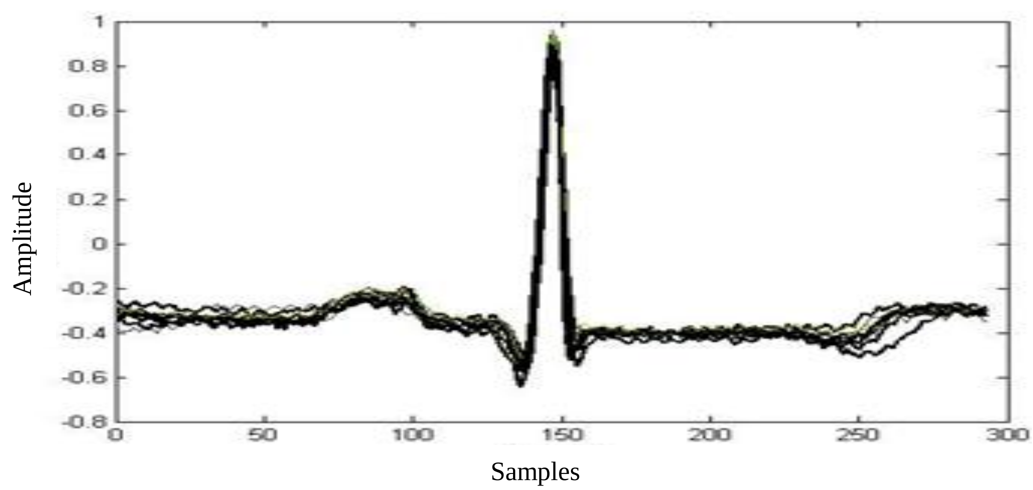


Figure 7. Waveform of 2-D ECG signal.

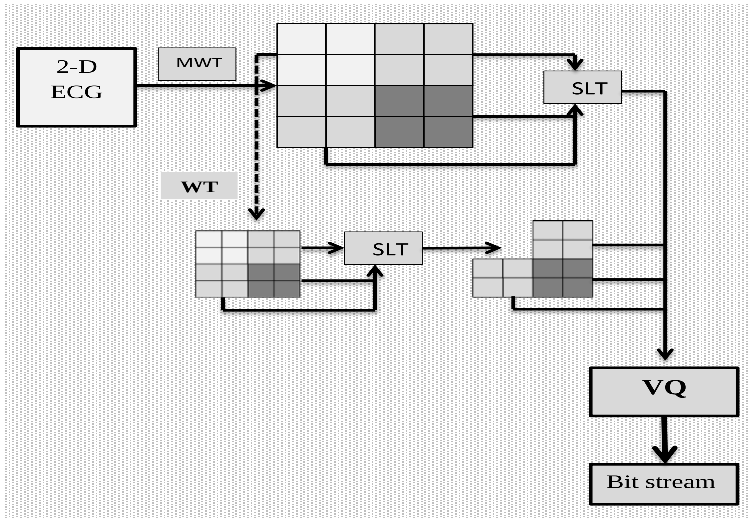


Figure 8. Proposed scheme of mixed transform and their compression processing.

