Selection of Mother Wavelet For Image Compression on Basis of Image

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Abstract

Recently discrete wavelet transform and wavelet packet has emerged as popular techniques for image compression. The wavelet transform is one of the major processing components of image compression. The results of the compression change as per the basis and tap of the wavelet used. This paper compares compression performance of Daubechies, Biorthogonal, Coiflets and other wavelets along with results for different frequency images. Based on the result, it is proposed that proper selection of mother wavelet on the basis of nature of images, improve the quality as well as compression ratio remarkably.

**Keyword**: Compression, Mother wavelet, Daubechies, Biorthogonal, Coiflets, Image

I. INTRODUCTION

In today’s modern era, multimedia has tremendous impact on human lives. It becomes inseparable part of our day-to-day activities. Image is one of the most important media contributing to multimedia. The image is one of the media of information. Thousand of words information can be replaced by a single image. It has been said that, “a picture is worth of thousand words”. This is all the more true in the modern era, in which information has become one of the most value of the assets. The unprocessed image heavily consumes very important resources of the system. Uncompressed image requires large memory to store the image and large bandwidth to transmit the image data. While the advancement of the computer storage technology continues at the rapid rate the means for reducing the storage requirement of image is still needed in most of the situations. And hence it is highly desirable that the image be processed, so that efficient storage, representation and transmission of it can be worked out. The processes involve one of the important processes - “Image Compression”. Methods for digital image compression have been the subject of research over the past decade. The image compression mechanism that is proposed by the Joint Photographic Expert Group (JPEG) [12] is today’s still image lossy compression standard and it is used for natural images. It combines block implementation of the Discrete Cosine Transform (DCT) quantization technique and then Huffman coding. Although these methods are efficient even if lower average bit rate is employed, the block noise (artifact) appears in the resulting image [8], [13].

Advances in Wavelet Transforms and Quantization methods have produced algorithms capable of surpassing image compression standards, like the Joint Photographic Expert Group (JPEG) algorithm. The recent growth of data intensive multimedia based applications have not only sustained the need for more efficient ways to encode the signals and images but also have made compression of such signals central to storage and communication technology.

The JPEG2000 standard employs wavelet for compression due to its merits in terms of scalability, localization and energy concentration [17]. It also provides the user with many options to choose to achieve further compression. JPEG2000 suffers from blurring artifacts and ringing artifacts [8]. This paper presents the result of image compression for different mother wavelets. It is concluded that selection of proper mother wavelet is one of the important parameters of image compression. We propose mother
wavelet db1 or db4, biorl.1 or bior6.8, coif1 or coif5 for image compression. This selection is based on nature of the image.

II. COLOR SPACE AND HUMAN PERCEPTION

The digital image is represented as two-dimensional array of picture elements having M rows and N columns. M × N defines the resolution of the image. Every sampled picture element is known as pixel in digital image processing. Each pixel is identified with unique positional tuple (x, y). In other words, image is stored as a two dimensional signal. It is represented by function \( f(x, y) \), where \( x \) and \( y \) are spatial co-ordinates of a pixel and the value of function \( f \) at any pair of co-ordinate \((x, y)\) is called as intensity of a pixel or gray level of a pixel of the image at that point in gray images. For color images the function \( f \) maps the color information associated with the pixel at \((x, y)\).

The use of color in image processing algorithm is motivated due to two-principle factors,

i) The color is powerful component, that often simplifies object identification and extraction of the scenes;

ii) The human visual perception can identify thousands of color shades and intensities, compared to about only few shades of gray color.

The color image processing is divided into two major areas: full color and pseudo color image processing. Basically the colors that humans and some other animals perceive an object are determined by the nature of the light reflected from the object. The human eye has two types of cells playing major role in object perception; Rod cell and Cone cell. Detail experimental evidence has established that the six to seven million cone cells in the human eye can be divided into three principle sensing categories corresponding roughly to red, green and blue. Approximately sixty-five percent of all cones are sensitive to red light, thirty-three percent are sensitive to green light and two percent are sensitive to blue light. Wavelength of red light is 700 nm, green light is 546.1 nm and blue light is 435.8 nm. The characteristics used to distinguish one color from another are brightness, hue, and saturation. Brightness embodies chromatic notation of intensity. Hue is an attribute associated with the dominant wavelength by an observer. Saturation refers to the relative purity or the amount of the white light mixed with a hue. Degree of saturation is inversely proportional to the amount of white light added. Hue and saturation taken together are called chromaticity and therefore a color may be characterized by its brightness and chromaticity.

