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Lossy Image Compression Using Modified Spiht Algorithm

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Abstract

Real time transmission of images through handheld mobile/portable devices require an image coding algorithm that performs best at very low bit rate. A number of very successful wavelet-based image coding algorithms have been proposed in the literature. The existing image coding methods cannot support content-based spatial scalability with high compression. In mobile multimedia communications, image retargeting is generally required at the user end. However, content-based image retargeting is with high computational complexity and is not suitable for mobile devices with limited computing power. The work presented in this paper addresses the increasing demand of visual signal delivery to terminals with arbitrary resolutions, without heavy computational burden to the receiving end. In this paper, the principle of seam carving is incorporated into a wavelet codec (i.e., MSPIHT). For each input image, block-based seam energy map is generated in the pixel domain and the integer wavelet transform (IWT) is performed. Different from the conventional wavelet-based coding schemes, IWT coefficients here are grouped and encoded according to the resultant seam energy map. The bit stream is then transmitted in energy descending order. At the decoder side, the end user has the ultimate choice for the spatial scalability without the need to examine the visual content; an image with arbitrary aspect ratio can be reconstructed. Experimental results show that, for the end users, the received images with an arbitrary resolution preserve important content while achieving high coding efficiency for transmission.

Keywords: *Seam carving, IWT, EZW, Subbands, SOT, SPIHT,MSPIHT*

1. INTRODUCTION

One important trend occurring in the whole digital imaging industry is the increase in image size and resolution. It is a consequence of the development of better and less expensive image acquisition devices. This trend is certain to continue because digital imaging can only replace other technologies by providing super resolution and quality. In recent years there is an explosion in the amount of information available in the form of digital image data. Though the storage/bandwidth constraints are

surmounted to a great extent an efficient image compression algorithm always adds to the overall system performance A lot of algorithms were proposed in the literature. These algorithms are mainly divided into zerotree and zeroblock methods. Though both of the algorithms provide embedded coding and good compression efficiencies, zerotree algorithms were most popular in the literature, after which the zeroblock algorithms found their significance. The general idea of tree based algorithms is explained as follows.At low bit rates (i.e., high compression ratios) most of the coefficients produced by a subband transform (such as the wavelet transform) will be zero, or very close to zero. This occurs because “real world” images tend to contain mostly low frequency information (highly) correlated). However some high frequency information does occur (such as edges in the image). This is particularly important in terms of human perception of the image quality, and thus must be represented accurately in any high quality coding scheme. By considering the transformed coefficients as a tree (or trees) with the lowest frequency coefficients at the root node and with the children of each tree node being the spatially related coefficients in the next higher frequency subband, there is a high probability that one or more subtrees will consist entirely of coefficients which are zero or nearly zero, such subtrees are called zerotrees. In zerotree based image compression schemes such as Embedded Zerotree Wavelet coding (EZW)[1] and Set Partitioning in Hierarchical Trees (SPIHT) [3], the intent is to use the statistical properties of the trees in order to efficiently code the locations of the significant coefficients. Since most of the coefficients will be zero or close to zero, the spatial locations of the significant coefficients make up a large portion of the total size of a typical compressed image. These algorithms make use of the relation among different subbands existing in the same spatial orientation of an image. Since the image is transformed using DWT, the relation among the neighboring pixels of the image is preserved in the higher and higher subbands. These are called the intra subband correlations existing within each subband. The zerotree algorithms don’t take care of these intra subband correlations of an image subband. To rectify this deficiency zero block algorithms were proposed.Set Partitioning Embedded Block Coder (SPECK) is one of the prominent algorithms used in zero block approaches. This algorithm divides the image subband into blocks of

coefficients and encodes them into a progressive bit stream. SPECK is different from SPIHT and EZW in that it does not use trees which span and exploit the similarity across different subbands of wavelet decomposition; rather it makes use of sets in the form of blocks of contiguous coefficients within subbands.
It is obvious from the above explanation, that the zero tree algorithms use the inter-subband correlations existing among different scales of subbands. The zero block algorithms use the intra-subband correlations existing within each subband. The proposed scheme incorporates the seam carving technique and the Modified SPIHT algorithm uses a quantization in progressive bitstreams encoded by the SPIHT algorithm. As a result the number of significant bits increase at a given bit rate, which results in the improvement of PSNR and hence visual quality.

