Nigerian Research Journal of Engineering and Environmental Sciences 7(1) 2022 pp. 353-362
p ISSN: 2635-3342; e ISSN: 2635-3350

Nigerian Research Journal of Engineering and Environmental Sciences
Journal homepage: www.rjees.com

Original Research Article

A Comparative Analysis of Various Image Compression Techniques

[1]Udo, E.U., *[1]Odo, K.O., [2]Ezeh, C. and [1]Nwogu, M.O.

[1]Department of Electrical and Electronic Engineering, Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria.
[2]Department of Computer Engineering, Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria.
*kayceebby@yahoo.co.uk; thought.umoren@gmail.com; noblenenye@gmail.com

http://doi.org/10.5281/zenodo.6726513

ARTICLE INFORMATION

Article history:
Received 09 Mar, 2022
Revised 22 Apr, 2022
Accepted 22 Apr, 2022
Available online 30 Jun, 2022

Keywords:
Image compression
Set partition in hierarchical tree
Discrete wavelet transform
Embedded zero tree wavelet
Digital image processing

ABSTRACT

Digital images in their uncompressed form require extremely large amount of storage capacity that needs large transmission bandwidth for their transmission over networks. Image compression is one of the important parts of digital image processing because it reduces the data transmission time and data storage space. This paper investigated different image compression techniques used in reducing image size such as embedded zero tree wavelet (EZW), set partition in hierarchical tree (SPIHT) and discrete wavelet transform (DWT) for achieving better image compression in high compression ratio. MATLAB programs were written for each of these methods and the performance was evaluated in terms of peak signal to noise ratio (PSNR), mean square error (MSE) and compression ratio (CR). The results obtained show that the set partition in hierarchical tree with three dimensions (SPIHT_3D) technique produced the highest PSNR value of 43.6dB and the lowest MSE value of 2.838. The embedded zero wavelet tree of level 5 produced the lowest PSNR value of 14.29dB and the highest MSE value of 2423 while the discrete wavelet transform produced a low PSNR value of 26.91dB and a low MSE value of 132.5. In conclusion, the SPIHT_3D technique produced the best image compression with better performance in high compression ratio compared to other existing image compression techniques.

1. INTRODUCTION

Image compression has been the key technology for transmitting massive amount of real-time image data through limited bandwidth channels (Sharma and Kaur, 2013). The data are in the form of graphics, audio, videos and images. These types of data have to be compressed during the transmission process. A digital image is basically an array of various pixel values. In a digital image, pixels that are closely related are correlated so that these pixels contain redundant bits. By using the compression algorithms redundant bits are removed from the image so that image size is reduced and compressed. Image compression has two main components namely, redundancy reduction and irrelevant data reduction (Masmoudi, 2015).

Image compression plays a key role in many applications such as image database, image communication, digital movies, tele-video conferencing, remote sensing, document and medical imaging, fax and in cameras (Kaur and Wasson, 2015). It speeds up the processing and transmission of compressed images due to the reduced size of the image. Today's electronic equipment comes with user friendly interfaces such as keypads and graphical displays. As images convey more information to a user, it is evident that many of the equipment today have image displays and interfaces. Image storage on these smaller devices is a challenge as they occupy huge storage space and image transmission also requires higher bandwidth. Therefore, there is need for efficient image compression techniques to reduce bandwidth and storage space and to perform the compression and decompression at a faster rate without any loss of information (Annadurai and Shanmugalakshmi, 2011).

There are several different ways in which image files can be compressed. For Internet use, the two most common compressed graphic image formats are the JPEG format and the GIF format. The JPEG method is more often used for photographs, while the GIF method is commonly used for line art and other images in which geometric shapes are relatively simple (Martnez, et., al, 2017).

However, the most important concern in the image processing domain is the growing of extremely large amounts of data every day. This issue makes it crucial to explore new image compression techniques. There is need to maintain the quality of an image even after compression. This leads to the need to obtain a model that minimizes image storage space and also keeps almost the quality of the original image (Khobragade, 2014).

