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# Self Organizing Map Cluster Approach for Wavelet Based Medical Image Compression

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## ABSTRACT

Digital medical powerful tools for diagnosis, treatment and surgery and plays a vital role in modern healthcare delivery. Large storage capacity is needed for storing these images and for transmitting them. This leads to the strong demand for digital medical image compression and reliable transmission. In this study, we have applied three compression methods to medical images. In all the methods discrete wavelet transform is applied followed by the corresponding compression methods. The experiments are carried on three medical images and the quality of reconstructed images is evaluated based on Compression Ratio (CR) and Peak Signal to Noise Ratio. The results show that the SOM algorithm has higher compression ratio than FCM and FKM while maintaining the image quality and preserving the information. The results show that the SOM algorithm outperforms the existing methods FCM and FKM for medical image compression.

**Keywords:** SOM, FCM, FKM, Compression Ratio (CR) Wavelets, Computerized Tomography (CT), Magnetic Resonance Imaging (MRI), Digital Medical, Noise Ratio

## 1. INTRODUCTION

Today the use of computers in medical imagery is growing. The amount of medical images like CT and MR scan has grown rapidly due to the application of digital imaging technology in the medical domain. It is a fast developing area with the richest source of information from variety of modalities such as X-Ray transmission imaging, Magnetic Resonance Imaging (MRI), Computerized Tomography (CT), X-Ray Mammography (MG) and many others. As medical images carry vital information it is necessary to compress them without losing any data.

The main goal of image compression is to reduce the bit rate for data storage or transmission at the same time maintaining the image quality (Antoini *et al*., 1992). Nowadays compression algorithms on wavelet transform is considered to be the most efficient technique for image compression as they give high compression ratios compared to other algorithms. Diagnosis will be effective if these algorithms preserve all the important information needed. Recently variety of medical image compression methods using wavelet transforms has been proposed by many researchers. For EEG data compression clustering using k means method is done (Dehkordi *et al*., 2011). A hybridization of the SPIHT and Jacquin style coding for mammography images has been proposed to reduce the time taken for fractal image coding (Nacera and Soumia, 2011). A context based medical image compression (Ansari and Anand, 2009) for ultrasound images provides significantly better compression rates than JPEG and JPEG2K (Gersho and Gray, 1992). A lossy technique based on wavelet transform for compression of breast ultrasound images is presented which preserves the clinical information fo the image (Penedo *et al*., 2003). Region based compression methods are used for digital mammography which are efficient than full-image compression methods (Bhavani and Thanushkodi, 2010). Medical image compression is used in applications like profiling patients data and transmission systems. Based on the importance of medical images information, lossy or lossless compression is preferred.

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### 1.1 Lossless Vs Lossy Compression

Image compression is a technique of reducing the redundancies in image and representing it in shorter manner. Image compression can be lossy or lossless. For high value images such as medical images where loss of critical information is not acceptable, lossless or visually lossless compression is preferred. Lossy encoding for images is obtained using transform encoding methods which remove the redundancies by mapping the pixels into a transform domain prior to encoding. An image reconstructed following lossy compression contains degradation relative to the original. Often this is because the compression scheme completely discards redundant information. However, lossy schemes are capable of achieving much higher compression. Under normal viewing conditions, no visible loss is perceived (visually lossless).

Popular image compression techniques like DCT based transform coding (Dehkordi *et al*., 2011) and vector quantization (Nacera and Soumia, 2011; Ansari and Anand, 2009) are lossy block based techniques.

In lossless compression schemes, the reconstructed image, after compression, is numerically identical to the original image. That is it can be reconstructed exactly without any change in the intensity values. Applications like Satellite Image processing and certain medical imaging do not tolerate any data loss and are compressed using lossless methods. Now the wavelet transform has emerged as a cutting edge technology within the field of image compression.

Simple Compression Technique is presented in **Fig. 1**. The input image was sent to an encode for compression and then, the compressed file was sent over a network. Using a decoder, the original image was received.

