ECG Data Compression Techniques—A Unified Approach

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Abstract—**A broad spectrum of techniques for electrocardiogram (ECG) data compression have been proposed during the last three decades. Such techniques have been vital in reducing the digital ECG data volume for storage and transmission. These techniques are essential to a wide variety of applications ranging from diagnostic to ambulatory ECG's. Due to the diverse procedures that have been employed, comparison of ECG compression methods is a major problem. Present evaluation methods preclude any direct comparison among existing ECG compression techniques. The main purpose of this paper is to address this issue and to establish a unified view of ECG compression techniques. ECG data compression schemes are presented in two major groups: direct data compression and transformation methods. The direct data compression techniques are: ECG differential pulse code modulation and entropy coding, AZTEC, Turning-point, CORTES, Fan and SAPA algorithms, peak-picking, and cycle-to-cycle compression methods. The transformation methods briefly presented, include: Fourier, Walsh, and K-L transforms. The theoretical basis behind the direct ECG data compression schemes are presented and classified into three categories: tolerance-comparison compression, differential pulse code modulation (DPCM), and entropy coding methods. The paper concludes with the presentation of a framework for evaluation and comparison of ECG compression schemes.**

I. INTRODUCTION

THE CONTINUING proliferation of computerized ECG processing systems along with the increased feature performance requirements and demand for lower cost medical care have mandated reliable, accurate, and more efficient ECG data compression techniques. The practical importance of ECG data compression has become evident in many aspects of computerized electrocardiography including: a) increased storage capacity of ECG's as databases for subsequent comparison or evaluation, b) feasibility of transmitting real-time ECG's over the public phone network, c) implementation of cost effective real-time rhythm algorithms, d) economical rapid transmission of off-line ECG's over public phone lines to a remote interpretation center, and e) improved functionality of ambulatory ECG monitors and recorders.

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The main goal of any compression technique is to achieve maximum data volume reduction while preserving the significant signal morphology features upon reconstruction. Conceptually, data compression is the process of detecting and eliminating redundancies in a given data set. Shannon [1] has defined redundancy as "that fraction of a message or datum which is unnecessary and hence repetitive in the sense that if it were missing the message would still be essentially complete, or at least could be completed." Redundancy in a digital signal exists whenever adjacent signal samples are statistically dependent and/or the quantized signal amplitudes do not occur with equal probability [2]. However, the first step towards ECG data compression is the selection of minimum sampling rate and wordlength. Consequently, further compression of the ECG signal can be achieved by exploiting the known statistical properties of the signal.

Data compression techniques have been utilized in a broad spectrum of communication areas such as speech, image, and telemetry transmission [3]–[11]. Data compression methods have been mainly classified into three major categories [12]: a) direct data compression, b) transformation methods, and c) parameter extraction techniques. Data compression by the transformation or the direct data compression methods contain transformed or actual data from the original signal. Whereby, the original data are reconstructed by an inverse process. The direct data compressors base their detection of redundancies on direct analysis of the actual signal samples. In contrast, transformation compression methods mainly utilize spectral and energy distribution analysis for detecting redundancies. On the other hand, the parameter extraction method is an irreversible process with which a particular characteristic or parameter of the signal is extracted. The extracted parameters (e.g., measurement of the probability distribution) are subsequently utilized for classification based on *a priori* knowledge of the signal features.

Existing data compression techniques for ECG signals lie in two of the three categories described: the direct data and the transformation methods. Direct data compression techniques for ECG signals have shown a more efficient performance than the transformation techniques in regard particularly to processing speed and generally to compression ratio [13]. Most of the transformation techniques have been developed specifically for data compression of

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multiorthogonal ECG leads. In the following section of this paper, we describe the strategy we adopted in presenting the existing ECG data compression schemes. The third section is divided into two subsections; the first provides presentation of the theoretical basis behind the classical direct data compression methods applied to ECG signals, while the second subsection discusses the direct ECG data compression schemes. In the fourth section we present the transformation techniques employed in ECG data compression. The last two sections are devoted to the discussion of the current status in evaluating ECG compression techniques and the establishment of a framework for the evaluation and comparison of ECG compression methods.

II. ECG Compression Techniques—The Presentation Protocol

Existing ECG data compression techniques have been developed and evaluated under different conditions and constraints. Independent databases, with ECG's sampled and digitized at different sampling frequencies (100–1000 Hz) and precisions (8–12 b), have been mainly employed. The reported compression ratios (CR) have been strictly based on comparing the number of samples in the original data with the resulting compression parameters without taking into account factors such as bandwidth, sampling frequency, precision of the original data, wordlength of compression parameters, reconstruction error threshold, database size, lead selection, and noise level.

We have adopted a protocol for presenting the ECG data compression schemes reported in the literature. This is done in an attempt to form some basis of comparison among ECG data compression techniques. Each compression scheme is presented in accordance to the following five issues: a) a brief description of the structure and the methodology behind each ECG compression scheme is presented along with any reported unique advantages and disadvantages. b) The issue of processing time requirement for each scheme has been excluded. In light of the current technology, all ECG compression techniques can be implemented in real-time environments due to the relatively slow varying nature of ECG signals. c) The sampling rate and precision of the ECG signals originally employed in evaluating each compression scheme are presented along with the reported compression ratio. d) Since most of the databases utilized in evaluating ECG compression schemes are nonstandard, database comparison has been excluded. We believe such information does not provide additional clarity and at times may be misleading. However, every effort has been made to include comments on how well each compression scheme has performed. The intent is to give the reader a feeling for the relative value of each compression technique. e) Finally, the fidelity measure of the reconstructed signal compared to the original ECG has been primarily based on visual inspection. Besides the visual comparison, many compression schemes have employed the percent root-mean-square difference (PRD). The PRD value for each compression scheme is presented whenever it is available. The PRD calculation is as follows:

$$\mathrm{PRD} = \sqrt{\frac{\sum_{i=1}^{n} \left[x_{\mathrm{org}}(i) - x_{\mathrm{rec}}(i)\right]^2}{\sum_{i=1}^{n} x_{\mathrm{org}}^2(i)}} * 100 \tag{1}$$

where x_{org} and x_{rec} are samples of the original and reconstructed data sequences.

III. Direct Data Compression Techniques

This section is presented in two major parts. The first part discusses the classical direct data compression methods applied to ECG signals. This is done for the purpose of building a hierarchical basis for the prominent ECG compression techniques presented in the second part of this section.

A. Classical Direct Data Compression Methods

Most of the direct data compression techniques rely on utilizing prediction or interpolation algorithms. These techniques attempt to reduce redundancy in a data sequence by examining a successive number of neighboring samples. A prediction algorithm utilizes *a priori* knowledge of some previous samples, while an interpolation algorithm employs *a priori* knowledge of both previous and future samples. Theoretical analysis of such compression techniques can be found in [14]–[19].

In light of the algorithmic structure of existing ECG data reduction schemes, we classify the direct data compression methods into three categories: tolerance-comparison compression, differential pulse code modulation (DPCM), and entropy coding methods. The compression techniques we call tolerance-comparison are the ones where a preset error threshold is employed to eliminate data samples. Higher values of the preset error threshold will, in general, result in higher data compression along with lower reconstructed signal fidelity and vice-versa. The tolerance-comparison and the DPCM compressors attempt to reduce signal redundancy by taking advantage of the intersample correlation. On the other hand, entropy coding reduces the signal redundancy that arises whenever the quantized signal amplitudes have a nonuniform probability distribution.

1) Tolerance-Comparison Data Compression Techniques: Most of the tolerance-comparison data compression techniques employ polynomial predictors and interpolators. The basic idea behind polynomial prediction/interpolation compressors is to eliminate samples, from a data sequence, that can be implied by examining preceding and succeeding samples. The implementation of such compression algorithms is usually executed by setting a preset error threshold centered around an actual sample point. Whenever the difference between that sample and a succeeding future sample exceeds the preset error threshold, the data between the two samples is approximated by a line whereby only the line parameters (e.g., length and amplitude) are saved.

Description of tolerance-comparison compression techniques based on polynomial predictors/interpolators was been consolidated in [20]. One of the early discussions on polynomial prediction compressors was presented and labeled "self-adaptive data compression" in [21] while further studies were given in [22], [23]. An early illustration of polynomial interpolation compressors was presented in [24]. A broad class of polynomial prediction/interpolation compressors along with comparisons of other data compression techniques can be found in [12], [19], [25]–[27]. One scheme of such polynomial compressors has been employed in speech data compression (called "aperture coding") [28], [29]. In contrast to speech data compression, polynomial compressors are widely utilized in ECG data compression. In general polynomial prediction/interpolation compression algorithms with a degree higher than one are rarely used [12], [25], [27]. Therefore, our discussion on polynomial predictors/interpolators is limited to zero and first order polynomials. One final historical point worth noting is that the order of the polynomial predictors/interpolators starts with the zero-order, while the order of the linear predictor, discussed in Section A-2, starts with the first-order. This paper will not attempt to alter such widely known terminology.

a) Polynomial Predictors: Polynomial predictors are based on a finite difference technique which constraints an nth-order polynomial to $K + 1$ data points. Predicted data are obtained by extrapolating the polynomial one sample point at a time. The polynomial predictor [21], [22] is

$$\hat{y}_n = y_{n-1} + \Delta y_{n-1} + \Delta^2 y_{n-1} + \cdots + \Delta^k y_{n-1} \tag{2}$$

where

$\hat{y}_n$ = predicted sample point at time t_n
y_{n-1} = sample value at one sample period prior to t_n
$\Delta y_{n-1} = y_{n-1} - y_{n-2}$
$\Delta^k y_{n-1} = \Delta^{k-1} y_{n-1} - \Delta^{k-1} y_{n-2}$.

The value of k represents the order of the polynomial prediction algorithm.

