Variable Quantization based DCT Compression by Extracting Region of Interest

Koyyana Seshu Babu[1], G. Moulika[2]

[1]M. Tech Scholar, Dept. Of ECE, Sai Ganapathi Engineering College, Visakhapatnam-531173, Andhra Pradesh, India.

[2]Assistant Professor, Dept. Of ECE, Sai Ganapathi Engineering College, Visakhapatnam-531173, Andhra Pradesh, India.

Abstract- In the field of DCT compression, if the image is RGB then we will first extract the luminance and chrominance components of the image and then we will do chroma down sampling which will compress only the chrominance part that is only the color information. This is because we are much more sensitive to changes in luminance (brightness) than we are to chrominance (color) differences. Because of this, the JPEG format can discard a lot more color information than luminance in the compression process. To facilitate the different compression requirements of the two " channels & quot; of image information, the JPEG file format translates 8-bit RGB data (Red, Green, Blue) into 8-bit YCbCr data (Luminance, Chroma Blue, Chroma Red). Now, with the brightness separated into a separate data channel, it is much easier to change the compression algorithm used for one channel versus the others. Then we will apply DCT compression algorithm in the blocks of (NXN) to further compress the image. After that we will apply otsu thresholding method to rank each block. The ranking of each block is done on the basis of minimum class variance. Those blocks will get the higher rank whose no. of pixels have value greater intensity value than the minimum class variance. After that quantization of the blocks is done on the basis of ranks. Those blocks will be quantized more who got higher ranks. Then the image is encoded and the compressed image and the rank information is stored in a different matrix.

I. INTRODUCTION

In today's information age, images are widely used as an effective means of communicating information. Images produced by TV s, satellites and medical imaging systems are typical examples. In these imaging systems, the image quality as perceived by the human observer is often the deciding factor of the overall quality of the system. The perceptual quality of the images produced by such systems depends to a large extent on the choices made while designing them. To obtain the desired image quality and to have a cost-effective design cycle, such decisions must be based on a knowledge of image quality and the factors which influence it. These demands have made a systematic study of perceptual image quality essential.

Every person has a notion of image quality. This notion may however depend on the context. It is difficult to find a genera! Definition of image quality that is applicable in all contexts. Roufs&Bouma (1980) defined perceptual image quality as "the degree of excellence of the image". The term 'subjective image quality' is often used instead of 'perceptual image quality'. Although both terms aim at the same concept, use of the word 'subjective' may sometimes lead to confusion (Roufs, 1992). The term subjective quality may imply that the impressions are personal and may differ widely across subjects. However, it is known that subjects are able to make consistent judgements of image quality and that judgements of different subjects coincide toa considerable extent. The term 'subjective image quality' may also mean that aesthetic components play a role. To avoid such confusion, the term 'perceptual image quality' is preferred (Roufs, 1992).

Perceptual image quality expresses the overall impression of an observer and hence is a global psychological attribute of an image. In addition to perceiving the global attribute image quality, human observers of images also perceive several other (basic) perceptual attributes of images: sharpness, brightness, brightness contrast, noisiness, etc. These basic attributes affect the overall impression of image quality. In genera!, it is relatively easier to study and understand the factors influencing these basic attributes than to directly study those affecting perceived quality. For example, the decrease in sharpness of an image may be mainly due to blurring. Similarly, an increase in the noisiness of an image may be directly related to an increase in noise variance. In addition to sharpness, noisiness and brightness contrast, we will also come across another related basic perceptual attribute, unsharpness, in this thesis. The perceived lack of sharpness of an image is referred to as unsharpness or perceived blur. Thus, unsharpness is an attribute that implies a meaning that is opposite to that of the attribute sharpness. Another concept often used in image quality\ research, similarly to the global attribute perceptual image quality, is (global or overall) perceptual impairment. Perceived global impairment implies a concept that is opposite to that of perceptual quality (de Ridder, 1992; Nijenhuis, 1993). It therefore means the 'perceived degree of degradation of the image'. The perceptual quality of an image can decrease due to many reasons, for example due to noise in the image or blurring of the image. The physical processes, such as blur and noise that lead to a decrease in the perceptual quality of images. By causing physical damage to images are called (physical) impairments or degradations.