### 1.2. Wavelet Transform

Nowadays wavelet based techniques has been a focus of research in the field of medical image compression. Applying the wavelet transform on images for compression may remove some of the redundancy and decorrelate the neighbour pixels. The discrete wavelet transform has been widely used in various medical image applications for reducing the size of medical images. They outperform JPEG (Pennebaker and Mitchell, 1992) in terms of image quality at a given compression ratio. To achieve better performance wavelet transform require filters that combine desirable properties like orthogonality and symmetry. The most well known techniques are Embedded Zerotree Wavelet by (Shapiro, 1993) and the Set Partitioning in Hierarchical trees (Said and Pearlman, 1996).

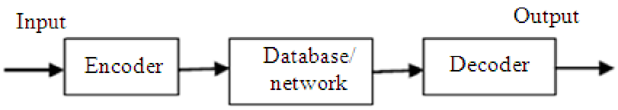


**Fig. 1.** Simple compression technique

In addition to efficient compression, it transmitted the most important co efficients first and then the remaining information which yields the largest distortion reduction.

## 2. MATERIALS AND METHODS

### 2.1. Embedded Zerotree Wavelet

It is a quantization (Linder *et al*., 1980) and coding strategy that incorporates certain characteristics of the wavelet decomposition. It is a remarkable image compression algorithm by Shapiro which generates the bits in the bitstream in order of importance giving a fully embedded code.

The dependencies between the wavelet co efficients of different sub bands are exploited to create zero trees. A zero tree is composed of a parent and its descendants which is shown in the **Fig. 2.**

The overall EZW coding system was given in **Fig. 3**. The original image was preprocessed and then Wavelet transformation was applied. The wavelet coefficients are compressed using EZW and then using a EZW decoder followed by an inverse wavelet transformation the image was decompressed to get the original image

### 2.2. Algorithm

#### 2.2.1. Initialization

Apply wavelet transform to the image and determine the threshold T0 which is given by:

$$T0 = 2 \log2 (|Cmax|)$$

where, Cmax is the largest wavelet coefficients.

### 2.3. Significance Test

The wavelet co efficients are scanned in the order shown in the **Fig. 4a and b** and a symbol is returned for every co efficient.

### 2.4. Sub Ordinate Pass

The significance test is always followed by a subordinate pass where the coded data get coded in 1 or 0 to be transmitted. The process for subordinate pass is illustrated below:

```
Subord-threshold=current-threshold/2;
for all elements on subordinate list do
 {
if coefficient>subord_threshold then
 {
output a one;
coefficient = coefficient- subord_threshold;
}
else output a zero;
}
```

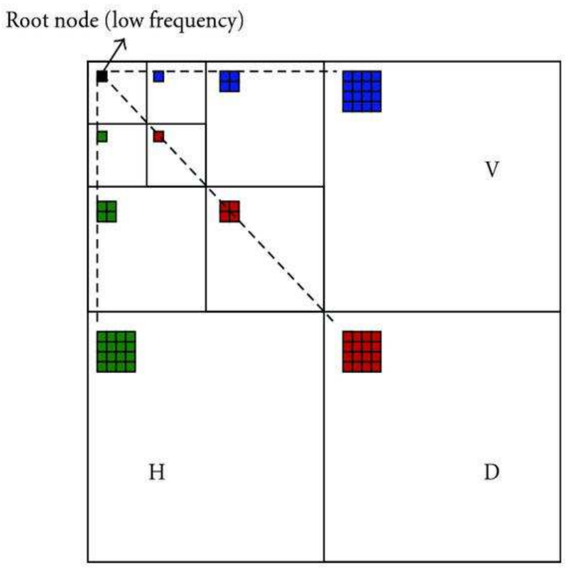


**Fig. 2.** Parent-descendant dependencies between sub bands

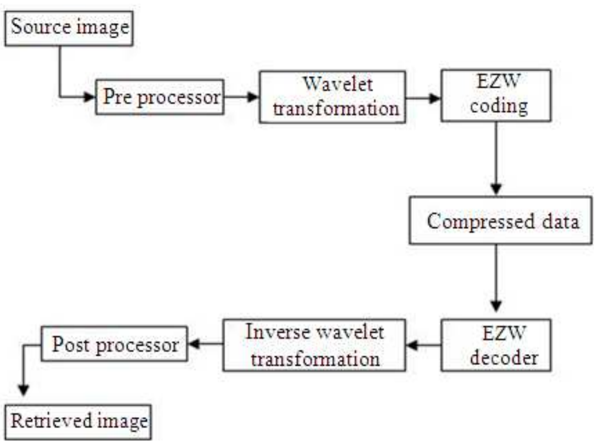


**Fig. 3.** EZW coding system

### 2.5. Proposed SOM Algorithm

The steps for the SOM are given as follows:

1. The SOM method starts with the initialization of the weight vectors
2. Select a sample vector randomly
3. Search the map of weight vectors to find which weight represents the sample in a best way
4. Every vector has neighboring weights which are close to it

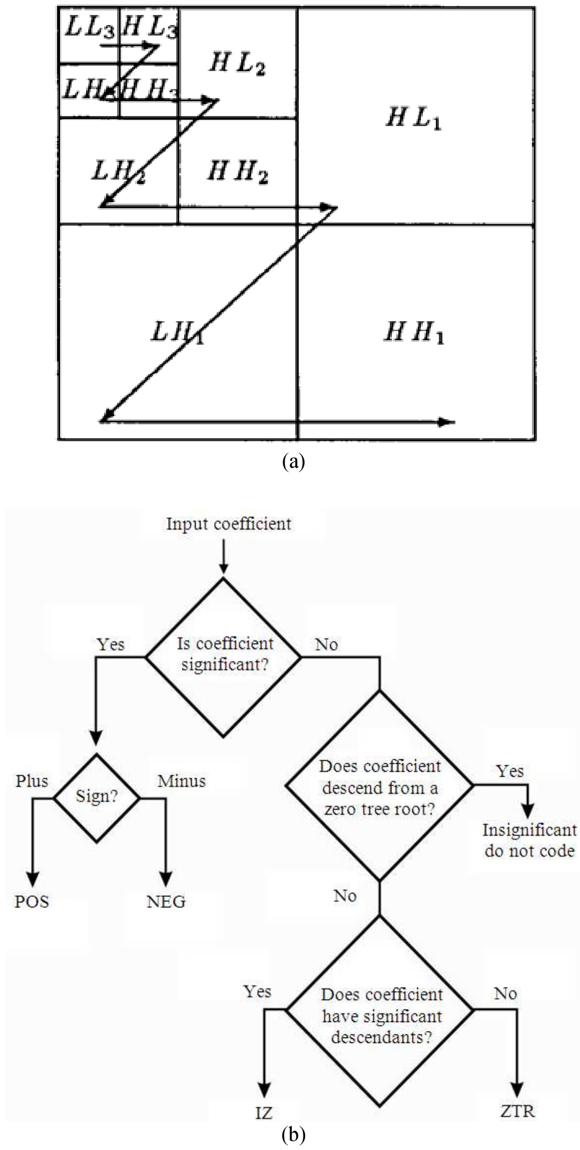


**Fig. 4.** (a) Scanning a zero tree; (b) Classifying a co efficient

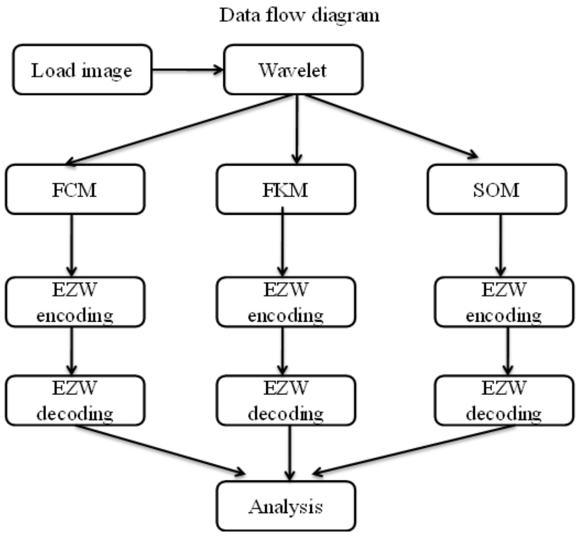


**Fig. 5.** Outline of the algorithm

5. The chosen weight is rewarded by becoming more like the randomly selected sample vector.
6. The neighboring weights are also rewarded by becoming like the chosen sample vector
7. The number of neighbors decreases over time
8. The whole process is repeated for N number of times

The schematic diagram of the proposed scheme is given in **Fig. 5.**

Compression can be achieved by transforming the data and then encoding the transform. The transform must be biorthogonal to avoid redundancy.

