Probabilistic Decision Logic based Image Coding for Biomedical Image Compression

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Summary

The domain of biomedical image processing has developed with various coding approaches, and novel techniques which are running from basic compression models to top notch applications. The improvement in this domain has given birth to novel methods for coding with images using Artificial Intelligence techniques which can be easily integrated with real-time clinical systems. In the field of medicine, clinical findings have all time remained a problem for precise treatment especially if the patient is in the remote location. To overcome this problem, automated systems were developed. These automated systems needs transmission of medical images at variable bit rates which is one of the major limitation the hospitals are struggling with. To overcome this problem the proposed work objective is to develop a new algorithm to maintain reduced processing overhead and transmit images over variable bit rate. However images are to be processed with optimal learning rule so that the complexity in coding should be reduced and transmission is made easy. With this objective, probabilistic decision logic for image coding is proposed. Various metrics were used to compare the results obtained using the proposed approach with JPEG image compression standard. The proposed approach has improved results in comparison to other traditional coding systems.

Key words:

Fuzzy logic, Image compression, Medical image processing, Probabilistic decision logic.

1. Introduction

Nowadays image processing applications are used in numerous medical domains for example image compression, telemedicine etc. From the earlier studies it is noted that the image coding approaches developed to compress the image are noise sensitive, thus the images which are intended to compress are need to be processed for noise elimination before going for compression. Various filtration approaches are developed in earlier for noise filtration, however they are observed to perform well at image regions and are worst at sharp regions. It is noted that the edge regions of image are noise sensitive thereby degrades the image information's. Several medical image samples like MRI, CT, and PET etc., carries more sensitive information through which the probability of accuracy in diagnosis increases. Current compression or processing approach introduces processing distortions which are to be eliminated for accurate processing. The variability of noise characteristics is limiting the image filters to remove all kinds of noises [6-9] in variant environments. Due to the involvement of extra noise coefficients the count of representative coefficients becomes huge by which there is a possibility of drastic effect on the compression. Even with the effective processing of image coefficients, the non-effective representation of image coefficients lead to heavy representing coefficients which result in very low compression and demands for high data rate to provide quality of service in medical sample processing. In case of remote applications, the requirement of high resources is a main constraint by which the quality of image processed is less. These problems are needed to be minimized for an effective processing of medical image sample for remote applications. A new coding approach is needed in such applications, where optimal coefficient selection should be made based on past learning, and optimal decision making approach should be developed over the selected coefficient. With this objective, a fuzzy model for image coding is proposed in this paper.

The organization of the paper is as follows. Section 2 explains the brief literature review followed by research methodology in section 3. Experimental results were presented in section 4 and the paper ends with conclusion in section 5.

2. Literature Review

In order to successfully deploy the telemedicine applications and to give accurate observations and results, novel algorithms has to be used for biomedical image compression. To achieve higher rate of accuracy large volume of data need to be transferred so that information can be retrieved accurately. However in current situation the transmission of large voluminous data requires high bandwidth. Allocation of sufficient bandwidth based on the data volume is not a feasible solution. In image compression, the visual quality of the image is not tampered, if the elimination of the non-significant pixels in the representation is removed as their coefficients are less significant. To achieve higher compression rate it is

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necessary to select coefficients which are more significant and in turn reduces coding difficulties. In the process of coefficient selection, however images are to be processed with optimal learning rule so that the complexity in coding and accuracy of coefficient selection should be equalized [10, 11]. Thus there is a need to develop an efficient compression approaches through there will be a minimum information loss and lowest error level.

Earlier studies revealed that JPEG image coding is the most commonly used transformation technique used for image compression. It is also observed that the JPEG based image coding approaches only discriminates the resolution information at lower levels only. They are not able to reveal the entire information about the resolution levels of the image, which results in less effective image coding.

The usage of Artificial Intelligence techniques helped a lot in coding systems for compression of medical images. E. Anna Saro and S. Durai [12] were proposed a "Cumulative distribution Function (CDF)" based back propagation algorithm for medical image compression. This method implements image compression by pixel mapping with the predicted CDF values. But the reconstructed image is fuzzy in nature which is not applicable for medical applications.