Since a strict definition of image quality is not available, operational definitions are often used. The operational definitions may vary depending on the context. At this point, it is important to introduce a distinction between two types of contexts in which image quality is used. First, there is the quality related to performing a task based on an image. Examples are: reading from a video display uriit (VDU), detection of a target from an image, such as a tumor in a CT image or a tank in an aerial photograph. The image quality in such environments is called the performance-oriented quality (Hunt & Sera, 1978). This is different from the quality of an image in an entertainment environment such as TV or film. In the case of TV or film, the quality is mainly concerned with appreciation or involvement, hence the name appreciation-oriented quality is used. These two kinds of qualities may also influence each other (Roufs&Boschman, 1991). In this thesis, we are concerned with appreciation-oriented quality, although the feature extraction methods developed here could also be used in applications involving performance-oriented quality.

II. LITERATURE SURVEY

Mean Structural Similarity Index Metric (M-SSIM) developed by Y. Ling et al [1], [2], [3] attracted attention of entire IQA researcher community. M-SSIM metric is based on the hypothesis that human eye is subjected to extract structural activity from any image. 10 Luminance comparison, structure comparison and contrast comparison between original image and distorted image is done using mean, variance and covariance of the images. They all are combined as SSIM. Block wise quality score of the image is computed. Average of block wise SSIM values is called as M-SSIM, the final quality score. This metric is based on similarity measure and it quantifies any variation between the reference image and the degraded image. The metric performed much better than conventional image fidelity measures on image databases comprising of different distortions. It is well known that HVS is attracted by different image textures with different degrees. Therefore authors have suggested a modification in the metric. Spatially variant weighted average of SSIM index map can improve the HVS consistency of this approach.

Literature shows that many further improvements in this model were suggested by researchers to improve the performance. Perceivability of details in an image is dependent on density of samples in the image, distance between observer and the image plane and finally, the perceiving capacity of the visual system of the observer. A single scale method of quality assessment is appropriate for specific settings. In order to provide more flexibility in case of variations in resolution of the image, resolution of the display system and viewing distance, a multi-scale M-SSIM model is proposed by Chow et al [4]. This approach makes an attempt to incorporate structural details at different resolutions. Iterative decomposition of images is performed at different scales using low pass filtering followed by down sampling. Structure and contrast comparison is done at every stage but luminance comparison is done only at last stage. Final quality score is computed from quality measures obtained at different scales. Distorted image often looks more similar to the distortion-less image if quality evaluation is done at larger scale. It is quite obvious that the single-scale model exhibits higher HVS consistency with the increase in scales. However, this method suffers from certain limitations. It is tested for only JPEG and JPEG2000 image dataset in LIVE database. The metric is not effective on blurred and noisy images. Authors have suggested incorporation of more systematic approach so that it can be applicable to a broad range of applications.

M-SSIM metric fails to predict quality of images distorted by blur and noise. X.Yang et al [5] proposed a dual scale structural similarity metric to improve the performance of MSSIM for images distorted by blur and noise. In the proposed measure the first scale describes the clumsy contours of the object called as macro edge image and the second scale describes 11 the subtle edges called as micro edges. Micro edges reflect the detailed edges of the objects. Subtraction of edge image from filtered image gives macro edge image and difference between this macro edge image and original image is used as micro edge image. Computation of macro edge similarity and micro edge similarity between original image and distortion image is used to generate the final quality score. The metric outperforms especially for blur and noise distortions.

Although M-SSIM metric evaluates the image quality accurately, it suffers from the limitation of its sensitivity to geometrical distortions. In order to increase immunity of the metric to such non structural distortions, C. Bargsten et al [6] extended M-SSIM in wavelet domain. Multilevel discrete wavelet transform is used to calculate wavelet coefficients of reference image and that of degraded image. LH, HL, HH bands of same decomposition level are combined to form one band each, for five levelsBeura et al [7]. These five bands and the lowest subband (LL) are used to get total six bands. DWT-SSIM is computed as similarity measure for each band. Weighted mean of DWT-SSIM gives the final quality score. As human eye is highly sensitive to mid frequency band it is assigned greater weight than that of other bands. Authors have concluded that this metric outperforms M-SSIM. Evaluation of the metric is done using LIVE image database after implementing non-linear regression. M-SSIM in spatial domain performs poor for Gaussian blurred images. However, the metric in wavelet domain shows improvement in the performance for Gaussian blurred images.