The discrete wavelet transform (DWT) is being increasingly used for image coding (Anandan and Sabeenian, 2016). This is because the DWT can decompose the signals into different sub-bands with both time and frequency information. It also supports features like progressive image transmission, compressed image manipulation and region of interest coding. In wavelet transforms, the original signal is divided into frequency resolution and time resolution contents. Embedded zero tree wavelet algorithm is a simple and powerful algorithm having the property that bits in the stream are generated in the order of their importance (Sukanya and Preethi, 2013).

For image compression, it is desirable that the selection of transform should reduce the size of the resultant data set as compared to source data set. EZW is computationally very fast and among the best image compression algorithm known today. This is a technique for image compression which uses the wavelet based image coding (Rehna and Jaya, 2012).

The set partitioning in hierarchical tree (SPIHT) is utilized for lossless image compression. It is one of the most powerful wavelet based image compression. This method can be employed for any type of data independent of the characteristics. The lossy type of image compression is used for images such as that of natural landscapes with comparably lower bit rate. In this compression technique, there are chances of loss of fidelity which is acceptable (Masmoudi et al., 2010).

This aim of this study is to compare and analyze various image compression techniques using MATLAB software to achieve better quality of image compression.

2. MATERIALS AND METHODS

The materials used in this study are wavelet analyzer, HP Laptop, JPEG Image format and MATLAB software. The three techniques of image compression were embedded zero tree wavelet, set partition in hierarchical tree and discrete wavelet transform. MATLAB software was installed to determine the image compression for each of the three techniques. Again, MATLAB server was deployed for compression and the original image were imported to the MATLAB environment. Also, selection of different images for compression was performed and the original image was implemented by adopting the three techniques such as EZW, SPHIT and DWT on jpeg image format to obtain the compressed image back to its reduced size. Analysis was done on the basis of the amount of distortion, which was calculated using important distortion measures such as mean square error MSE, peak signal-to-noise ratio PSNR and compression ratio CR measures were used as performance indicators.

2.1. Implementation of Compression Algorithms

In discrete wavelet transform, discrete analysis ensures space-saving coding and is sufficient for exact reconstruction. It performs discrete wavelet transform at level 5. The following steps were used in compressing and reconstructing of the images:

1. Read the image parameter form image dimension (512×512).
2. Apply 2D discrete wavelet transform (2D-DWT) using various wavelets and decompose the image from 1-level to 5 –level. (By using 2D wavelet decomposition with respect to a DWT, calculate from decomposition level with the estimate coefficients matrix CA and detail coefficient matrixes CH, CV, CD (horizontal, vertical & diagonal respectively) which is obtained by wavelet decomposition of the input matrix).
3. Apply compression process with desired wavelets family and compressed image.
4. Reconstruct an estimate of the original image by applying the corresponding inverse transform process.
5. Calculate compression ratio, mean square error and peak signal noise ratio values for different wavelets used as applied for reconstructed image or original image.
6. The same process is repeated for different resolution of images and compares its parameter and result.

Set partitioning in hierarchical tree (SPIHT) is a wavelet based image compression method. SPIHT introduces three lists namely: list of significant pixels (LSP), list of insignificant pixels (LIP) and list of insignificant sets (LIS).

First initialization is done, and then algorithm takes two stages for each level of threshold namely: the sorting pass (in which lists are organized) and the refinement pass. LIS is further divided into two types of sets of insignificant pixels. They are type A (all descendant are zero) and type B (all grandchildren and further descendants are zero).

SPIHT algorithm defines four types of sets, which are sets of coordinates of coefficients:

O (i,j): set of coordinates of all offspring of node i,j); children only.

D (i,j): set of coordinates of all descendants of node (i,j); children, grandchildren, great-grand. H(i,j): set of all tree roots (nodes in the highest pyramid level); parents

L(i,j): D(i,j) – O(i,j) (all descendants except the offspring); grandchildren, great-grand.

In embedded zero tree wavelet, the coding bits are ordered in accordance with their importance and all lower rate codes are provided at the beginning of the bit stream. By using an embedded code, the encoder can terminate the encoding process at any stage to satisfy the target bit-rate specified by the channel. To achieve this, the encoder can maintain a bit count and truncate the bit-stream whenever the target bit rate is achieved (Priyanka and Priti, 2011).