RGB color model is ideal for image color generation, but when it is used for color description, its scope is much limited. The HSI model is an ideal tool for developing image-processing algorithm based on color descriptions that are natural and intuitive to human eye.

Image is a two-dimension signal, it is represented by the positive function \( I = f(x, y) \), where \( x \) and \( y \) are the co-ordinates of pixel and \( I \) is value corresponding to the pixel. The digital color image is constituted by the three primary color values, i.e. RGB; such an image is referred as RGB color image. RGB color image is represented by a three dimensional array, where the first plane in the third dimension, represents the red pixel intensities, the second plane represents the green pixel intensities and the third plane represents the blue pixel intensities. Human visual perception is very sensitive to small change in the value of one of the colors when the remaining colors are fixed, and therefore the individual components of RGB color image cannot be analyzed independently.

For color image compression techniques, the selection of proper color model is extremely crucial because in lossy image compression technique data cannot be recovered exactly. Red, green and blue color components of pixel are correlated with visual appearance, therefore even though RGB is most common storage format for images; it is not used for image compression. If it is used, high visual distortion is introduced. It necessitates the conversion of RGB colors into another colors representation, which doesn’t have the correlation among the components.

The objective of this paper is to select the proper mother wavelet during the transform phase to compress the color image. This paper includes the discussion on principles of image compression, image compression methodology, the basics of wavelet and orthogonal wavelet transforms, the selection of discrete wavelet transform with results and conclusion.

III. PRINCIPLES OF IMAGE COMPRESSION

Image compression reduces the number of bits required to represent the image, therefore the amount of memory required to store the data set is reduced. It also reduces the amount of time required to transmit a data set over a communication link at a given rate. Different methods are developed to perform the image compression. The compression ratio is one of the quantitative parameters to measure the performance of compression methods. Compression ratio is defined as ratio of the size of original data set to the size of the compressed data set.

\[
\text{Compression Percentage} = \frac{A}{B} \times 100 \quad (1)
\]

Where

\( A = \) Number of Bytes in the original data set
\( B = \) Number of Bytes in the Compressed data set

The compression ratio is expressed as a single number or as two numbers with the second number typically being one. For example 10:1 means 10 bytes of the original data are represented by one byte.

The percentage of compression is also one of the alternative parameter to measure the performance of
the compression. It is the ratio of difference of number of bytes of original image and compress image to number of bytes of original image into hundred.

\[
\text{Compression Percentage} = \frac{A - B}{A} \times 100 \quad (2)
\]

Where
A = Number of Bytes in the original data set
B = Number of Bytes in the Compressed data set

Bits/pixel is another standard method of specifying a compression ratio. The average number of bits required to represent the data value for the single pixel of an image is referred as bits/pixel.

The common characteristic of most of the images is that, the neighboring pixels are correlated, and image contains redundant information [4]. Therefore the most important task in image compression is to find a less correlated representation of the image. The fundamental component of image compression is reduction of redundancy and irrelevancy. Redundancy reduction aims at removing duplication from image, and irrelevancy reduction omits parts of the signal that will not be noticed by Human Visual System (HVS) [18]. The redundancies in an image can be identified as spatial redundancy, spectral redundancy and temporal redundancy.

Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. Since the focus is only on still natural image compression, the temporal redundancy is not considered as it is used in motion picture.

IV. IMAGE COMPRESSION METHODOLOGY

There are various methods of compressing still images, but every method has three basic steps involved in any of the data compression scheme: Transformation, reduced precision (quantization or thresholding), and minimization of number of bits to represent the image (encoding). The basic block diagram of compression scheme is shown in Fig.1.

\[\text{Input Image} \rightarrow \text{Transformation} \rightarrow \text{Quantization / Thresholding} \rightarrow \text{Encoding} \rightarrow \text{Compressed Image}\]