Based on the concept of edge preservation, Wan Che [13] proposed a new medical image compression using neural networks to achieve increased retrieval accuracy. Quantization levels are used for the representation of the compressed patterns. The compression ratio is measured through the "Average Mean Square (AMS) value". An enhanced back propagation algorithm based image compression technique sis developed in [14] using neural networks. From the analytical results, it is observed that the proposed approach obtained a significant performance with less PSNR. A supervised Neural Network (NN) based wavelet medical image compression was suggested by khashman [15] using Haar wavelet with 9 compression ratios. Here the proposed NN is for learning of an optimal compression ratio associated with pixel values or image intensities. However the main drawback is this approach is degraded image quality at the receiver side, which is not tolerable in medical image applications. To attain an increased image quality, a NN with multi-resolution technique was developed in [16]. In this method, a filter bank [17-19] is accomplished by which the synthesis of the signal/image is carried out accurately through the reference coefficients which are well suited for low bit-rate coding applications and the detail coefficients are quantized coarsely [20]. Though this approach suffers for high bit rates, it has shown an optimal performance for low bit-rate coding applications. Huang [21] developed a new medical image compression technique by combining the "Principal Component Analysis (PCA)" with NN. Though this approach has obtained a better convergence speed, the image quality is witnessed to be poor at receiver side. A similar method is developed in [22]. This approach focused on the elimination of redundant information by dividing the large image into small size frames. However this approach observed to be a more complex though it has higher compression rate.

Zipser, Munro and Cottrell [23] proposed a "multi-layered perceptron NN" using back propagation algorithm as a function of learning. The compression ratio achieved through this approach is observed to be optimal. Dimililer and Khashman [1] proposed a DCT based image compression using NN. Here the compression is carried out over the transformed pixels using DCT [24] and the NN is for learning of an optimum compression ratio associated with pixel grey values or image intensities. Researchers in the past suggested many approaches for image compression [26, 27] especially for medical image compression in telemedicine applications using Neural Networks [28-33] and few works suggested using fuzzy logic [34, 35]. All these suggested approaches have their own advantages and disadvantages.

To achieve enhanced accuracy, this work mainly focused towards the transformation techniques. Further, the suguno model is incorporated through a multi-level fuzzy rule for medical image sample compression. The basic objective of incorporation of multi-level fuzzy logic is to acquire much finer information for preserving the edge information. The multiple rule definition results in lowering the coefficient number than the conventional JPEG image coding approach, by a hierarchical coding approach developing the inter band relationship among the pixel. This fuzzy set is then integrated with the learning approach [25] of neural network model to achieve higher level of image compression in medical imaging application.

3. Research Methodology

For the development of image compression logic, the image pixels are processed with pattern selection approach. The developed approach is outlined as follows.

3.1 Fuzzy based image compression

The proposed technique is accomplished in four steps;

- Pre-processing, Fuzzy logic based image enhancement, smoothing and crisp image creation.
- Dividing the total image into blocks of size 4X4 and then transforming each and every block using DCT.
- Selecting the maximum values based on the fuzzy membership function of the transformed block through the zigzag method.
- Obtaining cluster centers and their membership function values followed by performing the

segmentation and image compression through run-length coding.

Generally, the image will acquire an extra noise (low amplitude and high frequency noise) due the imperfect sampling which will be not visible to human beings. Human Visual System (HVS) eliminates these add on noise through the consideration of non-linear properties of retina and lens. Pre-filter was applied to reduce unwanted noise effects on the segmentation results based on the Characteristic of pre-filter similar to lens and retina of human system. Based on the characteristic of pre-filter similar to lens and retina of human system, unwanted noise effects are reduced on the segmentation results using pre-filter.

The Smoothing pre- filter is given by,

$$x^2(i) = x^1(i) + \frac{d_{-2}(i)+2d_{-1}(i)+2d_{+1}(i)+d_{+2}(i)}{8} \quad (1)$$

$$x^1(i) = x(i) + \frac{d_{-1}(i)+d_{+1}(i)}{4} \quad (2)$$

$$d_m(i) = \begin{cases} x(i+m) - x(i) | x(i+m) - x(i)| < L \\ L \ otherwise \end{cases} \quad (3)$$

