Journal of Theoretical and Applied Information Technology
10th July 2014. Vol. 65 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

RECENT DEVELOPMENTS IN IMAGE QUALITY ASSESSMENT ALGORITHMS: A REVIEW

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ABSTRACT

Image Quality Assessment (IQA) has become a subject of intense research interest in the recent years. The demand for accurate, consistent, computationally simple and easy-to-use quality assessment tools that can be used to measure, control, and improve the perceptual quality of images and video is increasing day by day. Applications of IQA include machine vision, medical imaging, multimedia communication, entertainment and other image processing activities. Systems embedded with IQA algorithms can replace humans for evaluating image quality in real-time applications and hard-to-reach environments. As most of the images are ultimately viewed by human observers, the best method to assess the quality of an image is by subjective tests by human observers. However, subjective tests are expensive, time consuming and difficult to perform in real-time applications. Therefore, these tests are done objectively using computer algorithms. These algorithms attempt to evaluate the quality of the image in the same way as how humans perceive image quality. In this article we present an up-to-date review on IQA research and its future trends, the principles and methodologies used in popular Full Reference IQA algorithms, the methodologies and parameters used for evaluating the performance of IQA algorithms and performance comparison of important IQA algorithms.

Keywords: *Image Quality Assessment, FR-IQA, NR-IQA, RR-IQA, HVS*

1. INTRODUCTION

Advancements in digital imaging and image processing technologies have revolutionized our way of life. Image acquisition, storage, transmission, viewing, sharing and processing technologies has undergone incredulous advancements during the recent years. The innovations in medical imaging techniques have changed the diagnosis and treatment procedures to such an extent that many such procedures were unimaginable a few years back. In our daily life, we are using a number of image processing applications with or without our knowledge. For example, when someone is capturing a scene using a mobile phone, the image captured by the sensor after suitable corrections, is compressed into JPEG format and stored in the memory. The image may be then transmitted to a social media network over a communication channel. The image may be later viewed by a user on a computer screen, of pixel size smaller than the actual size of the image. In that case, the image has to be resized in order to fit on the display screen. Similarly when a medical image captured at an imaging center is transmitted to a panel of experts located in another continent over a noisy communication channel, the received image might have been distorted. In general, in image processing applications, the original image captured by the camera or the acquisition device is subjected to a number of processing operations such as compression, storage, transmission, filtering, modulation, demodulation etc. During these operations, the original image is subject to alterations, which may impact the quality of the image. Therefore it is necessary to assess the suitability of the received/retrieved image for the intended purpose. As most of the images are ultimately viewed by human observers, the only reliable test to assess the quality of an image is by subjective tests by human observers by visually evaluating the image. Subjective image quality

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

assessment not only takes a long time, but also is very expensive and not practical in real-time applications. Further, there can be individual factors that may influence the perceived image quality. Therefore, it is necessary to evaluate the image quality objectively, keeping the human visual system (HVS) as a basis for such an evaluation. Any objective IQA algorithm shall meet the following requirements:(1) it must have a close correlation with the human perception of vision; (2) it must have consistent performance over a wide range of distortion types; (3) it must be computationally simple and efficient and (4) it can be embedded in real time image processing or communication systems. This explains why IQA is difficult. The applications of IQA algorithms are increasing day by day including, in defense, medical imaging, entertainment, and telecommunications and in image processing systems. In image processing, it can be used for monitoring the image quality for controlling quality of processing systems, for benchmarking image processing systems, for optimizing algorithms and parameter settings for image processing systems etc. [1]. The rest of this article is organized as follows. Section 2, gives a brief description of the Human Visual System. Section 3 gives the classifications of IQA algorithms with a detailed description of Full Reference Image Quality Assessment (FR-IQA) algorithms. Section 4 describes the performance evaluation of IQA algorithms and a comparison of some important FR-IQA algorithms. Section 5 gives the future trends in IQA and Section 6 gives the conclusion.

