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AN EFFICIENT COLOR CODING SCHEME FOR COMPRESSION OF HIGH DYNAMIC RANGE IMAGES WITH THE CONSIDERATION OF COLOR SAMPLES

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ABSTRACT: High dynamic images are increased in their quality which is frequently produced in the real world due to presence of more increased level of technologies. Sharing of high dimensional images would be more difficult task due to their higher image size. The image compression needs to be done before forwarding the HDR images to avoid the unwanted bandwidth utilization. Color image coding is the most popular technique which would reduce the illumination of color effects present in the HDR image by reducing HDR range into Low Dynamic Range (LDR). This is done by reducing the higher saturation effect into human visual effect based representation. In the existing system, High Efficiency Video Coding (HEVC) is used for compression, where the images are represented in the Y’CbCr format. This work would require more computational time and might create more computational overhead for interlinking the hue level of HDR to LDR. And also reconstruction quality of images would be poor in the existing color coding based compression technique. This problem is resolved in the proposed research methodology by integrating the existing color coding technique with the Tree-structured wavelet compressive sensing approach (TSWCSA) in which image pixels would be reconstructed based on predicting coefficient values of the image pixels. Thus the proposed research methodology can achieve good image reconstruction quality based on image pixel values. The experimental evaluation of the proposed research methodology is done in the matlab simulation environment from which it is proved that the proposed method can perform better compression and also HDR images can reconstructed with pixel loss in the end.

Keywords: [Image compression, coding, reconstruction quality, compressed sensing, HDR, LDR, saturation, hue level].

1. INTRODUCTION

High-dynamic-range imaging (HDRI) is a high dynamic range (HDR) technique used in imaging and photography to reproduce a greater dynamic range of luminosity than is possible with standard digital imaging or photographic techniques. The aim is to present a similar range of luminance to that experienced through the human visual system. The human eye, through adaptation of the iris and other methods, adjusts constantly for the broad range of luminance present in the environment. The brain continuously interprets this information so that a viewer can see in a wide range of light conditions.

HDR images can represent a greater range of luminance levels than can be achieved using more 'traditional' methods, such as many real-world scenes containing very bright, direct sunlight to extreme shade, or very faint nebulae. This is often achieved by capturing and then combining several different narrower range exposures of the same subject matter [1]. Non-HDR cameras take photographs with a limited exposure range, resulting in the loss of detail in highlights or shadows. The two primary types of HDR images are computer renderings and images resulting from merging multiple low-dynamic-range (LDR) [2] or standard-dynamic-range (SDR) [3] photographs. HDR images can also be acquired using special image sensors, like an oversampled binary image sensor.

Due to the limitations of printing and display contrast, acquiring an HDR image is only half the story; one must also develop methods of displaying the results. The method of rendering an HDR image to a standard monitor or printing device is called tone mapping. This method reduces the overall contrast of an HDR image to facilitate display on devices or printouts with lower dynamic range, and can be applied to produce images with preserved or exaggerated local contrast for artistic effect.

There are different methods to obtain HDR images. Computer rendering and merging multiple low dynamic range (LDR) images taken at different exposure settings are the two methods initially used to generate HDR images. Nowadays, HDR images can also be acquired using specific image sensors. There are two forms of visualization in HDR images. The first and the best solution is to use a specific HDR display that has the ability of representing a wider luminance range and color gamut. The second solution is to map the HDR image to a LDR display luminance range and color gamut, using a tone mapping operator (TMO).

In this research HDR compression and reconstruction of HDR images with the preserved HDR quality is done. This is done in the proposed research methodology by integrating the existing color coding technique with the Tree-structured wavelet compressive sensing in which image pixels would be reconstructed based on predicting coefficient values of the image pixels. Thus the proposed research methodology can achieve good image reconstruction quality based on image pixel values.

