Open access • Journal Article • DOI:10.1109/10.871403

ECG signal compression using analysis by synthesis coding — Source link

Yaniv Zigel, Arnon D. Cohen, Amos Katz

Institutions: Ben-Gurion University of the Negev

Published on: 01 Oct 2000 - IEEE Transactions on Biomedical Engineering (IEEE)

Topics: Data compression ratio, Signal compression, Data compression, Speech coding and Quantization (signal processing)

ECG Signal Compression Using Analysis by Synthesis Coding

Yaniv Zigel*, Arnon Cohen, and Amos Katz

Abstract—**In this paper, an elecrocardiogram (ECG) compression algorithm, called analysis by synthesis ECG compressor (ASEC), is introduced. The ASEC algorithm is based on analysis by synthesis coding, and consists of a beat codebook, long and short-term predictors, and an adaptive residual quantizer. The compression algorithm uses a defined distortion measure in order to efficiently encode every heartbeat, with minimum bit rate, while maintaining a predetermined distortion level. The compression algorithm was implemented and tested with both the percentage rms difference (PRD) measure and the recently introduced weighted diagnostic distortion (WDD) measure.**

The compression algorithm has been evaluated with the MIT-BIH Arrhythmia Database. A mean compression rate of approximately 100 bits/s (compression ratio of about 30 : 1) has been achieved with a good reconstructed signal quality (WDD below 4% and PRD below 8%). The ASEC was compared with several well-known ECG compression algorithms and was found to be superior at all tested bit rates.

A mean opinion score (MOS) test was also applied. The testers were three independent expert cardiologists. As in the quantitative test, the proposed compression algorithm was found to be superior to the other tested compression algorithms.

Index Terms—**Analysis by synthesis, beat codebook, ECG compression, electrocardiogram, long term prediction.**

I. Introduction

THE NEED for ECG signal compression exists in many transmitting and storage applications. Transmitting the ECG signal through telephone lines, for example, may save a crucial time and unnecessary difficulties in emergency cases. Effective storage is required of large quantities of ECG information in the intensive coronary care unit, or in long-term (24–48 hours) wearable monitoring tasks (Holter). Holter monitoring usually requires continuous 12 or 24-hours ambulatory recording. For good diagnostic quality, each ECG lead should be sampled at a rate of 250–500 Hz with 12 bits resolution. The information rate is thus approximately 11–22 Mbits/hour/lead. The monitoring device ("Holter") must have a memory capacity of about 100–200 Mbytes for a 3-lead recording. Memory costs may render such a solid state Holter device impractical. If efficient compression methods are employed, memory requirements may drastically drop to make the solid state high quality Holter commercially feasible.

In practice, efficient data compression may be achieved only with lossy compression techniques (which allow reconstruction error). In ECG signal compression algorithms the goal is to achieve a minimum information rate, while retaining the relevant diagnostic information in the reconstructed signal.

Many algorithms for ECG compression have been proposed in the last thirty years [1]–[15]. Until today, all ECG compression algorithms have used simple mathematical distortion measures such as the percentage rms difference (PRD) for evaluating the reconstructed signal. Such measures are irrelevant from the point of view of diagnosis. Moreover, the use of the measure is not an integral part of the compression algorithm; it is used only to evaluate the compression result.

In this paper, a new ECG compression algorithm called analysis by synthesis ECG compressor (ASEC) is presented. It is based on analysis by synthesis coding and consists of a beat codebook, long and short-term predictors, and an adaptive residual quantizer. The compression algorithm uses a defined distortion measure in order to efficiently encode every heartbeat, with minimum bit rate, while maintaining a predetermined distortion level. The compression algorithm was implemented and tested with both the PRD measure and the recently introduced weighted diagnostic distortion (WDD) measure.

II. The Distortion Measures

Two distortion measures were implemented in order to run and test the proposed compression algorithm, the PRD and the WDD measure.

The PRD is one of the most popular distortion measures used in ECG compression algorithms [12], [16] and is given by

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

where

$x(n)$ original signal;

$\tilde{x}(n)$ reconstructed signal;

$\overline{x}(n)$ mean of $x(n)$;

N length of the window over which the PRD is calculated.

Sometimes in the literature, another definition is used, where the denominator of (1) is $\sum_{n=1}^{N} x(n)^2$. One has to be very careful

Manuscript received December 23, 1999; revised June 14, 2000. *Asterisk indicates corresponding author.*

*Y. Zigel is with the Electrical and Computer Engineering Department, Ben-Gurion University, P.O. Box 653, Beer-Sheva 84105, Israel (e-mail: yaniv@ee.bgu.ac.il).

A. Cohen is with the Electrical and Computer Engineering Department, Ben-Gurion University, Beer-Sheva 84105, Israel.

A. Katz is with the Cardiology Department Faculty of Health Sciences, Ben-Gurion University, Beer-Sheva 84105, Israel.

Publisher Item Identifier S 0018-9294(00)08519-0.

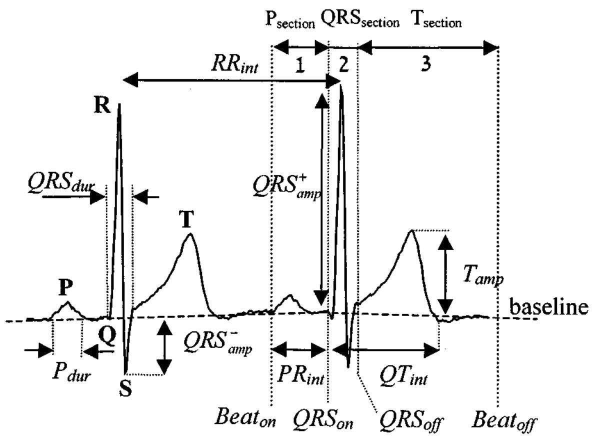

Fig. 1. Some of the diagnostic features used by the WDD (and beat segmentation).

with this definition, since it depends on the DC level of the original signal. If $x(n)$ contains a DC level, the PRD will show irrelevant low results. Moreover, for fair comparison of ECG signals, one has to flatten the baseline (see a baseline in Fig. 1). If the signal has fluctuated baseline, the variance of the signal will be higher, and the PRD will be artificially lower.

