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Efficient Retinal Image Compression Based on Modified Huffman Algorithm

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Abstract:

Medical image diagnosis acts an important role recently to protect the life and cure illnesses and therefore practice of medical images is radically improved. Developing technological developments to meet up the memory needs of everyday life looks not to satisfy the necessity of storage as data storage is proportionally improving. Image compression is the crucial solution to satisfy the storage necessities. The prior work presented a numerous compression methods dependent upon Region of Interest (ROI). In this work, an efficient retinal image compression method based on modified Huffman method is presented. The proposed method is designed for improving the storage efficiency and high security. First, the Pre-processing is performed by using Adaptive median filter. To separate out ROI from the preprocessed image, segmentation is performed using Improved Adaptive Fuzzy C-means Clustering. The separated ROI/non-ROI regions are compressed by using Integer Multi Wavelet Transform and Set Partitioning in Hierarchical Trees algorithms respectively. Further, threshold improved zero tree wavelet algorithm is applied on the whole image, and then modified Huffman encoding is performed to obtain compressed image for transmission. The proposed method is tested using a Local database which is collected from local hospitals. The proposed method is a suitable medical image compression with the expected image quality based on the experiments. It's found that the proposed method yields slightly better CR, PSNR and MSE values compared to existing methods.

Keywords: *Region of Interest, Retinal image, lossless compression and Modified Huffman coding*.

1. INTRODUCTION

Identification and analysis of diseases by means of medical images and their storage identifies much significant place on the other hand utilizes more band-width [1]. In case of telemedicine applications, these medical images should be transferred to diverse targets. Medical images for instance, Magnetic Resonance Imaging, Computed Tomography, Electrocardiogram, Ultrasound and Positron Emission Tomography need to be stored and forwarded for verifying by alternative medical expert if needed [2]. These massive volumes of data root to a huge volume of memory utilization and rise the time and traffic all through the transmission. Therefore, medical image compression is needed with the purpose of decreasing the storage and bandwidth needs [3].

There exist two prominent image compression techniques, namely, lossless and lossy compression algorithms [4]. According to lossless compression techniques, the recreated image is appropriate imitation of the real image, while in lossy image compression; the rebuilt image comprises deprivation proportionate to the original. Numerous progressive image compression techniques were presented in regard to the rising demands for medical images.

A wavelet-based compression method presented by Adrian Munteanu [5] is capable of working in the lossless mode. A manner of coding of the wavelet coefficients is developed by the quantization module which is efficient compared to the standard zero-tree coding. A Segmentation-based Multilayer (SML) coding technique was introduced by Xin Bai [6] for lossless medical image compression. A completely automated unseeded region growing segmentation method is utilized for processing diagnostically significant areas, that is to say the Regions of Interest. This presented SML compression technique could offer effective compression for numerous medical imaging data and provide possible benefits in semantic progressive transmission in telemedicine and content-based medical image retrieval.

2. LITERATURE REVIEW

Digital Pulse Code Modulation (DPCM) is one of the most widely used predictive coding techniques, which has been designed by Bhardwaj [7]. In DPCM, pixel correlation is removed and the unnecessary pixel values for storage or transmission is re-quantized. The variance of the redundant image is much smaller compared to the variance of the original image. Regardless of how the de-correlated pixel values are interrelated, the quantizer is fixed. The weakness point of the DPCM is limitation of the quantizer bit width of the redundant image, and hence in the DPCM, edges are not conserved well. Furthermore, when channel error occurs, reveals infrequent streaks across the image. Context Adaptive Lossless Image Compression (CALIC) was proposed by Wu et al [8]. The key step of that method is its utilization of a huge amount of modeling contexts to adapt the predictor to varying source statistics and state a nonlinear predictor. Via an error feedback mechanism, the nonlinear predictor can correct itself by learning from its mistakes under a specified context. The CALIC approximates only the expectation of prediction errors stated on a huge number of different contexts through the learning process rather than approximating a huge number of statistical error probabilities. CALIC is attributed by its low time and space complexities that made it efficient in terms of quantizing and forming modeling contexts. A novel lossless image compression scheme was designed by Weinberger et al [9]. Based on CALIC, a much simpler predictive encoding method JPEG-LS was developed. JPEG-LS is also known as LOCO-I (Low Complexity Compression for Image). Although the LOCO-I compression is slightly lower than CALIC, it has much lower complexity compared to CALIC.

