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RESIDUE ANALYSIS OF IMAGE QUALITY USING TENSORFLOW

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ABSTRACT: Residue analysis is important factor to enhance the quality of the image. Nowadays various image quality assessment and enhancement techniques are available. Layered High range dynamic image processing method is proposed to improve the image quality. The mapping of 8-bit conversion and code is applied for finding residue of images. In this case, each image characteristics are taken into account and create residue block for processing. The local characteristics are verified and find the residue signal ranges. In this paper, we used High dynamic range encoding scheme for calculating each residue block characteristics. This method is used to find different bitrates, spatial activities and dynamic ranges. The experiments are shown the 8-bit conversion method perform well and find the residue analysis. The final results are conducted by using linear and non-linear method. Our proposed method performs better and gives high quality visual images, trained data set and less computational cost.

KEYWORDS: Image quality, Residue analysis, TensorFlow, High dynamic range encoding, Image enhancement

I. INTRODUCTION

Recent years, image quality and enhancements are suggested by varies researches and liner interpolation methods are failed to find image structures, edges and image textures. The improved exploit model is developed for analysing colour images and representations. The colour images are represented in sparse plane and find their residues. Anti-aliasing and zipper are two factors to affect image quality. This case, we must take these two factor and find the residue block. Sparsity and Demosaicking is assigned to each coordinate values and get spectral value [1].

The challenges in high dynamic range are compression and highest storage. High dynamic range images are 8-bit representation and it is problem in floating point representation [2]. The higher storage and compression are affecting the image quality. The existing 8-bit representation can be changed to low range images and backward compatibility. TensorFlow is reducing this issue and it has dynamic recording and assessment pattern. TensorFlow is the tool for processing high range images and we can dynamically change the image characteristics [4][5].

Deep learning based high dynamic range method has used to train end to end data set and find the residue. This case colour images are grounded and interpolation factor is calculated. It is desirable and simulation method to mitigate the accumulation error. Denoising and Demosaicking are considered for evaluating image quality [6]. The existing work, the four channel image analysis method is applied for finding textures, images edges and deep joints. In this paper, convolutional neural network is proposed using tensorflow. This paper has following sections, section 1 describes related works, section 2 explain methods and algorithms, section 3 gives implementations and discussion and section 4 explains result and conclusion.

II. RELATED WORKS

The existing methods have two application categories. Low dynamic range images can be changed with respect to time and spatial position. High dynamic range has local artistic factors to affect coordinate positions. The above two methods have film masking coefficient value and each stage we need represent tidy post analysing results [7]. Kutan et al, the image quality can be determined by effective encoding techniques. The residue can be obtained from low level bandwidth to high level bandwidth [8].

Zerman et al, each residue block is calculated by low dynamic range method. The linear multiplication technique is applied to check lower level prediction. The residue is obtained from encoded result and interpolation values [9]. Each block frame is assigned to low level range and dynamically set offset values. This offset value is adopting the changes and mention the version. This is block wise prediction method so each bit can be noted and frame wise estimation is done. The low and high dynamic frames are marked for image enhancement [10].

Mai et al, low dynamic range image assessment has global tone mapping with each pixel values [11]. High dynamic image range has reconstruction and inverse mapping. Here encoding and decoding are major factor and set of interpolation operation is needed. The mean square value is measured in each residue block and set sequence number for each block. This is statistical model so tone mapping, encoding/decoding, inverse mapping and approximation are important. So we suggest high range dynamic image interpolation method for enhance image quality [12].

III. PROPOSED MODEL

In this work, we use light weight deep convolutional network and trained end to end tacking images. This network model is consisting of bottleneck, feature extraction, tone mapping and image reconstruction. Feature extraction block can train multilevel representations and verify connections and features. This stage image annotation values and resolutions are marked and set transformation factor. This method has efficient architecture and connected deep convolutional network. The residual transformation is calculated by using tone mapping.