B. Wang et al [8] proposed HVS based SSIM metric based on frequency and spatial characteristics of human eye. It is based on the hypothesis that human eye does not pay equal attention to all regions in the image. Frequency sensitivity weight is calculated using DCT coefficients. To mimic the foveated vision of human eye spatial affect weight is calculated in spatial domain. These weights are used in the calculation of M-SSIM. This metric gives HVS consistent results especially for badly blurred images. Content partitioned structural similarity metric proposed by Z. Pan et al [9] is also based on the similar hypothesis where foveated vision of human eye is taken into consideration to increase accuracy in prediction. Metrics proposed discussed above are complex as far as computation is concerned as they make use of transforms.

S. Wang et al [10] proposed an innovative approach in gradient magnitude similarity metric. It is based on the concept that image gradient is affected because of image distortions. Different local structures in a distorted image suffer by different amount due to degradations. The metric calculates pixel-wise similarity between the gradient magnitude maps of reference and distorted images and also local quality map for overall image quality prediction after pooling. The metric predicts perceptual image quality accurately and efficiently. J. Zhao et al [11] proposed FR-IQA using regional weight. Authors believe that gradient similarity reflects the image quality. The metric assigns different weights to different regions according to sensitivity of human visual system. Regional weight map is computed in gradient domain and weighted gradient metric gives single overall quality score. Results of experimentation prove that the metric outperforms M-SSIM metric.

III. SYSTEM ANALYSIS

Existing System BACKGROUND

Uncompressed graphics, audio and video data require considerable storage capacity and transmission bandwidth. Despite rapid progress in mass storage density, processor speeds and digital communication system performance, demand for data storage capacity and data transmission bandwidth continues to out strip the capabilities of the available technologies.

The recent growths of data intensive digital audio, image, and video based (multimedia) web applications, has sustained the need for more efficient ways. With the growth of technology and the entrance into the Digital Age, the world has found itself amid a vast amount of information. Dealing with such enormous amount of information can often present difficulties. Digital information must be stored and retrieved in an efficient manner in order to put it to practical use. Wavelet compression is one way to deal with this problem. For example, the FBI uses wavelet compression to help store and retrieve its fingerprint files. The FBI possesses over 25 million cards, each containing 10 fingerprint impressions. To store all of the cards would require over 250 Terabytes of space. Without some sort of compression, sorting, storing and searching for data would be nearly impossible. Typically television image generates data rates exceeding 10million bytes/sec. There are other image sources that generate even higher data rates. Storage and transmission of such data require large capacity and bandwidth, which could be expensive. Image data compression technique, concerned with the reduction of the number of bits required to store or transmit image without any appreciable loss of information. . Using wavelets, the FBI obtains a compression ratio of about 1: 20

NEED FOR COMPRESSION

The amount of data associated with visual information is so large that its storage would require enormous storage capacity. Although the capacities of several storage media are substantial, their access speeds are usually inversely proportional to their capacity. Typical television images generate data rates exceeding 10 million bytes per second. There are other image sources that generate even higher data rates. Storage and/or transmission of such data require large capacity and/or bandwidth, which could be very expensive. Image data compression techniques are concerned with reduction of the number of bits required to store or transmit images without any appreciable loss of information. Image transmission applications are in broadcast television; remote sensing via satellite, aircraft, radar or sonar; 3teleconferencing; computer communications; and facsimile transmission. Image storage is required most commonly for educational and business documents, medical images used in patientmonitoring systems, and the like. Because of their wide applications, data compression is of great importance in digital image processing.

PRINCIPLES OF COMPRESSION

The amount of data associated with visual information is so large that its storage would require enormous storage capacity. Although the capacities of several storage media are substantial, their access speeds are usually inversely proportional to the capacity.4Typical television image generate data rates exceeding 10 million bytes per second. There are other image sources that generate even higher data rates. Storage and transmission of such data require large capacity and bandwidth which could be very expensive. Image data compression techniques are concerned with reduction of the number of bits required to store or transmit images without any appreciable loss of information. The underlying basis of the reduction process is the removal of redundant data, i.e. the data that either provides no relevant information or simply restate that which is already known. Data redundancy is the central issue in digital image compression. If n1 and n2 denote the number of information carrying units in two data sets that represent the same information, then the compression ratio is defined as below:

$$\mathbf{CR = n1 / n2}$$

In this case, relative data redundancy RD of the first data set can be defined as follows:

$$\mathbf{RD = 1 - 1/ CR}$$

When n2=n1 then CR=1 and hence RD=0. It indicates that the first representation of the information contain no redundant data.

When n2<<n1 then CR->∞ and hence RD->1. It implies significant compression and highly redundant data.

