Performance Evaluation of Wavelet Filters for Compression of Retinal Images

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Abstract— **In this paper, a comparative study of a set of wavelet filters used for wavelet based retinal image compression system has been made. The performance of different wavelet filters is observed by decomposing the retinal image to various levels for a given compression ratio. The visual quality of the reconstructed retinal image is observed at each decomposition level. The statistical measures such as the peak signal to noise ratio (PSNR), laplacian mean squared error (LMSE) and structural similarity (SSIM) index are used to quantify the effect of wavelet filters. The subjective evaluation is also done by examining the quality of reconstructed image. The optimum decomposition level and a best suited wavelet filter for the compression of a set of retinal images can be chosen from the results presented in the paper.**

I. Introduction

The digital imaging techniques are very advantageous in medical applications. They are non-invasive, cause minimal discomfort to the patients and provide flexible means for anatomical or physiological analysis. The medical images thus obtained are used for diagnosis of diseases. For example, the retina- a layer of membrane at the back of the eye can be visualized as a retinal image (or photograph) by the fundus camera. Retinal images are widely used in the diagnosis and treatment of various eye diseases. Medical images require large storage space. The limited bandwidth and storage space calls for the compression of images before transmission or storage. The primary concern in compressing medical images is that, the reconstructed image should not lose diagnostic information required for the diagnosis of disease. Hence in medical image compression it is a great challenge to have compression methods that efficiently compress the image and still preserves the diagnostic information [1]. In 2-D block transform based compression methods, image data can be represented by coefficients of discrete image transforms. Usually the image is split into blocks of 8x8 or 16x16 pixels and then each block is transformed separately. The compression is achieved by discarding the transform coefficients that make only small contribution to the total energy of the signal. However this method does not take into account any correlation between blocks and creates blocking artifacts, which are not good if a smooth image is required. Over the past several years, the discrete wavelet transform (DWT) has gained more attention in image compression research. The DWT is applied to entire image rather than sub-images and hence avoids blocking artifacts. The property of dual localization of a signal in both the original and in the transformed domain by DWT makes it more suitable compared to other transforms. DWT splits the original image into several subband images and this decomposition is similar to human visual system (HVS) recognition process [2]. In recent years, the sub-band or wavelet coding is being used for lossy compression of medical images [3], [4], [5]. The DWT based method draws great attention because of its energy compaction capability, efficiency and easy implementation.
A wavelet based compression system consists of decomposition of the signal using a type of wavelet filter, thresholding and subsequent quantization of the wavelet coefficients followed by an entropy coder [6], [7]. Very few works based on wavelet transform are reported for retinal image compression [8], [9]. However no systematic study has been done to evaluate the performance of wavelet filters at various decomposition levels and at different compression rates. The intention of this paper is to compare and contrast the behavior of few general types of wavelet filters at various image decomposition levels. In this study, the wavelet compression method, set partitioning in hierarchical trees (SPIHT) [10] is applied to digital retinal images. The investigation starts by selecting a wavelet filter for a given compression ratio (CR) and examining the performance at different levels of image decomposition. The comparative evaluation of wavelet filters used in the compression method is investigated subjectively, considering the visual image quality test and by numerically computed objective measures, the peak signal to noise ratio (PSNR), laplacian mean squared error (LMSE) and structural similarity index (SSIM)-a HVS based quality measure [11].
The rest of the paper is organized as follows: Section 2 presents discrete wavelet transform (DWT) in image compression, Section 3 briefs the image quality measures used for evaluation, Section 4 contains the experimental results and discussion and the conclusion in Section 5.

II. DWT based retinal image compression

In DWT based coding, the entire image is transformed and compressed as a single data object rather than block by block. Hence, the typical blocking artifacts are avoided and better quality can be obtained [3]. The DWT offers better spatial resolution at high frequencies and better frequency resolution at low frequencies which is well matched with the properties of HVS [2].

