MEDICAL IMAGE COMPRESSION USING REGION GROWING SEGMENATION

R.Arun, M.E(Ph.D)
Research scholar
M.S University

Dr.D.Murugan Asst.Prof
Department of Computer science & Engg
M.S University

Abstract:
The easy, rapid, and reliable digital transmission and storage of medical and biomedical images would be a tremendous boon to the practice of medicine. Patients in rural areas could have convenient access to second opinions. Patients readmitted to hospitals could have earlier imaging studies instantly available. Rather than waiting for others to finish with hardcopy films, medical and surgical teams collaborating on patient care could have simultaneous access to imaging studies on monitors throughout the hospital. This long-term digital archiving or rapid transmission is prohibitive without the use of image compression to reduce the file sizes.
As medical/biological imaging facilities move towards complete film-less imaging, compression plays a key role. Although lossy compression techniques yield high compression rates, the medical community has been reluctant to adopt these methods, largely for legal reasons, and has instead relied on lossless compression techniques that yield low compression rates. The true goal is to maximize compression while maintaining clinical relevance and balancing legal risk.

Now-a-days in medical field the digitized medical information such as computed tomography (CT), magnetic resonance imaging (MRI), generates increasingly important volumes of data is an important challenge to deal with is the storage, retrieval and transmission requirements of enormous data, from one place to another place for urgent purpose including medical images. Compression is one of the indispensable techniques to solve this problem. In this paper we offer a lossless compression method with the segmentation for compression of medical images. In this method the medical image is segmented and compressed by wavelet method to increase the compression ratio and to store in a less space. Here we use the CT and MRI images and analyzed in detail.

Introduction:

Medical image compression:

There are two types of image compression: lossless and lossy. With lossless compression, the original image is recovered exactly after decompression. Unfortunately, with images of natural scenes it is rarely possible to obtain error-free compression at a rate beyond 2:1. Much higher compression ratios can be obtained if some error, which is usually difficult to perceive, is allowed between the decompressed image and the original image. This is lossy compression. In many cases, it is not necessary or even desirable that there be error-free reproduction of the original image. For example, if some noise is present, then the error due to that noise will usually be significantly reduced via some denoising method. In such a case, the small amount of error introduced by lossy compression may be acceptable. Another application where lossy compression is acceptable is in fast transmission of still images over the Internet.
Before the various image compression techniques are discussed, consider the motivation behind using compression. A typical 12-bit medical X-ray may be 2048 pixels by 2560 pixels in dimension. This translates to a file size of 10,485,760 bytes. A typical 16-bit mammogram image may be 4500 pixels by 4500 pixels in dimension for a file size of 40,500,000 (40 megabytes)! This has consequences for disk storage and image transmission time. Even though disk storage has been increasing steadily, the volume of digital imagery produced by hospitals and their new film less radiology departments has been increasing even faster. Even if there were infinite storage, there is still the problem of transmitting the images.

An image is a collection of measurements in two-dimensional (2-D) or three-dimensional (3-D) space. In medical images, these measurements or image intensities can be radiation absorption in X-ray imaging, acoustic pressure in ultrasound, or RF signal amplitude In MRI. If a single easurement is made at each location in the image, then the image is called a scalar image. With the growth of technology and the entrance into the Digital Age, the world has found itself amid a vast amount of information. Dealing with such enormous amount of information can often present difficulties. Digital information must be stored and retrieved in an efficient manner, in order for it to be put to practical use. Data compression is a fascinating topic when considered by it.