Kauret et al. [10] proposed a simple but efficient image compression method which is based on Run Length Encoding (RLE). They proposed a lossless data compression method, where it stores the runs of data as a single data value and count, instead of the original run. However, this technique seems to be useless when we try to compress natural language texts, since no long runs of repeating elements are available. But, when it comes to image compression, RLE is useful as images contain long runs pixels with identical color. Remya and Rasheed [11] designed a Resolution Progressive Compression (RPC) of encrypted images. RPC is an efficient method for encrypted grayscale image compression, which is mainly inspired by the Discrete Wavelet Transform (DWT). In RPC, the encoder creates a sampled version of the cipher text, performs an intra-frame prediction, and then sends it to the decoder. Then decode and decrypt the low resolution image to obtain a high resolution one. That predicted image along with the encryption key are called Side Information (SI), which is taken as an input for the next level of resolution. Thus, it is possible to reduce the complexity of coding/decoding in RPC to obtain best results for grayscale and color images. An efficient image technique known as Encryption-Then-Compression (ETC) was developed by Zhou et.al [12]. It is mainly based on the random permutation and prediction error clustering. From the viewpoint of the ETC technique, the security and easiness of compressing the encrypted data should be considered simultaneously by the design of the encryption algorithm. Via the random permutation and prediction error clustering, the image encryption is achieved within the designed framework.

3. PROPOSED METHODOLOGY

In this proposed work, set out to find an appropriate compression technique for retinal images. The steps involved in the compression process are depicted in Figures 1.

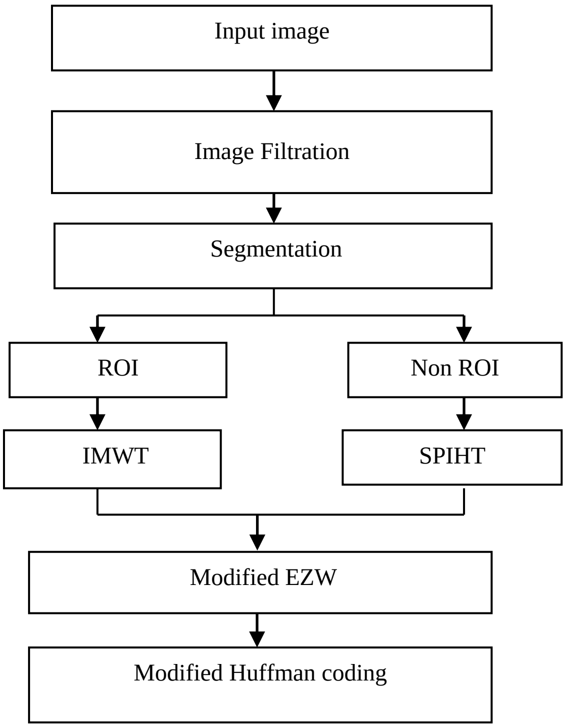

Figure 1: Overall flow of the proposed work

3.1 Image Filtration

Image filtration must be carried out as the primary step with the intention of creating the image noise free. This process is essential to enhance the image quality and produce more consistent images for additional processing. It is also an essential step when the image is acquired in noisy, unreliable or imperfect way. Therefore, image filtration will considerably increase the efficiency of compression.

Adaptive median filter: It is a linear filtering tool, which carries out spatial processing to find out which pixels are disturbed by impulse noise. The adaptive median filter does tackle the noises compared to Median filter since it modifies size of the neighborhood for the period of operation.

Consider, xi, j that situates at (i, j) is the color intensity of a M ×N image X and min max [L, L] is known as the dynamic range of X, that is to say mini, j max L ≤ x ≤ L for all that (i, j) that affords to the subsequent rule. In the traditional impulse noise model, the proposed method presumes Y is taken as the noisy image, the model is specified by,

$$(i, j) \in A=\{1,\ldots,M\}\times=\{1,\ldots, NN\}$$

Presuming the filtering window Wi,j is known as a window of size (2N+1)×(2N+1) placed at point at (i, j), Wi,j could be related in this manner:

Consider, w=2N+1 ≤Wmax. The algorithm attempts for enhancing the outcome image yi,j by the median in the window.

W_(i,j)={x_(i-N,i-N),…,x_(i,j),…x_(i+N,j+N))

Algorithm 1: Adaptive Median Filter

Step 1: Initialize: w =3.

