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A Blind Image Quality Assessment for Visual Quality Perception to Estimate the Quality of the Images

K. Girish Chandra[1], Dr. B. Prabhakara Rao[2]

M. Tech Scholar, Dept. of E.C.E, Jawaharlal Nehru Technological University Kakinada, U.C.E.K, Kakinada, India[1]

Professor, Dept. of E.C.E, Jawaharlal Nehru Technological University Kakinada, U.C.E.K, Kakinada, India[2]

ABSTRACT: Most of the existing Blind image quality assessment techniques can hardly characterize visual quality perception for various distortion types. The different blind image quality assessment algorithms cannot correlate with full-reference image quality assessment techniques. So, in this paper we first perform image quality assessment for the full-reference images on different distortion types and then the quality of the distorted image is found by using the Blind image quality assessment technique. The performance of the blind image quality assessment is compared with the performance of the full-reference image quality assessment techniques. This paper focuses on the measurement of quality for the distorted images which are used in the measurement of performance of the full-reference images. The experimental results show that algorithm exhibits high correlation with the novel full-reference image quality metrics when compared with the other Blind image quality metrics.

KEYWORDS: Quality assessment; Depth image quality metric; Distortion types; Full-reference image quality assessment.

I. INTRODUCTION

Many image processing applications which aim for high visual qualities or reducing the distortion in the image, we need to adopt elaborate computational image quality assessment (IQA) techniques to estimate the quality of the distorted images. Based on the reference images used the computational methods are classified as: No-reference (NR), Reduced-reference (NR), Full-reference (FR) [1]. This paper focuses on the No-reference image quality assessment technique.

In the full-reference image quality assessment technique a reference is considered for estimating the degree of quality for the distorted images. For full-reference image quality, structural similarity (SSIM) [2] reduces the modelling problems because it based on the assumption that the human visual system (HVS) extracts structural information from the image textures for obtaining the visual perception. So, many novel methods are obtained based on the structure and contract of the images. Structural contrast distance metric (SC-QI) and structural contrast distance metric (SC-DM) are the novel methods for calculating the performance of the full-reference images (FR) [3]-[5] for various distortion types.

A No-reference or blind image quality assessment does not use any reference image for the distorted image to predict the visual quality of the distorted images. The no-reference image quality assessment methods are classified as: No-reference pixel based method (NR-P), No-reference bit stream (NR-B) method and Hybrid of both pixel and Bit stream method. This paper fully focuses on the No-reference pixel based methods, where feature measure based methods are used. The measurement of the quality is an important task for finding the performance of the existing no-reference methods. The no-reference methods use an auto-regression algorithm to estimate the quality of an image. The main advantage of the auto-regression algorithms is that they do not train any images for measurement of the quality for various distorted images. In this paper we use a monotonic non-linear regression function to estimate the quality and performance of different distorted images.

Perceptual image distortion, noise quality and VSNR incorporate visibility characteristics of HVS to distortions such as contrast, luminance and contrast masking effect. These methods mainly assume that perceived visibility

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characteristics and perceived visual quality characteristics of human visual system are proportional to each other. SSIM is based on the assumption that HVS importantly extracts structural information from the image textures in visual perception.

II. RELATED WORK

A. *Characteristics of Human Visual System:*

The important characteristics of human visual system are contrast sensitive function (CSF) [6] and contrast masking (CM) effect. The contrast sensitive function indicates that HVS has different sensitivities to distortion based on the frequencies in cycles per degree (cpd). This shows that the HVS has different sensitivities of perception to changes in the sinusoidal grating pattern depending on spatial frequency, which is a band pass property [7]. The CM effect shows that, HVS has different sensitivities to distortion depending on background image characteristics. The HVS can easily perceive the distortion in the homogeneous region and cannot perceive the image of the complex texture pattern. So, CM effect must take into consideration to estimate the degree of image texture complexity.