In the final case when n1<<n2 then CR->0 and hence RD->-∞, indicating that the second data set contains much more data than the original representation. Various methods can be used for the compression of the image that contains redundant data. Here we use the *Discrete Cosine Transform* (DCT) method to get a compressed image of an original image.

A common characteristic of most images is that the neighbouring pixels are highly correlated and therefore contain highly redundant information. The foremost task is to find an image representation in which the image pixels are decorrelated. Redundancy and irrelevancy reductions are two fundamental approaches used in compressions. Whereasredundancy reduction aims at removing redundancy from the signal source (image or video), irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver. In general three types of redundancy in digital images and video can be identified:

• **Spatial redundancy** or correlation between neighbouring pixel values.
• **Spectral redundancy** or correlation between different color planes or spectral bands.
• **Temporal redundancy** or correlation between adjacent frames in a sequence of energies.

Image compression aims at reducing the number of bits needed to represent the image by removing the spatial and spectral redundancies as much as possible.

COMPRESSION TECHNIQUES

There are different ways of classifying compression techniques. Two of this would be mentioned here.

LOSSLESS VS LOSSY COMPRESSION

The first categorization is based on the information content of the reconstructed image. They are *lossless compression* and *lossy compression* scheme. In lossless compression, there constructed image after compression is numerically identical to the original image on a pixel by pixel basis. However, only a modest amount of compression is achievable in this technique. In lossy compression, on the other hand, the reconstructed image contains degradation relative to the original, because redundant information is discarded during compression. As a result, much higher compression is achievable and under normal viewing conditions no visible loss is perceived (visually lossless).

PREDICTIVE VS TRANSFORM CODING

The second categorization of various coding schemes is based on the space where the compression method is applied. These are *predictive coding* and *transform coding.* In predictive coding, information already sent or available is used to predict future values and the differences are coded. Since this is done in the image or spatial domain, it is relatively simple to implement and is readily adapted to local image characteristics. Differential Pulse Code Modulation (DPCM) is one particular example of predictive coding. Transform coding, on the other hand, first transforms the image from its spatial domain representation to a different type of representation using some well-known transforms mentioned later, and codes the transform values (coefficient). The primary advantage is that it provides greater data compression as compared to the predictive method, although at the expense of greater computation.

IV. PROPOSED SYSTEM

Background of Saliency Detection:

With the rapid uptake of smart devices and social networks, we are now immersed in massive amounts of digital media data every day. Considering the scarcity of our attention and time, it is urgent and advantageous to filter out only the most useful message for further processing among all of the available data to us. This concept equates to the saliency detection process when applied to images.

Saliency is usually referred to as local contrast, which typically originates from contrasts between objects and their surroundings, such as differences in color, texture, shape, etc. This mechanism measures intrinsically salient stimuli to the vision system that primarily attracts human attention in the early stage of visual exposure to an input image. Intermediate and higher visual processes may automatically judge the importance of different regions of the image, and conduct detailed processes only on the “salient object” that mostly related to the current task, while neglecting the remaining “background” regions. Figure 1.1 shows a few examples of natural images. As seen in Figure 1.1(c), the flower, the cookies, the girl, the cat and the toy car usually attract the most visual attention in their corresponding images, and thus are regarded as salient objects. On the other hand, Figure 1.1(b) shows illustrative results of saliency detection, or the “saliency maps” in formal terms. The general objective of saliency detection is to provide saliency maps of the input images as close to the ground truth as possible.

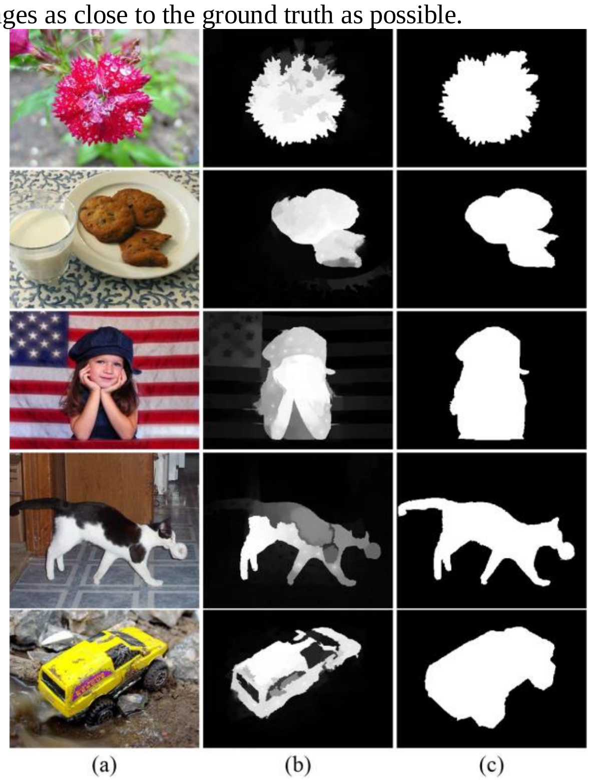

Fig.1: Examples of salient objects in natural images. (a) original images; (b) example saliency detection results; (c) ground truth.

