TIME SERIES ANALYSIS FOR ECG DATA COMPRESSION

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ABSTRACT

This work presents a new electrocardiogram (ECG) data compression method. By differentiating the signal and using proper thresholding, the ECG is first segmented into a sequence of straight lines. The vertices of these lines are used to encode the signal. The decoding part works by applying Korenberg's Fast Orthogonal Search (FOS) method to reconstruct the original signal. Simulation results have demonstrated the efficiency of the algorithm.

1. INTRODUCTION

ECG data compression is required for efficient use of storage capacity in computers and for fast transmission of the digitized signals using the public dial–up phone networks. In this paper, an ECG data compression algorithm is described. The algorithm is comprised of the encoder and decoder parts. The encoder works by approximating the ECG signal using a piece-wise linear approximation method. A five-point differentiation is applied to generate the differential signal which is used to segment the original signal into a set of line segments of positive, zero, and negative slopes. A slope threshold value is used to properly identify the three types of slope. The starting point of all segments will then represent the encoded signal. These points actually encode the instants at which the direction of data growth changes the most and thus represent the most informative part of the signal. At the decoder side, these points will be used to reconstruct a piecewise linear approximation of the signal. In order to obtain a good representation of the original signal and to remove the high frequency components introduced by the linear approximation, the Fast Orthogonal Search (FOS) [1] used for time series analysis is employed. The FOS method enjoys the property of identifying, with a large degree of accuracy, the frequency components comprising the signal even when the signal is corrupted with noise or when some of the original points are being missing, which is the case we are dealing with.

The paper is organized as follows. Section 2 describes the piecewise linear segmentation of the ECG signal and the encoding process. Section 3 discusses the application of the FOS method in the decoding process. In section 4, results of applying the proposed method to an ECG database comprised of six normal and abnormal cases are analyzed in terms of the resulting compression ratio, reconstruction error, and visual acceptability of the signal. The paper is finally concluded in section 5.

2. ECG SIGNAL SEGMENTATION

The basic idea of the algorithm is to select the minimum number of data points which can be used at the decoder to reconstruct the signal. These data points have to be selected in such a way that they fairly contain the important features of the signal, such as the peaks of the QRS segment, its onset and end, the integrity of the S–T Segment, and the peaks of the P and T waves. Some techniques, such as Turning Point [2], AZTEC [3], SAPA [4], and CUSAPA [5] have employed the idea of picking up the best candidate points which can reproduce the signal within a small error.

In this work, the original signal is differentiated using a 5–point difference derivative formula [2]. If $x[n]$ denotes the nth ECG sample, then the derivative, $x^{'}[n]$ is defined as

$$x^{'}[n] = \frac{1}{10}\left(2x[n+2] + x[n+1] - x[n-1] - 2x[n-2]\right).$$

When the differentiator is applied to the ECG signal in Fig. (1), a set of line segments of different slopes is produced. Each segment will have its own length and starting point (labeled $\times$ in figure). The waveform shown can be expressed as the following segment string: Z,P,Z,N,Z,N,P,N,Z,P,Z,N,Z where Z, P, and N

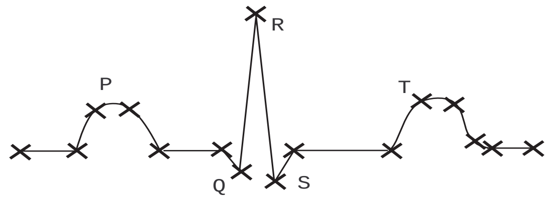

Figure 1: Line segmentation of the ECG signal

stand for zero, positive, and negative slope segments, respectively.