Step2: Calculate the highest, lowest and median value in window; they could be elucidated as W_(i,j)^maxx, W_(i,j)^min, W_(i,j)^medcorrespondingly.

Step3: When W_(i,j)^min<W_(i,j)^med<W_(i,j)^max , at that point go to step 5. else, set N=N+1.

Step4: When w ≤ Wmax, reach step 2. else, replace yi,j by W_(i,j)^med while the window size Wmax

Step5: When W_(i,j)^min<yi,j<W_(i,j)^max, at that point yi,j is noise free, otherwise the system substitute yi,j by W_(i,j)^med

The adaptive median filter could guarantee numerous noisy pixels could be identified and the noisy-free pixels remain unaltered.

3.2 ROI/Non ROI Segmentation

With the purpose of separating ROI from the analysis image, segmentation is carried out using improved adaptive fuzzy c-means clustering (IAFCM), which acts as a leading role in image analysis. IAFCM objective function regulates the gain field and evades resolving huge differential equation and provides quicker computational speed through diverse regulation term. IAFCM with a novel objective function provides improved background reimbursement and brings about enhanced segmentation. Consequently, segmentation could be utilized in medical diagnosis.

Clustering is a method for separating sets of objects. Fuzzy C-means clustering considers every object as a containing place in space. It needs that delay down the amount of clusters for the separation and a distance metric for computing how two objects are close to one another. In the proposed IAFCM, the objective function is described in Eq.1 [13]:

$$J_{IAFCM} = \sum_{i\in D}\sum_{k=1}^{NC} u_{ik}^{q}\left\|y_i - g_i c_k\right\|^2 + \lambda\sum_{i\in D}(g_i - (H*g)_i)^2 \quad (1)$$

The resolution of the above equation provides the ideal values of (u_{ik}, c_k, g_i), that bring about the algorithm defined as IAFCM. u_{ik} represents the membership function with within the range from 0 to 1, c_k represents the centers of the cluster, y_i represents the observable intensity at a certain location i, NC represents the number of clusters, D represents the entire area of the image, and q represents a weighting exponent on each fuzzy membership whereby the amount of fuzziness is decided. Using Eqns. (2-5), the optimum value of (u_{ik}, g_i, c_k) are calculated, as follows:

$$u_{ik} = \frac{||y_i - g_i c_k||^{-2/q-1}}{\sum_{i=1}^{NC}||y_i - g_i c_k||^{\frac{-2}{q-1}}} \quad (2)$$

$$c_k = \frac{\sum_{i\in D} u_{ik}^{q} G_i y_i}{\sum_{i\in D} u_{ik}^{q} G_i^2} \quad (3)$$

$$g_i = (H*g)\ \text{i}\in \text{D} \quad (4)$$

$$g_i = \frac{\sum_{k=1}^{NC} u_{ik}^{q} <y_i, C_k>}{\sum_{k=1}^{NC} u_{ik}^{q} <C_k, C_k>} \quad (5)$$

Algorithm 2: IAFCM

Step 1: Initialize g_i with 1 (i = 1… N); cluster centers c_k (k = 1… NC); and randomly selected values within the image intensity.

Step 2: Update the membership function u_{ik} by using Eq. (2).

Step 3: Update the cluster centers C_k by using Eq. (3).

Step 4: Calculate the gain field g_i by using Eq. (5).

Step 5: Update the gain field g_i by using Eq. (4).

Step 6: If the maximum change of u_{ik} < tolerance U and the maximum change of g_i < tolerance G, break.

Step 7: Otherwise, move to step 2

By means of the above stated equation the segmentation of retinal images is carried out. The recommended method initially split the image into sub areas in keeping with the dispersal of numerous textural descriptors that be owned by two major groups. Primarily, coherence analysis based measures and then, co-occurrence matrices based facets are matched up in this phase of the presented method. Every sub region is at that point categorized as texturally significant or insignificant using unsupervised fuzzy logic methods. The textural facets for the sliding window size of M=8 for a 256 x 256 images are taken by computing statistical metrics and co-occurrence matrices, such as entropy, correlation, inverse difference moment, energy-angular moment, are computed and coherence analysis is carried out. Based on the measures substantial as well as unimportant areas are identified by fuzzy logic unsupervised methods.

