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A Hybrid Lossless Compression Technique with Segmentation and Modified Arithmetic Coding

MAZHAR B.TAYEL*, MOHAMED A. ABDOU**
*Department of Electrical Engineering, Alexandria University, Alexandria, 21544, EGYPT
**Informatics Research Institute, Mubarak City for Scientific Researches, Alexandria, EGYPT

Abstract: - Compression of medical images (MI) is an important field of study in biomedical engineering. Although lossy compression could solve storage space and transmission bandwidth problems, it is not recommended by most physicians because of data loss. Lossless compression saves all details inside image; however it could not be applied for the whole image area. This paper introduces a hybrid lossless compression channel with two different steps. The first is an automatic segmentation technique, where a region of interest (ROI) is automatically segmented by aid of an artificial neural network (ANN) and an introduced difference fuzzy model (IDFM). The second is a modified arithmetic coding (MAC) lossless compression algorithm. This hybrid channel is to combine in parallel with a lossy compression channel that transmits non important parts of the MI progressively, using the fast algorithm of embedded zerotree wavelet (FEZW) [1]. The proposed technique reduces complexity, storage space, bandwidth, and saves time. Moreover, it is a fully automatic system. Several brain magnetic resonance images (MRI) and fluorescene ophthalmic images are analyzed.

Key-words: - Neural Network, Difference Fuzzy, ROI Segmentation, lossless compression, Modified Arithmetic Coding.

1 Introduction

Since only a small portion of the image might be diagnostically useful (ROI), a small number of studies on region- based coding have focused on providing different levels of image quality in different spatial regions [2, 3]. Methods based on thresholding, connectivity, and boundary smoothing [4] has the disadvantage that the background was not encoded, and was displayed as a black by the decoder. Discrete cosine transform with different coefficients population inside and outside ROI [5] and wavelet subbbands images [6, 7] suffered two main problems. The ROI was determined manually; moreover the refinement process of ROI during progressive transmission is not adaptive.

With segmentation, it could be possible for a compression algorithm to deliver lossless compression only inside ROI [8]. However, segmentation algorithms suffered complexity and large execution time problems, so methods based on neural network [9, 10] were introduced. A semi-automatic technique was presented by Chen in [11], where the center of ROI is determined manually. The critical points of ROI contour were detected by local mean and variance characteristics which require complex mathematical calculations and large time to converge. However, automatic segmentation of ROI could lead to combining lossy and lossless techniques to code a MI [12, 13, and14].

2 Hybrid Lossless Compression Channel

This paper introduces a hybrid segmentation-lossless compression channel. This channel consists of two main sections: ROI automatic segmentation technique and introduced modified arithmetic coding compression algorithm. The segmentation process is via an ANN and an IDFM. The MAC consists of two main blocks, an introduced zero filter (IZF) and a conventional arithmetic encoder. This hybrid lossless compression channel is to combine with a lossy channel, where the FEZW [1] is used as shown in fig.1. This algorithm improves time and reduces storage space by about 30% when compared to the Set Partitioning in Hierarchical Trees (SPIHT) [15].

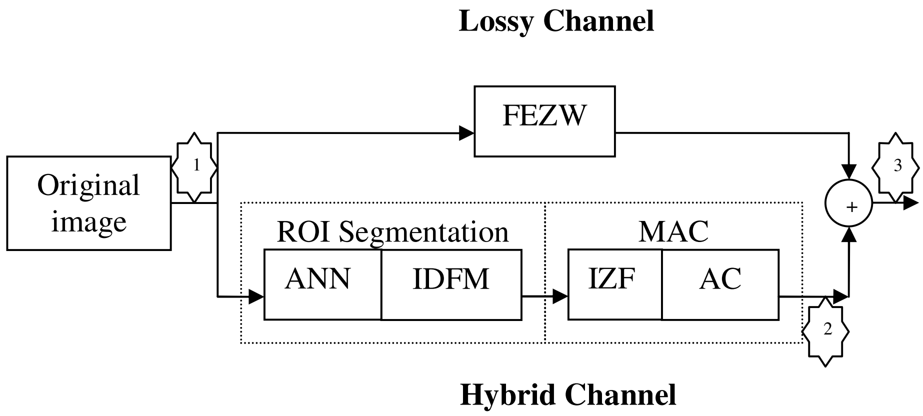


Figure (1): Hybrid lossless compression channel within the whole MI transmission system.

2.1 ROI Segmentation

A ROI is determined using an ANN and an IDFM. The idea of segmentation consists of assuming a ROI in the form of an irregular spider hexagon contour. The ANN is used to detect its center, while the IDFM detects critical points along radial lines depicted from the center. Connecting all critical points, the ROI contour is obtained.

