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Image Compression Using Radon Transform With DCT : Performance Analysis

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Abstract - ***Image compression is the significant research area in the field of image processing. The Transform selection in image compression has played a vital role since the size of the resultant compressed image should be reduced in comparison with the original image. Numerous image compression standards based on Wavelet Transform have been devoted in the literature but still there exist scope of yielding better compression with high quality in image reconstruction. Existing image compression technique using DWT with Biorthogonal filtering accommodates less compression ratio with poor image quality of reconstructed image. With that concern, image compression using Radon Transform with DCT (Discrete Cosine Transform) is proposed in this paper that contribute different dimension to the image compression. The image compression using Radon Transform with DCT accords best performance whereas the image compression using DWT with Bi-orthogonal filtering performs the least. Experimental evaluation has been effectuated to arrive at the conclusion that better results for PSNR and compression ratio is used for selecting best image compression technique.***

Keywords - Image Compression, Discrete Wavelet Transform (DWT), Radon Transform (RT), Discrete Cosine Transform (DCT).

I. INTRODUCTION

With the ever growing technology, it is significant to handle vast amount of image data and needs to be stored in a proper way by exploiting efficient techniques normally succeed in compressing the images. The representation of an image by reducing the amount of data is termed as image compression. Moreover, the ultimate goal of image compression is to reduce both spatial and spectral redundancy to accumulate or transmit data in a proper manner. Once the image is compressed it needs to be reconstructed at the receiver side to reproduce the source image. In literature, numerous image compression techniques are proposed to compress the image by accomplishing better image quality.

In image compression Discrete Wavelet Transform (DWT) has witnessed great success in enhancing the compressed image quality. 1-D, 2-D DWT based compression techniques are exploited for vertical and horizontal directions. In order to efficiently capture the point singularities of image, classical 2-Dim DWT are used. But, improper alignment of image in horizontal and vertical directions fails to capture the line singularities. With respect to the property of DWT, improper alignment of edges and contours create the energy of image that spreads across the sub bands. All the DWT based compression technique takes the advantage of either wavelet 9/7 filter or wavelet 5/3 filter for better image compression. The wavelet 9/7 filter is the famous Bi-orthogonal wavelet filter, which can be used as the default filter in the irreversible wavelet filter.

The wavelet based Bi-orthogonal filter coefficient introduced by V. Kumar, *et al*. [viii] accomplish good evaluation result in terms of metrics like PSNR and MSE as compared to conventional DWT based image compression techniques namely, wavelet 9/7 filter or wavelet 5/3 filter.

The existing image compression technique using DWT with bi-orthogonal filtering gives lower performance in terms of image quality metrics like PSNR. With that concern, an effective image compression technique using radon transform with DCT (Discrete Cosine Transform) is proposed. It acts as a more promising way of compressing texture images. The image compression technique DCT is integrated with Radon Transform, which is well suited for accomplishing better performance in terms of PSNR. The performance of existing image compression technique and proposed image compression method are analyzed.

The rest of the paper is composed as follows: Section 2 reviews the related works of existing image compression techniques. Section 3 describes proposed work and percolates a comparative study of existing image compression technique with the proposed approach for compressing the images. Experimental analysis is discussed in section 4. Finally, section 5 sums up the paper with conclusion and further direction.

II. RELATED WORKS

In the field of image processing, Wavelet transform has gained increasing attention and proved to be very useful tools. Wavelets are mathematical tool for hierarchically decomposing functions.

