

Proficient Image Compression using the Wavelet Transform and Fuzzy C-Means Clustering

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ABSTRACT: The proficient Image Compression of Medical Images Using the Discrete Wavelet Transformation (DWT) and the fuzzy c-means clustering technique. The goal is to achieve higher compression rates by applying different compression thresholds for the wavelet coefficients of each DWT band, in terms of how they are clustered according to their absolute values. Image compression methodologies utilizing the DWT apply it to the whole original image. That is, different compression ratios are applied to the wavelet coefficients belonging in the different regions of interest, in which either each wavelet domain band of the transformed image or the image itself is clustered, respectively. Regarding the first method, its reconstruction process involves using the inverse DWT on the remaining wavelet coefficients. Concerning the second method, its reconstruction process involves linear combination of the reconstructed regions of interest. An experimental study is conducted to qualitatively assessing both approaches in comparison with the original DWT compression technique, when applied to a set of medical images.

I. INTRODUCTION

Image Compression is necessary that medical images be transmitted so as that reliable, improved and fast medical diagnosis performed by many centres could be facilitated. Medical image compression applications, diagnosis is effective only when compression techniques preserve all the relevant and important image information needed. This is the case with Lossless compression techniques. DWT based medical image compression, the wavelet coefficients keep all the information needed for reconstructing the medical image.

This paper aims at investigating two novel compression schemes of medical images, with principles as discussed above, based on the discrete 2-D wavelet transform, both having as goal the preservation of important image characteristics. Both the two more sophisticated compression schemes involving the DWT, utilized here in order to achieve preservation of significant image characteristics, extend this original approach by using fuzzy c-means clustering either of the wavelet bands or of the original image.

Both these methodologies have been successfully applied, in terms of the trade-off between the preservation of important image features and achievement of high compression ratios, to two medical images, in comparison with the simple DWT compression approach. The goal of this paper is to achieve higher compression ratio in images using the two-dimensional DWT more effectively by exploiting wavelet domain structure characteristics and image structure characteristics, which are usually unemployed in image compression.

The first compression scheme outlined here exploits correlation characteristics of the DWT coefficients in order to assign different compression threshold to the different distribution of correlated coefficients. The main result of such a clustering method is to find out how wavelet coefficients are correlated in term of the magnitude of there absolute values.

Image Compression Fundamentals

Let P1 be a dataset, containing an image. The topic of compression is to reduce the number of bits the image is represented by (with or without changing the image content). Let P2 be the compressed version of P1. If it is possible to

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reconstruct P1 (exactly) from P2, the amount of information (i.e. the picture itself) in P1 and P2 is the same, hence the representation of the picture by P1 contains redundant parts of information.

To quantify the effect of compression, two measures are defined:

- Compression Ratio and
- Relative Data Redundancy

Let P1 consist of n_1 , P2 of n_2 bits.

The Compression Ratio is defined by: $Cr = n_1/n_2$

The Relative Data Redundancy is defined by $Rd = 1-1/Cr$

The Three Types of Redundancy

1. coding redundancy = red. with respect to data representation
2. interpixel redundancy = red. with respect to the image representation
3. psychvisual redundancy = red. with respect to the image content

A more effective way of interpixel redundancy reduction is the **LZW coding scheme** (Lempel Ziv Welch). The LZW coding applies codes to patterns of data sequences. The basic idea is to create codes with smaller bit length than the sequence represented. The speciality of the LZW algorithm is, that the codebook, i.e. the scheme for decoding, is implicitly given in the encoded data and therefore must not be explicitly specified.

II.EXISTING SYSTEM

Image compression plays a critical role in telemetric applications and especially in telemedicine. The difficulty, however, in several applications lies on the fact that, while high compression rates are desired, the applicability of the reconstructed images depends on whether some significant characteristics of the original images are preserved after the compression process has been finished.

III.PROPOSED SYSTEM

Image compression methodologies utilizing the DWT apply it to the whole original image. The different compression ratios are applied to the wavelet coefficient belonging in the different regions of interest, in which either each wavelet domain band of the transformed image or the image itself is clustered, respectively.

