

# LOSSLESS COMPRESSION OF JPEG CODED IMAGE COLLECTIONS

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## ABSTRACT

The explosion of digital photos has posed a significant challenge to photo storage and transmission for both personal devices and cloud platforms. It proposes a novel lossless compression method to further reduce the size of a set of JPEG coded correlated images without any loss of information. The proposed method jointly removes inter/intra image redundancy in the feature, spatial, and frequency domains. For each collection, first organize the images into a pseudo video by minimizing the global prediction cost in the feature domain. It then presents a hybrid disparity compensation method to better exploit both the global and local correlations among the images in the spatial domain. Furthermore, the redundancy between each compensated signal and the corresponding target image is adaptively reduced in the frequency domain. Experimental results demonstrate the effectiveness of the proposed lossless compression method. Compared to the JPEG coded image collections, our method achieves average bit savings of more than 31%.

*Index Terms*—Image Compression, lossless, JPEG, recompression, image set, image collection, image coding

## INTRODUCTION

The increasing number of digital photos on both personal devices and the Internet has posed a big challenge for storage. With the fast development and prevailing use of handheld cameras, cost as well as required photography skills are much lower than before. Users today have

gotten used to taking and posting photos with mobile phones, digital cameras, and other portable devices to record daily life, share experiences, and promote businesses. According to recent reports, Instagram users have been posting an average of 55 million

photos every day Facebook users are How to store, backup, and maintain these enormous amount of photos in an efficient way has become an urgent problem. The most popular way to reduce storage sizes of photos is via JPEG compression. It is designed for reducing the size of photos taken in realistic scenes with smooth variations of tone and color. Though several superior formats such as JPEG 2000 and JPEG XR have been developed subsequently, the JPEG baseline is exclusively used as a common and default format in almost all imaging devices like digital cameras and smart phones. Consequently, the overwhelming majority of images stored in both personal devices and the Internet are in JPEG format. In this paper, we focus on the lossy coded baseline JPEG image, which is referred to as the JPEG coded image in the rest of this paper.

Here it proposes a novel compression scheme to further compress a set of JPEG coded correlated images without loss. Given a JPEG coded image set, we propose to remove both inter and intra redundancies by a hybrid prediction in the feature, spatial, and frequency domains. We first evaluate the pair-wise correlation between images by introducing the feature-based measurement so as to determine the prediction structure which is robust to scale, rotation, and illumination. The disparity between images is then compensated by both the global (geometric and photometric) alignments and the HEVC-like local motion

uploading 350 million photos each day. estimation in the spatial domain. Furthermore, we reduce both the inter and intra redundancies via frequency domain prediction and context-adaptive entropy coding. Experimental results demonstrate the advantage of our scheme in terms of achieving much higher coding efficiency and lossless representation of JPEG coded files. Our scheme is able to greatly reduce the cost of storage and transmission of JPEG-coded image collections (e.g. geo-tagged images and personal albums) transparently for personal and cloud applications. The rest of this paper is organized as follows.

## II. EXISTING METHOD

### A). *Baseline JPEG Compression*

The JPEG group has specified a family of image coding standards. The most popular one is the baseline JPEG. Fig. 1 shows the key components of the baseline encoder. As shown in this figure, an input image is divided into  $8 \times 8$  blocks. Each block is then converted into a frequency domain by an  $8 \times 8$  DCT, followed by the scalar quantization which is usually implemented with a set of quantization matrices indexed by a quality factor  $Q$  2 f1; 2;.....; 100g. The quantized DC coefficients are predicted by DPCM (Differential pulse code modulation) while the AC ones are scanned in zigzag manner before

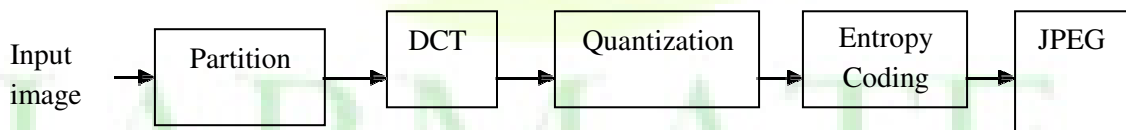
going through the Huffman-based entropy coding.

