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MRC Document Compression Using SPIHT

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Abstract:
Digital image compression technology is of special interest for the fast transmission and real-time processing of digital image information. Image compression is a technique developed for a long time, plus there are several approaches which reduce the compression rate, and accelerate computation time, still we need a lot to go to improve the efficacy of compression. In this paper, we are compressing document files containing images and text. In comparisons to state-of-the-art commercial MRC products and selected segmentation algorithms in the literature, our new algorithm achieves greater accuracy of non-text detection but with a lower false detection rate of text features.

1. Introduction

The mixed raster content (MRC) standard (ITU-TT.44) specifies a framework for document compression, which can dramatically improve the compression/quality trade off as compared to traditional lossy image compression algorithms.

Image compression is achieved by removing data redundancy while preserving information content. SPIHT is very fast and among the best image compression algorithms known today. According to the analysis of statistics the output binary stream of SPIHT encoding, Purpose a simple and effective method combined with Entropy for further compression that saves a lot of bits in the image data transmission.

2. Encoding

Encoding is the processes of putting a sequence of characters (letters, numbers, punctuation, and certain symbols) into a specialized format for efficient transmission or storage. The encoding process contains 3 Stages such as preprocessing and Segmentation, DWT, finally SPIHT.

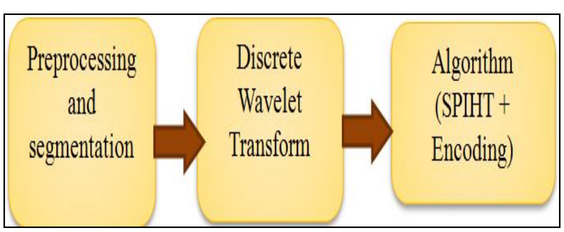

Figure 1: Encoding Process

2.1. Segmentation

The purpose of segmentation is to divide an image into “visually sensible” regions corresponding to objects of interest. Segmentation is the “dual “of edge detection where we focus on finding object boundaries. In most cases, the pixels inside a region are homogeneous (same brightness or color).

2.1.1. Thresholding

The basic idea of image thresholding is to divide the intensity range in an image into two categories based on threshold value T.

- Background ={0….T-1}
- Object ={T…255}

The key is finding the threshold value T that produces the most sensible results. Many interactive image processing systems allow users to select thresholds manually. Some systems use a priori domain knowledge to select appropriate thresholds (eg.fax).Most automatic threshold selection methods are based on the intensity distribution of the input image and optimize some quality metric. First we apply the thresholding in that document and that result is given to the watershed segmentation.

2.1.2. Watershed Segmentation

The watershed segmentation is well known a segmentation algorithm used for gray scale images watershed is used for in topographic digital elevation models. The gradient magnitude is used often to preprocess a gray scale image prior to using the watershed transform for segmentation. This image has high pixel values along object edges and low pixel values everywhere else the watershed transform would result in watershed ridge lines along object ridge. The Sobel operation is used in image processing, particularly within edge detection algorithm.

The watershed segmentation proves that it is powerful and fast technique for both contour detection and region based segmentation. In principal, watershed segmentation depends on ridges to perform a proper segmentation, a property which is often fulfilled in contour detection where the boundaries of the objects are expressed as ridges. Region-based segmentation converts the edges of the objects into ridges by calculating an edge map of the image. Normally watershed segmentation is implemented by region growing based on a set of markers to avoid over-segmentation [6, 7] which is occurred due to normal watershed function. Each watershed methods use slightly different distance measures, but they share the property that the watershed lines appear as the points of equidistance between two adjacent minima. Meyer [5] use the topographical distance function for segmenting images using watershed segmentation, while Najman and Schmitt [4] present the watershed differences with classical edge detectors. Felkel et al. [7] use the shortest path cost between two nodes, which is defined as the smallest lexicographic cost of all paths between two points which reflects the flooding process when the water reaches a plateau.

2.2. Discrete Wavelet Transform

A Discrete wavelet transform is any wavelet transform for which the wavelet are discretely sampled as with other wavelet transform a key advantage it has over Fourier transform is temporal resolution, its frequency and captures both frequency and location information.

In recent years, wavelet transform [1][2] as a branch of mathematics developed, which has a good localization property in the time domain and frequency domain[3], can analyze the details of any scale and frequency. so it is superior to Fourier transform and DCT. It has been widely applied and improved in image processing particularly in compression. We first start the compression process using this DWT. It starts first level of compression and remaining process is carried out using SPIHT.

2.2.1. 1-DDiscrete Wavelets Transform

The discrete wavelets transform (dwt), which transforms a discrete time signal to a discrete wavelet representation. The steps involves is to discrete the wavelet parameters, which is used to reduce the previously continuous basis set of wavelets to a discrete and orthogonal/orthonormal set of basis wavelets.

$\psi_{m,n}(t) = 2^{m/2}\,\psi(2^m t - n)$; $m, n \in Z$ such that $-\infty < m, n < \infty$

The 1-D DWT is given as the inner product of the signal x(t) being transformed with each of the discrete basis functions.