A Z–segment lying between an N(P)-segment and a P(N)-segment indicates a valley (peak) point. It should be noted that ECG waveforms are not so noise free as indicated in the figure. While the shown signal needed only 13 line segments for proper representation, it is expressed as a string of over 20 segments. The extra segments are produced due to the noise superimposed on the original signal. However, these extra segments are informationless, in the sense of the information gained from data behavior changes. Mostly, these segments are of small length and lie between segments of the same sign. Therefore, the resulting line segment string is postprocessed to remove the noisy segments. By identifying a line segment by the triplet: (Sign,Start, Length), for line segment, i, the slope sign, the starting point, and the length are expressed as Sign(i), Start(i), and Length(i), respectively. If the length of the current ith segment in the new string is less than a length threshold value and the sign of the most recently saved segment ($i-1$th segment) is the same as the sign of the next segment ($i+1$th segment) then the three line segments are merged together. Also, if the length of the most recently saved segment ($i-1$th segment) plus that of the current segment (ith segment) is less than the threshold, they too are merged. If the first (last) segment length is smaller than the threshold, it is merged with the next(previous) one. The location and value of the starting points of the final line segments will be used to encode the ECG waveform.

3. FAST ORTHOGONAL SEARCH FOR FREQUENCY ANALYSIS

The saved (or transmitted) points will be used to reconstruct the original signal. A time–series analysis approach is adopted where a parsimonious sinusoidal series (non–Fourier) which significant frequencies, amplitudes, and phases are to be estimated in order to approximate the time-series data. It should be noted here that the transmitted points need not be equi-distant. Assuming that $x[n], n = 1, \ldots, N$, represent the compressed ECG time–series, the parsimonious sinusoidal series representation can be expressed as

$$x[n] = \sum_{m=0}^{M} a_m \, p_m[n] + e[n] \qquad (1)$$

where

$$p_0[n] = 1, \qquad (2)$$

and for $i = 1, 2, \cdots$,

$$p_{2i-1}[n] = \cos \omega_i \; n, \quad p_{2i}[n] = \sin \omega_i \; n,$$

and $e[n]$ is the model error. The frequencies, ω_i, can be selected by systematically searching through a set of N_f candidate frequencies $\omega_a, a = 1, \cdots, N_f$. It is important to note here that the candidate frequencies need not be commensurate, nor integral multiples of a fundamental frequency, as it is required for the Fast Fourier Transform. The selection of frequencies is carried out by the fast orthogonal search (FOS) [6]. According to the FOS method, the difference equation (1) may be expressed as

$$x[n] = \sum_{m=0}^{M} g_m \, w_m[n] + e[n] \qquad (3)$$

where $w_m[n]$ are constructed from $p_m[n]$ using the modified Gram– Schmidt procedure to be mutually orthogonal over the interval $n = 0, \ldots, N$. The coefficients, g_m, are selected to minimize the mean-square error (MSE) over this interval (the overbar denotes the time average),

$$\overline{e^2[n]} = \overline{(x[n] - \sum_{m=0}^{M} g_m \, w_m[n])^2} = \overline{x^2[n]} - \sum_{m=0}^{M} g_m^2 \, \overline{w_m^2[n]} \qquad (4)$$

Assuming that $a_r p_r$ was the last difference equation term added to the model in (1), then it can be shown that the addition of this term reduced the MSE error by the amount $Q_r = g_r^2 w_r^2$ where $g_r = \frac{\overline{x[n] w_r[n]}}{\overline{w_r^2[n]}}$. The pool of all candidate frequencies is searched in order to select candidates which result in the greatest MSE reduction. The construction of the functions $w_m[n]$ is computationally intensive. The FOS method was developed in order to find a rapid and efficient system modeling. Having all $p_m[n]$ known *apriori*, the coefficients a_m are estimated using a Cholesky decomposition [1]. The algorithm goes as follows. First a constant term, $g_0 = \overline{x[n]}$, is introduced using (2). Next the candidates terms will be searched to select the proper frequencies. Adding the ith term pair, $T_i = a_{2i-1} \, p_{2i-1}[n] + a_{2i} \, p_{2i}[n]$ to the model of (1) decreases the MSE amount by the value

$$Q_i = g_{2i-1}^2 \overline{\omega_{2i-1}^2} + g_{2i}^2 \overline{\omega_{2i}^2}$$

At the stage of adding the ith term pair, $M = 2i$, the quantity Q_i is evaluated for each available candidate frequency. The frequency with the largest Q_i value is selected. The algorithm saves a substantial amount of computation by avoiding doing calculations previously performed at earlier searches. The search continues until the MSE in (4) becomes smaller than a certain threshold.