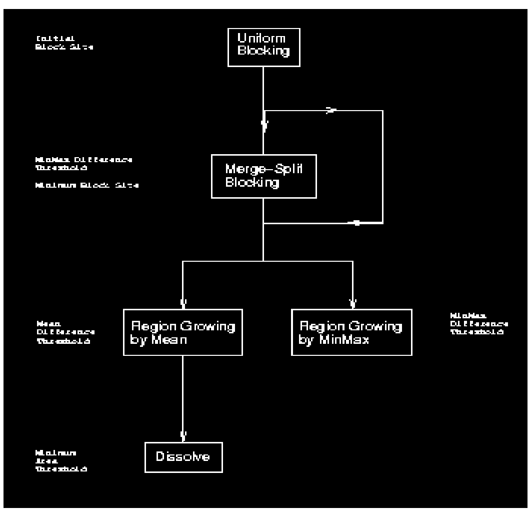
Segmentation:

It refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics

Region growing methods:
The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, δ, is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region.

Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed. Unseeded region growing is a modified algorithm that doesn't require explicit seeds. It starts off with a single region A_1 – the pixel chosen here does not significantly influence final segmentation. At each iteration it considers the neighboring pixels in the same way as seeded region growing. It differs from seeded region growing in that if the minimum δ is less than a predefined threshold T then it is added to the respective region A_j. If not, then the pixel is considered significantly different from all current regions A_i and a new region A_{n+1} is created with this pixel.

Block Diagram of Region Growing Algorithms



Compression Method:

3. Ezw Encoding

The EZW algorithm is based on four key concepts: 1) a discrete wavelet transform or hierarchical sub band decomposition, 2) prediction of the absence of significant formation across scales by exploiting the self-similarity inherent in images, 3) entropy-coded successive approximation quantization, and 4) universal lossless data compression which is achieved via adaptive Huffman encoding. The EZW encoder was originally designed to operate on images (2D-signals) but it can also be used on other dimensional signals. The EZW encoder is based on progressive encoding to compress an image into a bit stream with increasing accuracy. This means that when more bits are added to the stream, the decoded image will contain more detail, a property similar to JPEG encoded images. Using an embedded coding algorithm, an encoder can
terminate the encoding at any point thereby allowing a target rate or target accuracy to be met exactly. Also, given a bit stream, the decoder can cease decoding at any point in the bit stream and still produce exactly the same image that would have been encoded at the bit rate
corresponding to the truncated bit stream. In addition to producing a fully embedded bit stream, EZW consistently produces compression results that are competitive with virtually all known compression algorithm on standard test images It is similar to the representation of a number
like π (pi). Every digit we add increases the accuracy of the number, but we can stop at any accuracy we like. Progressive encoding is also known as embedded encoding, which explains the E in EZW.

Embedded zerotree wavelet (EZW) algorithm
The embedded zerotree wavelet algorithm (EZW) is a simple, yet remarkable effective, image compression algorithm, having the property that the bits in the bit stream are generated in order of importance, yielding a fully embedded code. Using an embedded coding algorithm, an encoder can terminate the encoding at any point thereby allowing a target rate or target distortion metric to be met exactly. Also, given a bit stream, the decoder can cease decoding at any point in the bit stream and still produce exactly the same image that would have been encoded at the bit rate corresponding to the truncated stream. In addition to producing a fully embedded bit stream, EZW consistently produces compression results that are competitive with virtually all known compression algorithms.

The algorithm
The EZW output stream will have to start with some information to synchronize the decoder. The minimum information required by the decoder is the number of wavelet transform levels used and the initial threshold, if we assume that always the same wavelet transform will be used. Additionally we can send the image dimensions and the image mean. Sending the image mean is useful if we remove it from the image before coding. After imperfect reconstruction the decoder can then replace the imperfect mean by the original mean. This can increase the PSNR significantly.