B. *Existing FR-IQA Technique :*

In order to compare the convergence of the blind image quality assessment methods to the full-reference image quality assessment techniques, first we need to obtain the performance of already existing novel full-reference image quality assessment technique. So, here we compare with structural contrast quality- index SC-QI. In Fig.1 the reference signal is represented as **X** and the distorted signal is represented as **Y.**

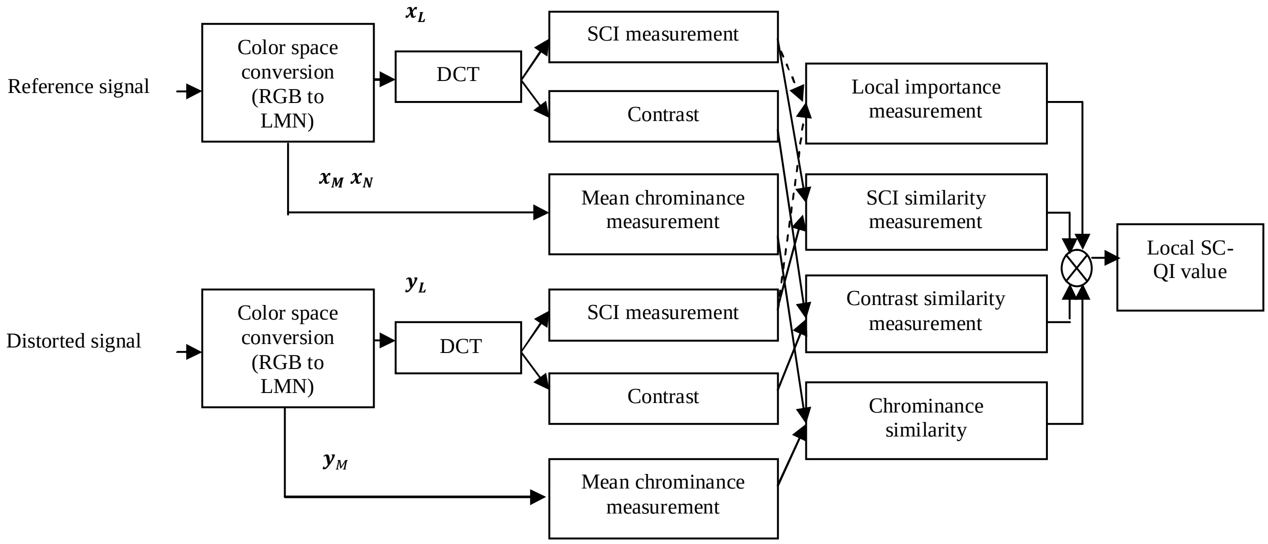

Fig.1. Block diagram for measurement of quality for full-reference image.

A local SC-QI is calculated for each 4×4 image block DCT between **X** and **Y**. Then pixel intensity values are normalised to [0,1]. We define x_L, x_M, x_N as local image blocks of the luminance and chrominance components [8] in **X**. The Similarity measure for the reference image and the distorted image is calculated by the multiplication of similarities s_k, k=1,2,3,4,5,6 as

$$f(x,y) = \prod_{k=1}^{6} s_k \qquad \text{eq. (1)}$$

The product form of the different similarities measures specifies that the perceived local visual quality is low when at least one similarity measure among the multiple similarities is low. Here all the

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$$s_k(\phi_{x(k)}, \phi_{y(k)}|\theta_{k,}v_k) = \left(\frac{2\phi_{x(k)}\phi_{y(k)}+\theta_k}{\phi_{x(k)}^2+\phi_{y(k)}^2+\theta_k}\right)^{v_k} \quad \text{eq. (2)}$$

Here $\phi_{x(k)} \in \mathbf{R}^1$ is the feature function of $\mathbf{x} \in \mathbf{R}^{N\times N}$ where N=4 for a k-th similarity measure. θ_k and v_k are model parameters which are used to avoid unstable results. These modal parameters are also used to control the descending gradient sensitivity to the similarity measure form.

C. *Literature survey on No-reference Image Quality Assessment :*

The No-reference image quality assessment is based on the principal that the natural images have some regular statistical properties that are measurable and can be altered by the existence of distortions. So, first the pixels which are altered by the distortion are found in order to find the quality of the image without any use of the reference images. In general the No-reference visual quality of an image is estimated based on three stages, they are: measurement of physical quantity relevant for visual quality called as feature, pooling the measured data over time or/and space, and mapping of pooled data. As shown in fig.2, the NR-IQA does not use any reference image.

Blind Image Quality Assessment methods are classified as: Opinion aware method and Opinion unaware methods. In Opinion aware method a large number of training samples are used and the distortion types are also known and use human subjective scores to predict the quality of the distorted images. In Opinion unaware method does not use any distorted sample of images or human subjective scores for training. The different Opinion aware methods are: BIQI, DIIVINE, BLIINDS & BLIINDS-II, BRISQUE and CORNIA. The different Opinion unaware methods are: NIQE, QAC and IL-NIQE. The opinion aware models work in the Discrete Cosine Transform (DCT) domain. A probabilistic model extracts both the contrast and structure features in DCT domain. A small number of sensitive features are computed from a Natural Scene Statistics (NSS) model block of DCT coefficients and are fed to regression function that gives a precise prediction values.