Zero-Order Predictor (ZOP): The ZOP is a polynomial predictor [see (2)] with $k = 0$. In this case,

$$\hat{y}_n = y_{n-1} \tag{3}$$

where the predicted value is merely the previous data point. Several implementations of this algorithm are exploited by employing different aperture (peak error) techniques [12], [22], [27]. The most efficient ZOP technique uses a floating aperture (sometimes called the step method) wherein a tolerance band $\pm\epsilon$ is centered around the last saved data point as shown in Fig. 1. Succeeding sample points that lie in the tolerance band ($\pm\epsilon$), centered around the last saved sample point, are not retained. The tolerance band actually "floats" with the nonredundant (saved) data points. Successive samples that fall within the tolerance band of the last saved sample are not retained. These samples are approximated by a horizontal line of an amplitude equal to the previous saved sample point. Hence, the line parameters, amplitude and length (number of data points), are substituted for the original data samples. Signal reconstruction is, however, achieved by expanding the stored line parameters to discrete data points.

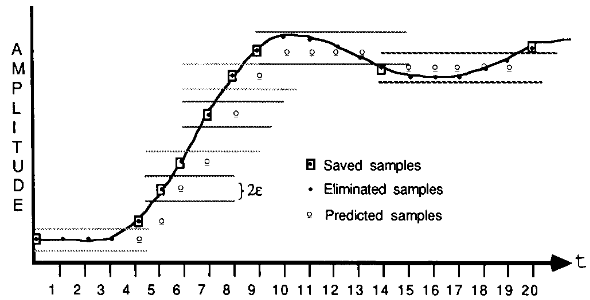


Fig. 1. Illustration of the ZOP floating aperture.

In general, the ZOP has proven to be very efficient for step-like data.

First-Order Predictor (FOP): The FOP is an implementation of (2) with $k = 1$ [12], [22], [27]. This yields a first-order polynomial of the form

$$\hat{y}_n = 2y_{n-1} - y_{n-2}. \tag{4}$$

The predicted value is a point on the straight line drawn between the last two data points (y_{n-1} and y_{n-2}). The FOP algorithm with a floating aperture (Fig. 2) is initiated by retaining the first two data points and drawing a straight line between these two points. An aperture of width $\pm\epsilon$ is centered around the obtained line. If the actual sample point (y_n) is within $\pm\epsilon$ of the predicted value, then that sample point is not saved. Otherwise, (y_n) is saved and a new prediction line is drawn through (y_n) and the previous predicted point. The signal reconstruction requires the nonredundant sample values along with the corresponding time.

b) Polynomial Interpolators: Unlike the case of prediction, polynomial interpolators utilize both past and future data points to decide whether or not the actual sample point is redundant. In other words, all samples between the last retained sample and the present sample point affect the interpolation. Low-order polynomial interpolators have been found to be very efficient in ECG data compression [24]–[26], [30], [31].

Zero-Order Interpolator (ZOI): The principal operation of the zero-order interpolator is illustrated in Fig. 3. The ZOI is similar to the ZOP in the sense that a horizontal (zero-order) line is employed to determine the largest set of consecutive data points within a preset error threshold. The main difference lies in selecting the sample point that represents the redundant set. The interpolator retained sample is determined at the end of the redundant

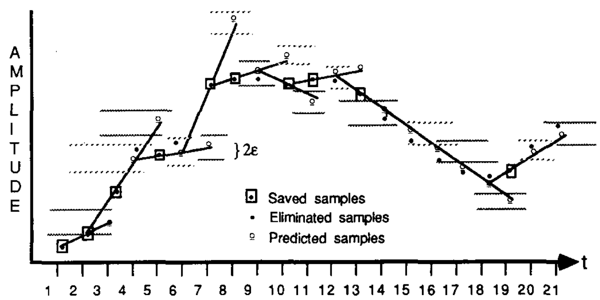


Fig. 2. Illustration of the FOP-floating aperture.

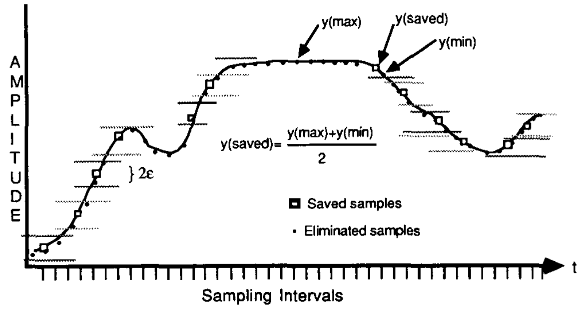


Fig. 3. Illustration of the zero-order interpolator.

set, in contrast to the first sample in the case of the predictor. Moreover, the saved sample for the interpolator algorithm is computed as the average between the minimum and the maximum sample values in the set. All samples in the set are within the preset error threshold from the saved sample point. Alternatively, whenever the current sample point exceeds the preset tolerance, the current sample becomes the first point in a new set and the average between the largest and the smallest sample values of the previous (redundant) samples is saved. The average value is saved as an approximation to the previous redundant set of samples.

First-Order Interpolator (FOI): The first-order interpolator (linear method) assumes that data will continue in the same direction (slope) once it has started. Instead of drawing a horizontal line as is the case in the zero-order method, a line is drawn to establish a slope. The first-order interpolator with two degrees of freedom (FOI-2DF) has been found to be the most efficient compression scheme among other first-order interpolators [12], [25]. The FOI-2DF draws a straight line between the present sample and the last saved sample so that intermediate data points are within a specified tolerance of the interpolated value. The encoded message contains information about the length of the line and its starting and ending points. The ending point of a line, in this interpolation scheme, is used as the starting point of the next line segment. This results in a reduced code word length with decreased flexibility (i.e., two degrees of freedom). In other words, only one data point (the ending point) needs to be retained for each line after the very first saved line.

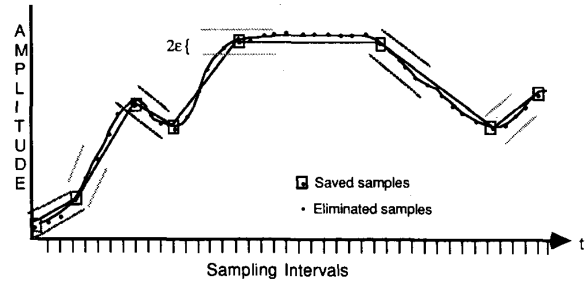


Fig. 4. Principal operation of the FOI-2DF.

The functional operation of the FOI-2DF is illustrated in Fig. 4. The algorithm starts with retaining the first data point. A line is drawn between the retained point and the third sample point to define a slope. If the second sample point value (the first sample after the saved one) is within a tolerance $\pm\epsilon$ of the interpolated value, then a straight line is drawn between the saved point and the fourth point. The interpolated value of the second and the third points are now checked to examine if they are within a preset error tolerance of the actual value. If at the Kth sample value, after the last retained sample value a line is drawn, and the actual value differs from the interpolated value by a quantity greater than the preset tolerance, then the $(K - 1)$th sample is saved and the process is repeated. The waveform is reconstructed by connecting the nonredundant (saved) samples with straight lines. The FOI-2DF is sometimes called "two point projection" method [24]. This is due to the fact that the interpolated sample values are projected on the straight line drawn between sample points (interpolation straight line).

2) Data Compression by Differential Pulse Code Modulation: The basic idea behind the differential pulse code modulation (DPCM) is that when data samples are estimated, the error (residual) between the actual sample and the estimated sample value ($e_n = y_n - \hat{y}_n$) is quantized and transmitted or stored [32], [33]. Consequently, waveform redundancy reduction by DPCM coders is basically achieved by representing the actual correlated signal, in terms of an uncorrelated signal, namely, the estimation error signal. Thus, since the estimation error sequence is saved in place of the actual data sequence, upon reconstruction the original signal is preserved without loss of information. Unlike the previously discussed tolerance-comparison compression schemes, the major source of reconstruction error in DPCM coders is due to the amplitude quantization noise incurred in quantizing the residual signal.

In general, the variance of the estimation error signal is smaller than the variance of the original signal, provided that the correlation of the input signal is high and the estimator coefficients were correctly chosen. For a specified signal-to-quantization noise ratio (SNR), DPCM coding of a correlated waveform will result in bit rate reduction over PCM coding. By the same token, for a given bit rate, the SNR is improved in going from PCM to DPCM. The gain (G) in the SNR of DPCM with respect to PCM can be expressed [34], [35] as follows:

$$G = \frac{\sigma^2}{\sigma_e^2} = \frac{E[y_n^2]}{E[(y_n - \hat{y}_n)^2]} \tag{5}$$

where σ^2 and σ_e^2 are the variance of the original signal (y_n) and the residual signal ($y_n - \hat{y}_n$), respectively.

Basically, the structure of a DPCM compression/reconstruction system encompasses a quantizer in the compressor and an estimator in both the compressor and the reconstructor. The estimation algorithm utilized in the compressor is also employed in the reconstructor so that the original signal can be recovered from the residual signal. Quantizer design is a very crucial issue in a DPCM system due to the fact that the SNR quantity is dependent upon the particular quantizer employed. Studies on quantizer design can be found in [36]–[38]. The estimator of a DPCM coder can be any estimation algorithm such as the polynomial predictors and interpolators discussed earlier. A more complex estimator such as the linear predictor [39] is usually employed in DPCM coding. The linear predictor is optimum, in the mean square error sense, under the constraint that the input signal has a Gaussian amplitude distribution. The rationale of the linear predictor is to predict the next data point by a linear combination of a number of samples known up to the present time. The predicted data point is evaluated by a linear weighting of M previous samples:

$$\hat{y}(t) = \sum_{j=1}^{M} \beta_j y(t_{n-j}) \tag{6}$$

where the order of the predictor is determined by the number of the preceding samples (M) that are stored for the prediction. As one can anticipate, the first-order linear predictor ($M = 1$) is equivalent to the zero-order polynomial predictor [see (3)]. The β_j are weighting coefficients so that the mean square error between the predicted and the actual sample value is minimum. The reason for endeavoring this minimum is that in most cases the residual signal has zero mean, thus mean square is equivalent to variance. Moreover, as it can be seen from (5), minimizing the residual signal variance (σ_e^2) would result in increased gain (G). The weighting coefficients β_j can be determined to minimize the mean-square prediction error as follows:

$$\sigma^2(M, N) = \frac{1}{N} \sum_{k=1}^{N} \cdot \left\{ y(t_{n-k}) - \sum_{j=1}^{M} \beta_j(M, N)\, y(t_{n-k-j}) \right\}^2 \tag{7}$$

where N is the window length. It should also be noted that if the residual signal has a Gaussian distribution, minimum variance implies minimum entropy [40]. In a speech/television DPCM system [41], where the residual signal has a nonGaussian distribution, the entropy was found monotonically related to the variance. In the case of ECG DPCM systems, a controversy arises to whether the entropy is monotonically related to the residual signal variance [30] or not necessarily related [42].