### ***B). Lossless Compression of Individual JPEG Images***

The most straightforward way to reduce the storage size of a JPEG coded image losslessly is to replace the Huffman coding by an arithmetic coder. In fact, the JPEG extension has already supported an adaptive binary arithmetic coder which can reduce the file size by 8-10%, as reported in. Enhanced performance is achievable by further exploiting inter-block correlation in the intra prediction and designing dedicated entropy coding as well. Ponomarenko et al., proposed a method to separate the quantized DCT coefficients into bit-planes and design context models with regard to the correlations of coefficients within a block, between neighbouring blocks and among different color layers. The quantized DCT coefficients can also be re-ordered or grouped based on

similar statistical properties, either via a sorting transform in which the order of DCT coefficients are predicted from those of the previous coded blocks or using three scan patterns for low, middle, and high bands for the adaptive arithmetic coding. Lakhani proposed a new prediction method which derives the one dimensional DCT coefficients of boundary columns/rows from those of adjacent blocks followed by an advanced predictive entropy coding method. Matsuda et al. proposed to employ the H.264 like intra prediction method to exploit the inter-block correlations of the quantized DCT coefficients before the adaptive arithmetic coder. Note that, all these methods exploit only the redundancy within each individual image. For photo collections that contain correlated images, inter-image redundancy is not exploited in these methods but will be efficiently reduced in our proposed lossless compression scheme.

*Fig. 1: Baseline JPEG coder*



### ***C). Image Set Compression***

For most digital cameras and smart phones in use today, photography is quite simple and cheap. Taking multiple shots becomes one of the best and general ways to ensure the quality of captured photos, resulting in large numbers of highly correlated image

collections in personal photo albums. Such collections may also come from various image sets, e.g. geo-tagged photo collections and burst images. When dealing with a group of correlated images, several image set compression schemes have been proposed in the

literature. They can be roughly divided into two classes. The first class of approaches generates a representative signal (RS) from all correlated images to extract the common redundancy among them. Then both the RS and the difference signal between each correlated image and the RS are compressed. These approaches work efficiently when images in a set are similar enough, but share the same limitations when dealing with general image sets. First, they are not robust enough with respect to rotation, scale, and illumination changes which are common in general image sets. Second, they are not sufficiently capable of exploiting the pair-wise correlation between images as different pairs of images may have different correlations. Rather than set level correlation, the second class of approaches focuses on pair-wise correlations between images. One group of methods finds the optimal coding order of an image set. Schmieder et al. evaluate the hierarchical clustering methods for image set compression. Chen et al., Optimize the coding order of correlated images by minimizing prediction costs. The image set can be clustered by a minimum spanning forest

(MSF) and each cluster can be described by a minimum spanning tree (MST) and coded with inter-image prediction. Lu et al. apply MPEG-like block-based motion compensation (BMC) to exploit the correlation between images. Au et al. introduce a pixel-wise global motion compensation before the BMC. Zou et al., apply the advanced BMC in HEVC to image set compression. Though more efficient than RS-based methods, these approaches may lose efficiency when dealing with image sets that have large variations in rotation, scale, and illumination. To address this problem, Shi et al., proposed to model the disparity among images with local features and introduced feature-based matching to better exploit the correlations among images in a collection. On the other hand, all these methods were proposed to compress the pixels in raw images in a lossy way. When extended for lossless compression of JPEG coded images, these methods may not perform well and may even be worse than using the original JPEG files since they take no consideration of the JPEG coding effects as well as the characteristics.

### **III. PROPOSED METHOD**

#### ***A) Lossless compression***

Lossless compression is a class of data compression algorithms that allows the original data to be perfectly reconstructed from the compressed data. By contrast, lossy compression permits reconstruction only of an approximation of the original data, though this usually improves compression rates. Lossless