The overall organization of the proposed research work is given as follows. In this section, detailed discussion about the E-Learning system is given. In section 2, Varying related research works that are proposed in terms of identification of the prediction of student's performance is given. In section 3, detailed discussion about the proposed research methodology is given. In section4, experimental evaluation of the proposed research methodology is given in detail. Finally in section 5 overall conclusion of the research work along with the detailed discussion of results section is given.

2. RELATED WORKS

Ji Won Lee et al. [4] proposes a noise reduction method and an adaptive distinguish enhancement for local tone mapping (TM). The proposed local TM algorithm compresses the luminance of high dynamic range (HDR) image and decomposes the compressed luminance of HDR image into multi-scale sub bands using the discrete wavelet transform. In case of noise reduction, the stale images are filtered using a soft-thresholding and bilateral filter then, the active ranges of the clean sub bands are enhanced by considering local contrast using the modified luminance compression function. At the color tone-mapped image is reproduced using an adaptive saturation control parameter and generate the tone-mapped image using the projected local TM. Computer imitation by noisy HDR images shows the effectiveness of the proposed local TM algorithm in terms of visual quality as well as the local distinguishes. It can be used in various displays with noise reduction and contrast enhancement. The images that can be tone-mapped with the proposed local TM algorithm give better image quality than those of the conventional TM algorithms. That is, the proposed local TM algorithm effectively reduces coarse-grain noise and enhances the local contrast.

Yen-Ching Chang and Chun-Ming Chang [5] have proposed a new framework for the contrast enhancement using histogram equalization .Here in this technique two support and boundary values are taken and the values of the image are set according to these value. The proposed technique successfully reduces the washout appearance and reduces artifacts of the image. Chen Hee Ooi and Nor Ashidi Mat Isa [6] proposed the new way of enhancing the contrast of the images using quadrant dynamic histogram equalizations. The proposed QDHE is the most robust method to extract the details of the low contrast images. Observing from the simulation results obtained, the QDHE has produced the best performance for both qualitative and quantitative evaluations.

Haiyan Zhao [7] offers the thought regarding article combines with human visual feature to check digital watermarking technique to insert watermarking, extracts watermarking in line with the harm state of affairs of watermarking, and that combines with other visual redundancy feature to attain an image scrambling algorithmic program that's simple to recover and a recovery theme for broken scrambling image. Abstract-HVS theory plays necessary role within the application of digital image watermarking method. Once insert watermarking, the visual masking feature of HVS can be totally wont to style digital watermarking algorithmic program with smart perceived performance. Once extracting watermarking from the broken image, human's visual feature can be combined to recover the broken image thus on acquire higher result. This rule might be applied in digital image watermarking rule to strengthen the hardiness of watermarking rule.

Wen-Chieh Lin and Zhi-Cheng Yan [8] proposed a local tone mapping method that compliments both attention and adaptation effects. We accept the High Dynamic Range (HDR) saliency chart to calculate an attention chart, which predicts the attentive regions and non attentative regions in an HDR image. The attention chart is then used to locally regulate the contrast of the HDR image according to attention and adaptation models found in psychophysics. These practical their tone mapping approach to HDR images and videos and compared with the results generated by three state-of-the-art tone mapping algorithms. This experiments show that their approach produces results with better image quality in terms of preserving particulars and chromaticity of visual saliency. Chulwoo Lee [9] has proposed an efficient algorithm for the contrast enhancement. A novel contrast enhancement algorithm based on the layered difference representation of histograms is proposed in these techniques.

Ji Won Lee, Rae-Hong Park, and Soon Keun Chang [10] proposed a local TM algorithm, in which the HDR image segmented using K-means algorithm and a show gamma parameter is put automatically for each segmented area and it compute the luminance of an input that is the radiance map generated from a set of LDR images with changeable exposure settings and this image is divided into several regions using a K-means algorithm. Then, the tone of HDR is reproduced by a linear TM method with adaptive gamma value. It is used for contrast and color enhancement in different display and acquisition devices.