A. Number of decomposition levels

The number of decompositions determines the lowest level resolution in wavelet domain and quality of the compressed image. The decomposition level changes the proportion of detail coefficients in the detail bands. Decomposing a signal to a greater level provides extra detail coefficients of low magnitude that can be thresholded in order to obtain higher compression rates. The image quality is better for larger number of decompositions as the important WT coefficients are selected more successfully from less important coefficients. However this leads to energy losses and at the same time computational complexity also increases. Decomposing to fewer levels, provides better energy retention but not as great compression. Hence it is required to compromise between computational complexity and quality. The experiments in this paper use decomposition levels from 2 to 8 for each wavelet filter and for different compression ratio.

B. Choosing the wavelet filters

The different wavelets are obtained by dilation and translated versions of a single mother wavelet function. Since large numbers of wavelet filters are available, investigators often have a difficulty in selecting an optimal wavelet for a specific image processing application. The selection of the wavelet filter depends on the important properties like-compact support, symmetry, orthogonality, regularity and degree of smoothness. How well a wavelet can pack the signal energy in as few coefficients as possible depends on the wavelet properties. But it is difficult for a wavelet filter to have all properties and has to sacrifice some property to satisfy the remaining properties. This compromise makes the filters to belong to the wavelet family of orthogonal, bi-orthogonal or symmetric. In each family, wavelet filters of different order(N) can be chosen. Generally the decomposition (Nd) and reconstruction (Nr) filters will be of same order but biorthogonal wavelet can have similar or different filter orders for decomposition and reconstruction. The lower order filters with compact support have good time localization and preserves high frequency features like edges. The higher order filters leads to higher degree of smoothing because of their wider support.
In this paper, five type of wavelet families such as Haar, Daubechies, Coiflet, Biorthogonal and Symmetric wavelets are considered. The following set of wavelet filters are examined : Haar wavelet (db-N) with N = 1; Daubechies wavelet (db-N) with N = 2 , 3 , 5 , 6 , 7 ; Coiflet wavelet (coif-N) with N = 1 , 2 , 3 , 4 , 5 and Biorthogonal wavelet (bior-Nr.Nd) with (Nr,Nd) = 2.2 , 3.3 , 4.4 , 5.5 , 6.8 and Symmetric wavelets (sym-N) with N = 2 , 4 , 5 , 6 , 7.

III. Image Quality Evaluation

The quality of the reconstructed image can be evaluated objectively and subjectively. Objective measures such as PSNR, LMSE, and SSIM are mathematically computable distortion measures. The PSNR is given by (1).

$$\text{PSNR} \;= 10\log_{10} \frac{(2^b-1)^2}{\frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}[x(i,j)-y(i,j)]^2} \tag{1}$$

where x and y are the original and reconstructed image of size RC and b is the number of bits used to represent an image pixel. For retinal images used here, b is 8. The digital retinal image consists of blood vessels structure. The changes in blood vessel pattern helps in the early detection of a disease called diabetic retinopathy (DR). The blood vessels have greater contrast, lower intensity values and appear dark in the retinal image. This variation in the intensity levels near the vessel border can be captured by gradient based operators. In this direction a 2-D discrete laplacian operator is used to detect the blood vessels as it captures information relating to edge features. Edge information is known to be an image property to which the human visual system is highly sensitive [2]. Therefore laplacian based error measure is more suitable to evaluate the quality of the retinal images. The two-dimensional laplacian operator based edge detector expressed by (2), is used to detect vessel structure in the retinal image [13]. Then LMSE is defined as the MSE between the laplacian of the original image and laplacian of the reconstructed image [14] and computed using (3).

$$\begin{aligned} O((\mathrm{x}(i,j)) = {} & \mathrm{x}(i+1,j)+\mathrm{x}(i-1,j)+ \\ & \mathrm{x}(i,j+1)+\mathrm{x}(i,j-1)-4\mathrm{x}(i,j) \end{aligned} \tag{2}$$

$$\text{LMSE} = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C}\;[O(x(i,j))-O(y(i,j))]^2}{\sum_{i=1}^{R}\sum_{j=1}^{C}\;[O(x(i,j))]^2} \tag{3}$$

