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Image Compression using Hybrid Slant Wavelet where Slant is Base Transform and Sinusoidal Transforms are Local Transforms

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Abstract: Many transform based image compression methods have been experimented till now. This paper proposes novel image compression method using hybrid slant transform. Slant transform is used as base transform to focus on global features of an image. Sinusoidal orthogonal transforms like DCT, DST, Hartley and Real-DFT are paired with slant transform to generate hybrid slant wavelet transform. Performance of hybrid slant wavelet can be compared by varying the size of its component transform. Along with RMSE which is commonly used parameter, Mean Absolute Error, AFCPV and SSIM are the parameters used to observe the perceptibility of compressed image. It has been observed that, hybrid slant wavelet generated using 8x8 Slant and 32x32 DCT gives lowest error at compression ratio 32 as compared to other sinusoidal transforms when paired with slant transform. Performance of hybrid slant wavelet is compared with its multi-resolution analysis which includes semi-global features of an image and with hybrid transform that includes global features of image. Comparison shows that, hybrid wavelet has given good image quality than hybrid transform and its multi-resolution analysis.

Keywords: Slant transform, Image compression, Compression ratio, RMSE, SSIM

I. Introduction

In today's internet world use of multimedia data is increasing tremendously. Due to digital technology transmission and storage of data in more and more compact form is necessary to achieve efficient bandwidth utilization. Digital Images are integral part of this data and hence image compression plays vital role to make better use of available bandwidth and storage space. Image compression schemes are generally classified as lossless compression and lossy compression. Lossless compression is error free because after decompression original image is reconstructed as it is. Hence it is applicable in text data compression, medical image compression where loss of data is not tolerable. On the other hand, lossy image compression produces some error between original image and reconstructed image. Performance of lossy image compression methods is measured using compression ratio which is ratio of number of bits in original image to number of bits in reconstructed image. Goal of any lossy compression technique is to maintain the tradeoff between compression ratio and quality of reconstructed image [1].

Till now many lossy image compression methods have been studied in literature. Predictive coding, transform based coding, wavelet based coding, vector quantization are few of them. Other than DCT and wavelet transform, fractal transform coding techniques were also developed but these techniques have not shown satisfactory results at low bit rate applications [2]. In transform based image compression Discrete cosine transform [3] is widely used. It is standard for JPEG image compression. Normally DCT is applied on individual NxN block of an image which introduces blocky effect in compressed image. JPEG 2000 uses wavelet transform coding. It analyzes the signal in time and frequency domain. It has higher energy compaction property than DCT. Hence wavelets provide better compression ratio [4]. It also reduces blocky effect considerably. Multi-resolution representation of image is another important feature of wavelet transforms. The wavelets can be scaled and shifted to analyze the spatial frequency contents of an image at different resolutions and positions [5]. Slant transform coding has been proven to be substantial [6] in bandwidth reduction as compared to pulse code modulation. It results in lower MSE for moderate sized image blocks. This paper focuses on hybrid wavelet transform and its multi-resolution analysis property. Wavelet transform is generated using orthogonal component transforms. Component transforms can be varied to generate hybrid wavelet transform.

II. Review of Literature

In last two-three decades, wavelet transform is emphasized in various image processing applications. Image compression is one of them. So far Haar wavelet transform has been studied as it is simple and fast. Modified fast Haar wavelet transform (MFHWT) has been discussed by Chang P. et al. [7]. Multilevel 2-D Haar wavelet transform is used for image compression by Ch. Samson and V.U.K. Sastry [8]. Image compression with multi-resolution singular decomposition is proposed by Ryuichi Ashino et al. [9]. In their paper wavelet transform is combined with singular value decomposition. Two level 9/7 biorthogonal wavelet is used to transform the image.

Transformed image is decomposed using Singular value Decomposition and then this decomposed image is compressed using SPIHT. In this method more levels of wavelets need to be applied to get lower value of bits per pixel. Multi-resolution segmentation based algorithm is proposed by Hamid R. Rabiee, R. L. Kashyap and H. Radha [2] in which high quality low bit rate image compression is achieved by recursively coding the Binary Space Partitioning (BSP) tree representation of images with Multi-level Block Truncation Coding (BTC). Jin Li Kuo et. al [10] proposed a hybrid wavelet-fractal coder (WFC) for image compression. The WFC uses the fractal contractive mapping to predict the wavelet coefficients of the higher resolution from those of the lower resolution and then encode the prediction residue with a bit plane wavelet coder. Multiwavelet transform based on zero tree coefficient shuffling has been proposed by M. Ashok, T. Bhaskara Reddy [11]. A non-linear transform called peak transform is proposed in [12]. It minimizes the high frequency components in the image to a greater extent thus making the image to get compressed more. Hybrid wavelet transform containing Kekre transform combined with other sinusoidal transforms is presented in [13]. It shows that use of full wavelet transform gives one third RMSE as compared to respective column and row hybrid wavelet transform. Alani et. al [14] proposes a well suited algorithm for low bit rate image coding called the Geometric Wavelets. Geometric wavelet is a recent development in the field of multivariate piecewise polynomial approximation. Here the binary space partition scheme which is a segmentation based technique of image coding is combined with the wavelet technique [15]. Kekre-Hartley hybrid wavelet transform is compared with its hybrid transform [16] and it shows that including global features of an image increases error in compression as compared to inclusion of only local features.