The PRD and other similar error measures [16] have many disadvantages, which result in poor diagnostic relevance. Therefore, the recently introduced WDD measure [17]–[19], [24] was also implemented in this work.

The WDD is based on comparing the PQRST complex features of the two ECG signals, the original ECG signal and the reconstructed one. The WDD thus measures the relative preservation of the diagnostic information in the reconstructed signal: the location, duration, amplitudes, and shapes of the waves and complexes that exist in every beat (PQRST complex). Fig. 1 shows some of the diagnostic features.

For every beat of the original signal and of the reconstructed signal, a vector of diagnostic features is defined.

$$\begin{aligned} \boldsymbol{\beta}^T &= [\beta_1, \beta_2, \ldots, \beta_p], \text{ original signal;} \\ \hat{\boldsymbol{\beta}}^T &= [\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_p], \text{ reconstructed signal} \end{aligned} \tag{2}$$

where p is the number of features in the vector.

The WDD (in percentage) between these two vectors is

$$\text{WDD}(\boldsymbol{\beta}, \hat{\boldsymbol{\beta}}) = \Delta\boldsymbol{\beta}^T \cdot \frac{\Lambda}{\text{tr}[\Lambda]} \cdot \Delta\boldsymbol{\beta} \times 100 \tag{3}$$

where $\Delta\boldsymbol{\beta}$ is the normalized difference vector

$$\Delta\boldsymbol{\beta}^T = [\Delta\beta_1, \Delta\beta_2, \ldots, \Delta\beta_p]. \tag{4}$$

Every scalar in this vector gives the relative distance between the original signal feature and the reconstructed signal feature. Λ [in (3)] is a diagonal weighting matrix [17]–[19], [24].

III. THE COMPRESSION ALGORTIHM

The ECG signal may be considered a quasiperiodic signal. The main redundancies in the ECG signal exist in the form of correlation between adjacent or past beats (interbeat correlation) and correlation between adjacent samples (intrabeat correlation) [12]. The interbeat correlation suggests the idea of using a long-term predictor (LTP) [12]. The frequent existence of abnormal beats in some pathological cases suggests using a beat codebook. The codebook is used to store "typical" past beats. The intrabeat correlation suggests using a short-term predictor, STP. With LTP, STP and a beat codebook, a predicted beat can be estimated, and a residual signal, which has lower variance, can be calculated. The analysis by synthesis model is used to efficiently code the residual signal, with minimum bit rate, while maintaining a predetermined error.

Fig. 2 shows the general scheme of the ASEC.

The ECG signal is first classified into one of two types: 1. Regular PQRST complex ECG signal (the lower branch), or to 2. Irregular ECG signal (the upper branch), such as ventricular fibrillation (VF) and ventricular tachycardia (VT). These irregular signals, in general are less probable than the regular PQRST signal. Because the irregular signals have no PQRST elements, they are not encoded like the regular ECG signal. In this article, only the compression algorithm of regular PQRST ECG signals is described. The algorithm of irregular signal detection and compression is described in [17].

The ASEC algorithm consists of three main subsystems: 1) preprocessing, 2) coding: codebook matching and long-term prediction (LTP), residue coding, error analysis, and 3) decoding. The ECG signal is processed beat by beat. The incoming beat is segmented into three time regions (Fig. 1), which are then coded separately. The beat is matched with the codebook to find the best matching stored beat ("codeword"). LTP coding is performed using the chosen codeword to produce the LTP estimated (predicted) signal $\hat{x}(n)$. The difference between the original signal $x(n)$ and the LTP estimated signal $\hat{x}(n)$ is defined as the residue. The residue undergoes STP coding and adaptive quantization to produce the coded signal. Prior to transmission, the signal to be transmitted is decoded, and the quality of the reconstructed signal is tested (by means of WDD or PRD measure). The residual signal is re-encoded with higher bit rate till the quality of the reconstructed signal is satisfied (below a predetermined distortion threshold).

A. The Preprocessing Stage

The ECG signal is processed prior to compression. The preprocessing stage consists of segmentation, nonuniform filtering, and baseline removal. The segmentation divides the ECG signal into beats (complexes), and every beat is further divided into the three sections: $\text{P}_{\text{section}}$, $\text{QRS}_{\text{section}}$, and $\text{T}_{\text{section}}$. Fig. 1 shows this segmentation.

The motivation for such beat segmentation arises from the fact that every one of the three sections has a different diagnostic meaning and a different power spectral density.

The nonuniform filtering consists of two different finite impulse response (FIR) filters. The P and T sections are filtered with a 0.01–50 Hz bandpass FIR filter, and the QRS section is filtered with 0.1–100 Hz bandpass FIR filter. The filters are switched according to segmentation. The last part of the preprocessing stage is the baseline removal [17].

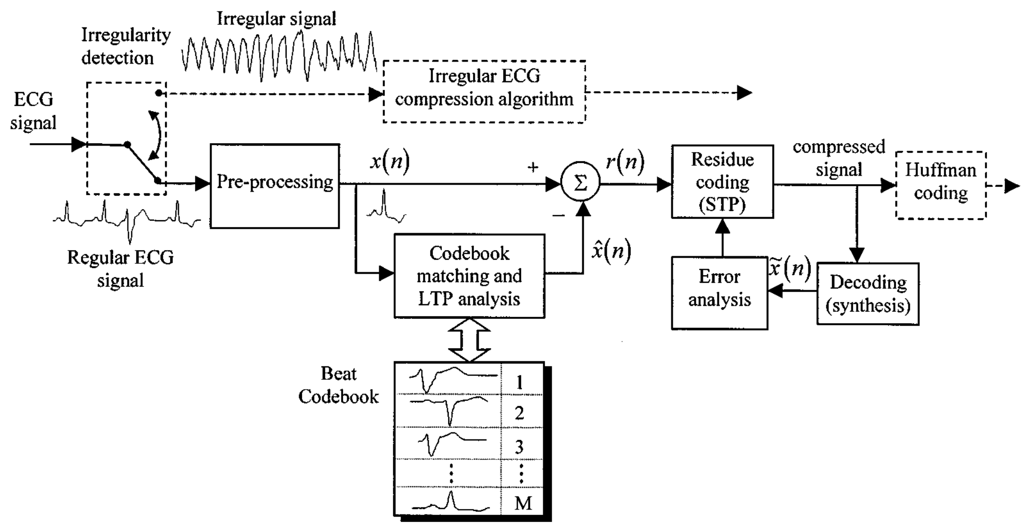

Fig. 2. General scheme of the ASEC. Huffman coding (which was not implemented) can improve the results by approximately 10%.