Where $x(i)$ is the value of the pixel at ith position in the image. L is a filtering constant (approximately set as 15). After pre-processing, the image will appear like an array with fuzzy singletons, every singleton having a single membership function value representing the degree of level of brightness according to the membership function as shown in Fig. 1 [1, 2].The image array can be written through the fuzzy set notations as,

$$X^{\sim} = \begin{bmatrix} \mu_{11}/X_{11} & \mu_{12}/X_{12} & \cdots & \mu_{1n}/X_{1n} \\ \mu_{21}/X_{21} & \mu_{22}/X_{22} & \cdots & \mu_{2n}/X_{2n} \\ . & . & \cdots & . \\ \mu_{m1}/X_{m1} & \mu_{m2}/X_{X2} & \cdots & \mu_{mn}/X_{mn} \end{bmatrix} \quad (4)$$

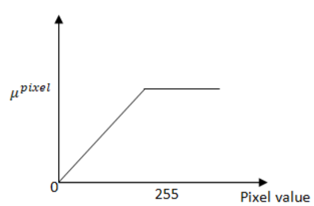

Fig. 1 Membership function of pixels in image

$$\mu_{mn}^1 = \begin{cases} 2(\mu_{mn})^2 & 0 < \mu_{mn} \le 0.5 \\ 1 - 2(1-\mu_{mn})^2 & 0.5 < \mu_{mn} \le 1 \end{cases} \quad (5)$$

The new membership function values μ_{mn}^1 will be obtained by equation (5) for enhancing the image pixels. A smoothing algorithm was used to remove the noise according to the equation (6) and as shown in Fig. 2.

$$\mu_{00} = \frac{\mu_{-10}+\mu_{10}+\mu_{01}+\mu_{0-1}}{4} \quad (6)$$

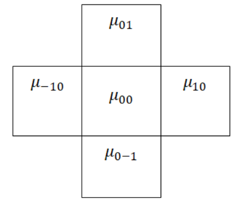

Fig. 2 Required pixels for smoothing algorithm around the centre pixel

After performing image smoothing, the obtained image was again suspended to enhancement through the relation mentioned in equation (7) and the obtained membership values are normalized to 0-255 to get the crisp image. Next, the obtained crisp image was divided into the blocks of equal size of 4X4 and the 2D-DCt was applied on every block. The mathematical representation of 2D-DCT for an image f(x,y) is given as,

$$\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}} & for\ u = 0 \\ \sqrt{\frac{2}{N}} & for\ u = 1,2, \ldots., N-1 \end{cases} \quad (7)$$

$$C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos\left(\frac{(2x+1)\mu\pi}{2N}\right) \cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (8)$$

Where x, y = ,1,2, … , iter-1 and $u, v = 0,1,2, \ldots, iter - 1$.

f(x,y) is a two dimensional image of size iter X iter.

$C(u,v)$is represents the NXN point DCT of f(x,y).

Then the obtained DCT coefficients ($D_i, i = 1,2, \ldots, 16$) are subjected to normalization through the equation (9) to obtain every value in between 0 and 255.

$$D_i^{(1)}(i) = \left(\frac{|min_i(D_i)| + D_i}{max_i(|min_i(D_i)|) + D_i}\right) \times 255 \quad (9)$$

Further in the next step, the normalized DCT coefficients redistributed row-wise in the order of low to high based on their frequencies by zig-zag method [3, 4] as show in Fig. 3. Then the obtained coefficients are compared with other block coefficients to find whether they are in same place or not and finally the high frequency coefficients are chosen. After the selection, the pixels are replaced with their own 4X4 block values. The selection order of peak membership values is done by arranging as of $D^1(1), D^1(2), D^1(3), \ldots, D^1(16)$ coefficients based on number of cluster.

D(1)	D(2)	D(6)	D(7)
D(3)	D(5)	D(8)	D(13)
D(4)	D(9)	D(12)	D(14)
D(10)	D(11)	D(15)	D(16)

Fig. 3 Zigzag scan order

Finally, the original pixels of membership function values are evaluated through the membership function of cosine transform.

$$S(x_0, x, y, z) = \begin{cases} \frac{1}{2} + 1/2\cos\left(\frac{(x-x_0)\pi}{x_0-y}\right) & y \le x \le x_0 \\ \frac{1}{2} + 1/2\cos\left(\frac{(x-x_0)\pi}{z-x_0}\right) & x_0 \le x \le z \end{cases} \quad (10)$$