This wavelet transform based image compression technique is highly preferred by scientists to acquire the compressed images with high PSNR values and high compression ratios [xiv]. Another Discrete Wavelet Transform proposed by Z. Ye, *et al*. [xvi] compress digital images and finger prints based on the horizontal, vertical and diagonal information obtained from the input image and then reconstruct the image. These kinds of image compression technique accomplish the task of handling discontinuities in data. Numerous works have been carried out in literature to minimize the calculation work in wavelet transform. One such algorithm is MFHWT (Modified Fast Haar Wavelet Transform) proposed by C. Phang, *et al*. [xi], which significantly reduce the mathematical work in FHT (Fast Haar Transform) and HT (Haar Transform). MFHWT is used for one dimensional approach whereas FHT aims to bring out the detail in N/2 coefficients at each and every level for a signal of length N. This one dimensional approach can also be extended to 2D images. To enhance the energy compaction for sharp image features, computation analysis based on anisotropic statistical image model is needed. With that concern C.L. Chang, *et al*.[ii] introduced DA-DWT (Direction Adaptive DWT) that locally adapts the filtering directions to image content based on directional filtering.

The mathematical analysis model quantifies the theoretical gain accomplished by adapting the filtering directions. Another image compression scheme for 3D images based on hybrid technique of DWT and DCT was developed by E. Elharar, *et al*. [v]. The transformation of DCT and DWT are integrated together, which then explore local features within each elemental image. Moreover, the redundant correlation characteristics between adjacent elemental images are also exploited in this hybrid architecture. The reconstructed image is obtained from the processed elemental image. In general, DWT (Decimated bi-orthogonal wavelet transform) presented by J.L. Starck, *et al*. [xiii] is the most widely used wavelet transform algorithm. Even though this kind of algorithm leads to successful implementation, achieving optimal result in image compression through this algorithm remains a concern. Some applications like data analysis, de-convolution, filtering, detection, etc. uses this algorithm fail to accomplish the optimal result in image compression. Similarly, another discrete wavelet transform based on direction adaptive was proposed by C.L. Chang, *et al.* [i] that facilitates better performance in image compression and offer ease mathematical computation. Furthermore, a bandeletization procedure is integrated with direction lifting in order to eliminate the correlation in the wavelet coefficients. The ADL (Adaptive Directional Lifting) technique introduced by W. Ding, *et al.* [iii] addressed the rigidity problem of the existing 2D wavelet transforms. The prediction step is performed on the direction of the strongest pixel correlation in each ADL lifting stage. Without imposing any constraint on the interpolation method, perfect reconstruction is guaranteed by this ADL Wavelet Transform.

To perform 2D decomposition, ADL framework allows the use of any 1-D wavelet filters namely, Haar, 9/7 and 5/3 wavelets. But, this technique leads some mismatch between update and predict steps. To encounter the problem in ADL, another adaptive lifting wavelet transform based on weight was proposed by Y. Liu, *et al.* [ix] that overcome the mismatch problem, invariant interpolation filtering coefficients, interpolation supporting either horizontal or vertical direction.

This enhance weighted lifting ensures consistency among update and predict steps and enhance the orientation property of interpolated images. Additionally, efficient coding and cost reduction of side information is accomplished by this WAL (Weighted Adaptive Lifting) based wavelet transform. Instead of deploying classical interpolation filter for the directional prediction and update W. Dong, *et al.* [iv] proposed another adaptive directional lifting based wavelet transform. This novel two dimensional adaptive filtering technique computes the adaptive filter for every fractional-pel direction in order to reduce the code overhead and prediction error.

Moreover, directional prediction is enhanced with respect to the adaptability in local textures and regions. Apart from DWT wavelet transforms, D. Wang, *et al.* [xv] proposed curved wavelet transform by applying 1-D filters along curves. This is entirely different from the conventional two dimensional wavelet transform that is restricted to horizontal and vertical directions, that ineffectively represents the lines and edges in images. The curve in wavelet transform is determined on the basis of image content to be coded, which builds a new image coder. In this curve wavelet transform, the small number of wavelet coefficients represents the pixels along these curves.