The proposed algorithm is given below:

- Load the test image
- Apply wavelet transform on the test image
- To the transformed image apply SOM, FCM and FKM techniques
- Apply EZW encoding to each of the output got from these techniques and decode them
- The output got from these techniques is analyzed

## 3. RESULTS

Metrics are required to judge the quality of the image obtained after any compression system. The quality of the image is assessed using metrics. It helps to rank the different compression methods so that the best compression algorithm for a specific application can be identified. Two error metrics are given below.

**Table 1**. CR for various compression algorithms

| Images | CR FCM | FKM | SOM |
|---|---|---|---|
| Brain1 | 3.0625 | 1.5469 | 3.4375 |
| Brain2 | 2.9688 | 1.5469 | 3.4844 |
| Brain3 | 2.7813 | 1.6250 | 3.5781 |
| Brain4 | 2.7813 | 1.5938 | 3.5000 |
| Mammogram 1 | 4.9531 | 1.9531 | 5.5781 |
| Mammogram 2 | 4.6875 | 2.0156 | 5.8594 |
| Mammogram 3 | 3.1406 | 1.9063 | 4.4844 |
| Mammogram 4 | 4.6250 | 1.7969 | 5.9219 |
| Kidney 1 | 5.4844 | 1.8906 | 5.7969 |
| Kidney 2 | 4.0156 | 1.8125 | 5.6406 |
| Kidney 3 | 5.0469 | 1.9531 | 5.0513 |
| Kidney 4 | 3.8594 | 2.0469 | 5.0469 |

Peak Signal to Noise Ratio (PSNR):

$$\text{PSNR} = 20 * \log_{10}\left(\frac{255}{\sqrt{\text{MSE}}}\right)$$

### 3.1. Compression Ratio

$$\text{CR} = \frac{\text{Size of the compressed image}}{\text{Size of the uncompressed image}}$$

A higher value of PSNR is good because the ratio of signal to noise is higher. Signal is the original image and noise is the reconstructed image.

## 4. DISCUSSION

Three wavelet-based compression techniques are presented in this study. They were analyzed to find the best algorithm for efficient image compression. Three images of 256×256 pixels in size are used. It can be seen that SOM outperforms FCM (Tamilarasi and Palanisamy, 2011) and FKM. The algorithms are evaluated in the terms of CR and PSNR.

The performance of the three test images using different compression algorithms is compared and the results are tabulated in **Table 1 and 2**. By analyzing the tables and graphs for the three test images, it is observed that SOM algorithm provides a better PSNR value than the other two algorithms.

The experimental results show significant performance for the SOM method for the compression of medical images, while, on the other hand achieving high compression rates.

**Figure 6 and 7** shows the plot of CR and PSNR for different images for the three compression algorithms. By analyzing the above graph, it is seen that the PSNR value is more for SOM compared to other techniques. Compression ratio is more for SOM and it is less for FKM than FCM. CR is more for mammogram and kidney images compared to brain image.

**Table 2.** PSNR (db) for various compression algorithms

| | PSNR | | |
|---|---|---|---|
| Images | FCM | FKM | SOM |
| Brain1 | 14.2102 | 18.8175 | 30.3200 |
| Brain2 | 14.5675 | 15.8427 | 29.3606 |
| Brain3 | 14.8484 | 17.1736 | 29.7620 |
| Brain4 | 14.9758 | 16.2402 | 31.1400 |
| Mammogram 1 | 10.8399 | 21.1833 | 30.0359 |
| Mammogram 2 | 14.0359 | 22.2979 | 31.0100 |
| Mammogram 3 | 15.9260 | 20.0290 | 29.6320 |
| Mammogram 4 | 14.4670 | 22.9903 | 30.9920 |
| Kidney 1 | 13.8384 | 19.3924 | 31.6802 |
| Kidney 2 | 13.2740 | 21.2155 | 32.0560 |
| Kidney 3 | 13.1270 | 22.2082 | 29.4700 |
| Kidney 4 | 13.8597 | 20.1486 | 29.7320 |