Since the images are ultimately viewed by human observers, a HVS based measure SSIM is also used to evaluate the quality of the image [11]. The SSIM is an objective image quality measure capable of reflecting perceptual qualities based on the HVS. It incorporates HVS in the form of three components-luminance, contrast and structural comparison between the original and reconstructed images and is computed as in (4).

$$\text{SSIM(x, y)} = \frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \tag{4}$$

where μ and σ are the mean and variance of the respective image. C1, C2 and C3 are small constants. For better image quality assessment, the SSIM is applied locally. The statistics within a local window are calculated. Then mean SSIM is obtained to measure overall image quality.
Any image compression method must ensure that there is no significant loss of diagnostic information for visual examination as well as subsequent medical image analysis. Hence in addition to objective measures, the perception and diagnostic based subjective evaluation quantified by the mean opinion score (MOS) is also considered [15]. The MOS values are obtained from two medical experts and six students working in different areas of signal processing. The MOS is obtained not only by overall grading but also giving scores by comparing the various diagnostic features such as optic disk, macula, blood vessel structure and pathological features between the original and compressed images.

TABLE I
MEAN OPINION SCORE (MOS): MOS AND ITS DESCRIPTION WITH RESPECT TO DIAGNOSIS

Rating	Image quality	Level of Distortion	Effect of distortion on Diagnostic features	Diagnosis
5	Very Good	Imperceptible	All diagnostic features are preserved	Correct
4	Good	Perceptible but not annoying	Most of the significant features are preserved	Meaningful
3	Fair	Slightly annoying	some of the features are distorted	Satisfactory
2	Poor	Annoying	Most of the diagnostic features are distorted	Poor
1	Bad	Very annoying	All diagnostic features are distorted	Not possible

The subjective test is conducted by displaying a pair of images on the screen. The first image is always the original image without compression. The second image is the reconstructed version of the original which possess some difference with respect to original. The assessor is asked to give the score for the second image taking the first image as reference. The viewers are allowed to assess without any constraint on viewing distance, time and lighting conditions. The 5 level scoring with description is given in Table I. The goal here is, to observe the performance of a given wavelet filter at different decomposition levels. The evaluation is done across all images and at a given CR. Then the whole process is repeated for other values of CR.

IV. RESULTS AND DISCUSSION

A very popular and publicly available wavelet based compression method SPIHT[10]is used for compressing the digital retinal images. This compression method exploits the inherent similarities across sub-bands in a wavelet decomposition of an image. The merits of this algorithm are good image quality, high PSNR, optimized for progressive image transmission and fast coding and decoding. The various wavelet filters are applied on 10 retinal images (01_test to 05_test and $36\_training$ to $40\_training$) randomly selected from test and training set of DRIVE (Digital Retinal Images for Vessel Extraction) database [11]. The green plane image is extracted from original color image and resized to 256 x 256. The compression ratio is varied from 2 to 10. The image is decomposed to levels 2 to 8.The experimental results are obtained by decomposing an image to all levels using a given wavelet filter and for different compression ratio. The quality of resulting image is quantitatively tested by computing the PSNR, LMSE and SSIM. The qualitative MOS is obtained from subjects for each of the reconstructed images. Similarly the observation is made for whole set of filters. It is observed that for some images with CR beyond 8,the diagnosis falls below satisfactory range and therefore not useful in the performance analysis. But still to have the full range of MOS and diagnosis, the results for CR=10 are also recorded.