III. Proposed Technique

Proposed methods compares the performances of hybrid Slant wavelet transform with hybrid transform and its multi-resolution analysis [17]. In hybrid slant wavelet transform, Slant wavelet acts as a base transform and other sinusoidal transforms act as local transforms. Hybrid wavelet is generated using Kronecker product of two different transform matrices as given in eq. (1). Here A is $p \times p$ slant transform matrix and B is any sinusoidal matrix of size $q \times q$. $B_q(1)$ indicates first row of matrix B. In general n^{th} row of B is represented as $B_q(n)$. Kronecker product of slant matrix with first row of matrix B is taken. It represents global features of image. Identity matrix of size $p \times p$ is used to translate the rows of 'B' to get local properties of image.

$$T_{AB} = \begin{bmatrix} A_p \otimes B_q(1) \\ I_p \otimes B_q(2) \\ I_p \otimes B_q(3) \\ \vdots \\ I_p \otimes B_q(n) \end{bmatrix} \quad (1)$$

Semi global features of image can be included by changing the transformation matrix T_{AB} in eq. (1) as

$$T_{AB} = \begin{bmatrix} A_p \otimes B_{q(0:i1)} \\ I_{r0} \otimes (A_{\frac{p}{r0}} \otimes B_{q(i1+1:i2)}) \\ I_{r1} \otimes (A_{\frac{p}{r1}} \otimes B_{q(i2+1:i3)}) \\ \vdots \\ I_{rn-1} \otimes (A_{\left(\frac{p}{rn}\right)-1} \otimes B_{q(i_{n-2}+1:i_{n-1})}) \\ I_p \otimes B_{q(i_n:q)} \end{bmatrix} \quad (2)$$

In above matrix we have flexibility to select number of rows that will contribute to local, global and semi global features of an image. Scaling is done by reducing the size of matrix 'A' to half in each row of matrix and shifting is done by using Identity matrix. In transformation matrix, global properties are included using simple Kronecker product of its two components transforms which is given as

$$T_{AB} = A_p \otimes B_q = a_{ij} [B_q] \quad (3)$$

It has no local properties. Since it is a Kronecker product of two different transform matrices, we call it as a Hybrid Transform.

To measure the performance of any compression method, compression ratio and traditional error measurement criteria like MSE, RMSE and PSNR are used. Here, RMSE is used, but as it gives perceived error this criterion is not sufficient. Hence Mean Absolute Error (MAE), Average fractional change in pixel value (AFCPV) and

Structural Similarity Index (SSIM) are also used to observe the perceptibility of compressed image to human eye. SSIM and AFCPV give change in perceived error. Mathematical formulae for these parameters are as given

$$MAE = \frac{\sum_{i=1}^p \sum_{j=1}^q (|x_{ij} - y_{ij}|)}{p * q} \quad (4)$$

$$AFCPV = \frac{\sum_{i=1}^p \sum_{j=1}^q (|x_{ij} - y_{ij}|) / x_{ij}}{p * q} \quad (5)$$

where x_{ij} = original Image, y_{ij} = Reconstructed image, p = Number of rows and q = Number of columns.

$$SSIM(x, y) = (2\mu_x\mu_y + c_1) (2\sigma_{xy} + c_2) / (\mu_x^2 + \mu_y^2 + c_1) (\sigma_x^2 + \sigma_y^2 + c_2) \quad (6)$$

Here, c_1 and c_2 are constants given by $c_1 = (k_1 L)^2$ and $c_2 = (k_2 L)^2$, where $k_1 = 0.01$, $k_2 = 0.03$ by default and $L = 2^8 - 1 = 255$. μ_x is average of image x ,

μ_y is average of image y ,

σ_{xy} is covariance of x and y ,

σ_x^2 and σ_y^2 are variance of image x and y respectively.

SSIM considers image degradation as perceived change in structural information.

IV. Results and Discussions

Proposed method is applied on 256x256 color images of different classes. Fig. 1 shows color images selected for experimental work.