Subsequent to the identification of co-occurrence matrices, next technique is the coherence analysis of the real image for originating textural aspects. The coherence measures undertake less-values in areas of the textures with identical pixels. And the difference is greater in these points, which are amongst the areas with dissimilar textural structure. The clustering is carried out with the aim of grouping the pixels of identical textures. Texturally important as well as unimportant patterns are combined into tagging of binary logic levels that is to say “1” and “0”. Briefly, initially texture characteristics are changed into fuzzy set. Then identify suitable fuzzy membership functions and set the values equivalent.

3.3 Lossless Compression Technique

The Integer Multi Wavelet Transform (IMWT) [14] is utilized to contain lossless processing. The IMWT is presented for an integer implementation of a multi wavelet method, dependent upon an easy multi–scalar function. Multi wavelet transform is developed by multi filter with vector series as its input and output. The wavelet transform, creates the coefficients, which are floating point values. Although the coefficients could be utilized to rebuild a real image exactly based on the principles, the usage of finite precision arithmetic and quantization outcomes is a lossy scheme. The main benefits of IMWT are its higher order of guesstimate, higher energy compaction capability, and quicker calculation.

3.4 Lossy Compression

In 1996, Amir Said and William Pearlman [15] presented Set Partitioning in Hierarchical Trees (SPIHT) algorithm, which is an expansion of the Embedded Zero Tree Algorithm (EZW). It is well-known to yield meaningfully inspiring outcomes in image compression when matched up with other methods. The SPIHT algorithm provides meaningfully enhanced quality compared to other image compression methods for instance vector quantization, JPEG and wavelets united with quantization.

The SPIHT Algorithm performs in two stages: Primarily, compute the wavelet transform of the input image and after that the wavelet coefficients are transferred to the SPIHT coding engine. Subsequent to the discrete wavelet transform is computed, SPIHT splits the wavelets in to spatial orientation trees, and every node in that tree relates to a separate pixel. Every pixel in the transferred image is coded based on its importance by matching up with a threshold value at every level. When the value of a pixel or any of its offspring is underneath the threshold, the method could state that each and every descendant are unimportant at that level and it is not required to be need passed. The threshold is divided by two subsequent to every pass, and the algorithm goes on further. In the wavelet coefficients, the info on the most significant bits would go before info on bits with lower-order of significance that are denoted as bit-plane ordering [13].

3.5 Modified EZW

According to the Embedded Zero trees of Wavelet transforms (EZW) [16], a "zero tree" contains a parent and its descendants are unimportant, the predecessor is coded as zero trees. EZW algorithm can be enhanced by fusing some alteration in the standard calculation. To start with consider the estimation of threshold values. Based on the input image wavelet coefficients, the initial threshold value has been computed. By ensuing the over whelming passes, in the decomposition process the threshold value has been factorized by 2 and not considering the rest of the coefficients.

When the coefficient value is lesser compared to the threshold value and contains one or more important offspring regarding j^{th} level, at that point, it is coded as "isolated zero". The substantial coefficients of the last sub-bands that don't agree offspring and themselves are not offspring of a zero tree are taken to be zero trees as well. The important symbols of the image coefficients are positioned in the predominant list. The scales of the important coefficients are situated in the subsidiary list. Their values in the converted image are get on with it zero with the aim of not going through the succeeding step. Lastly, modified Huffman coding is used to the above coefficients.

3.6 Modified Huffman Coding

The fundamental idea of the presented modified Huffman algorithm is its adaptation to the altering correlation in the image by sensibly building the binary tree. A tree with leaves is used by the algorithm, which represents sets of symbols with the same frequency, instead of individual symbols [17-18]. Therefore, the code for each symbol is created of a prefix that specifies the set or the leaf of the tree and a suffix that specify the symbol within the set of same-frequency symbols. This enhances the performance in two ways; first one by decreasing the number of levels in the tree, and the second one by bringing the maximum possible elements to the top of the tree.

As in Adaptive Huffman algorithm, with the incoming elements, the binary tree is constructed and the codes are framed by traversing the tree. The weights at every level are checked at every update and updated accordingly, and the higher weights will occupy the initial stages of the tree. At each step, the method computes the two leaves of lowest probability and those leaves are clubbed together to form a node. In a bottom up approach, the tree is constructed over N-1 steps, where N represents the number of symbols. A 0 is assigned to each left going path, and a 1 is assigned to each right going path. Then, using a top down approach, move down the tree in and build up the code for that symbol in order to construct the code corresponding to a given symbol. With the shortest codes, Huffman codes are assigned to the characters with the greatest frequency.