2.EXISTING IMAGE CODING ALGORITHMS

2.1 Embedded Zerotree Wavelet Coding
EZW [1] is a simple, yet remarkably effective image compression algorithm, having the property that the bits in the bit stream are generated in the 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 distortion metric to be met exactly. The algorithm can be explained as follows. 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. 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). A dominant pass is followed by a subordinate pass, in which all coefficients in the subordinate list are scanned and the specifications of the magnitudes available to the decoder are refined to an additional bit of precision.For each magnitude on the subordinate list, this refinement can be encoded using a binary alphabet with a ”1” symbol indicating that the true value falls in the upper half of the old uncertainty interval and a ”0” symbol indicating the lower half. The process continues to operate between dominant passes and subordinate passes where thehreshold is halved before each dominant pass. In the decoding operation, each decoded symbol, both during a dominant and subordinate pass, refines and reduces the width of the uncertainty interval in which the true value of the coefficient may occur. The encoding can cease at any time and the resulting bit stream contains all lower rate encodings.

2.2 Set Partitioning in Hierarchical trees (SPIHT)
The sorting algorithm divides the set of pixels into partitioning subsets *m* τ and performs the magnitude test If the decoder receives a “no” to that answer (the subset is insignificant), then it knows that all coefficients in *m* τ are insignificant. If the answer is “yes” (the subset is significant), then a certain rule shared by the encoder and the decoder is used to partition *m* τ into new subsets *m,l* τ and the significance test is then applied to the new subsets. This set division process continues until the magnitude test is done to all single coordinate significant subsets in order to identify each significant coefficient. To reduce the number of magnitude comparisons (message bits) we define a set partitioning rule that uses an expected ordering in the hierarchy defined by the subband pyramid. The sorting algorithm divides the set of pixels into partitioning subsets *m* τ and performs the magnitude test If the decoder receives a “no” to that answer (the subset is insignificant), then it knows that all coefficients in *m* τ are insignificant. If the answer is “yes” (the subset is significant), then a certain rule shared by the encoder and the decoder is used to partition *m* τ into new subsets *m,l* τ and the significance test is then applied to the new subsets. This set division process continues until the magnitude test is done to all single coordinate significant subsets in order to identify each significant coefficient. To reduce the number of magnitude comparisons (message bits) we define a set partitioning rule that uses an expected ordering in the hierarchy defined by the subband pyramid.

$$\underset{(i,j)\in T_m}{Max}\{|c_{i,j}|\} \geq 2^n \quad \text{---(1)}$$

2.3 Set Partitioning Embedded Block Coder (SPECK)
It exploits two fundamental characteristics of an image transform – the well-defined hierarchical structure and energy clustering in frequency and in space. SPECK is different from SPIHT and EZW in that it does not use trees which span and exploit the similarity across different subbands of wavelet decomposition; rather it uses the intrasubband correlations existing within each subband. The SPECK algorithm makes use of rectangular regions of image. These regions or sets, henceforth referred to as sets of type S, can be of varying dimensions. The dimension of a set S depends on the dimension of the original image and

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the subband level of the pyramidal structure at which the set lies.

3.PROPOSED METHOD

3.1 Seam Carving

The process allows the user to resize an image by removing a continuous path of pixels (a seam) vertically or horizontally from a given image. A seam is defined as a continuous path of pixels running from the top to the bottom of an image in the case of a vertical seam, while a horizontal seam is a continuous line of pixels spanning from left to right in an image.