V. Mugudeeswaran and and C. G. Ravichandran [11] proposed fuzzy logic based histogram equalization for the contrast improvement. The FHE have two stages. Initially, fuzzy histogram is computed based on fuzzy set theory to hold the inexactness of gray level values in a better way compared to typical crisp histograms. Another stage, the fuzzy histogram is divided into two sub histograms based on the median value of the original image and then equalizes them independently to preserve image brightness

3. EFFICIENT HIGH DYNAMIC RANGE IMAGE COMPRESSION/ DECOMPRESSION BASED ON COLOR SATURATION LEVEL

In the proposed research work, compression of HDR images are done to reduce the image size, thus the unnecessary utilization of the resources during image transmission/ sharing can be avoided. In the existing system HDR image is represented in the classical Y'CbCr format. In addition, a second scheme is proposed using a colorspace based on the CIE u'v' uniform chromaticity scale diagram. In each case, different prediction equations are derived based on a color model ensuring the hue preservation. This exiting work links the HDR image hue values with the LDR layer of hue levels to avoid the color effect that cannot be seen by human visual effects.

The existing research degraded from its reconstruction quality which is resolved in the proposed research method. In the proposed research methodology by integrating the existing color coding technique with the Tree-structured wavelet compressive sensing approach in which image pixels would be reconstructed based on predicting coefficient values of the image pixels. Thus the proposed research methodology can achieve good image reconstruction quality based on image pixel values. The steps followed in the proposed research method are given as follows:

Representing the HDR images in classical Y'CbCr format

Compression using Tree Structured Wavelet Compression Sensing

The detailed explanations of these steps are given in the following sub sections clearly.

3.1 IMAGES IN THE CLASSICAL Y'CbCr FORMAT

In the Y'CbCr scheme, the OETF is applied to the R, G, and B components independently and the resulting R0G0B0 components are converted to Y'CbCr color space using the standard conversion matrix from the ITUR BT-709 recommendations. This is very similar to the color space generally used for the compression of LDR images, the only difference being that the usual gamma correction is replaced by the PQ-OETF which better models human perception, particularly for high luminance values. Then, the chroma channels Cb and Cr are down sampled and the image is sent to a modified version of HEVC including our inter-layer prediction mode.

Then the true luminance Y is computed and the PQ-OETF is applied only to this achromatic component to form the luma channel YPQ. Then, the CIE u'v' color coordinates are computed from the linear RGB values. The modified u'v' components are noted u"v" and are computed with the following formula :

$$u'' = (u' - u'_r).\frac{Y_{PQ}}{\max(Y_{PQ}, Y_{th})} + u'_r$$

$$v'' = (v' - v'_r).\frac{Y_{PQ}}{\max(Y_{PQ}, Y_{th})} + v'_r$$

where u'_r and v'_r are the u'v' coordinates of the standard D65 illuminant : u'_r = 0; 1978 and v'_r= 0:4683. And Yth is a threshold on the luma YPQ that we set to 1000 which corresponds to an absolute luminance value of 4.75 cd/m2. This modification allows a coarser quantization of the color in dark regions that may contain invisible color noise. In the decoding process, the u'v' coordinates are retrieved by performing the inverse operations.

3.2. TREE STRUCTURED WAVELET COMPRESSION SENSING

Tree-structured wavelet compressive sensing (TSW-CS) model is constructed in a hierarchical Bayesian learning framework. In this setting a full posterior density function on the wavelet coefficients is inferred. Within the Bayesian framework , a spike - and - slab model is imposed for Bayesian regression. The prior for the ith element of θ (corresponding to ith transform coefficient) has the form shown in equation 1.

$$\theta i \sim (1-\pi i)\ \delta 0 + \pi i\ \mathcal{N}\ (0, \alpha_i^{-1})\ ,\ i=1,2,..M \quad (1)$$

which has 2 components. The first component δ0 is a point mass concentrated at zero, and the second component is a zero-mean Gaussian distribution with (relatively small) precision α_i^{-1}. the former represents the zero coefficients in θ and the latter the non-zero coefficients. This is a two-component mixture model, and the two components are associated with the two states in the HMT. The mixing weight πi, the precision parameter αi, as well as the unknown noise precision αn, are learned from the data. The proposed Bayesian tree-structured wavelet (TSW) CS model is summarized as follows.

