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ECG Image Compression: Essentially Non-Oscillatory Interpolation Technique and Lifting Schemes

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Abstract: Out of many transform methods the paper is making use of (i) Cohen-Daubechies-Feauveau 9/7 (cdf9/7) wavelet transform (ii) Le Gall 5/3 (legall5/3) wavelet transform (iii) Two Dimensional Essentially Non-Oscillatory cell-average decomposition (ENOCA2) (iv) Two Dimensional Max-lifting morphological wavelet transform (Maxlift2) and (v) Two Dimensional Med-lifting morphological wavelet transform (Medlift2) for ECG image compression. This study aims at recreating the image using inverse transform after compressing the ECG image by making the use of the above mentioned transforms. There was an inverse relationship between image quality and image compression. This study was undertaken to compare the different transform methods for ECG image compression.

Keywords: Cohen-Daubechies-Feauveau 9/7 wavelet transform; Le Gall 5/3 wavelet transform; Two Dimensional: Essentially Non-Oscillatory cell-average decomposition (ENOCA2), Max-lifting morphological wavelet transform (Maxlift2), Med-lifting morphological wavelet transform (Medlift2).

I. INTRODUCTION

The aim of compression is to represent an ECG image with the smallest possible number of bits [1]. Traditionally there were various methods to compress an image such as Fourier transforms, Cosine transform etc [2]. But wavelet transform (WT) provides a novel approach for the analysis of the image. This is due to fact that WT supports features like progressive image transmission (by quality and resolution), ease of compressed image manipulation, region of interest coding etc [3]. Wavelets are non-adaptive sachems. Hence large coefficients always appear at discontinuities when wavelets are used. The edges in an image are vital information and constitute discontinuity in the data. Therefore, it is necessary to preserve them while efficiently representing the image [4]. However, essentially non-oscillatory (ENO) interpolation technique avoids the discontinuity which reduces large coefficients at edges and results in better compression capabilities. The ENO interpolatory is a data dependent, nonlinear technique [5] can eliminate the Gibbs phenomenon [6] [10]. In this paper, two dimensional ENO cell average (ENOCA2) decomposition is used for ECG compression.

Wavelet transform are linear tool and traditionally implemented by convolution or FIR filter bank structures [7]. However, implementation requires a large number of arithmetic computations and a large storage capacity. But these features are not desirable for high speed or low power image processing application [7]. Sweldens [7] developed the algorithm for nonlinear WT by introducing lifting schemes. Lifting schemes has many advantages over the convolution based approach. These are discussed as follows (i) it requires less computation (up to 50%) compared to the convolution based approach (ii) During lifting implementation, no extra memory buffer is required because of the in-place computation feature of lifting (iii) it offers integer to integer transformation suitable for lossless image compression [7]. In this paper, Cohen-Daubechies-Feauveau 9/7 (CDF 9/7) and Le Gall 5/3 (legall5/3) wavelet transform along with two dimensional Maxlift and Medlift lifting schemes methods [8] were used for ECG image compression.

Section II describes the performance metrics. Section III presents the methodology. Finally, results and concluding remarks are given in section IV and V respectively.

II. Performance Metrics

The metrics like number of approximation components and Peak signal to noise ratio (PSNR) were used for the performance analysis. There was always a problem to present image with few components of image approximation coefficient. However, it is need to present image with least no. of image approximation coefficient. This is similar to lossy image compression, but ignoring the problems of quantization and encoding. PSNR is the comparison between an original image and a reconstructed image. Higher the PSNR value, better will be the image quality [10, 11]. Typical values for the PSNR in lossy image were between 30 and 50 dB [10, 11].

III. Methodology

First, the input ECG image is converted from RGB to the JPEG Y'CbCr colorspace. The Y'CbCr ECG image is transformed using various transforms, all but the significant transform coefficients were set to zero, and then inverse transformed. The inverse transformed ECG image was converted into Y'CbCr to the RGB [10].

The following steps were to be incorporated for ECG image compression:

(i) ECG image was converted from RGB to JPEG Y'CbCr colorspace.

(ii) Transform the Y'CbCr to another domain.

(iii) Apply a threshold.

(iv) Inverse-transform

(v) Calculate the PSNR

(vi) Converted from Y'CbCr JPEG to RGB colorspace ECG image.