B. The Encoding System

The Beat Codebook Matching and LTP: This subsystem consists of an adaptive beat codebook. The codebook holds M past "typical" PQRST beat waveforms. Fig. 3 shows the exact process of codebook matching, LTP analysis, and predicted signal production.

The encoder matches the current preprocessed beat $x(n)$ with the best codeword $CW(n)$ from the beat codebook, and estimates the LTP coefficients $\mathbf{a}$ (five-dimension vector) [12]. This LTP coefficients vector undergoes vector quantization. The quantized vector, $\mathbf{a}_q$, forms an MA filter by means of which the estimated (predicted) beat $\hat{x}(n)$ is generated from the beat codeword $CW(n)$. The residual between the original beat and the predicted one is calculated

$$r(n) = x(n) - \hat{x}(n). \tag{5}$$

The beat (pattern) codebook stores M ECG beats, called codewords (CW_i; $i = 1, 2, \ldots, M$). Each pattern is a PQRST vector of N_i samples. When a new beat is to be coded, it is matched with the beat codebook. The choice of the best suitable beat codeword (from the codebook) is performed by a similarity or error measure, such as maximum correlation, or minimum error (E) for each one of the beat codewords. In this paper, the mean squared error between the current beat of the analyzed signal and the ith codeword E_i is calculated (after R wave synchronization). If the length of the ith codeword (N_i) is different from the length of the original beat (N), the codeword is cut or zero padded at the edges. The best matched codeword, $CW(n)$ is the one yielding minimum error

$$\begin{aligned} j &= \underset{i=1,2,\ldots,M}{\arg\min} \{E_i\} \\ CW(n) &= CW_j(n). \end{aligned} \tag{6}$$

Fig. 4 shows the process of selecting the beat codeword.

From observing a large amount and variety of pathological ECG signals, one sees that for a specific patient, in most cases, there are up to three different types of beats. This may lead to

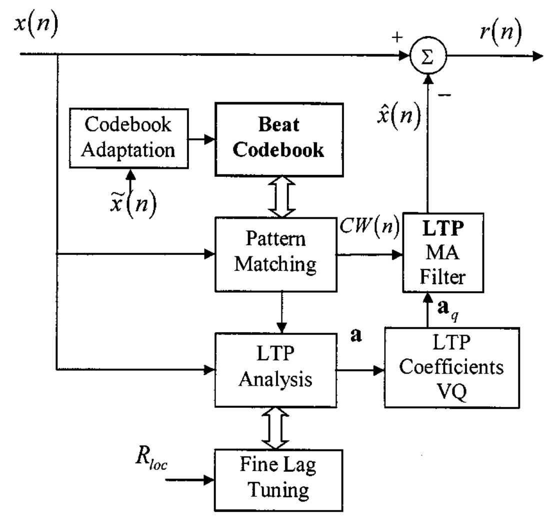

Fig. 3. The process of codebook matching, LTP analysis, and residue signal production.

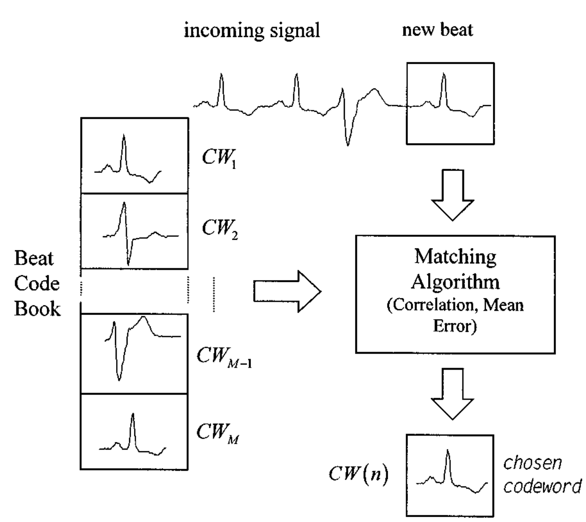

Fig. 4. Beat codeword selection process.

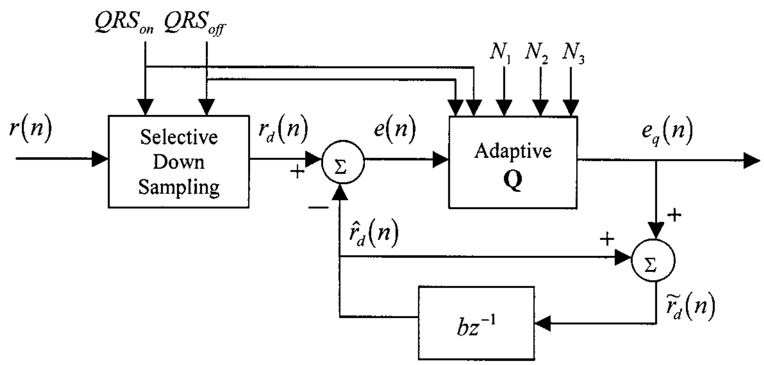

Fig. 5. The residual encoder.

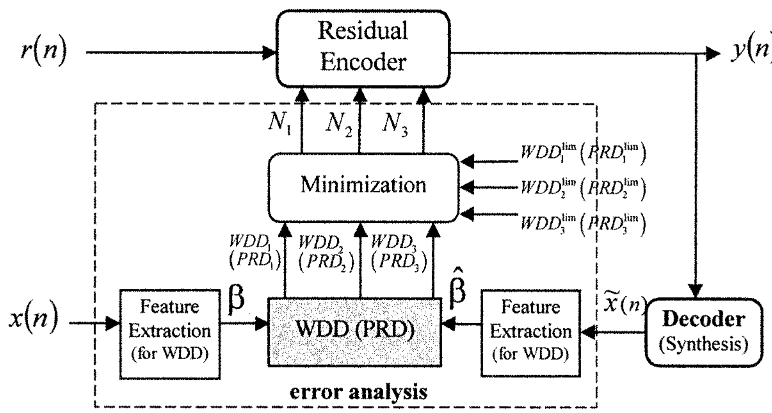

Fig. 6. The block diagram of the error analysis by synthesis subsystem (using WDD or PRD measure).

the conclusion that for a patient dependent case a codebook of size $M = 3$ is sufficient. However, taking into account changes within each type of beat (for instance a change of the QT interval value depending on the heart rate), leads to the conclusion that a larger size of codebook is required. In this work, the size of the beat codebook (M) was chosen to be eight.