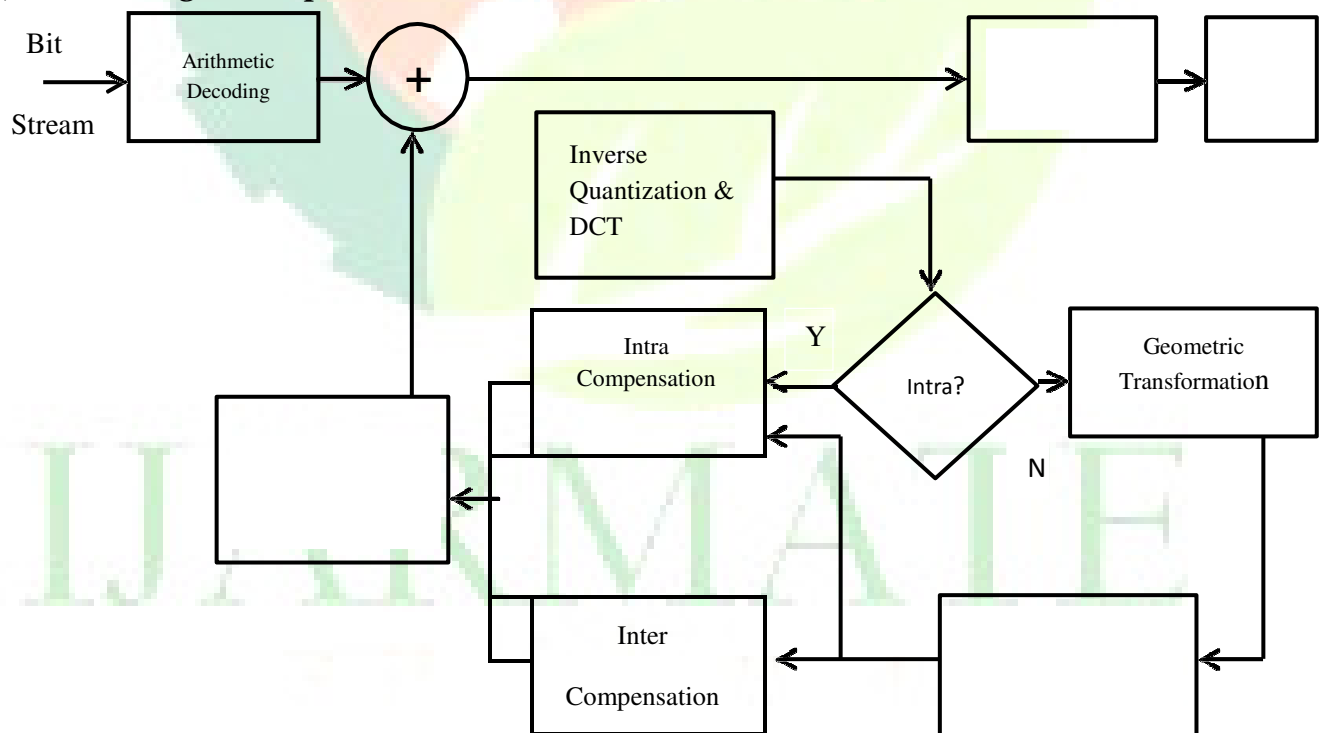
compression is a class of data compression algorithms that allows the original data to be perfectly reconstructed from the compressed data. By contrast, lossy compression permits reconstruction only of an approximation of the original data, though this usually improves compression rates (and therefore reduces file sizes). Lossless data compression is used in many applications. For example, it is used in

**Block Diagram Representation**

The diagram illustrates the block structure of an audio decoder. It starts with a 'Bit Stream' input entering an 'Arithmetic Decoding' block. The output of this block is fed into a circular adder (+). The adder also receives input from a block labeled 'Inverse Quantization & DCT'. The output of the adder is then processed by an 'Intra Compensation' block. The output of 'Intra Compensation' is fed into a block labeled 'Y'. The output of 'Y' is then processed by an 'Intra' block. The output of 'Intra' is fed into a block labeled 'X'. The output of 'X' is then processed by a block labeled 'Z'. The output of 'Z' is then processed by a block labeled 'W'. The output of 'W' is then processed by a block labeled 'V'. The output of 'V' is then processed by a block labeled 'U'. The output of 'U' is then processed by a block labeled 'T'. The output of 'T' is then processed by a block labeled 'S'. The output of 'S' is then processed by a block labeled 'R'. The output of 'R' is then processed by a block labeled 'Q'. The output of 'Q' is then processed by a block labeled 'P'. The output of 'P' is then processed by a block labeled 'O'. The output of 'O' is then processed by a block labeled 'N'. The output of 'N' is then processed by a block labeled 'M'. The output of 'M' is then processed by a block labeled 'L'. The output of 'L' is then processed by a block labeled 'K'. The output of 'K' is then processed by a block labeled 'J'. The output of 'J' is then processed by a block labeled 'I'. The output of 'I' is then processed by a block labeled 'H'. The output of 'H' is then processed by a block labeled 'G'. The output of 'G' is then processed by a block labeled 'F'. The output of 'F' is then processed by a block labeled 'E'. The output of 'E' is then processed by a block labeled 'D'. The output of 'D' is then processed by a block labeled 'C'. The output of 'C' is then processed by a block labeled 'B'. The output of 'B' is then processed by a block labeled 'A'.