1. Set the initial threshold T_0= 2($\log_2$cmax). Here cmax is the maximum coefficient value.

2. Set k=0
3. Conduct dominant pass by scanning the data outputs with any of 4 conditions below i.e.
   a. If value of coefficient is greater than the threshold and the value is positive, it means the output significant positive.
   b. If value of coefficient is greater than the threshold and the value is negative, it means the output significant negative.
   c. If magnitude of coefficient is less than the threshold and all its descendants have magnitudes less than the threshold then coefficient is labeled as zero tree roots.
   d. If magnitude of coefficient is less than the threshold and all its descendants have values greater than the threshold then coefficient is labeled as isolated zero
4. Conduct a subordinate pass or refinement pass by scanning through the data to refine the pixels already known to be significant in current bit plane.
5. Set k=k+1 and the threshold Tk=Tk-1/2.
6. Stop if the stopping criterion is met or go to step 3.

2.2. Performance Assessment

In this paper, importance was given to the amount of compression used and how good the compressed image is in comparison to the original image. The key performance indicators used in assessing the performance of the image compression are:

1. Mean square error
2. Peak signal-to-noise ratio measured in decibels (dB)
3. Compression ratio

2.2.1. Mean square error

The most frequently used objective assessment of the quality of a compressed image is mean square error (Chandresh and Kruti, 2013). A lower value of MSE means lesser error. This can be given as shown in Equation (1).

$$MSE = \frac{\sum_{M,N}\left(Image1(m,n) - Image2(m,n)\right)^2}{mxn} \quad (1)$$

Image 1 is original image, Image 2 is the compressed image while m and n are dimensions of the image.

2.2.2. Peak signal-to-noise ratio

PSNR is a measure of the peak error. Many signals have very wide dynamic range and for that reason, PSNR is usually expressed in terms of the logarithmic decibel scale in (dB). Normally, a higher value of PSNR is good which indicates that the ratio of signal to noise is higher. PSNR decreases as the compression ratio increases for an image as shown in Equation (2).

$$PSNR = 20 \times \log_{10}(255^2/MSE) \quad (2)$$

2.2.3. Compression ratio

Compression ratio is a measure of the reduction of the detailed coefficient of the data. The objective of the compression ratio is to measure the capacity of image data compression and can be determined by comparing the size of the original image against compressed image. Compression ratio can be expressed as shown in Equation (3).

$$\text{Compression ratio} = (\text{original image size}) / (\text{compressed image size}) \quad (3)$$

E.U. Udo et al. / Nigerian Research Journal of Engineering and Environmental Sciences
7(1) 2022 pp. 353-362

3. RESULTS AND DISCUSSION

The experimental results make use of the images of one of the researchers to ascertain how the quality, storage size, level, loops were compressed using EZW, SPIHT and DWT. The qualities of the images were evaluated by the PSNR, MSE and CR values computed for each image before compression and after compression. DWT used global thresholding with frequency dependent method such as GBL_MMC_F and GBL_MMC_H.

The results of the image compression using embedded zero wavelet tree (level 5 and 10) are shown in Figures 1 and 2 for easy evaluation. The original size of the image was 815 kilobytes and the image dimension was 512 by 512. Figure 1 shows the result of the image compression using embedded zero wavelet tree method (level 5). It was observed that the values of the mean square error, peak signal-to-noise ratio and the compression ratio were 2423, 14.29 dB and 2.45 respectively. The original size of the image before compression was 815 kb while the final image compression size was 332 kb. The performance of the compressed image using the values of MSE, PSNR and CR indicated a bad compression image with low PSNR and high MSE. This indicates a poor quality of the compressed image with worst recovery. Figure 2 shows the result of the image compression using embedded zero wavelet tree method (level 10). It can be seen that the values of the mean square error (MSE), peak signal-to-noise ratio (PSNR) and the compression ratio (CR) were 191.3, 25.31 dB and 3.37 respectively. The original size of the image before compression was 815 kb while the final image compression size was 242 kb. The performance of the compressed image using the values of MSE, PSNR and CR indicated a good compression image with high PSNR and low MSE. This signifies a good quality of the compressed image with moderate recovery. When the compressed image of embedded zero tree wavelet of level 5 from Figure 1 was compared with the compressed image of embedded zero tree of level 10 from Figure 2, it was observed that the quality of compressed image in level 5 was not as good as the one of level 10. This implies that the quality of signal in level 5 was affected by distortion during compression (Manchanda and Sharma, 2016).