Where x_0 is peak co-ordinate, x is the independent pixel value and y, z is the bandwidth. The mathematical formulation for the evaluation of cluster center [5] is given as,

$$V_i = \frac{\sum_{j=1}^{N} \mu_{ij}^m x_j}{\sum_{j=1}^{N} \mu_{ij}^m}; \quad 2 \le i \le C \quad (11)$$

Where $\mu_{ij}(i = 1,2,\dots,c, j = 1,2,\dots,iter)$ is the value of membership. μ_{ij} denotes the data point j's fuzzy membership which belongs to the ith class. $v_i(i = 1,2,\dots,c)$ is the center of each cluster. $x_j(j = 1,2,\dots,iter)$ are the values of pixels in the image, m is the parameter used to represent fuzzification. Then the image is encoded with run length coding once the cluster centers and membership values are obtained.

4 Results

The evaluation results along with the performance are presented for the proposed developed approach in this section. The sample sizes of medical images considered for this experiment are 512 × 512 pixels. Matlab software with NN tool box is used to encode medical images at 0.25 bit per pixel in order to obtain simulation results. Visual comparison results of given and retrieved sample medical image in comparison to conventional JPEG coding and the proposed Fuzzy coding under normal conditions are as shown in Fig. 4.

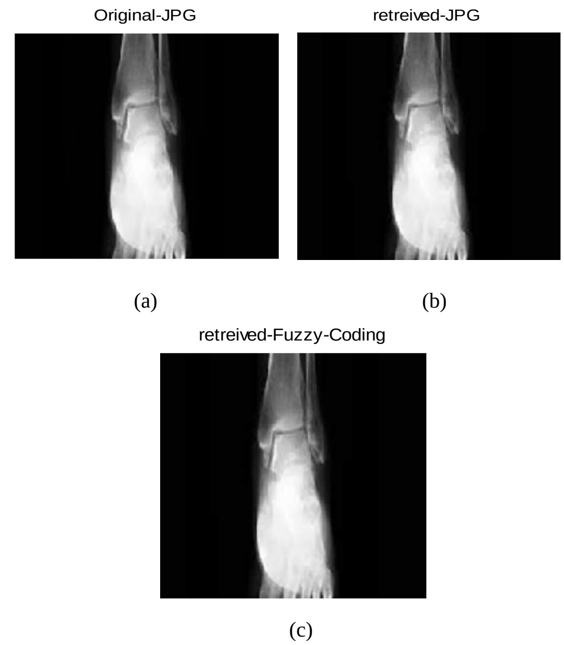

Fig.4 (a) Given sample image, (b) Retrieved sample image using JPEG coding (c) Retrieved sample image using Fuzzy coding

The experimental results for the developed Fuzzy coding are evaluated using the following parameters and compared with traditional JPEG coding system.

- Compression Rate (CR),
- Encoding Time (ET),
- Decoding Time (DT),
- Total Time (TT)
- Peak Signal to Noise Ratio (PSNR)

The following figures Fig. 5, Fig. 6 and Fig. 7 shows the intermediary results observed during the execution of fuzzy coding on sample medical image.