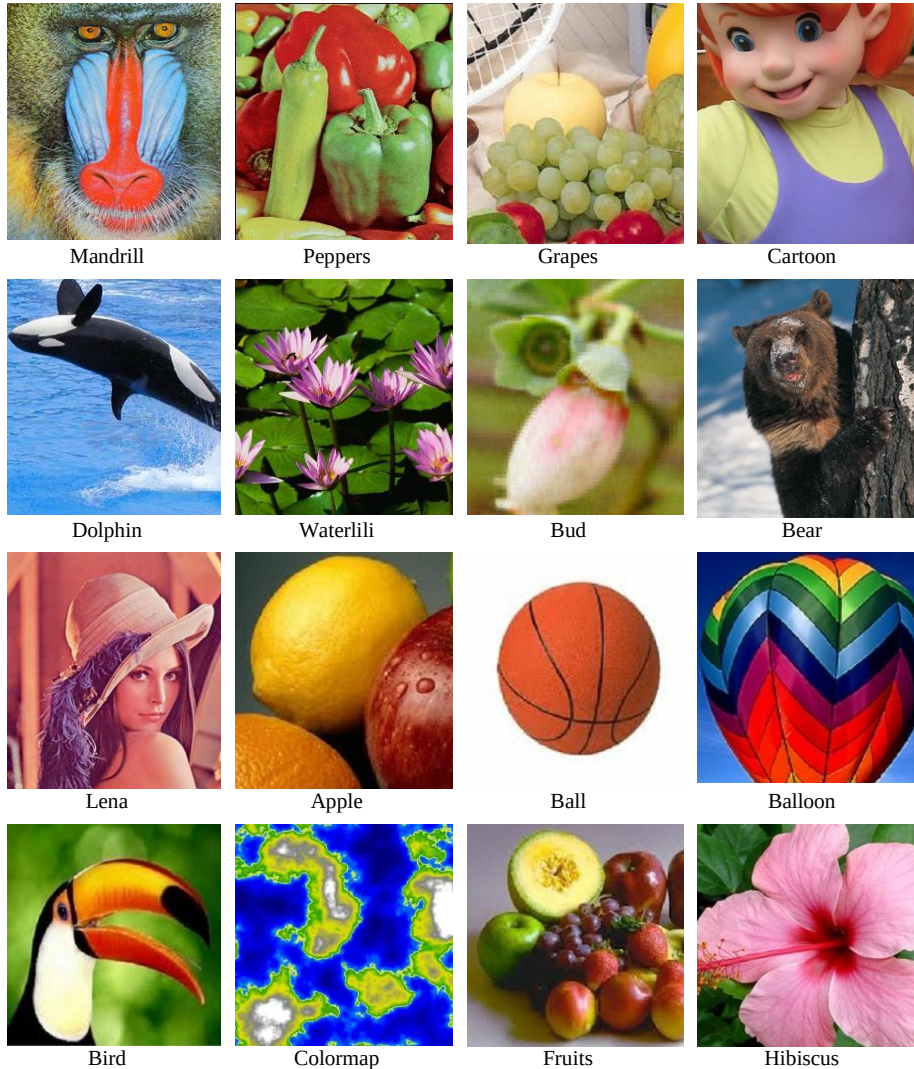




Fig. 1 Color Images of Different Classes used for Experimental Work

Proposed hybrid wavelet transform is applied on above images. For this Slant is selected as a base transform and sinusoidal transforms such as DCT, DST, Hartley and Real-DFT are used as local transforms. Comparative results are given below in Fig. 2.

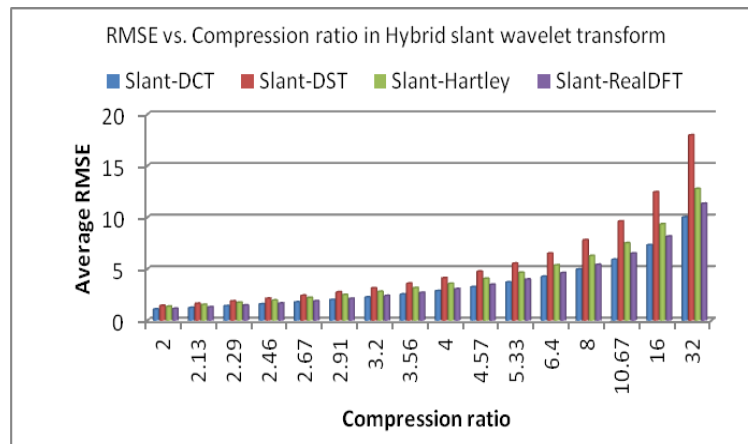


Fig. 2 Average RMSE vs. Compression ratio in Hybrid Slant Wavelet Transform with variation in component transforms and size slant 8x8 and local transform 32x32 (8-32)

Fig. 2 shows average RMSE against compression ratio for different slant wavelet transform. 8x8 Slant transform matrix and 32x32 local component transform is used to generate 256x256 transform matrix. It is then used to transform the image. As shown in graph, when DCT is used as local transform, less RMSE is obtained. For various compression ratios up to 32, Slant-DCT proves to be better. At compression ratio 32, RMSE 10 is obtained using this pair.