In this work, a Huffman coder would undergo the source image region, every input image is transformed into a suitable binary Huffman code, and the resultant bits to the output file are disposed. Subsequent to the compression, the compressed image is transferred over TCP at bit-rate 587 kb/s.

4. EXPERIMENTAL RESULTS

The proposed method was tested over a Local retinal image database. The database contains 570 images collected from the University Malaya Medical Centre (UMMC). The images are captured using 24-bits per pixel at 615×820 pixels using a Top-Con TRC-NW7SF Mydriatic/Non-Mydriatic Dual type retinal camera and stored in TIFF format. 225 images were captured at 45˚ FOV and the remaining 345 images were captured at 50˚ FOV. The performance evaluation of the proposed method was based on three criteria, which are Compression Ratio (CR), Peak Signal to Noise Ratio (PSNR), and Mean Squared Error (MSE).

4.1.1 Compression Ratio

Compression Ratio (CR) is used to find the ratio between the original image and the corresponding compressed one. Mathematically it is denoted as CR and it is calculated using the formula:

$$CR = \frac{\text{Size of Compressed Image}}{\text{Size of Original Image}} \tag{6}$$

Figure 2 shows randomly selected images obtained from the Local database. The size of image 1, image 2 and image 3 is 200KB. After compression, the image1, image 2 and image 3 sizes became 150.7500 KB, 168.0000 KB and 156.0000 KB respectively.

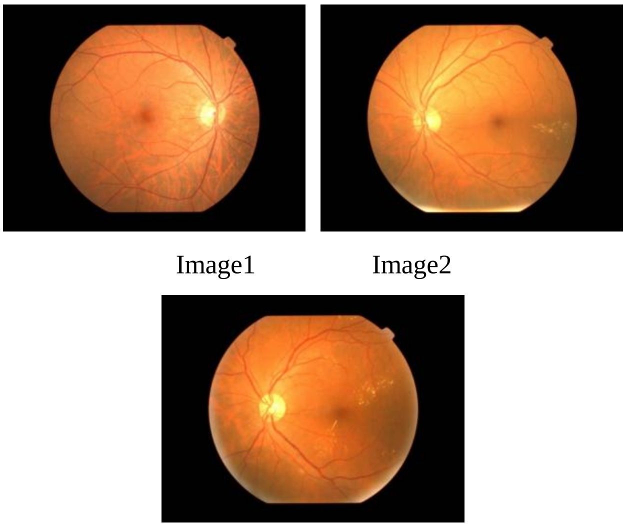

Figure 2: Sample images from the Local database

The comparison chart of compression ratio performance for presented DPCM, JPEG LS, RLE, CALIC, RPC, ETC and modified Huffman coding based image compression method is shown in Fig. 3. In x-axis, Local database is considered and in y-axis, compression ratio is considered. The proposed method achieves high compression compared to other existing methods.

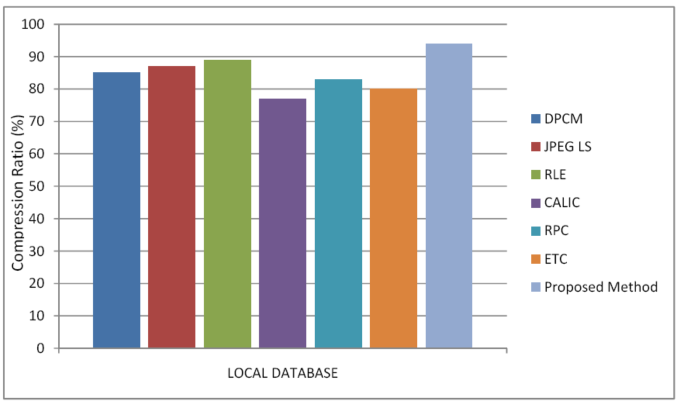

Figure 3: Performance evaluation with Compression Ratio metric

4.1.2 Peak Signal To Noise Ratio (PSNR)

It is generally utilized as a degree of quality of rebuilding of image. A greater PSNR will generally point to that the rebuilding is of greater quality.

$$\left\lfloor PSNR = 20 * \log 10\left(\frac{255}{\sqrt{MSE}}\right)\right\rfloor \tag{7}$$

The comparison chart of PSNR performance for presented DPCM, JPEG LS, RLE, CALIC, RPC, ETC and modified Huffman coding based image compression approach is shown in Fig. 4. In x-axis, the Local database is considered and in y-axis, PSNR is considered. The proposed modified Huffman coding methods provides superior outcome compared to the existing methods that is showed in the experimentation outcome.