Among various image compression algorithms SPIHT (Set Partitioning in Hierarchical Trees) has gained increased attention because of its best rate distortion performance. The listless modified SPIHT proposed by H. Pan, *et al.* [x] is an efficient image coding algorithm that works on the basis of lifting wavelet transform. This algorithm incorporates the characteristics of progressive transmission and outperforms the conventional SPIHT algorithm. Moreover, it reduces the compression speed as compared to SPIHT. Discrete cosine transform is another image compression approach that integrates the progressive growth of various methods. An extension in discrete cosine transform was proposed by N. N. Ponomarenko, *et al*. [xii] that divides an image into blocks of different sizes based on vertical-horizontal partition scheme. This advanced version of DCT proves significantly better performance than other DCT based compression method and JPEG based techniques.

Another image compression technique proposed by A. Kingston, *et al.* [vii] incorporates the properties of Mojette transform. The usage of crypto compression scheme enables fast compression of large amount of data. This technique is fully security oriented and transmits only uncorrelated data with the encrypted part. The evaluation results show the good compression ratio with this method. A. Khashman, *et al.* [vi] proposed an image compression technique based on neural networks and Haar transform. Neural networks can be trained to determine the non linear relationship among the image intensity and its compression ratio. . To address the above issues, an efficient image compression technique DCT with Radon Transform is designed to overcome the weakness of existing image compression technique.

III. IMAGE COMPRESSION APPROCHES

Digital images are widely used in computer applications. Uncompressed digital images require considerable storage capacity and transmission bandwidth. Efficient image compression solutions are becoming more critical with the recent growth of data intensive, multimedia based web applications.Data compression is the process of converting data files into smaller files for efficiency of storage and transmission. As one of the enabling technologies of the multimedia revolution, data compression is a key to rapid progress being made in information technology.

3.1 IMAGE COMPRESSION USING DWT WITH BI-ORTHOGONAL FILTERING

The discrete wavelet transform acts as a powerful tool in many applications like segmentation, image compression, image enhancement, telecommunication, astronomical image compression and analysis. The DWT comprises the advantage of performing an analysis of multi-resolution of a signal with localization in both time and frequency. Technically, DWT construct multi-scale representation of an input image by mapping an input image into a set of coefficients. The DWT of a signal is calculated by fed up of those input signal by means of series of Bi-orthogonal filters [viii]. The image compression using DWT with bi-orthogonal filtering performs the compression process by undergoing the following tasks namely, image filtering, image encoding, acquired encoded values and image reconstruction.

Initially, the input image is acquired and then selection of low pass filter and high pass filter is carried out based on bi-orthogonal filtering to divide the range of frequency. Both low pass and high pass filter are applied for each row of data to acquire the low and high frequency components. Now, the filtering is performed on the intermediate data of each column and obtains the filtered image. Then the next stage is the image encoding, which encode the output taken from filtered image since the output of filter bank is down sampled and needs to be encoded. DWT is applied to each block of input to encode the image and then encoded values are obtained. The perfect reconstruction of image (Bi-orthogonality) is built after retrieving the encoded values.

The image statistics namely, MSE (Mean Squared Error) and PSNR (Peak Signal to Noise Ratio) afford the performance measure of an image compression technique. Based on this statistics an efficient image compression technique that is well suited for texture images are determined. Image quality is measured by means of PSNR between the original image and reconstructed image. The PSNR value is computed in dB using the equation given below:

$$PSNR = 10\ log_{10} \frac{I^2}{MSE} \quad (1)$$

Where MSE is Mean Square Error and I is the pixel intensity level of an image. The MSE is defined in equation (2). It produces the distortion level by comparing reconstructed and original image.

$$MSE = \frac{1}{AB} \sum_{i=1}^{A} \sum_{j=1}^{B} (P_{i,j} - Q_{i,j})^2 \quad (2)$$

Where P is the original image of size A x B and Q is the reconstructed image of size A x B. The existing image compression using DWT with Bi-orthogonal exhibit low performance in terms of PSNR based performance measure. Compression ratio is the most significant measure in image compression that estimates the ability of data compression by comparing the image size being compressed to the size of the source image. The above analysis of existing approach for image compression using DWT with bi-orthogonal filtering exhibits some of the drawbacks when it comes to represent straight lines and edges in images. Moreover, it shows very low performance in terms of PSNR and compression ratio. The Bi-Orthogonal Filtering with DWT image compression scheme is exposed in Fig 1.

