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No Reference Image Quality Assessment Based On Machine Learning Approach Using Discrete Cosine Transform And Wavelet Features

Abhijit Chitre[1], Anita Patil[2], Yogesh Dandawate[3]

[1]Department of Electronics and Telecommunication VIIT Pune, Chitreabhijit77@gmail.com
[2]Department of Electronics and Telecommunication VIIT Pune, Anitapatil2001@gmail.com
[3]Department of Electronics and Telecommunication VIIT Pune, yhdandawate@gmail.com

Abstract - Conventionally, image quality assessment (IQA) algorithms represent image quality as linearity with a "reference" or "perfect" image. Obvious drawback of this method is that the many times original image may not be accessible for the QA algorithm. This paper proposes an image quality assessment of natural-scene statistic-based on DCT score prediction approach. It operates in transform domain. Major artifacts like ringing, blocking and blur are observed in image quality assessment technique. In this paper DCT is used to extract different features of the image. We train and test our algorithm on LIVE database with respective subjective mean opinion score (MOS) on scale of (1-10) and manifest that the recommended work has good regularity with subjective interpret values and the objective estimation results. This paper well replicates the visual quality of images as well as quantifies possible losses of "naturalness" in the image. This paper presents a statistical approach for image quality analysis. In this approach degradation in an image are explored through DCT and wavelet transformation of images and computing statistical parameters like mean, standard deviation, skewness and kurtosis

Keywords - Discrete Cosine Transform Kurtosis Natural-Scene Statistics No-Reference Image Quality assessment Artificial Neural Network Support Vector Machine.

I. INTRODUCTION

Nowadays for representing and communicating information there is magnificent use of digital images. Many times images are passes through acquisition, compression, transmission, processing, and reproduction which incorporate distortions. This may or may not be perceptual by human visual system. To preserve and improve the quality of images, it is important to identify and quantify image quality degradations. Calibrating this measurement against human judgments' of quality is image quality assessment. Subjective assessment and objective assessment are used for this purpose. However, subjective evaluations are bulky and costly. The objective image quality assessment models can predict apparent image quality perfectly and mechanically. Objective image quality assessment divided into three categories: full-reference image quality assessment, reduced-reference image quality assessment, and no-reference image quality assessment. FR:- full-reference algorithm need original high quality images. RR: - Reduced reference algorithm extorts features from the original and certain images and evaluate them to one another. Obvious limitation of full reference and reduced reference is that it requires full or fractional access to the original image. But many times, plagiarized images available. NR:-In no-reference quality assessment image quality estimate without the reference image, has been very popular. There are three types of No reference –image quality assessment approaches

Distortion-specific approach, Feature extraction and learning approach, Natural scene statistics (NSS) approach: 1) Distortion-specific approach compute a detailed distortion in exclusion of other factors. Quantify the image accordingly. Examples of such approaches are (1)*blockiness* [2] and [3],(2) *blur* [4] (3)and *ringing* effects[5]. 2) Feature extraction and learning approach train the model based on number of features extracted from images. An example of such approach [6]–[8] 3) Natural scene statistics (NSS) approach Using high-quality devices natural images are captured. This approach assumes that natural scenes are distortion free and resides in small subspace in space of all images. As any alterations are introduced to image the statistics of images change.[9]. The limitation of distortion specific approach is distortion; hence application has a specific approach. There are wide ranges of distortions introduced in images. Tedious compute every type of distortion by using first approach. The feature extraction and learning approach is only useful for the features extraction of image. Finally, the NSS approach is a very capable one, but extensively based on statistical representation. This paper represents combination 2 and 3 of approaches. It shows how certain statistical features of original images changes because of distortion. To make blind (or no-reference) predictions about the quality of the natural image, these features are used to train a statistical model. The estimated no reference image quality approach is based on a DCT and wavelet transformation entirely. Here DCT of images compressed different qualities. After taking DCT and Wavelet transformation, statistical features like Local contrast, Global Contrast, Mean, Standard Deviation, Skewness and Kurtosis of AC coefficient in DCT and approximate related coefficient in wavelet are computed. Since computed statistics do not show linearity machine learning approch instead of computation modeling is used. The paper is organized as follows, Section I gives Introduction, Section II gives Existing IQA methods. Section III gives a brief description about natural Scene statistics Section IV the Feature selection of the images based on DCT section V gives result and VI contains conclusion and references.