Figure 3 shows the result of the image compression using global thresholding with Huffman encoding method. It is seen that the values of the mean square error, peak signal-to-noise ratio and the compression ratio were 48, 31.32 dB and 2.70 respectively. The original size of the image before compression was 815 kb while the final image compression size was 302 kb. Figure 4 shows the result of the image compression using global thresholding with frequency dependent method. It was observed that the values of the mean square error, peak signal-to-noise ratio and the compression ratio were 132.5, 26.91 dB and 2.61 respectively. The original size of the image before compression was 815 kb while the final image compression size was 312 kb. The performance of compressed image using the values of MSE, PSNR and CR indicated a good compression image with high PSNR and low MSE. This showed a good quality of the compressed image with better recovery.

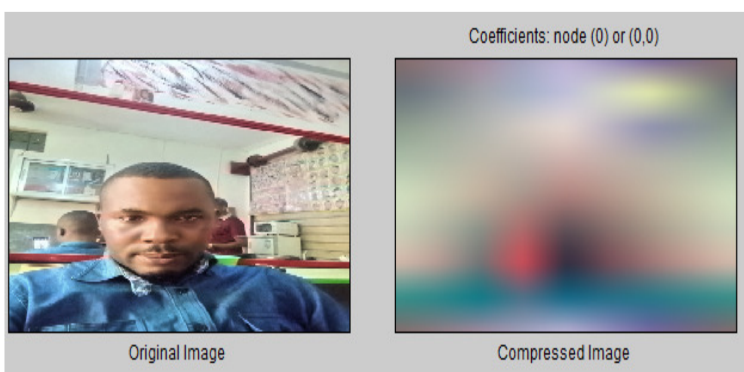

Figure 1: Image compression using embedded zero tree wavelet method

E.U. Udo et al. / Nigerian Research Journal of Engineering and Environmental Sciences
7(1) 2022 pp. 353-362