3) Entropy Coding: The theoretical basis of entropy coding can be traced back to Shannon's theorem of communication theory [43]. Data compression by entropy coding is obtained by means of assigning variable-length codewords to a given quantized data sequence according to their frequency of occurrence. This compression method attempts to remove signal redundancy that arises whenever the quantized signal levels do not occur with equal probability.

The method of constructing variable-length codes was pioneered by Huffman in his well-known paper on minimum redundancy coding [44]. The Huffman coding scheme provides a method for the assignment of codewords for L quantizer outputs, with average wordlengths ranging from 1 to $|\log_2 L|$, based on the signal amplitude probability distribution. Values occurring with higher probability are assigned shorter code lengths compared to the less probable ones. This results in the minimization of the mean code length, and as Huffman named it "optimum code." Many other later techniques were developed based on the Huffman's method [45]–[49]. For an ample discussion on such schemes, the reader is referred to a recent review [3]. It should be noted that entropy coding has been widely utilized in DPCM systems. Design considerations of such systems can be found in [50]. The impact of these coding systems on ECG data compression will be discussed in the following section.

B. Direct ECG Data Compression Schemes

This section presents the direct data compression schemes developed specifically for ECG data compression. The AZTEC, Fan/SAPA, TP, and CORTES ECG compression schemes, which are mainly based on the tolerance-comparison compression methods of Section A-1), are presented. Next, the considerable work that has been directed towards ECG data compression by DPCM and entropy coding is discussed. Peak-picking and cycle-to-cycle ECG compression techniques, which have yet to receive wide research attention, are also presented.

1) The AZTEC Technique: The amplitude zone time epoch coding (AZTEC) algorithm originally developed by Cox *et al.* [51] for preprocessing real-time ECG's for rhythm analysis. It has become a popular data reduction algorithm for ECG monitors and databases with an achieved compression ratio of 10:1 (500 Hz sampled ECG with 12 b resolution) [52], [53]. However, the reconstructed signal demonstrates significant discontinuities and distortion. In particular, most of the signals distortion occurs in the reconstruction of the P and T waves due to their slow varying slopes.

The AZTEC algorithm converts raw ECG sample points into plateaus and slopes. The AZTEC plateaus (horizontal lines) are produced by utilizing the zero-order interpolation (ZOI) discussed in Section A-1.b). The stored values for each plateau are the amplitude value of the line and its length (the number of samples with which the line can be interpolated within aperture ϵ). The production of an AZTEC slope starts when the number of samples needed to form a plateau is less than three. The slope is saved whenever a plateau of three samples or more can be formed. The stored values for the slope are the duration (number of samples of the slope) and the final elevation (amplitude of last sample point). Signal reconstruction is achieved by expanding the AZTEC plateaus and slopes into a discrete sequence of data points.

Even though the AZTEC provides a high data reduction ratio, the fidelity of the reconstructed signal is not acceptable to the cardiologist because of the discontinuity (step-like quantization) that occurs in the reconstructed ECG waveform. A significant reduction of such discontinuities is usually achieved by utilizing a smoothing parabolic filter [53]–[55]. The disadvantage of utilizing the smoothing process is the introduction of amplitude distortion to the ECG waveform.

A modified AZTEC algorithm is proposed in [56] whereby the error threshold, for the ZOI part of the AZTEC algorithm, is made adaptive to the ECG signal variations. The adaptivity of the error threshold is based on recursive calculation of the first three moments of the signal. This technique, based on a single ECG, has resulted in a slight improvement (better compromise between compression ratio and reconstructed signal fidelity) in the percent root-mean-square difference [PRD, (1)] over the AZTEC algorithm for the same compression ratio. Another technique based on the AZTEC algorithm [57], [58] has been developed for the purpose of alleviating the problem of discontinuity in the AZTEC reconstructed signal. Instead of utilizing the ZOI for producing plateaus, the Fan technique (discussed later in this paper) was employed for generating sloping lines. This is done due to the fact that the signal discontinuity is introduced by the nature of the ZOI algorithm. The ECG signal is reconstructed by connecting these sloping lines and the AZTEC slopes, which, in turn, results in a discontinuity-free signal. Preliminary evaluation of the technique has showed a 50% improvement in compression ratio and signal fidelity (PRD) when compared to the AZTEC algorithm.

2) The Turning Point Technique: The turning point (TP) data reduction algorithm [59] was developed for the purpose of reducing the sampling frequency of an ECG signal from 200 to 100 Hz without diminishing the elevation of large amplitude *QRS*'s.

The algorithm processes three data points at a time; a reference point (X_0) and two consecutive data points (X_1 and X_2). Either X_1 or X_2 is to be retained. This depends on which point preserves the slope of the original three points. The TP algorithm produces a fixed compression ratio of 2 : 1 whereby the reconstructed signal resembles the original signal with some distortion. A disadvantage of the TP method is that the saved points do not represent equally spaced time intervals.

3) The CORTES Scheme: The coordinate reduction time encoding system (CORTES) algorithm [60] is a hybrid of the AZTEC and TP algorithms. CORTES applies the TP algorithm to the high frequency regions (*QRS* complexes), whereas it applies the AZTEC algorithm to the isoelectric regions of the ECG signal. The AZTEC and TP algorithms are applied in parallel to the incoming sampled ECG data. Whenever an AZTEC line is produced, a decision based on the length of the line is used to determine whether the AZTEC data or the TP data is to be saved. If the line is longer than an empirically determined threshold, the AZTEC line is saved, otherwise the TP data are saved. Only AZTEC plateaus (lines) are generated; no slopes are produced. The CORTES signal reconstruction is achieved by expanding the AZTEC plateaus into discrete data points and interpolating between each pair of the TP data. Parabolic smoothing is applied to AZTEC portions of the reconstructed CORTES signal to reduce distortion. Detailed description of the CORTES implementation and reconstruction procedures are discussed in Tompkins and Webster [61].

Performance evaluation of the AZTEC, TP, and CORTES algorithms were reported in [60] (ECG's sampled at 200 Hz with 12 b resolution) with compression ratios of 5 : 1, 2 : 1, and 4.8 : 1 respectively, and PRD's of 28, 5, and 7, respectively. Fig. 5, taken from [60], shows the effect of the AZTEC and CORTES algorithms on the ECG.

4) Fan and SAPA Techniques: Fan and scan-along polygonal approximation (SAPA) algorithms, developed for ECG data compression, are based on the first-order interpolation with two degrees of freedom (FOI-2DF) technique discussed in Section A-1.b). A recent report [62] claimed that the SAPA-2 algorithm is equivalent to an older algorithm, the Fan. However, both algorithms will be presented.

1) The Fan Algorithm: In essence, the Fan is a method of implementing the FOI-2DF without requiring the storage of all the actual data points between the last transmitted point and the present point during program execution. Moreover, it draws the longest possible line between the starting point and the ending point so that all intermediate samples are within the specified error tolerance. The Fan method was originally reported and tested on ECG signals by Gardenhire [24], [63]. Recent reports have appeared in the literature offering further description [64] and exhaustive evaluation [65], [67] of the Fan method.

An illustration of the Fan method is shown in Fig. 6. The Fan algorithm starts by accepting the first data point as a nonredundant (permanent) point (t_o) and functions as the origin. Two slopes (U_1, L_1) are drawn between the originating point and the next sample plus a specified threshold ($\pm\epsilon$). One upper slope (U_1) passes through a point greater than the second sample point value by a tolerance (ϵ), while the other lower slope (L_1) passes through a point less than the second sample point value by an ϵ. If the third sample point (t_2) falls within the area bounded by the two slopes, then new slopes (U_2, L_2) are

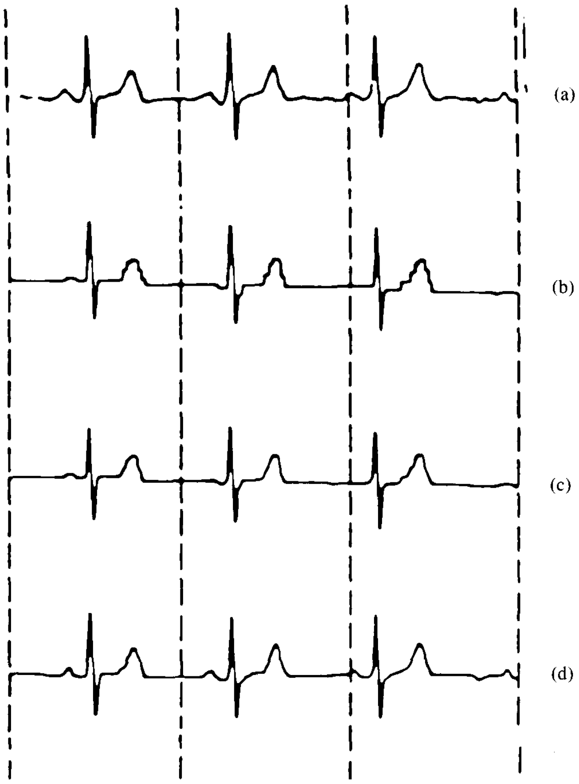


Fig. 5. ECG signal processed with different algorithms. (a) Original ECG sampled at 200 Hz. (b) AZTEC. (c) Filtered AZTEC. (d) CORTES.

