ECG signal from those which can be interpreted as noise. This is carried out by investigating the phase spectral contents of the first twenty or so ECG beats.

To this end, the Fourier transform representation is evaluated for the signal using the Fast Fourier Transform (FFT) algorithm developed by Monro[17]. The forward FFT of an N-point sequence yields (N) Fourier coefficients. The number of coefficients (L) to be retained is determined by evaluating σ_{ϕ} as explained in the previous section equation (8).

Having determined the number of harmonics to be retained, the second step is to apply the FFT algorithm to the on-line ECG data sequentially taking N-points at a time.

Theoretically, it is not necessary to apply a tapering window to the FFT operation because of the inherently finite character of the signal. However, owing the variability of the heart-rate, the N-point segments of the ECG signal may not be identical. It is therefore advisable to apply a mild form of tapering, e.g. 10% raised cosine Hanning function [15].

Also, in order to reduce the effect of truncation, 10% of the retained coefficients are tapered by a tapering Hanning function. All higher harmonic coefficients are discarded.

The real and imaginary parts of the L coefficients to be stored are floating-point numbers. The frastional parts are all truncated to the nearest integer and stored as a single word (compressed) with the same precision as the original data. This enables us to obtain an effective compression ratio CR = N/L

For reconstruction, the real and imaginary parts are separated and expressed as floating-point numbers (with zero fractional part), (N - L) floating-point zeros are added to both the real and imaginary coefficients, and the resulting sequence is inverse transformed.

The reconstructed waveforms using the compressed data are compared to the original signals visually and by calculating the performance index PRD (the percent rms difference), defined as:

$$PRD = \sqrt{\frac{\sum_{i=1}^{N}\left[x_o(i) - x_r(i)\right]^2}{\sum_{i=1}^{N} x_o^2(i)}} \times 100 \qquad (9)$$

Where $x_o(i)$ and $x_r(i)$ are samples of the original and reconstructed data sequences.

IV- RESULTS

We applied the proposed technique to the comprerssion of 15-minute ECG data. The ECG signal is recorded at a bandwidth of 100 Hz using a philips ECG monitoring system type XV 1503. Two subjects are considered: a normal one and one suffering from old inferior infarction. The subject was sitting at rest and breathing quietly. The recorded signal, was then digitized using a 12-bit A/D converter and the sampling rate was 250 HZ. The signal was low-pass filtered using a Hanning filter with coefficients (1/4, 1/2, 1/4) to remove any artifact due to interference from the mains.

Twenty beats were used for each subject to determine the ensemble standard deviation of phases σ_ϕ. Fig. 1 shows a typical example of an ECG normal beat. Fig.3 shows results of the typical ensemble standard deviation $\sigma_\phi(f)$ as a function of number of harmonics. The expected behaviour of the $\sigma_\phi(f)$ curve is basically present. Theoretically, the limiting value of $\sigma_\phi(f)$ is $\Pi/\sqrt{3} = 1.841$. However, we notice that $\sigma_\phi(f)$ is fluctuating considerably This is due to the variance of the estimator of σ_ϕ[16]. The plot shows that the maximum frequency component (harmonic) present in the signal is the 25th harmonic. Starting from this harmonic, σ_ϕ begins oscillation about the theoretical limiting value. This suggests that all harmonics lower than the 25th, perhaps tapering down to harmonic (28) are basic components of the signal. All higher harmonics can be regarded as noise and can be discarded. Accordingly, it is argued to store the first 28 real and imaginary parts for each 256-sample ECG segment, resulting a compression ratio CR OF 256/28 = 8.4.

Fig.4 shows a waveform reconstructed from the compressed data. As seen from the figure, the waveform is still retaining the main pattern features, specifically, the QRS morphology. The figure also shows a reconstructed ECG waveform obtained from the application of the AZTEC, CORTES and Variable Threshold algorithms. Fig.5 shows a reconstructed ECG beat for the abnormal subject. It can be deduced that the present technique enables the signal to be reconstructed without loss of the main pattern features necessary for a physical to interpret the ECG.

Table I shows the results for the normal subject; the compression ratio (CR) and the average percent rms difference (APRD) for four techniques. APRD is calculated after all the signal segments have been processed . It is the average of the PRD's. It can be concluded that the proposed technique optimizes the tradeoff between data reduction and information content of the signal.

Table I
Summary of the Features of four
ECG Data Compression Algorithms

Techique	Compression Ratio	APRD	Post-processing
1- AZTEC	9.9	14.49	Required
2- CORTES	5.0	12.98	Required
3- VARIABLE THRESHOLD	7.6	11.90	Required
4- IMPROVED FOURIER DESCRIPT.(Present mtd.)	8.4	11.78	Not Required.

V. CONCLUSION

We presented a real-time algorithm for on-line compression and transmission of ECG data. Compression ratio of the algorithm is comparable to the existing compression techniques. The main advantage of the present technique is its capability to effectively handle noisy records as it is based on retaining the harmonics which are basic components of the signal and discarding those which can be described as noise. The technique also allows the reconstruction of the compressed signal in a clinically acceptable form without the need of postprocessing.

