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***Absract*-The aim of our paper is to examine a set of wavelet functions for implementation in an electrocardiogram (ECG) image compression system. Eight different wavelets are evaluated for their ability to compress ECG as image. Image quality is compared objectively using mean square error (MSE) and peak signal to noise ratio (PSNR) along with visual appearance. Results show that clinically useful information in original ECG image is preserved by 15:1 compression and in some cases 20:1 compression is clinically useful.**

I. Introduction

The overall goal of compression is to represent an image with the smallest possible number of bits. It can facilitate the transmission & processing of image. Among many medical signal sources, the compression of electrocardiogram (ECG) is in great demand [1-3]. Many types of ECG recordings generate a vast amount of data. These include 24 and 48 hour Holter recordings, telemetry recordings, continuous ECG performed in intensive care units and stress test ECG. With the growing use of these ECG signals to detect and diagnose heart disorders, ECG compression becomes mandatory to efficiently store and retrieve this data from medical database. Other practical importance includes transmitting real time ECG over the public phone network and storing patient data in a medical smart card.

In this paper we treated ECG signal as image recorded on an ECG paper. ECG paper is traditionally divided into 1mm squares [4]. Vertically, ten blocks usually correspond to 1 mV, and on the horizontal axis, the paper speed is usually 25mm/s, which makes one block 0.04s (or 40ms). We also have "big blocks" which are 5mm on their side. Knowing the paper speed, its easy to work out heart rate. If the number of big block is 1, the rate is 300, if it is 2, the rate is 150 and so on. Rates in between these numbers are easy to interpolate. This ECG image is compressed using wavelet image compression system which can be created by selecting a type of wavelet function, quantizer and statistical coder. Here we do not intend to give a technical description of a wavelet compression system rather we used a few general types of wavelets and compared the effects of wavelet analysis and synthesis along with compression ratio and picture quality of the compressed ECG image.

The outline of the paper is as follows: A short summary of wavelet transform (WT) and more particularly the discrete wavelet transform (DWT) is given in section II. Section III explains the comparison methodology employed. In section IV results are shown for different wavelets followed by conclusions in section V.

II. Wavlet transform

Wavelet transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales [5]. Any decomposition of an image into wavelets involves a pair of waveforms: one to represent the high frequencies corresponding to the detailed parts of an image (wavelet function) and one for the low frequencies or smooth parts of an image (scaling function). The result of wavelet transform is a set of wavelet coefficients, which measure the contribution of the wavelets at these locations and scales.

A. Multiresolution Analysis

WT performs multiresolution image analysis [6]. The result of multiresolution analysis is simultaneous image representation on different resolution levels [7]. The resolution is determined by a threshold below which all details are ignored. The difference between two neighboring resolutions represents details. Therefore, an image can be represented by a low-resolution image (approximation or average part) and the details on each higher resolution level. Let us consider a one-dimensional (1-D) function f(t). At the resolution level j , the approximation of the function f(t) is $f_j(t)$. At the next resolution level j+1, , the approximation of the function f(t) is $f_{j+1}(t)$. The details denoted by $d_j(t)$ are included in $f_{j+1}(t)$, i.e. $f_{j+1}(t) = f_j(t) + d_j(t)$. This procedure can be repeated several times and function can be viewed as

$$f(t) = f_j(t) + \sum_{k=j}^{n} d_k(t) \qquad (1)$$

Similarly, the space of square integrable functions L^2 (R) can be viewed as a composition of scaling subspaces V_j and wavelet subspaces W_j such that the approximation of f(t) at resolution j($f_j(t)$) is in V_j and the details are in W_j. V_j and W_j are defined in terms of dilates and translates of scaling function φ and wavelet function ψ. V_j and W_j are localized in dyadically scaled frequency "octaves" by the scale or resolution parameter 2^j (dyadic scales are based on powers of two) and localized spatially by translation . The scaling subspace V_j must be contained in all subspaces on higher resolutions ($V_j \subset V_{j+1}$). The wavelet subspaces W_j fill the gaps between successive scales:

$$V_{j+1} = V_j + \oplus_{j=0 \text{ to } \infty} W_j \qquad (2)$$

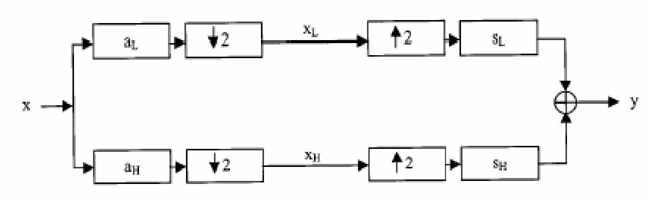


Fig. 1. Two Channel filter bank

Since $\varphi \in V_0 \in V_1$, it follows that the scaling function for multiresolution approximation can be obtained as the solution to a two-scale dilational equation

$$\varphi(x) = \sum_k a_L(k)\varphi(2x-k) \qquad (3)$$

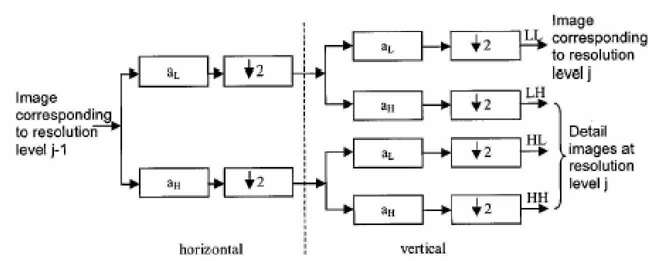
for some suitable sequence of coefficients . Once has been found, an associated mother wavelet is given by the following formula

$$\psi(x) = \sum_k a_H(k)\varphi(2x-k) \qquad (4)$$

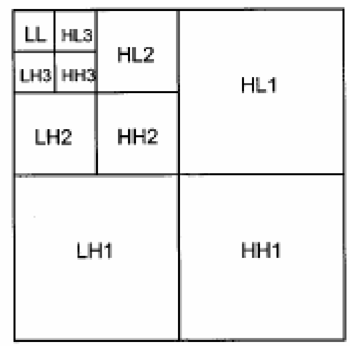
B. Discrete Wavelet Transform

One of the big discoveries for wavelet analysis was that perfect reconstruction filter banks could be formed using the coefficient sequences $a_L(k)$ and $a_H(k)$ (Fig. 1). The input sequence x is convolved with high-pass (HPF) and low-pass (LPF) filters $a_H(k)$ and $a_L(k)$ and each result is downsampled by two, yielding the transform signals x_H and x_L. The signal is reconstructed through upsampling by two and convolution with high and low synthesis filters $s_H(k)$ and $s_L(k)$. For properly designed filters, the signal is reconstructed exactly. By cascading the analysis filter bank with itself a number of times, a digital signal decomposition with dyadic frequency scaling known as discrete wavelet transform (DWT) can be formed. The mathematical manipulation that calls for synthesis is known as inverse DWT. An efficient way to implement this scheme is given in details in Ref. [7]. DWT for an image as a 2-D signal can be derived from 1-D DWT. The easiest way for obtaining scaling and wavelet function for two dimensions is by multiplying two 1-D functions. The scaling function for 2-D DWT can be obtained by multiplying two 1-D scaling functions: $\varphi(x,y) = \varphi(x)\varphi(y)$. Wavelet functions for 2-D DWT can be obtained by multiplying two wavelet functions or wavelet and scaling function for 1-D analysis. For the 2-D case, there exist three wavelet functions that scan details in horizontal $\psi^{(I)}(x,y) = \varphi(x)\psi(y)$., vertical $\psi^{(II)}(x,y) = \psi(x)\varphi(y)$., and diagonal directions: $\psi^{(III)}(x,y) = \psi(x)\psi(y)$. This may be represented as a four-channel perfect reconstruction filter bank as shown in Fig. 2(a). Now, each filter is 2-D with the subscript indicating the

type of filter (HPF or LPF) for separable horizontal and vertical components. The resulting four transform components consist of all possible combinations of high- and low-pass filtering in the two directions. By using these filters in one stage, an image can be decomposed into four different bands. There are three types of detail images for each resolution: horizontal (HL), vertical (LH), and diagonal (HH). The operations can be repeated on the low–low band using the second stage of identical filter bank. Thus, a typical 2-D DWT,



(a)



(b)

Fig. 2. (a) One filter stage in 2-D DWT, (b) Pyramidal structure of wavelet decomposition

used in image compression, will generate the hierarchical pyramidal structure shown in Fig. 2(b).