A. Selection of optimum decomposition level

Decomposing the image to fewer levels means better energy retention and better image quality but not as great compression. Decomposing to higher levels provides better compression but more energy loss and degraded image quality. The experiments in this work show that the best trade-off between energy loss, compression and image quality is provided by decomposing to a level of 5 or 6. The results required for selecting the optimum decomposition level for a given wavelet filter for all ten images across all compression ratios are shown from Table II. The optimum decomposition level can be determined by plotting the PSNR against decomposition levels at different compression rates as shown in Fig.1(a). After some point of decomposition level, the PSNR tends to saturate and that level is taken as the optimum decomposition level. Similarly Fig.1(b) shows the LMSE variation with decomposition levels. The LMSE decreases from a higher value from initial decomposition levels to a much lower value at later levels upto an optimum decomposition level and thereafter the variation is very little. Fig.1(c) gives the SSIM values at different decomposition levels. The SSIM value increases initially upto an optimum decomposition level and remain almost the same for further decomposition levels. For the case of retinal image compression considered in this paper, the level 5 is taken as optimum decomposition level.

B. Selection of best suited filter

A best wavelet filter is chosen by considering the effect of all wavelet filters on the quality of a set of 10 images at the optimum decomposition level and at various compression rates. The comparison results of objective quality measures- the PSNR, LMSE and SSIM averaged over 10 images for each wavelet filter are recorded in TableIII. It is noted from the results presented in Table III that among all wavelet filters considered, the filter bior6.8 performs better by having maximum PSNR, minimum LMSE and best SSIM value at different CR. It is also possible to find out the better filter from a particular family of filters using the same criterion.
Fig.2 shows the 2 level decomposition of the preprocessed original image 04_test. In this result, the best suited wavelet filter bior 6.8 is used.

V. CONCLUSION

The wavelet compression of digital retinal image using SPIHT is performed using various wavelet filters. The perceptual effect of different wavelet filters, filter orders, decomposition levels at different CR is examined. The performance comparison of wavelet filters is done on the basis of objective quality parameters- the PSNR, LMSE and SSIM. These measures help in selecting the optimum decomposition level which is chosen as 5 and bior6.8 as the best suited filter for retinal image compression. We also focused on the experts' assessment of diagnostically acceptable quality of compressed retinal images to ensure sufficient accuracy. The results of this

TABLE II

AVERAGE VALUES OF PSNR, LMSE AND SSIM AT ALL DECOMPOSITION LEVELS FOR WAVELET FILTER DB5.

	CR=2			CR=4			CR=6			CR=8			CR=10		
Level	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM
2	45.5812	74.5942	0.9631	29.9154	377.3251	0.64104	24.2738	438.2921	0.5338	21.2931	452.2332	0.4897	17.6754	512.6224	0.3282
3	54.1145	5.2589	0.9973	43.3901	58.4485	0.9692	39.7813	114.8377	0.9363	37.0941	176.7749	0.9006	34.6207	259.0209	0.8600
4	56.7421	3.0959	0.9984	45.8521	37.0479	0.9812	42.4427	70.8622	0.9621	40.7597	98.1077	0.9456	39.3950	121.4702	0.9316
5	57.4016	2.6391	0.9986	46.4079	32.4026	0.9835	42.9953	63.0446	0.9663	41.3057	89.7835	0.9511	40.1537	106.9521	0.9396
6	57.5395	2.5547	0.9987	46.5270	31.4340	0.9839	43.1054	61.5864	0.9671	41.4197	87.8071	0.9522	40.2900	104.5200	0.9412
7	57.5627	2.5408	0.9987	46.5472	31.2559	0.9840	43.1239	61.3252	0.9672	41.4386	87.4348	0.9524	40.3135	104.2126	0.9414
8	57.5659	2.5888	0.9987	46.5499	31.2302	0.9840	43.1268	61.2898	0.967	41.4416	87.3918	0.9524	40.3170	104.1776	0.9415