Probability or frequency of occurrence for each possible value of the source symbol. As in other entropy encoding methods, more common symbols are generally represented using fewer bits than less common symbols. Huffman's method can be efficiently implemented, finding a code in time linear to the number of input weights if these weights are sorted.

### *B) Block Diagram Representation*



*Fig 2: Representation of Block Diagram*



**Arithmetic coding** is a form of entropy encoding used in lossless data compression. Normally, a string of characters such as the words "hello there" is represented using a fixed number of bits per character, as in the ASCII code. When a string is converted to arithmetic encoding, frequently used characters will be stored with fewer bits and not-so-frequently occurring characters will be stored with more bits, resulting in fewer bits used in total. Arithmetic coding differs from other forms of entropy encoding, such as Huffman coding, in that rather than separating the input into component symbols and replacing each with a code, arithmetic coding encodes the entire message into a single number, an arbitrary-precision fraction  $n$  where  $[0.0 \leq n < 1.0]$ . **Huffman coding** is a lossless data compression algorithm. The idea is to assign variable-length codes to input characters lengths of the assigned codes are based on the frequencies of corresponding characters. The most frequent character gets the smallest code and the least frequent character gets the largest code. **Geometric Transformation** approximates by partitioning an *image* into smaller rectangular sub images, for each sub image, a simple geometric transformation, such as the affine is estimated using pairs of corresponding pixels. Geometric transformation is then performed separately in each sub image. **Quantization**, involved in image processing, is a lossy compression technique achieved by compressing a range of values to a single quantum value. When the number of

discrete symbols in a given stream is reduced, the stream becomes more compressible. For example, reducing the number of colors required to represent a digital image makes it possible to reduce its file size. Specific applications include DCT data quantization in JPEG and DWT data quantization in JPEG 2000. A **discrete cosine transform** (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (MP3) and images (JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical for compression, since it turns out that fewer cosine functions are needed to approximate a typical signal, whereas for differential equations the cosines express a particular choice of boundary conditions. **Scale-invariant feature transform** (SIFT) is an algorithm in computer vision to detect and describe local features in images. SIFT key points of objects are first extracted from a set of reference images and stored in database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of keypoints that agree on the object and its location, scale, and

orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalized Hough transform. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and

subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence.

#### **IV. Coding Method for Lossless Compression**

In the proposed method, a new coding method for lossless compression of JPEG coded images is developed. Specifically, it compresses a JPEG coded image collection by making use of both the inter correlation among images and the intra correlation within each image in the feature, spatial, and frequency domains jointly. The figure shows the architecture of lossless encoder. For each input JPEG coded image collection, decode all JPEG files before further compression, results in the corresponding YUV image set. Then the prediction structure of the image set is determined based on the similarity between each pair of images in the feature domain. The prediction structure is formed in a tree structure generated from a directed graph via the minimum spanning tree (MST) algorithm in which parent nodes (i.e. images) can be used as references to predict their children.