3.2 PROPOSED IMAGE COMPRESSION USING RADON TRANSFORM WITH DCT

An efficient image compression technique is proposed to address the problem occurred in existing image compression technique. The proposed approach exploits the use of Radon Transform with DCT (Discrete Cosine Transform) to efficiently reconstruct the image from the original image. The proposed image compression scheme is exposed in Fig 2.

The working procedure of the proposed scheme is halved into the process namely, selection of input image (Original image), acquisition of binary points, apply Radon Transform to obtain the radon points, Encode the radon points using DCT computation, Decode the radon points using inverse DCT, image reconstruction through inverse radon transform. The detailed description of each sub processes are given subsequently in the following segment.

3.2.1 RADON TRANSFORM

Initially the binary point is acquired from the input image and produces features by applying radon transform in the range of $\theta = 0^{\circ} - 360^{\circ}$. This Radon Transform denotes the image representation as a collection of projections along different directions. The Radon Transform encompasses a radon function that computes the projections of an image along specified directions of x' axis and y' axis.

$$R_{\theta}(x') = \int_{-\infty}^{\infty} f\,(x'\cos\theta - y'\sin\theta,\ x'\sin\theta + y'\cos\theta)\,dy' \quad (3)$$

A projection in radon transform is computed using the equation (3) at an angle θ. Here $\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$. The radon points are obtained by applying Radon Transform using radon function.

3.2.2 IMAGE RECONSTRUCTION

To reconstruct (compress) the non-binary projections of the image, an efficient transform is used in the proposal called DCT, by which compression is accomplished by exploiting DCT to the projection and encode a fraction of radon points. The compression algorithm is summarized below:

- Apply radon transform on the binary points of input image with the range of $\theta = 0^{\circ} - 360^{\circ}$ to obtain the radon points.
- Compute the DCT to encode the radon points.
- Exploit IDCT (Inverse Discrete Cosine Transform) to decode the radon points.
- Reconstruct the image by deploying Inverse Radon Transform.
- Measure the quality of compressed image by computing MSE and PSNR.

In the encoding process of DCT, the image is broken down into K*K blocks of pixels, where K denotes 2, 4, 6, etc. The DCT computation for a sequence *f(i)* of length K is given in equation (4).

$$D(u) = \alpha(u) \sum_{i=0}^{K-1} f(i) \cos\left[\frac{\pi(2i+1)u}{2K}\right] \quad (4)$$

Where, u is a range from 0 to K-1 and the DCT coefficients is *D (u)*. The inverse DCT (IDCT) is expressed as,

$$f(i) = \sum_{u=0}^{K-1} \alpha(u) D(u) \cos\left[\frac{\pi(2i+1)u}{2K}\right] \quad (5)$$

Where, i=0, 1, …K-1 and $\alpha(u) = \begin{cases} \sqrt{\frac{1}{K}} & when\ u = 0 \\ \sqrt{\frac{2}{K}} & otherwise \end{cases}$.

The DCT coefficients are obtained from each block of input data. Then encode the radon points from the computed DCT coefficients. DCT is having best energy compaction capability for highly correlated images. At the receiver, the projections are decoded by IDCT and the same is used to reconstruct the image. This IDCT is reconstructed by applying inverse radon transform. Then finally reconstructed image is obtained. The computation of PSNR and MSE are carried out using equation (1) and (2) to measure the performance of proposed image compression technique. Moreover, the compression ratio is also measured. The experimental evaluation of the proposed image compression scheme in comparison with existing image compression using DWT with bi-orthogonal filtering is illustrated in next section.

