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,

\[
T^x = \{t_i^x\}_{i=1}^N = \{x(i), i\}_{i=1}^N
\]

where \( x \) is a mapping of \( x : [1, \ldots, N] \rightarrow [1, \ldots, M] \). 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,

\[
t^* = \arg \min \sum_{i=1}^N E[I(t_i)]
\]

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

\[
C(i,j) = E(i,j) + \min\{C(i-1,j-1),C(i-1,j),C(i-1,j+1)\}
\]

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.
b. Daubechies Wavelet

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

![Fig.2 Daubechies Wavelet Function Waveform](image)

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](image)

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.3 Symlet Wavelet Function Waveform](image)
Biorthogonal Wavelet

Biorthogonal wavelets exhibit the property of linear phase, which is useful for image reconstruction. Biorthogonal bases use two wavelets instead of one, one for decomposition and another for reconstruction. Some of the members of biorthogonal wavelets is shown in the Figure 5.

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

\[
CRT_j(a,b,\theta) = \int_{\mathbb{R}} \psi_{a,b,\theta}(x)f(x)dx
\]  

The Figure 6 shows the ridgelet function oriented at an angle \( \theta \) and constant along the lines \( x_1 \cos \theta + x_2 \sin \theta = \text{const} \).

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.
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.

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

<table>
<thead>
<tr>
<th>Wavelet Families</th>
<th>Sample 1</th>
<th>Sample 2</th>
<th>Sample 3</th>
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<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>MSE</td>
<td>CR</td>
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<tr>
<td>Haar</td>
<td>57.9858</td>
<td>0.1034</td>
<td>71.9786</td>
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<tr>
<td>Db 2</td>
<td>58.4985</td>
<td>0.0919</td>
<td>83.0897</td>
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<tr>
<td>Db 3</td>
<td>58.4221</td>
<td>0.0935</td>
<td>85.5860</td>
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<tr>
<td>Db 5</td>
<td>58.5880</td>
<td>0.0900</td>
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<td>Db 7</td>
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<td>Db10</td>
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<td>Bior6.8</td>
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</table>

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 re-target 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.

REFERENCES


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