4. SIMULATION RESULTS

The proposed compression algorithm is applied to a set of ECG signals. The signals are sampled at 200 Hz and quantized using 12 bits/sample. The set represents both normal and abnormal cases. To assess the algorithm, several performance evaluation measures were analyzed. These measures are: the **Compression Ratio**, CR $= \frac{N}{P}$ where N is number of original samples, and P is the number of transmitted samples and the Percentage Root-Mean Square Difference (**PRD**), which is a normalized value that indicates the error between the original and the reconstructed signals. The PRD is calculated as PRD $= \sqrt{\frac{\sum_{i=1}^{N}(x[i]-\hat{x}[i])^2}{\sum_{i=1}^{N} x^2[i]}}$ where $x[i]$ is the original ith sample, $\hat{x}[i]$ is the reconstructed ith sample. Although the PRD is a good statistical measure of goodness, it does not reflect the visual acceptability of the new signal. A better error measure used here is the signal-to-noise ratio, **SNR**, calculated as SNR $= \frac{\sum_{i=1}^{N}(x[i]-\overline{x[i]})^2[i]}{\sum_{i=1}^{N}(x[i]-\hat{x}[i])^2}$ which relates the signal power to the noise power. The final factor is the error in detecting the QRS segment. Applying the QRS detector suggested in [7] where the length of the QRS segment is calculated by locating the onset and end points of the segment. The procedure employs a five-step procedure which acts as a high-pass filter to filter out the high frequency QRS complexes without declaring the sharp T waves or the abrupt changes in the baseline as QRS complexes.

Table (1) shows the results of applying the proposed algorithm to the six cases of the ECG signals. The cases indicated in the table are the normal sinus rhythm (NSR), the atrial flutter (AFLUT), the atrial fibrillation (AFIB), the ventricular tachycardia (VTACH), the ventricular fibrillation (VFIB), and the partial heart block (PHB). In reconstructing the signal using the FOS method, we have a used a set of 250 candidate frequencies which range from 0.5 Hz to 100 Hz. Since the FOS method was used in the missing–data mode of operation, we have increased the number of points by adding the points which are clearly lie on the base line. The lowest CR values were attained with the AFIB, AFLUT, and VFIB, cases in that order. These signals contain large number of oscillations when compared with other cases. Thus, they are represented by a fairly larger number of points. The PHB case produced the largest CR (20) since the signal contains a large isoelectric region which needed very few points to represent. These results indicate the proportional relationship between the oscillating behavior of the signal and the compression ratio. Due to the large offset for all signals, the resulting PRD values were very small which do not really reflect the goodness of the algorithm. The SNR, on the other hand, displays more realistic assessment of the resulting reproduction error. Again, the SNR was smaller with signals of large baseline segments (PHB, NSR, VBIB). The largest QRS error was detected with the PHB signal (about 15 msec). This was mainly due to the incorrect choice of the beginning of one of the QRS complexes. With the other cases, the average error was about 5 msec (one sampling instant). A slight modification of the point selection algorithm can remedy this problem. Comparing the algorithm with previously published ones, we find that the average CR obtained with the proposed algorithm is about 14 which far exceed those obtained using the Fast Fourier Transform [8](5.0) and the First Order Interpolation [9](3.7). It should be noted, however, that this compression ratio represents an upper bound as we have used the smallest number of necessary points needed to represent the signal. We have also found that the QRS detection error is much larger with the other two algorithms. It is also evident from the results shown in Fig. (5) that the proposed method has preserved the diagnostically significant features of the ECG waveforms.