IV.EXPERIMENTAL RESULTS AND DISCUSSIONS

For experimental analysis 10 images were taken from the image database in order to verify the efficiency of proposed image compression method Radon Transform with DCT. The image statistics namely MSE and PSNR are used to analyze the original image (input image) taken for this experimental evaluation exposed in Fig 3.

Fig 3. Original Image

The image compression using DWT with bi-orthogonal filtering reconstructs the image with the MSE and PSNR value of 2.1971 and 44.71dB [viii]. Moreover, it exhibits some drawbacks when it comes to represent straight lines and edges in images. Switch on to our novel image compression scheme, it determine the binary points of original image and then apply Radon Transform that maps the input image into Radon points.

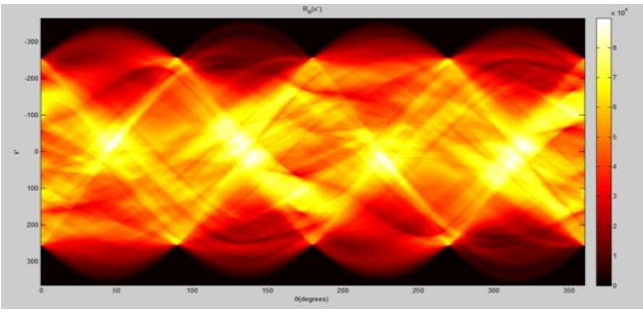

Fig 4. Output from Radon transform theta=0° - 360°

In other words, Radon transform maps a line into a point in the Radon domain i.e. maps the line singularity to point singularity. The radon points that are mapped from the line using the Radon function are shown in Fig 5.

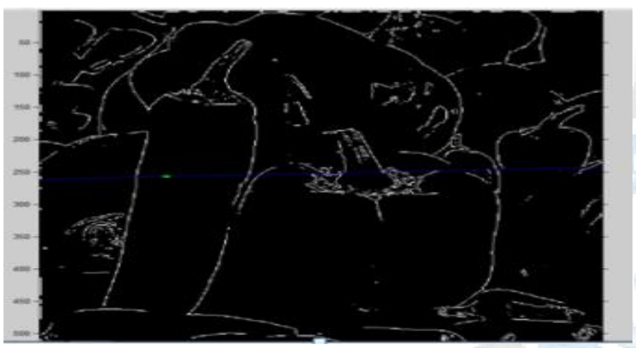

Fig 5. Radon points mapped by Radon Transform

It is clear that Radon Transform maps the line into Radon point and the resultant Radon points are encoded by applying DCT as given in equation (4). At the receiver side, the encoded Radon points are decoded through IDCT described in equation (5).

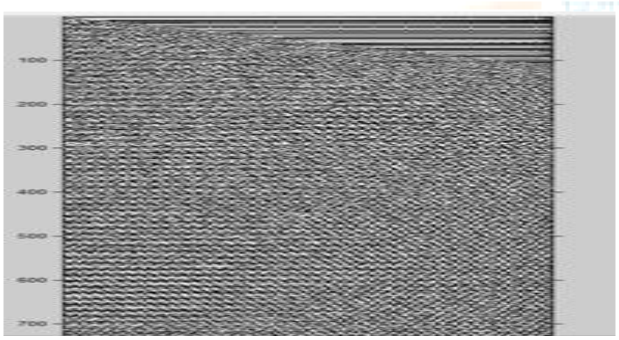

Fig 6. Encoded radon points by DCT

The output of encoded Radon points after applying DCT is shown in Fig 7. Sequentially, decoding is performed by applying Inverse Radon Transform.

Fig 7. Obtained Reconstructed Image

From Fig 7, it is obvious that reconstructed image is obtained by exploiting Inverse radon transform. The MSE and PSNR value are computed between the original image and reconstructed image in order to measure the performance of proposed image compression scheme. The computation is carried out using the equation (1) and (2). The MSE and PSNR value of proposed image compression technique is 1.8056 and 45.5646dB respectively. The comparison of existing image compression scheme [viii] with proposed image compression using Radon Transform with DCT based on PSNR (dB) and MSE is proposed in Fig 8 and 9.