$$\frac{V}{\theta} \sim (1-\pi_{s,i})\delta_0 + \pi_{s,i}\ N\ (0,\alpha_s^{-1}), \text{with } \pi_{s,i} \quad (2)$$

$$= \begin{cases} \pi_s^0, \text{if } 2 \le s \le L, \theta_{pa(s,i)} = 0 \\ \pi_s^1\ , \ \text{if } 2 \le s \le L, \theta_{pa(s,i)} \neq 0 \end{cases} \quad (3)$$

$$\alpha_n \sim \text{Gamma}\ (a_0, b_0) \quad (4)$$

$$\alpha_s \sim \text{Gamma}\ (c_0, d_0),\ \ s = 1,2, \dots L \quad (5)$$

$$\pi_r \sim \text{Beta}\ (e_0^r, f_0^r) \quad (6)$$

$$\pi_s^0 \sim \text{Beta}\ (e_0^{s0}, f_0^{s0}) \quad (7)$$

$$\pi_s^1 \sim \text{Beta}\ (e_0^{s1}, f_0^{s1}) \quad (8)$$

where θs,i denotes the ith wavelet coefficient (corresponding to the spatial location) at scale s, for i= 1,2...,MS (MS is the total number of wavelet coefficients at scale s) , πs,i is the associated mixing weight, and θpa(s,i)denotes the parent coefficient of θ s,i . In equation 3 it is assumed that all the nonzero coefficients at scale s share a common precision parameter αs. It is also assumed that all the coefficients at scale s with a zero-valued parent share a common mixing weight πs0, and the coefficients at scale s with a nonzero parent share a mixing weight πs1.

Gamma priors are placed on the noise precision parameter αn and the nonzero coefficient precision parameter αs, and the posteriors of these precisions are inferred according to the data. The mixing weights πr,πs0,πs1 are also inferred, by placing beta priors on them. To impose the structural information, depending on the scale and the parent value of the coefficients, different Beta priors are placed. For the coefficients at the root node, a prior preferring a value close to one is set in equation 6, because at the low-resolution level many wavelet coefficients are nonzero; for the coefficients with a zero-valued parent, a prior preferring zero is considered in equation 7, to represent the propagation of zero coefficients across scales; finally, equation 8 is for the coefficients with a nonzero parent, and hence no particular preference is considered since zero or nonzero values are both possible.

We now present our direct and adaptive approach to compressed sensing. Instead of acquiring the visual data using a representation that is incoherent with wavelets, such as pseudo-random binary masks, we sample directly in the wavelet domain. This might seem as a paradox to the reader familiar with signal processing, since computing the fast wavelet transform of an N pixel image requires O(N) computations, whereas we want to take only n measurements with n << N . Furthermore, computing even one single low-frequency wavelet coefficient requires an integration calculation over a significant portion of the image pixels, again an operation requiring O(N) computations. This paradox is in fact solved by using the DMD array architecture in a very different way than in the prior art:

1. Any wavelet coefficient is computed from a fixed number of specific measurements (2-4) of the DMD array.

2. We take advantage of the ‘feed-back’ architecture of the DMD where we make decisions on future measurements based on

values of existing measurements. This adaptive sampling process relies on a well known modeling of image edges using a wavelet coefficient tree-structure and so decisions on which wavelet coefficients should be sampled next are based on the values of wavelet coefficients obtained so far.

