FAST HARTLEY TRANSFORM DATA-COMPRESSION ALGORITHM: ECG APPLICATIONS

خوارزم لاختزال بيانات رسم القلب الكهربى باستخدام تحليل هارتلى Hartley

Fatma Abou-Chadi

Department of Electrical Communications
Faculty of Engineering - Mansoura University

الخلاصه ــ فى هذا البحث تم دراسة امكانية استخدام تحليل هارتلى Hartley فى اختزال بيانات رسم القلب الكهربى • والخوارزم بسيط يحتاج فقط الى تطبيق تحويل هارتلى الامامى والعكسى • وبا ستعمال مجموع مربعات الفروق RMS كقيا س لصلاحية الاشارات التى تم استعادتها • تم تحديد الحد الاقصى الذى يمكن عنده اختزال البيانات • وقد تمت مقارنة النتائج لعدد من التسجيلات لعدة حالات عاديه واخرى غير عاديـة •

ABSTRACT- The feasibility of using the fast Hartley transform (FHT) algorithm for ECG data compression was studied. The technique is simple and requires the implementation of forward and inverse FHT. Using the percent rms difference as a measure of the utility of the reconstructed signals, the limit to which an ECG signal could be compressed and still yield an acceptable reconstructed waveform was determined. Results of compression of ECG data obtained from normal and abnormal subjects are presented.

I. INTRODUCTION

Holter monitoring, a 24-hour cassette recording system of the electrocardiogram (ECG), is useful for detecting cardiac disorders and arrhythmias [1]. However, Holter monitors with a digital IC memory card is now expected to improve fidelity of recording and make the system more compact.

The amount of digitized ECG data for two channels for 24 hours is about 20MB, and the memorizing capacity of an available IC memory card is 256KB to 512KB. Therefore, data compression is indispensable for a digital Holter system. In order to store a 24-hour electrocardiogram recording of 2 channels into an IC memory card of 512KB, a data compression rate of 1:30 is necessary.

In response to this need a number of computer-based ECG data-compression algorithms have been proposed, implemented and evaluated. Among these are data-compression algorithms which use an orthogonal transformation technique [2-7].

The operation of an orthogonal transformation data-compression algorithm is illustrated in Fig.1. The digital representation of the ECG ($X(n)$, $n = 0, \ldots, N-1$) is operated by the orthogonal tranform $P(n)$ to produce the sequence $Y(n)$. The terms of $Y(n)$ are the magnitudes of the projection of $X(n)$ into an N-dimensional vector space. To be useful as data-compression

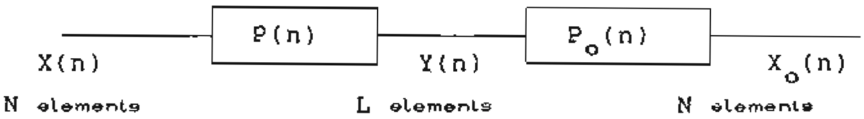

Fig.1 Orthogonal transformation data-compression system

algorithm the process P(n) must produce Y(n) that can be used to reconstruct X(n) within some acceptable error. The reconstructed signal $X_o(n)$, produced by the process $P_o(n)$ operating on Y(n), can be represented as the sum of the input sequence X(n) and an error sequence E(n)

$$X_o(n) = X(n) + E(n) \qquad (1)$$

The overall utility of data-compression algorithm is a function of at least three interrelated factors:
1- the degree of which $X_o(n)$ approximates X(n).
2- the degree to which the data are compressed, typically axpressed as the ratio N/L.
3- The complexity of the compression and reconstruction processes.

In developing the orthogonal transformation ECG compression algorithm presented here, although an attempt was made to address all of these factors, special emphasis was placed on the issue of approximating $X_o(n)$ to X(n). The main concern was the location of any error relative to the main features of the ECG. Because small error at the beginning of the QRS complex can have greater diagnostic significance than errors of the same magnitude in the other portions of the ECG, the most obvious error criterion would be a limit on the maximum difference between corresponding points on the original and reconstructed signals.

The most natural error criterion for analysing orthogonal transformation data-compression algorithms is, however, a normalised mean square error [2]. Although certain data compression algorithms can produce reconstructed signals with low mean square error caused by a few large differences concentrated in a small region, this is not the case when an orthogonal transformation data-compression algorithm is used. Since the mean square error of a reconstructed signal obtained from an orthogonal transformation data-compression technique is well correlated to the maximum difference that can be expected at any point, it can be used as a measure of the utility of a reconstructed ECG.