Two types of codebooks were considered in this work: 1) *A Universal Codebook*—used for coding a relatively large number of subjects (for example patients in Intensive Coronary Care Unit). The codebook generation requires the identification and clustering of the beats of the database and will require more than eight beats (this type of CB was not tested here). 2) *An Individual Codebook*—designed for a specific subject (subject-dependent compression). The codewords are the typical beats appearing in the subject's ECG signal. The codebook may be acquired by starting with universal codebook and adapting the codewords to fit the specific subject.

In this work an adaptive codebook was chosen, in which the adaptation is made by averaging the beat codeword that was used for prediction with the current beat, thus:

$$\mathbf{CW_j^k} = \theta \cdot \mathbf{CW_j^{k-1}} + (1-\theta)\tilde{\mathbf{x}} \tag{7}$$

where $\mathbf{CW_j^{k-1}}$ is the jth beat codeword (template) that was used for prediction, $\mathbf{CW_j^k}$ is the new jth beat codeword (after adaptation), $\tilde{\mathbf{x}}$ is the reconstructed beat, and θ is a constant whose value is between 0–1. Adaptive rule (7) was used in this work. Better adaptation schemes may be considered, for example one that includes dynamic time warping (DTW) [20] averaging.

The Residue Encoder: In this stage, the residual signal, which was produced in the previous stage undergoes residual coding. This consists of down sampling by a factor of two (to 125 Hz) in $\mathrm{T_{section}}$ and in $\mathrm{P_{section}}$ and short time correlation reduction [by short time prediction (STP)]. The short-time correlation is reduced by DPCM with a first-order linear predictor. The remaining signal $e(n)$ is quantized adaptively to produce $e_q(n)$. This uniform quantizer separately quantizes every section: $\mathrm{P_{section}}$ with N_1 bits/sample, $\mathrm{QRS_{section}}$ with N_2 bits/sample, and $\mathrm{T_{section}}$ with N_3 bits/sample. These bits/sample values (N_1, N_2, N_3) are determined by the error analysis subsystem. Fig. 5 shows the residual encoder.

Error Analysis by Signal Reconstruction (Synthesis): The idea of analysis by synthesis coding, is that the coder reconstructs the signal as the decoder does, and uses the error to improve coding [21]. This coding is used in this subsystem in order to efficiently code the residual signal with minimum bits/transmitted beat (PQRST complex), while maintaining a predetermined distortion level (PRD or WDD). Fig. 6 shows the block diagram of the error analysis subsystem, where the minimization is performed with the WDD measure (the overall compression algorithm is then signed $\mathrm{ASEC_{WDD}}$), or with PRD measure (the overall compression algorithm is then signed $\mathrm{ASEC_{PRD}}$).

In this stage, the residual signal is encoded with minimum bit rate. The encoded beat $y(n)$ is decoded before it is transmitted, to get a reconstructed signal $\tilde{x}(n)$. The quality of the re-

TABLE I
THE BIT ALLOCATION

Parameter #	Name	Sign / partition	No. of Bits	Remarks
1	Number of Quantizer levels & Complex Type	Q_N	7	Coded no. of Q levels for each section (P, QRS, T)
2	Beat Code Word	*index(CW)*	3	Codebook size is 8
3	LTP Coefficients	*index*($\mathbf{a}_q$)	6	The index of the LTP vector
4	Timing Vector (**L**)	RR_{int}	8	No. of samples: $(R - R)$
		$Beat_{off}$	6	$(Beat_{off} - R)$
		QRS_{on}	5	$(R - QRS_{on})$
		QRS_{off}	5	$(QRS_{off} - R)$
5	Quantizer's Ranges	$P_{section}$	16	Transmitted if $Q_P \neq 0$
		$QRS_{section}$	16	Transmitted if $Q_{QRS} \neq 0$
		$T_{section}$	16	Transmitted if $Q_T \neq 0$
6	Residuals	$e_q(n)$	0-4	(per sample)
Total Range (bits per beat)			40 - 1848	see remarks in the text
Total Range (bits per second)			40 - 2696	(CR = 75:1 – 1.11:1)

constructed signal is tested by means of PRD or WDD by comparing it with the original beat. If the quality of the reconstructed beat is satisfactory, the encoded beat $y(n)$ is transmitted; if not, the residue signal $r(n)$ is re-encoded with a higher bit rate and tested again.

In order to exploit the spectral and diagnostic qualities of the different sections in the ECG complex, every section ($\mathrm{P_{section}}$, $\mathrm{QRS_{section}}$, $\mathrm{T_{section}}$) is tested separately with the partial distortion measure: WDD_j or PRD_j.

The partial WDD [17] measures the diagnostic features difference between the original signal and the reconstructed one in every section (WDD_1 for $\mathrm{P_{section}}$, WDD_2 for $\mathrm{QRS_{section}}$, and WDD_3 for $\mathrm{T_{section}}$). For each section, a partial feature vector $\boldsymbol{\beta}_j$ is defined. This vector contains the features that belong to the specific section

$$\boldsymbol{\beta}^T = \left[\boldsymbol{\beta}_1^T \vdots \boldsymbol{\beta}_2^T \vdots \boldsymbol{\beta}_3^T\right] \tag{8}$$

and a partial distortion measure, WDD_j $(j = 1, 2, 3)$ such that

$$\mathrm{WDD}_j\left(\boldsymbol{\beta}_j, \hat{\boldsymbol{\beta}}_j\right) = \Delta\boldsymbol{\beta}_j^T \cdot \frac{\Lambda_j}{\mathrm{tr}[\Lambda_j]} \cdot \Delta\boldsymbol{\beta}_j \tag{9}$$