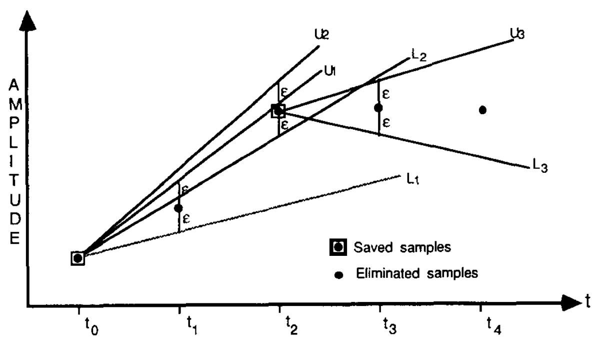


Fig. 6. Illustration of the Fan method. Upper and lower slopes (U and L) are drawn within threshold (ϵ) around sample points taken at t_1, t_2, etc.

calculated between the originating point and an ϵ greater and an ϵ lower than the third sample point. These new slopes (U_2, L_2) are compared to the previously stored slopes (U_1, L_1) and the most converging (restrictive) slopes are retained (U_1, L_2). The process is repeated whereby future sample values are compared with the values of the most convergent slopes. Whenever a sample value falls outside the area bounded by the converging slopes, the sample immediately preceding this sample point is saved as the next permanent sample. This permanent sample point also becomes the new originating point and the algorithm repeats.

The sketch of the slopes drawn from the originating sample to future samples form a set of radial lines similar to a "fan," giving this algorithm its name. Upon signal reconstruction, the retained (permanent) samples are connected with straight lines. The Fan method guarantees the error between the line, joining any two permanent sample points, and any actual (redundant) sample along the line is less than or equal to the magnitude of the preset error tolerance (ϵ). Gardenhire compared the Fan performance to that of the step method (i.e., ZOI) and the two point projection method (i.e., FOI-2DF), concluding that the Fan method provided the best performance regarding both compression ratio and signal fidelity.

2) SAPA-2 Algorithm: Ishijima *et al.* [69] presented three algorithms, for representing ECG signals by a series of straight-line segments, based on scan-along polygonal approximation (SAPA) techniques [69], [70]. The SAPA-2 algorithm, one of the three SAPA algorithms, showed the best results. The theoretical bases of this algorithm is that the deviation between the straight lines (approximated signal) and the original signal is never more than the preset error tolerance (ϵ). The only difference between the Fan and SAPA-2 algorithms is that, in addition to the two slopes calculated in the Fan algorithm, SAPA-2 calculates a third slope between the originating sample point and the actual future sample point (called center slope). Whenever the center slope value does not fall within the two converging slopes boundary, the immediately preceding sample point is considered as a permanent sample. In other words, the SAPA-2 algorithm uses the center slope criterion, for verifying whether the sample is permanent or redundant, instead of the actual sample value criterion as is the case in the Fan algorithm.

5) ECG Data Compression by DPCM: The simplest DPCM system for data compression is a system that employs the predictor given in (3) ($\hat{Y}_n = Y_{n-1}$). Hence, the first-difference signal (amplitude between successive samples ($e_n = Y_n - \hat{Y}_n$)) is substituted for the actual signal itself. ECG data compression based on such a system has been referred to as "delta coding." An ECG delta coding system is proposed in [71] and implemented in [72]. Stewart *et al.* [73] described a modified technique called "delta coding with threshold" for compression of three-lead (X, Y, Z) ECG signals. Whenever the absolute value of the difference between adjacent pair samples in any of the three ECG lead signals exceeds a preset threshold, data are saved. Otherwise data are considered redundant and, hence, eliminated. The retained data comprises the amplitude difference, between the pair samples at the time slot for each of the three-lead ECG signals, along with the time elapsed since the last saved data. It should be noted that, according to the terminology advocated in this paper, such a scheme can be classified as a tolerance-comparison compression since it ultimately eliminates data according to a preset error threshold. The reported compression ratio of such a scheme was 10 : 1 for ECG's sampled at 1000 Hz. A later implementation of the delta coding with threshold scheme [73] employed a 300 Hz sampling rate for each of the three ECG leads with 8 b resolution. A compression ratio of 4 : 1 was reported along with some degradation in the fidelity of the reconstructed P wave. Evaluation of ECG DPCM systems, employing the polynomial predictor given in (2) with $K = 0$, 1, and 2, can be found in [42], [75]. It was concluded that the polynomial predictor with $K = 1$ (referred to as second-order predictor since the resulted DPCM output is a second difference signal) provided the best results.

A more complex DPCM system which employs the linear predictor of (6) has been utilized for ECG data compression [30], [42], [76], [77]. Ruttimann *et al.* [76] studied the performance of the DPCM system with linear prediction as a function of the order of the predictor. They concluded their study by stating that a DPCM system with linear predictors of order higher than two would not result in a substantial increase in data compression. Referring to (6), the order of the predictor is represented by the variable M. An implementation of a DPCM system with linear prediction [77] has resulted in a 2.5 compression ratio for ECG's sampled at 250 Hz. Another study [30] compared the performance of a DPCM code utilizing a second order linear predictor and a second-order interpolator ($\hat{Y}_n = aY_{n-1} + bY_{n+1}$ where $a = b = 0.5$). The performance of the interpolator was found superior to that of the predictor. However, a later comment on the same study suggested that the two estimators are equivalent [78]. Even though there is no clear answer as to whether utilizing interpolation or prediction estimators in a DPCM system would be more efficient, all researchers agree that increasing the order of the linear interpolator or predictor higher than the second order will not result in a significant increase in data compression of ECG's.

6) Entropy Coding of ECG's: ECG data compression by Huffman or variable length coding has been implemented as part of some of the ECG DPCM systems discussed in the previous section [30], [42], [75], [79], [80]. The output of an ECG DPCM encoder is, however, mapped into variable length codewords instead of fixed length ones. A disadvantage of variable length encoding is the possibility of serious decoding errors that may occur due to transmission errors. If the codewords are not delimited by special means, a single-channel error may lead to a long sequence of erroneous receiver outputs. No special error control techniques were presented in all the ECG Huffman coding schemes discussed here. However, such a problem could be tackled by the employment of data block coding with known error control techniques [81]. Consequently, the added error control overhead should be kept to a minimum in order not to substantially reduce the data reduction rate.

Cox and Ripley [79] utilized a modified Huffman coding technique for ECG data compression. A DPCM system, comprising the predictor of (2) with $K = 1$ (i.e., resulting in a second difference ECG signal) was employed. The codewords of the second difference ECG data were partitioned into a frequent and an infrequent sets. This was done for reducing the number of entries in the Huffman code lookup table which, in turn, would facilitate the practical implementation of Huffman coding. Huffman coding was applied to the frequent codewords set, while a fixed wordlength coding technique was applied to the infrequent set. A 2.8 : 1 data compression ratio was reported using 250 Hz sampled ECG's with 10 b resolution.

Ruttimann and Pipberger [30] applied the Huffman coding procedure described in [79] to two different DPCM systems, namely, one DPCM system utilizes linear prediction while the other employs interpolation. It was reported that the interpolation DPCM encoding followed by Huffman encoding resulted in a higher data compression ratio. The achieved compression ratio was 7.8 : 1 with a PRD of 3.5 percent when referred to the original 8 b ECG samples digitized at 500 Hz. Pahlm *et al.* [42] proposed a modified Huffman coding whereby the residual codewords of a DPCM system were partitioned into several sets instead of only two sets as it is the case in [79]. Stewart *et al.* [75] presented another modified Huffman coding scheme (in appendix form), implemented in three-lead ECG (X, Y, Z) DPCM system, whereby no source code partitioning was advocated.

7) Peak-Picking Compression of ECG's: The peak-picking compression techniques are generally based on the sampling of a continuous signal at peaks (maxima and minima) and other significant points of the signal. The basic operation of such techniques involves the extraction of signal parameters that convey "most" of the signal information. These parameters include the amplitude and location of the maxima and the minima points, slope changes, zero-crossing intervals, and points of inflection in the signal. These parameters are substituted in place of the original signal. Upon reconstruction, the signal is restored by polynomial fitting techniques such as straight-lines or parabolic functions.

The implementation of two general compression techniques based on signal peak-picking have been proposed [82]; basic peak-picking and adaptive peak-picking systems. The implementation of the basic peak-picking technique is performed by detecting the zero crossings of the first-difference signal, and saving the samples at these instances. On the other hand, the adaptive system involves comparing the amplitude of each new peak with the amplitude of the last saved peak. If such peaks differ by less than a predetermined tolerance, then a 1 b flag indicating that the same peak occurs, is inserted in place of the new peak.

Peak-picking compression schemes developed specifically for ECG data compression have been documented in the literature [83]–[86]. Imai *et al.* [83] proposed an ECG peak-picking compression system where the signal reconstruction was achieved by using spline functions. The system employes detecting points of maxima and minima, as well as those of large curvature. The extraction of such points was accomplished by using the second-order difference. The point with the large second-order difference is the point with large curvature. Consequently, the maxima and the minima points of the original signal are selected "picked" whenever the second-order difference becomes large. Once these signals are selected and saved, the signal is restored by utilizing spline functions. The performance of this ECG data compression method was compared to the AZTEC method. It was reported that the rms error of the spline method was approximately half that of the AZTEC method for the same compression ratio. Another scheme for ECG data compression using spline functions is presented in [85]. A peak-picking compression scheme where the signal reconstruction is achieved by straight line fitting techniques is proposed in [86]. The peak selection procedure in this scheme is based on direct analysis of the actual ECG sample points instead of the second difference signal.

8) ECG Cycle-to-Cycle Compression: Basically, the rationale of the cycle-to-cycle compression method is to substitute a periodic signal by one cycle period and a count of the total number of cycles that occur in the signal. Yet this approach is only applicable to periodic signals with the constraint that all the signal cycles are exactly the same, which is not the case in ECG waveforms. However, the ECG is a quasi-periodic signal which does not change appreciably in morphology except as a result of a change in the heart function. The cycle-to-cycle ECG compression technique may potentially result in a high compression ratio when applied to Holter ECG's. This is best justified by noting that in the case of Holter ECG's [87] only certain short-period segments of the 24 h recording show abnormality relative to the large number of normal sinus ECG's.