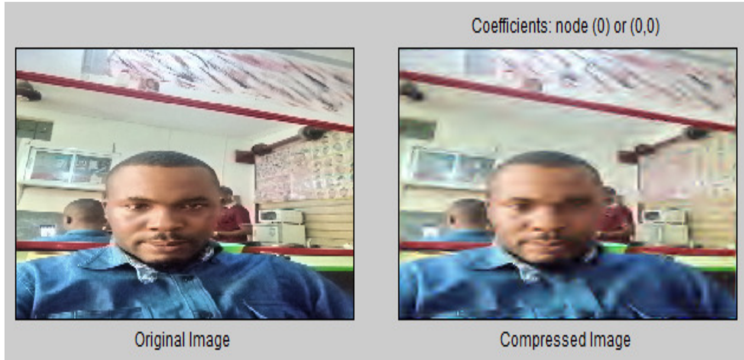

Figure 2: Image compression using embedded zero wavelet tree method

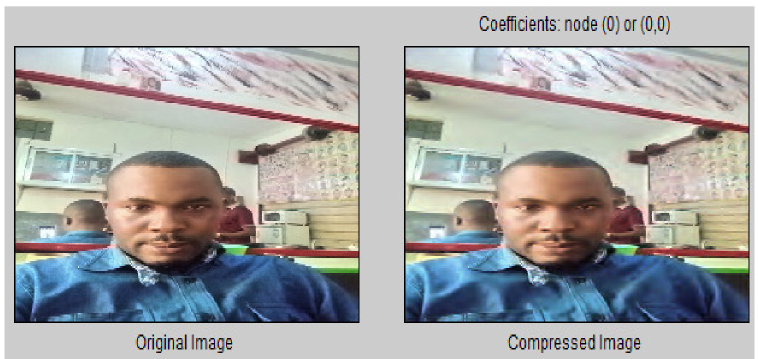

Figure 3: Image compression using global thresholding with Huffman encoding

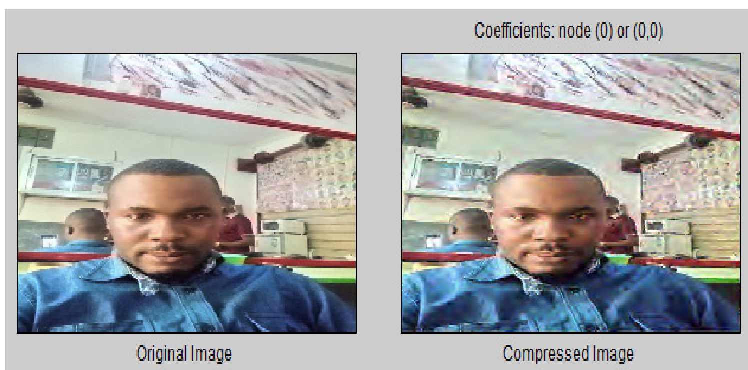

Figure 4: Image compression using global thresholding with frequency dependent method

Figure 5 shows the result of the image compression using global thresholding with level dependent method. It was observed that the values of the mean square error (MSE), peak signal-to-noise ratio (PSNR) and the compression ratio (CR) were 132.5, 26.91 dB and 2.89 respectively. The original size of the image before compression is 815 kb while the final image compression size is 282 kb. The performance of compressed image using the values of MSE, PSNR and CR indicated a good compression algorithm with high PSNR and low MSE. This indicates a good quality of the compressed image with better recovery. Figure 6 shows the result of the image compression using set partition in hierarchical tree, (SPIHT, loop 7) method. It was observed that the values of the mean square error, peak signal-to-noise ratio and the compression ratio were 1269, 17.1 dB and 4.47 respectively. The original size of the image before compression was 815 kb while the final image compression size was 182 kb. The performance of compressed image using the values of

MSE, PSNR and CR indicates a bad compression image with low PSNR and high MSE. This signifies a poor quality of the compressed image with worst recovery.

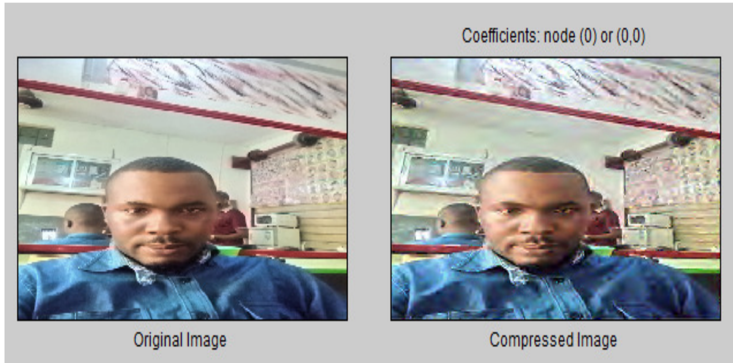

Figure 5: Image compression using global thresholding with level dependent method