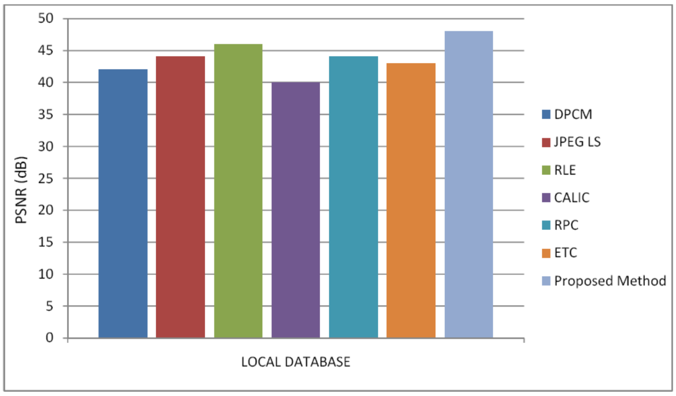

Figure 4: Performance evaluation with PSNR metric

4.1.3 Mean Squared Error (MSE)

Mean Squared Error (MSE) is also known as "the cumulative squared error between the compressed and the original image". The MSE value is calculated by using Eq. (8), as follows:

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2 \tag{8}$$

where $I(x,y)$ is known as the real image, $I'(x,y)$ is called the estimated version (that is the decompressed image) and M and N are known as the magnitudes of the images. A lesser value for MSE signifies less error, and as considered from the inverse relation amid the MSE and PSNR, this turns to a greater value of PSNR. The evaluation chart of MSE performance for presented DPCM, JPEG LS, RLE, CALIC, RPC, ETC and modified Huffman coding based image compression method is shown in Fig. 5. In x-axis, the Local database is considered and in y-axis, MSE is considered. The proposed modified Huffman coding provides enhanced result compared to existing methods that is showed in the experiment outcome.

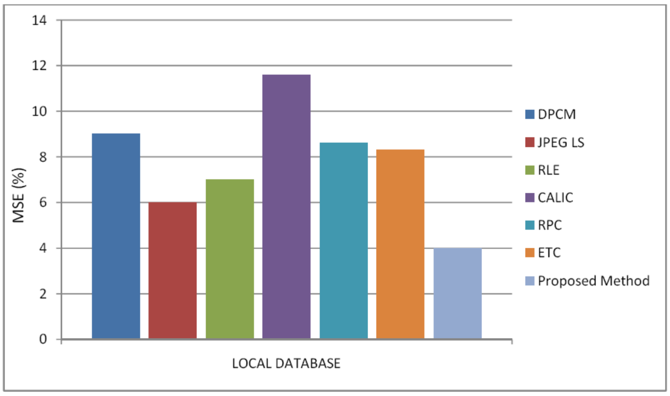

Figure 5: Performance evaluation with MSE metric

5. CONCLUSION

In this paper, an efficient retinal image compression method based on modified Huffman method has been presented. The proposed method is designed for improving the storage efficiency and high security. Color retinal image is taken as an input. To get rid of the expected presence of noise, preprocessing is accomplished by utilizing adaptive median filter. Then, Improved Adaptive Fuzzy C-means Clustering (IAFCM) based segmentation is performed to separate out ROI from the preprocessed image. The separated ROI/non-ROI regions are compressed by using Integer Multi Wavelet Transform (IMWT) and Set Partitioning in Hierarchical Trees (SPIHT) algorithms respectively. Further, threshold improved zero tree wavelet algorithm is applied on the whole image, then, modified Huffman encoding is performed to obtain a compressed image for transmission. The proposed method has been tested over a Local database collected from local hospitals. Three criteria, namely Compression Ratio, Peak Signal to Noise Ratio, and Mean Squared Error have been used to measure the performance of the proposed method. The experiments show that the proposed method yields slightly better than other existing methods in terms of CR, PSNR and MSE values.