First we explain how the DMD architecture can be used to calculate a wavelet coefficient from a fixed number of measurements. We recall that the univariate Haar scaling function φ and wavelet ψ are given by:

$$\phi(x) := \begin{cases} 1 & x \in [0,1] \\ 0 & \text{otherwise} \end{cases}$$

$$\psi(x) := \begin{cases} 1 & x \in [0,\frac{1}{2}) \\ -1 & x \in [\frac{1}{2},1] \\ 0 & \text{otherwise} \end{cases}$$

This implies that for the purpose of computing a wavelet coefficient of the first type using a binary DMD array, we simply need to rotate and collect twice, into the photodiode, responses from two subsets of micro-mirrors, each supported over neighboring rectangular regions corresponding to the scale j and location k . By (2.2), the value of the wavelet coefficient we wish to acquire is simply the difference of these two outputs multiplied by 2 j . Similar computation shows that sampling the wavelet coefficient of the second kind also requires two measurements, while the third kind requires four. Moreover, there exist DMD arrays with the functionality where which micro-mirror can produce a grayscale value, not just 0 or 1 (contemporary DMD can produce 1024 grayscale value). We can use these devices for computation of of arbitrary wavelet transforms, where the computation of each coefficient requires only two measurements, since the result of any real-valued functional acting on the data can be computed as a difference of two 'positive' functionals, i.e. where the coefficients are positive. Our adaptive TWS algorithm works as follows:

1. Acquire the values of all low-resolution coefficients up to a certain low-resolution J . Each such computation is done using a fixed number of DMD array measurements. In one embodiment the initial resolution J can be selected as

$$\left\lceil \frac{\log_2 N}{2} \right\rceil + \text{const}$$

In any case, J should be bigger if the image is bigger. Note that the total number of coefficients at resolutions ≥ J is 22(1−J)N , which is a small fraction of N .

2. Initialize a 'sampling queue' containing the indices of each of the four children of significant coefficients at the resolution J .

3. Process the sampling queue until it is exhausted as follows:

a. Compute the wavelet coefficient corresponding to the index (e, j, k) at the beginning of the queue using a fixed number of DMD array measurements.

b. If the coefficient's resolution in bigger than 1 and the coefficient's absolute value is above a given threshold, then add to end of queue the indices of its four children (e, j −1, (2k1, 2k2)) , (e, j −1, (2k1, 2k2 +1)) , (e, j −1, (2k1 + 1, 2k2)) and (e, j −1, (2k1 +1, 2k2 +1)). In some embodiments, one can use a different threshold for each resolution.

c. Remove the processed index from the queue and go to (a).

4. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed method, this work use following metrics for performance assessment of lossy based image compression method. This work applied proposed method on high dynamic range images and compares the performance of the proposed compression method with other compression methods.

Compression Ratio (CR): Image Compression Ratio (CR) is defined by the ratio between the uncompressed image size and compressed image size, which is denoted by as follows:

$$CR = \frac{\text{Uncompressed image size}}{\text{compressed image size}}$$

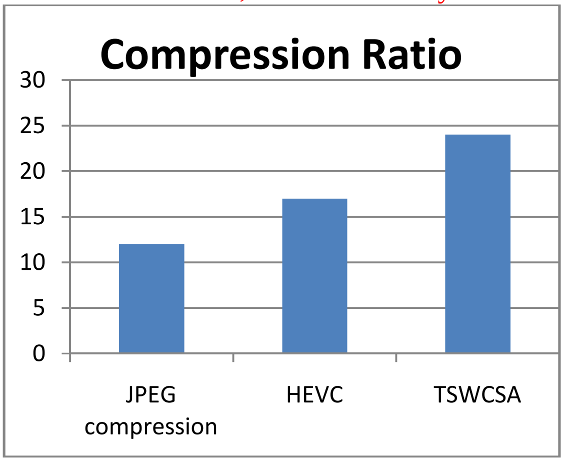


Figure 1- Compression ratio comparison

Mean Square Error: The Mean Square Error is the error rate between the original image and the decompressed image, The MSE is defined as follows equation.

$$MSE = \frac{1}{MxM}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}(q_{i_j} - \hat{q}_{ij})^2 \quad ()$$

where $N_1 x N_2$ is the image size, q_{ij} and $\hat{q}_{ij}$ denote the pixel value at the location (i, j) of original and decompressed images, respectively