with the partial diagonal weighting matrix Λ_j $(j = 1, 2, 3)$ given by

$$\Lambda = \mathrm{diag}(\Lambda_j); \quad j = 1, 2, 3. \tag{10}$$

As the partial WDD, The partial PRD (PRD_j; $j = 1, 2, 3$) measures the relative PRD in every section. Depending on the application, each partial distortion measure is given a desired limit $\mathrm{WDD}_j^{\mathrm{lim}}$ or $\mathrm{PRD}_j^{\mathrm{lim}}$. The algorithm will adjust the compression parameters (namely the number of the residual quantizer's bits/sample N_j in the encoder) so that the resulted distortion measure becomes less or equal to its desired limit. If the jth partial distortion exceeds its allowed level, N_j is increased by one (the initial bit allocation is $N_1 = N_2 = N_3 = 0$). The encoded beat signal $y(n)$ is not transmitted until the distortion is below the permitted level, or with maximum number of quantization levels (16 levels = 4 bits/sample).

The System's Parameters and Bit Allocation: The inputs of the compressor are the original ECG signal (sampled at 250 Hz) and the values of the predetermined distortion thresholds ($\mathrm{WDD}_j^{\mathrm{lim}}$ or $\mathrm{PRD}_j^{\mathrm{lim}}$; $j = 1, 2, 3$). The parameters that are transmitted every heartbeat must be optimized with respect to the number of bits. Table I summarizes the bit allocation, which is transmitted (stored) for every heartbeat (complex). The bit rate is at least 40 bits/complex, and it goes higher as the number of the residual quantizer levels increases. The gray areas in the table denote the parameters that are not always transmitted (depending on parameter 1). The last two lines in Table I show the range of compression in bits/beat and in bits/s. The higher rate (bits/beat) was calculated for beat rate of 60 beats/min, where the length of the QRS complex is 130 ms. The higher rate (bits/s) was calculated for heart rate of 120 beats/min, where the length of the QRS complex is 130 ms. The lower rate was calculated

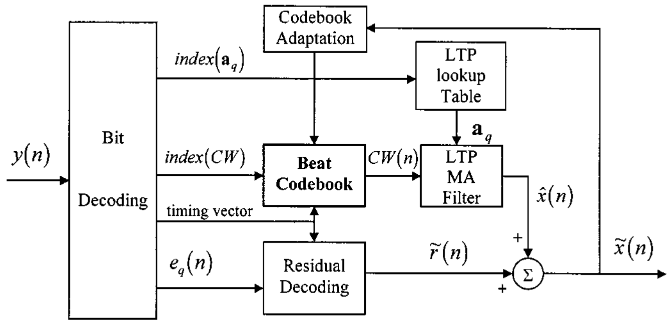

Fig. 7. The decoding system.

for heart rate of 60 beats/min. The compression ratio (CR) was calculated assuming the uncompressed signal was sampled at 250 Hz with 12-bit resolution.

C. The Decoding System

The decoding system is shown in Fig. 7. This system exists at the transmission side as well as the receiver side. The decoding system consists of bit decoding, beat codebook, and LTP decoding (which consists of an LTP coefficients codebook), which are identical to these elements in the encoder. For every heartbeat (complex), the decoder decodes the bits, and estimates the predicted signal $\hat{x}(n)$ with the LTP and beat codebook. The residual signal $\tilde{r}(n)$ is reconstructed by residual decoding (Fig. 8). The predicted signal $\hat{x}(n)$ is added to the reconstructed residual $\tilde{r}(n)$ and the reconstructed signal $\tilde{x}(n)$ is calculated. The reconstructed signal is also used for beat codebook adaptation.

IV. Results and Discussion

The MIT-BIH Arrhythmia database [22] was used to evaluate the proposed compression algorithm and compare it with other known compression methods. Two ASECs were implemented. One used the WDD measure for minimization (ASEC_{WDD}) and the other used the PRD measure for minimization (ASEC_{PRD}). We have also implemented the AZTEC [3] algorithm, SAPA2 [7], and LTP [12] (without entropy coding) and evaluated them with the same database signals. These compressors were chosen for comparison, because AZTEC and SAPA2 are often referred for comparison in the literature, and LTP is one of the best ECG compressors.

Two types of test were performed: 1) Quantitative test—which is assessed using rate-distortion curves of the compression algorithms. In this test, the distortion measures are the PRD and the WDD. 2) Qualitative tests—which are also assessed using rate-distortion curves, but the distortion measure is produced by mean opinion score (MOS) of cardiologists evaluation ($\text{MOS}_{\text{error}}$).

The Quantitative Test: The rate was chosen to be expressed in terms of bit/s of the compressed ECG, and the distortion was chosen to be the PRD and the WDD measures (in percentage units) between the reconstructed signal and the original one.

Fig. 9 shows an example of an original and reconstructed ECG signal, which was compressed by the proposed compression algorithms (ASEC_{WDD} and ASEC_{PRD}). The original ECG signal was taken from the MIT-BIH database (record 119). Note that the ASEC_{PRD} reconstructed signal Fig. 9(d) has the average bit rate of 85.5 bits/s (compression ratio of 35 : 1), while the PRD is 7.93%.

For the quantitative tests, the first minute of 18 MIT-BIH records were processed: 104, 107, 111, 112, 115, 116, 118, 119, 201, 207, 208, 209, 212, 213, 214, 228, 231, and 232. These signals were chosen by an experienced cardiologist and they consist of a large variety of pathological cases. Fig. 10 shows the distortion-rate curves of the ASEC_{WDD}, ASEC_{PRD}, LTP, SAPA2, and AZTEC, of the same signals. Each line is a polynomial fit (from order two or three) of the resulting points of one compression method.

Fig. 10(a) shows the distortion-rate curves with the WDD measure and Fig. 10(b) shows the distortion-rate curves with the PRD measure. From Fig. 10, one can see that the ASEC algorithm is superior to the other tested compressors in all cases and for all bit rates. It is also worthwhile noting that both the LTP and the ASEC have much lower WDD error than the other tested methods, in all bit rates. Namely, these compression methods better preserve the diagnostic features of the ECG signal.