Case	CR	PRD(%)	SNR(%)
NSR	15.90	0.04	4.28
AFLUT	10.59	0.08	7.51
AFIB	9.93	0.07	6.42
VTACH	16.33	0.13	5.76
VFIB	12.12	0.03	3.87
PHB	20.00	0.08	5.66

Table 1: Results of the proposed algorithm

5. CONCLUSION

In this work an ECG data compression method is proposed. The encoder part of the algorithm converts the waveform to a set of linear segment each of them is identified by its starting point, length, and slope. The starting point of all segments represent the encoded signal. The decoder part applies the FOS search method to reconstruct the signal from the partial data generated by the encoder. Results show that the method produces high compression ratios when compared to other methods while maintaining small reconstruction error. Diagnostic features of the waveform are also preserved. The algorithm can be improved by enhancing the encoder to better select the optimal points and also by increasing the pool of the candidate frequencies at the decoder part.

6. REFERENCES

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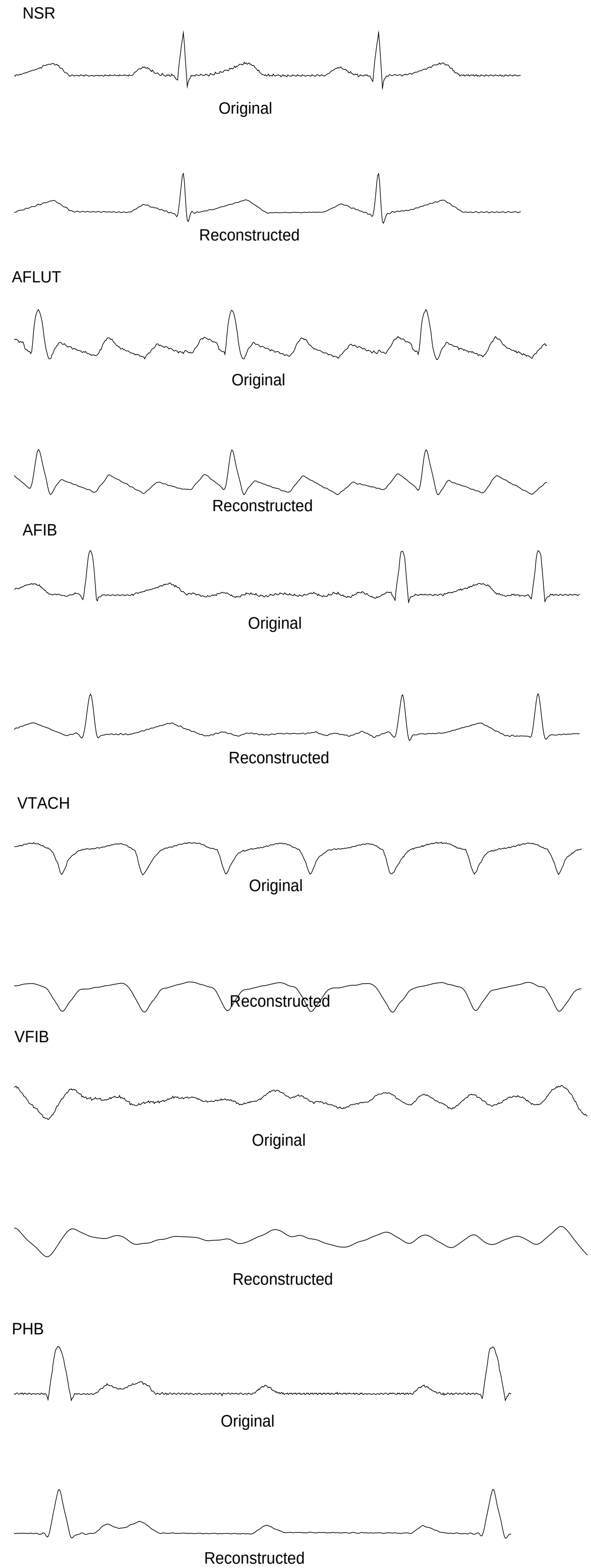

Figure 2: Compression of ECG waveforms