Image Quality Assessment using Elman Neural Network Model and Interleaving Method

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Abstract

Imaging systems introduce distortions and artifacts to the image. It is crucial to know the quality of the image before processing. In any image processing application it is important to know reliability of the imaging system and the quality metrics of the image acquired using the imaging system. This research aims to develop, reference image quality measurement algorithms for JPEG images. A JPEG image database was created and subjective experiments were conducted on the database. A newly proposed image pixel reduction technique was applied to the image to reduce its size. An attempt to design a computationally inexpensive and memory efficient feature extraction method has been developed along with the interleaving method. Subjective test results are used to train the neural network model, which achieves good quality prediction performance without any reference image. In particular the Elman neural network model predicts the mean opinion score of the human observer. The system has been implemented and tested for its validity. Experimental results show that the proposed algorithms have an accuracy rate of 90.23% for image quality recognition.

Keywords: Image Quality Assessment, Vertical Interleaving, Feature Extraction, Neural Network.

1. INTRODUCTION

Over the years, many researchers have taken different approaches to the problem of image quality assessment and have contributed significant research in the area with claims to have made progress in their respective domains. The topic of image quality assessment has been around for more than four decades, but the last few years have seen a sudden acceleration in progress and interest in this area. This corresponds with the rapid rise in interest in digital

imaging in general, driven by technological advances and by the ubiquity of digital images and videos on the Internet. Image quality assessment plays an important role in various image processing applications. The field of image and video processing generally deals with signals that are meant for human consumption, such as images or videos over the Internet [1]. An image or video may go through many stages of processing before being presented to a human observer and each stage of processing may introduce distortions that could reduce the quality of the final display. For example, images and videos are acquired by camera devices that may introduce distortions due to optics, sensor noise, color calibration, exposure control, camera motion etc [2]. After acquisition, the image or video may further be processed by a compression algorithm that reduces the bandwidth requirements for storage or transmission. Such compression algorithms are generally designed to achieve greater savings in bandwidth by letting certain distortions happen to the signal. Similarly, bit errors, which occur while an image is being transmitted over a channel or (rarely) when it is stored, also tend to introduce distortions. Finally, the display device used to render the final output may introduce some of its own distortion, such as low reproduction resolution, bad calibration etc. The amount of distortion that each of these stages could add depend mostly on economics and/or physical limitations of the devices [3].

One is obviously interested in being able to measure the quality of an image or video, and to gauge the distortion that has been added to it during different stages. One obvious way of determining the quality of an image or video is to obtain opinion from human observers as these signals are meant for human consumption [4]. However, such a method is not feasible not only due to the sheer number of images and videos that are available, but also because quality measurement techniques have to be embedded into the very algorithms that process images and videos, so that their output quality may be maximized for a given set of resources.

The goal of research in objective image quality assessment is to develop quantitative measures that can automatically predict perceived image quality [5]. Generally speaking, an objective image quality metric can play an important role in a broad range of applications, such as image acquisition, compression, communication, displaying, printing, restoration, enhancement, analysis and watermarking [5]. First, it can be used to dynamically monitor and adjust image quality. Second, it can be used to optimize algorithms and parameter settings of image processing systems. Third, it can be used to benchmark image processing systems and algorithms. In short, objective quality measurement (as opposed to subjective quality assessment by human observers) seeks to determine the quality of images or videos algorithmically. The goal of objective quality assessment (QA) research is to design algorithms whose quality prediction is in good agreement with subjective scores from human observers [7]. From the previous researches on image quality assessment it was observed that only few researchers have used the neural network to predict the quality of the image [8, 9]. In this paper, the various camera setting parameters and the feature extracted from the image database are used as the input to the neural network and the mean opinion score obtained from the subjects is used as the output to train the neural network model.

