Block-Wise Encryption Scheme for Gray Scale Images

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Abstract-The image compression is the technique if image processing which is applied to reduce size of the input image. The image compression is broadly classified into lossy and lossless type of compression. The WDR algorithm is the lossy type of compression. In this paper, improvement in the WDR algorithm is been proposed and improvement is based on decision tree algorithm. The proposed algorithm is been implemented in MATLAB and it is been analyzed that compression ratio and PSNR is increased in the proposed algorithm.

Keywords-WDR; PSNR; Compression ratio; lossy; lossless.

I. INTRODUCTION

Image Processing is a method to enhance raw images received from cameras/sensors set on satellites, space probes and air ships or pictures taken in normal day-today life for different applications. Different methods have been developed in Image Processing amid the last four to five decades. The majority of the strategies are developed for enhancing images got from unmanned spacecrafts, space probes and military reconnaissance flights. Image Processing systems are getting to be distinctly popular because of simple availability of powerful staff PCs, extensive size memory devices, graphics software and so forth [1]. The system incorporates Image processing module and knowledge management and prediction module. Image processing module deals with operations on image up to pattern acknowledgment. The knowledge about medical palmistry is fed into the system in second module. In this module, sample patterns are fed into knowledge base. Finally these two modules consolidate their work items, and system creates last output, that is prediction. Classification between the objects is simple task for humans yet it has turned out to be a complex problem for machines. The raise of high-capacity computers, the availability of high quality and low-priced video cameras, and the increasing requirement for automatic video analysis has generated an interest in object classification algorithms [2]. A simple classification system consists of a camera fixed high over the interested zone, where images are captured and thus processed. Classification includes image sensors, image preprocessing, object detection, object segmentation, feature extraction and object classification. Classification system consists of database that contains predefined patterns that compares with recognized object to classify into proper category. The objective of image compression is to reduce irrelevance and redundancy of the image data keeping in mind the end goal to have the capacity to store or transmit data in an efficient form. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size permits more images to be stored in a given amount of disk or memory space [3]. It likewise reduces the time required for images to be sent over the Internet or downloaded from Web pages. There are a few different ways in which image files can be compressed. For Internet utilize, the two most basic compressed graphic image formats are the JPEG format and the GIF format. The JPEG method is all the more regularly utilized for photographs, while the GIF method is ordinarily utilized for line art and different images in which geometric shapes are relatively simple. Different methods for image compression incorporate the utilization of fractals and wavelets. These methods have not gained widespread acceptance for use on the Internet as of this writing. Be that as it may, both methods offer promise because they offer higher compression ratios than the JPEG or GIF methods for a few sorts of images. Another new method that may in time supplant the GIF format is the PNG format [4]. A text file or program can be compressed without the introduction of errors, however just up to a specific extent. This is called lossless compression. Beyond this point, errors are introduced. In text and program files, it is crucial that compression be lossless because a single error can seriously damage the meaning of a text file, or cause a program not to run. In image compression, a small loss in quality is generally not noticeable. There is no "critical point" up to which compression works perfectly, yet beyond which it becomes impossible. The JPEG has been the most common image format on the web for a long time. Standardized in 1994, it is capable of retaining high caliber with small file sizes. Its ability to pack so much visual information into a small file is to a great extent because of exploiting the capacities, or rather limitations, of the human eye [5]. Linear algebra is the ideal form of math for registering. JPEG images are a collection of numbers in arrays corresponding to various color channels. The data including a digital image resembles a matrix in that it has discrete values, and unlike calculus, which is continuous. Three steps are used in JPEG compression: a discrete cosine transformation, quantization, and entropy encoding. The Discrete Cosine Transformation (from this point forward alluded to as DCT) resembles a discrete Fourier transform in that it turns the spatial domain of an image into its frequency domain. The spatial domain contains numbers that reflect the intensity of each channel at a given pixel, while the frequency domain contains the change of intensity starting with one pixel then onto the next [6]. The frequency domain ordinarily contains less information than the spatial domain. The objective of quantization is to reduce the precision and to accomplish higher compression ratio. For instance, the original image utilizes 8 bits to store one element for each pixel; on the off chance that we utilize less bits, for example, 6 bits to save the information of the image, then the storage quantity will be reduced, and the image can be compressed. The shortcoming of quantization is that it is a lossy operation, which will result into loss of precision and unrecoverable distortion [7]. After the quantization has been connected to the image, a symbol encoding system is connected to the image. Entropy is the measure of information present in the data, and an entropy coder encodes the given set of symbols with the minimum number of bits required to represent them. Entropy coding techniques for the most part gives lossless compression.