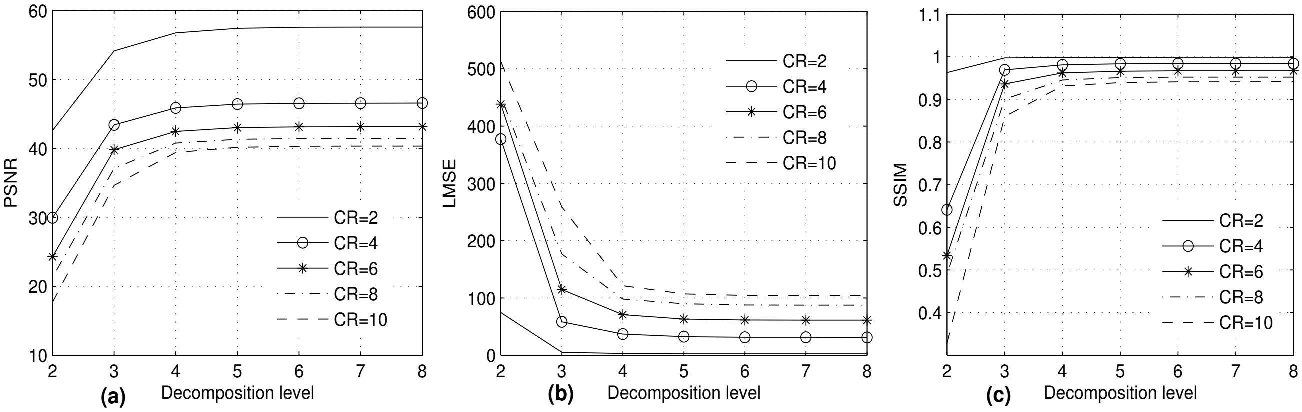

Fig. 1. Average values of PSNR (a), LMSE (b) and SSIM (c) at different decomposition levels for CR = 2, 4, 6, 8, 10 and Wavelet filter used is db5.

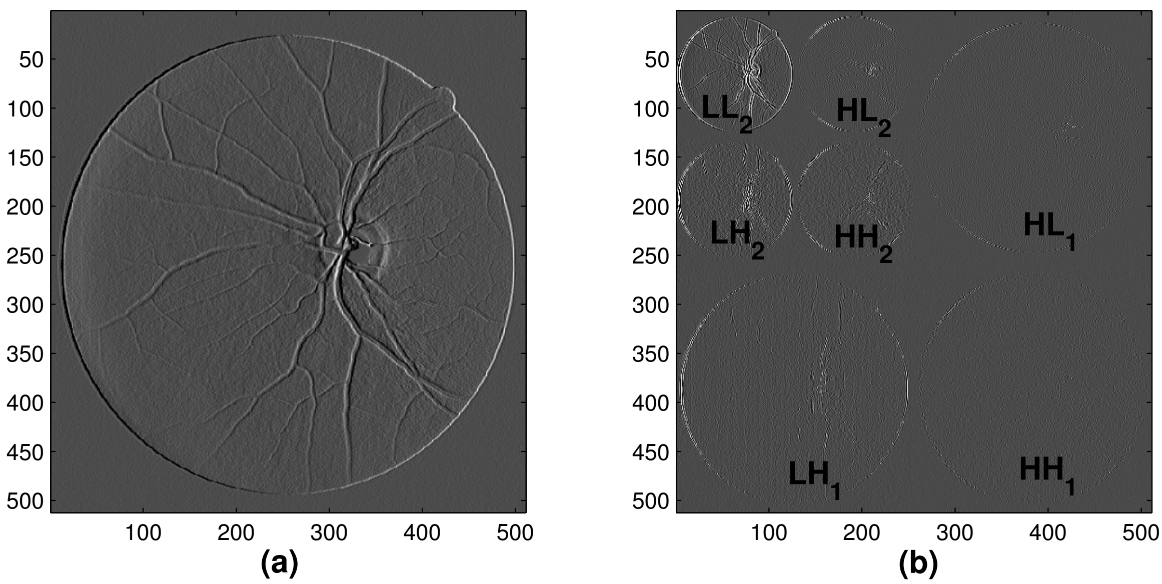

Fig. 2. (a) Original image (512x512) (b) 2-level decomposition of the image

study showed that there is relatively good agreement among medical experts and student observers in their capacity to perceive diagnostic distortion due to compression. The results also gave an idea of how much compression is tolerable before the diagnostic quality of an image has been compromised (the MOS below satisfactory level). This study indicates that high compression ratios are not acceptable in the diagnostic sense and also that the tolerance for compression varies across images.