III. Image Quality Evaluation

The image quality can be evaluated objectively and subjectively [8,9]. A standard objective measure of image quality is reconstruction error. Two of the error metrics used to compare the various image compression techniques are the mean square error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N} [\, I(x,y) - I'(x,y)]^2 \qquad (5)$$

$$PSNR = 20 * \log10\,(255 / \mathrm{sqrt}(MSE)) \qquad (6)$$

where I(x,y) is the original image, I'(x,y) is the approximated version (which is actually the decompressed image) and M,N are the dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Subjective quality is measured by psychophysical tests or questionnaires with numerical ratings.

TABLE I

MSE AND PSNR RESULTS FOR DIFFERENT WAVELET FAMILIES AND DIFFERENT COMPRESSION RATIOS FOR ATRIAL FIBRILLATION

Compression ratio		Harr	DW-3	DW-5	DW-10	CW-2	CW-3	BW-2.2	BW-4.4
5:1	MSE	97.46	121.27	124.33	131.04	114.88	114.92	124.38	119.82
	PSNR	28.42	27.29	27.18	26.95	27.53	27.53	27.18	27.34
10:1	MSE	201.39	211.92	196.01	188.18	190.19	206.45	197.62	199.21
	PSNR	25.09	24.86	25.21	25.38	25.33	24.98	25.17	25.13
15:1	MSE	267.98	249.06	266.11	246.25	231.57	262.27	254.07	250.39
	PSNR	23.85	24.16	23.88	24.22	24.48	23.94	24.08	24.14
20:1	MSE	400.37	322.198	314.27	315.92	297.33	398.99	371.64	368.99
	PSNR	22.10	23.05	23.16	23.13	23.39	22.12	22.43	22.46

TABLE II

MSE AND PSNR RESULTS FOR DIFFERENT WAVELET FAMILIES AND DIFFERENT COMPRESSION RATIOS FOR SINUS ARRHYTHMIA

Compression ratio		Harr	DW-3	DW-5	DW-10	CW-2	CW-3	BW-2.2	BW-4.4
5:1	MSE	91.96	122.64	122.67	133.18	113.06	111.96	119.04	118.13
	PSNR	28.49	27.24	27.24	26.89	27.59	27.64	27.37	27.41
10:1	MSE	182.73	181.37	191.86	186.18	166.38	175.81	187.04	168.99
	PSNR	25.51	25.54	25.30	25.43	25.92	25.68	25.41	25.85
15:1	MSE	247.61	231.86	237.93	282.86	212.63	209.65	220.31	216.97
	PSNR	24.19	24.47	24.37	23.61	24.85	24.91	24.70	24.76
20:1	MSE	366.77	330.61	279.90	314.80	244.66	254.89	271.15	271.33
	PSNR	22.48	22.94	23.66	23.15	24.24	24.07	23.79	23.79

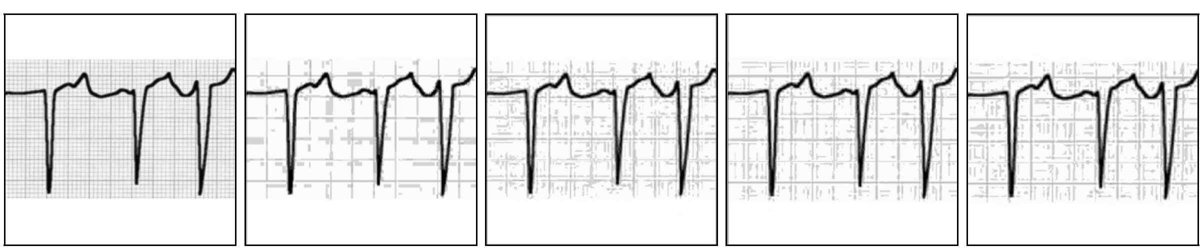
IV. RESULTS

In this preliminary study, we compared compressions at various ratios from 5:1 to 20:1 for eight different types of wavelets. They include: Haar, Daubechies-3 (DW-3), Daubechies-5 (DW-5), Daubechies-10 (DW-10), Coiflet -2 (CW-2), Coiflet-3 (CW-3), Biorthogonal -2.2 (BW-2.2) and Biorthogonal -4.4 (BW-4.4) wavelet. Discrete wavelet transform of the image was calculated with 5 levels of resolution for the wavelets mentioned earlier.

