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STEREOSCOPIC IMAGE COMPRESSION USING CURVELET

[1]THAFSEELA KOYA POOLAKKACHALIL, [2]SARAVANAN CHANDRAN

[1]PhD Scholar, National Institute of Technology, Department of Computer Science and Engineering, Durgapur, India

[2]Associate Professor. National Institute of Technology, Department of Computer Science and Engineering, Durgapur, India

E-mail: [1] thafseelariyas@hotmail.com, [2] dr.cs1973@gmail.com

ABSTRACT

Recent advancements in the field of stereoscopic image display brings up new challenges, especially in the transmission of images and their storage. This factor arises as in stereoscopy where two similar images with different phases are sent to the human brain to produce a 3D visual perception, the amount of space required for their transmission and storage is twice when compared to normal image display. Digital image compression is the sound solution to these challenges. The features of curvelets, viz. anisotropic scaling and better directional sensitivity assists in the efficient illustration of image edges with lower number of non-zero coefficients and hence the motivation for this novel approach, Stereoscopic Image Compression using Curvelet and Arithmetic Coding (SICCAC). Here, thresholded, quantization depended mechanism is exploited to preserve few important coefficients of the curvelets followed by arithmetic encoding. The experimental analysis display high compression ratio and PSNR. The proposed method is compared with Image Compression Algorithm based on Curvelet Transforms and Comparative Analysis with JPEG and JPEG 2000(ICACT). It is observed that proposed SICCAC outperforms ICACT.

Keywords: *Curvelet, Stereoscopic Image, Image Compression, Lossy Compression, Quantization, Compression Ratio, PSNR*

1. INTRODUCTION

In today's world of digitalization, image processing is the technique that has captured the attention of many. The main reason for the representation of an image in digital form is in order to obtain high transmission rate, reduced memory size for storing the images and to make use of image processing techniques that helps in the manipulation of images in improved and efficient manner [1]. Image compression is one of the essential challenges in the field of image processing that has attracted many researchers. In order to reach high compression for digital images, one of the important process is removal of spatial redundancy [2]. Data compression technique is classified into lossless and lossy technique. Even though lossless technique provides undistorted images, they often fail to produce desirable compression ratio (CR) [3]. Stereoscopic image compression is a new area that has got attention more recently. Stereoscopic image compression in the curvelet domain curvelets is the focus of this research article.

The aim of stereoscopy (also named as 3D imaging) is to create a delusion of depth, for depiction, and projection of imageries and videos, in order to simulate the human binocular vision. The principle of binocular vision is that when two images that are slightly different is presented to the left and right human eye separately, the viewer's human brain viewer gives the perception of 3D vision. The Human Vision System (HVS) is able to deduce depth spaces in the sight by means of comparison of these two images. Images with different polarization are projected to the screen by applying this principle in order to submit slightly distinct images to each eye. When an eyeglass which enclose pair of contrasting polarizing filters is worn by the viewer, the respective filter prevents the contrasting polarized light and respective eye perceives only individual image [4].

Application of stereoscopic includes aerial stereo photography, stereoscopic surgery, and digital cinema, etc. This field has acquired a great deal of attention over the last few decades [5].

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When the transmission and storage of stereoscopic monochrome images is considered, the amount of bandwidth and storage required is twice when compared to normal monochrome images. However, when stereoscopic color images are considered, the storage space requirement is six times when compared to normal monochrome image. This is where the need of compression arises and hence the motivation behind this research work.

A good Image compression techniques' trait is the reduction in amount of bits required for the representation of an image without much hindrance to the quality of the image. Hence, researchers aim at deducing algorithms that exhibit high compression ratio (CR) while at the same time exhibits high quality retrieved image.