Human visual saliency detection has long been studied by cognition scientists and has recently draw much of interest in the computer vision community mainly because of its assistance in finding the objects or regions that efficiently represent a scene, and thus harness complex vision problems such as scene understanding. Early researches of saliency detection mostly focus on human eye fixation. Which approximates the visual attention of semantic objects in a given image, such as human faces, texts, or daily objects. The detection results of eye fixations, however, are often presented as sparse dots without details about the objects. On the other hand, the recent researches of saliency detection are capable of locating and segmenting the whole salient object with complete boundary details, and thus has received broad research interests. The detection of the salient objects in images is of significant importance, as it not only improves the subsequent image processing and analyses, but also directs the limited computational resources to more efficient solutions. Saliency detection has received recognized success in various areas, such as computer vision, graphics, and robotics. More specifically, the proposed models have been broadly applied in object detection and recognition object discovery, photo collage and thumb nailing image quality assessment image segmentation, content based image retrieval, image editing and manipulating image and video compression video summarization, visual tracking, and human-robot interaction.

Existing Challenges

Since emergence, intensive researches have been conducted on saliency detection. The majority of existing saliency detection methods is based on hand-crafted low-level features. However, there are multiple critical issues on the existing methods that prevent them from perfection.

Problematic Pre-assumptions

Among many conventional low-level feature based saliency detection methods, specific pre-assumptions or prior knowledge are required in order to make them properly functioning. Most of the pre-assumptions are largely empirical, e.g. image boundary regions are assumed as background or image central regions are assumed as foreground. These pre-assumptions are easily violated on broader datasets with more unusual-patterned images, such as the example in Figure 1.2, where the upper two images have salient objects on the boundary, while the lower two images have background regions in the center. The atypical patterns of these images lead to the failure of conventional low-level feature based methods, as seen in Figure 1.2(b). To overcome the limitations above, multiple more robust improvements of the pre-assumptions have been proposed

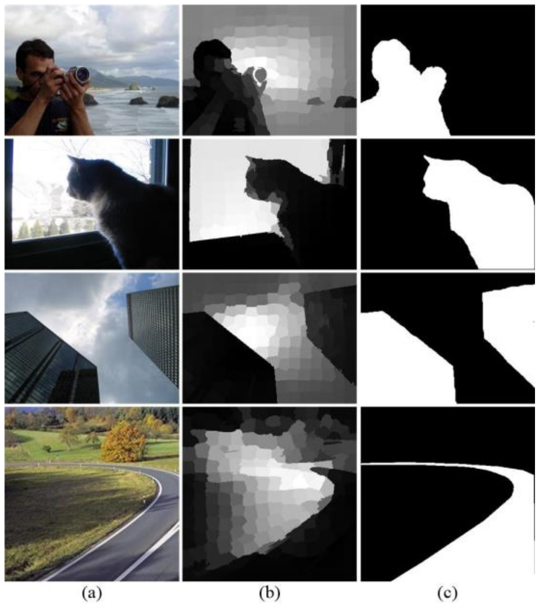

Fig.2: Examples showing the problematic pre-assumptions in conventional low-level feature based saliency detection methods. (a) original images; (b) failed detection results by a conventional low-level feature based method; (c) ground truth

Saliency Detection

From the perspective of computer vision, the methods of saliency detection are broadly categorized into two major groups, namely the bottom-up methods and the top-down methods. Besides that, more methods using unconventional models and features have also been proposed in recent years.

Bottom-Up Methods

The bottom-up methods are largely designed for non-task-specific saliency detections, in which low-level features are mainly involved as fundamentals for the detections. These features are usually data-driven and hand-crafted.