Qualitative Tests—MOS: As the quantitative tests, the qualitative tests are also presented with rate-distortion curves, however the distortion measure is assessed by subjective evaluates. In order to find a qualitative distortion measure for each of the tested signals, MOS test was performed, which contains a blind and a semi-blind tests. The evaluators for this test were three experienced cardiologists. The results of the MOS test are combined in a qualitative distortion measure, called: $\text{MOS}_{\text{error}}$. Every tested signal (the same signals as in the quantitative tests), was printed on paper, in the form and the scale that a cardiologist is used to see.

In the **blind-test** every cardiologist was given one strip of signal, which contained the unknown signal and some mean estimated features. The signal was one channel, 27 s in length. For every tested signal, the cardiologist was asked to fill a questionnaire, which contained questions about the quality of the signal and wave shapes interpretation [17].

In the **semi-blind test** every cardiologist was given one strip of signal, which contained the original signal marked as "original" and the reconstructed signal marked as "reconstructed" (13.5 s for each signal). For every tested signal, the cardiologist was asked to fill a questionnaire, which contains a question about the measure of similarity between the signals.

A **weighted MOS error** was calculated from the results of the blind and semi-blind tests of three independent cardiologists for every tested signal [17], [24].

The lower the value of the $\text{MOS}_{\text{error}}$ the better the quality evaluation of the reconstructed signal. This is perhaps different from other applications (such as the speech MOS test), where the higher the value of the MOS the better the signal quality. The $\text{MOS}_{\text{error}}$ was defined like this in order to be similar to the PRD/WDD measures.

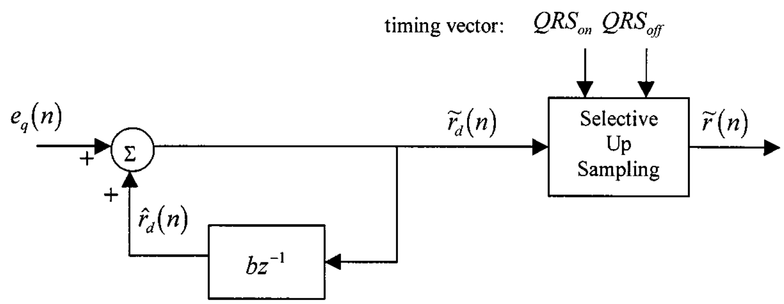

Fig. 8. The residual decoder.

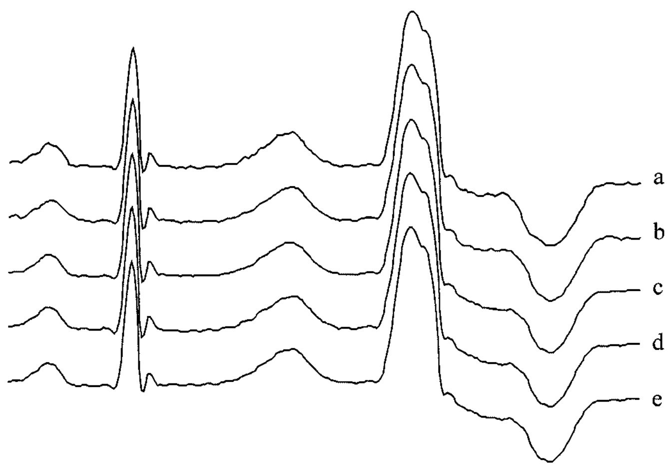

Fig. 9. Original and reconstructed signals of record 119 (MIT-BIH). (a) original signal. (b) ASEC_{PRD} reconstructed signal (bit rate = 189 bps; PRD = 5.48%). (c) ASEC_{WDD} rec. signal (bit rate = 199 bps; WDD = 2.09%). (d) ASEC_{PRD} rec. signal (bit rate = 85.5 bps; PRD = 7.93%). e) ASEC_{WDD} rec. signal (bit rate = 134 bps; WDD = 2.68%).

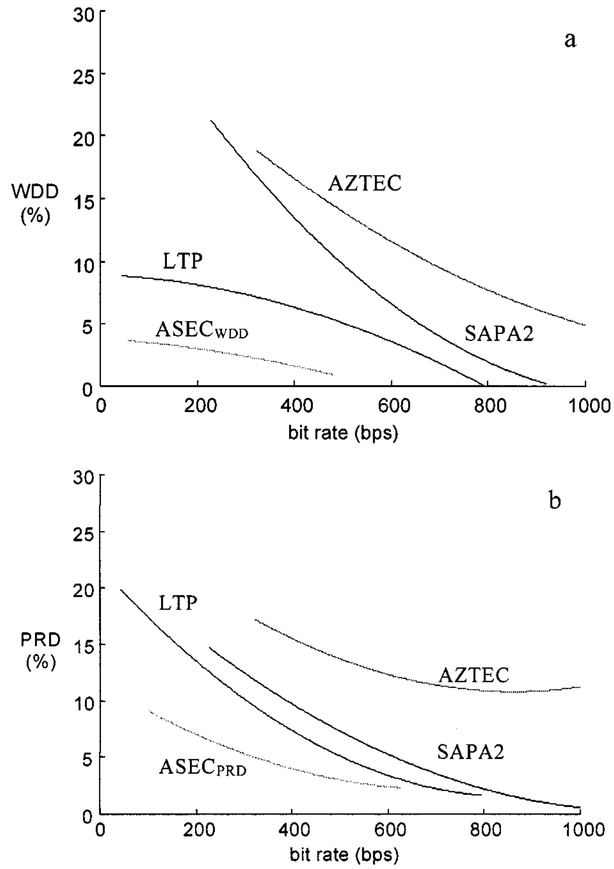

Fig. 10. The distortion-rate curves of the algorithms: ASEC_{WDD}, ASEC_{PRD}, LTP, SAPA2, and AZTEC. (a) with WDD measure. Standard deviations: ASEC_{WDD} = 2.32, LTP = 4.75, SAPA2 = 3.58, AZTEC = 6.45, (b) with PRD measure. Standard deviations: ASEC_{PRD} = 1.43, LTP = 4.92, SAPA2 = 3.06, AZTEC = 3.61.

The $\text{MOS}_{\text{error}}$ was used to construct rate-distortion curves, similar to those used for the quantitative measures.