TABLE III

AVERAGE VALUES OF PSNR, LMSE AND SSIM AT OPTIMUM DECOMPOSITION LEVEL.

Wavelet	CR=2			CR=4			CR=6			CR=8			CR=10		
	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM	PSNR	LMSE	SSIM
bior2.2	56.810	3.233	0.998	46.149	36.491	0.983	43.030	65.974	0.967	41.306	94.210	0.953	40.245	109.509	0.943
bior3.3	54.067	6.208	0.997	44.412	54.035	0.976	41.674	85.917	0.958	40.089	112.634	0.944	38.891	135.523	0.932
bior4.4	57.626	2.345	0.999	46.660	28.822	0.985	43.287	56.622	0.969	41.591	82.305	0.954	40.487	98.782	0.944
bior5.5	56.782	2.252	0.998	46.011	27.249	0.983	42.430	55.080	0.963	40.992	79.151	0.949	39.869	95.420	0.937
bior6.8	57.675	2.503	0.999	46.675	30.760	0.984	43.324	59.448	0.969	41.611	85.415	0.954	40.494	101.910	0.944
coif1	57.407	2.618	0.999	46.496	31.528	0.984	43.108	62.218	0.967	41.402	89.255	0.952	40.262	107.073	0.941
coif2	57.558	2.546	0.999	46.620	30.658	0.984	43.216	60.355	0.968	41.525	86.435	0.953	40.401	103.284	0.943
coif3	57.527	2.571	0.999	46.541	31.309	0.984	43.145	60.970	0.967	41.471	86.878	0.952	40.341	103.567	0.942
coif4	57.465	2.613	0.999	46.452	32.238	0.984	43.056	62.591	0.967	41.378	88.865	0.952	40.241	105.802	0.940
coif5	57.395	2.653	0.999	46.400	32.521	0.983	42.987	63.198	0.966	41.312	89.976	0.951	40.151	106.876	0.940
db1	56.067	3.569	0.998	46.199	33.543	0.982	42.738	67.729	0.964	41.015	96.059	0.947	39.723	119.450	0.935
db2	57.326	2.658	0.999	46.433	32.007	0.983	43.022	63.170	0.966	41.316	90.063	0.951	40.164	107.981	0.940
db3	57.446	2.608	0.999	46.520	31.541	0.984	43.113	61.610	0.967	41.425	88.149	0.952	40.287	105.493	0.941
db5	57.402	2.639	0.999	46.408	32.403	0.984	42.995	63.045	0.966	41.306	89.784	0.951	40.154	106.952	0.940
db6	57.355	2.680	0.999	46.315	32.953	0.983	42.903	64.145	0.966	41.223	91.636	0.950	40.059	109.074	0.938
db7	57.302	2.718	0.999	46.307	33.289	0.983	42.854	64.907	0.965	41.174	92.495	0.950	39.983	110.418	0.937
sym2	57.326	2.658	0.999	46.433	32.007	0.983	43.022	63.170	0.966	41.316	90.063	0.951	40.164	107.981	0.940
sym4	57.553	2.546	0.999	46.606	30.803	0.984	43.179	60.990	0.967	41.483	87.016	0.953	40.354	104.173	0.942
sym5	57.630	2.502	0.999	46.627	30.308	0.985	43.230	60.145	0.968	41.540	86.106	0.953	40.414	103.087	0.942
sym6	57.591	2.528	0.999	46.594	30.959	0.984	43.177	60.974	0.967	41.495	86.744	0.953	40.368	103.592	0.942
sym7	57.512	2.569	0.999	46.525	31.554	0.984	43.108	61.452	0.967	41.449	87.062	0.952	40.314	104.322	0.941

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