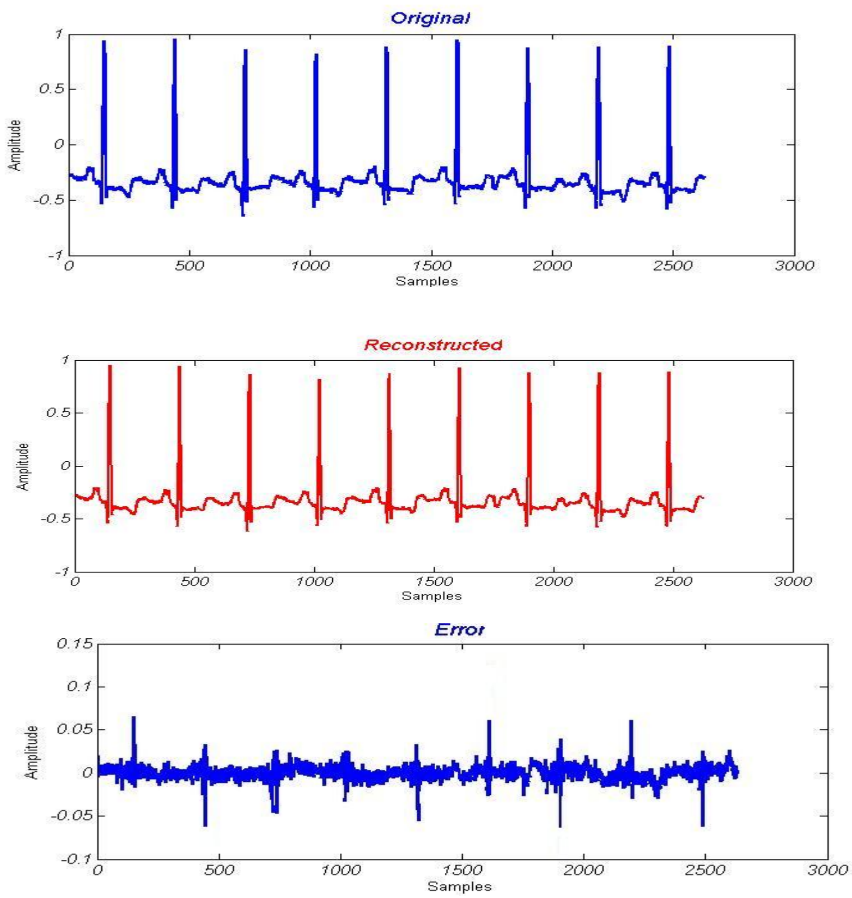


Figure 9. Original, reconstructed and error for ECG signal of record 100 for CR=24.4 and PRD=2.5%.

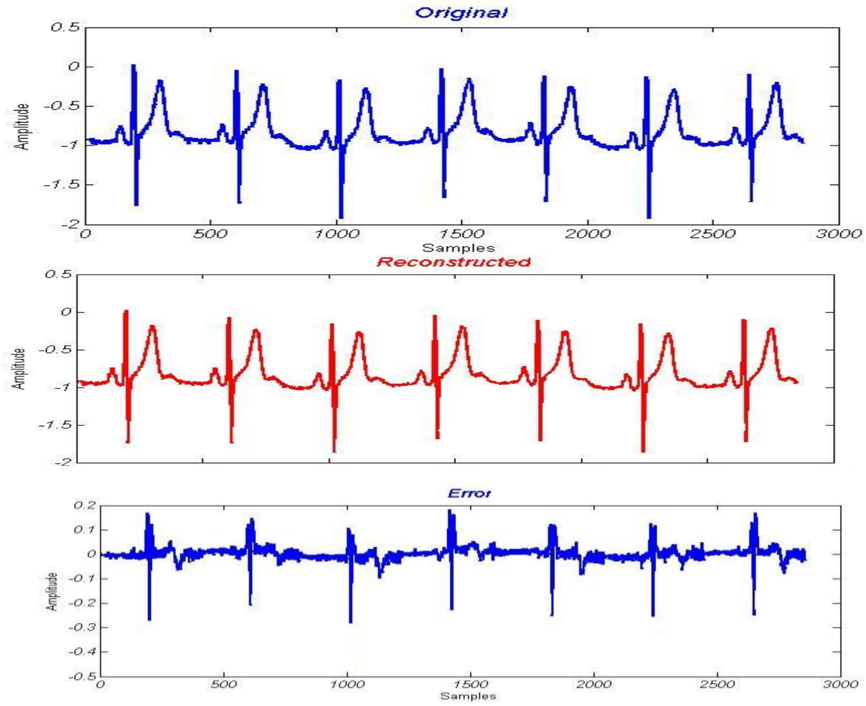


Figure 10. Original, reconstructed and error for ECG signal of record 109 for CR=24.3 and PRD=3.1%.