We considered two ECG images: supraventricular tachycardia (in our study atrial fibrillation) and Sinus arrhythmia. These images were initially scanned at 300 dpi and then converted into 8-bit grayscale images. Statistical results are presented in Table I and Table II. Results show that, in most of the cases for both images and at all compression ratios tried, MSE results between original and compressed images were significantly smaller for Coiflet-2 wavelet than for other wavelets. However comparing with other wavelets Haar wavelet based compression shows higher PSNR value for lower Compression ratio. Although PSNR value decreases rapidly at higher compression ratios large blocks (5mm X 5mm blocks) of ECG paper are clearly identifiable at compression ratio 15 in most of the cases and at 20 with Coiflet-2 wavelet. Fig.3 shows compressed image of atrial fibrillation with different wavelets with compression ratio (CR) 20:1. Fig. 4 shows compressed images with CW-2 for both ECG images at CR=15:1 and 20:1.

V. CONCLUSION

In this paper we examined the effects of different wavelet functions, filter orders, image contents and compression ratios in ECG image compression CW-2 is clearly the best performer in the statistical measures. Of course, none of these qualities are a good measure of image quality and there is no such measure known. What truly matters is the subjective quality as judged by a diagnostic expert. In ECG image the presence of big blocks is vital for correct diagnosis. We are carrying out more detailed studies for a much larger set of ECG images based on both objective measure and diagnostic performance.



(a) (b) (c) (d) (e)

Fig. 3. Atrial fibrillation (a) Original image compressed image at ratio 20:1 with (b) Haar, (c) DW-5, (d) CW-2, (e) BW-4.4

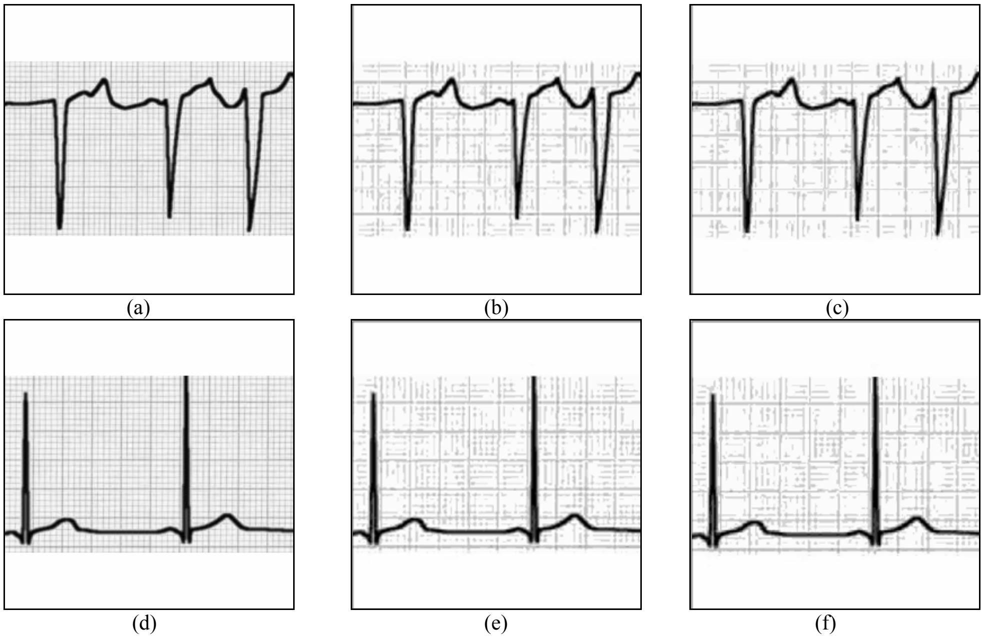


Fig. 4. Original test image (a) Atrial fibrillation with compressed image (b) CR= 15:1,(c) CR=20:1
(d) Sinus arrhythmia with compressed image (e) CR= 15:1,(f) CR=20:1.

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