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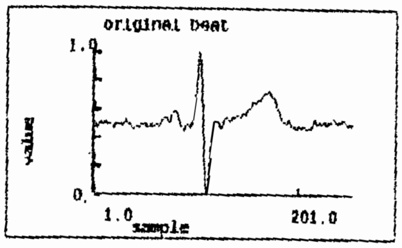

Fig.1 A typical example of ECG beat.

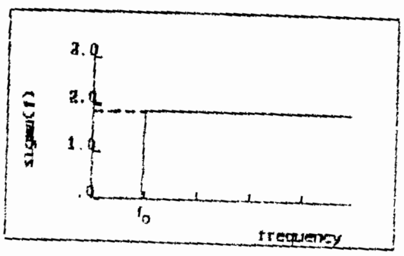

Fig.2 Relation between standard deviation of phases and frequency of ensemble of waveforms

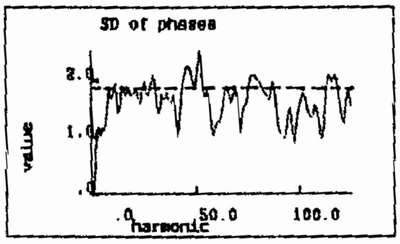

Fig.3 σ_ϕ curve for an ensemble of 20 ECG waveforms

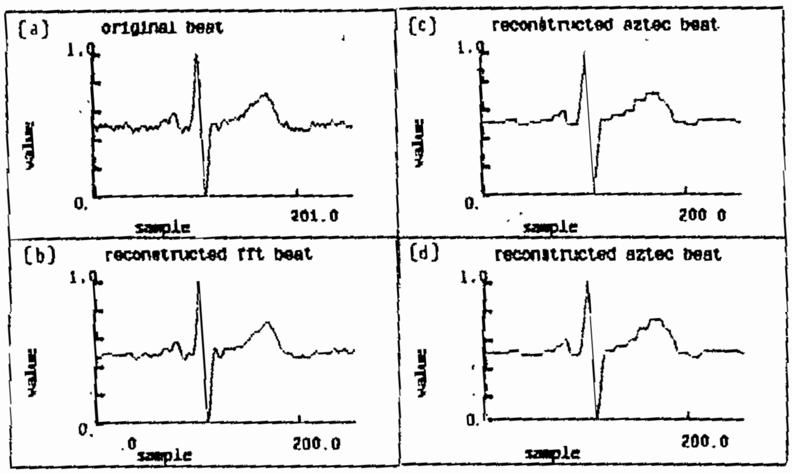

Fig.4 Comparison between four compression techniques (a) waveform of the original ECG signal (b) Reconstructed signal using the proposed FFT algorithm (c) Reconstructed AZTEC signal (before smoothing) (d) Reconstructed AZTEC signal (after smoothing) (e) Reconstructed CORTES signal (before smoothing) (f) Reconstructed CORTES signal (after smoothing) (g) Reconstructed Variable Threshold signal (before smoothing) (h) Reconstructed Variable Threshold signal (after smoothing)

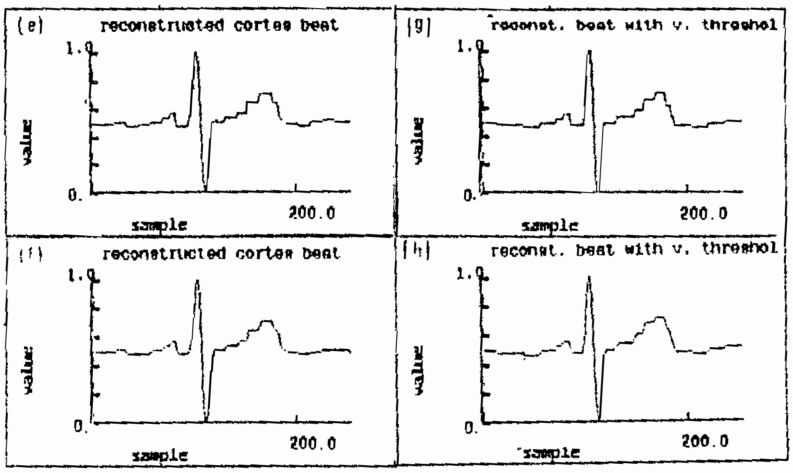

Fig.4 (continued)

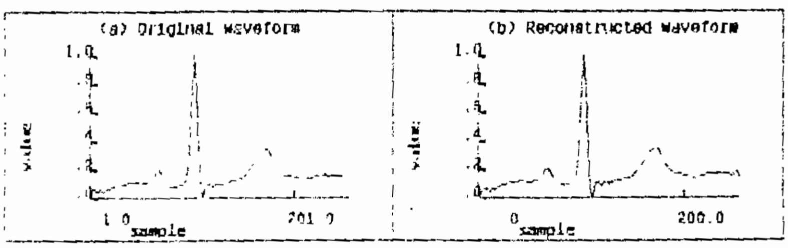

Fig.5 (a) Typical ECG waveform of the abnormal subject (old inferior Infarction)
(b) Reconstructed signal using the proposed algorithm