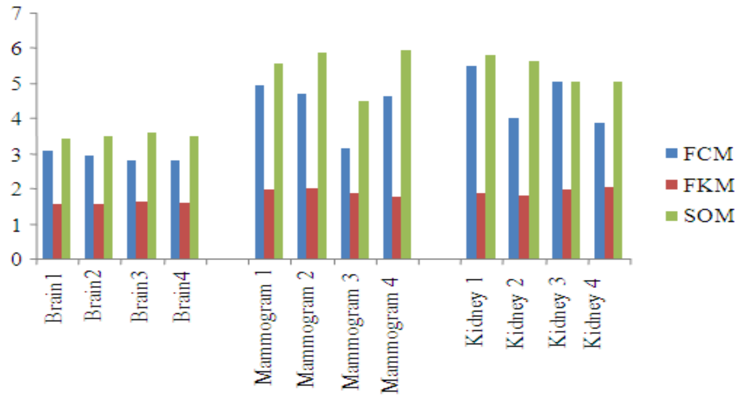


**Fig. 6.** Compression ratio compression chart

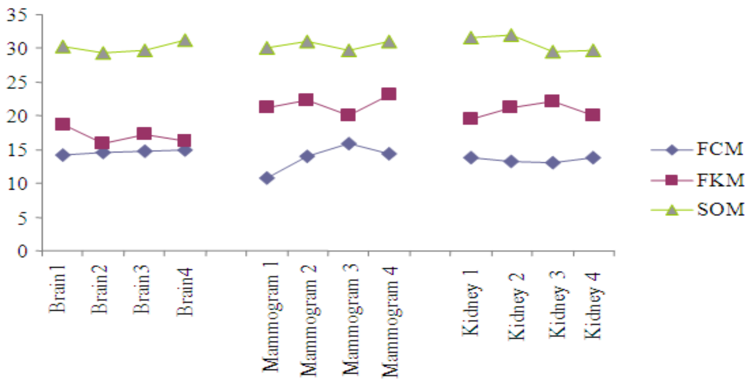


**Fig. 7.** PSNR comparison chart

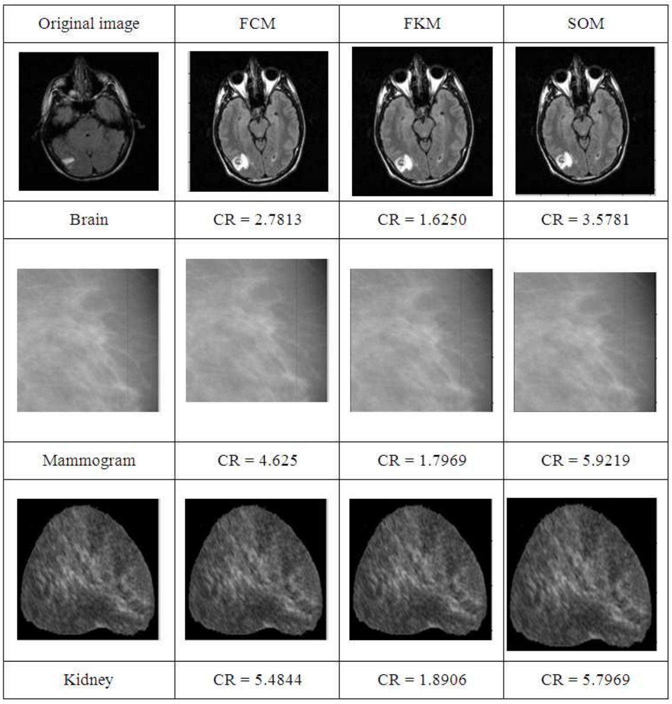


**Fig. 8.** Results obtained from experimentation with 3 test images

## 4. CONCLUSION

The experimental results show significance improvement of the SOM method for the compression of medical images at the same time achieving high compression rates. The results obtained from experimentation with three test images are shown in **Fig. 8.** The SOM algorithm gives better CR values than FCM and FKM. Hence, a better image reconstruction is possible with less number of bits, by using SOM.

## 5. ACKNOWLEDGEMENT

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