Fig. 11 shows the distortion-rate curves of the qualitative test. As in the quantitative test, one can see that the proposed compression algorithms (ASEC_{WDD} and ASEC_{PRD}) are superior to the other tested compression algorithms. Moreover, the cardiologists preferred the ASEC_{WDD} algorithm over all other tested algorithms including the ASEC_{PRD}.

A multichannel version of the proposed compression algorithm was implemented and yielded very good results [23].

The proposed compression algorithms were found to have the best performances at any bit rate. The most important achievement is the fact that mean low transmission rates (50–100 bits/s) may be used while maintaining a good reconstructed signal quality (WDD of 2%–4% and PRD of 6%–9%. Note that these are the true results while Fig. 10 gives polynomial smoothing). This performance is better than other known compression algorithms in the literature. For example in [2], a minimum bit rate of 380 bits/s was achieved at PRD of 8.5% (not on the same database as was used in this work). Some results reported in the literature are not comparable [6], [8], [10], because the signal was not processed to have zero mean for the PRD calculation and as a result nonrelevant low PRD's were thus achieved. The results in [6], [8], [10] are slightly worse than the results of the ASEC even with the reported (wrong) PRD. With DC level elimination, the PRD will become larger emphasizing the superiority of the ASEC.

The compression system is more computationally complex than most of the published ECG compression algorithms. It can however be implemented in real time using inexpensive DSP chip. The heavy part in the compression algorithm, in point of view of computational complexity, is the diagnostic feature extraction for the calculation of the WDD measure. In many cases, the physician is interested not only in the compression, but also in the analysis performance. Therefore, the calculated features can be used as a diagnostic tool. The complexity of the WDD

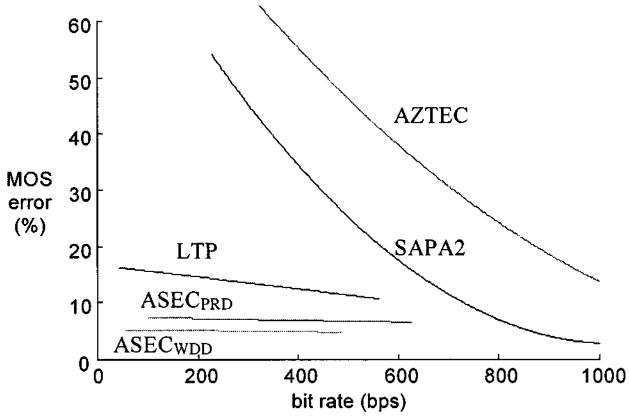

Fig. 11. The distortion-rate curves of the algorithms: $\mathrm{ASEC}_{\mathrm{WDD}}$, $\mathrm{ASEC}_{\mathrm{PRD}}$, LTP, SAPA2, and AZTEC. with **MOS error**. Standard deviations: $\mathrm{ASEC}_{\mathrm{WDD}} = 3.46$, $\mathrm{ASEC}_{\mathrm{PRD}} = 3.84$, LTP = 9.3, SAPA2 = 9.8, AZTEC = 14.83.

calculation can be decreased by the extraction of fewer features, or by developing more efficient extraction algorithms. The $\mathrm{ASEC}_{\mathrm{PRD}}$ algorithm is of course much less complex than the $\mathrm{ASEC}_{\mathrm{WDD}}$ algorithm, since it does not require the extraction of the diagnostic features.

REFERENCES

[1] J. P. Abenstein and W. J. Tompkins, "A new data reduction algorithm for real time ECG analysis," *IEEE Trans. Biomed. Eng.*, vol. BME-29, pp. 43–48, Jan. 1982.

[2] G. D. Barlas and E. S. Skordalakis, "A novel family of compression algorithms for ECG and other semiperiodical, one dimensional, biomedical signals," *IEEE Trans. Biomed. Eng.*, vol. 43, pp. 820–828, Aug. 1996.

[3] J. R. Cox, F. M. Nolle, H. A. Fozzard, and C. G. Oliver, "AZTEC, a preprocessing program for real time ECG rhythm analysis," *IEEE Trans. Biomed. Eng.*, vol. BME-15, pp. 128–129, Apr. 1968.

[4] D. J. Hamilton, D. C. Thomson, and W. A. Sandham, "ANN compression of morphologically similar ECG complexes," *Med. Biol. Eng. Comput.*, vol. 33, pp. 841–843, November 1995.

[5] P. S. Hamilton and W. J. Tompkins, "Compression of the ambulatory ECG by average beat subtraction and residual differencing," *IEEE Trans. Biomed. Eng.*, vol. 38, pp. 253–259, Mar. 1991.

[6] M. L. Hilton, "Wavelet and wavelet packet compression of electrocardiograms," *IEEE Trans. Biomed. Eng.*, vol. 44, pp. 394–402, May 1997.

[7] 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.

[8] J. Chen and S. Itoh, "A wavelet transform-based ECG compression method guaranteeing desired signal quality," *IEEE Trans. Biomed. Eng.*, vol. 45, pp. 1414–1419, Dec. 1998.

[9] S. M. Jalaleddine, C. G. Hutchens, R. D. Strattan, and W. A. Coberly, "ECG data compression techniques—a unified approach," *IEEE Trans. Biomed. Eng.*, vol. 37, pp. 329–343, Apr. 1990.

[10] H. Lee and K. M. Buckley, "ECG data compression using cut and align beats approach and 2-D transforms," *IEEE Trans. Biomed. Eng.*, vol. 46, pp. 556–564, May 1999.

[11] T. Uchiyama, K. Akazawa, and A. Sasamori, "Data compression of ambulatory ECG by using multi-template matching and residual coding," *IEICE Trans. Inform Syst.*, vol. E76-D, no. 12, pp. 1419–1424, Dec. 1993.

[12] G. Nave and A. Cohen, "ECG compression using long term prediction," *IEEE Trans. Biomed. Eng.*, vol. 40, pp. 877–885, Sept. 1993.

[13] C. Paggetti, M. Lusini, M. Varanini, A. Taddei, and C. Marchesi, "A multichannel template based data compression algorithm," *Comput. Cardiol. 1994*, pp. 629–632, 1994.

[14] U. E. Ruttiman 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.