Figure 1: The block diagram of compression scheme

A. Transformation

For image compression, it is desirable that the selection of transform should reduce the size of resultant data set as compared to source data set. Few transformations reduce the number of data items in the data set. Few transformations reduce the numerical size of the data items that allows them to represent by the fewer binary bits. In data compression, transform is intended to decorrelate the input signals by transformation. The data represented in the new system has properties that facilitate the compression. Some mathematical transformations have been invented for the sole purpose of data compression; selection of proper transform is one of the important factors in data compression scheme. It still remains an active field of research. The technical name given to these processes of transformation is mapping. Some mathematical transformations have been invented for the sole purpose of data compression, other have been borrowed from various applications and applied to data compression. The partial list includes:

- Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Hadamard-Haar Transform (HHT), Karhune-Loeve Transforms (KLT), Slant-Haar Transform (SHT), Walsh-Hadamard Transform (WHT), Short Fourier Transforms (SFT), and Wavelet Transforms (WT).

B. Quantization/Thresholding

In the process of quantization each sample is scaled by the quantization factor. Where as in the process of thresholding the samples are eliminated if the value of sample is less than the defined threshold value. These two methods are responsible for introduction of error and it leads in degrading the quality. The degradation is based on selection of quantization factor and threshold value. For the high value of threshold the loss of information is more, and for low value of threshold the loss of information is less. By considering the resultant loss of information, the selection of threshold should be low, but for the low value of threshold there is negligible compression of data. Hence quantization factor, or threshold value should be selected in such a way that it should satisfy the constraints of human visual system for better visual quality, and high compression ratio. Human Visual System is less sensitive to high frequency signal and more sensitive to low frequency signal [19]. By considering this phenomenon, the threshold value or quantization factor is selected and thresholding / quantization take place in image compression.

In image compression technique two types of thresholding are used as:
- Hard Thresholding
- Soft Thresholding.

In hard thresholding technique, if the value of the coefficient is less than defined value of threshold, then the coefficient is scaled to zero, otherwise the value of the coefficient is maintained as it is. This process is repeated until all the pixels in the image are exhausted.

In soft thresholding technique, if the value of the coefficient is less than defined value of threshold, then the coefficient value is scaled to zero and otherwise the value of coefficient is reduced by the amount of defined value of threshold. This process is repeated until all the pixels in the image are exhausted.
C. Encoding

This phase of compression reduces the overall number of bits needed to represent the data set. An entropy encoder further compresses the quantized values to give better overall compression. This process removes the redundancy in the form of repetitive bit patterns in the output of quantizer. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller than the input stream. The most commonly used entropy encoders are Huffman encoder and the Arithmetic encoder.

The Huffman algorithm requires each code to have an integral number of bits, while arithmetic coding methods allow for fractional number of bits per code by grouping two or more such codes together into a block composed of an integral number of bits. This allows arithmetic codes to outperform Huffman codes, and consequently arithmetic codes are more commonly used in wavelet-based algorithm

V. WAVELET

The signal is defined by a function of one variable or many variables. Any function is represented with the help of basis function. An impulse is used as the basis function in the time domain. Any function can be represented in time as a summation of various scaled and shifted impulses. Similarly the sine function is used as the basis in the frequency domain. However these two-basis functions have their individual weaknesses: an impulse is not localized in the frequency domain, and is thus a poor basis function to represent frequency information. Likewise a sine wave is not localized in the time domain [20]. In order to represent complex signals efficiently, a basis function should be localized in both time and frequency domains. The support of such a basis function should be variable, so that a narrow version of the function can be used to represent the high frequency components of a signal while wide version of the function can be used to represent the low frequency components. Wavelets satisfy the conditions to be qualified as the basis functions.

Sinusoidal wave is one of the popular waves, which extend from $-\infty$ to $+\infty$. Sinusoidal signals are smooth and predictable; it is the basis function of Fourier analysis. Fourier analysis consists of breaking up a signal into sine and cosine waves of various frequencies. A wavelet is waveform of limited duration that has an average value of zero. Wavelets are localized waves and they extend not from $-\infty$ to $+\infty$ but only for a finite time duration, as shown in Fig. 2.

The wavelet as shown in Fig. 2, is a mother wavelet $(h(t))$. The mother wavelet and its scaled daughter functions are used as a basis for a new transform. Unfortunately, if $h(t)$ is centered around $t = 0$, with extension between $-T$ and $+T$, no matter how many daughter wavelets we use, it will not be possible to properly represent any point at $t>T$ of a signal $s(t)$.