2.1.1 Artificial Neural Network (ANN)

Wavelet transform (WT) is applied first to reinforce local characteristics of image textures and to avoid using raw image. Then, an introduced 4 layers ANN (input layer consisting of 64 neurons- two hidden layers each consisting of 10 neurons- and an output layer consisting of two neurons) is used to detect the center or a point inside the ROI. Network growing and pruning is used to design the ANN parameters. The ANN has converged after 1492 epochs.

2.1.2 IDFM for Critical Points Determination

Critical points are determined using the IDFM. It has three inputs: intensity at the center of ROI determined by the ANN, intensity difference (between center and final), and intensity at the point to be studied. There is only one output for the system: decision, either inside ROI (value 1) or outside (value 0). The proposed difference fuzzy technique reduces the large number of rules of the conventional fuzzy system by about 38%. Moreover, the used ANN and IDFM for ROI contour determination have shown better performance than the semi- automatic technique presented by Chen. Table 1 shows the error when comparing both techniques with a manually selected ROI for six different case studies.

Table 1: Percentage error calculated when comparing two techniques to manual.

	Percentage Error	
	Chen [11]	**IDFM**
Casestudy14	0.4647	0.1843
Tumorssarcoma3	3.8617	0.0027
Tumorssarcoma4	3.1646	3.1646
Retinal angioma	0.9282	0.77
Melanoma1	1.4892	1.0555
Melanoma9	3.4166	0.2445

2.2 Modified Arithmetic Coding

After ROI automatic segmentation, a MAC is introduced within the hybrid channel. This consists of an introduced zero filter and an arithmetic encoder.

2.2.1 Arithmetic Coding Algorithm

The arithmetic coding (AC) algorithm is used in image compression to maintain all image data. In this paper, a modified arithmetic encoder (MAC) is introduced to save time. The flowchart of the MAC algorithm is shown in fig. 2. First, it starts with image scanning, raster technique is used. Next, quantization stage starts (64 quantization levels are used) for image intensity varying from 0- 256. Image histogram is the next stage, where the whole image is analyzed to see the number of pixels that exist in each quantization level. Two outputs are to be entered to the arithmetic encoder: (x, n), where x is the number of pixels in each level and n is the level values.

2.2.2 Introduced Zero Filter (IZF)

Working with all previous data leads to algorithm high complexity and large execution time. These problems are to be avoided using an introduced zero filter (IZF) modification.

It was found when working with an intensity MI that there exist several inactive quantization levels (quantization levels that do not contain pixels in the image histogram); these inactive levels could better be omitted before entering data to AC to generate the symbols. Therefore, an IZF is inserted before the AC. Consequently, two modified outputs are obtained (X, N), where X is the number of pixels in active levels and N is the active levels values. The outputs of the IZF are counted, ordered, and assigned a number of symbols according to the number of active levels. The assigned symbols depend on the frequency of occurrence of each symbol. This causes a noticeable reduction in the execution time of the algorithm.

3 Simulation Results

The proposed technique is applied to different types of MI to evaluate the proposed system performance. Several brain MRI and fluorescene ophthalmic images are analyzed. Each image is processed over fig. 1 terminal points: 1(original image), 2 (hybrid channel output), and 3 (complete image sent over the communication channel). The results of 4 different case studies at are shown in figs. (3 and 4). For different progressive transmission levels, several quantities are calculated and results are shown in table II. Overall compression ratio, rms error, peak signal to noise ratio (PSNR), and percentage of ROI area to the total image area are observed at the terminal point.