As Slant-DCT gives less RMSE, further different sizes of these component transforms are used to find better size combination. Results are shown in Fig. 3.

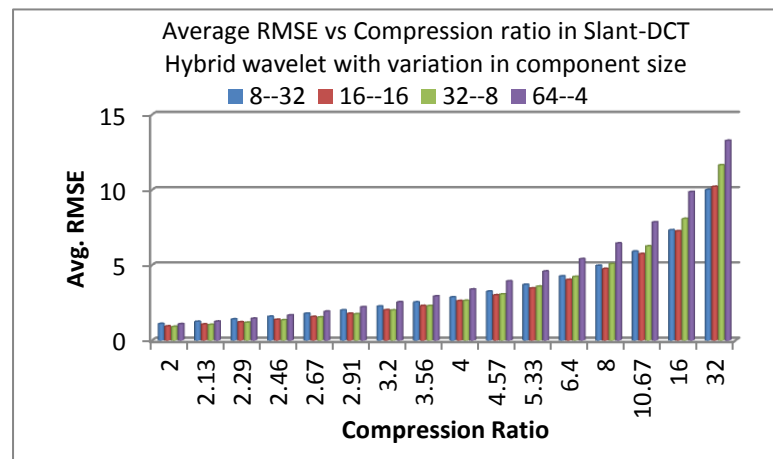


Fig. 3 Average RMSE vs. Compression ratio in Slant-DCT Hybrid Wavelet with different sizes of component transforms

As observed from Fig. 3, for lower compression ratios up to 4, 16-16 and 32-8 pair of Slant-DCT gives less error. Here 32-8 means 32x32 is size of base transform i.e. slant transform and 8x8 is size of local component. For higher compression ratios up to 16, less RMSE is given by 16-16 pair. For highest compression ratio 32, 8-32 and 16-16 pair give almost equal error.

Fig. 4 shows RMSE in multi-resolution analysis of hybrid Slant wavelet transform.

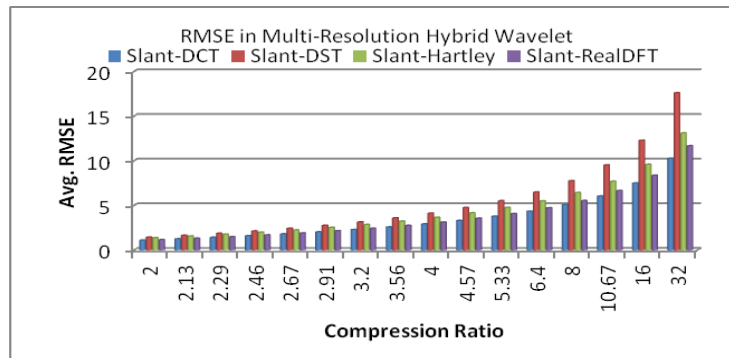


Fig. 4 Avg. RMSE vs. Compression Ratio in Multi Resolution Analysis of Hybrid Slant Wavelet Transform with different local component transforms

In multi-resolution analysis also Slant-DCT produces less error for all compression ratios. Further different sizes of Slant and DCT are combined to observe the best size giving less RMSE. Respective graph is plotted in Fig. 5.

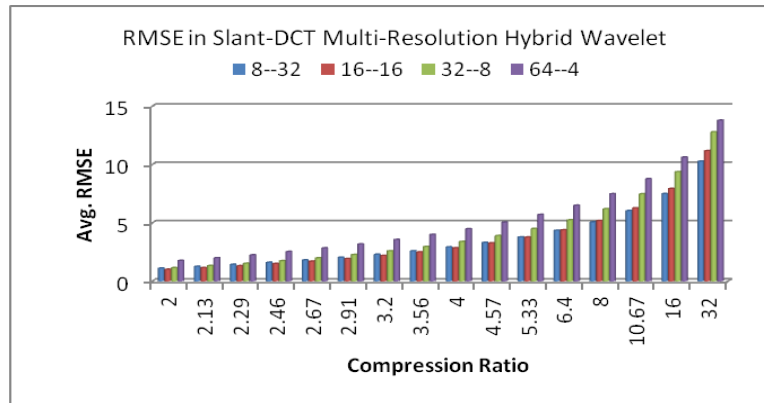


Fig. 1 Average RMSE against compression ratio in Slant-DCT Multi-Resolution Analysis with variation of component transforms

As shown in Fig. 5, for lower compression ratio up to 8, slant-DCT multi resolution hybrid wavelet with 8-32 and 16-16 component size shows almost equal error. For compression ratio 8 onwards, 8-32 pair clearly shows less error than other size combinations. 64-4 pair shows maximum RMSE at all compression ratios. After analyzing performance of hybrid wavelet and multi resolution hybrid wavelet, full Kronecker product of Slant transform with other sinusoidal transforms is taken which is hybrid transform of two components. Variation of RMSE for these different hybrid transforms is observed at different compression ratios in Fig. 6.