IV. Results and Discussions

The efficiency of the various transforms was tested by experimentation on the ECG image database [9]. In this paper four ECG images were taken to check the suitability of transform for ECG compression. The ECG image was transformed using ENOCA2 with one stage and five degree interpolation. Level used for decomposition was 1 in case of Maxlift2 and Medlift2. In wavelet cdf9/7 and legall5/3 the decomposition levels were 5. The results were presented in Table I, Table II, Table III and Table IV. Table I represents that Wavelet legall5/3 gives high PSNR from other transforms. Similar observations were taken from the Table II and Table III. But in case of Table IV high PSNR value was observed from Wavelet cdf9/7. This concludes that the wavelet cdf9/7 and legall5/3 were better from other transforms. Figure 1-4 shows the original ECG images. Further, Figures 5-9 represents the reconstructed ECG images after compression with various transforms.

TABLE I
Comparative Performance of various transforms on image_121(800*416)

image_121 (800*416)					
Transform	**ENOCA2**	**Maxlift2**	**Medlift2**	**Waveletcdf97**	**Waveletlegall53**
Number of approximation components	**PSNR**	**PSNR**	**PSNR**	**PSNR**	**PSNR**
3:1	55.3	63.7	61.4	77.9	78.1
4:1	39.1	42.6	40.5	52.3	52.2

5:1	34.0	34.7	32.9	43.6	43.9
6:1	31.3	30.6	29.7	39.3	39.7
7:1	29.6	28.1	27.7	36.8	37.3
8:1	28.3	26.4	26.1	35.2	35.6
9:1	27.3	25.1	24.8	34.0	34.4
10:1	26.3	23.8	23.6	33.1	33.5

TABLE II
Comparative Performance of various transforms ON ecg-exigency-003-b (800*160)

ecg-exigency-003-b (800*160)					
Transform	**ENOCA2**	**Maxlift2**	**Medlift2**	**Waveletcdf97**	**Waveletlegall53**
Number of approximation components	**PSNR**	**PSNR**	**PSNR**	**PSNR**	**PSNR**
3:1	39.5	39.6	39.6	60.1	59.9
4:1	38.5	39.2	39.0	56.3	56.4
5:1	37.0	38.1	37.7	51.6	51.9
6:1	35.8	36.7	36.3	48.2	48.8
7:1	34.9	35.4	35.0	45.9	46.6
8:1	34.0	34.0	33.5	44.2	45
9:1	32.9	32.2	31.6	42.9	43.7
10:1	31.8	29.9	29.5	41.8	42.6

TABLE III
Comparative Performance of various transforms ON ECG-Exigency-004-d (376*306)

ECG-Exigency-004-d (376*306)					
Transform	**ENOCA2**	**Maxlift2**	**Medlift2**	**Waveletcdf97**	**Waveletlegall53**
Number of approximation components	**PSNR**	**PSNR**	**PSNR**	**PSNR**	**PSNR**
3:1	48.5	56.5	52.6	64.0	64.5
4:1	36.5	37.1	35.5	45.1	45.3
5:1	32.0	31.0	30.4	39.3	39.5
6:1	29.2	27.5	27.4	36.1	36.4
7:1	27.3	25.2	25.4	34.0	34.3
8:1	25.7	23.5	23.7	32.5	32.8
9:1	24.3	22.2	22.2	31.4	31.6
10:1	22.9	20.9	20.6	30.5	30.7

TABLE IV
Comparative Performance of various transforms ON ECG-exigency-005-b (1200*630)

ECG-exigency-005-b (1200*630)					
Transform	**ENOCA2**	**Maxlift2**	**Medlift2**	**Waveletcdf97**	**Waveletlegall53**
Number of approximation components	**PSNR**	**PSNR**	**PSNR**	**PSNR**	**PSNR**
3:1	41.1	41.1	41.1	61.3	61.0
4:1	40.4	40.9	40.9	59.7	59.4
5:1	39.3	40.4	40.1	57.1	56.9
6:1	38.4	39.4	39.0	54.5	54.4
7:1	37.6	38.4	38.0	52.4	52.3
8:1	37.0	37.4	37.1	50.9	50.7
9:1	36.5	36.5	36.3	49.6	49.4
10:1	36.0	35.5	35.3	48.6	48.3

Fig. 1 Original ECG image of image_121 (800*416).