Please note that the wave transform did not have this problem, as the wave function was defined for every value of $t$. For the case using a localized wave or wavelet, it must be possible to shift the center location of the function. In other words, it must include a shift parameter, $b$, and the daughter wavelets should be defined as

$$h_{ab}(t) = \frac{1}{\sqrt{a}} h\left(\frac{t-b}{a}\right)$$

The reason for choosing the factor $\frac{1}{\sqrt{a}}$ in the above equation is to keep the energy of the daughter wavelets constant.

![Wave and Wavelet](image)

Figure 2. Wave and Wavelet

Thus, the wavelet transform has to be a two-dimensional transformation with the dimension being $a$, the scale parameter, and $b$, the shift parameter. The wavelet transform maps 1-D time signals to 2-D scale (frequency) and shift parameter signals.

It is observed that for periodic functions, Fourier analysis is ideal. However, wavelet transforms are not restricted to only the periodic function, but for any function, provided it is admissible. In many cases of signal processing, one can choose the signal itself or a theoretical model as the mother wavelet. The advantage of doing this is that only few wavelet transform coefficients are then required to represent the signal. Wavelets tend to be irregular and asymmetric. The original wave is known as Mother wavelet. Wavelet analysis consists of breaking up of signal into shifted and scaled versions of the original (mother) wavelet.

VI. ORTHOGONAL DISCRETE WAVELET TRANSFORM

In case of orthogonal discrete wavelet transforms (DWT), the image is decomposed into a discrete set of wavelet coefficients using an orthogonal set of basis functions. Haar basis is first orthonormal wavelet basis developed in 1910 [21]. Several other orthonormal wavelet bases have been constructed. These bases share the best features of both the Haar basis and Shannon basis; that is, these new bases have excellent
localization properties both in time and frequency. We will list a few of them here. For example, in 1982, Stromberg constructed bases, which have exponential decay in time and frequency. In 1985, Mayer constructed a base in which $\Psi(\omega)$ is compactly supported in the frequency domain. In 1987, Tchamitchian constructed the first example of biorthogonal wavelet bases. In 1987 and 1988, constructed identical families of orthonormal wavelets bases with exponential decays. In 1989, Daubechies constructed a new family of compact supported wavelets and Coifman constructed a family of symmetrical wavelets [21].

VII. SELECTION OF ORTHOGONAL DISCRETE WAVELET TRANSFORM

Haar [22] described the first wavelet basis in 1910. In 1986 many researchers performed pioneering work in wavelets, particularly in multi-resolution and fast wavelet transforms. The researchers developed a wide variety of wavelets. The major wavelets are Daubechies Wavelet, Coiflets Wavelet, Biorhogonal Wavelet, Symlets Wavelet, Morlet Wavelet, and Mayer Wavelet. These wavelets are used to transform the signals from one domain to another domain. Wavelet transform is a two-dimensional time-frequency signal analysis method. Wavelet Transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales [23]. Any decomposition of an image using wavelet involves a pair of waveforms, one to represent the high frequencies corresponding to the detail parts of an image (wavelet function), and another for the low frequencies or smooth parts of an image (scaling function). Integer Wavelet Transform and Discrete Wavelet Transform is used for lossy compression. In the paper [24] the researchers claimed that Integer Wavelet Transform could lead to too much larger degradation than the Discrete Wavelet Transform; especially Discrete Wavelet Transform is popular in the field of compression for small quantization rather than Integer Wavelet Transform. All the wavelets are not suitable for the image compression. Among the many suitable wavelets, for image compression choice of wavelet is crucial for coding performance in image compression. The choice of the wavelet function should be adjusted to image content. The compression performance for images with high spectral activity is fairly insensitive to choice of compression method (for example, test image Mandrill), on the other hand coding performance for the images with moderate spectral activity (for example, test image Lena), are more sensitive to choice of compression method. The best way for choosing wavelet function is to select optimal basis for images with moderate spectral activity. It is noticed that selection of the optimal wavelet for image compression is based on objective picture quality measures, and subjective picture quality measures.