Based on the prediction structure, it then exploits both the inter and intra redundancies in the spatial domain. For inter coded images, the disparity between each pair of target and reference images is reduced by joint global and local

compensations in the pixel space. Specifically, larger geometric deformations and illumination differences are compensated by the global homography and photometric transforms, while smaller disparities are further compensated by the HEVC-like block based intra/inter prediction. For the root image in each MST, the global compensation is bypassed and only intra prediction is performed. All the parameters of MST, transformations, and modes are entropy coded and stored for use in decoding. Unlike previous photo collection compression schemes, it evaluates and generates the predictive difference between each pair of compensated reference block and the target one in the frequency domain. Rather than the decoded pixel values of input JPEG images, in this step we use the entropy decoded DCT coefficients from the input JPEG image as the target information. It also transforms each compensated reference block to the DCT domain followed by the scalar quantization. The resulting quantized DCT coefficients are subtracted from the target ones. The generated residues are coded by the context adaptive arithmetic coding method. Finally, the coded

residues and parameters are mixed up to generate the coded binary file. Since all operations generating the target files are invertible, lossless recovery of the original JPEG files is guaranteed. Figure 2 shows the corresponding decoding process. After parsing the prediction structure, the intra-coded root image in the MST is first decoded. For each block, quantized DCT coefficients are recovered by adding decoded residues to the DCT transformed and quantized intra-compensated predictions. They are then inversely quantized and DCT transformed, resulting in recovered pixels of the block which are buffered as reference for subsequent decoding. For each inter-coded image, quantized DCT coefficients are also recovered by adding decoded residues to the compensated signal in the frequency domain where the compensated signal is generated by global and local compensations. After the inverse quantization and DCT, we get the pixels of the original JPEG coded image.

### ***Feature-Domain Determination of Prediction Structure***

Unlike natural video sequences which have strong temporal correlations, images in a collection usually have loose correlations and may vary in rotation, scale, and illumination. The inter-image disparities in image collections can be more complicated than those in videos. Traditional pixel-level disparity measurements, e.g. MSE, are not capable of effectively measuring the correlation between images. Photo Album Compression for cloud storage using local features introduce the feature-domain similarity to measure the inter-

The JPEG binary file of the image, on the other hand, is recovered by re-compressing the quantized DCT coefficients using the entropy coding method in JPEG. In this case, we will first cluster a set into small collections via a K-means based clustering method similar to Photo Album Compression for cloud storage using local features, in which the distance between two images are defined as the average distance of matched SIFT descriptors. Then for each small collection, our presented scheme is applied. Though our MST-based prediction determination is also able to perform clustering, this will be very time consuming. In the following, three modules in our hybrid lossless compression scheme, feature-domain determination of the prediction structure, spatial-domain disparity compensation, and frequency-domain redundancy reduction, will be introduced in greater detail.

image correlation by the distance of their SIFT descriptors to deal with large geometric transformations and luminance changes. A SIFT descriptor describes the distinctive invariant feature of a local image region, which consists of the location, scale, orientation, and feature vector. The key-point location and scale are determined by finding the maxima and minima of the difference of Gaussian filtered signals. The feature vector is a 128-dimensional vector which characterizes the local region by the histogram of the gradient directions, and the orientation denotes the dominant



direction of the gradient histogram. SIFT descriptors have been demonstrated to have a high level of distinctiveness and thus are widely used in image search and

object recognition. It approximates the prediction cost between images by the average distance of their SIFT descriptors.