2. METHODOLOGY

An image acquisition process is subjected to many environmental concerns such as the position of the camera, number of cameras used, lighting sensitivity and background condition due to which the quality of the image is affected. The proposed system will predict the quality of the image using neural network models. The data are collected in three different locations with different environmental. Figure 1 shows the 3 different locations where the data collection were carried out .The images are captured using Sony DSR camera.   While

collecting the data the aperture diameter (f1.0-f14), shutter speed (8-2000), ISO (160-3200) [8], light illumination and Pixel values are noted and used as features for the network model. Human observers can easily assess the quality of distorted images without using any reference image, for this reason the subjective evaluation of the image database is carried out [10]. There are 467 test images in the database, for collecting the mean opinion score 16 subjects were used and the pictures in the database are shown to them one by one. The subjects were asked to assign each image a quality score between 1 and 10 (10 represents the best quality and 1 the worst). The 16 scores of each image were averaged to a final Mean Opinion Score (MOS) of the image. Subjective experimental results on JPEG compressed images are used to train the network model. The proposed system has three processing stages namely preprocessing, feature extraction and classification. Figure 2 shows the block diagram of the proposed system. In the preprocessing stage the image is resized to reduce the computational time using interleaving method.
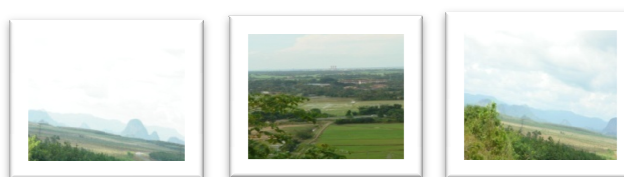
FIGURE 1: Three different Data collection locations
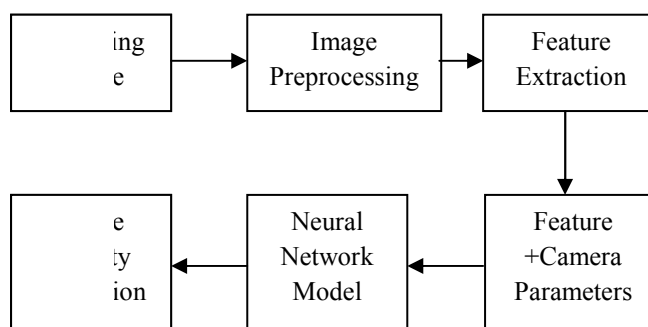
FIGURE 2: Block Diagram of Proposed System

3. VERTICAL INTERLEAVING METHOD

Interleave is a pixel reduction technique where interleave method interleaves the image pixel either row-by-row or column-by-column. In this research a simple interleave method is proposed and carried out by comparing the pixel values either row-by-row or column-by-column. During the comparison the maximum pixel value will be taken and the minimum value is discarded. If the pixel value is equal then any one pixel value is taken. The pixel values are compared column by column in this research and hence the proposed method is called vertical maximum interleaving. Figure.3 shows the image before interleaving and after interleaving. The vertical maximum interleaving method algorithm is as follows.
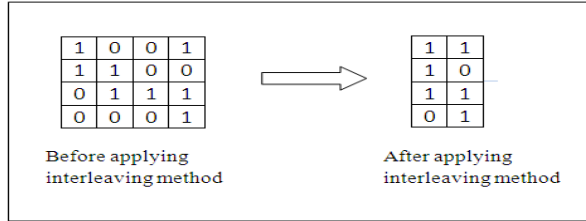
Vertical Maximum Interleaving method Algorithm:

Step 1: Acquire the segmented region
Step 2: Compare the pixel value of each alternative columns with the corresponding adjacent column and find the maximum value.

Step 3: If both the pixel value are same then take any one value.
Step 4: Acquire the new vertical interleaved image using Step 2 and Step 3
After applying interleaving method on the image and the features are extracted from the input images.

FIGURE 3: Vertical Maximum Interleaving method

4. FEATURE EXTRACTION

JPEG is a block DCT-based lossy image coding technique. It is lossy because of the quantization operation applied to the DCT coefficients in each 8×8 coding block. Both blurring and blocking artifacts may be created during quantization. The blurring effect is mainly due to the loss of high frequency DCT coefficients, which smoothes the image signal within each block. Blocking effect occurs due to the discontinuity at block boundaries, which is generated because the quantization in JPEG is block-based and the blocks are quantized independently. Blurring and blocking are the most significant artifacts generated during the JPEG compression process [11]. We denote the test image signal as $x\,(m,n)$ for $m \in [1,M]$ and $n \in [1,N]$, Calculating the differencing signal along each horizontal axis:

$$d_h(m,n)=x(m,n+1)-x(m,n), n\in[1,N-1]) \tag{1}$$

First, the blocking estimated as the average differences across block boundaries:

$$B_h=\frac{1}{M\left(\left[\frac{N}{8}\right]-1\right)}\sum_{i=1}^{M}\sum_{j=1}^{\left[\frac{N}{8}\right]-1}|d_h(i,8j)| \tag{2}$$