The primary objective of the present study was to investigate the operational characteristics of a fast Hartley transform ECG data compression algorithm. Lead II ECG data of a number of normal subjects and patients with morphological abnormalities have been compressed and the results are presented.

II. FAST HARTLEY TRANSFORM DATA-COMPRESSION ALGORITHM

The data-compression technique used in this study employed the discrete Hartley transform. The discrete Hartley transform (DHT) representation of a real-valued length-N sequence X(n), $0 \le n \le N - 1$, is defined by [8]

$$H(k) = \sum_{n=0}^{N-1} X(n)\ \mathrm{cas}\left[\frac{2\pi}{N} kn\right] \qquad 0 \le k \le N - 1 \qquad (2)$$

with an associated inverse transform

$$X(n) = \sum_{k=0}^{N-1} H(k)\ \mathrm{cas}\left[\frac{2\pi}{N} kn\right] \qquad 0 \le n \le N - 1 \qquad (3)$$

where cas(x) = cos(x) + sin(x). The symmetry of the transform pair is a valuable feature of the DHT. It should be observed that the forward transform differs from the discrete Fourier transform (DFT) only by the lack of the "-j" multiplying the sine term. The convenience of not having to manage the real and imaginary parts either in separate arrays, or interleaved in one array of double length, or in other ingenious ways that have been adopted in various embodiments of the Fourier transform commends the DHT for consideration in application to numerical spectral analysis [8]. These convenient features make the DHT a suitable substitute for the Discrete Fourier transform (DFT) and it is expected to achieve compression ratios higher than that could be obtained using the DFT.

If the DHT is computed using Eq.(2), N^2 operations would be required. A number of algorithms have been developed that can compute an N-point Hartley transform in $N \log_2 N$ rather than N^2 operations [9, 10]. An algorithm developed by R. N. Bracewell [9] and using a radix-2 decimation-in-time technique was used in this study. It is as fast as or faster than the fast Fourier transform (FFT).

A data-compression system using this orthogonal representation of the sampled ECG signals is shown in Fig.2. The method involves the determination of the forward fast Hartley transform of the N-sample sequence ECG data. The N real coefficients resulting from the FHT procedure are truncated to L coefficients to obtain the effective compression ratio given by $m = N/L$. The coefficients to be retained are the lower order harmonics. Higher order harmonics are discarded. For reconstruction (N - L) zeros are added and the resulting sequence is inverse transformed. The reconstructed waveforms are compared to the original signals by visual examination of plotted waveforms and also by a measure of goodness as described in Section III.

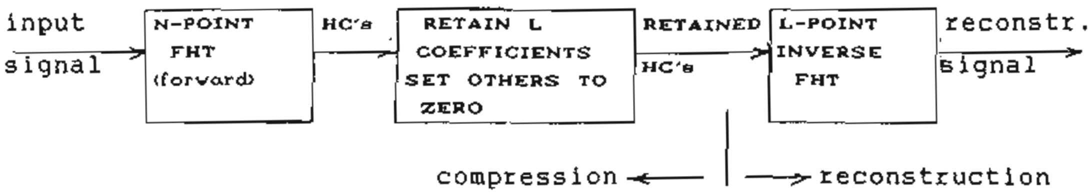

Fig.2 Block Diagram of data compression scheme using Hartley coefficiets

III. METHODS AND RESULTS

III.1 Data Acquisition

35-sec Lead II ECG signals were recorded using a Philips ECG recorder type XV1503. The signals were separated into two classes, namely normal and abnormal. The abnormals showed old inferior infarction. The bandwidth of the signal was chosen to be 100 Hz. The output of the ECG recorder was then connected to a 12-bit analog-to-digital converter and sampled at a rate of 250 sps. The digital data were transferred to an IBM PS2/80 computer by a program written in Basic.

III.2 Preprocessing

The method described here requires delineation of the QRS complexes. This is usually accomplished using a search procedure on the first derivative of the signal. Once the QRS is detected, backward and forward searches are performed with a lower threshold to locate its beginning and end.

III.3 Performance Index

In order to assess the performance of the compression scheme, in addition to visual comparison, an index of performance is employed. It represents a measure of "goodness" of the reconstructed waveforms. The index is the percent rms difference (PRD), which is computed as

$$PRD = \left[\frac{\sum_{i=1}^{N} \left[X(i) - \hat{X}(i) \right]^2}{\sum_{i=1}^{N} \left[X(i) \right]^2} \right]^{1/2} * 100 \qquad (4)$$

where X and $\hat{X}$ are samples of the original and reconstructed data sequence.

Using this method, we can either compute the error between the original and reconstructed waveforms for a specified compression ratio or obtain the permissible ratio for the specified error limit.

