Compression for Saliency Detected Images

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***Abstract*—An image compression technique is proposed, for the efficient representation of images. The method is called hybrid, as it performs lossless compression in the salient region and a lossy compression technique in the non-salient region of the image. This is done based on the key observation that, most of the important information in an image lies in the salient region. The discrete wavelet transform based compression, preserves the region quality in the salient region, while discrete cosine transform based lossy compression in the background region provides good compression ratio. Initially, a label propagation based approach is used for saliency detection. Here, both the background as well as the foreground information are propagated to detect the salient region in an image. Experimental results on various test images show noticeable improvements in the quality of the image and better reduction in size, when compared to other compression techniques.**

Keywords*— Saliency detection, Hybrid compression, Discrete wavelet transform, Discrete cosine transform.

I. INTRODUCTION

In this digital world, the transmission of information takes place worldwide by means of communication channels. This information has to be transmitted faster and in a very compact size. Reducing the size of data content sent, increases the rate of transmission and saves the energy required for transmission. In particular, when the image is sent, it becomes necessary to compress it, while doing this, quality of the recovered image should not be compromised. Hence, selection of efficient compression techniques is necessary. The more a particular image is compressed, the more the number of new images that acquire memory. This would imply the need for a compression scheme that would give a very high compression ratio. There are two compression techniques for image compression, lossy and lossless image compression. Lossy compression techniques achieve a high compression ratio, but it compromises the quality of recovered image ie.,low PSNR. Lossless compression achieves high quality of recovered image - high PSNR, but unable to achieve a good compression ratio. Method of compression, which can achieve good compression ratio without risking the quality of recovered image can be the best substitute for these two compression techniques.

A hybrid compression technique is proposed in the paper, which helps in efficient storage and transmission of large amount of images. The method make use of both lossy and lossless compression techniques for performing efficient content based compression. The method is called hybrid, as it performs lossless compression in the salient region and a lossy compression technique in the non-salient region of the image. This is done based on the key observation that, most of the important information in an image lies in the salient region. The discrete wavelet transform based compression, preserves the region quality in the salient region, while discrete cosine transform based lossy compression in the background region provides good compression ratio. Thus the proposed system ensures, good image compression without risking the quality of the salient region, the region which contains most of the important information in that image.

For the purpose of detecting the salient region in an image, a label propagation algorithm [4] is performed initially. The approach is based on the observation
that, propagation of the extracted foreground and back-ground labels helps in estimating saliency efficiently. For images with uniform background, border super-pixels are selected as the background labels and these are propagated to detect saliency. In case of complex scenes, foreground labels are also selected along with the background labels for saliency detection. Thus, the system automatically select the regions of high priority and then applies the compression technique intelligently, ensuring efficient storage of images while preserving the confidential data.

II. RELATED WORKS

Visual saliency is originally a task of predicting the eye-fixations on images, and recently has been extended to identifying a region containing the salient object. Saliency detection plays important role in many image processing applications. The proposed approach focuses on the salient object detection. Identifying the region of interest in an image mainly comes under two categories: top-down approach and bottom-up approach. In top-down approach we look for specific object. Prior knowledge about the target object is known. This approach is used in object recognition algorithms. On the other hand in bottom-up approach, we do not have prior knowledge about the region to be detected. This approach is used in detecting regions which are prominent or salient. In most of the bottom-up algorithms, low level cues like contrast [1], uniqueness, focussness [3] etc are exploited. Shen and Li [4] introduce an approach, which integrates both low level and high level cues [14] to detect the salient region with greater accuracy. This method is used to detect the important region in the proposed system.

In medical field, the salient region corresponds to the area under treatment. Any quality deficiency in this region is not affordable. Hence a compression technique, which helps in effective storage and trans-mission of large range of image while maintaining the quality of the salient region, is required. Application of lossy compression [13] will guarantee a high a compression ratio but the quality loss of the important region will be high. Recently, a number of adaptive compression

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 08, August-2016

techniques, making use of content [17] ,texture [7], object [10] etc., are adopted for efficient compression. But these approaches are limited to small range of images. Here a hybrid compression technique is proposed, which combines both lossy and lossless compression technique and applies adaptively in the non-salient and salient region respectively. The efficient saliency detection method accurately detects important regions in uniform as well and complex images. Hence the approach works on wide range of images providing good compression ratio, at the same time maintaining the quality of the salient region.