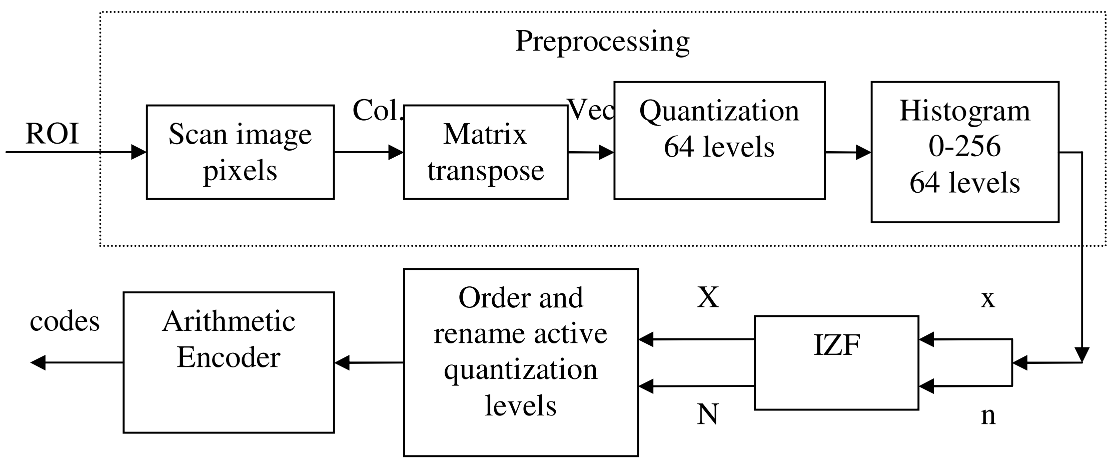
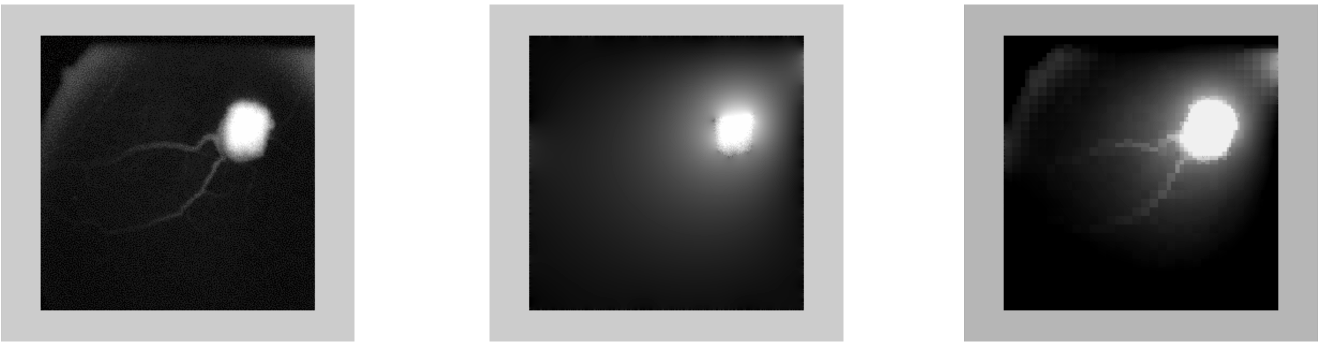
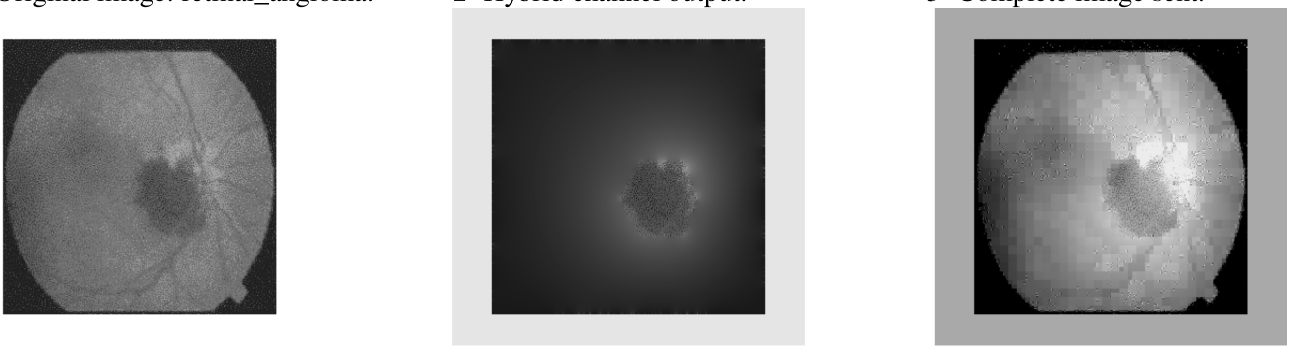


Figure (2): The MAC Lossless compression of the hybrid channel.