Following figure 1 demonstrates that stereo image compression is classified according to the relation between the quantization parameters (QPs) of the left-eye image (QP_L) and the right-eye image (QP_R). They are classified as:

- Symmetric-Stereo compression: $QP_L \approx QP_R$.
- Asymmetric-Stereo compression: $QP_L \neq QP_R$.[6]

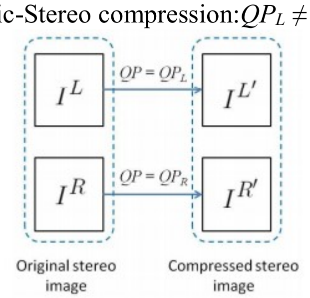

Fig. 1: Stereo Image Compression Types [6]

In this research article, focus is on Symmetric-Stereo compression using curvelet. One important limitation of Discrete Wavelet Transform (DWT) is the absence of directionality. This leads to impedance in performance in the case of edge coding, especially curve edges. Solution to this problem is capturing of edges explicitly or implicit application of directional transforms [7]. Curvelet transforms comes into action across applications where representation of functions that have incoherence along d^2 edges. Emmanuel Cand`es et al. introduced curvelet transforms [8] which provides effective representation of objects that have incoherencies along d^2 curves [7] [9].

Curvelets obey a parabolic scaling relation i.e., at any scale 2^{-j}, every distinguished element has an envelope that is aligned along a "ridge" of length $2^{-j/2}$ and width 2^{-j}, which implies that width ≈ length^2. The following figure 2 shows the curvelet tiling of space and frequency.

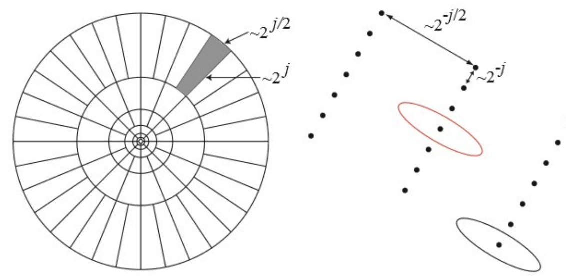

Fig.2: Space (Left) And frequency (Right) Tiling Of Curvelet [8]

The occurrence of dyadic length in curvelets is what that makes curvelet unique. This is shown in following figure 3.

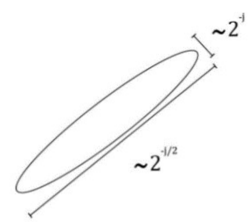

Fig. 3: Dyadic Lengths In Curvelet

In the construction of curvelet transform, initial step is Fourier transformation of the 2D signal. The division of frequency plain into polar wedges takes place in the next step. This is shown in the right of the figure 2. In the final step, by taking the inverse FFT of each wedge at scale j and oriented at angle θ, the curvelet transform coefficients at a particular scale is obtained. Two algorithms have been designed that has resulted in two curvelet implementations, namely the wrapping-based transform and unequally-spaced fast Fourier transform (USFFT). The difference in implementations occurs due to the choice of spatial grid that is used to transform curvelets at each scale and angle. In USSFT, a decimated rectangular grid is tilted along the main direction of each curvelet. In the case of wrapping, a decimated rectangular grid aligned with the image axes is used [10]. In this paper, the focus is USFFT. The mathematical and implementation details of the transform is available [8].

In this research work, arithmetic coding is used as the entropy coder. In arithmetic coding, the coded symbol is represented by a codeword that is generated by the arithmetic coder. In the proposed approach, the first job completed by the coder is the segmentation of the rate controlled coefficients of the curvelet in subintervals according to the amount of output received after curvelet transform. The subinterval's size depends upon the probability of occurrence of rate controlled coefficients, which will be discussed in detail in the proposed approach. The generated codeword promises the inverse process that retrieves the original coefficients without any loss of data [11].

2. LITERATURE REVIEW

Nasser Eslahi et al. proposed a novel approach where sparsity regularization was applied using an adaptive curvelet thresholding criterion. This approach exhibited extensive convergence property [12]. This motivated to apply curvelet transforms in the proposed research work. Hsin-Chang Feng developed a model for perceptibility thresholds for stereoscopic images. In this model the left and right stereo pair images were jointly compressed using the visibility thresholds. It was observed from the experiments that the resulting images are visually lossless [5].This motivated to include thresholds and quantization (lossy) for stereoscopic images.

Shuyuan Zhu et al. proposed a coding scheme where interpolation-compression directed filtering (ICDF) was used to convert each 16×16 macroblock into an 8×8 coefficient block. Error-compensated scalar quantization (ECSQ) was applied for compression where initially 16x16 blocks were initially converted to 8x8 coefficients. The coding scheme was specifically applied to Y, Cb and Cr components. This method gave significant compression gain over existing other methods [2]. This gave motivation to split the color image into separate color channels.