Secondly, the blurring in the image is evaluated using two activity measures. The first activity measure is the average absolute difference between in-block image samples and is calculated as:

$$A_h=\frac{1}{7}\left[\frac{8}{M(N-1)}\sum_{i=1}^{M}\sum_{j=1}^{N-1}|d_h(i,j)|-B_h\right] \tag{3}$$

The second activity measure is the zero-crossing (ZC) rate. Define $n\in[1,N-2]$,

$$z_h(m,n)=\begin{cases}1 & horizontal\ ZC\ at\ d_h(m,n)\\0 & otherwise\end{cases} \tag{4}$$

Then the horizontal *ZC* rate can be calculated from the below equation

$$Z_h=\frac{1}{M(N-2)}\sum_{i=1}^{M}\sum_{j=1}^{N-2}z_h\,(m,n) \tag{5}$$

Using similar methods, we calculate the vertical features of *Bv*, *Av*, and *Zv*. Finally, the overall features are given by:

$$B=\frac{B_h+B_v}{2}, A=\frac{A_h+A_v}{2}, Z=\frac{Z_h+Z_v}{2}.$$

(6)

These feature extraction methods are computationally inexpensive and memory efficient [12].

5. NEURAL NETWORK MODELING

Artificial Neural Network (ANN) provides alternative form of computing that attempts to mimic the functionality of the brain [13].To classify the image based on its quality an Elman neural network has been developed. Typical Elman network has one hidden layer with delayed feedback. The Elman neural network is capable of providing the standard state-space representation for dynamic systems [14]. The neural network architecture has three layers consisting of an input layer, one hidden layer and an output layer. To predict the quality of the image a simple neural network model using error back propagation was developed. The network model has 8 input neurons representing the features (aperture diameter, shutter speed, pixel value, ISO, light illumination, *B*, *A* and *Z*), 3 hidden neurons and 4 output neurons. The network initial weights are chosen randomly between 0 to 1. The network is trained with 60 % of samples i.e., 281 samples and tested with the remaining 40 % i.e., 186 samples. For each trail, the network is trained for five times (with five different initial weights) and the mean classification rate, minimum and maximum epochs are recorded. In the experimental analysis, five such trails were made and the results are tabulated in Table 1.

Number of Input neurons:8   Number of hidden neurons:6
Number of output neurons:4   Momentum Factor: 0.9
Activation Function: Binary sigmoid   Training Tolerance: 0.001
Learning Rate: 0.5   Testing Tolerance: 0.1
Number of samples used for training: 281
No. samples used for testing:186
Total Samples:467

Trail	No of Epoch:			Classification Rate:		
	Minimum Epoch for Training	Maximum Epoch for Training	Mean Epoch for Training	Minimum Classification Rate (%)	Maximum Classification Rate (%)	Mean Classification Rate (%)
1	5697	7006	6723	88.62	91.32	89.12
2	6135	6690	6340	88.33	92.24	89.33
3	6211	7836	6915	89.19	91.91	89.16
4	6172	6862	6435	89.32	90.33	88.91
5	5015	8466	8156	88.74	92.46	89.62
Average	6846	7172	8713	88.64	91.05	90.23

TABLE 1: Network architecture for image quality prediction

6. RESULTS AND DISCUSSION

The learning rate, momentum factor, training and testing tolerance for the image quality prediction network are also shown in Table 1.From Table 1 it is observed that the maximum classification accuracy for the developed network model is 92.46% and the minimum

classification rate is 89.19%. The maximum epoch value obtained for the developed network model is 8466 and the minimum epoch value is 5015. The mean epoch value for the developed network model is 8713. The interleaving method showed improvements in reducing the processing time. Experimental results shows that the neural network model correlates highly with the mean opinion scores based on the classification results obtained.

7.   CONCLUSION

The current research in image quality assessment has come a long way from its beginning few decades ago. This work presented an automated system for objective assessment of image quality a new approach for image quality assessment using neural network model was proposed. Using the Elman neural network model the quality of the images where obtained. A new image interleaving algorithm was proposed in this paper. The image interleaving method reduces the pixel values and hence the processing time was reduced. The proposed system has a mean classification accuracy of 90.23%. The experimental results confirm that the developed system can recognize the quality metrics of the image correctly. In future a neural network based controller is proposed to be used to control the camera parameters to obtain good quality image.

8. ACKNOWLEDGMENT

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