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Characterization of Alzheimer MRI Image based on Image Compression Techniques

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The motive of this work is to develop an Algorithm for compression with high compression and good value of PSNR. The target presently changed by including appropriate transform and encoding strategies to accomplish the task. The ideal of image compression is chosen depending on a trade off among PSNR and CR. The goal is additionally discovering an ideal algorithm for medical image compression. The MR imaging are used in this work. To guarantee the nature of the planned methods, the component extraction strategies, which are the pre-solicitation of the grouping calculations, have been discovered and the outcomes uncover that the use of image doesn't modify the portrayal conduct of the medical images.

Keywords: CR, Encoding, EZW, PSNR, SPIHT

Introduction

Storage and transmission of images require a large amount of memory. In this work, the Symlet wavelet transform is used for decomposition of images. Encoder is applied to achieve the compression process. The quality and amount of compression are evaluated finally. Alzheimer's disease is among the most financially costly disorders. Several scholars have focused on developing a high precision software system for the diagnosis of AD and normal control instances. Recent neuro-imaging developments in acceptance of machine-learning technologies are particularly useful for pattern analysis in radiography to assist the doctor in early detection of Alzheimer. In this research, an MRI (magnetic resonance imaging) of normal brain and Alzheimer affected image with an axial view are used for the compression process.[1] The image quality is measured by the values of PSNR.[2] The amount of compression is estimated with the value of Compression ratio.[3] To ensure the quality of the proposed algorithm, the feature extraction techniques[4], which are the pre-requisite of the classification algorithms, have been found out and the results reveal that the application of compression does not alter the characterization behavior of the medical images.[5]

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Materials and Methods

Image Data Base

The MRI of brain is taken in this work. The MRI Images are collected from Sathyabama University Hospital in DICOM format from different peoples. The normal and Alzheimer affected MRI images are shown in Fig.1 (a) and (b) respectively.

Wavelet Transform

The images are diagrammatical by a collection of basic functions. One epitome-operate referred to as the mother transform is employed for account the premise operate, by translating and dilating the mother wavelet.[6] The wavelets are often viewed as a decomposition of images within the continuance plane. during this work, the symlets are used for decomposition of the MRI images as a requirement for the projected compression algorithms[7], since, symlets are designed with very part and highest range of decomposition levels for a given support width.[8] They are typically used for resolution pattern issues and signal discontinuities.

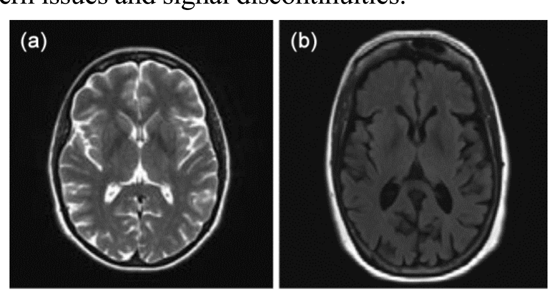

Fig. 1 — Imagaes of Brain: (a) normal (b) Alzheimer affected

Encoding

The redundant and irrelevant data are eliminated by encoding methods. In this work, embedded zero tree wavelet (EZW) and set partitioning in hierarchical trees (SPIHT) are used. The optimum encoding methods are identified by amount of compression and quality of images.

Feature Extraction

Since, the accuracy of a arrangement principally supported the right selection of the feature, it's essential to spot an honest set of options. during this planned work, a GLCM was employed[9], a statistical procedure that utilizes the abstraction relationship of pixels. This approach makes the statistics a bit strong to clarification of variation than within the case of GLCM. The Features are Extracted from ten images.[10] The values of features are shown in Table 1 and Table 2. The classification may be outlined either as traditional or Alzheimer affected. The higher cognitive process work of classification may be simply done by the use of neural networks.[11] The options, which are able to lean to the inputs of neural networks, so as to classify them into the categories. To perform economical feature extraction[12], the options should have lesser intra category variance. Hence, the most objective of this work is to identify and formulate the set of options, that should be distinct enough from every category. Further, the network are going to be trained to classify the corresponding images, which is able to be classified as either normal or Alzheimer affected one.[12] The derived options, that ar tabulated provides a wide distinction between the conventional and Alzheimer images additionally, the compression don't have an effect on the values abundant.