The first step in the EZW coding algorithm is to determine the initial threshold. If we adopt bitplane coding then our initial threshold t_0 will be

$$t_0 = 2^{FLOOR\left(\log_2\left(MAX\left(\left|\gamma(x,y)\right|\right)\right)\right)}$$

Here MAX(.) means the maximum coefficient value in the image and $\gamma(x,y)$ denotes the coefficient. With this threshold we enter the main coding loop (I will use a C-like language):

```
threshold = initial_threshold;
do
{
 dominant_pass(image);
 subordinate_pass(image);
 threshold = threshold/2;
}
while (threshold>minimum_threshold);
```

We see that two passes are used to code the image. In the first pass, the *dominant pass*, the image is scanned and a symbol is outputted for every coefficient. If the coefficient is larger than the threshold a **P** (positive) is coded, if the coefficient is smaller than minus the threshold an **N** (negative) is coded. If the coefficient is the root of a zerotree then a **T** (zerotree) is coded and finally, if the coefficient is smaller than the threshold but it is not the root of a zerotree, then a **Z** (isolated zero) is coded. This happens when there is a coefficient larger than the threshold in the subtree. The effect of using the **N** and **P** codes is that when a coefficient is found to be larger than the threshold (in absolute value or magnitude) its two most significant bits are outputted (if we forget about sign extension).

Note that in order to determine if a coefficient is the root of a zerotree or an isolated zero, we will have to scan the whole quad-tree. Clearly this will take time. Also, to prevent outputting codes for coefficients in already identified zerotrees we will have to keep track of them. This means memory for book keeping.

Finally, all the coefficients that are in absolute value larger than the current threshold are extracted and placed without their sign on the subordinate list and their positions in the image are filled with zeroes. This will prevent them from being coded again.

The second pass, the *subordinate pass*, is the refinement pass. In [Sha93] this gives rise to some juggling with uncertainty intervals, but it boils down to outputting the next most significant bit of all the coefficients on the subordinate list. In [Sha93] this list is ordered (in such a way that the decoder can do the same) so that the largest coefficients are again transmitted first. Based on [Alg95] we have not implemented this sorting here since the gain seems to be very small but the costs very high.

The main loop ends when the threshold reaches a minimum value. For integer coefficients this minimum value equals zero and the divide by two can be replaced by a shift right operation. If we add another ending condition based on the number of outputted bits by the arithmetic coder then we can meet any target bit rate *exactly* without doing too much work.

We can summarize the above with the following code fragments, starting with the dominant pass.

```
/*
 * Dominant pass
 */
initialize_fifo();
while (fifo_not_empty)
{
 get_coded_coefficient_from_fifo();
 if coefficient was coded as P, N or Z then
 {
  code_next_scan_coefficient();
  put_coded_coefficient_in_fifo();
  if coefficient was coded as P or N then
  {
   add abs(coefficient) to subordinate list;
   set coefficient position to zero;
  }
 }
}
```

Here we have used a FIFO to keep track of the identified zerotrees. If we want to enter this loop we will have to initialize the FIFO by “manually” adding the first quad-tree root coefficients to the FIFO. Depending on which level we start in the left of figure 2 this means coding and putting at least three roots in the FIFO. The call of code_next_scan_coefficient() checks the next uncoded coefficient in the image, indicated by the scanning order and outputs a **P**, **N**, **T** or **Z**. After coding the coefficient it is put in the FIFO. This will automatically result in a Morton scan order. Thus, the FIFO contains only coefficients which have already been coded, i.e. a **P**, **N**, **T** or **Z** has already been outputted for these coefficients. Finally, if a coefficient was coded as a **P** or **N** we remove it from the image and place it on the subordinate list.

This loop will always end as long as we make sure that the coefficients at the last level, i.e. the highest subbands (HH1, HL1 and LH1 in figure 2) are coded as zerotrees.

After the dominant pass follows the subordinate pass:

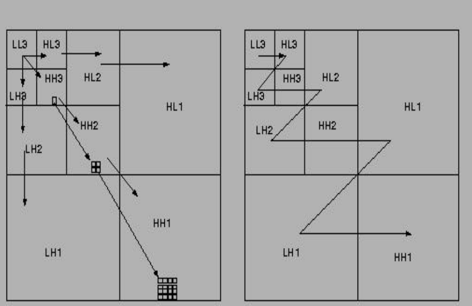
```
/*
```

```
 * Subordinate pass
 */
subordinate_threshold = current_threshold/2;
for all elements on subordinate list do
{
  if (coefficient>subordinate_threshold)
  {
    output a one;
    coefficient = coefficient-subordinate_threshold;
  }
  else output a zero;
}
```

If we use thresholds that are a power of two, then the subordinate pass reduces to a few logical operations and can be very fast.