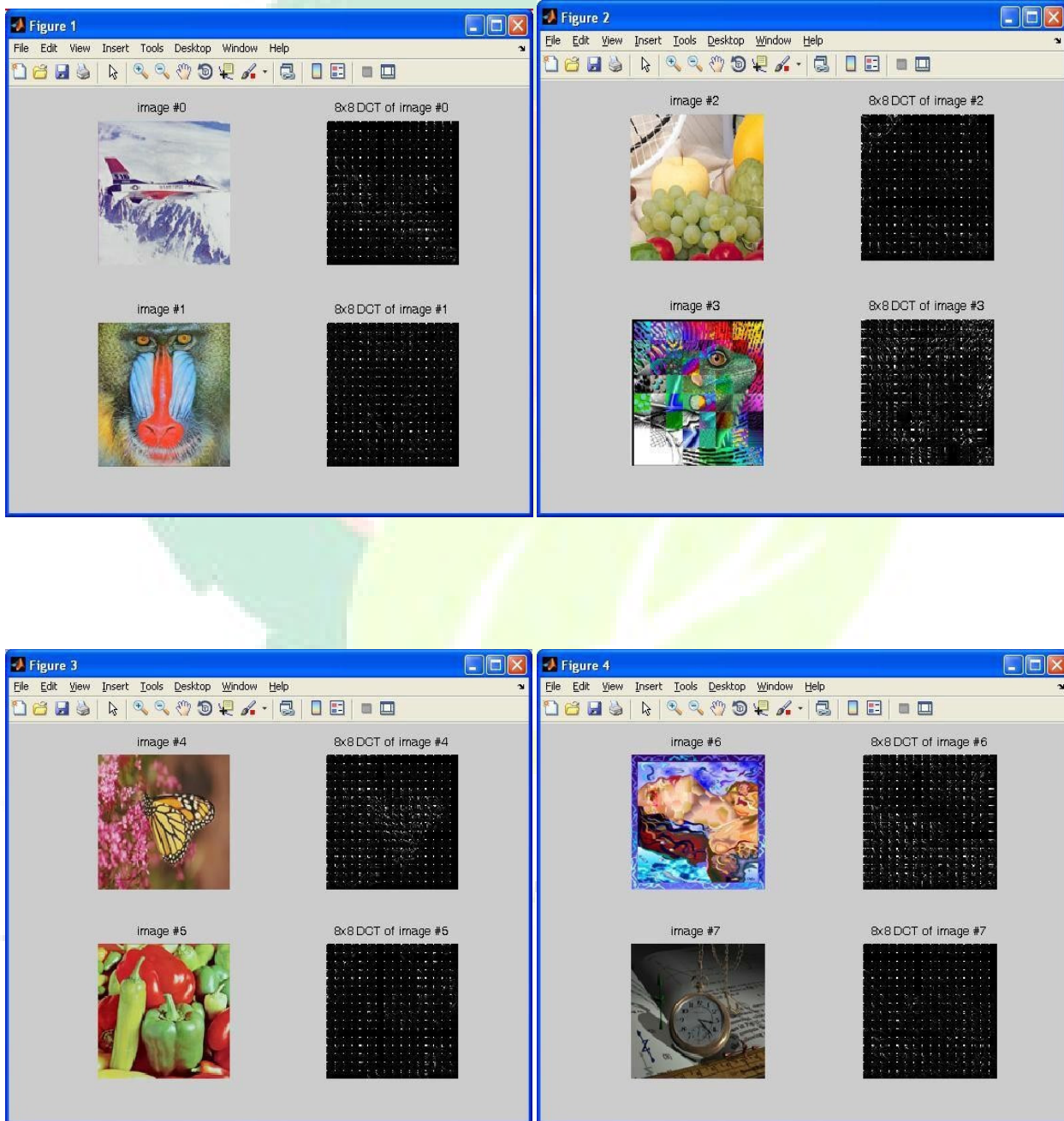
## V. EXPERIMENTAL RESULTS

It proposes a new hybrid compression method to further reduce the file size of JPEG coded image collections without any fidelity loss. In our proposed method, it determines the prediction structure of each image collection by a feature domain distance measure. The disparity between images is then reduced by joint global and local compensations in the spatial domain. In the frequency domain, the redundancy between the compensated and target images is reduced and the remaining weak intra correlations are further exploited in our entropy coding schemes. By exploiting the correlations in the feature, spatial, and frequency domains, our scheme achieves up to 48.4% bit-savings and outperforms all state-of-the-art JPEG recompression. I believe it can greatly reduce the storage cost for backup and archive of JPEG coded image collections for both personal and cloud applications. In this paper, we focus on the efficient compression method for a set of clustered JPEG images. We notice that the clustering can be time consuming if one collection is too large. Possible solutions may involve advanced fastclustering

methods and introducing assistant information. For example, It can make use of the time stamps or GPS information in the meta data of images to separate a large collection to smaller ones. We would like to pay attention to reduce the complexity of the clustering module for large scale image sets in our future work. Besides, the performance of our proposed scheme could be further improved in several ways. First, we could speed up the encoding and decoding process by introducing parallel techniques. Second, we can further reduce the complexity of the local compensation in our scheme by not only leveraging some fast algorithms proposed for HEVC but also reducing complexity by direct operating on the JPEG coded DCT coefficients. Finally, we notice that the feature based distance approximation may not be always efficient. In the future, we would like to investigate advanced distance metrics in which the number as well as the overlapped area of matched feature is taken into account. We may also introduce a light weight version of the distance metrics so that the pixel-domain distance between two images can be measured much more accurately at low computational cost.