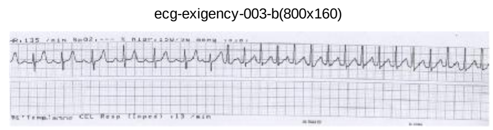

Fig. 2 Original ECG image of ecg-exigency-003-b (800*160)

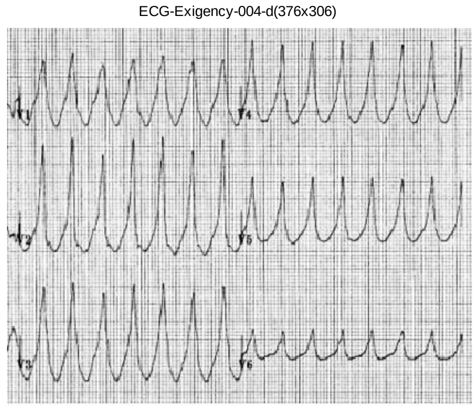

Fig. 3 Original ECG image of ECG-Exigency-004-d (376*306)

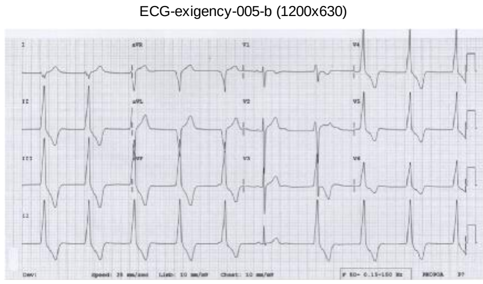

Fig. 4 Original ECG image ECG-exigency-005-b (1200*630)

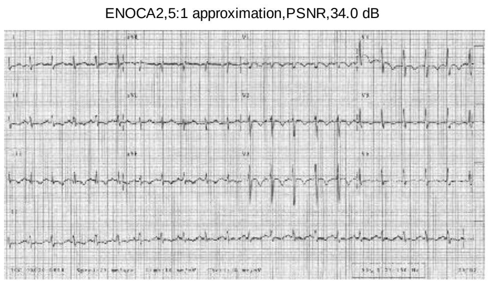

Fig. 5 Reconstructed ECG image of image_121 (800*416) using ENOCA2

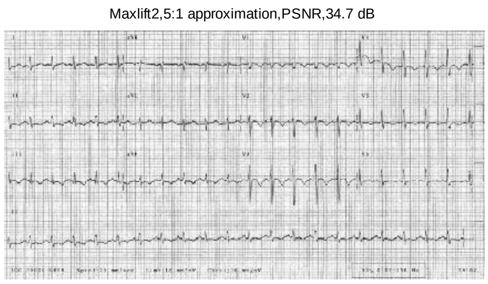

Fig. 6 Reconstructed ECG image of image_121 (800*416) using Maxlift2

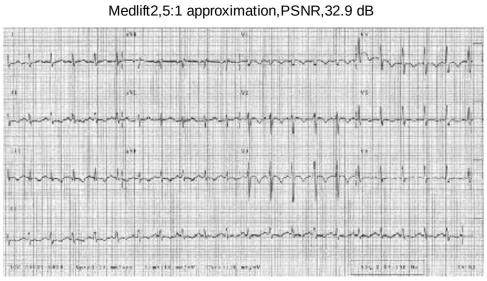

Fig. 7 Reconstructed ECG image of image_121 (800*416) using Medlift2

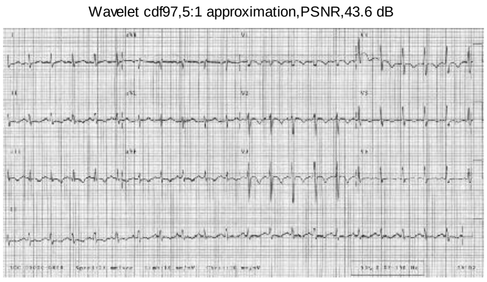

Fig. 8 Reconstructed ECG image of image_121 (800*416) using Wavelet cdf9/7

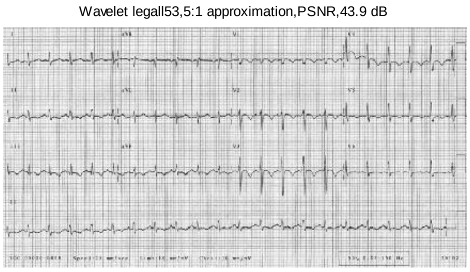

Fig. 9 Reconstructed ECG image of image_121 (800*416) using Wavelet legall5/3

V. CONCLUSION

This paper represents the comparative analysis of Wavelet cdf9/7, wavelet legall5/3, ENOCA2, Maxlift2 and Medlift2 for ECG image compression. In case of, image_121 using wavelet cdf9/7 gives PSNR of 77.9 and 33.1 db at 3:1 and 10:1, respectively. The corresponding PSNR values for wavelet legall5/3, ENOCA2, Maxlift2 and Medlfit2 were 78.1 and 33.5 db, 55.3 and 26.3 db, 63.7 and 23.8 db, and 61.4 and 23.6 db, respectively at 3:1 and 10:1. The above sited results justify the statement that high number of approximation components of the image gives a poor PSNR and hence the poor quality. Also the image quality of wavelet cdf9/7 and legall5/3 was better among the considered transforms.

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