III. PROPOSED METHODOLOGY

The proposed method performs an intelligent compression technique in which the confidential data lying in the salient region of an image is preserved. This is achieved through 2 main steps: saliency detection and hybrid compression. Initially, an efficient saliency detection method is used to automatically detect the salient region in the image. The proposed system works on the assumption that most of the important data lies in the salient region of the image. After the saliency detection process, both the salient and the non-salient region is segmented out. Finally, the salient region is compressed using lossless DWT compression technique and a lossy compression is applied to the non-salient region. The framework of the proposed method is illustrated in Fig.1.

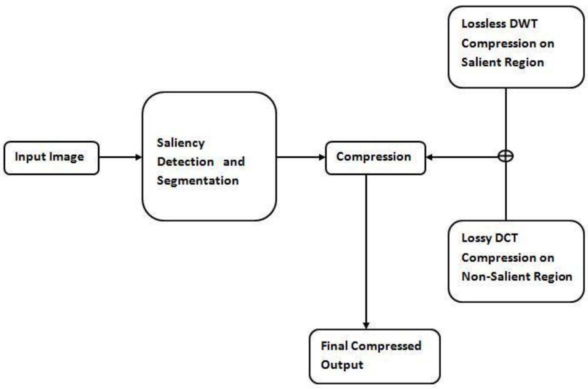

Figure 1. Flowchart of the proposed system

A. Label Propagation Based Saliency Detection

A label propagation saliency algorithm [4] is used to detect the salient object in the image. Given an image, it is first segmented using SLIC superpixel segmentation. The superpixels generated at the border regions are selected as boundary nodes B. Then an affinity matrix A is constructed among the superpixels to calculate the similarity between superpixels. With the help of this similarity measure, the final saliency mapping id performed.

Propagation Algorithm

The constructed affinity matrix A is utilized to propagate the background information to estimate the saliency measure. Given a dataset $R = \{r_1,\ldots r_l, r_{l+1},\ldots r_N\} \epsilon R^{DxN}$,where the former l regions serve as query labels, a similarity function $V = [V(r_1),\ldots,V(r_N)]^T$ such that $V : R \rightarrow [0,1] \epsilon R^{Nx1}$ is developed. The function V indicates the possibility of how similar each data point is to the labels. The similarity measure $V(r_i)$ satisfies

$$V_{t+1}(r_i) = {}_{j=1}^{N} a_{ij} V_t(r_j) \qquad (1)$$

where a_{ij} is the affinity entry and t is the recursion step.

Initialize the similarity measure of the query labels to 1 and the measure of the unlabelled nodes to 0, during the recursion process. For a given region, the similarity $V(r_i)$ is learned iteratively via propagation of the similarity measures of its neighbours $V(r_j)$ such that a region's final similarity to the labels is effectively influenced by the features of its surroundings.

Figure 2. Saliency Detection

In majority of the images, the inner propagation using background information alone works well. But in some cases, like in complex images, both the back-ground as well the foreground information is required to efficiently detect saliency. In-order to make this decision, a compactness score is calculated to measure the quality of the saliency map. Only if the compactness score is less than or equal to a compactness threshold $_2$ will be updated by the inter propagation using foreground and background information. Such a scheme not only ensures high quality of the saliency maps, but also improves the computational efficiency. The system utilizes three main cues, such as multi-scale saliency (MS), colour-contrast (CC) and edge density (ED) to detect the foreground labels [4]. Then, both the boundary as well as the foreground labels are propagated like the above algorithm and the results are combined to get the final saliency map.

B. Salient and Non-Salient Region Segmentation

After the detection of salient region using label propagation method, a segmentation map is done to segment out the salient region and the non-salient region. The saliency detection algorithm creates a gray scale image, is first converted to a black and white image by choosing an appropriate threshold. The boundaries of the salient region are extracted from the saliency detected image. These are then utilised to segment out both background and the foreground region of an input colour image. Thus, the segmented salient and non-salient region can be further used for lossless and lossy compression respectively, as proposed. Fig.3 shows the segmented result of an input image with respect to saliency detected image.