Shaou-Gang Miaou et al. proposed a novel coding scheme for medical images that combined the JPEG-LS and an interframe coding with motion. It was observed from the results that their approach produced a compression gain of 13.3% and 26.3% over the methods of using JPEG-LS and JPEG2000 alone, respectively for endoscopic images and a compression gain of 77.5% and 86.5% correspondingly for an MRI image sequence [13]. This motivated to include lossless compression technique also. Sulthana et al. proposed a novel coding scheme using wavelet coding and adaptive arithmetic coding. It was observed from the results that this approach resulted good compression ratio and less execution time requirement. This motivated to apply arithmetic coding after application of curvelet transform [14].

Seyum and Nam proposed an approach using color transform where the correlation between the RGB pixels was eliminated. Upon the analysis of the results, it was observed that the average bit rate reduced by 7.105%, 13.55%, and 5.52% respectively over Kodak image set, some medical images, and digital images[15][16]. This motivated to split the image into R, G, and B components before performing compression.

Jinlei Zhang et al. proposed a novel coding pattern that was specifically concentrated for compression of hyperspectral [HS] images. The main difference in this approach was that data decorrelation was shifted to the decoder side. It was observed from the experimental results that high compression ratio was obtained for this low complexity encoder [17] [16]. This motivated to design a low complexity encoder. From the experimental analysis completed by Pascal Peter, it was observed that high quality reconstruction of color data was possible by introduction of a new colorization technique. This motivated to introduce a pixel replacement technique based on the difference between stereo image pair [18] [16]. Kim, Han Tai, and Kim proposed a new technique on salient region detection via high-dimensional color transform and local support. It was observed from the results that high compression ratio was obtained using this approach. This motivated to exploit the location of pixel and their pixel values for research [19] [16]. Rushi Lan et al. proposed a novel approach where the color channels were merged to obtain the reconstructed image. It was observed from the results that reconstructed image was of high quality. This motivated to merge the color channels during decoding [20] [16].

The novel approach proposed by Jose et al. encoded the error that arises between original values and color component predictions. It was

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observed from the results that this approach was suitable for static images that applies adaptive logarithmical quantization [2] [16]. This directed to focus on stereoscopic image compression where disparity vector is considered. In the novel coding scheme proposed by Wu-Lin et al., three grayscale image was extracted from the color image and then partitioning was applied to obtain variable-sized blocks. The partitioning was performed using quadtree segmentation. It was observed from the results that this approach displayed high PSNR value at low bit rates [21] [16]. This motivated to obtain the different color channels from the color image.

Priya Darshini Kumari et al. proposed an algorithm for image compression based on curvelet transform where Huffman Coding (ICACT) was used as an encoder [1]. The algorithm for ICACT is as follows.

1. Level shift the image so as to have the input image pixel values are equally shifted around zero.
2. Calculate the curvelet coefficient by application of Fast Forward Transform (FFT) and Inverse Fast Forward Transform (IFFT).
3. Rearrange the transformed coefficients in descending order to get an array consisting of curvelet coefficients in descending order
4. Threshold value calculation followed by rate control.
5. Application of quantization.
6. Application of Huffman coding
7. Perform inverse.

The performance comparison of the proposed method in this paper is performed with ICACT. The aim of this research article is to propose a novel compression scheme for stereoscopic image using curvelet transform which code images with straight edges or curve edges. The focus of this research article is for color images, even though the algorithm works well with greyscale images. This research article is based on Unequally-Spaced Fast Fourier Transforms (USFFT) [8].

The following Section III describes the proposed SICCAC image compression technique. The following Section IV Experiments and Results, analyses the proposed SICCAC technique with lossy and lossless conditions and Image Compression Algorithm based on Curvelet Transforms (ICACT) [1]. Standard images are used in this experiment. Conclusions are drawn in section V.

3. IMAGE COMPRESSION

The two main quality metric used here is Compression Ratio (CR) and Peak Signal to Noise ratio (PSNR). CR gives indication of the rate of compression. The quality of the reconstructed image is measured through PSNR. CR is the ratio of original image size to the compressed image size. The calculation of PSNR is completed with the help of mean squared error (MSE) present in the image. MSE maintains an inverse relation with PSNR. Lower value of MSE indicates minimum error. A higher value of PSNR is an indication that the ratio between signal and noise is high. Signal refers to the original image and noise refers to the error in the reconstructed image. A compression technique having lower MSE (High PSNR) is an indication of good quality of the technique. Measurement of PSNR is evaluated in the scale of logarithmic decibels (dB). Typical PSNR values fall in the range of 25 to 35dB [1].