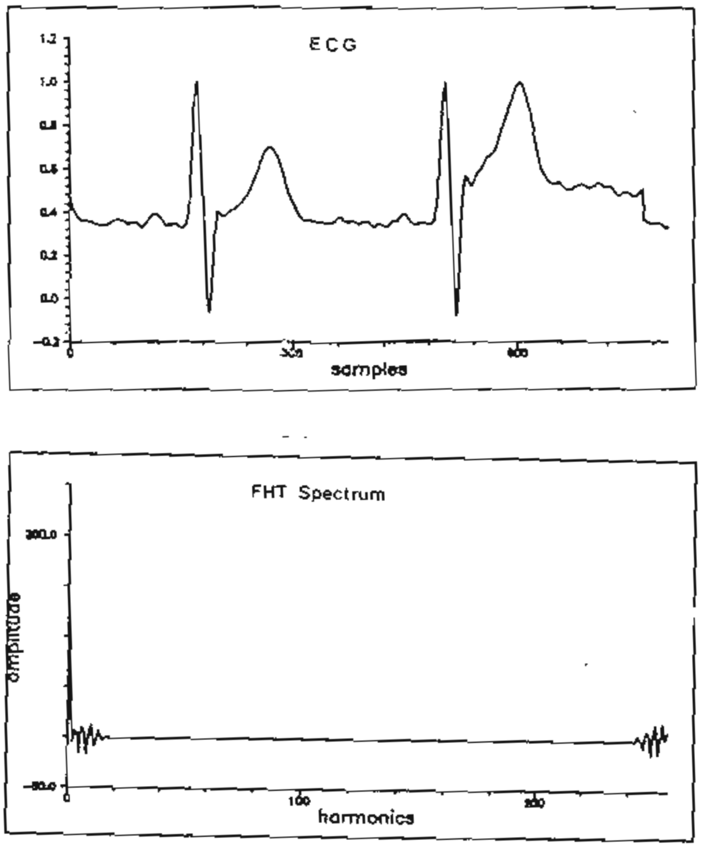

Fig.3 Typical ECG and corresponding Hartley spectrum

III.4 Results

A typical ECG record and its corresponding Hartley spectrum is shown in Fig.3. Figures 4 and 5 show reconstructed waveforms (continuous line) superimposed over the original signal (dotted) using different compression ratios for a normal subject and an abnormal case having old inferior infarction, respectively. As seen from the figures, the distortion in the shape of QRS with increasing compression ratio becomes appreciable for $m > 12$.

The performance indexes described above are computed for the ECG signals. Table I shows the average percent rms difference APRD's for the different compression ratios obtained from normal subjects, using the FHT. The corresponding APRD's obtained using the fast Fourier transform (FFT) [11] is also presented in the table. Fig.6 is a graphical representation of results presented in Table I. As can be seen the FHT results in smaller values of APRD's than those of the FFT for the same compression ratios.