## a) Simulation

Initially all the sample images are transformed into  $8 \times 8$  DCT, they are as follows, The images 0 to 9 are transformed into  $8 \times 8$  Discrete Cosine Transform, and it is given in the following images.



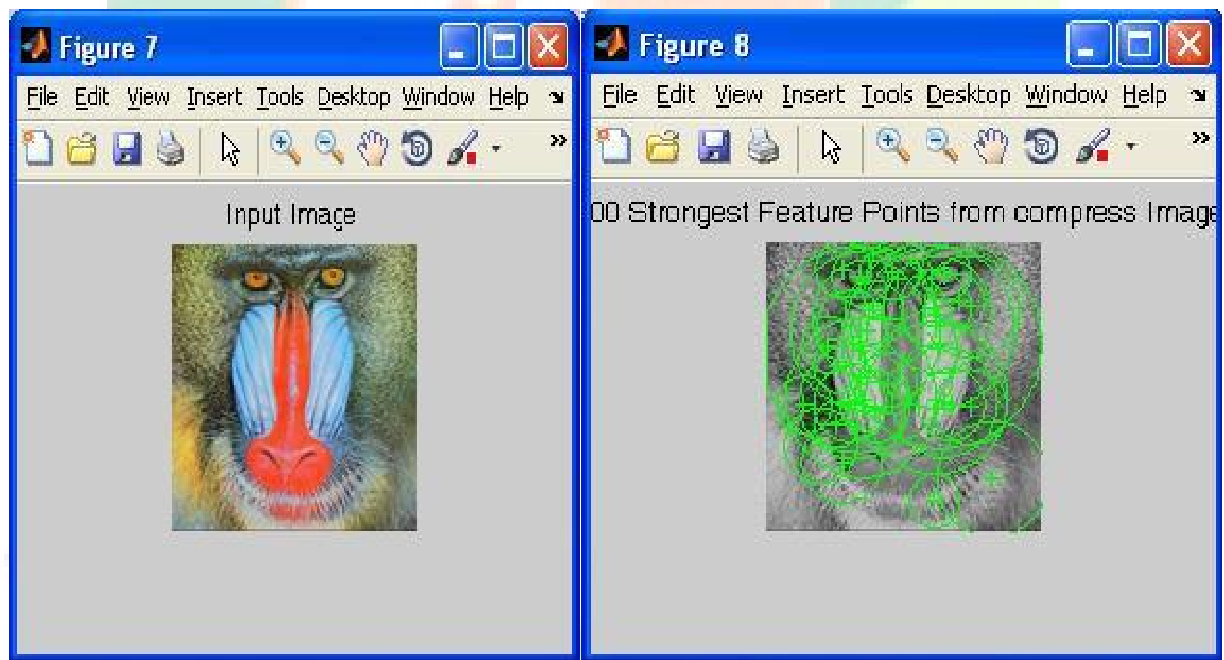
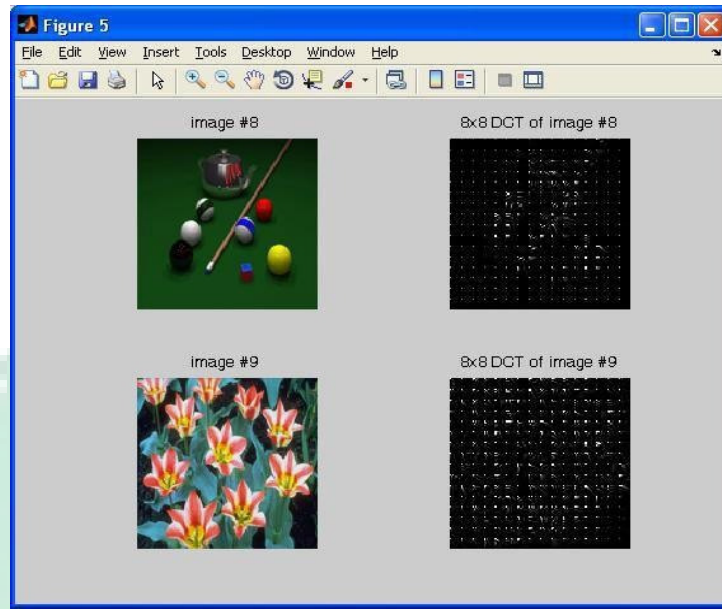
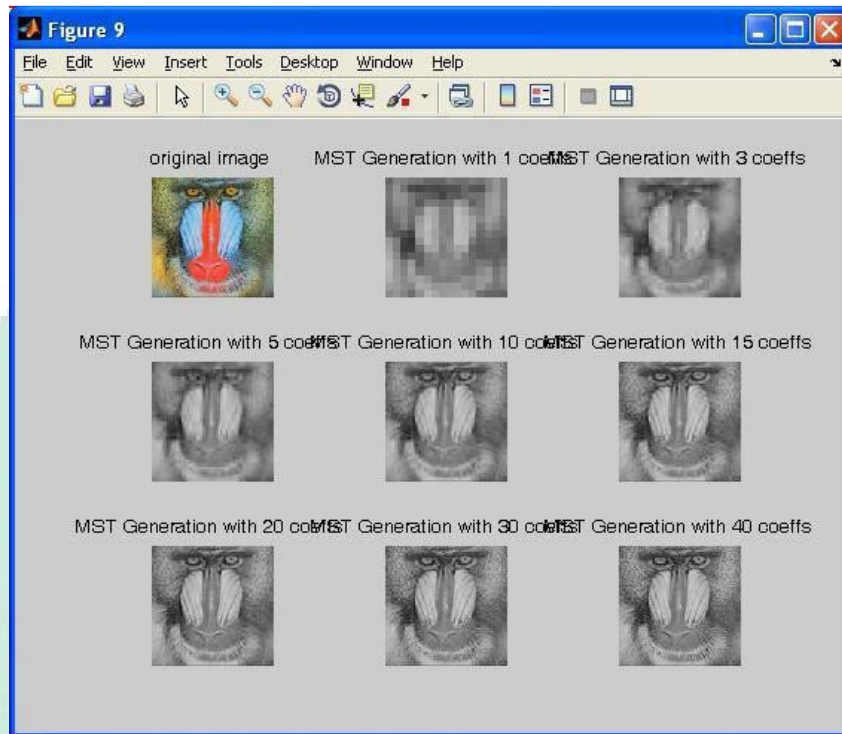