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REFERENCES

[1] Deever, A. T., Hemami, S. S., "*Lossless image compression with projection-based and adaptive reversible integer wavelet transforms*", *IEEE Transactions on Image Processing*, Vol. 12, pp. 489-499, 2003.

[2] Xiong, Z., Wu, X., Cheng, S., Hua, J., "*Lossy to Lossless Compression of Medical Volumetric Data using 3d Integer Wavelet Transforms*", *IEEE Transactions on Medical Imaging*, Vol.22, pp.459–470, 2003.

[3] Sriraam, N., Shyamsunder, R., "3-D *Medical Image Compression using 3- D Wavelet Coders*", *Digital Image Processing*, Vol. 21, pp.100-109, 2011.

[4] Salih , N. D., Eswaran, C., "*Lossy and Lossless Image Compression Schemes - An Experimental Study*", *International Journal of Pure and Applied Mathematics*, Vol. 117, No. 21, pp. 467-487, 2017.

[5] Munteanu, A., Cornelis, J., Cristea, P., "*Lossless Compression of Medical Image By Hierarchical Sorting*", *IEEE Transactions on Medical Imaging*, Vol. 18, No. 3, March 1999.

[6] Bai, X., Jin, J. S., Feng, D., "*Segmentation-Based Multilayer Diagnosis Lossless Medical Image Compression*", In: *Proceeding of Conferences in Research and Practice in Information Technology*, Vol. 36, pp. 9-14, 2004

[7] Bhardwaj, T. K., "*Generalized Digital Pulse Code Modulation and its comparison with other compression schemes*", *International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)*, Vol. 3, No. 3, pp. 25-29, 2014.

[8] Wu, X., Memon, N., "*Context-Based, Adaptive Lossless Image Coding*,", *IEEE Transactions on Communications*, Vol. 45, No. 4, pp. 437–444, Apr. 1997.

[9] Weinberger, M. J., Seroussi, G., Sapiro, G., " *The LOCO-I Lossless Image Compression Algorithm: Principles and Standandization into JPEG-LS*", *IEEE Transactions on Image Processing*, Vol.9, No. 8, pp. 1309 – 1324, 2000.

[10] Kaur, K., Saxena, J., Singh, S., "*Image Compression Using Run Length Encoding (RLE)*", International *Journal on Recent and Innovation Trends in Computing and Communication*, Vol.5, No. 5, pp. 1280-1285, 2017.

[11] Remya, S., Rasheed, D., "*Resolution Progressive Compression of Encrypted Images*", *International Journal of Signal Processing Systems*, Vol. 1, No. 1, pp. 7-10, 2013.

[12] Zhou, J., Liu, X., Au, O. C., Tang, Y. Y., "*Designing an efficient image encryption-then-compression system via prediction error clustering and random permutation*", *IEEE Transactions on Information Forensics and Security*, Vol. 9, No. 1, pp. 39-50, 2014.

[13] Amirthavarsinipriya, A., Sangeetha, K. K., Marimuthu, C. N., "*Classification of Retinal Images using Improved Adaptive Fuzzy C-Means Clustering Algorithm", International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)*, Vol. 2, No. 2, pp: 137-142, 2013.

[14] Cheung, K. W., Po, L. M., "*Integer Multiwavelet Transform for Lossless Image Coding*", in: *Proceedings of 2001 International Symposium on Intelligent Multimedia, Video and Speech Processing*, pp. 117-120, Hong Kong, 2001.

[15] Said, A., Pearlman, W., A. A, "*New Fast and Efficient Image Codec Based on Set Partitioning in Hierarchical Trees*", *IEEE Transactions on Circuits and Systems for Video Technology*, Vol. 6, pp. 243-250, 1996.

[16] Shapiro, J. M., "*Embedded Image Coding using Zerotrees of Wavelet Coefficients*", *IEEE Transactions on Signal Processing*, Vol. 41, No. 12, pp. 3445-3462, 1993.

[17] Rufai, A. M., Anbarjafari, G., Demirel, H., "*Lossy Medical Image Compression using Huffman Coding and Singular Value Decomposition*", *IEEE Signal Processing and Communications Applications Conference (SIU),* pp. 1-4, 2013.

[18] Venkatasekhar, D., Aruna, P., "*A Fast Fractal Image Compression using Huffman Coding*", *Asian Journal of Computer Science & Information Technology*, Vol. *2, No. 9, pp. 272-275, 2012*.