Figure 3. Segmented Foreground and Back-ground Region.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 08, August-2016

C. Lossy DCT Compression in the Background

The segmented background region is then subjected to lossy compression. The JPEG process is a widely used form of lossy image compression that centres around the Discrete Cosine Transform [13]. The DCT works by separating images into parts of different frequencies. During quantization, where part of compression actually occurs, the frequencies which are less important is discarded, hence the use of the term lossy. The JPEG process first slices the image into 8x8 blocks of pixels. Then DCT is performed on each block from left to right, top to bottom. Each of these blocks are then compressed using the quantization process. These compressed blocks are the stored in a drastically reduced amount of space.

The DCT equation computes the i, jth entry of the DCT of an image. The following equation is used to get the matrix form of DCT equation.

$$C(u) = \begin{cases} \frac{1}{\sqrt{N}} & \text{if i = 0} \\ \sqrt{\frac{2}{N}} \cos\left[\frac{(2j+1)i\Pi}{2N}\right] & \text{if i > 0} \end{cases} \qquad (2)$$

N is the size of the block that the DCT is done. The equation transforms the pixel values of the original image matrix. For an 8x8 block, N is substituted with 8 and corresponding matrix is generated. The first row ie., i=1, of the matrix has all the entries equal to 1/sqrt(8) as expected.

Once the DCT matrix is calculated, the image is divided into 8x8 blocks of pixels. There are hundreds or even thousands of 8x8 blocks of pixels in an image, what is done to one block is done to all of them. Let the first selected block be M of image pixel values, perform Discrete Cosine Transform, which is accomplished by matrix multiplication.

$$D = TMT' \qquad (3)$$

The row is transformed by first multiplying the DCT matrix T on the left of the matrix M. The columns are then transformed by multiplying on the right by the transpose of DCT matrix T'. The block matrix now consists of 64 DCT coefficients, cij, where i and j ranges from 0 to 7. The top left coefficients indicate the lower frequencies and at the same time the bottom right coefficients shows the higher frequencies. It is important to note that, the lower frequencies are the important frequencies and that the human eye is most sensitive to these frequencies.

The block of DCT coefficients is then subjected to compression by quantization. During this step, varying levels of image compression are obtainable through selection of quantization matrices. Quantization is achieved by dividing each element in the DCT transformed matrix D by the corresponding element in the quantization matrix Q, and then rounded to the nearest integer value. Once the quantization process is completed, majority of the matrix elements will be replaced by zeros. The zeros representing the less important coefficients ie., the higher frequencies that have been discarded, giving rise to the lossy part of compression. The rest of the non-zero coefficients are used to reconstruct the image. JPEG take advantage of this zero valued coefficients, by encoding quantized coefficients in the zig-zag sequence. The advantage lies in the consolidation of relatively large run of zeros, which compress very well.

Reconstruction of the image begins by decoding the bit stream representing the quantized matrix. Each element of the quantized matrix is then multiplied by the corresponding element of the quantization matrix used. The Inverse Discrete Cosine Transform is next applied to the resultant matrix R, which is rounded to the nearest integer. The decompressed JPEG N of the original 8x8 image block M is generated by the following equation:

$$N = round(T'RT) \qquad (4)$$

Thus, DCT compresses [13] the background region efficiently so that the resultant image have good compression ratio.

D. Lossless DWT Compression in the Salient Region

Since the salient region of the image contains most of the important information, they should be compressed losslessly. Lossless compression maintains the quality of the salient region. The proposed method make use of Discrete Wavelet Transform [12] for lossless compression, the design follows the JPEG2000 standards. In discrete wavelet transform technique, parts of image is described using other parts of image, hence the redundancy of similarity is exploited. There exist different types of wavelet transforms, the proposed method make use of Haar Wavelet Transform, since this provides efficient lossless compression.

In case of JPEG2000 encoding, the source image data is first discrete transformed. These transformed coefficients are then quantized and entropy encoded. Thus an output codestream is generated. The decoder is the reverse of the encoder, thus resulting in the reconstructed image data.