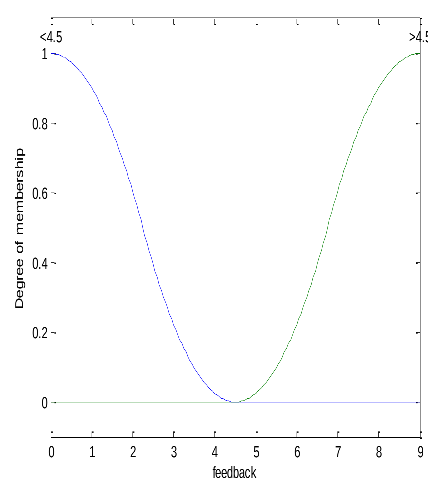

Fig. 5 Degree of membership function for a given input feedback

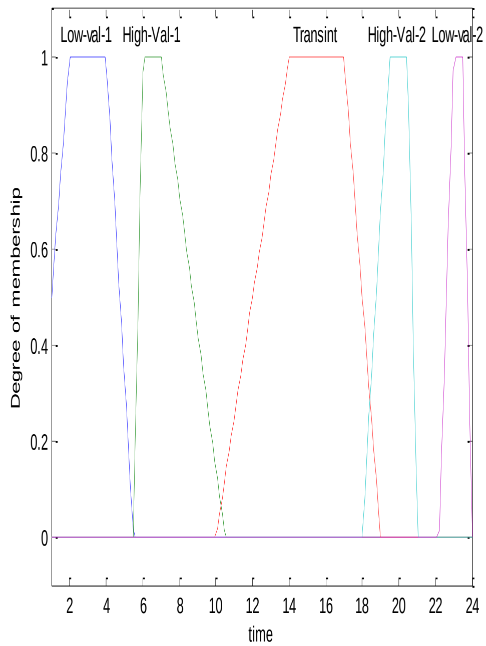

Fig. 6 Degree of membership function for varying time

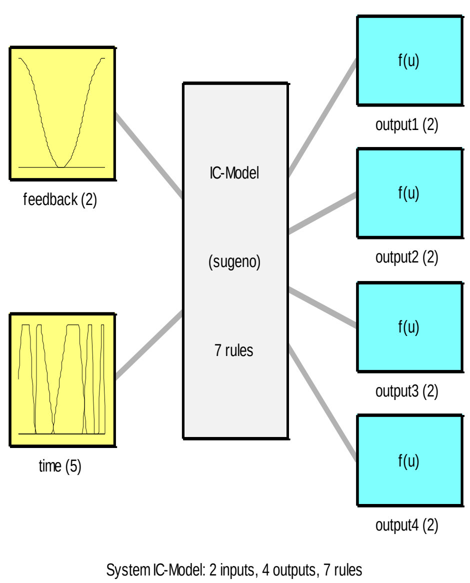

Fig. 7 The model of proposed Fuzzy logic based image coding

Evaluation metric values shown in Table 1 are obtained from the experiment using the above sample medical image depicts the comparison between the developed Fuzzy coding and JPEG coding approaches.

Table 1: Evaluation metrics

Metric	JPEG	Fuzzy
Compression Rate (Bpp)	1.25	3.475
Encoding Time Taken (sec)	5.125	5.125
decoding Time Taken (sec)	9.0625	2.3281
Total processing Time (sec)	14.1875	7.4531
PSNR (dB)	40.2530	50.6670

This experiment was performed considering more samples (S1, S2 and S3) for testing and observed values are noted and presented in Table 2.

Table 2: Evaluation metrics

Metric	S1		S2		S3	
	JPEG	Fuzzy	JPEG	Fuzzy	JPEG	Fuzzy
CR	2.01	4.3	1.20	4.07	1.67	4.00
ET	5.21	4.46	4.64	4.78	5.25	4.53
DT	9.40	2.18	7.21	2.18	9.76	2.25
TT	14.62	6.65	11.85	6.96	15.01	6.78
PSNR	39.88	50.30	42.59	50.62	39.55	49.96

An analysis of the developed approach for different level of fuzzy membership value and on variation of cluster center is carried out. Results using developed approach are as shown below. The performance obtained for the test medical sample under different cluster center is shown in Fig. 8, Fig. 9 and Fig. 10.

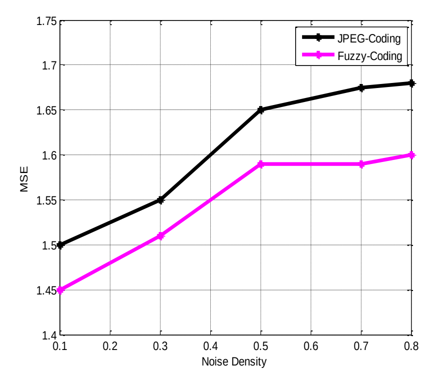

Fig. 8 MSE values over different Noise Density

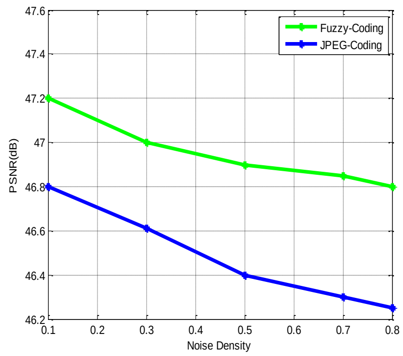

Fig. 9 PSNR values over variation in Noise Density

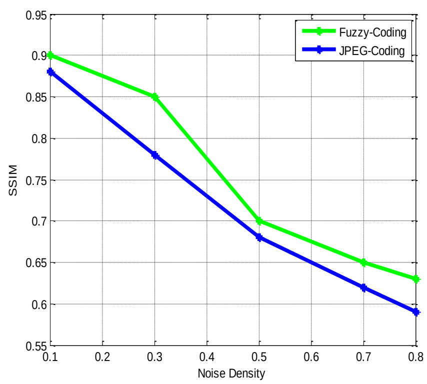

Fig. 10 Observed SSIM values over varying noise density

The experimental metric values for sample medical image carried out for variant cluster center is tabulated in Table 3.