II. LITERATURE REVIEW

Marco Conoscenti, et.al, (2016) improved predictive lossy compression in a few ways, utilizing a standard issued by the Consultative Committee on Space Data Systems, to be specific CCSDS-123, as an example of application. In the first place, exploiting the flexibility in the blunder control prepare, a constant-signal-to-noise-ratio algorithm is proposed that bounds the maximum relative mistake between every pixel of the reconstructed picture and the corresponding pixel of the original picture [8]. Second, another rate control algorithm is proposed that has low complexity and provides performance equal to or superior to existing work. These advances make predictive lossy compression an amazingly appealing framework for onboard systems because of its simplicity, flexibility, and coding efficiency.

Miguel Hernandez-Cabronero, et.al, (2015) presented a progressive lossy-to-lossless plan to tackle this problem [9]. Firstly, the consistent structure of the RQ intervals is abused to characterize a lossy-to-lossless coding algorithm called the Progressive RQ (PRQ) coder. Secondly, an improved variant that prioritizes a region of interest, called the PRQ-ROI coder, is depicted. Experiments indicate that the PRQ coder offers progressivity with lossless and lossy coding performance practically identical to the best techniques in the literature, none of which is progressive. Thusly, the PRQROI displays fundamentally the same as lossless coding results with preferable rate contortion performance over both the RQ and PRQ coders.

Azam Karami, et.al, (2016) proposed another lossy compression method for hyperspectral images that aims to optimally compress in both spatial and spectral spaces and all the while minimizes the impact of the compression on linear spectral unmixing performance [10]. The resulting enhancement problem is solved by a particle swarm advancement algorithm. An approximate method for fast estimation of the free parameters is introduced also. Our recreation results demonstrate that, in comparison with surely understood state-of-the-art lossy compression methods, an improved compression and spectral unmixing performance of the reconstructed hyperspectral picture is obtained. The proposed algorithm achieves a superior performance (higher SNR variance and smaller MSE) in comparison with two state-of-the-art compression algorithms, particularly at high CRs. A fast approximate method that fixes the core tensor dimensions is introduced also.

Younghee Kwon, et.al, (2015) proposed an efficient semi-local approximation scheme to large-scale Gaussian processes [11]. This allows efficient learning of task-specific image enhancements from example images without reducing quality. In that capacity, our algorithm can be effortlessly customized to specific applications and datasets, and we demonstrate the efficiency and effectiveness of our approach crosswise over five domains: single-image super-resolution for scene, human face, and text images, and artifact removal in JPEG-and JPEG 2000-encoded images. This algorithm provides interesting conceptual insights, allows for high-quality image enhancement in different scenarios, and allows us to alter the degradation models efficiently since the training time is short. In the future, our algorithm could be connected to other computer vision problems, for example, video super-resolution, and image and video deblurring.

Sung Kyu Lee, et.al, (2015) formulated the encoding mode selection of a multimode image compression algorithm, which adaptively determines the encoding mode to encode a patch of a given image, as a multiple-choice backpack problem (MCKP). At that point, we present a multimode image compression algorithm that exploits the MCKP-formulated mode selection problem and a memory-efficient implementation of the MCKP-based mode selection algorithm [12]. To emphasize the impact of the MCKP-based mode selection, the proposed multimode image compression algorithm adopts encoding modes from conventional multimode image compression algorithms. In experiments utilizing the Kodak test image set, the proposed algorithm outperformed benchmark algorithms by 2.6-7.8 dB in the average peak signal-to-noise ratio when the target compression ratio is 1/6.

Mansour Nejati, et.al, (2016) proposed a boosted dictionary learning framework to construct an ensemble of complementary specific dictionaries for sparse image representation. Boosted dictionaries alongside a competitive sparse coding form our ensemble model which can provide us with more efficient sparse representations [13]. The constituent dictionaries of the ensemble are obtained utilizing a coherence regularized dictionary learning model for which two novel dictionary improvement algorithms are proposed. These algorithms improve the speculation properties of the trained dictionary compared to several incoherent dictionary learning methods. Our algorithm is evaluated for compression of natural images. Test results demonstrate that the proposed algorithm has better rate distortion performance as compared with several competing compression methods including analytic and learned dictionary schemes.