Lossy and lossless compression are the two main categories of image compression. This is based on the presence or absence of quantization step. The quantization makes loss of data and the scheme is referred as lossy. In lossless approach, the reproduced image retains pixels value of the source image. The scaling of data set by quantization factor is the cause for irreversible data loss in quantization [22], [16], [23]. Due to scaling, all trivial samples are eliminated during quantization and hence higher compression ratios are obtained in comparison to lossless compression, but at the cost of the quality of the reconstructed image [16].

3.1 Proposed SICCAC Encoding Scheme

The aim in this section is to explain the new compression model SICCAC. The following figure 4 and figure 5 displays the block diagram of lossy and lossless SICCAC respectively. In the case of lossless SICCAC, quantization step is ignored.

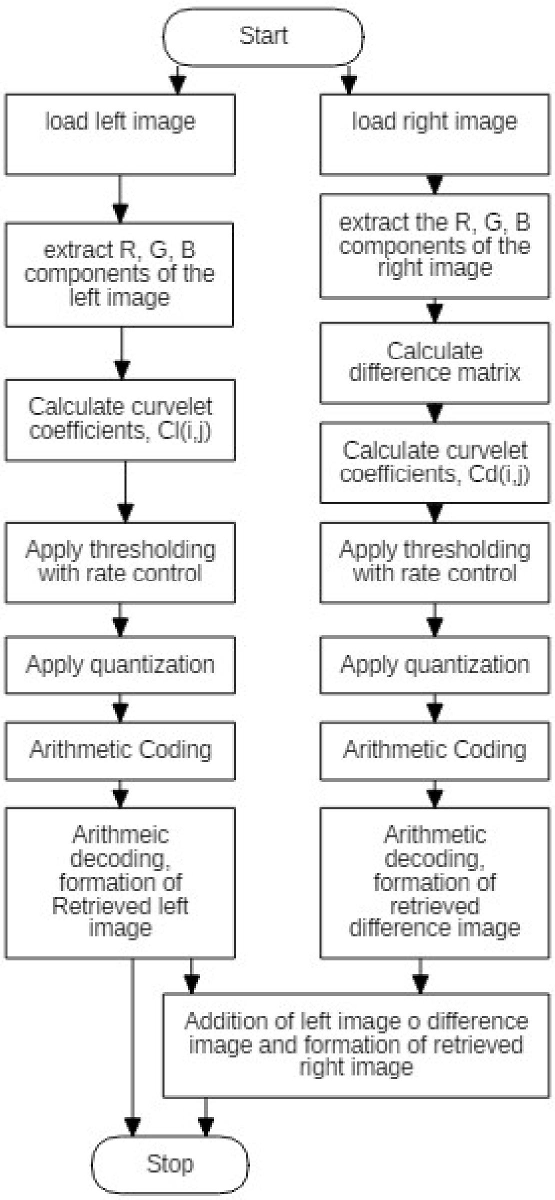

Figure 4: Block diagram of lossy SICCAC

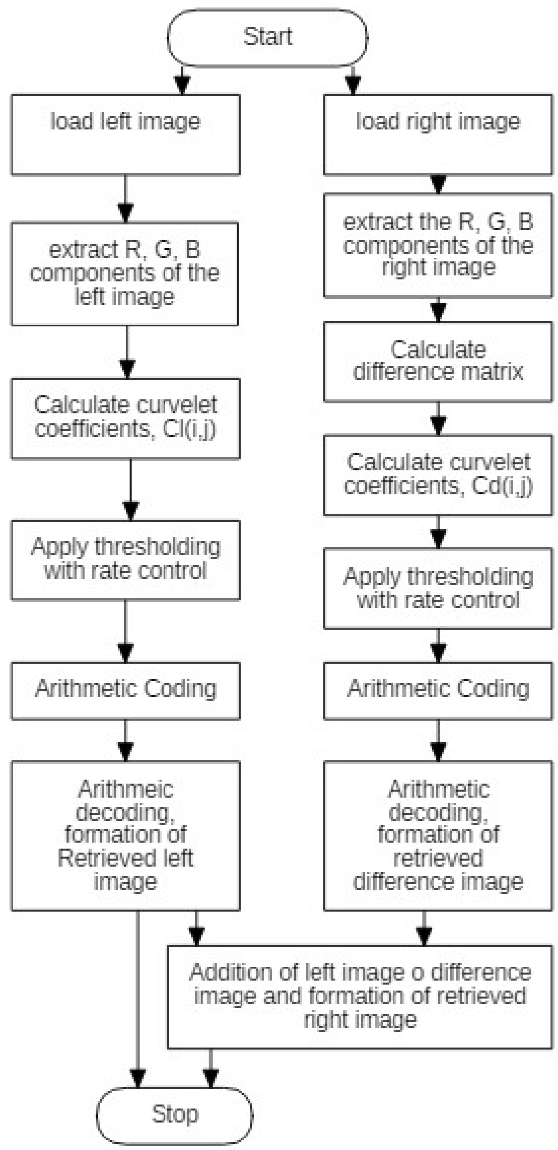

Figure 5: Block diagram of lossless SICCAC

Following is the algorithm for the proposed lossy SICCAC. In the case of lossless SICCAC, quantization step is ignored.

1. Transform the stereopair image into matrix L’ and R’.
2. Calculate the difference image L’ and R’, namely D’.Do the following steps to L’ and D’.
3. Calculate curvelet coefficients using Equation 1.

   $$C(\boldsymbol{i},\boldsymbol{j}) = \int f(\boldsymbol{x}).\boldsymbol{\psi}_{j,l,k}(\boldsymbol{x})\boldsymbol{dx}\ \boldsymbol{R^2}\ ; \qquad (1)$$

   where R denotes,real−line.
4. Obtain the curvelet coefficient array Co(i,j) in descending order by rearrangement. Obtain the highest coefficient value Hmax.