Table 3: Evaluation values under variant noise values

Cluster Center	JPEG system			Proposed Fuzzy system		
	MSE	PSNR	SSIM	MSE	PSNR	SSIM
0.1	1.48	46.8	0.88	1.45	47.2	0.9
0.3	1.54	46.63	0.78	1.52	47.0	0.86
0.6	1.63	46.41	0.67	1.58	46.9	0.7
0.8	1.67	46.25	0.59	1.6	46.77	0.61

The observation for measured parameter for different membership function is presented in Fig. 11, Fig. 12 and Fig. 13.

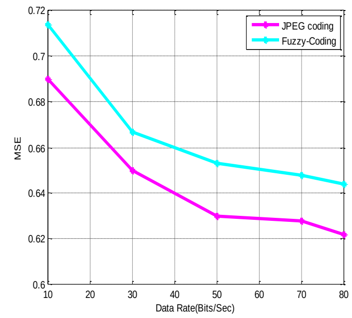

Fig. 11 MSE values observed for variant membership function

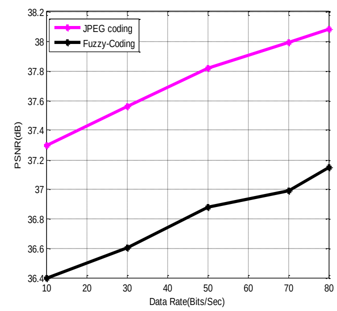

Fig. 12 PSNR values observed for variant membership function

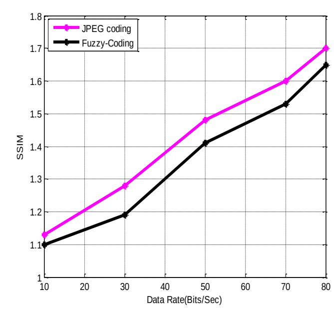

Fig. 13 SSIM values observed for variant membership function

Table 4 depicts the values obtained from the experiment under different membership function.

Table 4: Evaluation values under different membership function

Membership function	JPEG system			Proposed fuzzy system		
	MSE	PSNR	SSIM	MSE	PSNR	SSIM
10	0.714	36.4	1.1	0.69	37.3	1.13
30	0.667	36.61	1.19	0.65	37.56	1.28
60	0.653	36.88	1.41	0.63	37.82	1.48
80	0.644	37.15	1.65	0.622	38.08	1.7

Fig. 14 and Fig. 15 show the comparative analysis of test samples for compression rate and PSNR. Fig. 16 and Fig. 17 present the time taken for encoding and decoding process.