Zerotree data structure

A wavelet coefficient *x* is said to be insignificant with respect to a given threshold *T* if $|x|<T$. The zerotree is based on the hypothesis that if a wavelet coefficient at a coarse scale is insignificant with respect to a threshold, then all wavelet coefficients of the same orientation in the same spatial location at the finer scale are likely to be insignificant with respect to the same threshold. More specifically, in a hierarchical subband system, with the exception of the highest frequency subbands, ever coefficient at a given scale can be related to a set of coefficients at the next finer scale of similar orientation. The coefficient at the coarse scale is called the *parent*, and all coefficients corresponding to the same spatial location at the next finer scale of similar orientation are called *children*. Similar, we can define the concepts *descendants* and *ancestors*.The data structure of the zerotree can be visualized in Figure . Given a threshold *T* to determine whether or not a coefficient is significant, a coefficient *x* is said to be an element of a *zerotree* for the threshold *T* if itself and all of its descendents are insignificant with respect to the threshold *T*. Therefore, given a threshold, any wavelet coefficient could be represented in one of the four data types: zerotree root (ZRT), isolated zero (IZ) (it is insignificant but its descendant is not), positive significant (POS) and negative significant (NEG).



(a) Zerotree data structure. (b) Coefficients scaning order

Dominant pass

Shapiro's algorithm creates rooted trees using a pixel of the LL subband for the root of each tree and a specific order of similarly positioned pixels from the other subbands for children. There are two types of passes performed: a dominant pass and a subordinate pass. The dominant pass finds pixel values above a certain threshold, and the subordinate pass quantizes all significant pixel values found in this and all previous dominant passes previous.

A dominant pass checks all trees for significant pixel values with respect to a certain threshold. The initial threshold is chosen to be one-half of the maximum magnitude of all pixel values. Subsequent dominant pass thresholds are always one-half the previous pass threshold. When an insignificant pixel value is found, and a check of all it's children reveals that they too are insignificant, then it is possible to encode that pixel and all it's children with one symbol, a zerotree root, in place of a symbol for that pixel and a symbol for each of that pixel's children, thus achieving compression. Pixel values found to be significant in the dominant pass are encoded with the symbol positive, for a value greater than zero, or negative, for a value less than zero, then those pixel values are added to a subordinate list for quantization, and the pixel value in the subband is then set to zero for the next dominant pass. Pixel values found to be insignificant in the dominant pass but with significant children are coded as isolated zeros. So, the dominant passes map pixel values to a four symbol alphabet which can then be further encoded by using an adaptive arithmetic coder.

Subordinate pass

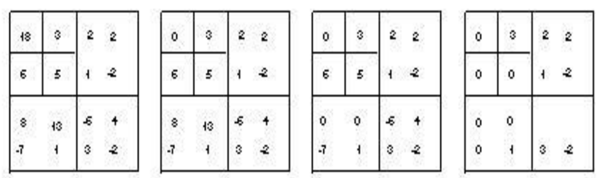
After each dominant pass, a subordinate pass is then performed on the subordinate list which contains all pixel values previously found to be significant. The subordinate pass performs pixel value quantization which achieves compression by telling the decoder with a symbol roughly what the pixel value is instead of exactly what the pixel value is. Since the initial threshold is one-half the maximum magnitude of all pixel values for the first dominant pass, then in the first subordinate pass only two ranges are specified in which a significant pixel value could lie: the upper half of the range between the maximum pixel value and the initial threshold, or the lower half of the same range. A pixel value in the upper half of the range gets coded with the symbol upper (for upper part of the range), while a pixel value in the lower half gets coded with the symbol lower. A pixel value found to be in a particular range is quantized, from the decoders viewpoint, to the midpoint of that range. Upon subsequent subordinate passes the threshold has been cut in half and so there are twice as many ranges as the last subordinate pass plus two new ranges corresponding to the new lower threshold. By reading the subordinate symbol corresponding to a significant pixel and knowing the threshold, the decoder is able to determine the range in which the pixel lies and reconstructs the pixel value to the midpoint of that range. Thus from the decoders viewpoint the rough estimate of a significant pixel's value is getting more refined and accurate as more subordinate passes are made. So, the subordinate passes quantize pixel values to a two symbol alphabet which then get encoded by using an adaptive arithmetic coder as described by Witten, Neal, and Cleary, thus achieving compression.

