ECG Compression by Multirate Processing of Beats

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This paper presents a new compression scheme for single channel ECG, by delineating each ECG cycle. It uses multirate processing to normalize the varying period beats, followed by amplitude normalization. These beats are coded using vector quantization, with each beat being treated as a vector of uniform dimension. The average amplitude scale factor and the average beat period are made available at the decoder, along with the codebook of period and amplitude normalized beat vectors, to facilitate reconstruction of the signal. The actual beat period and the actual maximum amplitude of the beat are sent to the decoder by DPCM. It achieves a high quality approximation at less than 30 bits per second, with a compression ratio of around 100 : 1 to 200 : 1. To assess the technique properly we have evaluated two measures of error. Finally, the merits and demerits of the technique are discussed.

1. Introduction

With continuing proliferation and widespread use of computerized ECG, compression of digitized ECG has assumed importance. Signal compression is defined as the reduction in redundancy present in the signal. The aim of any ECG compression scheme should be not only to transmit or store the signal with fewer bits per sample and achieve low reconstruction error but also to retain the clinically significant information. The need for ECG compression arises in the following contexts:

1. Large ECG databases in hospitals.
2. Ambulatory (24 hr) monitoring of ECG.
3. Economical transmission of off-line ECG over public phone lines to a remote interpretation center.
4. Medical education systems.

The current ambulatory ECG monitors store the data in solid state memories where the sampled ECG data generated during 24 hr needs to be first compressed before it can be stored. Because of memory limitations, the sampling rate is normally only 128 Hz. With better compression schemes one can store a higher quality ECG and/or more channels. In medical education systems, a very large number of ECG patterns is required to familiarize the students of cardiology with different kinds of diseases which can be detected using the ECG signal. Thus, for efficient storage of these large variety of waveforms, compression is essential. All these applications (both on-line and off-line) demand compression algorithms which can achieve very high data compression.

The techniques used so far, for ECG compression, can be divided into the following categories:

1. Time domain techniques such as AZTEC, SAPA etc. (*1*).
2. Transform domain techniques such as DFT, Walsh transform, etc. (*2*, *3*).
3. Parametric modeling such as AR and ARMA models (*4*).
4. Combined transform domain and parametric modeling (*5*).
5. Vector quantization (*6*, *7*).

ECG belongs to a class of signals that are oscillatory in nature, though not exactly periodic in a strict mathematical sense. By looking at the time evolution of these signals, one can observe a concatenation of similar events or periods, which almost never identically reproduce themselves.

ECG waveform has a very high degree of similarity from beat to beat. Thus, most of the times, the amplitude, position, and width of the components do not vary much across cycles for the same subject. Generally the main variation is in the beat period. This particular property of the ECG waveform is exploited in our technique to achieve high compression ratio with low error.

So far, vector quantization has been applied on blocks of direct signal samples (*6*) or characteristics (amplitude, position, and width) of constituent P, QRS, and T waves (*7*). In this paper, we propose a novel method of achieving high compression ratio by quantizing vectors, each of which is a period and amplitude normalized (PAN) beat.

Any performance criterion used to evaluate an ECG compression algorithm must consider two factors, namely, the extent of compression and the fidelity of the reconstructed signal. We have quantified the extent of compression by means of the compression ratio (CR), defined as the ratio of the number of bits per sample of the original signal to the number of bits per sample of the stored signal. The most widely used estimate of the reconstruction error is the normalized root mean square error (NRMSE). However, being an average estimate, it gives no idea either about the maximum amplitude of error or whether clinically significant information has been lost. So, in addition to the NRMSE, we have computed the normalized maximum amplitude of error (NMAE) and also performed visual inspection of the reconstructed waveform by a cardiologist.

2. Materials and Methods

First, we give a brief overview of the method and then describe the individual steps in detail in subsections 2.1 to 2.4. The central idea of our scheme is period and amplitude normalization of the ECG beats, through which we obtain beat vectors of uniform dimension for coding. In fact, the period normalization of each beat will minimize the variations between cycles, thereby facilitating a higher degree of compression, if each of the beats is treated as an entity. To delineate the individual cycles and hence to select the total number of samples making up a beat, QRS detection has been performed prior to beat period normalization. To bring further similarity between the beat patterns, amplitude normalization has been performed.

