

# Comparative Analysis of Image Compression Using Wavelet and Ridgelet Transform

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**ABSTRACT:** Image Compression reduces the number of bits required to represent an image. Content based image compression become more significant in the field of medical and multimedia compression in order to preserve the important region in an image. Images when transmitted as whole, reduces the resources in the device and also causes many problems during transmission. For efficient transmission of images, optimized amount of storage space and bandwidth are required. Many compression standards are existing. But still there is a scope for higher compression with quality reconstruction. In this paper an attempt have been made to analyse wavelet and ridgelet technique for image compression. Initially, the principle of seam carving is applied on image. Haar wavelet, Daubechies wavelet, Symlet wavelet, Coiflet wavelet, Biorthogonal wavelet and Ridgelet Transform have been applied to the retargeted image and results have been compared in terms of PSNR values, MSE and Compression ratio.

**KEYWORDS:** Image Compression, Seam Carving, Wavelet Transform, Ridgelet Transform

## I. INTRODUCTION

Image Compression is the representation of an image in digital form with few bits while maintaining an acceptable level of image quality. Due to rapid increase in multimedia and medical applications it requires to reduce the amount of information for the purpose of efficient storage and transmission. There are many multimedia devices with different display. As the size of multimedia devices is continually changing the quality of the shared content also gets reduced. One solution to this problem is to reduce the volume of content without losing important information in an image so that more images can stored in the given space. Content based image compression with less computational complexity and to retarget the image with optimal solution. In this paper, the principle of seam carving is used along with wavelet and ridgelet to compress the image. The proposed method is useful for obtaining high compression ratio with less complexity in most of the applications.

Existing image compression method based on discrete wavelet transform (DWT) [1] such as SPIHT [2], JPEG 2000 [3] etc, can meet high quality to the decompressed image. This compresses image as a whole so it does not support content based image compression. In edge based inpainting [4] which skips some information during encoding process so the compression can achieve but complexity is high. Same way data pruning [5] based image compression method compress the image by pruning it to the smaller size before the transmission. These methods do not support content based color image compression. SPIHT [6] can compress effectively, which is a wavelet based compression technique. Efficient image compression cannot be achieved with SPIHT alone. Image compression based on concentration and dilution [7] uses the principle of seam carving for image concentration and interpolation for image resizing at the receiving end. Wavelets is good for piecewise smooth functions in one dimension but not in the case of two dimension [8]. Wavelet fails to represent efficiently singularities along lines or curves and geometrical structure in smooth edges of images. To overcome the weakness of wavelets, Candes developed a ridgelet analysis [9].

To address the drawbacks of the above methods, the advantages of seam carving and transform techniques are combined and content based compression scheme is proposed. The original image is considered as whole and not divided into components (ROI and non ROI), while seam carving is performed and resultant seam energy map is used for encoding the DWT coefficients. The ridgelet transform are also performed on retargeted image.

## II. SEAM CARVING

Seam carving is an effective image resizing method [10]. Standard image resizing techniques such as scaling and cropping are not efficient for displaying images on a variety of display devices of different resolutions. A seam is defined as a continuous path of pixels running from the top to the bottom of an image in the case of a vertical seam, while a horizontal seam is a continuous line of pixels spanning from left to right in an image. Seam carving is mainly for content based image compression. It produces high quality in retargeted image. It removes the low energy pixels from an image.

If  $t_i$  be the  $i^{th}$  part of seam, then  $t_i^x$  and  $t_i^y$  be the horizontal and vertical aspects. A vertical seam is defined as,

$$T^X = \{t_i^x\}_{i=1}^N = \{x(i), i\}_{i=1}^N \quad (1)$$

where  $x$  is a mapping of  $x : [1, \dots, N] \rightarrow [1, \dots, M]$ . Similarly we can write for horizontal seam. The importance of pixels is defined by an energy function. The first step in calculating a seam for removal or insertion involves calculating the gradient image for the original image. The gradient image is a common image that is used in both horizontal and vertical seam calculation. From this we need to calculate the energy map to indicate importance of pixel in image that is to be calculated separately for horizontal and vertical seams. For each pixel  $(i, j)$  in the gradient image, the value at  $(i, j)$  in the energy map is the sum of the current value at  $(i, j)$  from the gradient image and the minimum of the three neighbouring pixels in the previous row [11].