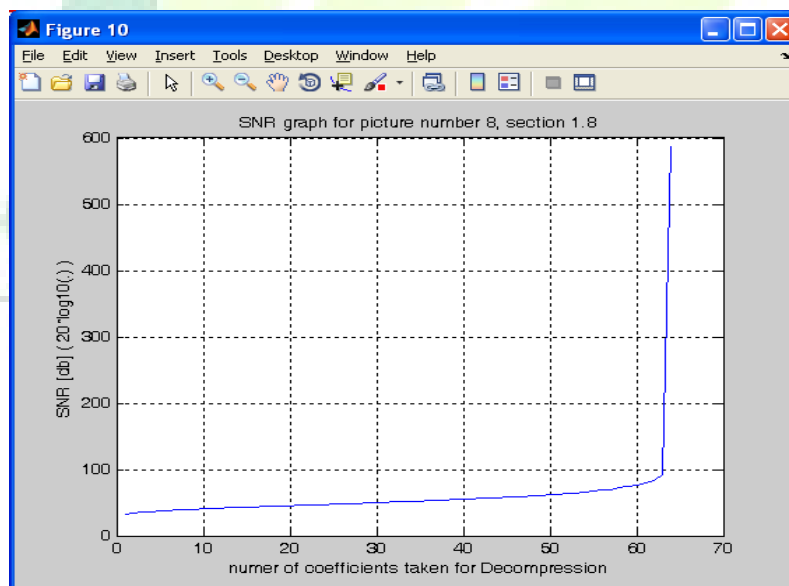
Figure 7 and 8 shows the Input Image and the strongest feature points from the compressed image. The compressed image is used as the original image. It determines the Generation of Minimum Spanning Tree with its Coefficients.



*Fig 3: MST Generation with Coefficients*

## b) Result

The graph shows the SNR values and the number of coefficients for decompression of the input image.



**Fig 6.9: Graph of SNR Value**



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