Vector quantization of the PAN beats has then been performed. For each subject, the initial part of the subject's data has been used in forming the codebook, using the LBG algorithm (*8*). After the codebook is ready, the coding of vectors not used in the design of the codebook is done by transmitting the index of the codebook vector to which the input vector maps, based on a minimum distortion criteria. This index is transmitted to the decoder, which also has the same codebook in memory. The average period and the average maximum amplitude of cycles are obtained from the data used in designing the codebook and they are also made available to the decoder. Thus, we need to transmit only the difference between the actual cycle period and the average period, and the difference between the actual maximum amplitude and the mean maximum amplitude for individual cycles, thereby reducing the dynamic range, and thus resulting in even higher a compression ratio. The decoder receives the index from the transmitter and outputs the corresponding normalized beat vector. Then the actual amplitude and period of the beat are recovered (from the transmitted differences of maximum amplitude and period) so as to get the reconstructed vector. The performance of the method is evaluated for the entire data in terms of the compression ratio achieved and different error criteria mentioned earlier. Figure 1 shows the block diagram of the encoder, and Fig. 2 shows the block diagram of the decoder.

2.1. Beat Detection

In order to delineate the cycles, we define each ECG cycle as the signal from one R-wave to the next R-wave. Thus the first step in our technique is automatic QRS detection. We used the technique reported in (*9*). The cycle period thus obtained is subtracted from the average period and sent to the decoder, along with the difference between the original and the mean maximum amplitude and the code index. The average period and the mean amplitude are obtained from all the cycles that determine the codebook and these are also made available at the decoder along with the codebook.

2.2. Period Normalization

Individual uniform period vectors are formed from each ECG cycle. We normalize each delineated beat using multirate signal processing techniques (*10*). Since originally the beat vectors in an ECG waveform are of varying length, sampling rate change by fractional factors is required, to normalize the period.

2.2.1. Multirate processing. If $x(n)$ is the input to an interpolation filter with an impulse response $h(n)$, and an upsampling factor of L, then the output $y(n)$ is given by

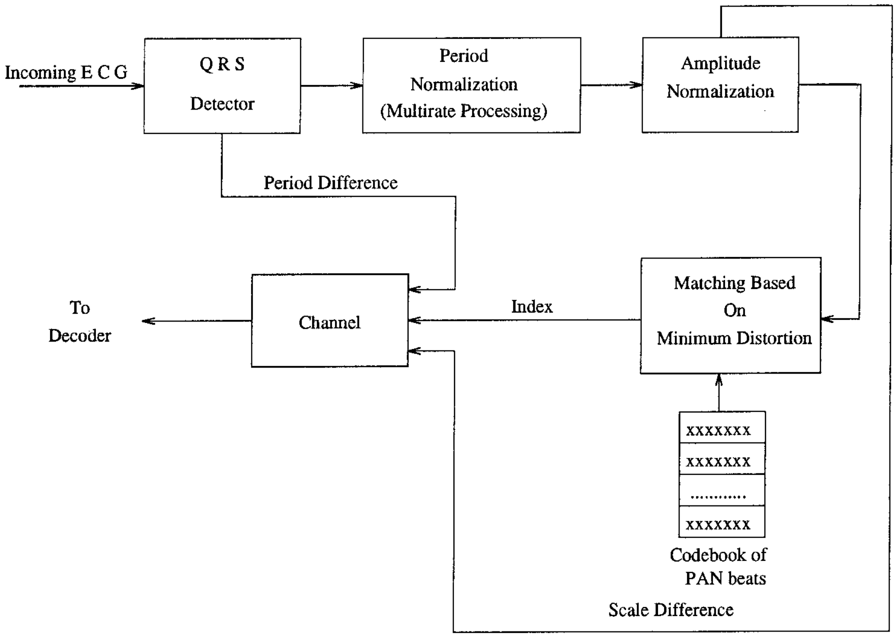

FIG. 1. Block schematic of the encoder.

$$y(n) = \sum_{k=-\infty}^{\infty} h(k)x(n - kL). \qquad [1]$$

The upsampler simply inserts $L - 1$ zeros between successive samples and the interpolation filter $h(k)$, which operates at a rate L times that of the input signal, replaces the inserted zeros by interpolated values. The interpolation has been performed efficiently using polyphase implementation of these filters (*10*). The output $y(n)$ of a decimation filter, with an impulse response $h(k)$, and a downsampling factor of M, is given by

$$y(n) = \sum_{k=-\infty}^{\infty} h(k)x(nM - k), \qquad [2]$$

where $h(k)$ is a low pass filter used to remove aliasing that could result from downsampling. In case the signal does not contain frequencies above π/M, there is no need for the decimation filter; simply downsampling by a factor of M can be performed.