Implementation of the cycle-to-cycle ECG compression is proposed in [57], [58]. The *QRS* complex was chosen to be the repetitive wave in the ECG signal. The hypothesis of such a scheme is based on two observations: a) existing compression techniques, such as the Fan and ZOI schemes, have resulted in high compression ratios when applied to slow varying and low amplitude ECG waves, and b) in a 24 h Holter ECG recording, the difference between a generated QRS template and the actual normal *QRS*'s may result in a low amplitude and slowly varying signal (difference signal). This proposed compression scheme can be summarized as follows: a) extract the abnormal beats from the 24 h Holter ECG recording, b) apply any existing ECG compression technique to the extracted abnormal beats to preserve their high clinical information content, and save, c) automatically generate a *QRS* template from the nonextracted beats (normal ECG's), and save, d) superimpose and calculate the difference between the *QRS* template and each of the normal *QRS* complexes, e) replace the normal *QRS*'s with the corresponding generated difference signal, and f) apply the Fan compression scheme to the resulted signal and save. Even though the preliminary evaluation of this compression scheme has showed no improvement over the Fan compression algorithm, recommendations for tasks that may improve the performance of such scheme were presented [57], [58]. It should be noted that the cycle-to-cycle ECG compression technique requires *QRS* wave detection. For recent surveys of ECG wave detection techniques, the reader is referred to [88], [89].

IV. Transformation Compression Techniques

Unlike direct data compression, most of the transformation compression techniques have been employed in VCG or multilead ECG compression and require ECG-wave detection. In general, transformation techniques involve preprocessing the input signal by means of a linear orthogonal transformation and properly encoding the transformed output (expansion coefficients) and reducing the amount of data needed to adequately represent the original signal. Upon signal reconstruction, an inverse transformation is performed and the original signal is recovered with a certain degree of error. However, the rationale is to efficiently represent a given data sequence by a set of transformation coefficients utilizing a series expansion (transform) technique.

Many discrete orthogonal transforms [90]–[92] have been employed in digital signal representation such as Karhunen-Loeve transform (KLT), Fourier (FT), Cosine (CT), Walsh (WT), Haar (HT), etc. The optimal transform is the KLT (also known as the principal components transform or the eignevector transform) in the sense that the least number of orthonormal functions is needed to represent the input signal for a given rms error. Moreover, the KLT results in decorrelated transform coefficients (diagonal covariance matrix) and minimizes the total entropy compared to any other transform. However, the computational time needed to calculate the KLT basis vectors (functions) is very intensive. This is due to the fact that the KLT basis vectors are based on determining the eigenvalues and corresponding eigenvectors of the covariance matrix of the original data, which can be a large symmetric matrix. The lengthy processing requirement of the KLT has led to the use of suboptimum transforms with fast algorithms (i.e., FT, WT, CT, HT, etc). Unlike the KLT, the basis vectors of these suboptimum transforms are input-independent (predetermined). For instance, the basis vectors in the FT are simply sines and cosines (fundamental frequency and multiples thereafter), whereas the WT basis vectors are square waves of different sequences. It should be pointed out that the performance of these suboptimal transforms is usually upper-bounded by the one of the KLT.

During the early 1960's, many reports on the representation (compression) of ECG's by transformation method were presented: FT [93], [94], orthonormal exponentials [95], and KLT [96]–[98]. Later work on the utilization of the KLT [99]–[103] and FT [104] have also been reported. HT and CT were also used in [100]. Discussion on the employment of WT in ECG data compression is given in [105] and further studied in [106]–[107]. Among these ECG transformation techniques, the highest compression ratio for multilead ECG data was achieved (as expected) by utilizing the KLT.

Dual application of the KLT [101] to a vector lead ECG (X, Y, and Z leads of the VCG in the Frank coordinate system) partitioned into a P wave and a ORST segment have resulted in a compression ratio of 12:1. The first KLT application performs reduction of the respiration effects that may be imposed on ECG waveforms and requires the solution of a 3×3 matrix. The second application attempts to compress the ECG data by applying the KLT expansion (requires the solution of a 150×150 matrix) and retaining only a certain number of the large eigenvalues and corresponding eigenvectors. The ECG signal was reconstructed using 20 KLT coefficients (60 for the three leads) compared to the 250 Hz sampled original signal.

Ahmed *et al.* [100] applied the KLT, CT, and HT to a single-lead canine ECGs. It was reported that the KLT resulted in the highest compression ratio (3:1 over 400 Hz sampled ECG's among the other transforms. Reddy and Murthy [104] employed the two-dimensional FT for the compression of two-orthogonal ECG leads (X, Y). A compression ratio of 7.4:1 was reported with PRD of 7%, when tested on ECG signals sampled at 250 Hz with 12 b precision. Shridhar *et al.* [108] compared FT among DPCM with linear prediction and slope change detection (actually the FOP of Section A-1.a) for single-lead ECG compression. They concluded that compression by FT results in the least performance compared to the other two direct data compression techniques.

TABLE I
SUMMARY OF SOME ECG DATA COMPRESSION SCHEMES

Method	CR	SF (Hz) Precision (Bits)	PRD (%)	Wave—Recognition	Comments
AZTEC [51]	10.0	500 12	28.0	Implied	Poor P and T Fidelity
TP [59]	2.0	200 12	5.3	No	Sensitive to SF
CORTES [60]	4.8	200 12	7.0	Implied	Sensitive to SF, Poor P Fidelity
Fan/SAPA [24]	3.0	250 —	4.0	No	High Fidelity
Entropy Coding of second-difference ECGs [79]	2.8	250 10	—	No	Susceptible to transmission errors
Peak-Picking (Spline) with Entropy Encoding [83]	10.0	500 8	14.0	Implied	Limited Results
DPCM—Delta Coding with Threshold [73]	4.0	300 8	—	No	Sensitive to SF, Poor P Fidelity, (X,Y,Z) Leads
DPCM—Linear Prediction [77]	2.5	250 12	—	No	High Fidelity
DPCM–Linear Predict ,Interpl.,and Entropy Coding [30]	7.8	500 8	3.5	No	Sensitive to SF and Quantization
Orthogonal Transforms- CT, KLT, HT [100]	3.0	250 —	—	Yes	Lead-I
Dual application of K-L Transformation [101]	12.0	250 12	—	Yes	(X,Y,Z) Leads
Fourier Descriptors [104]	7.4	250 12	7.0	Yes	(X,Y) Leads

V. DISCUSSION

As can be anticipated from the previous sections, direct data compression methods are widely employed in ECG data compression. This is mainly due to the ease of implementation of such techniques. On the other hand, limited work has been reported on ECG data compression by transformation techniques. This has been primarily due to the computational requirement, and in some cases due to the low achieved compression ratios (especially in single-lead ECG compression). It should be noted, however, that the state-of-the-art technology such as VLSI design (i.e., digital signal processing (DSP) chips) has not been employed in implementing transformation ECG data compression schemes. The employment of DSP chips would allow the development of efficient real-time transformation ECG compression techniques.

As discussed in Section II, ECG data compression techniques comparison, based in absolute terms on the reported compression ratios, is improper. In fact, the compression ratio calculation of such techniques has been based on comparing the resulted compression parameters with the number of samples in the original data. Among many factors, sampling rate and precision of the "input" ECG data, and the word-length of the "output" compression parameters, which directly affect the compression ratio value, have not been taken into consideration. Table I provides a summary of ECG data compression techniques in terms of compression ratio (CR), sampling frequency (SF) and A/D precision level, percent rms difference (PRD), ECG wave-detection requirement, and pertinent reported comments whenever available. The sampling rate and precision of ECG signals originally employed in each compression method are reported in an attempt to form some basis of comparison among such techniques. For example, the AZTEC yields a CR of 10:1 when referred to the original ECG samples digitized at 500 Hz. However, when one considers ECG's sampled at 200 Hz, the compression ratio is expected to deteriorate (e.g., a CR of 5:1 as reported in [60]).

A comparison among five ECG data compression techniques using idealized ECG waveforms was reported in [65]. The compared techniques were voltage-triggered (ZOP of Section A-1.a), two-point projection (FOI-2DF of Section A-1.b), second differences (FOP of Section A-1.a), CORTES, and the Fan. In comparison with the other methods, the Fan algorithm produced reconstructed waveforms with the lowest rms error for greater or the same data compression ratio as the other four methods. It was also reported that the performance of the CORTES deteriorated substantially whenever it was used with sampling rates higher than the original 200 Hz sampling rate. Another study [42] has compared the performance of DPCM systems using polynomial [see (2)] and linear [see (6)] predictors. It was found that DPCM systems employing linear predictors are to be preferred only in the case when the ECG is oversampled.

One strategy for arriving at a profound conclusion in comparing ECG compression techniques, is to process all these techniques using one large set of ECG's and their performance are evaluated with a common measure of "goodness." The employment of the PRD in evaluating ECG compression schemes has no practical value. Although the rms error between original waveforms and reconstructed waveforms is a common form of comparison, it does not reveal whether or not an algorithm can preserve diagnostically significant features of the ECG waveform. The sampling frequency, precision, and the noise level of the original ECG's should not be chosen to accord the compression algorithm, but rather they should be determined according to the required ECG waveform information to be preserved.

VI. Framework for ECG Compression Techniques Comparison

In order to assess the relative merits of ECG data compression techniques, a framework for comparison must be established. Six factors must be considered for ensuring a solid basis of comparison among ECG compression techniques. All comparisons must be made on a) identical application lead bandwidth (i.e., monitoring, diagnostics, or Holter) while meeting the minimum acceptable error criteria for ECG preservation [109], [110]. b) All data should be from standard databases (e.g., AHA [111], MIT-BIH [112], and/or CSE [113]. Database must be of wide bandwidth to include all ECG information and quantized to meet sensitivity requirements. c) Filtering of wideband data, to meet application bandwidth criteria (i.e., Holter monitoring [114]), must be linear phase to preserve all essential information [115]–[118] while minimizing phase distortion. d) Quantization levels must be sufficiently large to ensure preservation of information, while quantization into the noise floor only increases storage overhead. e) The final output rate compared to the input rate (compression ratio) should be presented in bits/second so that sampling and quantization effects on the calculation of the compression ratio be alleviated. f) Finally, the reconstructed ECG signals must meet or exceed specific error criteria for ECG segments and waves. These error criteria must be clinically application dependent. For instance, changes in the *P* wave of the ECG signal impose little effect on the computerized Holter ECG analysis. The development of such criteria is beyond the scope of this paper.