Table 1. Sample MSE and PSNR value for the Biorthogonal filter with DWT and Radon Transform with DCT

Images	(Biorthogonal Filter With DWT)			(Radon Transform With DCT)		
	MSE	PSNR	CR	MSE	PSNR	CR
Baboon	20.35	35.05	25	5.93	40.4	20
Barbara	3.53	42.5	27	3.48	42.71	25
Goldhill	5.38	40.82	29	2.12	44.86	27
Lake	7.14	39.59	12	2.92	43.47	11
Lena	1.73	45.74	57	1.69	45.84	56
Livingroom	5.11	41.04	26	2.73	43.76	25
Peppers	2.20	44.71	33	1.80	45.56	32
Pirate	5.84	40.46	26	2.17	44.77	25
Walkbridge	19.66	35.19	13	3.76	42.37	12
Women_ Blonde	3.16	43.13	26	2.37	44.38	25
Average	7.41	40.82	27.4	2.89	43.812	25.8

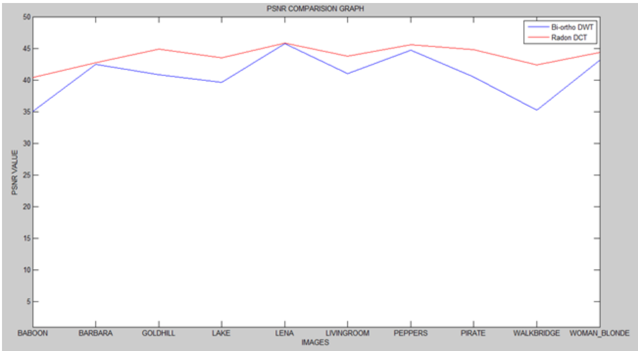

Fig 8. PSNR (dB) comparison of DWT with Bi-Orthogonal filtering and RT with DCT

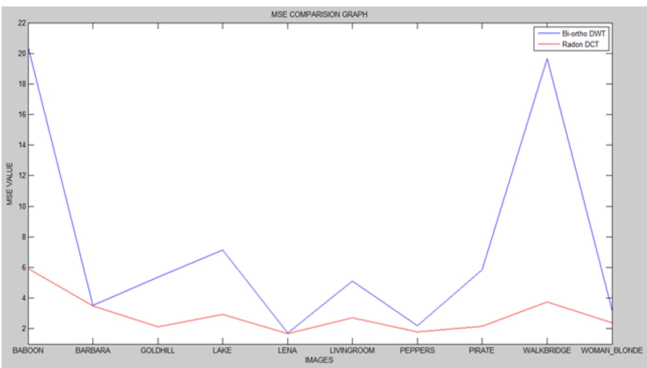

Fig 9. MSE comparison of DWT with Bi-orthogonal filtering and RT with DCT

Moreover, the compression ratio (CR) is measured using the expression below:

$$CR = \frac{\text{size of the image being compressed}}{\text{size of the source image}} \quad (6)$$

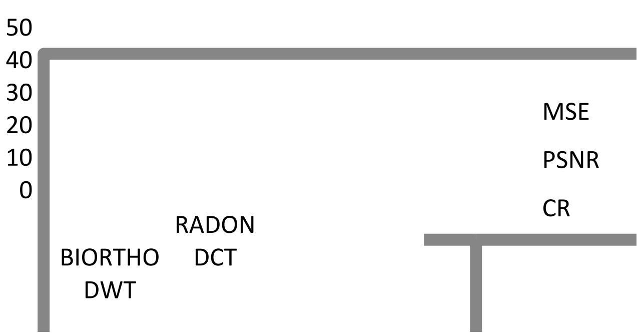

Fig 10. Comparison chart for Biorthogonal filter with DWT and Radon Transform with DCT