Haar wavelet transform is one of the simplest transform for image compression. Here averages and differences of adjacent pixels are calculated. Implementing the discrete Haar transform consists of acting on a matrix row-wise finding the sums and differences of consecutive elements. The matrix is split in half from top to bottom the sums are stored in one side and the differences in the other. Next operation occurs columnwise, splitting the image in half from left to right, and storing the sums on one half and the differences in the other. The process is repeated on the smaller square, power-of-two matrix. The number of times this process occurs can be thought of as the depth of the transform. Thus the salient region with confidential data, is compressed without affecting its quality.

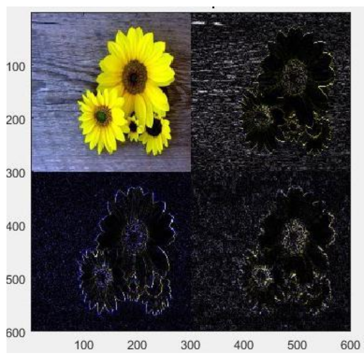

Figure 4. DWT Compression.

Once the lossy compression on non-salient region and lossless compression on salient region is computed, these are combined efficiently to get the final compressed image. The system thus provides efficient storage of images while preserving the important data. Its also ensures better utilization of transmission bandwidth and saves transmission time.

IV. EXPERIMENTS AND RESULTS

The following section describes the results obtained from the implementation of the system. The proposed method is evaluated on three typical datasets. The first MSRA-1000 is a widely used datasets with simple images. The second CSSD contains more salient objects under complex scenes and some images come from challenging Berkeley dataset. The saliency of these images are calculated using Label Propagation method. The efficiency of this method is tested using precision-recall analysis.

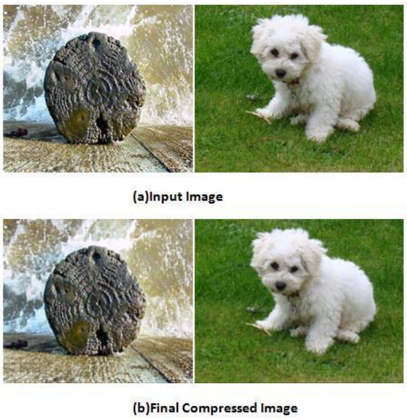

Figure 5. Output of the Proposed Hybrid Compression Technique

The proposed method then, separates background and foreground region using segmentation. The salient region is compressed losslessly using Discrete Wavelet Transform, thus the quality of the salient region in the image is preserved. A lossy DCT compression is applied to the background region, which ensures better compression ratio. The proposed compression technique is evaluated using distortion, PSNR, size and compression ratio(CR) analysis.

A. Compression Performance

A.1 Distortion Analysis

The proposed image compression technique ensures better quality with respect to discrete cosine transform compression [13]. The mean distortion analysis is used for measuring the quality difference between outputs of both the compression techniques. The compressed image is first divided into 10x10 blocks and mean difference of each pixel in each block to the corresponding pixel in the original image is calculated.

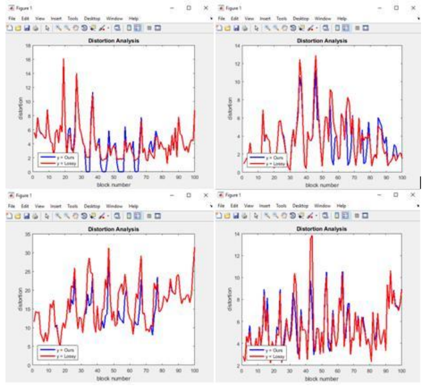

Figure 6. Distortion Analysis on Four CSSD Dataset Images.

In the above graph, the blue line indicates proposed compression technique and the red line corresponds to the lossy DCT compression technique [13]. It is clear that the proposed method ensures better quality in the salient region compared to the salient region in the DCT compressed image. That is why, the blue line shows less distortion ie., high quality in some region of the image with respect to the red line.

A.2 Size and CR Analysis

The proposed system achieves good compression while preserving the quality of the salient region, thus it ensures better storage, saves transmission time and bandwidth. Fig 7 shows the size comparison of five images, compressed using lossless DWT [12] and proposed compression technique, belonging to MSRA dataset. The output of the proposed method, represented by the yellow bar in the graph, achieves reduced size compared to other two.