5. Compute the thresholding value TH to discard the low frequency coefficients. Apply rate control to deduce rate controlled thresholded curvelet coefficients (RCT) using Equation 2.

   $\boldsymbol{T}\mathrm{H} = \mathrm{Hmax}(\boldsymbol{i},\boldsymbol{j})/\mathbf{2}$;

   $\boldsymbol{if}$, C(**i**,j) < **T**H , **Set C(i,j) = 0**;

   else, **set** RCT(**i**,**j**) = **Rate∗ C**(**i**,**j**). (2)
6. Apply quantization to RCT(i,j) using Hmax .This step reduce the coefficients further. This step is eliminated in the case of lossless SICCAC.

   $Q(\boldsymbol{i},\boldsymbol{j}) = ([RCT(\boldsymbol{i},\boldsymbol{j})/\ \boldsymbol{T}H]+\mathbf{0.5}\ )*\boldsymbol{T}H$;
7. Apply Arithmetic Coding (AC) which is an entropy coder to *QC(i,j)*, the quantized coefficients. This step reduces the number of bits required to represent the image to minimum. The output of this step is ACL and ACD which are the compressed images for left image and difference image.
8. Perform inverse of the above steps in sequence to retrieve the reconstructed matrices namely, RL and RD.
9. Retrieve the reconstructed left image and difference image.
10. Add RL and RD to obtain the retrieved right image, RR.

4. RESULTS

Following table I and table II shows the results for CR, PSNR, and MSE for lossy and lossless SICCAC respectively.

Table I: CR, PSNR and MSE values for Lossy compression

Images	Lossy Compression		
	CR	PSNR	MSE
im3	6.4846	45.3085	1.9153
im5	7.6735	42.1850	3.9317
im10	7.0402	29.3575	75.3922
im12	7.1589	44.5473	2.2822
im13	14.8460	46.5170	1.4500
Average	8.6406	41.5831	16.9943

Table II: CR, PSNR and MSE values for Lossless compression

Images	Lossless Compression		
	CR	PSNR	MSE
im3	3.3065	45.5162	1.8258
im5	4.4158	42.2176	3.9023
im10	4.6701	29.4265	74.2050
im12	4.1251	44.6467	2.2305
im13	4.2267	46.8723	1.3361
Average	4.1488	41.7359	16.6999