$W_{m,n} = \langle x(t), \psi_{m,n}(t) \rangle$; $m, n \in Z$

The 1- D inverse DWT is given as:

$$x(t) = \sum_m \sum_n W_{m,n}\psi_{m,n}(t) \quad ; m, n \in Z$$

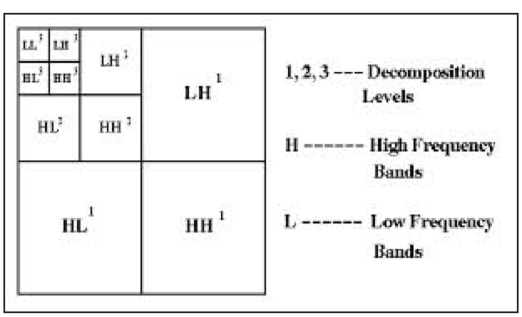

Figure 2: Discrete Wavelet Transforms

2.3. SPIHT

SPIHT means set partitioning in hierarchical trees. It is an image compression algorithm that explodes the inherent similarities across the sub bands in a wavelet decomposition of an image. SPIHT is computationally very fast and among the best compression algorithms know today. According to the analysis of statistics the output binary stream of SPIHT encoding, purpose a simple and effective method combine with Huffman encode for further compression.

One of the most efficient algorithms in the area of image compression is the Set Partitioning in Hierarchical Trees (SPIHT).In essence it uses a sub-band coder, to produce a pyramid structure where an image is decomposed sequentially by applying power complementary low pass and high pass filters and then decimating the resulting images. These are one-dimensional filters are applied in cascade (row then column) to an image where by creating four-way decomposition: LL (low pass then another low pass), LH (low pass then high pass), HL (high and low pass) and finally HH (high pass then high pass).

There exists a spatial relationship among the coefficient at different levels and frequency sub-bands in the pyramid representation has four direct descendants (off-springs) at locations:

(1)(,){(2, 2),(2,21),(21,2),(21,21)}ijijijijij=+++O

And each of them recursively maintains a spatial similarity to its corresponding four off-spring. This pyramid structure is commonly known as spatial orientation tree. The SPIHT algorithm takes advantage of the spatial similarity present in the wavelet coefficient that is significant by means of a binary search algorithm.

The SPIHT algorithm sends the top coefficient in the pyramid structure. That is performed using a progressive transmission scheme. It allows obtaining a high quality version of the original image from the minimal amount of transmitted data. By many research that the progressive transmission can significantly reduced the Mean Square Error (MSE) distortion for every bit-plane which was send.

To take advantage of the spatial relationship among the coefficient at different levels and frequency bands, the orders of the wavelets coefficient according to the significance test defined as follows:

$$\max_{(i,j) \in \tau_m} \left| C_{i,j} \right| \geq 2^n$$

Where the terms defined are, c means wavelet coefficient at the nth bit plane, at location (i, j) of the, *,ijm*τ subset of pixels, representing a parent node and its children. If the result of the significance test is YES an S flag is set to 1indicating that a particular test is significant. Suppose if the answer is NO, then the S flag is set to 0, and that coefficient is insignificant. Wavelets coefficients which are not significant at the nth bit-plane level may be significant at (n-1) the bit-plane or lower. This information is arranged in three separate lists according to the significance, they are list of insignificant sets (LIS), the list of insignificant pixels (LIP) and the list of significant pixels (LSP).In decoder, the SPIHT algorithm replicates the same number of lists. It uses the basic principle that if the execution path of any algorithm is defined by the results on its branching points and Because of the same sorting algorithm for encoder and decoder, it is easy for the decoder to recover the ordering information. Now the results of SPIHT encode show through the Figure3 and Figure4. After the result of encode it is given as input for the decode process. Figure shows the resize of encoded image.

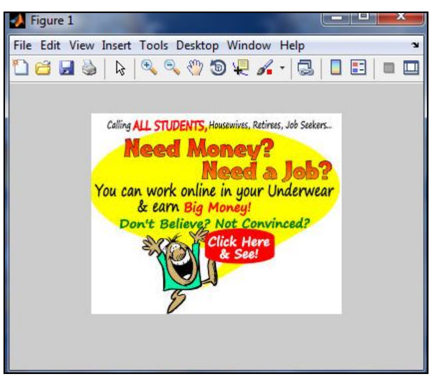

Figure 3: Original image

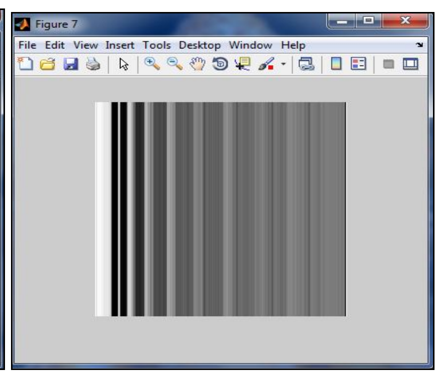

Figure 4: Encoding Image

3. Decoding

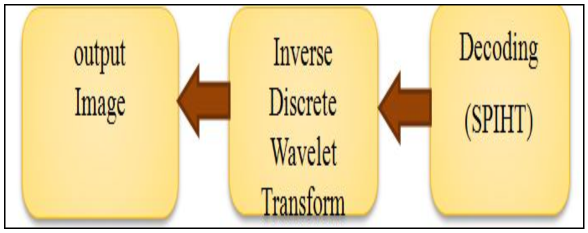

Figure 5: Decoding process

Decoding is the opposite process of an encoding process. That converts the encoded sequence to original sequence of characters. Encoding and decoding are used in many applications such as data communications and networks.