Then remove the low energy pixel from the image. The method to identify seam is the minimum value in the last row saving the pixel location for use in removal, then working backwards by finding the minimum of the three neighbouring pixels of  $(i, j)$  in the  $(i-1)$ th row and saving that pixel to the seam path. This process is repeated until the first row is reached.

Optimal seam is found out by using,

$$t^* = \arg \min \sum_{i=1}^J E[I(t_i)] \quad (2)$$

Where  $E[.]$  denotes the energy function. A cumulative energy cost for vertical seam  $C(i, j)$  is calculated as,

$$C(i, j) = E(i, j) + \min\{C(i-1, j-1), C(i-1, j), C(i-1, j+1)\} \quad (3)$$

The energy cost is calculated for three connected path of neighbouring pixels.

## III. WAVELET TRANSFORM

Image Compression is one of the applications of wavelet. Wavelets are localized in both time and frequency domain. Wavelet involves pair of transform: one to represent the high frequencies or detailed parts of an image and one for the low frequencies or smooth parts of an image.

### A. Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) refers to Wavelet Transforms for which the wavelets are discretely sampled. A Transform which localizes a function both in space and scaling and has some desirable properties compared to the Fourier Transform. DWT decomposes an image into coefficients called sub-bands and then the resulting coefficients are compared with a threshold. Coefficients below the threshold are set to zero.

### B. Wavelet Families

Several families of wavelets are included in the wavelet toolbox. Haar, Daubechies, Symlet, Coiflet and Biorthogonal wavelets has used in this paper.

#### a. Haar Wavelet

Haar wavelet is the first and simplest wavelet. It resembles a step function and represents the same wavelet as Daubechies db1. The disadvantages of haar wavelet is not continuous and therefore not differentiable.

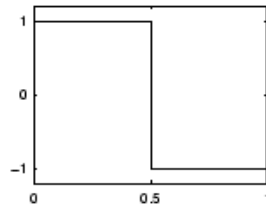


Fig.1 Haar Wavelet Function Waveform

*b. Daubechies Wavelet*

Ingrid Daubechies constructed the orthonormal wavelet of compactly supported functions  $DbN$ ,  $N=1, 2, \dots$ . The  $Db1$  wavelet is the same as haar wavelet. The wavelet functions of the next members are the family is shown here in Figure 2.

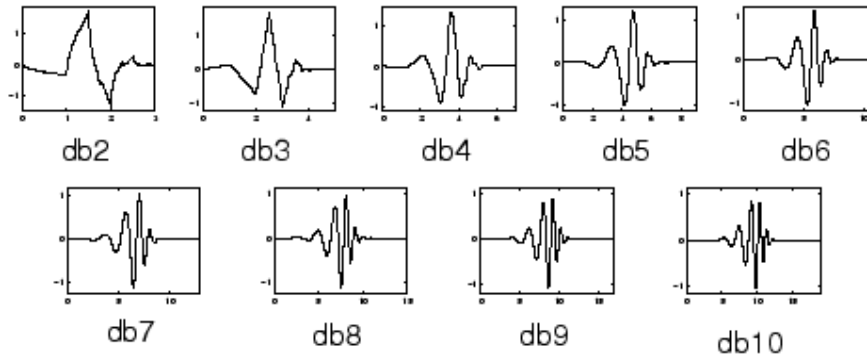


Fig.2 Daubechies Wavelet Function Waveform

*c. Coiflet Wavelet*

The Coiflet wavelet is near symmetric. The wavelet functions has  $2N$  moments equal to 0 and the scaling function has  $2N-1$  moments equal to 0 and has been used in many applications.

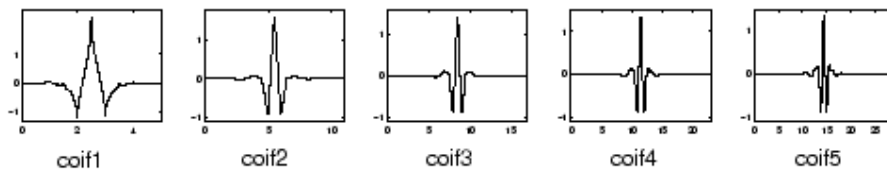
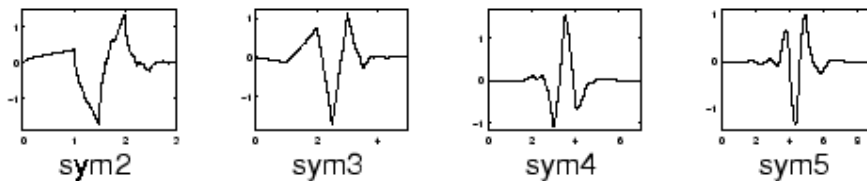


Fig.3 Coiflet Wavelet Function Waveform

*d. Symlet Wavelet*

Symlet wavelet is a modification of Daubechies wavelets to improve their symmetry. The properties of wavelet is similar to Daubechies wavelet. Seven different symlet functions are available from  $sym2$  to  $sym8$ . The symlet function waveform is shown below.