3.1.1 Seam Carving Implementation

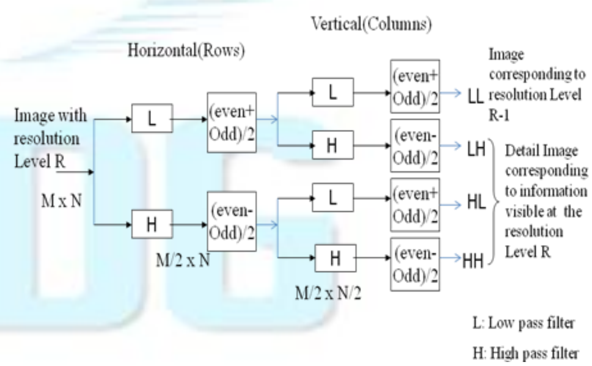
The first step in calculating a seam for removal or insertion involves calculating the gradient image for the original image. The gradient image is a common image that is used in both horizontal and vertical seam calculation, and can be calculated either from the luminance channel of a HSV image, or calculated for each of the R, G, and B channels, then averaging the three gradient images. The sobel operator was chosen for calculation of the gradient image in this project, but other gradient operators may be used. Once the gradient image is calculated, the next step is to calculate the energy map image. The energy map image needs to be calculated separately for either vertical or horizontal seams, and also needs to be recalculated after every seam removal. It is calculated by the following process for the vertical seam case (a horizontal energy image can be calculated using the same function, where the input image is transposed): for each pixel (i,j) in the gradient image (see Table 1), the value at (i,j) in the energy map is the sum of the current value at (i,j) from the gradient image and the minimum of the three neighboring pixels in the previous row, i.e. *min*((i-1,j-1),(i-1,j),(i-1,j+1)), from the energy map. For i=1 (the initial row), the values in the energy map image are set to those in the gradient image, and for when the pixel (i, j) is along the edge of an image, only (i-1,j) and either (i-1,j-1) or (i-1,j+1) are used depending on if (i,j) is on the right or left edges, respectively.

(i-1,j-1)	(i-1,j)	(i-1,j+1)
(i,j-1)	(i,j)	(i,j+1)
(i+1,j-1)	(i+1,j)	(i+1,j+1)

Table 1: Pixel indices

Once the energy map is calculated, the method to find the optimal seam is to first find the minimum value in the last row (which becomes the (i,j)th pixel), saving the pixel location for use in removal, then working backwards by finding the minimum of the 3 neighboring pixels of (i,j) in the (i-1)'th row and saving that pixel to the seam path. After the optimal seam is found, the path of pixels that make up the seam are removed from both the gradient image and the original RGB image, and the remaining pixels are shifted right or up to form a continuous image.
The process can be repeated to remove a set of seams, horizontally or vertically and will result in an image with reduced dimensions, but with the overall scene content intact. For the case of seam insertion (increasing the image size), a seam can be calculated along a given direction, and the average of the two neighboring pixels along the seam can be inserted. If the desired image size is to be increased by *N* pixels in a given direction, the computation of the first *N* seams to be removed along that direction must first be completed, and then averaged pixels are inserted along each successive seam, hence the limitation on the maximum increase in image size in my implementation noted earlier in the features and functionality section. This method of calculating *N* seams is used to avoid inserting pixels along the same seam repeatedly.

DWT BLOCK DIAGRAM



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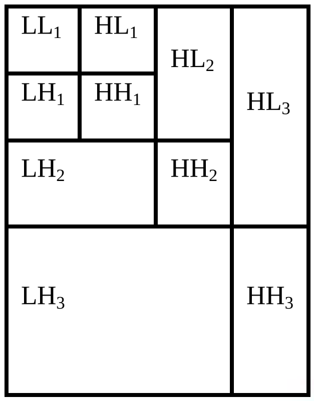


DWT SUB BAND STRUCTURE

3.2 Mspiht Algorithm

The SPIHT coder is a powerful image compression algorithm that produces an embedded bit stream from which the best reconstructed images in the mean square error sense can be extracted at various bit rates. The Modified SPIHT coding uses a Quantization Matrix which compresses the encoding redundant bits in the SPIHT encoded bitstreams. The perceptual image quality, however, is not guaranteed to be optimal since the coder is not designed to explicitly consider the human visual system (HVS) characteristics. Extensive HVS research has shown that there are three perceptually significant activity regions in an image: smooth, edge, and textured or detailed regions. By incorporating the differing sensitivity of the HVS to these regions in image compression schemes such as SPIHT, the perceptual quality of the images can be improved at all bit rates. Further, Hence MSPIHT can improve the above image qualities effectively.