Several factors set the required quantization level for the ECG including the preservation of sensitivity [109], [110], [113], the required addition of a dynamic range to avoid signal clipping, and the noise floor associated with ECG amplifier electronics and lead electrodes [119], [120]. An early study by Berson *et al.* [121] demonstrated that 10 b of quantization to be adequate for eliminating any significant "observable" error in the ECG waveform. The required quantization level (n) to achieve the necessary sensitivity requirement is given by

$$n_{\min} \geq \frac{20 \log \left(\dfrac{V_{FS}}{|V_{ECG}|} \right) + 20 \log \left(\dfrac{|V_{ECG}|}{V_{SEN}} \right)}{6 \text{ dB/bit}}$$

where

V_{FS} —the peak-to-peak input of the A/D converter referred to the amplifier input

V_{ECG}—the ECG *QRS* magnitude, classically assumed to be 1 mV_{pp}

V_{SEN}—the desired signal preservation level.

For instance, if $V_{FS} = \pm 5$ mV, $V_{ECG} = 1$ mV, and $V_{SEN} = 10\ \mu$V, then $n \geq 10$ b.

The maximum useful quantization level can be estimated by calculating the effective rms noise at the ECG amplifier input. This rms noise is given by

$$V_N = \sqrt{V_{EN}^2 + V_{AN}^2}$$

where

V_{AN}—the effective noise at the ECG amplifier input due to the amplifier electronics

V_{EN}—the equivalent electrical noise of the electrodes.

The maximum noise in diagnostic electrocardiographic noise is set by ANSI [119]. For a typical ECG amplifier front-end (e.g., analog devices AD-2865) V_{AN} equal 1 μV rms. By equating the rms A/D quantization noise to the signal noise, the maximum useful quantization level can be calculated as follows:

$$n_{\max} \leq \frac{20 \log (V_{FS}/V_N)}{6 \text{ dB}} - 1.$$

The required sampling rate for the elimination of aliasing is dependent on the quantization level, ECG information bandwidth, and filtering. It can be shown that the required sampling rate (f_s) to avoid spectral foldover must be

$$f_S \geq 2 f_F \left[\log^{-1} \left[\frac{\left(6n - k_{ECG} \log \left(\dfrac{f_F}{F_{ECG}} \right)\right)}{k_{ECG} + k_F} \right] \right]$$

where

f_F —the 3 dB filter frequency

f_{ECG} —the break frequency of the final slope of the ECG spectrum (approximately 60 Hz)

k_{ECG}—the high frequency rolloff (dB/Decade) of the ECG spectrum beyond 60 Hz (approximately 20 dB/Decade)

k_F —the slope of the low-pass linear phase filter function applied to the wideband ECG signal in dB/Decade

n —the quantization level (number of bits).

This results in a conservative choice for f_s. The k_{ECG} and F_{ECG} values can be estimated as 20 dB/DEC and 60 Hz respectively from [114], [122], [123]. If one assumes a seven-pole linear phase filter (e.g., Bessel filter) with a cutoff frequency of 75 Hz and $n = 10$, then f_s should be greater than 457 Hz.

In summary we have offered an analytical base for selecting the sampling frequency (f_s) and the quantization level (n) for ECG's prior to compression processing. ECG data must be from a wideband standard database, processed to an application bandwidth by linear phase filter, and reconstructed without violating ECG segment and wave error criteria. Following these recommendations, straight forward comparison among ECG compression techniques can be made based on the output data rate (bits/second) for identical leads and applications. The authors are unaware of specific recommendations that set acceptable error criteria for ECG waves and segments as such for specific applications (i.e., monitoring, diagnostics, or Holter). The objective of such error criteria would be to preserve only essential diagnostic information while allowing efficient ECG data compression. This will also meet that plea of Willems [124] for a means to compare computer ECG analysis algorithms in addition to comparing compression ratios.

Conclusion

The authors have attempted to unify three decades of ECG data compression techniques. We have reviewed all popular techniques and demonstrated the analytical relation of each to the body of digital signal processing theory. Direct comparison of ECG methods is not possible and will not be possible without the establishment of standards. These include standards for databases, preprocessing for quantization, and ECG preservation for each specific application. ECG presentation standards consists of acceptable or allowable error criteria which are lead and application specific. The objective of these criteria is to preserve the minimum essential information required to ensure reliable clinical diagnosis for a specific ECG lead(s) application. Standards must, for the present, include diagnostic, Holter, monitoring, and fetal ECG's.

Untold dollars, research, and clinician time will continue to be used inefficiently until the NBS, FDA, or NIH along with the research and clinical communities establish and maintain purposeful standards for ECG compression and diagnosis.

The results of this standardization effort will include the following benefits: 1) a direct comparison of existing ECG compression techniques, 2) the focusing of limited research personnel and technological resources on the real problem, 3) target performance objectives for manufacturers of medical equipment and services, 4) long awaited and overdue methods to allow direct comparison of vendors equipment and services by the clinical engineering community, and 5) improved quality of health care through a) more uniform, consistent, and proven methods, and b) elimination of proprietary solutions which are too often less than optimum, poorly substantiated, and costly.

References

[1] C. E. Shannon and W. Weaver, *The Mathematical Theory of Communication* Urbana, IL: Univ. Illinois Press, 1949.

[2] M. P. Ristenbatt, "Alternatives in digital communications," *Proc. IEEE*, vol. 61, pp. 703-721, June 1973.

[3] D. A. Lelewer and D. S. Hirschberg, "Data compression," *ACM Computing Surveys*, vol. 19, pp. 261-296, Sept. 1987.

[4] T. J. Lynch, *Data Compression: Techniques and Applications.* Belmont, CA: Lifetime Learning Publications, 1985.

[5] W. R. Daumer, "Subjective evaluation of several efficient speech coders," *IEEE Trans. Commun.*, vol. COM-30, pp. 567-573, Apr. 1982.

[6] H. K. Reghbati, "An overview of data compression techniques," *IEEE Comput.*, vol. 14, pp. 71-75, May 1981.

[7] A. K. Jain, "Image data compression," *Proc. IEEE*, vol. 69, pp. 349-389, Mar. 1981.

[8] A. N. Netravali and J. O. Limb, "Picture coding: A review," *Proc. IEEE*, vol. 68, no. 3, pp. 366-406, Mar. 1980.

[9] L. D. Davisson and R. M. Gray, Eds., *Data Compression.* New York: Halsted, 1976.

[10] A. Habibi and G. S. Robinson, "A survey of digital picture coding," *IEEE Comput.*, pp. 22-34, May 1974.

[11] L. C. Wilkins and P. A. Wintz, "Bibliography on data compression, picture properties, and picture coding," *IEEE Trans. Inform. Theory*, vol. IT-17, pp. 180-197, Mar. 1971.

[12] C. A. Andrews, J. M. Davies, and G. R. Schwarz, "Adaptive data compression," *Proc. IEEE*, vol. 55, pp. 267-277, Mar. 1967.

[13] M. Shridhar and N. Mohankrishnan, "Data compression techniques for electrocardiograms," *Can. Elec. Eng. J.*, vol. 9, no. 4, pp. 126-131, 1984.

[14] L. D. Davisson, "The theoretical analysis of data compression systems," *Proc. IEEE*, vol. 56, pp. 176-186, Feb. 1968.

[15] R. W. Schafer, and L. R. Rabiner, "A digital signal processing approach to interpolation," *Proc. IEEE*, vol. 61, pp. 692-702, June 1973.

[16] J. Makhoul, "Linear prediction: A tutorial review," *Proc. IEEE*, vol. 63, pp. 561-580, Apr. 1975.

[17] L. D. Davisson, "An approximation of prediction for data compression," *IEEE Trans. Inform. Theory*, vol. IT-13, pp. 274-278, Apr. 1967.

[18] —, "Data compression using straight line interpolation," *IEEE Trans. Inform. Theory*, vol. IT-14, pp. 390-394, May 1968.

[19] L. Ehrman, "Analysis of some redundancy removal bandwidth compression techniques," *Proc. IEEE*, vol. 55, pp. 278-287, Mar. 1967.

[20] Special issue on redundancy reduction, *Proc. IEEE*, vol. 55, Mar. 1967.

[21] D. R. Weber and F. J. Wynhoff, "The concept of self-adaptive data compression," in *Proc. IRE Nat. Symp. Space Electron. Telemetry*, IEEE LG-SET REC., Sect. 4.1, 1962, pp. 1-10.

[22] J. E. Medlin, "Sampled-data prediction for telemetry bandwidth compression," *IEEE Trans. Space Electron. Telem.*, vol. SET-11, pp. 29-36, Mar. 1965.

[23] D. R. Weber, "A synopsis on data compression," in *Proc. 1965 Nat. Telemetering Conf.* (NTC), 1965, pp. 9-16.

[24] L. W. Gardenhire, "Redundancy reduction the key to adaptive telemetry," in *Proc. 1964 Nat. Telemetry Conf.*, 1964, pp. 1-16.

[25] C. M. Kortman, "Redundancy reduction-a practical method of data compression," *Proc. IEEE*, vol. 55, pp. 253-263, Mar. 1967.

[26] R. van Blerkom, G. R. Schwarz, and R. J. Ward, "An adaptive composite data compression algorithm with reduced computation requirements," in *Proc. 1968 Nat. Telemetry Conf.*, 1968, pp. 90-95.

[27] G. Benelli, V. Cappellini, and F. Lotti, "Data compression techniques and applications," *Radio Electron. Eng.*, vol. 50, no. 1/2, pp. 29-53, 1980.

[28] N. S. Jayant and S. W. Christensen, "Adaptive aperture coding for speech waveforms-1," *Bell Syst. Tech. J.*, vol. 58, pp. 1631-1644, Sept. 1979.