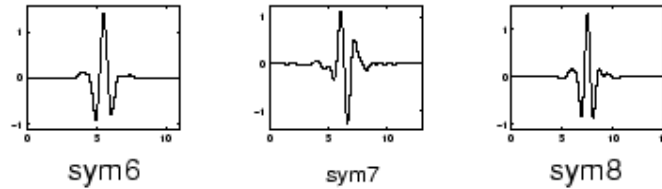


Fig.4 Symlet Wavelet Function Waveform

*e. Biorthogonal Wavelet*

Biorthogonal wavelets exhibits the property of linear phase, which is useful for image reconstruction. Biorthogonal bases uses two wavelets instead of one, one for decomposition and another for reconstruction. Some of the members of biorthogonal wavelets is shown in the Figure5.

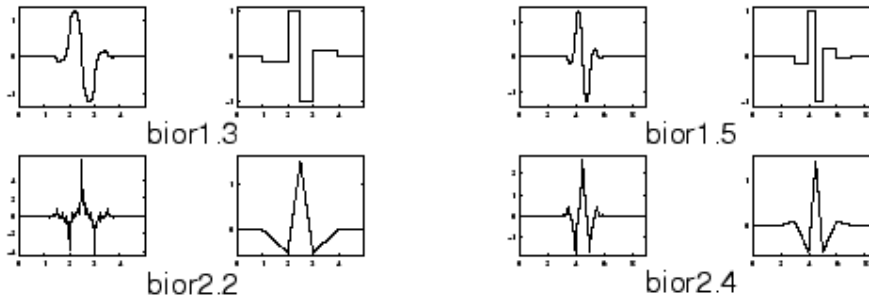


Fig.5 Biorthogonal Wavelet Function Waveform

**IV. RIDGELET TRANSFORM**

The success of Wavelets is mainly due to the good performance for piecewise smooth functions in one dimension. Unfortunately, such is not the case in two dimensions. While simple, these methods work very effectively, mainly due to the property of the Wavelet Transform that most image information is contained in a small number of significant coefficients around the locations of singularities or image edges. Therefore, new image processing schemes called Ridgelet Transform which are based on true two-dimensional (2-D) Transforms are expected to improve the performance over the current Wavelet-based methods [9].

The continuous Ridgelet Transform function  $f(x)$  is given by

$$CRT_f(a, b, \theta) = \int_R \psi_{a,b,\theta}(x) f(x) dx \tag{4}$$

The Figure 6 shows the ridgelet function oriented at an angle  $\theta$  and constant along the lines  $x_1 \cos \theta + x_2 \sin \theta = const$

For practical applications, the development of discrete versions of the Ridgelet Transform that lead to algorithmic implementations is a challenging problem. Due to the radial nature of Ridgelets, straightforward implementations based on discretization of continuous formulae would require interpolation in polar coordinates, and thus result in Transforms that would be either redundant or can not be perfectly reconstructed.