To achieve period normalization, we first interpolate the unequal period beat vectors by a factor of L, where L is the fixed normalized beat period (the total number of samples making up the normalized beat vector). Then we downsample the signal in each cycle by the appropriate factor, so that the length of all the

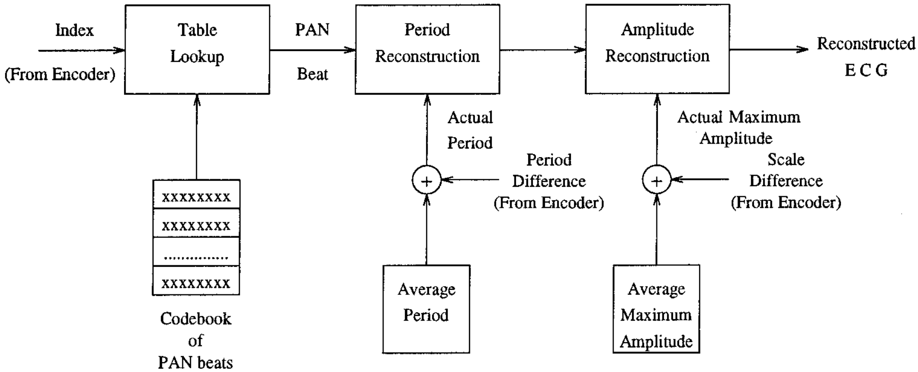

FIG. 2. Block schematic of the decoder.

cycles become uniform. In our case, since the signal has been interpolated by a sufficiently high value, no error occurs due to the downsampling operation. Thus the interpolation filter needs to be followed by downsampling and decimation is not necessary.

The change of sampling rate as performed above is a reversible process; if the newly obtained resampled beat vector is brought back to the original sampling rate once again by multirate processing, the difference between this vector and the original vector is zero.

The output of the multirate processing system is given by

$$Y_i(n) = \sum_{k=0}^{P_i-1} X_i(k)h(nM_i - kL_i), \qquad [3]$$

where

$X_i(n)$	is the n^{th} sample of the i^{th} input beat;
$Y_i(n)$	is the n^{th} sample of the i^{th} output PAN beat;
$h(k)$	is the impulse response of the multirate filter;
P_i	is the total No. of samples in i^{th} original beat vector;
L_i	is the upsampling factor for the i^{th} beat vector; and
M_i	is the downsampling factor for the i^{th} beat vector.

The block schematic for this step is shown in Fig. 3. For efficient implementation, the interpolation is performed in multisatages (*10*) (see Fig. 4).

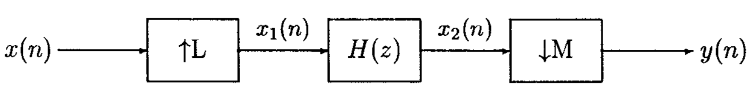

FIG. 3. Period normalization of beats through multirate processing.

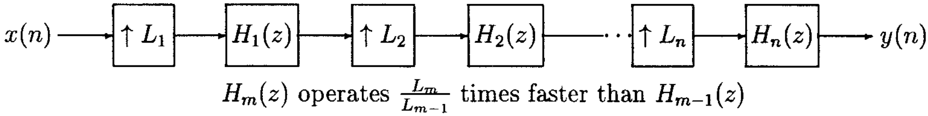

FIG. 4. Efficient interpolation scheme by multistage implementation.

2.3. Amplitude Normalization

In order to further improve the similarity between the period normalized beat patterns, amplitude normalization is performed. Each individual beat sample is divided by the magnitude of the sample having maximum amplitude in that particular beat. This makes the highest amplitude sample(s) of each beat equal unity. The average maximum amplitude of the training beats is made available to the decoder, and the difference between the maximum amplitude of each cycle and the mean maximum amplitude is sent to the decoder.

2.4. Vector Quantization of the PAN Beat

2.4.1. Codebook formation. Each of the amplitude and period normalized beats obtained as above is treated as a vector of dimension L. Codebooks have been designed using the Linde Buzo Gray algorithm (*8*). Steps involved in arriving at the codebook are as follows:

1. Initial part of the subject's transformed data (i.e., the beat vectors formed as explained in Section 2.3.) is chosen as the training vector set.

2. An initial codebook of size S is formed by selecting S vectors from the training vector set with the constraint that each of the beat vectors chosen have a different 2-norm:

$$\|Z_i - Z_j\|_2 = \sqrt{\sum_{p=0}^{L-1} (Z_i(p) - Z_j(p))^2} \neq 0, \qquad [4]$$

where

Z_i is the i^{th} training vector chosen;
Z_j is the j^{th} training vector chosen; and
$\|\cdot\|_2$ denotes the 2-norm.