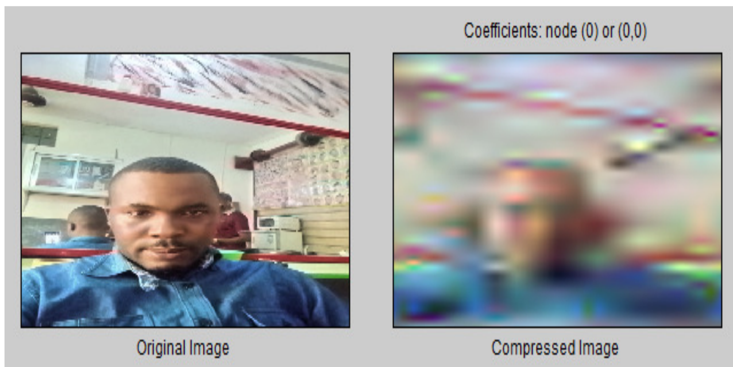

Figure 6: Image compression using set partition in hierarchical tree method

Figure 7 shows the result of the image compression using set partition in hierarchical tree, (SPIHT, loop 13) method. It can be seen that the values of the mean square error (MSE), peak signal-to-noise ratio and the compression ratio were 21.95, 34.72 dB and 3.70 respectively. The original size of the image before compression was 815 kb while the final image compression size was 220 kb. It was observed that the quality of compressed image in Figure 6 was not as good as the one of Figure 7. This indicates that the quality of image in loop 7 was affected by distortion during compression (Singh and Rai, 2015). Figure 8 shows the result of the image compression using set partition in hierarchical tree, (SPIHT_3d, loop 7) method. It is seen that the values of the mean square error, peak signal-to-noise ratio and the compression ratio were 446.2, 21.64 dB and 4.71 respectively. The original size of the image before compression was 815 kb while the final image compression size was 173 kb. Figure 9 shows the result of the image compression using set partition in hierarchical tree, (SPIHT_3d, loop 13) method. It was observed that the values of the mean square error, peak signal-to-noise ratio and the compression ratio were 2.838, 43.6 dB and 3.90 respectively. The original size of the image before compression was 815 kb while the final image compression size was 209 kb. When the compressed image of set partition in hierarchical tree with three dimensions of loop 7 from Figure 8 was compared with the compressed image of set partition in hierarchical tree with three dimensions of loop 13 from Figure 9, it was observed that the quality of the compressed image in Figure 8 was not as good as the one of Figure 9. This indicates that the quality of the image in loop 7 was affected by distortion during compression (Shahriyar et al., 2016).

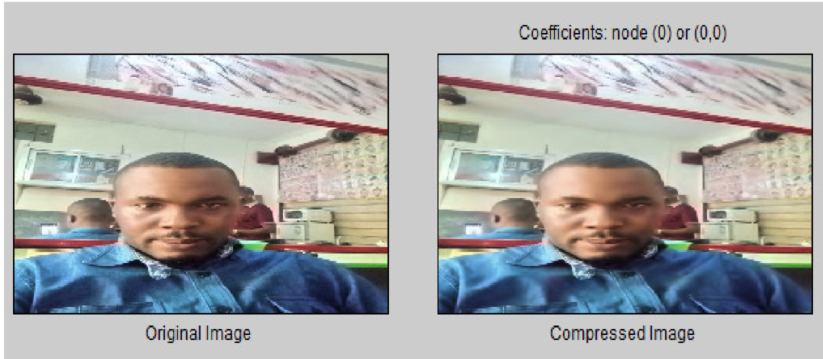

Figure 7: Image compression using set partition in hierarchical tree method

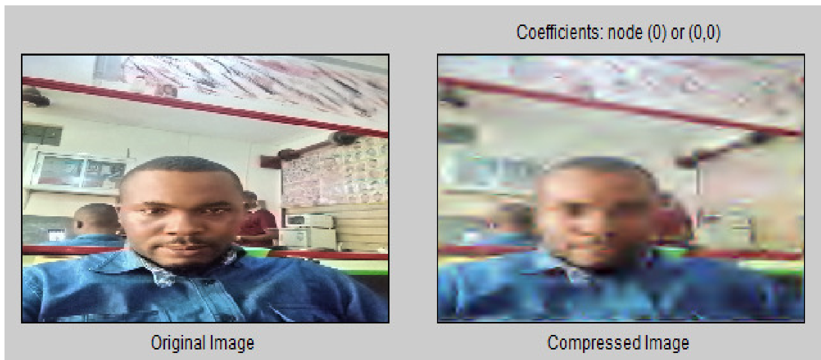

Figure 8: Image compression using set partition in hierarchical tree method in three dimensions

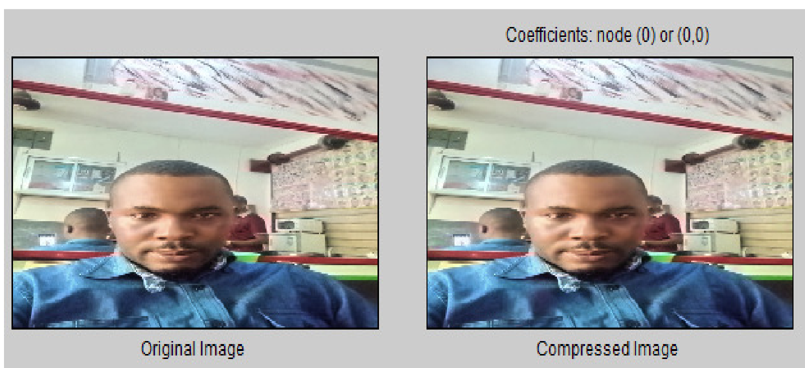

Figure 9: Image compression using set partition in hierarchical tree method in three dimensions