Before the 2010s, the researches of saliency detection are in the stage of fundamental developments, which draws interest across multiple disciplines including cognitive psychology, neuroscience, and computer vision. At this time, usually only the most basic features in conventional image processing, such as pixel color value, histogram, frequency spectrum, etc., are exploited in the methods. As a pioneer .present a center-surround model that integrates color, intensity and orientation at different scales for saliency detection. Rahtu*et al* detect saliency by measuring the center-surround contrast of a sliding window over the input image. Exploit Shannon's self-information measurement on local context to computesaliency. Pixel-wise color histogram and region-based contrast are utilized in establishing the histogram-based and region-based saliency maps.measure global contrast based saliency with spatially weighted feature dissimilarities. Propose a frequency-tuned method based on color and luminance, in which the saliency value is computed by the color difference with respect to the mean pixel value. Fourier spectrum analysis has also been utilized in visual saliency detection.

Since the 2010s, more advanced models, and especially the graph based models, have been introduced to saliency detection, which have greatly improved the overall detection accuracy. It is also notable that the majority of conventional low-level feature based saliency detection methods were proposed during this period. Establish a 2-ring graph model that calculates saliency values of different image regions by their Markov absorption probabilities. To overcome the negative influence of small-scale high-contrast image pattern propose a multi-layer approach that optimizes saliency detection by a hierarchical tree model Unify the contrast and saliency computation into a single high dimensional Gaussian filtering framework. Apply background priors and geodesic distance to compute visual saliency. Exploit the graph-based manifold ranking in extracting foreground queries for the final saliency map, in which the four image boundaries are used as background prior knowledge. In the image boundaries are refined before being used as background prior knowledge, and a random-walk based ranking model is applied for saliency optimization. The saliency of different image cells is computed by synchronous update of their dynamic states via the cellular automata model.

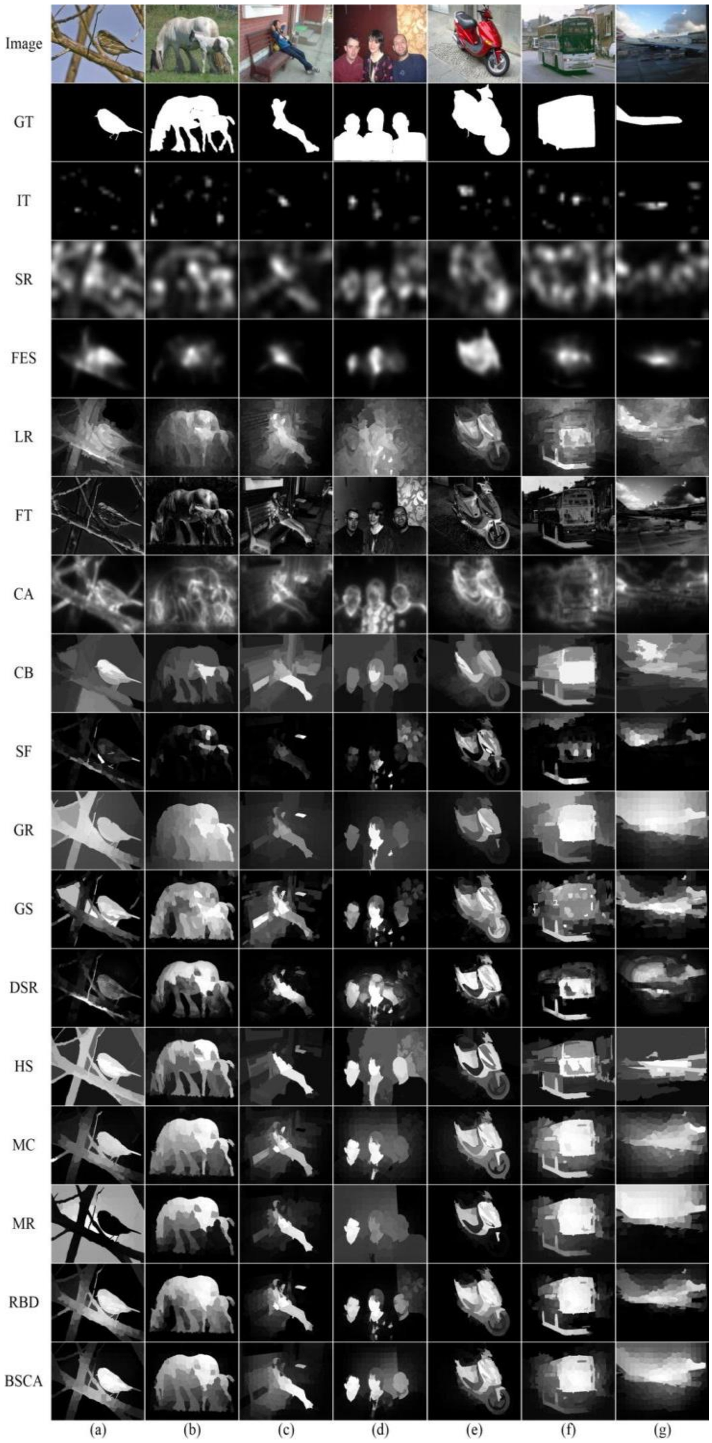

Fig.3: Example saliency maps of prevalent bottom-up saliency detection methods. (a) – (g): image case IDs.