3. The minimum distortion for the i^{th} training vector is calculated as,

$$D(i) = \min_j \|Z_i - C_j\|_2, \qquad [5]$$

where

C_j is the j^{th} codebook vector, $j = 1$ to S.

This is calculated for each of the training vectors, and the average distortion is obtained as

$$\text{AVD} = \frac{1}{N_T}\sum_{i=1}^{N_T} D(i), \qquad [6]$$

where N_T is the total number of training vectors.

4. A new codebook is formed, with the j^{th} entry in the new codebook obtained by averaging the vectors from the training set which mapped to the current codebook's j^{th} entry (i.e., those vectors which had least distortion with respect to the previous j^{th} codebook entry).

5. Steps 3 and 4 are repeated till the codebook converges.

2.4.2. Encoding and decoding. The codebook obtained is now made available both at the encoder and at the decoder. When the incoming vector is received, the index of that codebook entry is transmitted which has minimum distortion with respect to the incoming vector. Thus for each normalized beat, there is transmission of only $\log_2 S$ bits, where S is the size of the codebook. On receiving the transmitted codebook index, the decoder outputs the corresponding vector. This vector is PAN.

The difference between the original periods and average period having been transmitted to the decoder, the actual period can be calculated. From this actual period and the PAN beat, the original period beat is reconstructed using the same technique mentioned in section 2.2, with an appropriate change of parameters.

The difference between the maximum amplitude in each beat and the average of maximum amplitudes is transmitted to the decoder from which the original amplitude is obtained. The period recovered vector obtained above is multiplied by the original maximum amplitude to get the reconstructed beat vector.

3. Results

The proposed method was tested using ECG data obtained from the National Institute of Mental Health and Neuro Sciences (NIMHANS) (Bangalore, India). The ECG signal was sampled at 250 Hz and quantized with 12 bits resolution. Through period normalization, we have made the number of samples in each beat equal 250, although any other number greater than 250 could have been as good, since the total number of samples in any of the original beats is found to be between 120 and 240 for the sampling frequency of 250 Hz. So, downsampling after interpolation by such a factor, for a highly correlated signal, like ECG sampled at 250 Hz, does not result in any loss. Hence for each normalized beat (i.e., a total of 250 samples), we are transmitting only $\log_2(S)$ bits, where S is the size of the codebook. In our work, we have tried codebooks of size 8 and 16.

The expression for the compression ratio is given by

$$CR = \frac{b_o \sum_{i=1}^{K} N_i}{K(\log_2(S) + b_a + b_p)}, \qquad [7]$$

where

b_o is the number of bits used to quantize the digitized ECG;
K is the total number of beats transmitted;
N_i is the original period of the i^{th} beat;
S is the size of the codebook;
b_a is the No. of bits used for transmitting each scale factor difference; and
b_p is the No. of bits used for transmitting each period difference.

The expression in our case reduces to

$$CR = \frac{12 \sum_{i=1}^{K} N_i}{K(\log_2(S) + 12)}. \tag{8}$$

In the above equation, $S = 8$ or 16 (which are the different codebook sizes we have tried). Besides visual inspection of the original and reconstructed waveforms by a cardiologist, we have quantified the deviation of the reconstructed waveform from the original waveform by two measures of error defined below:

Normalized Root Mean Square Error (NRMSE)

This is the most commonly used (in the literature) error measure. The expression for NRMSE is given by

$$NRMSE = \sqrt{\frac{\sum_{i=0}^{N-1} (x_o(i) - x_r(i))^2}{\sum_{i=0}^{N-1} x_o^2(i)}}, \tag{9}$$

where

N is the total number of samples being transmitted;
$x_o(i)$ is the i^{th} sample of the original ECG; and
$x_r(i)$ is the i^{th} sample of the reconstructed ECG.

However, the NRMSE is only an average estimate and gives no idea about the maximum error. Therefore, we have also evaluated the normalized maximum amplitude of error, defined below.