Comparison of compression performance in terms of bpp (received bits per reconstructed pixel including the overhead information). For the BIORTHOGONAL FILTER WITH DCT and proposed Seam- RADON TRANSFORM WITH DCT. In existing system MSE average value is 7.14, in proposed system MSE values is just 2.89 only. And also PSNR average value in existing system is 40.82 but this value in proposed system is 43.82. So the compression ratio in existing system is 27.4.But in the new proposed system it is around 25.8.The proposed image compression technique accomplishes the compression ratio of 99.21%, which is 0.83% higher than the existing image compression technique. Greater the compression ratio expose greater Wavelet function. By comparing the performance of these two image compression techniques using performance criteria, it is shown that proposed image compression using Radon Transform with DCT accomplish greater PSNR value than the existing image compression using DWT with Bi-orthogonal filtering. Experimental results reveal that proposed image compression scheme achieves excellent reconstructed image quality than the DWT with Bi-orthogonal.

V.CONCLUSION

A novel technique for image compression, Radon Transform with DCT is proposed as a tool for obtaining Radon points and encoding process. DCT is used to encode the radon points and IDCT is used to decode the Radon points. The reconstructed image is generated through inverse Radon Transform. The comparative analysis of image compression techniques using two Transforms i.e. DWT and Radon Transform are performed. Each technique has its own pros and cons. Based on the perspective of high image quality on reconstructed image, the proposed work outperforms the existing image compression using DWT with Bi-orthogonal filtering. Experimental results expose the performance of proposed image compression technique that accomplishes high PSNR value and compression ratio as compared to the existing image compression technique.

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Bi-Orthogonal Filtering with DWT Algorithm

Input : Bitmap Image
Output : Compressed Image

Step 1: Initialize the given image. In this, estimate the size of the image and resize the given image to required size. Here it is checked whether the given image was single sample or not. If the image was more than one sample, convert into single sample intensity image (Gray scale image).

Step 2: By using orthogonal filtering separate the odd number of pixels and even number of pixels. These filters make the pixels in an image which separates level of the pixel intensities. The levels are LL, LH, HL, and HH.

Step 3: In filter process, it defines only the details of pixels. In DWT, this extracts the features of these ranged pixels. Then the level of that pixels were separated and finally it gives the features for that pixel ranges.

Step 4: It just encodes the features from DWT output. This encoded result was made to transmit.

Step 5: This step was done at receiver stage. Here at the receiver side, it first decodes the received encoded result. Then this is given to inverse DWT stage.

Step 6: In this stage, it performs inverse DWT to the decoded result. This made the conversion of feature values to separated pixel ranges. Then by using orthogonal filter, it rearranges the pixels to form reconstructed image.

Step 7: Finally calculate MSE and PSNR value to find the quality of output image. Here the compression ratio for that image can also be found.

Radon Transform with DCT Algorithm

Input : Bitmap Image

Output : Compressed Image

Step 1: Initialize the image by getting input from user selection and resize the image for required size.

Step 2: Then this image is given to radon transformation method. In this the edges for the given image are detected. Then from this by using radon transformation, the feature points from the image are extracted.

Step 3: In radon transformation, it extract feature points by making a rotation pattern on the image and by using this it extracts the feature points.

Step4: Then these feature points are given to DCT transformation. In this block, it encodes the output from radon transform.

Step5: Then this encoded result is given to image reconstruction stage.

Step 6: In image reconstruction, first provide inverse DCT to the encoded result to decode it into radon feature points.

Step 7: In the next step, inverse radon transform is provided. This extract feature points to the image pixel points for the given degree.

Step 8: Finally calculate MSE and PSNR value to find the quality of output image. Here the compression ratio for that image can also be found.

Fig 2. Radon Transform with DCT Algorithm