Important properties of wavelet in image compression are: compact support (leads to efficient implementation), symmetry (useful in avoiding dephasing in image processing), orthogonality (allows fast algorithm), regularity and degree of smoothness (related to filter order or filter length) [23]. The wavelets are implemented by using different ordered quadratic filters. The subband coding system is based on the frequency selectivity property of the filter banks. An alias free frequency split and perfect inter-band decorrelation of coefficients can be achieved only with ideal filter bands with infinite duration basis functions. Since time localization of the filters is very important in visual signal processing, one cannot use an arbitrarily long filter. In addition properties such as vanishing moments, phase linearity, time-frequency localization, energy compaction, influence the coding performance. Filter length is determined by filter order, the relationship between filter order and filter length is different for different wavelet families. Higher filter order gives wide function in the time domain with higher degree of smoothness its results blurring of an image even if the PSNR is high, and filter has good frequency localization, which in turns increases, the energy compaction. The regularity of wavelets also increases with filter order. In addition more vanishing moments can be obtained with a higher order filter. Filter with lower order has a better time localization and preserves important edge information. The low order filters provides less energy compaction and more blockiness. Wavelet based image compression prefers smooth functions, but complexity of calculating Discrete Wavelet Transform increases by increasing the filter length. Therefore, in image compression there is a need to find a balance between filter length, degree of smoothness and computational complexity. Inside each wavelet family, one can find wavelet function that represents optimal solution related to filter length and degree of smoothness, but this solution depends on image contents [23]. The length of the filter and computational complexity of the wavelet transform for an image of size $M \times M$, employing dyadic decomposition is approximately:

$$L = 2 \times N \text{ for Daubechies Wavelet family},$$

$$L = 6 \times N \text{ for Coiflet Wavelet family and}$$

$$L = \max (2Nd, 2Nr) + 2 \text{ for Biorhogonal Wavelet family}$$

and

Computational Complexity,

$$C = 16 \times M^2 \times L \left(1 - 4^{-J}\right) / 3$$

Where $N$ is the order of filter, $L$ is the length of the filter, $J$ is number of level decomposition.

In the analysis process four families of wavelets, mostly used and examined by the researchers are named: Haar wavelet, Daubechies wavelet, Coiflet wavelet, and Biorthogonal wavelet. These wavelets are tested over many test images, which include different natural images of varying frequencies, and synthetic images having characteristics different than natural images. Each wavelet family can be parameterized by integer $N$, which determines the filter order. Biorthogonal wavelets can use filters with similar or
dissimilar order for decomposition and reconstruction of signals. \( N_d \) denotes the order of decomposition filter, and \( N_r \) denotes the order of reconstruction filter. Each wavelet family is tested with different filter orders. The Daubechies wavelets \( \text{db}_N \) is tested for the order of filter, \( N = 1 \) to 44, the Coiflet wavelet \( \text{Coif}_N \) is tested for the order of filter, \( N = 1, 2, 3, 4, 5 \); and the Biorthogonal wavelet \( \text{Bior}_{N_dN_r} \) is tested for the order of reconstruction and decomposition filter \( (N_r, N_d) = 1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8, 3.1, 3.3, 3.5, 3.7, 3.9, 4.4, 5.5, \) and 6.8. The experimental results are given in terms of percentage of zeros, energy retained, and peak signal to noise ratio for the fixed value of threshold. The peak signal to noise ratio is one of the important objective measures. Higher the value of PSNR better the quality of an image, more percentage of zeros might be responsible for more compression, and high value of the energy retained shows the less loss of the information.

Many lossy compression algorithms are proposed by different researchers for the natural images. The images include large low frequency components and few components of high frequency and higher derivatives. The compression algorithm proposed here is for natural images and line map images. The maps of the different locations, line diagram of different plans and few medical images are in terms of horizontal, vertical and diagonal lines. For the line map images the performance of \( \text{db}1 \) or \( \text{bior}1.1 \) has remarkably improved as compared to the popular \( \text{db}4 \) or \( \text{bior}2.4 \). For natural images, the performance of \( \text{db}4 \) or \( \text{bior}2.4 \) is very good and hence the proper selection of mother wavelet improves the performance of compression. We suggest the minimum two steps for the wavelet decomposition. In first step, decompose the image by using any mother wavelet. On the basis of energy content of approximation and detail coefficients, the image is classified as line image or natural image. Then select the proper mother wavelet for further decompositions as mentioned above.