Figure 10 shows the compression ratio for different image compression techniques. It was observed from the plot that SPIHT_3D (loop 13) had the highest CR value of 4.71 and was closely followed by SPIHT (loop 13) with the CR value of 4.47 while EZW (level 5) had the least CR value of 2.45. The implication of these results is that compression image with low CR provides a poor quality of the compressed image while other compression image with high CR indicates a good quality of the compressed image. Figure 11 shows the plot of mean square error for different image compression techniques. It was observed that EZW (level 5) recorded the highest MSE value of 2423, which was closely followed by SPIHT (loop 7) with an MSE value of 1269. EZW (level 10) had an MSE value of 191.3, while SPIHT_3D (loop 13) had the least MSE value of 2.838, which indicated a better picture quality. Figure 12 shows the plot of peak signal to noise ratio for different image compression techniques. It was observed that SPIHT_3D (loop 13) had the highest PSNR value of 43.6dB which was closely followed by SPIHT (loop13) with a PSNR value of 34.9dB while EZW (level 5) had the least PSNR value of 14.29 dB. The implication of these results indicates that compression image with high PSNR provides a good quality of the compressed image while other compression image with low PSNR indicates a bad quality of the compressed image.

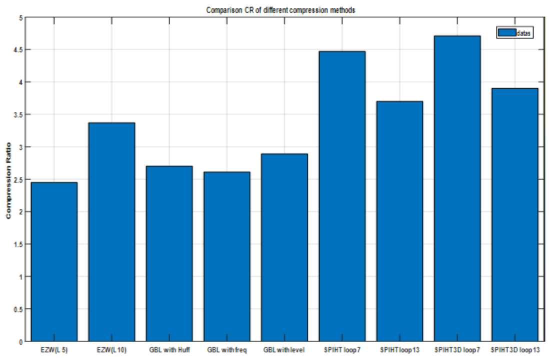

Figure 10: Plot of compression ratio for different image compression techniques

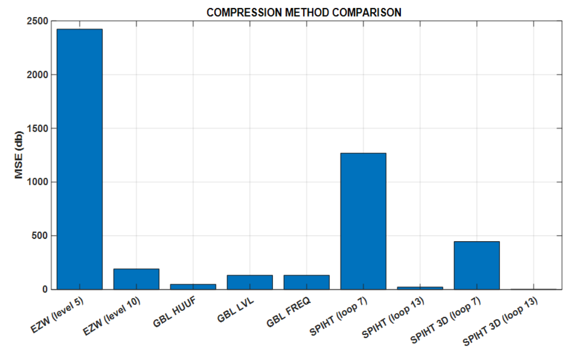

Figure 11: Plot of mean square error for different image compression techniques

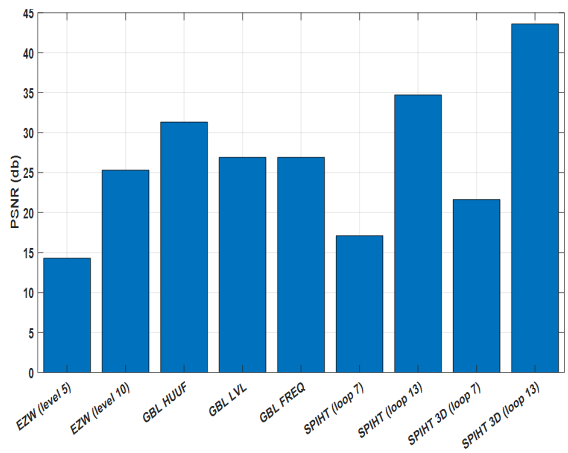

Figure 12: Plot of peak signal to noise ratio of different image compression techniques