The evaluation of quality is divided into two types: subjective and objective methods. The subjective methods are more precise measure of perceptual quality. Whereas, the objective method is a quantitative approach in calculating the image quality scores.

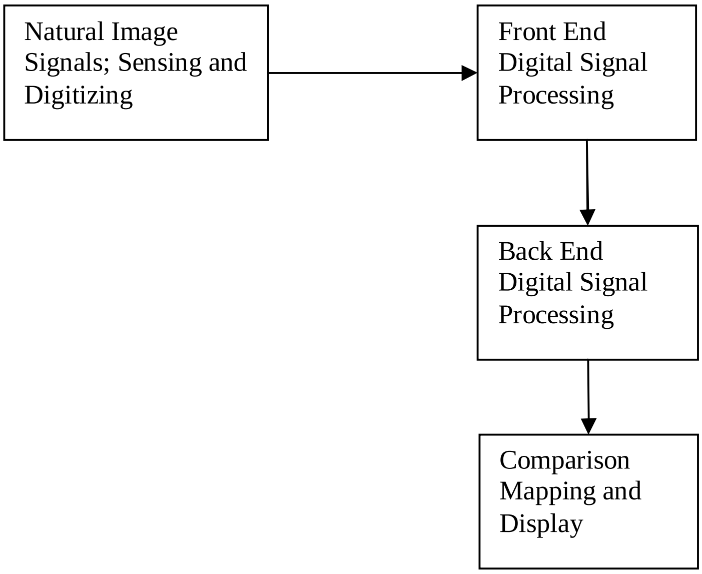

Fig.2. Block diagram for No-reference Image Quality Assessment.

III. PROPOSED METHOD

The proposed method for computing the performance and quality for the full-reference is carried out in two steps: first, the contrast sensitive map for the image is computed to locate the pixels which are most susceptible to noise

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artifacts. The second step involves, for each compression sensitive pixel (CSP) a histogram of the neighbourhood is constructed and computed to obtain the quality index of the distorted image. The proposed method uses the shape of the histogram to predict the quality index.

It is known that the boundary regions between objects at different depth levels are susceptible to compression artifacts compared to the homogeneous areas in images. So, the magnitude gradient of the image is use full in evaluating the compression sensing artifacts. The compression sensitivity map is computed from its gradients magnitudes. Which is given as,

$$\text{Sensitive map}= \sqrt{G_X^2 + G_Y^2} \qquad \text{eq. (3)}$$

In eq.(3) G_X, G_Y are the gradients along horizontal and vertical directions and are computed with sobel operators. The gradient magnitude is used to select sensitive depth pixels that are used to estimate the quality index. Then the threshold is performed by dropping the pixels with SM $\leq \tau$ is used to locate the most compression sensitive pixels; it is observed that this choice has also a positive side effect since it dramatically reduces the computational cost of the whole metric. The compression sensitive pixel belongs to the sharp discontinuity representing between the boundaries.
Now, to predict the quality of an image we need to estimate the histogram dispersion by measuring the area which lies on the top of the histogram curve. An area value which are associated to each sensitive pixel and then averaged together to compute the final quality index. Here we select patch p_k of size w×w centred at (x,y) and calculate the local histogram. Let H_K^i denote the histogram distribution of patch p_k with i equally sized bins. The quality value is evaluated by using the proposed Blind depth quality method using the parameters: w=15, τ=5, i=10.

$$Q_K = \sum_{t=1}^{i}\left[max\,(\mathrm{H}_K^i) - \mathrm{H}_K^i\right] \qquad \text{eq. (4)}$$

Let S be the set of sensitive pixels of image and let $p_k \in$ S be a sensitive pixel with coordinates (x,y) $\{1 \leq x \leq M;\ 1 \leq\ y \leq N\}$. Finally the quality value of all the sensitive pixels is averaged of the image.

$$\text{Quality}= \frac{1}{S}\sum_{K=1}^{|S|} Q_K \qquad \text{eq. (5)}$$

To evaluate the performance of the blind image quality metric we select either a Pearson linear correlation coefficient (PLCC) for prediction accuracy test and spearman rank order correlation coefficient (SROCC) and Kendall rank order correlation coefficient (KROCC) for prediction monotonicity test. The estimation of the prediction error is also an important measurement, so we estimate the prediction error by using a Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) measures. Before computing the actual performance measures the blind quality assessment metric predicted score Q is mapped to PSNR with a non-linear regression function and a logistic function and is used for the regression mapping.

$$Q_P = \beta_1\left(\frac{1}{2} - \frac{1}{exp\beta_2(Q-\beta_3)}\right) + \beta_4 Q + \beta_5 \qquad \text{eq. (6)}$$

In eq. 6, Q_P is the mapped score and β_1, β_2, β_3, β_4, β_5 are the regression model parameters.