Normalized Maximum Amplitude Error (NMAE)

The maximum amplitude of error in the entire record is normalized by the dynamic range of the original signal. The expression for NMAE is

$$NMAE = \frac{\max|X_o - X_r|}{\max X_o - \min X_o}. \tag{10}$$

We have achieved compression ratios of 100 to 200 depending on the size of the

TABLE 1

COMPRESSION RATIOS ACHIEVED ALONG WITH NRMSE AND NMAE FOR EIGHT INDIVIDUAL SUBJECTS

Sl No	CR	PRD%	NMAE%
1	150	12.14	13.25
2	145	13.21	8.52
3	144	11.67	12.84
4	115	9.71	6.50
5	144	12.33	15.67
6	141	14.18	9.68
7	189	15.02	14.91
8	108	10.07	5.03

codebook used. Table 1 gives the figures for the NRMSE, NMAE, and CR obtained for eight different subjects. Figures 5a and 5b show the original and reconstructed ECG for two different subjects, where the quality of reconstruction by our technique is seen to be acceptably good. The waveforms shown in Fig. 5 are typical and represent neither the best nor the worst case.

4. DISCUSSION

The method described is elegant and can work even with complex waveforms provided the complexity is consistently present. For example, in the case of uniformly noisy data or data with consistently abnormal morphology in the waveform, the proposed method will be able to catch the uniformly abnormal patterns in the codebook of the same size. Thus the technique remains unaltered, as does its performance. Under similar circumstances, the modeling techniques such as DCT-SM (*5*) may not perform well unless the model order is increased (*11*). According to the authors (*11*), each monophasic component (such as *P*, *Q*, *T*, etc.) requires a model order of 2 and thus a minimum order of 10 is required for any normal cycle, with which, as per their calculation, they have achieved a maximum compression ratio of 40 : 1. The presence of any additional deflections will naturally require an appropriate increase in the model order and hence a corresponding decrease in the CR. Also, modeling methods require component identification for model order selection and also proper cycle separation (*11*).

In case a stray abnormal complex occurs for which the nearest match in the codebook is not satisfactory (i.e., the distortion between the beat and the best possible match in the codebook exceeds a given threshold value), then we can transmit the waveform as it is, instead of transmitting the index. In our case, with the limited data sets we have experimented, such a situation did not arise.

With our technique, we have realized high compression ratios of 100 to 200. The bit rate achieved is under 20 bits per second, which, to our knowledge, is less than that reported by most of the existing ECG compression techniques.

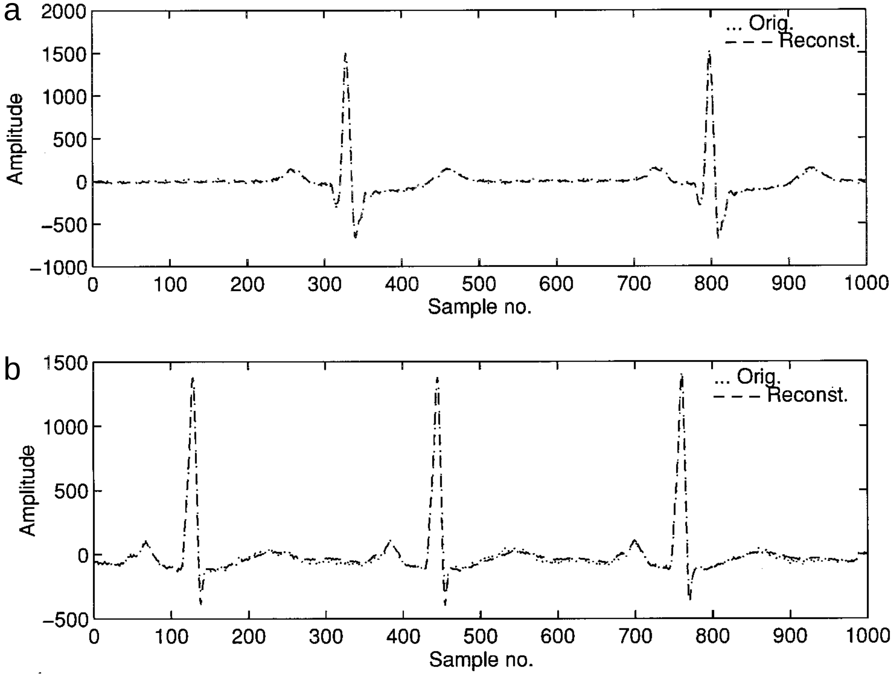

FIG. 5. (a and b) Original and reconstructed waveforms for 2 different subjects. [(a) CR = 150:1; NRMSE = 11.0%; (b) CR = 198:1; NRMSE = 12.8%].

AZTEC achieves a compression ratio of 10:1, with a NRMSE of 28% (*1*). SAPA achieves a compression ratio of 3:1, with a NRMSE of 4% (*1*). The disadvantages of the method are that it requires a codebook *a priori* and also high coding time compared to techniques such as AZTEC, SAPA (*1*), etc. Hence, at present we recommend it for off-line applications only.

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