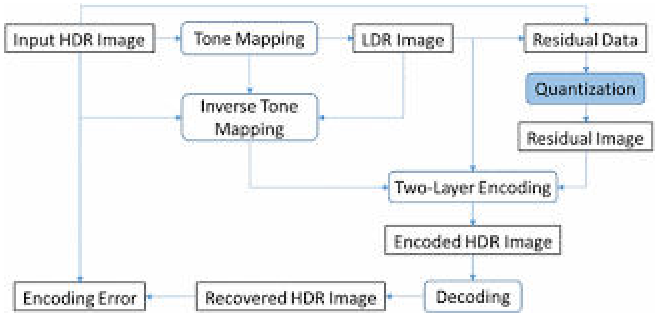

Figure 1: Proposed model for tone mapping and High dynamic range system

The above figure 1 shows that processing input image and high dynamic range convolution method for quality enhancement. In this method, tone mapping is applied to input images and divided to set of blocks. Each block images are converted to low dynamic range model and converted residual data. Quantization method is applied to residual data and represented as residual images. These stage residual images are stored in deep convolutional network and high dynamic range encoding/decoding is applied. The residue frame is represented as r_n and 8-bit conversion is applied.

We examine the content based solution using tone mapping and inverse tone mapping is applied in decoding stage. The reconstructed images are stored and find data rate value for representations. The distortion test is applied by using following formula and set reside value. 8-bit auto covariance method is applied in residue frame

$R_s(x,y) = P_1^{|rn|} .P_2^{|rn|}$ where as P1 and P2 are horizontal and vertical interpolation values

The residual blocks are strong correlation with directions and representations. So autocorrelation factor is calculated by

$R_{sc}(x,y) = P_1^{|rcosx+rsiny|} .P_2^{|rsinx+rcosy|}$ where this calculated for horizontal and vertical directions

Figure 1: High dynamic range images with tone mapped

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The above figure 1 shows that various high dynamic range images with tone mapped. The deep convolutional network is applied for above images. The convolution graph is generated below figure 2.

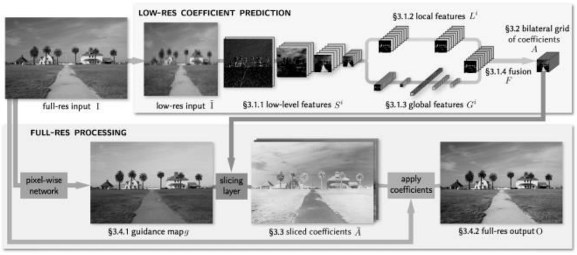


Figure 2: Deep convolutional network for residue calculation

Algorithm – Deep Convolution network model for residue calculation

Input: Horizontal and vertical residue blocks

Condition: TensorFlow – Deep convolutional model

Step 1: The input coordinates (x,y) = (0,1) is normalized and set maximum and minimum values

Step 2: The normalized sigmoid function is calculated

S_{rn}= 1 / e^{-Rs} from this 255 and 8-bit images are represented in bit plane

Step 3: m is arithmetic mean and value for set of n values. The s is selected as mean square error. SO the residue and reconstruct the image by using iteration policy, recursively.

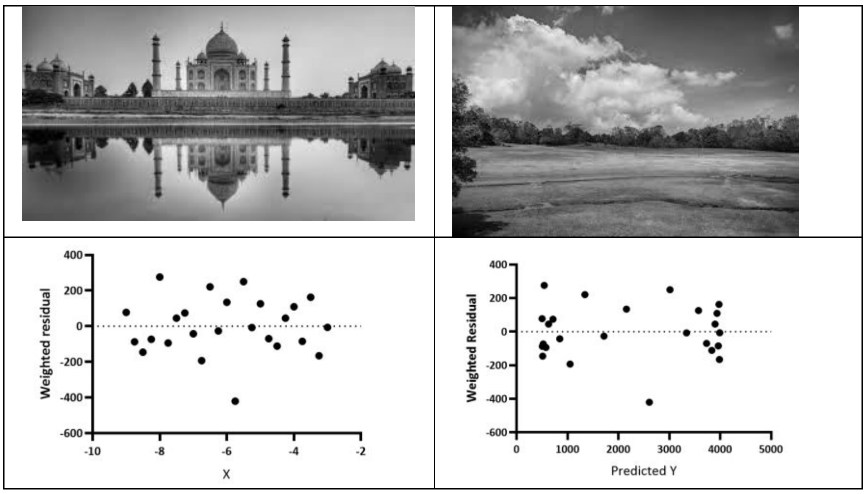
$S_k = (S_{rn} \text{ X } (\sum_{i=0}^{n-1} fi(m)/n))$

So the normalization of Sk is represented as

$^{n}S_k = Sk / (R_{sg} \text{ X } \sum_{i=0}^{n-1} \frac{fi(m) - f(i-1)(m-1)}{n}))$

Step 4: The generalized model is selected from each normalized residue images and iterate the process

The input high dynamic range size is 1870 X 1047 and range is 0.024 to 0.02. The selected images are applied in 8-bit representation plane and divers the performance. The following figure 3 shows that diverse representation of selected images.