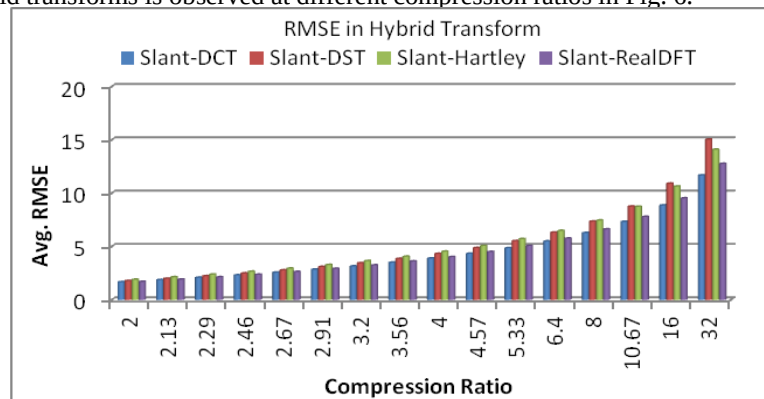


Fig. 2 RMSE vs. Compression Ratio in Hybrid transform with Slant as base transform

In hybrid transform, like hybrid wavelet and its multi resolution analysis Slant-DCT performs better than Slant-DST, Slant-Hartley and Slant-RealDFT. Slant-DST shows high error in all three types of transforms.

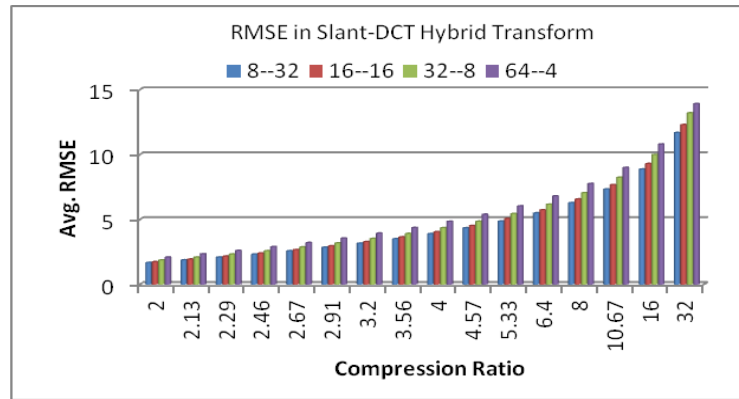


Fig. 3 RMSE at different compression ratios in Slant-DCT Hybrid transform with variation in component size.

Fig. 7 plots average RMSE against compression ratio in Slant-DCT hybrid transform. Size of base transform and local component is varied and error is observed at different compression ratios. For all compression ratios, 8-32 pair gives less RMSE. From all above figures, it has been observed that 8-32 slant-DCT gives minimum RMSE in hybrid wavelet, its multi-resolution analysis and hybrid transform than other component sizes in respective transform types. Figure 8 shows comparison of RMSE in three types of transforms i.e. hybrid wavelet, its multi-resolution analysis and hybrid transform using specific size of component transforms 8-32.

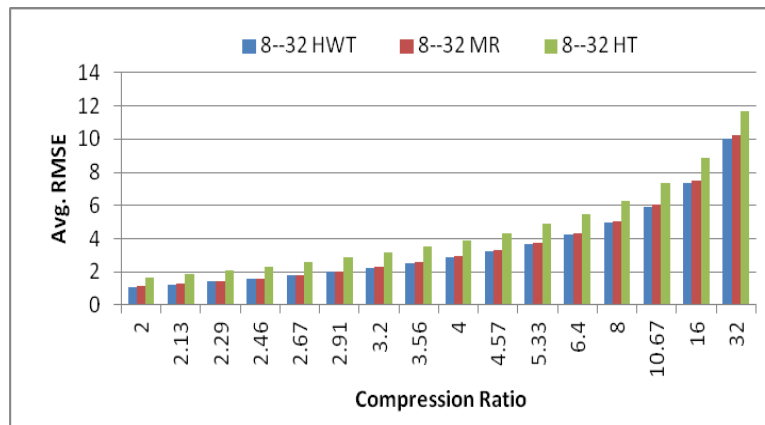


Fig. 4 Comparison of RMSE at various compression ratios using 8-32 component size in hybrid wavelet, multi resolution analysis and hybrid transform

From Fig. 8 it is observed that Slant-DCT hybrid wavelet gives lower RMSE than hybrid transform and multi-resolution hybrid wavelet keeping component size same in all three transforms. As Slant-DCT gives lower RMSE than other hybrid slant wavelet transforms, its performance is measured in terms of Mean absolute error (MAE). It gives absolute difference in pixel values and hence better perceptibility of compressed image. Using different component sizes, MAE is plotted against compression ratio in hybrid wavelet, multi-resolution hybrid wavelet and hybrid transform as shown in fig 9, 10 and 11 respectively.