3.1. Wavelet Reconstruction

The reconstruction of the image is achieved by the inverse discrete wavelet transform (IDWT).the values are first up sampled and then passed to the filter. This represented as shown in fig 6.

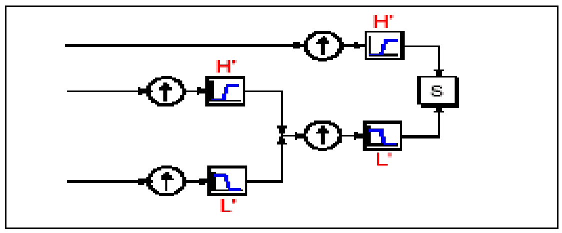

Figure 6: Wavelet Reconstruction

The wavelet reconstruction process consists of filtering and up sampling. Up sampling is the process of lengthening a signal component by inserting zeros between samples as shown in fig7:

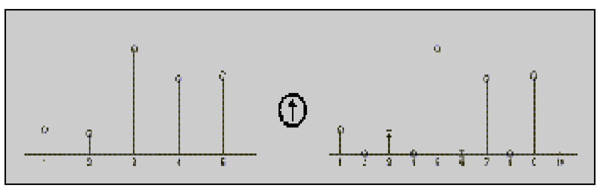
Figure 7: Reconstruction using up sampling

3.2. Inverse SPIHT

SPIHT decoding we use the original SPIHT decoder in order to obtain the decompressed images. After decoding process, we obtain a transform domain image (wavelet or contour let).In order to obtain the reconstructed image, we apply the inverse discrete wavelet transform (IDWT) or inverse wavelet-based contour let transform(IWBCT) as a result we obtain the final decompressed image.

The inverse process of the SPIHT is carried out for decoding. After the decoding the validated process is carried out to check the PSNR (Peak Signal to noise ratio), CR (Compression Ratio), Encoding time, Decoding time**.** The below figure: 8 show the PSNR status for the above fig: 4 encoded image. Comparison to other algorithm its PSNR is efficient**.**

CR = (Number of bits in the original image) / Number of bits in the compressed image)

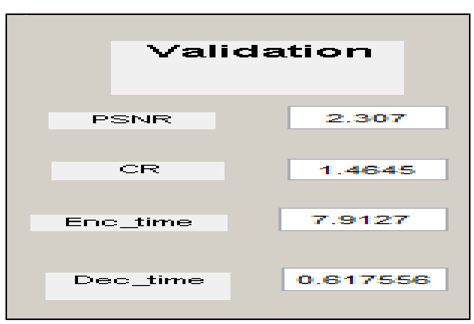

Figure 8: Validation Form

4. Conclusion

SPIHT is a simple and efficient algorithm with many unique and desirable properties. We demonstrated the outstanding efficiency of the DWT-SPIHT image compression solution. Thus we compress the mixed raster content with lower detection rate in text area and greater accuracy in non-text area. The segmentation will also improve for achieving the greater accuracy of text detection.

5. References

1. Antonini, M.; Barlaud, M,; Mathieu,p.; Daubechies, I. “Image Coding Using Wavelet Transform, ”IEEE trans. on Image Processing, Vol.1, no.2, pp.205-220.1992.
2. Ronald ore; Bjorn Jawerth; Bradley j.Lucier “image compression through Wavelet Transform coding” IEEE Trans. On Information Theory, Vol.38NO.2, pp.719-746, MARCH 1992
3. Lewis, A.S.; Knowles,g”Image Compression Using the 2-D Wavelet Transform, ”IEEE Trans. on Image Processing,Vol.I.NO.2,pp244-250,APRIL 1992.
4. Najman, L., Schmitt, M.: Watershed of a continuous function. Signal Processing38 (1) (1994)99-112
5. Meyer. Topographic distance and watershed lines. Signal Processing 38(1) (1994)113-125
6. Vincent, L., Soille, P.: Watersheds in digital spaces: An efficient algorithm based on immersion simulations. IEEE Trans.Pattern Anal.Mach.Intell.13 (6) (1991)583-598
7. Felkel, P., Bruckscheaiger, M., Wegenkittl, R.: Implementation and complexity of the watershed-from-marker algorithm computed as a minimal cost forest .Computer Graphics Forum 20(3) (2001)