Top-Down Methods

On the other hand, the top-down saliency detection methods are usually task-driven. These methods break down the saliency detection task into more fundamental components, and task-specific high-level features are frequently involved as prior knowledge. Supervised learning approaches are commonly used in detecting image saliency. In the work, joint learning of conditional random field (CRF) is conducted in discriminating visual saliency. Apply a graph-based diffusion process to learn the optimal seeds of an image to discriminate object and background. Train a CRF model to aggregate saliency maps from various models, which benefits not only from the individual saliency maps, but also from the interactions among different pixels. And in the work of samples from a weak saliency map are exploited as the training set for a series of supply vector machines (SVMs), which are subsequently applied to generate a strong saliency map.

Since 2013, benefitted from the tremendous success of deep learning and other high-level feature extraction techniques, more learning based methods arise with significantly improved performances. Regard saliency detection as a regression problem, which fuses regional contrast, property and back roundness into a random forest classifier for multi-level image saliency segmentation. Represent the saliency map as a linear combination of different high-dimensional color space, where the salient regions and the background distinctively separated. Train two separate DNNs with image patches (DNN-L) and object proposals (DNN-G) for local and global saliency, the two results are then integrated by a weighted summation to create the final saliency map. Establish a multi-context DNN model for super pixel-wise saliency classification, which exploits DNN for per-super pixel saliency value classification. Propose a similar multi-scale DNN model for feature extraction, the outputs of which are then aggregated for the final saliency map. Two stacked DNNs are utilized to build the saliency detection model, among which the first one provides a coarse saliency estimation with the whole image as input, while the second one focuses on the local context to produce fine-grained saliency map.

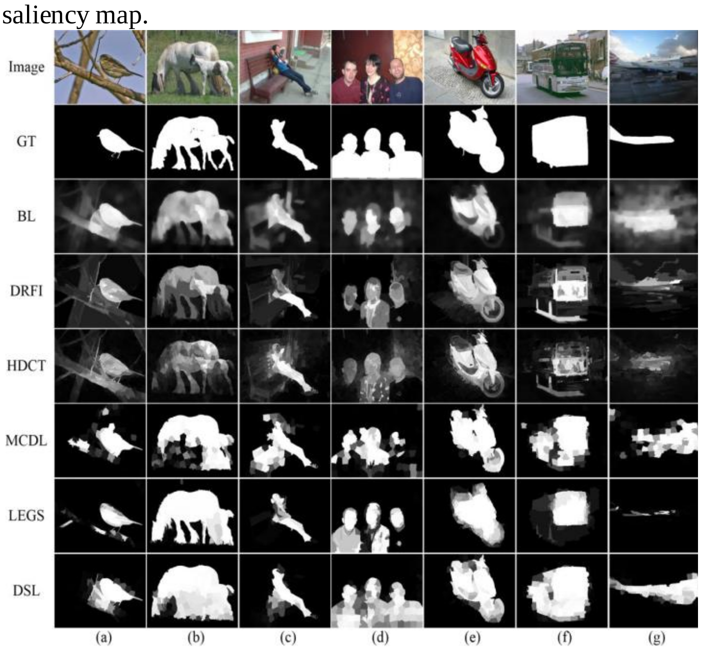

Fig.4: Example saliency maps of prevalent top-down saliency detection methods. (a) – (g): image case IDs.