II. RELATED WORK

Most existing image compression standards are based on block based methods. Most of block based image compression image being encoded is first partitioned into 8×8 blocks then local DCT is applied to pixels in each block. At low bit rates, the most prominent types of artifacts are created Such as interblock blurring and blocking artifacts. Due to the defeat of high frequencies during quantization the blurring effect occur[10]–[15]. while blocking artifact images may exhibit cyclic horizontal and vertical edges .[16]. Most blocking quantification methods quantify blocking either in the spatial domain [3]–[5] or in the frequency domain [7][17][18]. As above mentioned methods would fail for other distortion such as ringing or blurring .The model described here is unique it employ natural scene statistics models to provide a "reference," beside which the distorted images can be assessed.

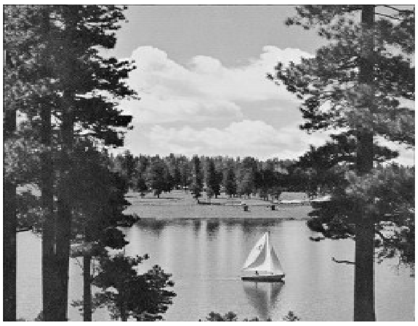

Fig1.Natural Image

Fig2.Artificial image

Images captured using high-quality devices are categorized as natural scenes. Artificial images are text, computer generated graphics scenes, cartoons, and animations, paintings and drawings, random noise, radar and sonar, X-rays, ultrasounds, etc. Natural images are highly structured images and acquire certain regularity. Statistical properties of natural images measurably customized because of distortions. In natural images the deformation found in nonlinear addiction can be measured for making approximation of feature selection. This approch for quality assessment of image using wavelet based features selection represented by Authors. [30] Positional similarity measure of wavelet coefficient based spectral fall off curves by the use of a neural network represented in [26]. The limitation of this approach to be applicable only to JPEG2000 images .By using contourlet transform authors show that wavelet transform does not completely illustrate the artefacts present in the image [27].The idea of the impact of distortions on NSS has been used in [25] for prediction of video quality. Quality values and statistical relationship between the features in NSS images was studied in [28].It present the feature ranking of filtered natural images, a histogram of a grouping of Curvelet, wavelet ,and cosine transform is computed. By the use of Support vector machine the distortion identification-based image quality estimation method proposed in [29]. It estimate feature scale and orientation careful statistics, spatial correlation, noise ratio (PSNR) and SSIM.

III. FEATURE SELECTION

As human visual system is easily distinguish high quality images in comparison with distorted one. Feature selection process relies on the basic fundamental fact that natural images are highly ordered in the sense that their pixels shows sturdy dependencies. These dependencies carry important information about the natural scene. Since HVS is highly sensitive to numbers of features, here we extract image structure features as well as image contrast feature. In general high contrast in an image is more desirable property, which makes image visually more appear. As shown in fig.3 most of viewers prefer fig.3 as compared to fig.4. Additionally, two more features are extracted 1) images sharpness and 2) orientation anisotropies. This is property of image for which HVS is highly sensitive. However, image sharpness, is highly content dependent. For example as shown in fig.5 image background is blurred, it is required property of this specific image. This is why we do not seek to quantify sharpness or blur. For this reason it is necessary to know how statistics of spatial frequency domain features changes in natural images. This approach uses discrete cosine transform and wavelet transform to extract number of features of image.

A. DCT-Based Contrast

Contrast is a basic perceptual quality of an image. We can easily differentiate between local contrast and global contrast. This model compute the contrast based on local DCT patches and illustrate that statistics of this local contrast associate with distortion. In this model after dividing an image in 17×17 patches, the 2-D DCT is applied to every pixel in each patches [20]. The local DCT contrast is then calculated as, average of the ratio total of the non-DC DCT coefficient magnitudes in the local patch stabilized by the DC coefficient of that patch. The local contrast scores from all patches of the image are then pooled together by averaging the computed values to obtain a global image contrast value.