PIXEL CLASSIFICATION

- 1.The input image can be converted into matrix form using the intensity value.
- 2.It contain two steps:

Co-Occurrence

Sliding window

Co-Occurrence Matrix

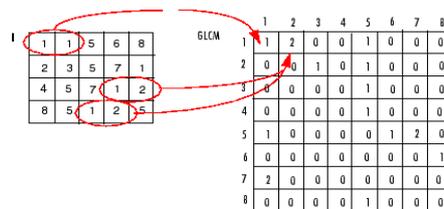
A Co-Occurrence matrix, also referred to as a co-occurrence distribution, is defined over an image to be the distribution of an co-occurring value of the given offset.

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EXAMPLE IMAGE 8 TONES



Gray-Level Co-occurrence Matrices (GLCMs)

Consider the image (below left). If we use the position operator “1 pixel to the right and 1 pixel down” then we get the gray-level co-occurrence. The first entry comes from the fact that 4 times a 0 appears below and to the right of another 0.

The factor 1/16 is because there are 16 pairs entering into this matrix, so this normalizes the matrix entries to be estimates of the co-occurrence probabilities. For statistical confidence in the estimation of the joint probability distribution, the matrix must contain a reasonably large average occupancy level.

Achieved either by (a) restricting the number of amplitude quantization levels (causes loss of accuracy for low-amplitude texture), or (b) using large measurement window. (causes errors if texture changes over the large window).

Typical compromise:

- 16 gray levels and window size of 30 or 50 pixels on each side. Now we can analyze C
- maximum probability entry
- element difference moment of order k: $\sum_i \sum_j |i - j|^k c_{ij}$
- This descriptor has relatively low values when the high values of C are near the main diagonal.
- For this position operator, high values near the main diagonal would indicate that bands of constant intensity running “1 pixel to the right and 1 down” are likely. When k = 2, it is called the contrast:
- This is a measure of randomness, having its highest value when the elements of C are all equal. In

Problems associated with the co-occurrence matrix methods:

- they require a lot of computation (many matrices to be computed)
- features are not invariant to rotation or scale changes in the texture

Sample Question on GLCMs

Here are 4 different texture patches of size 96x96 pixels. All the pixels in the patch (quantized to 16 levels) were used to form GLCMs shown below. The position operator was “one down and one to the right.” Decide which texture patch gave rise to each GLCM. Note that 3 of the plots show perspective views of the GLCM from the vantage point of the (0,0) position. However, one of the plots has the (0,0) matrix coordinate position placed in the upper left corner since that provides a better view. So check the axis labels.

Sliding Window

The goal of the first stage of this second methodology is therefore, to cluster the image into two classes, namely, in significant and non significant textural regions. To this end, first, the image is raster scanned with sliding window of M*M dimensions. We have experimented with 256*256 images and we have found that M=8 is a good size for the sliding window.

For each such window we perform a texture identification analysis based on co-occurrence matrices.

We have considered only four features namely:

1. Energy Angular Second Moment:

$$F1 = \sum_i \sum_j p(i, j)^2$$

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2. Correlation:

$$F2 = \frac{\sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i*j) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

3. Inverse Difference Moment:

$$F3 = \sum_i \sum_j \frac{1}{1+(i-j)} p(i,j)$$

4. Entropy:

$$F4 = \sum_i \sum_j p(i,j) \log_2(p(i,j))$$

Clustering Fuzzy C-Means

This algorithm works by assigning membership to each data point corresponding to each cluster centre on the basis of distance between the cluster centre and the data point. More the data is near to the cluster centre more is its membership towards the particular cluster centre. Clearly, summation of membership of each data point should be equal to one. After each iteration membership and cluster centres are updated according to the formula:

$$\mu_{ij} = 1 / \sum_{k=1}^c (d_{ij} / d_{ik})^{(2/m-1)}$$

$$v_j = (\sum_{i=1}^n (\mu_{ij})^m x_i) / (\sum_{i=1}^n (\mu_{ij})^m), \forall j = 1, 2, \dots, c$$

Where,

'n' is the number of data points.

'v_j' represents the jth cluster centre.

'm' is the fuzziness index m ∈ [1,

∞]. 'c' represents the number of cluster centre.