V. RESULTS

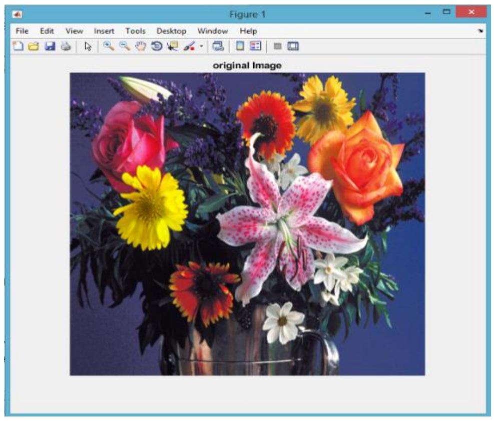

Fig.5: Input Original Image

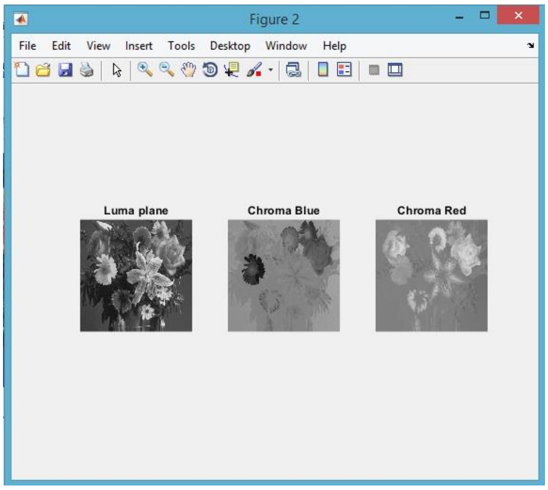

Fig.6: YCbCr Color space Images

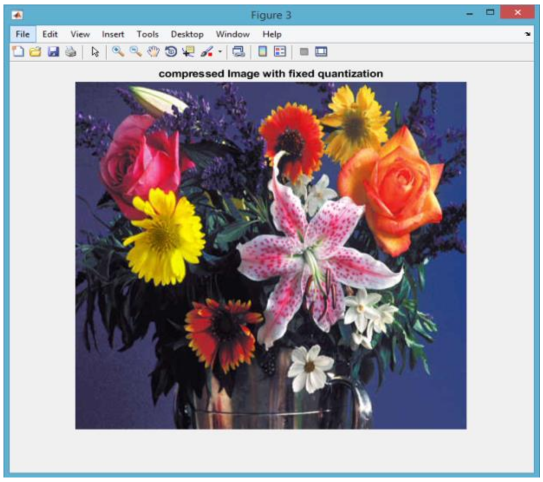

Fig.7: Compressed with fixed quantization

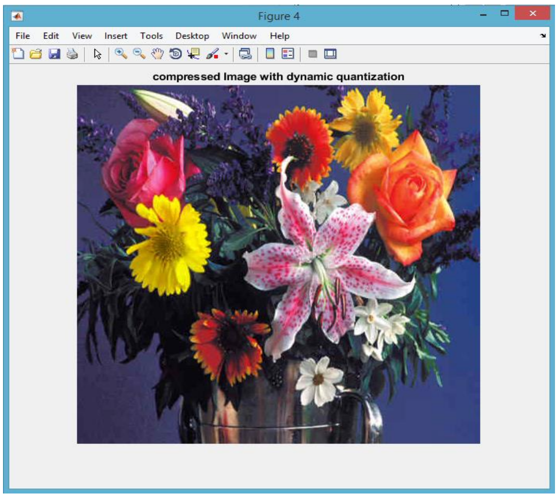

Fig.8: Compressed with dynamic quantization

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psnr_roi =

   29.3920


compression_ratio_after_jpeg_roi_without_overhead =

   21.8405
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VI. CONCLUSION

This paper has presented an original color image coding scheme combining scalable compression and image description at region level.There are quite a few applications in which one would like certain portions of an image to be encoded with higher quality than other portions. Medical images and some scientific images are among the few where people argue that higher quality should actually mean lossless quality. (Indeed, many physicians and scientists have argued that medical and scientific images must always be compressed losslessly everywhere.) However, we propose thatregionally lossless compression methods have the potential for widespread medical acceptance, since they are responsive to the nature of medical images (spatially varying importance levels and statistical characteristics) and to the needs of the radiologist (guaranteed accuracy for diagnostically important regions, no ambiguity about what portions are reliable).

We have investigated an important and timely emerging research topic - quality evaluation of screen content images. Images of screen content typically involve virtual desktop applications and remote processing systems, which access remote computational resources as well as acquiring and managing remote data through the network. Unlike natural scene images, screen content images arise by a process of algorithmic generation and/or assembly. While natural scene images are generally rich in color, shape complexity and detail, screen content images often have limited color variation, and contain simple shapes and fine lines. Such differences render the design theories developed for assessing the quality of natural scene images less reliable. This paper provides some practical solutions to the screen content IQA problem.

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