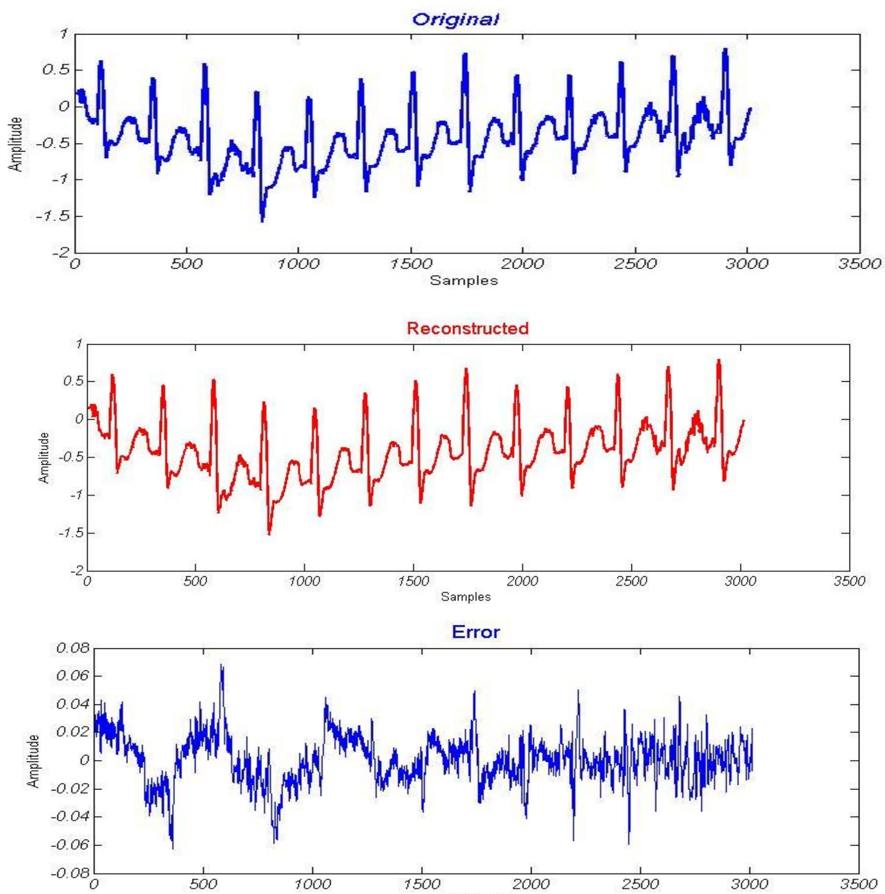


Figure 11. Original, reconstructed and error for ECG signal of record 117 for CR=24.2 and PRD=4.7%.

Table 1. CR and PRD for the proposed mixed transform.

Codebook size		256	64	16
Record 100	CR	10.5	21.5	26.9
	PRD%	3.27	4.1	4.77
Record 107	CR	11.19	21.77	26.6
	PRD%	4.7	5	5.2
Record 109	CR	10.5	20.4	24.9
	PRD%	3.22	3.4	3.53
Record 117	CR	10.47	20.38	24.9
	PRD%	5.34	5.69	5.89

Table 2. Comparison of different ECG compression algorithms.

Algorithm	Record	CR	PRD%
Polania, et al., 2011	100	23.61	8.4
	117	10	2.5
Hossain, et al., 2008	100	13.89	5.16
	107	14.18	5.39
	109	12.01	3.92
	117	15.12	2.33
Khalaj, Naimi 2009	100	13.79	11.06
	109	17.39	11
	117	14.64	4.5
Proposed	100	24.4	2.56
	107	23.6	4.3
	109	24.33	3.1
	117	24.2	4.74