'μ_{ij}' represents the membership of ith data to jth cluster center

'd_{ij}' represents the Euclidean distance

between ith data and jth cluster center

Main objective of fuzzy c-means algorithm is to minimize:

$$J(U, V) = \sum_{i=1}^n \sum_{j=1}^c (\mu_{ij})^m \|x_i - v_j\|^2$$

Where, '||x_i - v_j||' is the Euclidean distance between ith data and jth cluster centre.

Algorithmic steps for Fuzzy c-means clustering

Let X = {x₁, x₂, x₃ ..., x_n} be the set of data points and V = {v₁, v₂, v₃ ..., v_c} be the set of centres.

1) Randomly select 'c' cluster centres.

$$\mu_{ij} = 1 / \sum_{k=1}^c (d_{ij} / d_{ik})^{(2/m-1)}$$

2) Calculate the fuzzy membership 'μ_{ij}' using:

3) Compute the fuzzy centres 'v_j' using:

$$v_j = (\sum_{i=1}^n (\mu_{ij})^m x_i) / (\sum_{i=1}^n (\mu_{ij})^m), \forall j = 1, 2, \dots, c$$

4) Repeat step 2) and 3) until the minimum 'J' value is achieved or ||U^(k+1) - U^(k)|| < β.

where

'k'

is

the

iteration

step.

'β'

is

the

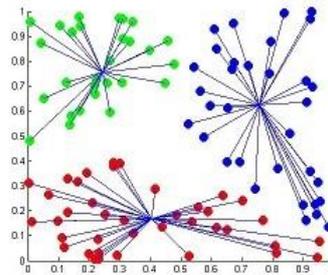
termination

criterion

between

[0, 1].

' $U = (\mu_{ij})_{n \times c}$ ' is the fuzzy membership matrix.
' J ' is the objective function.



IV. RESULT OF FUZZY C-MEANS CLUSTERING

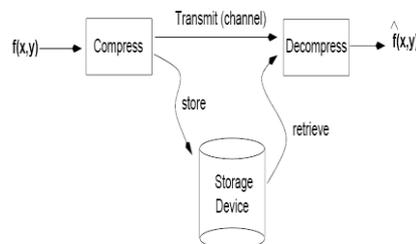
Advantages

- 1) Gives best result for overlapped data set and comparatively better than k-means algorithm.
- 2) Unlike k-means where data point must exclusively belong to one cluster centre here data point is assigned.

Goal of Image Compression:

Digital images require huge amounts of space for storage and large bandwidths for transmission.

1. A 640 x 480 colour image requires close to 1MB of space.
2. The goal of image compression is to reduce the amount of data required to represent a digital image.



Reduce storage requirements and increase transmission rates

Discrete Wavelet Transformation (DWT):

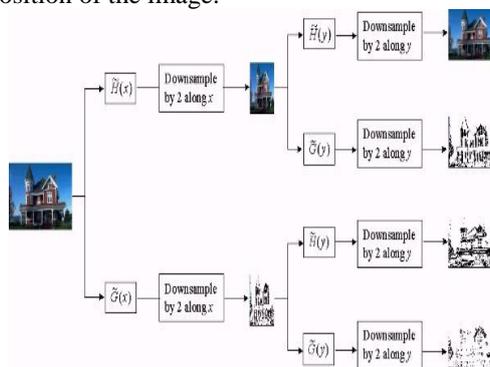
- ♦ The wavelet transform (WT) has gained widespread acceptance in signal processing and image compression.
- ♦ Because of their inherent multi-resolution nature, wavelet-coding schemes are especially suitable for applications where **scalability** and **tolerable degradation** are important
- ♦ Recently the JPEG committee has released its new image coding standard, JPEG-2000, which has been based upon DWT.
- ♦ Wavelet transform decomposes a signal into a set of basis functions.
- ♦ These basis functions are called **wavelets**
- ♦ Wavelets are obtained from a single prototype wavelet $y(t)$ called mother **wavelet** by **dilations** and **shifting**.

One-Dimensional Discrete Wavelet Transform

Two main methods exist for the implementation of 1D-DWT: the traditional convolution-based implementation [14] and the lifting-based.