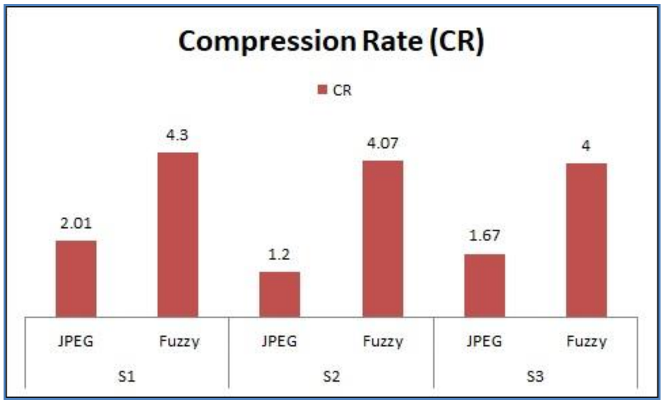

Fig. 14 Compression rate comparative analysis

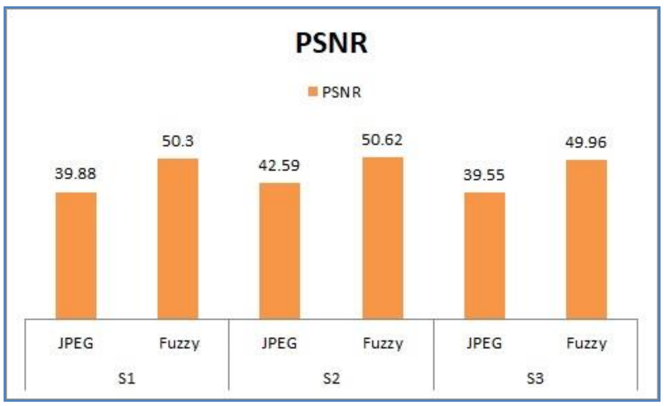

Fig. 15 PSNR comparative analysis

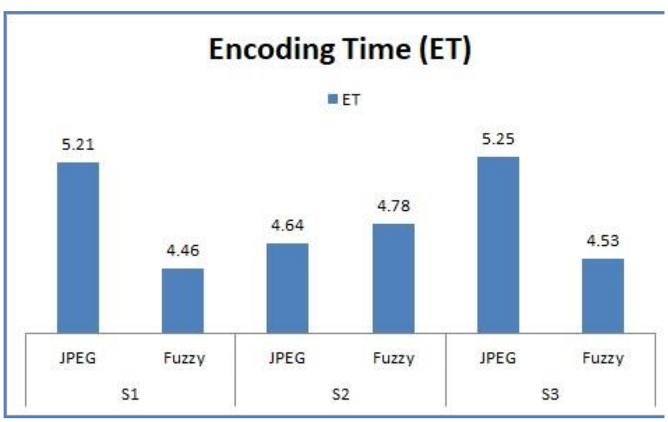

Fig. 16 Encoding time comparative analysis

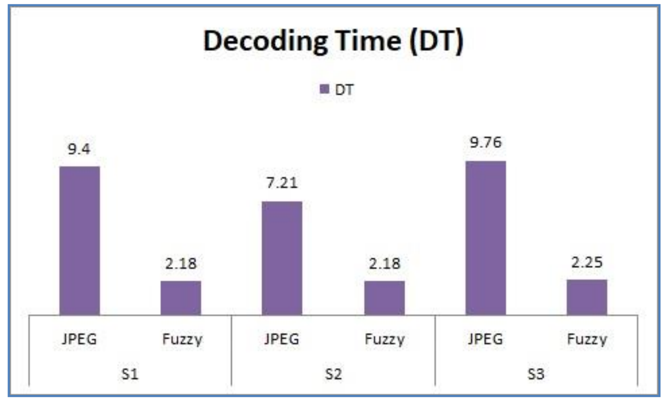

Fig. 17 Decoding time comparative analysis

Total time comparative analysis of test samples is presented in Fig. 18.

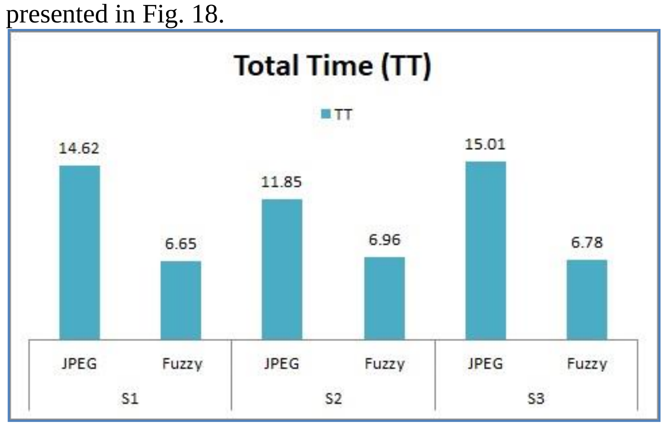

Fig. 18 Total time comparative analysis

5 Conclusions

The obtained observation illustrates the significance of the developed approach for the proposed image compression logic based on fuzzy rules. The developed approach defines a membership function using the fuzzy rules, where the pixels are selected based on the spectral energy content of the test image using DCT operation. All the testing samples to perform this experiment are medical image samples. The developed probabilistic decision logic based image coding for biomedical image compression gives enhanced results when tested with biomedical images using the evaluation metrics. The observed PSNR and SSIM improvement validates the suggested approach of proposed image compression approach. The future work for this research work can be an integrated model using Neural Networks and Fuzzy Logic and comparison of the results with neural network and fuzzy logic individually.

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