Decoding

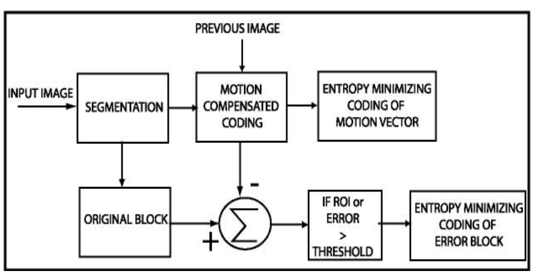
What is needed for decoding an image compressed by Shapiro's algorithm is the initial threshold, the original image size, the subband decomposition scale and, of course, the encoded bit stream. The decoder then decompresses the arithmetically encoded files into symbol files, creates all the proper size subbands needed since it knows the subband decomposition scale and the original image size, and proceeds to undo the Shapiro compression since it knows the initial threshold and the subband scanning order.

An example

We use a two scale wavelet image as a simple to show the algorithm. The original image is shown in Figure.

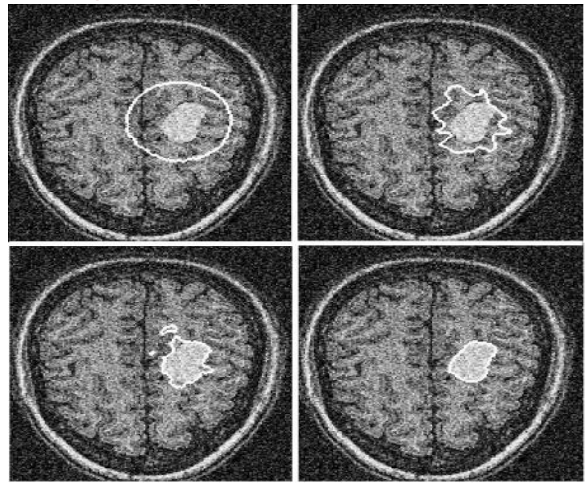


(c) Initial image (d) After DP 1 (e) After DP 2 (f) After DP 3



Conclusion:

In this paper we used the seeded region growing algorithm for segmentation for segmenting the medical image and EZW for compression method and the compression ratio is high and the segmentation



Test Image Compression Ratio

Image1	11.78 34.03
Image2	13.84 33.39

References:

[3] A. Abu-Hajar and R. Shankar, “Enhanced Partial-EZW for Lossless Image Compression” Acoustics, Speech and Signal processing 2003, Proceedings (ICASSP ’03)

[9] Park, K., and Park, H.W.: ‘Region-of-interest coding based on set partitioning in hierarchical trees’, IEEE Trans. Circuits Syst. Video Technol., 2002, 12, (2), pp. 106–11

[3] Yian-Leng Chang, Xiaobo Li, “Adaptive image region-growing”, IEEE Transactions on Image Processing, vol.3, no.6, Nov. 1994, pp.868-72.

[4] Rolf Adams and Leanne Bischof, “Seeded Region Growing”, IEEE Transactions on Image processing, Vol.16, No.6, June, 1994, pp.641-47

[5] Hojjatoleslami SA, Kittler J., “Region growing: a new approach”, IEEE Transactions of Image Processing, vol.7, no.7, July 1998, pp.1079-84.