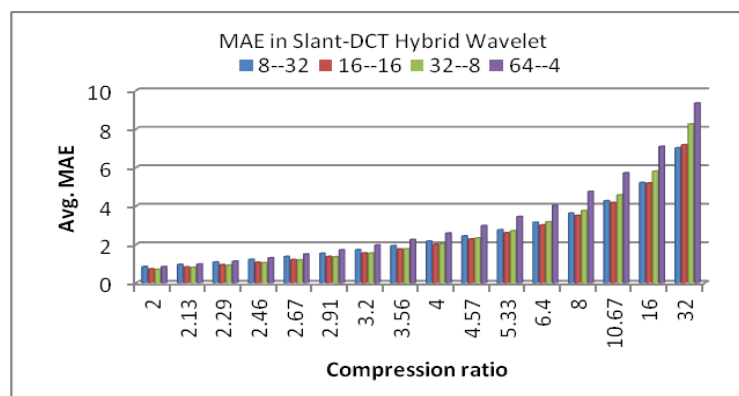


Fig. 5 Average MAE vs. Compression ratio in Slant-DCT hybrid wavelet with variation in component sizes

As shown in Fig 9, at lower compression ratios up to 4.57, 16-16 and 32-8 pair gives almost equal MAE like RMSE. For higher compression ratios this size changes to 16-16. At compression ratio 32, 8-32 pair gives slight less MAE than 16-16 pair.

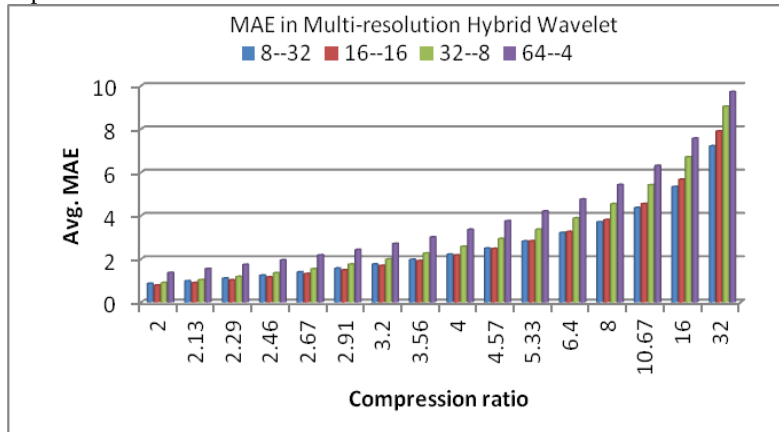


Fig. 6 Average MAE vs. Compression ratio in Slant-DCT Multi-resolution Hybrid wavelet with variation in component sizes

As shown in fig. 10, in multi resolution analysis, 8-32 size of slant-DCT gives lower MAE. For lower compression ratios this size is 16-16.

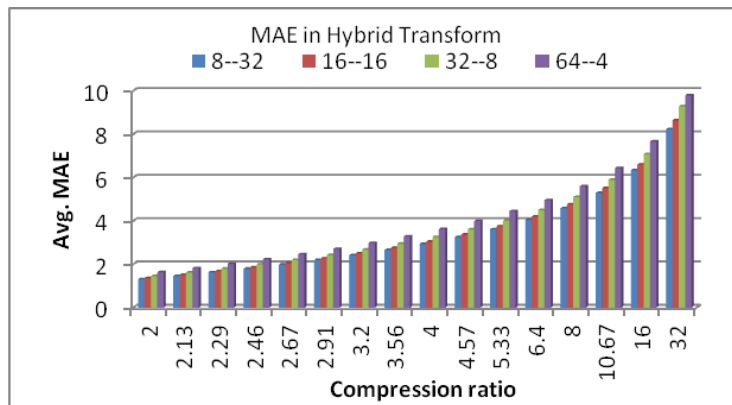


Fig. 7 Average MAE vs. Compression ratio in Slant-DCT Hybrid Transform with variation in component sizes

As shown in Fig. 11, 8-32 size of Slant-DCT gives lower MAE at all compression ratios. Further the performance of Slant-DCT hybrid wavelet is measured in terms of Average Fractional Change in Pixel value (AFCPV). Component size is varied as in RMSE and MAE comparison to observe the best size combination. Fig. 12 shows AFCPV against compression ratio for slant-DCT hybrid wavelet with variation in component size. Similar to RMSE and MAE, 32-8 pair gives less AFCPV at lower compression ratio up to 4. For compression ratios 4 to 16, 16-16 pair works better. At highest compression ratio 32, equal AFCPV is obtained by 8-32 and 16-16 pair.