There are various other FR-IQA methods which are significant [9]-[11], but those methods are distortion specific. This method first evaluates the quality of the image based on the amount of distortion added to the image while transmitting or receiving the image.

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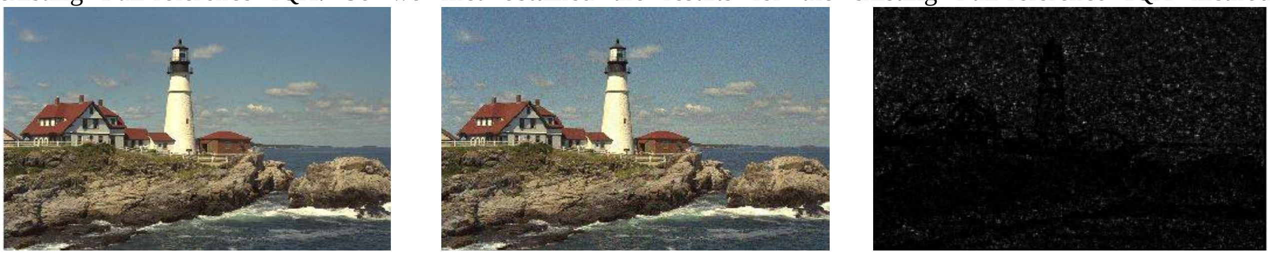
IV. SIMULATION RESULTS

In order to compare the proposed method results for no-reference IQA, first we need to obtain the results for the existing Full-reference IQA. So we first obtained the results for the existing Full-reference IQA method.



a b c

Fig.3. Mapped image for Gaussian Noise.

The Fig.3a and Fig.4a are the original images which are used as a reference images for the distorted images. The Fig.3b and Fig.4b are Gaussian Noise and Gaussian Blur images respectively. The perceived distortions are affected from the blurred edges and texture regions, while there are less visible in homogeneous regions.

a b c

Fig.4. Mapped image for Gaussian Blur.

The Fig.3c and Fig.4c represents the higher visual quality in homogeneous regions and lower visual quality in complex regions. The performance of the full-reference images are calculated by using the Pearson linear correlator coefficient (PLCC). The performance evaluation for the Fig.3c and Fig.4c are 0.90.

For the proposed method, quality of the different distorted images is shown in Fig.5a and Fig.5b with quality as 326.05 and 319.76. Depending on the quality of image, the performance and prediction accuracy are varied. As the quality of the image is low the performance of the image is also low. The performance of the proposed method when performed on TID2008 for Gaussian noise is 0.9697. So, by comparing this performance with the FR-IQA method the performance of the proposed method is better. Since the performance of FR-IQA method is 0.90

a b

Fig.5. Gaussian noise with Q=326.5 and Gaussian Blur with Q=319.76

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The table.1 shows the performance evaluation of the proposed method when performed on the different data sets. The data sets which are used in calculating the performance are from TID2013 and TID2008 [12].

DATA SET	GAUSSIAN NOISE		GAUSSIAN BLUR	
	Quality	Performance	Quality	Performance
TID2013	326.05	0.9697	319.76	0.9616
TID2008	301.46	0.9432	353.92	0.9954

Table.1. Performance of the proposed method.

The performance which are shown in Table.1 are performed by using Pearson linear correlation coefficient(PLCC). We can use any correlation coefficients like SROCC, KROC and RMSE for evaluating the performance of both the FR-IQA and NR-IQA methods.

So, in this paper the results obtained are performed on two different distortion types namely Gaussian noise and Gaussian blur.

V. CONCLUSION AND FUTURE WORK

In this paper the quality and the performance of different distorted images are calculated. The performance results shows that, if quality of the distorted image is low then the performance evaluation of the distorted image is also low and if the quality of the distorted image is high then the performance evaluation of the distorted image is also high. The performance evaluation of the proposed blind image quality assessment is compared with the FR-IQA method and the performance of the proposed method shows better results. As the performance of the proposed method is dependent on the quality of the image, this work can be further extended for evaluating the performance independent of the image quality.

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