In the case of Lossy SICCAC, CR is highest for im13 and equals 14.8460. The lowest CR is for im3 and equals 6.4846. The average CR for lossy SICCAC is 8.6406. In the case of Lossless SICCAC, CR is highest for im10 and equals 4.6701. The lowest CR is for im3 and equals 3.3065. The average CR for lossless SICCAC is 4.1488. The comparison between CR, MSE and PSNR for lossy and lossless SICCAC is shown in following figure 6, figure 7 and figure 8 respectively. It is observed from the comparison that CR value exhibited by lossy SICCAC is twice that of lossless SICCAC while PSNR values are similar. The overall result brings us into conclusion that lossy SICCAC is a better choice than lossless SICCAC.

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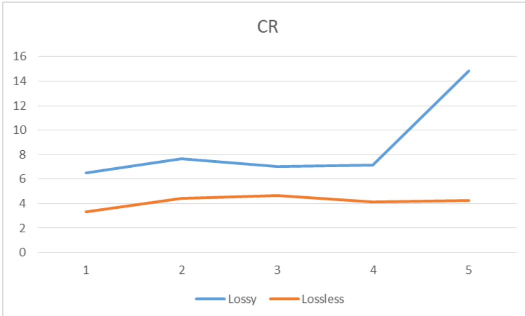


Figure 6: CR comparison between lossy and lossless SICCAC

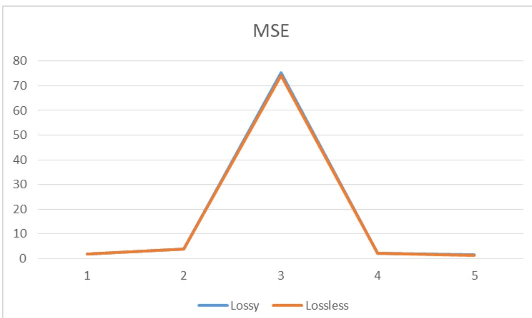


Figure 7: MSE comparison between lossy and lossless SICCAC

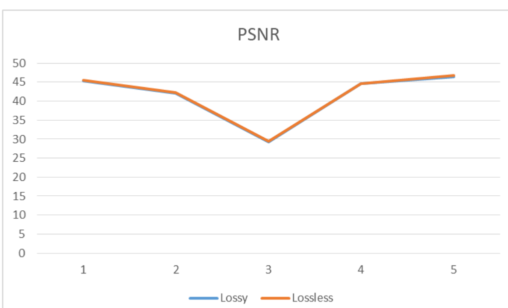


Figure 8: PSNR Comparison between lossy and lossless SICCAC

Following table III shows the comparison between PSNR and MSE of SICCAC with ICACT.

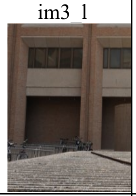
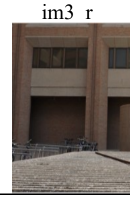
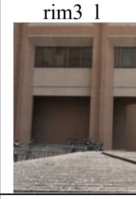
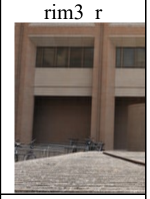
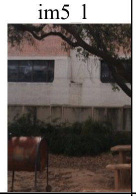
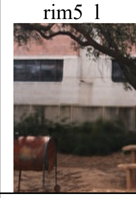
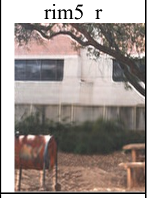
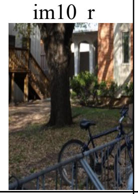
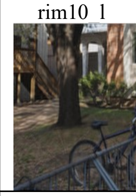
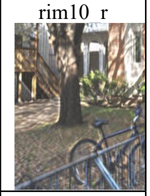
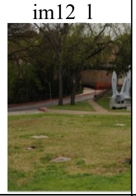
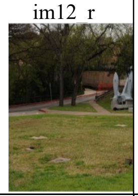
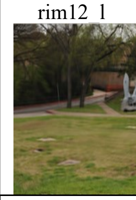
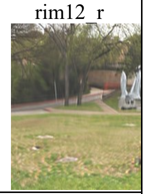
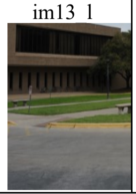
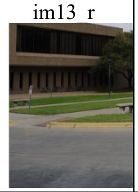
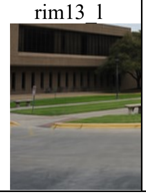
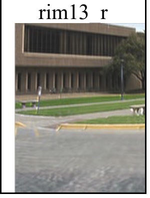
Table III: Comparison between PSNR and MSE of SICCAC with ICACT