[29] N. S. Jayant and P. Noll, *Digital Coding of Waveforms: Principles and Applications to Speech and Video.* Englewood Cliffs, NJ: Prentice-Hall, 1984, pp. 480-482.

[30] U. E. Ruttimann and H. V. Pipberger, "Compression of the ECG by prediction or interpolation and entropy encoding," *IEEE Trans. Biomed. Eng.*, vol. BME-26, pp. 613-623, Nov. 1979.

[31] —, "Date compression and the quality of the reconstructed ECG," in *Optimization of Computer ECG Processing*, H. K. Wolf, and P. W. MacFarlane, Eds. New York: North-Holland, 1980, pp. 77-85.

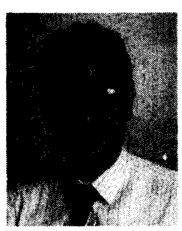
[32] B. M. Oliver, "Efficient coding," *Bell Syst. Tech. J.*, vol. 31, pp. 724-750, July 1952.

[33] P. Elias, "Predictive coding—Part I and Part II," *IRE Trans. Inform. Theory*, vol. IT-1, pp. 16-33, Mar. 1955.

[34] R. A. McDonald, "Signal to noise and idle channel performance of DPCM systems—particular application to voice signals," *Bell Syst. Tech. J.*, vol. 45, pp. 1123-1151, Sept. 1966.

[35] R. W. Donaldson and D. Chan, "Analysis and subjective evaluation of differential pulse-code modulation in voice communication systems," *IEEE Trans. Commun.*, vol. COM-17, pp. 10-19, Feb. 1969.
[36] C. S. Xydeas and R. Steele, "Dynamic ratio quantizer," in *Proc. Instn. Elect. Eng.*, vol. 125, Jan. 1978, pp. 25-29.
[37] N. S. Jayant, "Digital coding of speech waveforms: PCM, DPCM, and DM quantizers," *Proc. IEEE*, vol. 62, pp. 611-632, May 1974.
[38] P. Cummiskey, N. S. Jayant, and J. C. Flanagan, "Adaptive quantization in differential PCM coding of speech," *Bell Syst. Tech. J.*, vol. 52, pp. 1105-1118, Sept. 1973.
[39] L. R. Rabiner and R. W. Schafer, *Digital Processing of Speech Signals.* Englewood Cliffs, NJ: Prentice-Hall, 1978.
[40] J. B. O'Neal, Jr., "A bound on signal-to-quantizing noise ratios for digital encoding systems," *Proc. IEEE*, vol. 55, pp. 287-292, Mar. 1967.
[41] —, "Entropy coding in speech and television differential PCM systems," *IEEE Trans. Inform. Theory*, vol. IT-17, pp. 758-761, Nov. 1971.
[42] O. Pahlm, P. O. Börjesson, and O. Werner, "Compact digital storage of ECGs," *Comput. Programs Biomed.*, vol. 9, pp. 292-300, 1979.
[43] C. E. Shannon, "A mathematical theory of communication," *Bell Syst. Tech. J.*, vol. 27, pp. 379-423, July 1948.
[44] D. A. Huffman, "A method for the construction of minimum-redundancy codes," *Proc. IRE*, vol. 40, pp. 1098-1101, Sept. 1952.
[45] I. H. Witten, R. M. Neal, and J. G. Cleary, "Arithmetic coding for data compression," *Commun. ACM*, vol. 30, pp. 520-540, June 1987.
[46] H. Tanaka, "Data structure of Huffman codes and its application to efficient encoding and decoding," *IEEE Trans. Inform. Theory*, vol. 33, pp. 154-156, Jan. 1987.
[47] G. V. Cormack, and R. N. Horspool, "Algorithms for adaptive Huffman codes," *Inform. Process. Lett.*, vol. 18, pp. 159-165, Mar. 1984.
[48] E. N. Gilbert, "Codes based on inaccurate source probabilities," *IEEE Trans. Inform. Theory*, vol. 17, pp. 304-314, May 1971.
[49] E. S. Schwartz, "An optimum encoding with minimum longest code and total number of digits," *Inform. Control*, vol. 7, pp. 37-44, Mar. 1964.
[50] S. K. Goyal and J. B. O'Neal, Jr., "Entropy coded differential pulse-code modulation systems for television," *IEEE Trans. Commun.*, vol. COM-23, pp. 660-666, June 1975.
[51] J. R. Cox, F. M. Nolle, H. A. Fozzard, and G. C. Oliver, "AZTEC, a preprocessing program for real-time ECG rhythm analysis," *IEEE Trans. Biomed. Eng.*, vol. BME-15, pp. 128-129, Apr. 1968.
[52] J. R. Cox, H. A. Fozzard, F. M. Nolle, and G. C. Oliver, "Some data transformations useful in electrocardiography," in *Computers and Biomedical Research vol. III*, R. W. Stacy and B. D. Waxman, Eds. vol. III. New York: Academic, 1974, pp. 181-206.
[53] J. R. Cox, F. M. Nolle, and R. M. Arthur, "Digital analysis of the electroencephalogram, the blood pressure wave, and the ECG," *Proc. IEEE*, vol. 60, pp. 1137-1164, Oct. 1972.
[54] C. A. Steinberg, S. Abraham, and C. A. Caceres, "Pattern recognition in the clinical electrocardiogram," *IRE Trans. Biomed. Electron.*, vol. BME-9, pp. 35-42, 1962.
[55] J. P. Abenstein, "Algorithms for real-time ambulatory ECG monitoring," *Biomed. Sci. Instrument.*, vol. 14, pp. 73-79, 1978.
[56] B. Furht and A. Perez, "An adaptive real-time ECG compression algorithm with variable threshold," *IEEE Trans. Biomed. Eng.*, vol. 35, pp. 489-494, June 1988.
[57] S. M. S. Jalaleddine, C. G. Hutchens, W. A. Coberly, and R. D. Strattan, "Compression of Holter ECG data," *Biomed. Sci. Instrument.*, vol. 24, pp. 35-45, Apr. 1988.
[58] —, "Data compression of Holter ECG's," M.S. thesis, Univ. Tulsa, Tulsa, OK, 1987.
[59] W. C. Mueller, "Arrhythmia detection program for an ambulatory ECG monitor," *Biomed. Sci. Instrument.*, vol. 14, pp. 81-85, 1978.
[60] J. P. Abenstein and W. J. Tompkins, "New data-reduction algorithm for real-time ECG analysis," *IEEE Trans. Biomed. Eng.*, vol. BME-29, pp. 43-48, Jan. 1982.
[61] W. J. Tompkins and J. G. Webster, Eds., *Design of Microcomputer-Based Medical Instrumentation.* Englewood Cliffs, NJ: Prentice-Hall, 1981.
[62] R. C. Barr, S. M. Blanchard, and D. A. Dipersio, "SAPA-2 is the Fan," *IEEE Trans. Biomed. Eng.*, vol. BME-32, p. 337, May 1985.
[63] L. W. Gardenhire, "Data compression for biomedical telemetry," in *Biomedical Telemetry*, C. A. Caceres, Ed. New York: Academic, 1965, ch. 11.
[64] L. D. Davisson, "The Fan method of data compression," 1966 Goddard summer workshop, NASA TM X-55742, X-700-67-94, Final Rep., pp. 23-30, 1967.
[65] S. M. Blanchard and R. C. Barr, "Comparison of methods for adaptive sampling of cardiac electrograms and electrodcardiograms," *Med. Biol. Eng. Comput.*, vol. 23, pp. 377-386, July 1985.
[66] D. A. Dipersio and R. C. Barr, "Evaluation of the Fan method of adaptive sampling on human electrocardiograms," *Med. Biol. Eng. Comput.*, vol. 23, pp. 401-410, Sept. 1985.
[67] A. E. Pollard and R. C. Barr, "Adaptive sampling of intracellular and extracellular cardiac potentials with the Fan method," *Med. Biol. Eng. Comput.*, vol. 25, pp. 261-268, May 1987.
[68] M. Ishijima, S. B. Shin, G. H. Hostetter, and J. Sklansky, "Scan-along polygon approximation for data compression of electrocardiograms," *IEEE Trans. Biomed. Eng.*, vol. BME-30, pp. 723-729, Nov. 1983.
[69] J. Sklansky and V. Gonalez, "Fast polygonal approximation of digitized curves," *Pattern Recog.*, vol. 12, pp. 327-331, 1980.
[70] I. Tomek, "Two algorithms for piecewise-linear continuous approximation of functions of one variable," *IEEE Trans. Comput.*, pp. 445-448, Apr. 1974.
[71] H. K. Wolf, J. Sherwood, and P. M. Rautaharju, "Digital in transmission of electrocardiograms—A new approach," in *Proc. 4th Can. Med. Biol. Conf.*, 1972, pp. 39a-39b.
[72] M. Bertrand, R. Guardo, G. Mathieu, P. Blondeau, and R. LeBlanc, "A microprocessor-based system for ECG encoding and transmission," in *Proc. 28th Annu. Conf. Eng. Med. Biol.*, 1975, p. 435.
[73] D. Stewart, G. E. Dower, and O. Suranyi, "An ECG compression code," *J. Electrocardiol.*, vol. 6, no. 2, pp. 175-176, 1973.
[74] M. Bertrand, R. Guardo, F. Roberge, and P. Blondeau, "Microprocessor application for numerical ECG encoding and transmission," *Proc. IEEE*, vol. 65, pp. 714-722, May 1977.
[75] D. Stewart, D. Berghofer, and R. G. Dower, "Data compression of ECG signals," *Eng. Foundation Conf. Computerized Interpretation of the ECG*, Asilomar, CA., pp. 162-177 & A1-A8, Jan. 1979,
[76] U. E. Ruttimann, A. S. Berson, and H. V. Pipberger, "ECG data compression by linear prediction," *Computers Cardiol.*, pp. 313-315, St. Louis, MO 1976.
[77] A. S. Krishnakumar, J. L. Karpowicz, N. Belic, D. H. Singer, and J. M. Jenkins, "Microprocessor-based data compression scheme for enhanced digital transmission of Holter recordings," *Computers Cardiol.*, Long Beach, CA, pp. 435-437, 1980.
[78] P. Borjesson, G. Einarsson, and O. Pahlm, "Comments on Compression of the ECG by prediction or interpolation and entropy encoding," *IEEE Trans. Biomed. Eng.*, vol. BME-27, pp. 674-675, Nov. 1980.
[79] J. R. Cox and K. L. Ripley, "Compact digital coding of electrocardiographic data," in *Proc. VI Int. Conf. Syst. Sci.*, Jan. 1973, pp. 333-336.
[80] J. Whitman and H. K. Wolf, "An encoder for electrocardiogram data with wide range of applicability," in *Optimization of Computer ECG Processing*, H. K. Wolf and P. W. MacFarlane, Eds. New York: North-Holland, 1980, pp. 87-90.
[81] H. O. Burton and D. D. Sullivan, "Error and error control," *Proc. IEEE*, vol. 60, pp. 1263-1301, Nov. 1972.
[82] R. W. McCaughern, A. M. Rosie, and F. C. Monds, "Asynchronous data compression techniques," in *Proc. Purdue Centennial Year Symp. Information Process.*, vol. 2, Apr. 1969, pp. 525-531.
[83] H. Imai, N. Kimura, and Y. Yoshida, "An efficient encoding method for electrocardiography using Spline functions," *Syst. Comput. Japan*, vol. 16, no. 3, pp. 85-94, 1985.
[84] T. S. Ibiyemi, "A novel data compression technique for electrocardiogram classification," *Eng. Med.*, vol. 15, no. 1, pp. 35-38, 1986.
[85] G. Lachiver, J. M. Eichner, F. Bessette, and W. Seufert, "An algorithm for ECG data compression using spline functions," *Comput. Cardiol.*, Boston, MA, Oct. 1986, pp. 575-578.
[86] E. A. Giakoumakis and G. Papakonstantinou, "An ECG data re-