Table 1 — Features of the Normal brain image

Features	Before compression	After compression
Image entropy	5.61	5.3
Auto correlation	21.9	22.87
Contrast	0.48	0.55
Correlation	0.97	0.91
Cluster prominence	832.2	834.6
Cluster shade	111	114.72
Dissimilarity	0.21	0.24
variance	65.6	65.91
Information measure of correlation	0.94	0.94
INN	0.89	0.87
Energy	0.31	0.30
Maximum probability	0.39	0.39
Entropy	2.02	1.96
Homogeneity	0.91	0.89

Results and Discussion

In this work, MRI images are undergone the developed algorithms. Symlet2 is in use for the image decomposition with Levels 1, 3, five and nine. Once the decomposition, embedded zero tree and set partitioning in hierarchical trees are utilized for additional reduction, the developed algorithms are measured by MSE, PSNR, compression magnitude relation and Bits per constituent, that are shown in Table 3.

Table 2 — Features of the Alzheimer disease affected image

Features	Before compression	After compression
Image entropy	7.22	6.74
Auto correlation	18.72	19.02
Contrast	0.43	0.49
Correlation	0.89	0.90
Cluster prominence	645.09	615.2
Cluster shade	59.23	61.95
Dissimilarity	0.31	0.27
Information measure of correlation	0.88	0.87
INN	0.94	0.94
Energy	0.20	0.29
Maximum probability	0.47	0.49
Entropy	3.12	2.66
Homogeneity	0.88	0.87

Table 3 — Performance of compression with various decomposition levels of symlet wavelet

Brain Image Type	Encoding Scheme					
		LEVEL	1	3	5	9
Normal (Tiff format)	EZW	MSE	0.06	0.4	3.9	85.03
		PSNR (dB)	60.02	52.15	42.22	28.53
		BPP	5.96	3.53	1.40	0.3
		CR (%)	74.44	44.08	17.52	2.62
		LEVEL	2	3	4	5
	SPIHT	MSE	5.94	6.87	16.71	105.30
		PSNR (dB)	40.34	39.79	35.90	27.91
		BPP	7.34	1.76	0.56	0.15
		CR (%)	41.8	22	7.37	1.85
		LEVEL	1	3	5	9
Alzheimer affected (Tiff format)	EZW	MSE	0.06	0.39	4.08	73.87
		PSNR (dB)	60.02	52.17	42.02	29.45
		BPP	6.30	3.37	1.21	0.81
		CR (%)	78.81	42.07	15.13	2.3
		LEVEL	1	3	5	9
	SPIHT	MSE	4.48	3.19	15.17	183.30
		PSNR (dB)	41.62	43.1	36.32	25.5
		BPP	7.15	1.65	0.5	0.05
		CR (%)	89.4	20.63	6.29	0.63

The mean square Error is defined in Eq. 1

$$MSE = \sigma_q^2 = \frac{1}{N} \times \sum (f_{j,k} - g_{j,k})^2 \quad \dots (1)$$

The PSNR is given in Eq. 2.

$$PSNR = 10log_{10}\left(\frac{255^2}{MSE}\right) \quad \dots (2)$$

In this work, the high compression of 89.4% is obtained. From Table 1 and Table 2 it is clearly understand that the proposed algorithms distinctly classify the images into normal and Alzheimer's affected image.

Conclusions

The high compression and high quality is o btained by Symlet 2 with the first level of decomposition. The BPP also decreased if decompositions are increased. The maximum compression ratio, higher PSNR values are obtained with the symlet 2, level 1 of decomposition. Even though the Embedded Zero Tree Encoding and set partitioning in hierarchical trees are used. It is proven that the normal and Alzheimer brain images can be classified with the aid of the features, with the feature extraction technique, proposed in this paper. The proposed compression algorithm does not change the information, behind the image, which assures the proper diagnosis.

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