Comparison Factor	SICCAC	ICACT
PSNR	41.5831	14.9946
MSE	16.9943	160.7065

The average PSNR using the proposed SICCAC technique is 41.5831 while with that of ICACT is 14.9946. The average MSE using the proposed SICCAC technique is 16.9943 while with that of ICACT is 160.7065. MSE holds inverse proportion to PSNR and this is reflected in table II and table III. From the analysis, it is observed that SICCAC outperforms ICACT.

The following table IV shows the original and reconstructed images using Lossy SICCAC. Popular LIVE 3D image quality presented in [24] is used perform the simulations.

Table IV: Original and reconstructed image using the proposed Lossy SICCAC technique

Original images		Lossy SICCAC	
Left Image	Right Image	Left Image	Right Image
im3_l 	im3_r 	rim3_l 	rim3_r 
im5_l 	im5_r 	rim5_l 	rim5_r 
im10_l 	im10_r 	rim10_l 	rim10_r 
im12_l 	im12_r 	rim12_l 	rim12_r 
im13_l 	im13_r 	rim13_l 	rim13_r 

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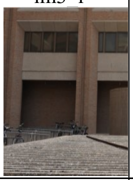
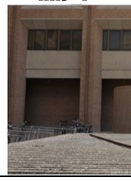
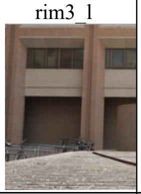
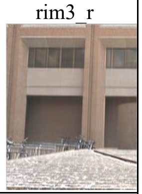
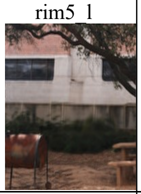
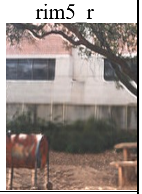
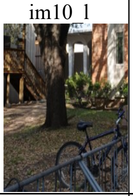
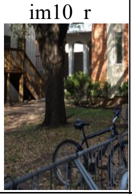
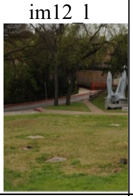
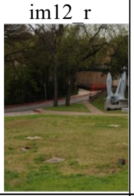
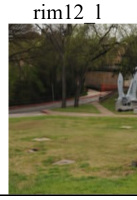
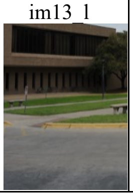
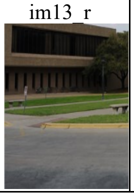
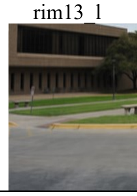
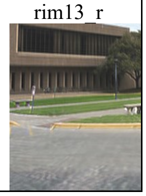
The following table V shows the original and reconstructed images using Lossless SICCAC

Table V: Original and reconstructed image using the proposed Lossless SICCAC technique

Original images		Lossless SICCAC	
Left Image	Right Image	Left Image	Right Image
im3_l 	im3_r 	rim3_l 	rim3_r 
im5_l 	im5_r 	rim5_l 	rim5_r 
im10_l 	im10_r 	rim10_l 	rim10_r 
im12_l 	im12_r 	rim12_l 	rim12_r 
im13_l 	im13_r 	rim13_l 	rim13_r 

5. CONCLUSION

In this article, we proposed a novel coding scheme based on curvelet transform. It is observed from the results that the average compression ratio using lossy approach is twice that obtained through lossless approach, while the PSNR values were in the comparable range. The increase in compression ratio in lossy SICCAC is due to the presence of quantization. This prove that lossy SICCAC is a better choice when compared to lossless SICCAC. This method is also compared with Image Compression Algorithm based on Curvelet Transforms and Comparative Analysis with JPEG and JPEG 2000(ICACT). It is observed from the results that the PSNR values obtained for ICACT was far less when compared with that of SICCAC, proving that SICCAC is a better choice than ICACT.

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