Algorithm

1) Output n = $\lfloor \log_2(\max_{(i,j)}\{|c_{i,j}|\}) \rfloor$ to the decoder

2) Output μ_n, followed by the pixel coordinates $\eta(k)$ and sign of each of the μ_n coefficients such that $2^n \le |c_{i,j}| < 2^{n+1}$ (sorting pass).

3) Output the nth most significant bit of all the coefficients with $|c_{i,j}| \ge 2^{n+1}$ (i.e., those that had their coordinates transmitted in previous sorting passes), in the same order used to send the coordinates (refinement pass);

4) Decrement n by one, and go to Step 2).

A tree structure, called spatial orientation tree, naturally defines the spatial relationship on the hierarchical pyramid. Fig.3.6 shows how our spatial orientation tree is defined in a pyramid constructed with recursive four-subband splitting. Each node of the tree corresponds to a pixel and is identified by the pixel coordinate. Its direct descendants (offspring) correspond to the pixels of the same spatial orientation in the next finer level of the pyramid. The tree is defined in such a way that each node has either no offspring (the leaves) or four offspring, which always form a group of 2 x 2adjacent pixels. In Fig 3.6, the arrows are oriented from the parent node to its four offspring. The pixels in the highest level of the pyramid are the tree roots and are also grouped in 2 x 2adjacent pixels. However, their offspring branching rule is different, and in each group, one of them (indicated by the star in Fig.3.6) has no descendants.

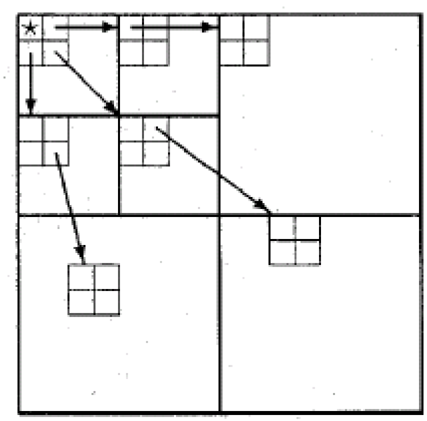
The following sets of coordinates are used to present the new coding method:

O (i,j): set of coordinates of all offspring of node (i, j);

D (i, j) : set of coordinates of all descendants of the node

H: set of coordinates of all spatial orientation tree roots (nodes in the highest pyramid level);

L(i, j) = D(i, j) - O(i, j) .



Structure in Modified SPIHT

3.3 Performance Measures

The Quality of the reconstructed image is measured in terms of mean square error (MSE) and peak signal to noise ratio (PSNR) ratio. The MSE is often called reconstruction error variance σ_q^2. The MSE between the original image f and the reconstructed image g at decoder is defined as

$$\text{MSE} = \sigma_q^2 = \frac{1}{N} \sum_{j,k} (f[j,k] - g[j,k])^2$$

Where the sum over j, k denotes the sum over all pixels in the image and N is the number of pixels in each image. From that the peak signal-to-noise ratio is defined as the ratio between signal variance and reconstruction error variance. The PSNR between two images having 8 bits per pixel in terms of decibels (dBs) is given by:

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

Generally when PSNR is 40 dB or greater, then the original and the reconstructed images are virtually indistinguishable by human eyes.

4. Conclusion

In this work, the Modified SPIHT(MSPIHT), the algorithm makes use of Seam carving & both intra- and inter-subband correlations in a single algorithm. This algorithm performs better at very low bit rate, compared to other state of art algorithms. This is mainly due to clustering of insignificant bits at each pass. Due to this, the number of significant bits at constant bit rate gets increases and adds significant information to the image at the receiver side which eventually increases the PSNR as well as visual quality. There is a sharp increase in the image quality, for the images reconstructed from MSPIHT than that of SPIHT algorithm.

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