Two-Dimensional Discrete Wavelet Transform

The basic idea of 2-D architecture is similar to 1-D architecture. A 2-D DWT can be seen as a 1-D wavelet scheme which transform along the rows and then a 1-D wavelet transform along the columns,. The 2-D DWT operates in a straightforward manner by inserting array transposition between the two 1-D DWT. The rows of the array are processed first with only one level of decomposition. This essentially divides the array into two vertical halves, with the first half storing the average coefficients, while the second vertical half stores the detail coefficients. This process is repeated again with the columns, resulting in four sub-bands (see Fig. 2) within the array defined by filter output. Fig. 2 shows a threelevel2-DDWT decomposition of the image.



V.THREE LEVEL DECOMPOSITION FOR 2D – DWT

Image consists of pixels that are arranged in two dimensional matrix, each pixel represents the digital equivalent of image intensity. In spatial domain adjacent pixel values are highly correlated and hence redundant. In order to compress images, these redundancies existing among pixels needs to be eliminated. DWT processor transforms the spatial domain pixels into frequency domain information that are represented in multiple sub bands, representing different time scale and frequency points. One of the prominent features of JPEG2000 standard, providing it the resolution scalability [3], is the use of the two-dimensional Discrete Wavelet Transform (2D-DWT)to convert the image samples into a more compressible form. It is considered as the key difference between JPEG and JPEG2000 standards. Since there is no need to divide the input image into non-overlapping 2-D blocks and its basis functions have variable length, wavelet-coding schemes at higher compression ratios avoid blocking artifacts.

Hence the compression artifacts are dispersed over a correspondingly larger area, and reducing the visual impact. Let Human visual system is very much sensitive to low frequency and hence, the decompose data available in the lower sub-band region and is selected and transmitted, information in the higher sub-bands regions are rejected depending upon required information content. Up to now, much work has been performed on DWT theory and many VLSI architectures have been proposed. paper [1] summarizes various schemes. Most popular one is the DA-DWT scheme that is suitable on FPGA, as it consumes fewer resources and has high throughput.

DWT Architecture

In this work, a modified DA-DWT architecture is designed based on the work reported in [15].This architecture uses Hare Transformation technique. The hardware architecture is shown in Fig. 4. It calculates the 2D-DWT in row-column fashion on the input image. The row filter calculates the DWT of each row of the external memory image data. Then, the resulting decomposed high pass and low-pass coefficients are stored in intermediate buffers, and the column filter calculates the vertical DWT as soon as there are sufficient coefficients generated by the row filter.

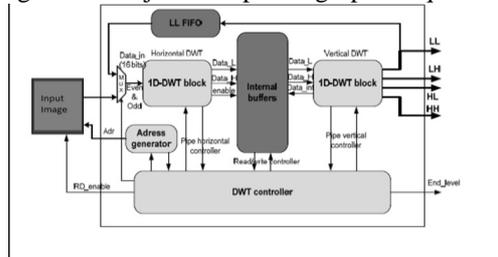
The architecture framework is composed of the following parts: two 1D-DWT blocks, internal buffers, LL FIFO used for multilevel decomposition, DWT theory and many VLSI architectures have been proposed. Paper [1] summarizes various schemes. Most popular one is the DA-DWT scheme that is suitable on FPGA, as it consumes fewer resources and has high throughput. . Let Human visual system is very much sensitive to low frequency and hence, the decompose data available in the lower sub-band region and is selected and transmitted,

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Information in the higher sub-bands regions are rejected depending upon required information content. Up to



Address generator block and Controller block.

The block diagram of DWT architecture

Shows DWT System in which adder, subtractor and right shifter are used to find out avg and difference components first even and odd samples are given to the adder then output of adder right shifted by one to give average components . The difference component is calculated by subtracting average and odd components. HDL model for the architecture uses Verilog it is simulated by using Xilinx.