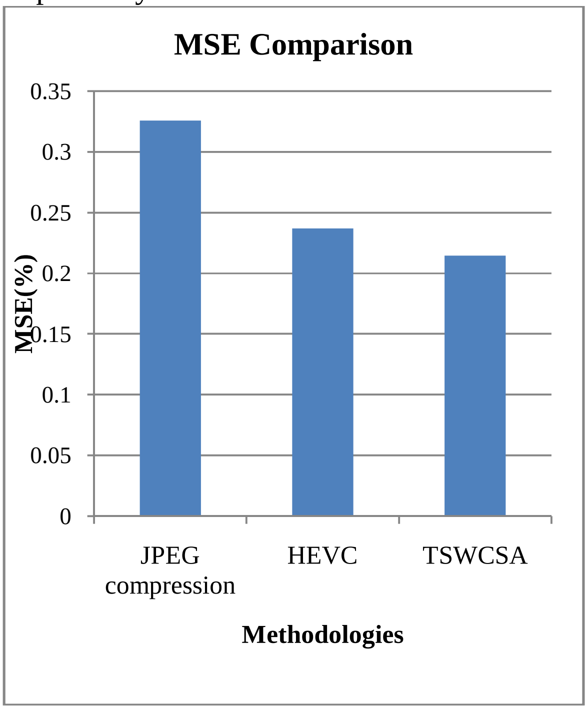
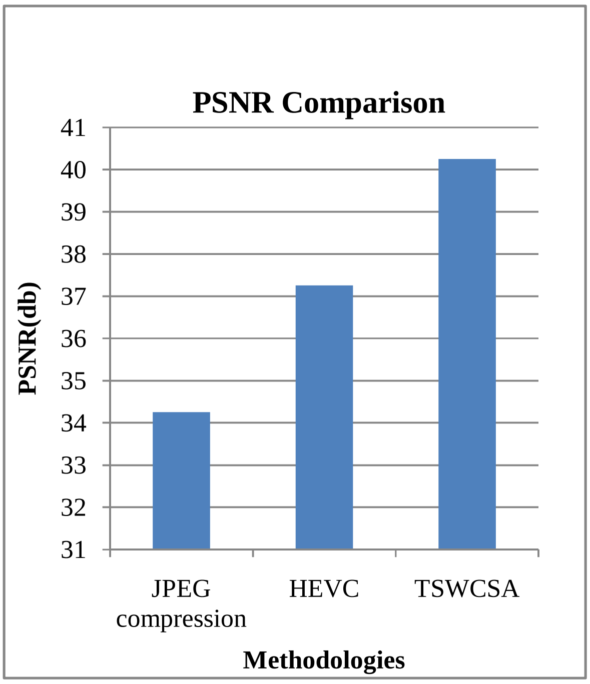


Figure 2- MSE comparison

Peak Signal-to-Noise Ratio (PSNR): The quality of encoded image was evaluated using the peak signal-to-noise ratio (PSNR). The PSNR values is denoted in a logarithmic unit of decibel (dB).The PSNR is defined as

$$PSNR = 10 \log_{10} \frac{G^2}{MSE} \quad ()$$

The G is the maximum of gray level and MSE is the mean square error between the original image and the decompressed image.



CONCLUSION

HDR compression is the major task in the real world environment where the generation and sharing of HDR images are increased considerably. In this research work, efficient compression sharing with the concern of high reconstruction quality is done in order to share the HDR images efficiently with the preservation of color saturation levels. in the proposed research methodology by integrating the existing color coding technique with the Tree-structured wavelet compressive sensing approach (TSWCSA) in which image pixels would be reconstructed based on predicting coefficient values of the image pixels. Thus the proposed research methodology can achieve good image reconstruction quality based on image pixel values. The experimental evaluation of the proposed research methodology is done in the matlab simulation environment from which it is proved that the proposed method can perform better compression and also HDR images can reconstructed with pixel loss in the end.

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