III. RESEARCH METHODOLOGY

Vector Quantization: Vector quantization is an image compression algorithm that is applied to vectors rather than scalars, and it can be easily understood through scalar quantization. Scalar quantization maps a large set of numbers to a smaller one and includes such operations as "rounding to the nearest integer," although in general the quantization levels do not have to be neither integer nor evenly spaced. Vector quantization rounds off (or quantizes) groups of numbers together instead of one at a time. These groups of numbers are called input vectors, and the quantization levels are called reproduction vectors. To specify a vector quantizer, one needs the set of possible reproduction vectors and a rule for mapping input vectors to the reproduction vectors. The dots represent the reproduction vectors and the mapping rule is indicated by the lines, which delineate the boundaries between regions. Any input vector lying in a given region maps to the reproduction vector in that same region. The encoder operates in a nearest neighbor or minimum distortion fashion. A full search VQ is an unstructured collection of code words. The encoder determines the closest one by an exhaustive search. A structured codebook uses a constrained search to speed up the encoding, but it is not guaranteed to find the overall nearest neighbor in the codebook. The choice of distortion measure permits us to quantify the performance of a VQ in a manner that can be computed and used in analysis and design optimization. By far the most commonly used distortion measure for image compression is the mean squared error, in spite of its often cited shortcomings. Although there are many approaches to code design, the algorithms surveyed here are all based on clustering techniques, such as the Lloyd (Forgey, Isodata, k-means) algorithm. It iteratively improves a codebook by alternately optimizing the encoder for the decoder (using a minimum distortion or nearest neighbor mapping) and the decoder for the encoder (replacing the old codebook by generalized "centroids"). For squared error, centroids are the Euclidean mean of the input vectors mapping into a given index. Code design is usually based on a training set of typical data rather than on mathematical models of the data.

As illustrated in the Figure 1, the flowchart which is defined above shows the procedure which is being followed in the proposed work. In the proposed flowchart, the vector quantization techniques have been applied with the DCT transformation. The vector quantization will extract the pixels of the input image whether it is in the gray scale form or in the RGB form. In the implementation of proposed algorithm, the gray scale pixels are divided and each pixel is analyzed individually. In the second phase of the vector quantization, the image is converted into RGB and each pixel is analyzed in terms of their RGB factors. The final step of vector quantization is to extract the pixel value of the pixels which are in the input image.

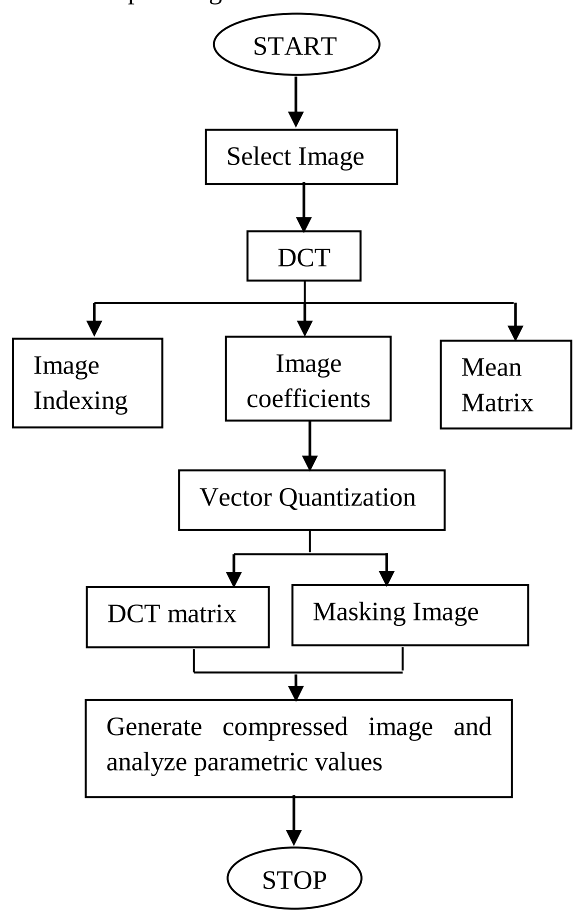

Fig. 1: Proposed Flowchart

In the above given flowchart the steps of the method are explained.