[15] A. Cohen, P. M. Poluta, and R. Scott-Millar, "Compression of ECG signals using vector quantization," in *Proc. IEEE-90 S. A. Symp. Communications and Signal Processing*, Johannesburg, 1990, COMSIG-90, pp. 45–54.

[16] M. Ishijima, "Fundamentals of the decision of optimum factors in the ECG data compression," *IEICE Trans. Inform. Syst.*, vol. E76-D, no. 12, Dec. 1993.

[17] Y. Zigel. (1998, Aug.) ECG Signal Compression. Electr. Comput. Eng. Dept., Ben-Gurion University, Beer-Sheva, Israel. [Online]. Available: HTTP: http://www.ee.bgu.ac.il/~spl

[18] Y. Zigel, A. Cohen, and A. Katz, "A diagnostic meaningful distortion measure for ECG compression," in *Proc. 19th Conv. IEEE in Israel*, 1996, pp. 117–120.

[19] Y. Zigel, A. Cohen, A. Abu-Ful, A. Wagshal, and A. Katz, "Analysis by synthesis ECG signal compression," *Comput. Cardiol. 1997*, vol. 24, pp. 279–282, 1997.

[20] L. R. Rabiner and B.-H. Yuang, *Fundamentals of Speech Recognition*. Englewood Cliffs, NJ: Prentice-Hall, 1993.

[21] W. B. Kleijn and K. K. Paliwal, *Speech Coding and Synthesis*. Amsterdam, The Netherlands: Elsevier, 1995.

[22] G. B. Moody. (1992, August) The MIT-BIH Arrhythmia Database. Harvard-MIT Division of Health Sciences and Technology. [Online]. Available: CD-ROM

[23] A. Cohen and Y. Zigel, "Compression of multichannel ECG through multichannel long-term prediction," *IEEE Eng. Med. Biol.*, vol. 17, no. 1, pp. 109–115, Jan./Feb. 1998.

[24] Y. Zigel, A. Cohen, and A. Katz, "The weighted diagnostic distortion measure for ECG signal compression," *IEEE Trans. Biomed. Eng.*, Nov. 2000, to be published.

[25] A. Cohen, *Biomedical Signal Processing*. Boca Raton, FL: CRC, 1986.

[26] A. Gersho and R. M. Gray, *Vector Quantization and Signal Compression*. Norwell, MA: Kluwer Academic, 1992.

[27] F. Gritzali, G. Frangakis, and G. Papaconstantinou, "Detection of P and T waves in ECG," *Comput. Biomed. Res.*, vol. 22, pp. 83–91, 1989.

[28] P. S. Hamilton and W. J. Tompkins, "Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmia database," *IEEE Trans. Biomed. Eng.*, vol. BME-33, pp. 1157–1165, Dec. 1986.

[29] N. S. Jayant and P. Noll, *Digital Coding of Waveforms*. Englewood Cliffs, NJ: Prentice-Hall, 1984.

[30] P. Laguna, N. V. Thakor, P. Caminal, R. Jane, and H.-R. Yoon, "New algorithm for QT interval analysis in 24-hour Holter ECG: Performance and applications," *Med. Biol. Eng. Comput.*, vol. 28, pp. 67–73, January 1990.

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

[32] S. H. Meij and C. Zeelenberg, "A fast real-time algorithm for the detection of ventricular fibrillation," *Proc. Comput. Cardiol. 1986*, pp. 707–710, 1986.

[33] G. B. Moody and R. G. Mark, "The MIT-BIH arrhythmia database in CD-ROM and software for use with it," *Comput. Cardiol. 17*, pp. 185–188, 1990.

[34] O. Pahlm and L. Sornmo, "Software QRS detection in ambulatory monitoring—A review," *Med. Biol. Eng. Comput.*, pp. 289–297, July 1984.

[35] J. G. Proakis, *Digital Communications*, 3rd ed. New York: McGraw Hill, 1995.

[36] W. J. Tompkins, *Biomedical Digital Signal Processing*. Englewood Cliffs, NJ: Prentice-Hall, 1993.

[37] R. Veldhuis and M. Breeuwer, *An Introduction to Source Coding*. Eindhoven, The Netherlands: Prentice-Hall, 1993.

Yaniv Zigel was born in Tel-Aviv, Israel, in 1970. He received the B.Sc. and M.Sc. degrees in electrical and computer engineering from the Ben-Gurion University, Beer-Sheva, Israel, in 1992 and in 1998 respectively. He is working toward the Ph.D. degree at the Department of Electrical and Computer Engineering of the same university.

From 1992–1995, he was a Technical Officer at the communication and computer corps in the Israeli Defense Forces (IDF). Currently, he is working as a Teaching and Research Assistant at the Department of Electrical and Computer Engineering of the Ben-Gurion University. His research interests include one-dimensional signal processing, signal compression, and speech and speaker recognition.

Arnon Cohen was born in Haifa, Israel, in 1938. He received the B.Sc. and M.Sc. degrees in electrical engineering from the Technion-Israel Institute of Technology, Haifa, Israel, in 1964 and 1966 respectively, and the Ph.D. degree in electrical and biomedical engineering, from Carnegie-Mellon University, Pittsburgh, PA, in 1970.

Since 1972, he has been with the Department of Electrical and Computer Engineering, and the Biomedical Engineering Program, Ben-Gurion University, Beer-Sheva, Israel, where he is a Professor of Electrical and Biomedical Engineering. His research interests are in signal processing, mainly with biomedical and speech applications. He is the author of *Biomedical Signal Processing*, (Boca Raton, Fl: CRC, 1986).

Amos Katz was born in Ramat Gan, Israel, in 1952. He received the M.D. degree from the Faculty of Health Sciences at Ben Gurion University of the Negev, Beer Sheva, Israel. He was trained in cardiology at the Soroka Medical Center, Beer Sheva, and in electrophysiology at the St. Vincent Hospital, Indianapolis, IN.

He is currently the Director of the Electrophysiology Laboratory at the Soroka Medical Center. He is a Senior Lecturer in Cardiology in the Faculty of Health Sciences and Vice Dean for Student Affairs at Ben Gurion University. His research interests are in cardiac electrophysiology, sudden death, pacemakers, implantable defibrillators, and heart rate variability.