B. DCT- and Wavelet Structure Features

From the local DCT frequency coefficients Structure features are derived. Higher frequency DCT coefficients in the image patch whose magnitude is usually much larger are ignored. Ignoring the DC coefficient unaffected the local structural content of the image. Natural images show statistical consistency in wavelet space also. Minimal difference has been observed in natural image wavelet coefficients, consistently have pointed peaks near zero and elongated tails than Gaussian. This reflects exact intuitive properties of images .Most of natural images is even. This consistency is broken up by thin distortion represent large amplitude discontinuities. Such highly kurtosis distributions have important allegation with respect to natural scenes.

Fig3.Low Contrast Image

Fig4.High Contrast Image

Fig5.Sharp object on blurred background

By computing Kurtosis (quantifies the measure of pointedness and tail weight) we can capture statistical traits of the DCT and Wavelet features which is given by

$$K(x) = E(x-\mu)^\wedge 4 / \partial ^\wedge 4 \qquad 3.1$$

$$STD = (1/(n-1)\sum_{x=1}^{n}(x_i - x)^\wedge 2)^\wedge 1/2 \qquad 3.2$$

$$s = E(x-\mu)^3)/\partial^3 \qquad 3.3$$

where mu is mean of x and sigma is its standard deviation. The parameters vary as degradation varies. It has been noticed that kurtosis variation is perfect in comparison with other parameters. In some cases there is no linear variation in magnitude with respect to degradation.

IV. RESULTS

A. Simulation Details

The nonlinearity of the parameter calculated is the key problem in the developing a model for quality analysis. Back propagation neural network with number of inputs based on the number of parameters. The neurons in the hidden layer are fixed to 10 and a single output which is scored (MOS). The model is tried with changing number of inputs for better optimization. It has been found that kurtosis in DCT and wavelet domain contrast and skewness input give better result.

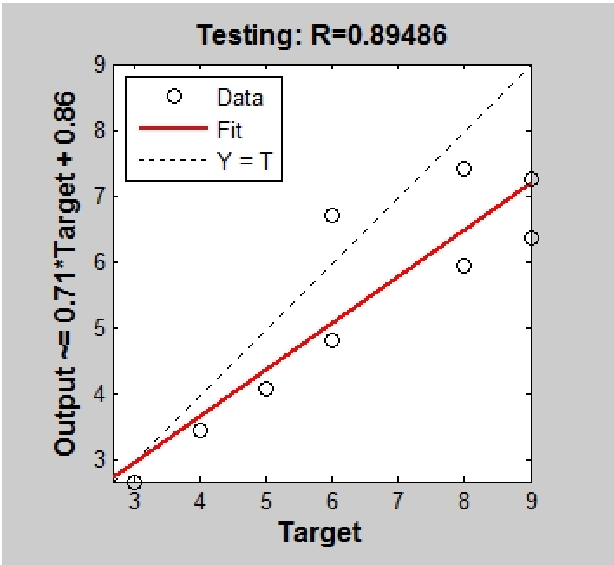

Fig6.Regression Plot

The regression plot of images tested is as shown in the figure below. MATLAB with neural net toolbox, image processing, wavelet and statistics toolbox is used. Multiclass Support Vector Machine (SVM) is used for estimation of the score but in this case artificial neural network performs better than SVM.

V. CONCLUSION

The paper presents statistical approach for the image quality analysis/ In this approach the degradation in an image are explored through DCT and wavelet transformation of the images and computing statistical parameters like mean standard deviation, skewness and kurtosis which indicate shift according to the degradations. It has been observed that even though there is certain steeped variation in the statistics the parameters show non linear behavior for certain degradations, which do not help in formulating computational model for estimating the quality score. Neural network approach is proposed for the estimation of score and it is observed that around 89% correlating exist in actual and estimated quality scores. Support machine approach has been also tried, but ANN approach work better.Other parameters can also be used for training. Images with different noise and other degradations not available in JPEG can also explored

VI. REFERANCES

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