Data compression ratio, also known as compression power, is used to quantify the reduction in data representation size produced by a compression algorithm. It is defined as the ratio between the uncompressed size and compressed size:

$$\textit{Compression Ratio} = \frac{\textit{Uncompressed Size}}{\textit{Compressed Size}} \qquad (5)$$

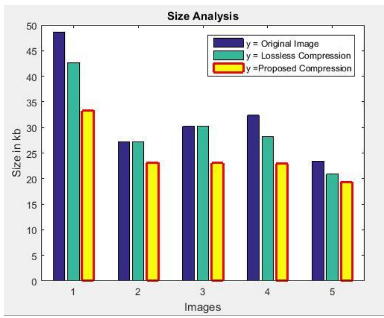

Figure 7. Comparison of Sizes of Original, Loss-lessly Compressed [12] and Proposed Hybrid Compressed Images

The table 1 shows the comparison of compression ratio of proposed method with lossless and lossy compression methods. The system achieves better compression than lossless DWT compression.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 5 Issue 08, August-2016

Table 1. Compression Ratio Analysis on CSSD and MSRA Image Dataset.

Compression Ratio			
Image	DCT Compression	Proposed Compression	DWT Compression [12]
Rock	1.72	1.46	1.13
Orange	1.40	1.31	0.99
Cat	1.34	1.17	1.002
Coffee	1.29	1.20	1.12
Puppy	1.50	1.41	1.15

A.3 MSE and PSNR Analysis

The proposed image compression technique is also compared using Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) analysis. The MSE is the cumulative squared error between the compressed and the original image. The mathematical formula is given by:

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2 \qquad (6)$$

where I(x; y) and I'(x; y) represents the original image and the compressed image respectively and M; N indicates the dimensions of the images. A lower value of MSE means lesser the error and if lesser the error, then the compression method is said to be better.

The PSNR is a measure of the peak error between the compressed and the original image and it is expressed as:

$$PSNR = 20 * log10(255/\sqrt{(MSE)}) \qquad (7)$$

MSE is inversely related PSNR, as the PSNR value increases, MSE decreases and the quality of the compressed image increases.

Mean Squared Error		
Image	DCT Compression	Proposed Compression
Cat	4.3544	2.9149
Puppy	9.6983	10.3939
Coffee	6.4930	5.6887
Cow	6.6815	5.5879
Orange	5.4893	5.0794

Table 2. MSE Comparison on CSSD and MSRA Image Dataset.

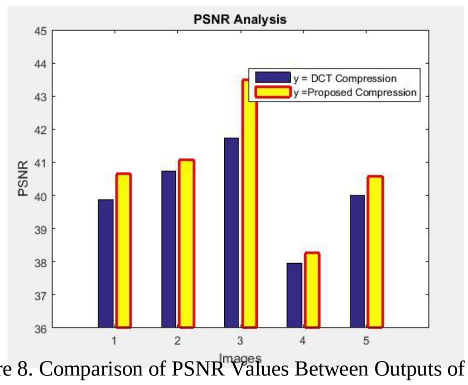

Figure 8. Comparison of PSNR Values Between Outputs of Lossy Compression [13] and Proposed Compression Method.

V. SUMMARY

The system proposes a novel approach to intelligently compress an image. The key observation is that most of the important information lies in the salient region. Therefore, a label propagation algorithm is used to detect salient region in an image. The algorithm make use of the background and foreground information. The confidential data residing in the salient region is then preserved by applying a DWT lossless compression technique. The remaining non-salient region is then compressed by a lossy technique. Thus the proposed system ensures good compression ratio while keeping the data in salient region. The system is therefore highly applicable in medical fields, to store more number of image records while preserving the important information in the diagnostic area.

In recent years, image storage and transmission has become an important research problem. So further improvement in the compression technique is appreciable. Currently, the proposed hybrid compression technique is used only for still images, this can be further extended by implementing the technique in videos. This preserves the important regions in the video while reducing the size. Thus efficient storage and transmission is achieved.

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