VI.DECOMPRESSION-ROI

Most image-related tasks can process a subset of the pixels in an input image. Depending on the task, the selected pixels may either be a fairly arbitrary region, or only a regular sub image of the input image. The task parameter, region, which gives the region-of-interest, consists of a combination of subcommands. Each subcommand specifies either a sub region or the units of the coordinates used in subsequent sub-commands. The sub regions selected by multiple subcommands are effectively 'OR-ed' together to form the overall region. That is, the overall region selected is the 'union' (not intersection) of the sub regions. Region specification is composed of one or more of the following subcommands. Each subcommand can be abbreviated to uniqueness, and subcommands are separated by a comma.

images (z1,z2)

This selects the image planes $z1$ to $z2$ inclusive. $z2$ is optional, defaulting to the same value as $z1$.

quarter (z1,z2)

This is somewhat like the images command, except that it selects only the central quarter of each plane. Both $z1$ and $z2$ are optional.

box (xmin,ymin,xmax,ymax)(z1,z2)

This subcommand selects the pixels within a box whose corners are $xmin$, $ymin$, $xmax$ and $ymax$. $z1$ and $z2$ are optional, and are the same as in the image subcommand. If the $(z1,z2)$ part is missing, a default is used (generally all planes are selected).

polygon(x0,y0,x1,y1,x2,y2,...)(z1,z2)

This gives the vertices of a polygon. $\text{box}(xmin,ymin,xmax,ymax)$ is equivalent to $\text{poly}(xmin,ymin,xmax,ymin,xmax,ymax,xmin,ymax)$. $z1$ and $z2$ are the same as with the images and boxes subcommands.

mask(name)

This selects pixels according to the mask given by the mask item in the dataset *name*. The units used for the coordinates are controlled by the following subcommands:

abspixel

Subsequent coordinates are given as absolute pixel values (i.e. values ranging from 1 to $NAXISi$ - see [prthd](#) or [itemize](#)). This affects image coordinates and the coordinates along the third dimension. This is also the default.

relpixel

Subsequent image coordinates are relative to the reference pixel, as defined by the header of the map of interest. Use [prthd](#) to see the reference pixel is ($CRPIXi$).

relcenter

Subsequent image coordinates are relative to the central pixel of the image. This is somewhat like the relpixel command, but used the image centre, rather than the reference pixel.

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arcsec

Subsequent image coordinates are given in arcseconds, and are relative to the reference pixel of the map of interest.

kms

Subsequent coordinates in the third dimension are given in km/s.

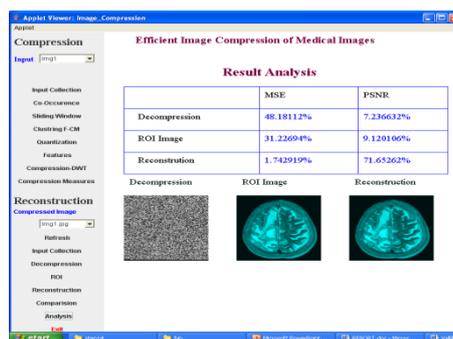
The region-of-interest specifications can become rather involved, when complex regions are used. As with visibility data selection, @ files (see Section 2.5) are a convenient way to store these.

There are some warnings for those accustomed to the select visibility data selection method:

- The subcommands of a region of interest are logically OR'ed together, whereas in the visibility data selection it is a logically AND. For *u-v* select the logical OR must be explicitly given by use of the or subcommand.
- The subcommands do not allow a plus or minus prefix, like the visibility data selection does.
-

RECONSTRUCTION OF AN IMAGE

The original image can be recovered from the Region of Interest (ROI) and also remove Gaussian noise.



Decompression Result Analysis

VII.CONCLUSION

Two novel image compression schemes for medical images have been presented based on the 2-D DWT and the fuzzy C-Means based clustering. The promising results obtained concerning reconstructed images quality as well as preservation of significant image details, while, on the other hand achieving high compression rates, illustrate that the proposed approaches deserve further investigations. The main problem remaining to be dealt with is the elimination of blocking effects in the partitions boundaries that is there is need for smoothing the reconstructed image in these boundaries.

VIII.FUTURE ENHANCEMENT

It is necessary that medical images be transmitted so as that reliable, improved and fast medical diagnosis. It supports the people those who have no proper Hospitalization Facilities. The future dream about this project is to implement this project in Every Hospitals.

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