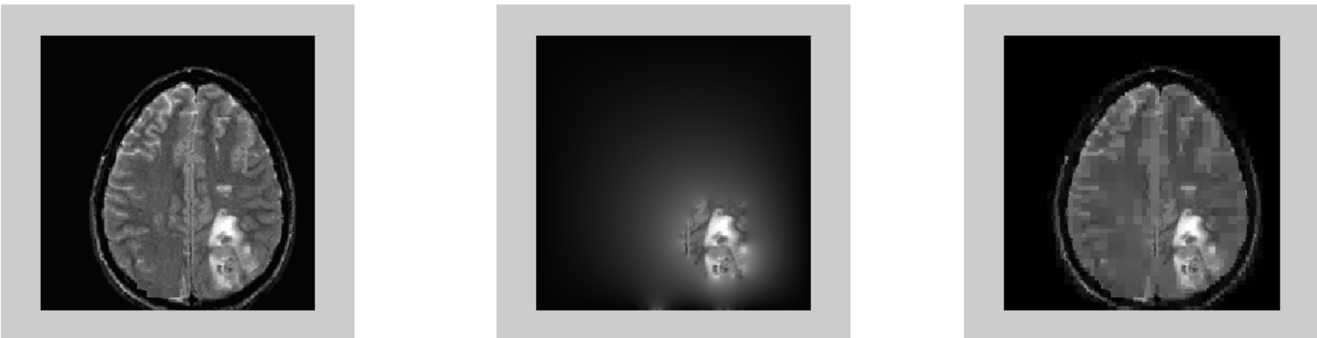


1- Original image: retinal_angioma. 2- Hybrid channel output. 3- Complete image sent.

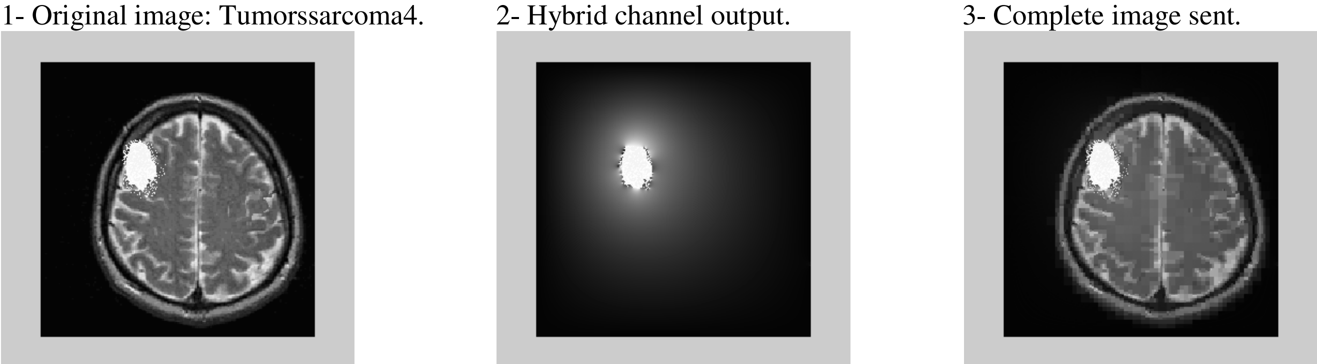


1- Original image: Melanoma1. 2- Hybrid channel output. 3- Complete image sent.

Figure (3): Two fluorescene ophthalmic case studies.



1- Original image: Tumorssarcoma4. 2- Hybrid channel output. 3- Complete image sent.



1- Original image: Casestudy14. 2- Hybrid channel output. 3- Complete image sent.

Figure (4): Two MRI brain case studies.

Table 2: Simulation results for 4 different case studies.

Case study	Feature	Level 1	Level 3	Level 5
Retinal angioma	Comp.ratio	100:2.8	10:3	100:7
	rms error	18	19.3	1.5
	PSNR	53	51	103.1
	%ROI	1.74%		
Melan-oma1	Comp.ratio	100:11.3	10:12.5	100:20
	rms error	27.5	16	16
	PSNR	44	55	56
	%ROI	9.1%		
Tumor-ssarcoma4	Comp.ratio	100:6.6	10:8	100:12.5
	rms error	9	5	4.9
	PSNR	68	78	79
	%ROI	5.3%		
Casestu-dy14	Comp.ratio	100:3	10:5	100:13
	rms error	29	13	8
	PSNR	43	60	70
	%ROI	1.6%		

The obtained results are satisfying the concept that the rms error increases as the compression ratio increases, while the PSNR is inversely proportional to the rms error. From different levels of progressive transmission, it could be observed that there may be an unexpected variation in error values from one level to the other; this is because the wavelet coefficients are sent progressively according to a decreasing sequence of thresholds. The number of coefficients sent could vary widely from one level to another. In all cases, the compression ratio decreases as the image goes into progressive refinement levels. The %ROI shown in the table is the output ROI area detected by the IDFM measured to the total image area.

4 Conclusion

A hybrid channel with Segmentation and lossless compression for medical image processing has been presented in this paper. This channel provides several merits. The introduced neuro-difference fuzzy model for ROI segmentation is fully automatic and gives accurate region contours compared with manual and semi- automatic techniques. Moreover, the MAC surpasses conventional lossless compression techniques in complexity and algorithm execution time by omitting all non fittest quantization levels. Finally, by combining the hybrid lossless channel with the FEZW lossy channel, better compression ratios and higher image qualities are obtained.

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