duction algorithm," *Comput. Cardiol.*, Boston, MA, Oct. 1986, pp. 675-677.
[87] N. J. Holter, "New method for heart studies," *Science*, vol. 134, pp. 1214-1220, 1961.
[88] S. M. S. Jalaleddine and C. G. Hutchens, "Ambulatory ECG wave detection for automated analysis: A review," *ISA Trans.*, vol. 26, pp. 33-44, Oct. 1987 and *Biomed. Sci. Instrument.*, vol. 23, pp. 95-106, Apr. 1987.
[89] O. Pahlm and L. Sörnmo, "Software *QRS* detection in ambulatory monitoring—A review," *Med. Biol. Eng. Comput.*, vol. 22, pp. 289-297, 1984.
[90] N. Ahmed and K. R. Rao, *Orthogonal Transforms for Digital Signal Processing.* New York: Springer, 1975.
[91] K. R. Rao and N. Ahmed, "Orthogonal transforms for digital signal processing," *IEEE Internat. Conf.* ASSP, pp. 136-140, 1976.
[92] D. F. Elliott and K. R. Rao, *Fast Transforms: Algorithms, Analysis and Applications.* New York: Academic, 1982.
[93] E. C. Lowenberg, "Signal theory applied to the analysis of electrocardiograms," *IRE Trans. Med. Electron.*, vol. ME-7, pp. 7-12, Jan., 1960.
[94] L. D. Cady, M. A. Woodbury, L. J. Tick, and M. M. Gertler, "A method for electrocardiogram wave-pattern estimation," *Circ. Res.*, vol. 9, pp. 1078-1082, 1961.
[95] T. Y. Young, and W. H. Huggins, "On the representation of electrocardiograms," *IEEE Trans. Biomed. Eng.*, vol. BME-10, pp. 86-95, July 1963.
[96] A. M. Scher, A. C. Young, and W. M. Meredith, "Factor analysis of the electrocardiograms—A test of electrocardiography theory: Normal leads," *Circ. Res.*, vol. 8, pp. 519-526, 1960.
[97] T. Y. Young and W. H. Huggins, "The intrinsic component theory of electrocardiography," *IEEE Trans. Biomed. Eng.*, vol. BME-9, pp. 214-221, Oct. 1962.
[98] L. G. Horan, N. C. Flowers, and D. A. Brody, "Principal factor waveforms of the thoractic *QRS* complex," *Circ. Res.*, vol. 12, pp. 131-145, 1964.
[99] A. R. Hambley, R. L. Moruzzi, and C. L. Feldman, "The use of intrinsic components in an ECG filter," *IEEE Trans. Biomed. Eng.*, vol. BME-21, pp. 469-473, Nov. 1974.
[100] N. Ahmed, P. J. Milne, and S. G. Harris, "Electrocardiographic data compression via orthogonal transforms," *IEEE Trans. Biomed. Eng.*, vol. BME-22, pp. 484-487, Nov. 1975.
[101] M. E. Womble, J. S. Halliday, S. K. Mitter, M. C. Lancaster, and J. H. Triebwasser, "Data compression for storing and transmitting ECGs/VCGs," *Proc. IEEE*, vol. 65, pp. 702-706, May 1977.
[102] A. M. Zied and E. Womble, "Application of a partitioned Karhunen-Loeve expansion scheme to ECG/VCG data compression," in *Proc. Eighth New England Bioeng. Conf.*, vol. 7, 1979, pp. 102-105.
[103] M. E. Womble and A. M. Zied, "A statistical approach to ECG/VCG data compression," in *Optimization of Computer ECG Processing*, H. K. Wolf and P. W. MacFarlane, Eds. New York: North-Holland, 1980, pp. 91-101.
[104] B. R. S. Reddy and I. S. N. Murthy, "ECG data compression using Fourier descriptors," *IEEE Trans. Biomed. Eng.*, vol. BME-33, pp. 428-434, Apr. 1986.
[105] W. S. Kuklinski, "Fast Walsh transform data-compression algorithm; ECG applications," *Med. Biol. Eng. Comput.*, vol. 21, pp. 465-472, July 1983.
[106] G. P. Frangakis, G. Papakonstantinou, and S. G. Tzafestas, "A fast Walsh transform-based data compression multi-microprocessor system: Application to ECG signals," *Math. Comput. Simulation*, vol. 27, pp. 491-502, 1985.
[107] T. A. De. Perez, M. C. Stefanelli, and F. D'Alvano, "ECG data compression via exponential quantization of the Walsh spectrum," *J. Clin. Eng.*, vol. 12, pp. 373-378, Sept.-Oct. 1987.
[108] M. Shridhar and M. F. Stevens, "Analysis of ECG data, for data compression," *Int. J. Bio-Med. Comput.*, vol. 10, pp. 113-128, 1979.
[109] American Heart Association Committee on Electrocardiography, "Recommendations for standardization of leads and specifications for instruments in electrocardiography and vectorcardiography," *Circulation*, vol. 52, no. 2 (Suppl.), pp. 11-31, Aug. 1975.
[110] American Heart Association Committee on Electrocardiography and Cardiac Electrophysiology of the Council on Clinical Cardiology," Recommendations for standards of instrumentation and practice in the use of ambulatory electrocardiography," *Circulation*, vol. 71, 626A-636A, Mar. 1985.
[111] R. Hermes, D. B. Geselowitz, and G. Oliver, "Development distribution, and use of the American Heart Association database for ventricular arrhythmia detector evaluation," *Comput. Cardiol.*, Long Beach, CA, pp. 263-266, 1980.
[112] R. G. Mark, P. S. Schluter, G. B. Moody, P. H. Devlin, and D. Chenroff, "An annotated ECG database for evaluating arrhythmia detectors," in *Proc. IEEE Frontiers Eng. Health Care*, 1982, pp. 205-210.
[113] The CSE European Working Party, "Establishment of a reference library for evaluating computer ECG measurement programs," *Comput. Biomed. Res.*, vol. 18, pp. 439-457, 1985.
[114] V. K. Murthy *et al.*, "Analysis of power spectral densities of electrocardiograms," *Math. Biosci.*, vol. 12, pp. 41-51, 1971.
[115] R. G. Gold, "Do we need a new standard for electrocardiographs?," *Brit. Heart J.*, vol. 54, pp. 119-120, 1985.
[116] D. Taylor and R. Vincent, "Signal distoration in the electrocardiogram due to inadequate phase response," *IEEE Trans. Biomed. Eng.*, vol. BME-30, pp. 352-356, June 1983.
[117] D. Taylor, P. Finch, and R. Vincent, "Linear phase filtering—A new approach to distortion-free electrocardiograms," *Comput. Cardiol.*, Linkoping, Sweden, pp. 283-286, Sept. 1985.
[118] R. L. Longini, J. P. Giolma, C. Wall, III, and R. F. Quick, "Filtering without phase shift," *IEEE Trans. Biomed. Eng.*, vol. BME-22, pp. 432-433, Sept. 1975.
[119] American National Standard for Diagnostic Electrocardiographic Devices. ANSI/AAMI EC18-1982. Arlington, VA, Association for the Advancement of Medical Instrumentation, 1983.
[120] American National Standard for Pregelled Disposable Electrodes. ANSI/AAMI EC12-1983. Arlington, VA, Amer. Assoc. Advanc. Med. Instrument., 1983.
[121] A. S. Berson, J. M. Wojick, and H. V. Pipberger, "Precision requirements for electrocardiographic measurements computed automatically," *IEEE Trans. Biomed. Eng.*, vol. BME-24, pp. 382-385, July 1977.
[122] A. M. Scher and A. C. Young, "Frequency analysis of the electrocardiogram," *Circ. Res.*, vol. 8, pp. 344-346, Mar. 1960.
[123] D. Tayler and R. Vincent, "Artefactual ST segment abnormalities due to electrocardiograph design," *Brit. Heart J.*, vol. 54, pp. 121-128, 1985.
[124] J. L. Willems, "A plea for common standards in computer aided ECG analysis," *Comput. Biomed. Res.*, vol. 13, pp. 120-131, 1980.



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