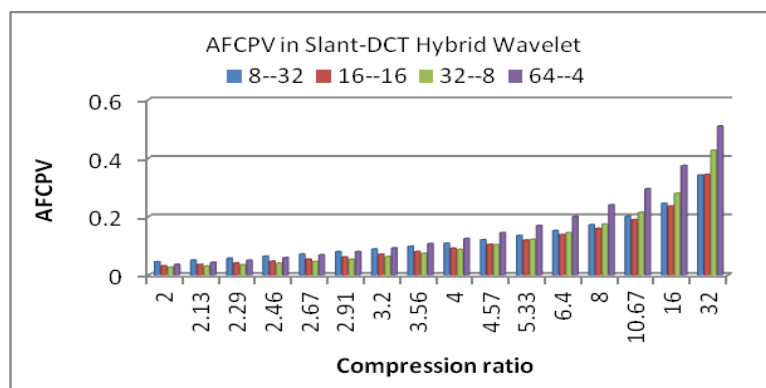


Fig. 8 AFCPV vs. Compression ratio in Slant-DCT Hybrid Wavelet with variation in component size

Fig. 13 and 14 shows AFCPV versus compression ratio in multi-resolution analysis and hybrid transform of Slant-DCT respectively. Sizes of component transforms are varied to choose the size giving less AFCPV.

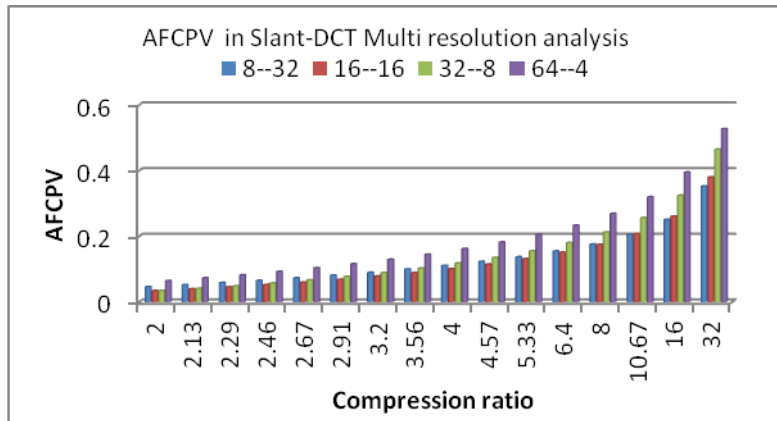


Fig. 9 AFCPV vs. Compression ratio in Slant-DCT Multi-resolution Hybrid Wavelet with variation in component size

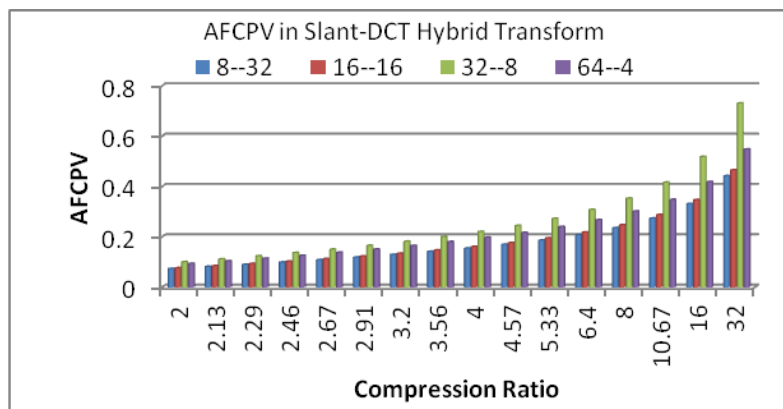


Fig. 10 AFCPV vs. Compression ratio in Slant-DCT Hybrid Transform with variation in component size

In multi-resolution analysis as well as in hybrid transform, 8-32 pair of Slant-DCT gives lower AFCPV like hybrid wavelet. 64-4 pair gives high AFCPV and hence should not be considered.

Till now performance using various parameters is compared. Structural similarity index is an error metric that gives more accuracy than above mentioned metrics. The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate perceived errors; on the other hand, SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene. Fig. 15 shows blocked SSIM plotted against compression ratio.