4. CONCLUSION

Image compression is an important technique in digital image processing. For good compression and better quality, image compression must be received with no loss or minimal loss of data and the compressed image must have high PSNR value, low CR and low MSE. In this paper, set partition in hierarchical tree with three dimensions (SPHIT_3D) technique produced the best image compression with the highest value of peak signal to noise ratio of 43.6dB and the lowest value of mean square error of 2.838. However, the embedded zero wavelet tree, level 5 produced the lowest PSNR value of 14.29 dB and the highest MSE value of 2423. Again, set partition in hierarchical tree (SPHIT, loop 13) and global thresholding with Huffman encoding techniques showed better results in terms of PSNR and MSE as compared to other existing image compression techniques. Also, it was observed that the set partition in hierarchical tree with three dimensions (SPHIT_3D) technique is more efficient than the other image compression techniques which have the least value of MSE, highest value of PSNR, better image quality and best recovery compared to other existing image compression techniques. The image compression using SPHIT_3D technique did not only achieve high compression ratio but also kept high resolution in salient regions and the quality of compressed image decreases as compression ratio increases.

5. ACKNOWLEDGMENT

The authors wish to acknowledge the assistance and contributions of the laboratory staff of Department of Electrical/Electronic Engineering and Department of Computer Engineering, Michael Okpara University of Agriculture, Umudike toward the success of this work.

6. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

REFERENCES

Anandan, P. and Sabeenian, R. (2016). Medical image compression using wrapping based fast discrete curvelet transform and arithmetic coding. *Circuits and Systems,* 7(08), pp. 20-59.

Annadurai, S. and Shanmugalakshmi, R. (2011). Fundamental of digital image processing. Pearson education.

Chandresh K. P. and Kruti P. (2013). A Review on Image Compression Techniques. *Journal of Information, Knowledge and Research in Electrical Engineering,* 2(2), pp. 281-284.

Kaur M.and Wasson V. (2015). Region of Interest (ROI) based Medical image compression for Telemedicine Application proceedings of the 4th international conference on Eco-friendly computing and communication systems, Procedia Computer Science, 70, pp. 579-585.

Khobragade P. B. (2014). Image Compression Techniques - A Review. *International Journal of Computer Science and Information Technologies,* Vol. 5(1), pp. 272-275.

Manchanda, M. and Sharma, R. (2016). A novel method of multi modal medical image fusion using fuzzy transform. *Journal of Visual Communication and Image Representation,* 40, pp. 197–217.

Martnez, L.A., Bribiesca, E. and Guzman, A. (2017): Chain coding representation of voxel-based objects with enclosing, edging and intersecting trees. *Pattern Analysis and Applications,* 20(3), pp. 825-844.

Masmoudi, A., Puech,W and Bouhlel, M.S. (2010). Efficient adaptive arithmetic coding based on probability distribution for lossless image compression. *Journal of Electronic Imaging,* 19(2), pp. 023014-1-023014.

Masmoudi, A. (2015): A new arithmetic coding model for a block-based lossless image compression based on exploiting inter-block correlation. *Signal, Image and Video Processing*, 9(5), pp. 1021-1027.

Mayank N., Lalita G. and Trivedi N. R. (2012), Video Compression using SPIHT and DWT Wavelet. *International Journal of Electronics and Communication Engineering,* 5(1), pp. 1-8.

Priyanka S. and Priti S. (2011). Design and Implementation of EZW and SPIHT Image Coder for Virtual Images. *International Journal of Computer Science and Security*, 5(5), pp. 433-442.

Rehna V. J, and Jeya K. M. K. (2012). Wavelet Based Image Coding Scheme. *International Journal of Computer Science and Communication,* 3(3), pp. 101-118.

Shahriyar, S., Murshed, M., Ali, M. and Paul, M. (2016). Lossless depth map coding using binary tree based decomposition and context-based arithmetic coding. In: Multi-media and Expo (ICME), 2016 IEEE International Conference on Multi-media and Expo (ICME), pp. 1-6.

Sharma S. and Kaur S. (2013) Image compression usig hybrid of DWT, DCT and Huffman Coding. *International journal for science and Emerging Technologies,* 5(1), pp. 19-23.

Singh, P K. and Rai, K. N. (2015). Comparative Study between DCT and Wavelet Transform based Image Compression Algorithm. *Journal of Computer Engineering,* 17(1), pp. 53-57.

Sukanya, Y and Preethi, J. (2013). Analysis of image compression algorithms using wavelet transform with GUI in Matlab. *International Journal of Research in Engineering and Technology,* 2(10), pp. 595–603.