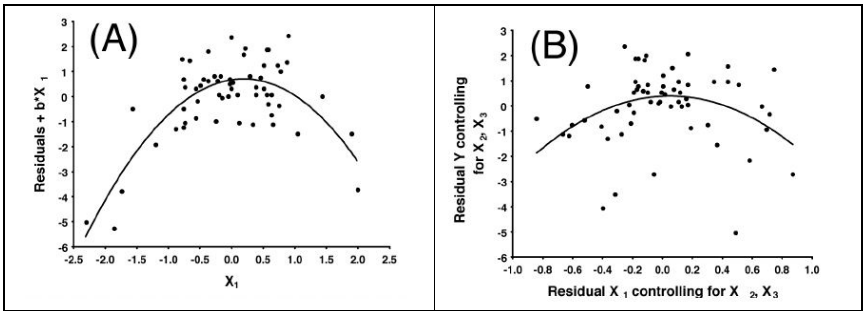


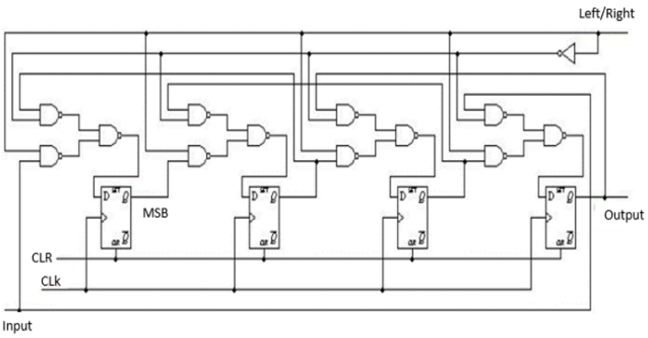
Figure 3: Residual image and controlling points representation

Our proposed light weight deep convolutional network model high dynamic range encoding method has end to end learning method. Each pixel values are identified and created residual block. TensorFlow is used to generate convolution graph and deep residue is denoising results. The performance is compared with existing model in below section.

IV. PERFORMANCE EVALUATION

The implementation is done in TensorFlow and we used Picaso image dateset with 1500 high quality images. Training set as 1000 images and test data set is 500 images. The high range images are 100 x100 resolution and 50 residue block is created. The data augmentation process is applied with minimum of 8bit representations.

The comparison of residue coding is in bit rate mode in base layer. The bit rates are 25,50,75 and 100. By applying 8-bit conversion and reconstruct the high range images. The residue layer generates peak and weak signal.



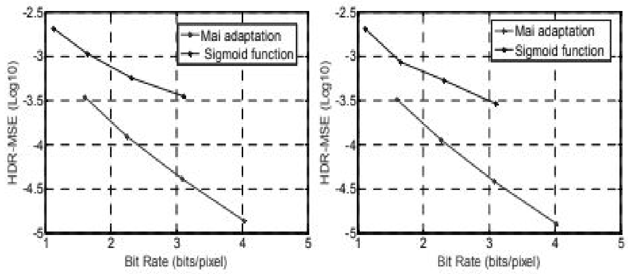


Figure 4: 8 bit rate residue comparison using TensorFlow

The comparison results shows that high range dynamic images are having different prediction values. The direction is specifies texture region and edges. Our proposed method provides better results and compared with existing results it gives enhanced images.

V. CONCLUSION

In this paper, we proposed novel high dynamic range image coding method with residue features for enhancing image quality. The images are processed by different directional characteristics and test the performance. Original and inverse tone mapping is applied and get residue block for each images. The directional coordinates are represented using 8-bit conversion. This method is light weight model and experiments are done using TensorFlow. The major advantage of our method has convolutional network model and aggregated residual results. Experimental results shows good result and reduced computational cost.

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