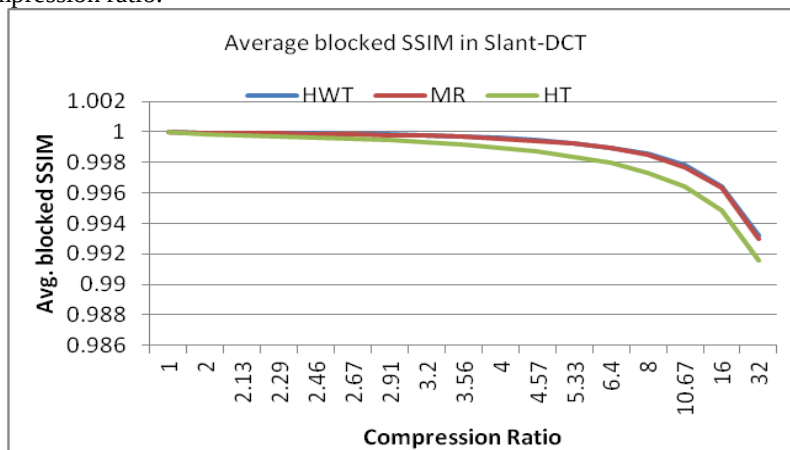


Fig. 11 Average blocked SSIM against compression ratio in Slant-DCT hybrid wavelet with component size 8-32

Image is divided into 16x16 block and SSIM is computed for each block. Average of SSIM for all blocks is calculated for specific compression ratio and is plotted in fig. 15. SSIM varies from -1 to 1. For two similar images it is one. As image is compressed more, error increases and SSIM decreases. At lower compression ratios it is almost equal to one. In hybrid transform SSIM decreases up to 0.991 at compression ratio 32. In hybrid wavelet and multi resolution it is 0.993 at same compression ratio. It indicates that when image is compressed using hybrid wavelet transform or its multi-resolution analysis, better image quality is obtained than one obtained in hybrid transform. As shown in above graph, in hybrid wavelet and multi resolution it is almost equal which is indicated by overlapping of graphs in these two cases.

Fig. 16 show 'Lena' image reconstructed using hybrid slant wavelet transform at compression ratio 32. Local component transforms are varied as DCT, Hartley, Real-DFT and DST. In each case SSIM is observed at highest compression ratio 32. Slant-DCT pair shows SSIM 0.993 using hybrid wavelet and its multi resolution analysis. In Slant-DCT hybrid transform it decreases to 0.991 degrading the image quality. Lowest SSIM is observed as 0.98 in Slant-DST hybrid wavelet transform showing grids in reconstructed image.

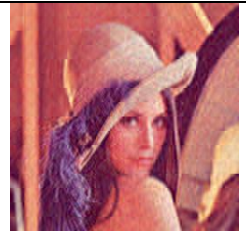
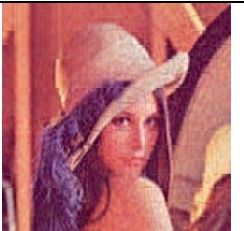
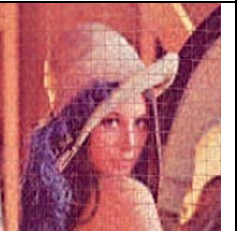
	Slant-DCT	Slant-Hartley	Slant-Real DFT	Slant-DST
Hybrid Wavelet				
SSIM	0.993	0.9924	0.992	0.98
Multi-resolution Hybrid Wavelet				
SSIM	0.993	0.9922	0.992	0.984
Hybrid Transform				
SSIM	0.991	0.99	0.991	0.988

Fig. 12 Reconstructed 'Lena' image at Compression ratio 32 using Slant (16x16) as Base Transform in Hybrid Wavelet, its Multi Resolution Analysis and Hybrid Transform with different Local Component Transforms of Size 16x16

V. Conclusion

In this paper three different cases of hybrid slant wavelet have been experimented and compared for color image compression. Hybrid wavelet i.e. bi-resolution analysis, multi-resolution analysis and hybrid transform are compared using different error parameters. Various sinusoidal orthogonal transforms are used as local component and combined with Slant transform. Different sizes of component transforms like 8-32, 16-16, 32-8 and 64-4 are used to generate 256x256 hybrid wavelet transform matrix. It is then applied on color image of same size. Different fidelity criteria are used as RMSE gives perceived error. At lower compression ratios, 16-16 slant-DCT hybrid wavelet transform gives less error which is closely followed by 8-32 size at higher compression ratios. In multi resolution analysis and in hybrid transform 8-32 component size gives less error. Slant-RealDFT ranks second in performance followed by Slant-Hartley pair whereas slant-DST gives maximum error and hence it is not recommended. Apart from RMSE, MAE and AFCPV are also used to observe the reconstructed image quality. Structural Similarity Index gives clear idea about subjective image quality in three different types of transforms as compared to traditional error metric like RMSE. SSIM obtained in hybrid wavelet is 0.993 which is closest to one indicating better reconstructed image quality. In hybrid transform SSIM obtained is 0.991 that indicates slight degradation in image quality.

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