VIII. EXPERIMENTAL RESULTS

We have taken the results of standard images woman, \( \text{wbarb} \), and horizontal, vertical and diagonal line images. We have used mother wavelet \( \text{db}1, \text{db}4, \text{db}15, \text{coif}1, \text{coif}3, \text{coif}5, \text{bior}1.1, \text{bior}2.4 \) and \( \text{bior}2.4 \). Results are observed in terms of percentage of zeros, percentage of energy retained and signal to noise ratio. The best results are presented in paper. Fig. 3: shows the original \( \text{wbarb} \) image and results using \( \text{db}1, \text{db}4 \) and \( \text{db}15 \) the mother wavelets. Fig. 4: shows the original \( \text{wbarb} \) image and results using \( \text{bior}1.1, \text{bior}2.2 \) and \( \text{bior}6.8 \) the mother wavelets. Fig. 5: shows the original horizontal line base image and results using \( \text{db}1, \text{db}4 \) and \( \text{db}15 \) the mother wavelets. Fig. 6: shows the original horizontal line base image and results using \( \text{bior}1.1, \text{bior}2.2 \) and \( \text{bior}6.8 \) the mother wavelets. 
The graph of percentage of zeros vs threshold for the images is given in Fig. 7, Fig. 8, Fig. 9, and Fig. 10.

Table 1: Results of mother wavelet db1

<table>
<thead>
<tr>
<th>Type of image</th>
<th>Name of image</th>
<th>Percentage of zeros</th>
<th>Percentage of Energy retained</th>
<th>SNR in db</th>
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<tr>
<td>Natural Image</td>
<td>mandrill</td>
<td>61.38</td>
<td>99.37</td>
<td>50.79</td>
</tr>
<tr>
<td></td>
<td>wbarb</td>
<td>85.61</td>
<td>99.37</td>
<td>50.81</td>
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<tr>
<td></td>
<td>woman</td>
<td>76.69</td>
<td>99.37</td>
<td>50.71</td>
</tr>
<tr>
<td>Line Based Image</td>
<td>horizontal</td>
<td>91.58</td>
<td>99.99</td>
<td>126.00</td>
</tr>
<tr>
<td></td>
<td>vertical</td>
<td>92.279</td>
<td>99.99</td>
<td>140.96</td>
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<td></td>
<td>digonal</td>
<td>86.92</td>
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Table 2: Results of mother wavelet db4

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Table 3: Results of mother wavelet db15

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Table 4: Results of mother wavelet bior 1.1

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<td></td>
<td>digonal</td>
<td>86.92</td>
<td>100</td>
<td>702.54</td>
</tr>
</tbody>
</table>

Table 5: Results of mother wavelet bior 2.4

<table>
<thead>
<tr>
<th>Type of image</th>
<th>Name of image</th>
<th>Percentage of zeros</th>
<th>Percentage of Energy retained</th>
<th>SNR in db</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural Image</td>
<td>mandrill</td>
<td>63.11</td>
<td>99.40</td>
<td>48.78</td>
</tr>
<tr>
<td></td>
<td>wbarb</td>
<td>86.87</td>
<td>99.55</td>
<td>51.85</td>
</tr>
<tr>
<td></td>
<td>woman</td>
<td>79.83</td>
<td>99.49</td>
<td>50.54</td>
</tr>
<tr>
<td>Line Based Image</td>
<td>horizontal</td>
<td>90.83</td>
<td>99.98</td>
<td>81.42</td>
</tr>
<tr>
<td></td>
<td>vertical</td>
<td>85.55</td>
<td>99.88</td>
<td>64.29</td>
</tr>
<tr>
<td></td>
<td>digonal</td>
<td>79.65</td>
<td>99.98</td>
<td>90.29</td>
</tr>
</tbody>
</table>
The results show that db4 or bior2.4 performs significantly better for woman, wbarb and wmandrill. And db1 or bior1.1 perform significantly better for horizontal, vertical and diagonal line based images.

IX. CONCLUSION

In this paper, selection of mother wavelet on the basis of nature of image has been presented. The input image is first categorized as natural image or line based image on the basis of energy contained. Extensive result has been taken based on different mother wavelets. The results demonstrate significant gain in percentage of zero using db1 for line based images and db4 for natural images.

REFERENCES
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