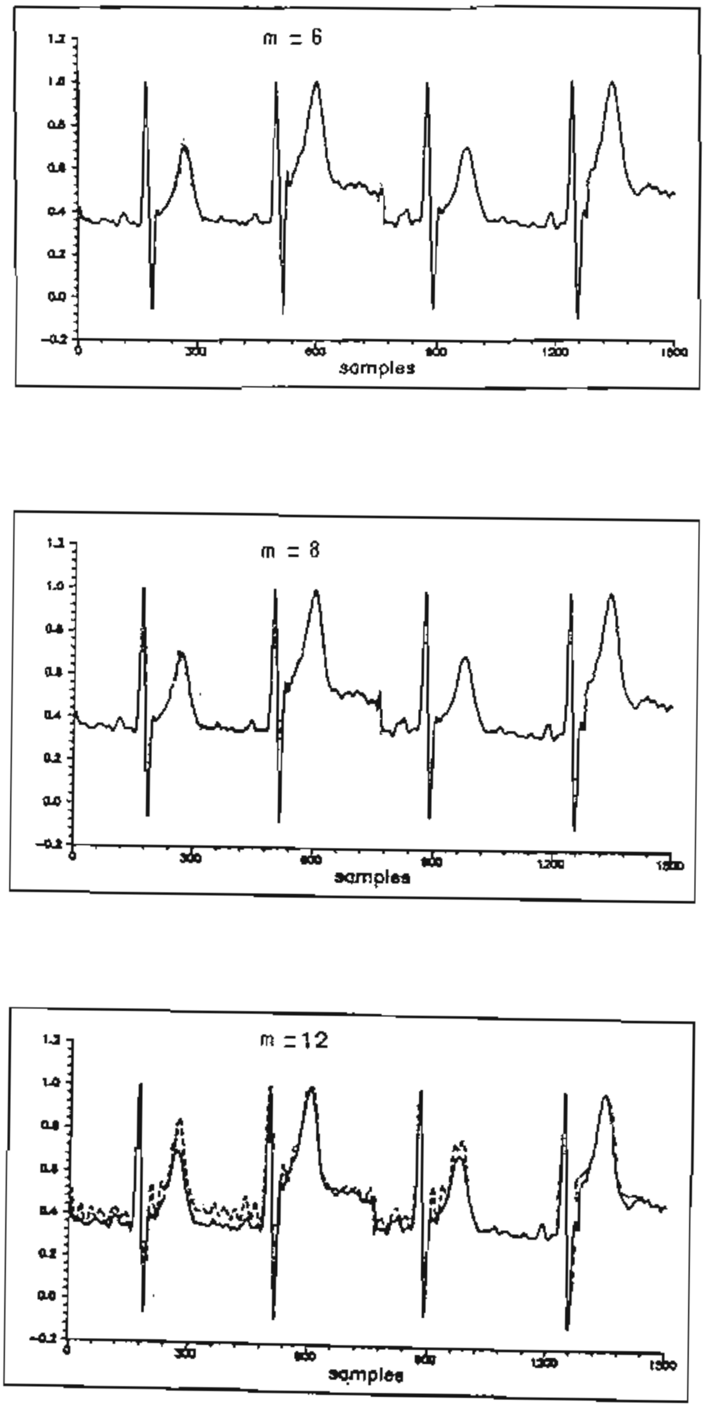

Fig.4 Reconstructed ECG data (dashed) superimposed over the original signal for a normal subject for m = 6, 8, and 12

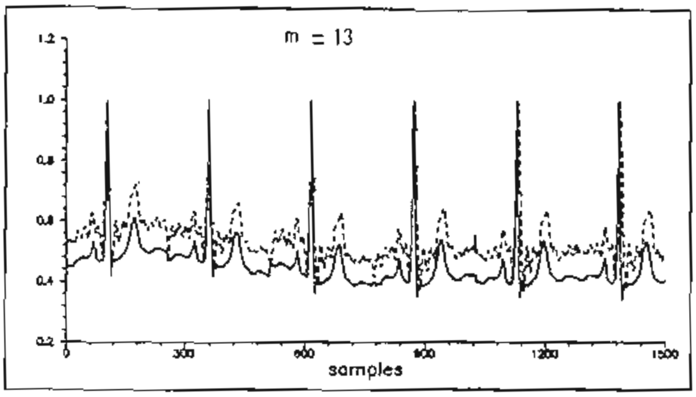

Fig.5 Reconstructed ECG data (dashed) superimposed over the original signal for a subject having inferior infarction (m = 13)

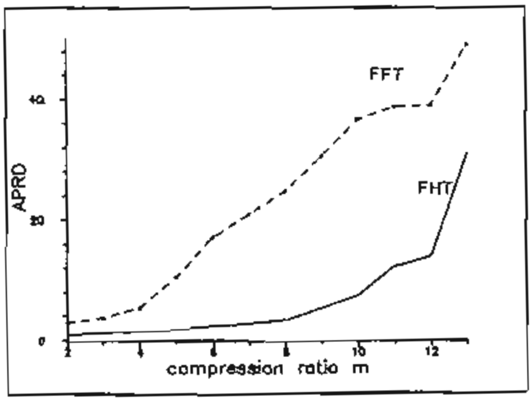

Fig.6 Graphical representation of Table I. Variation of APRD with compression ratio for the ECG record shown in Fig.4.

TABLE I

Variation of Percent rms Difference with compression ratio m (normal cases)

Compression ratio m	APRD using FHT	APRD using FFT
2	0.946	2.197
3	1.339	3.856
4	1.630	5.452
5	1.972	10.584
6	2.449	17.124
7	2.907	20.956
8	3.477	24.783
9	5.446	30.428
10	7.573	36.562
11	12.429	38.725
12	13.970	40.759
13	30.969	48.969

IV. DISCUSSION

An ECG data compression algorithm based on the use of the Fast Hartley transform is presented. The results obtained in this study demonstrate the feasibility of using the fast Hartley transform in ECG data compression. Because the fast Hartley transform can be computed using real-valued coefficients, compression ratios higher than those obtained using the fast Fourier transform can be obtained with better quality of reconstructed waveforms that is suitable for morphological analysis. The technique allows the reconstruction of the compressed signal in a clinically acceptable form without the need for postprocessing.

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