A. Discrete Coefficient Transformation (DCT): The DCT technique is the coefficient based transformation in which the colored features of the input image are been analyzed and processed. In the proposed technique the image indexing is being done according to the pixel value of input image. To apply vector quantization the coefficients of the input image are calculated which the color intensity values are and in the last step the matrix of color intensity values is generated by taking mean of the pixels.

B. Vector Quantization: The vector quantization of the input value is generated from the mean matrix which is generated in the previous step. In the vector quantization, three steps are followed. In the first step, the gray scale pixels of the input image are divided to analyze individual gray scale pixels. In the second step, the RGB pixels are divided to analyze individual part of the pixel. In the last step, the DB values of the pixels are generated to generate final compressed image.

C. DCT and Image Masking: In the last step, the technique of DCT and image masking is being applied in which the pixels which have least importance are removed from the image. The importance of the pixels of the image is being analyzed through the DB values which are generated in the vector quantization. This leads to generation of the final compressed image which has less size than the input image.

IV. EXPERIMENTAL RESULTS

The proposed work is implemented in MATLAB and the results are evaluated by making comparisons against proposed and existing approaches in terms of several parameters.
As shown in figure 2, the PSNR value of proposed approach is compared amongst proposed and existing techniques which show that the PSNR value of proposed approach is improved.
As shown in figure 3, comparisons are made against proposed and existing approach in terms of CR which shows that the proposed approach provides improvement in CR and thus provides better outcomes.

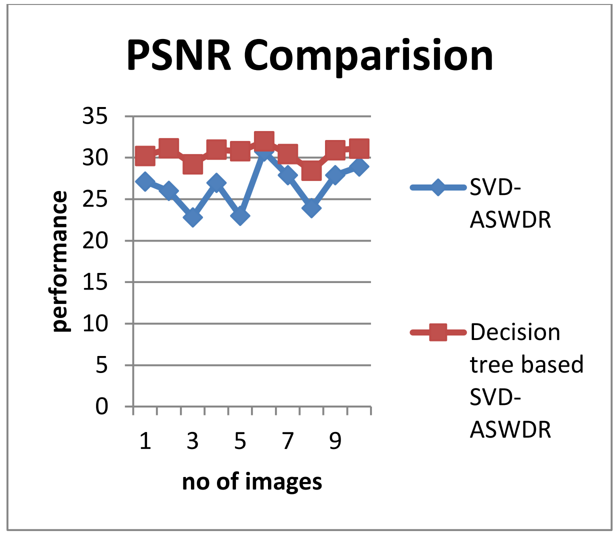

Fig. 2: PSNR Comparison

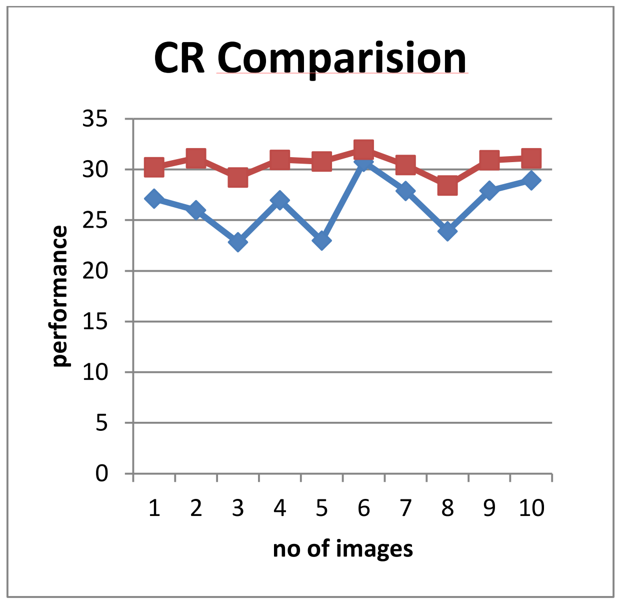

Fig. 3: CR Comparison

V. CONCLUSION

The image compression is the technique in which size of the image is reduced by removing the unwanted pixels from the image. The WDR is the efficient technique in which the whole image is divided into small matrix and matrix which has dissimilar properties are removed from the image. In this work, the greedy algorithm is been proposed in which tree like structure is leaf metrics are removed from the images. The result of the proposed algorithm is compared with existing

WDR algorithm and it is been analyzed that PSNR is increased, compression ratio is increased.

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