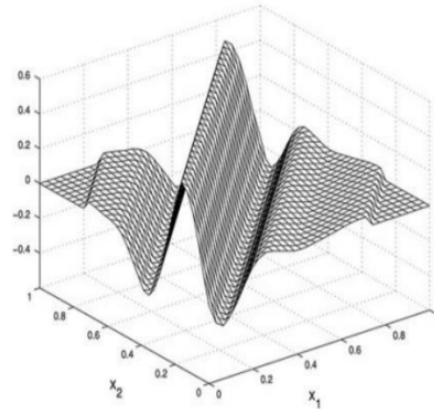


Fig.6 Ridgelet Function

## V. RESULT AND DISCUSSION

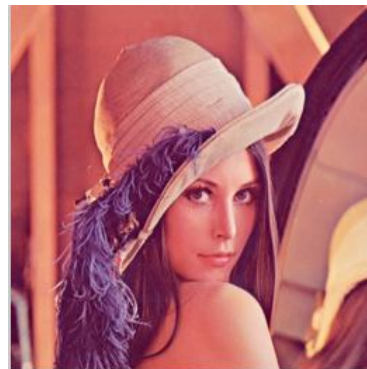
This section discusses the simulation results of wavelet and ridgelet methods. Experiments are conducted in MATLAB. Input image is first resized using seam carving algorithm and retargeted image is transformed using wavelet and ridgelet techniques. Quantitative analysis have been performed by measuring PSNR, MSE and Compression ratio. Comparative analysis of various families of wavelet and ridgelet are also presented. We have analysed wide range of images.



Sample 1



Sample 2



Sample 3

Fig.7 Input images

Results are measured in terms of Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Compression Ratio (CR). The comparison of PSNR, MSE and CR values of seam carving with each wavelet of wavelet family and ridgelet transform for different test images is shown in the Table 1.

**Table 1: Parameter Comparison Using Wavelet Families and Ridgelet Transform**

Wavelet Families	Sample 1			Sample 2			Sample 3		
	PSNR	MSE	CR	PSNR	MSE	CR	PSNR	MSE	CR
Haar	57.9858	0.1034	71.9786	57.0772	0.1275	62.0546	56.9859	0.1032	62.0833
Db 2	58.4985	0.0919	83.0897	57.1873	0.1198	65.9874	57.5897	0.1002	64.9871
Db 3	58.4221	0.0935	85.5860	57.2147	0.1103	66.2547	57.4210	0.0987	66.4107
Db 5	58.5880	0.0900	87.8277	57.2986	0.1087	66.9587	57.5960	0.0952	68.7412
Db 7	58.9145	0.0835	87.5440	57.4211	0.1079	68.1278	57.9612	0.0914	71.5617
Db 8	58.9682	0.0825	87.1193	57.3010	0.1063	69.2019	57.9578	0.0899	75.8761
Db10	58.7074	0.0876	87.5822	57.5947	0.0987	72.3104	57.0124	0.0812	79.5847
Coif1	58.3880	0.0943	83.9292	57.6598	0.1274	68.3741	56.3214	0.1120	74.5674
Coif3	58.7715	0.0863	87.8751	57.6687	0.1030	75.3673	56.8473	0.0956	79.9954
Coif5	58.8434	0.0849	87.9809	57.8124	0.0857	79.7410	57.1243	0.0891	83.4103
Sym3	58.4221	0.0935	85.5860	57.2314	0.1169	76.3125	57.8430	0.0974	84.0111
Sym4	58.7633	0.0864	86.7255	57.6899	0.0912	79.4872	57.8149	0.0847	84.7820
Sym7	58.5886	0.0900	87.4732	57.7132	0.0879	80.1254	57.9142	0.0827	85.1247
Sym8	58.8288	0.0852	87.9420	57.7953	0.0812	83.6100	57.7563	0.0812	86.4723
Bior1.5	58.3457	0.0952	75.2365	57.0238	0.9874	79.2147	57.1349	0.0987	78.8457
Bior2.4	58.7132	0.0874	82.1564	57.6924	0.0845	82.1069	57.3698	0.0971	82.9634
Bior2.8	58.7199	0.0873	83.6571	57.7368	0.8147	83.4721	57.5274	0.0876	84.1020
Bior3.7	58.7234	0.0852	84.4479	57.6610	0.8245	83.9632	57.5933	0.0842	85.1274
Bior4.4	58.7300	0.0814	85.1024	57.5691	0.0789	84.0214	57.6584	0.0814	86.9751
Bior6.8	58.7430	0.0897	86.0012	57.8700	0.0945	85.0185	58.0163	0.0824	86.1234
Ridgelet	59.5876	0.0869	88.9438	57.1631	0.0787	86.5102	58.2147	0.0799	87.5521

## VI. CONCLUSION

Seam Carving and Ridgelet method provides better result than wavelet for image compression in mobile multimedia applications and medical image. In case of multimedia applications content based color image compression is achieved with low computational complexity and retarget the images with optimal resolution. In this paper, the various parameters PSNR, MSE and CR for each wavelet and ridgelet are compared. The Ridgelet Transform is more suitable for the color image data to represent the line singularities properly than Wavelet Transform. Hence Ridgelet Transform can be effectively used for the compression of color images with high quality reconstruction.

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