2. HUMAN VISUAL SYSTEM

Human visual system is very complex and not yet fully understood [2]. Some key features of HVS are luminance nonlinearity, contrast sensitivity, visual masking effects, multi-channel parallel and visual attention. *Luminance non-linearity* means the poor ability of human eye to judge the absolute brightness of an object, while having a strong ability to judge the relative brightness. The range of intensity levels to which the human visual system can adapt is of the order of 10^{10}. Perceived brightness is a logarithmic function of the light intensity [3]. *Contrast sensitivity* refers to the spatial frequency response characteristics of the human visual system [4]. The contrast sensitivity function is band-pass in nature. Human vision is least sensitive to very low frequency and very high frequency and the peak sensitivity is at 4-6 cycles of visual angle (c/degree). *Visual masking* is a general term that refers to the perceptual phenomenon in which the presence of a masking signal reduces the subject's ability to detect a given target signal. It is the reduction of visibility of one image component due to the presence of another masker. Luminance masking and pattern masking are the two common forms of masking. The threshold of detection increases due to an increase in the luminance of the background. This phenomenon is believed to be mediated by the retinal adaptation. Pattern masking is the phenomenon of increase in the threshold of detection when the contrast of the masks containing spatial patterns is increased. *Multichannel Model* of the HVS indicates that different visual information components are preprocessed through different neural channels at the input of the visual cortex. They will be analyzed and processed by the different types of cortical cells. This means that there are multiple independent channels which have selection to spatial frequencies in human visual system memory. HVS performs a local spatial-frequency decomposition of a stimulus in which the frequency components are detected independently via multiple spatial frequency channels. *Visual attention* is the phenomenon by which one gives attention to one or some scene so that certain spot or area of the image is selected as the representation of the scenery.

3. CLASSIFICATION OF IQA ALGORITHMS

Detailed classifications of IQA algorithms have already been done by Chandler [4] and Tsung-Jung Liu *et al* [5] and it is not the intention to redo the same in this paper. However, it is worthwhile to mention the classification of IQA algorithms based on the availability of a reference image or not. Accordingly, IQA algorithms can be broadly classified into three categories namely No-Reference IQA, Reduced Reference IQA and Full Reference IQA.

3.1 No-Reference IQA (NR-IQA or Blind IQA)

NR-IQA refers to image quality assessment without a reference image. These algorithms predict quality of the image without any knowledge on the reference image and correlate well with human perception of quality [6]. Our visual system can easily distinguish high-quality images and low-quality images with little effort and without seeing the original image. In our brains, there are models of high quality reference images and we have the

Journal of Theoretical and Applied Information Technology
10th July 2014. Vol. 65 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ability to use these models to assess the quality of an image [7]. There are three basic approaches towards NR-IQA based on how the objective algorithm derives the quality score [8], [9]. They are: 1). Distortion-Specific approach: it employs a specific distortion model to drive an objective algorithm to predict a subjective quality score. Examples of such distortion types are blur, blocking, ringing etc. 2). Feature extraction and learning based approach: this approach extracts features from images and trains a learning algorithm to distinguish distorted images from undistorted images. 3). Natural Scene Statistics based approach (NSS): this approach is based on the hypothesis that natural images (e.g. images captured by an optical camera) possess certain statistical properties between their pixel values and that the presence of distortions alters these statistical properties. By characterizing this un-naturalness using scene statistics, one can identify the distortion and perform NR-IQA [10]. It is worth mentioning here that at present no NR-IQA algorithm has been proven consistently reliable in performance [9]. Examples of some popular algorithms for NR-IQA are BIQI [6], BLIINDS [8], DIIVINE [10] and BRISQUE [11].

3.2 Reduced-Reference IQA (RR-IQA)

In Reduced Reference IQA model, the quality of the distorted image is assessed with partial information from the reference image [7], [12]. The partial information are the features extracted from the reference image such as coefficients of wavelet, curvelet, bandelet, contourlet transforms or other statistical parameters of the image [13], [14]. RR-IQA is a compromise between FR and NR approaches in terms of quality prediction accuracy and amount of information required to describe the reference image [15]. In the case of FR-IQA, the reference image is always required to estimate the quality of the distorted image, but the results are reliable and in good agreement with the perceived quality. But obtaining a reference image may not be always feasible or it may be too expensive. NR-IQA does not require any reference image. However, its prediction accuracy and consistency are poor. RR-IQA is a practical and convenient tool for real time multimedia communication over a wireless or wired channel.

3.3 Full-Reference IQA (FR-IQA)

FR-IQA uses a reference image for the assessment of quality of the distorted image. Since this method has the complete information about the reference image, the results of FR-IQA are supposed to be superior to other IQA algorithms. Some approaches towards FR-IQA are based on image fidelity, accumulated errors, HVS, image structures, information content, image statistics and machine learning etc.[4,5] Some important FR-IQA algorithms are explained below.

3.3.1 Mean squared error (MSE)

This algorithm computes the mean square error of the test image with reference to the original image on a pixel by pixel basis [3], [16]. MSE is usually calculated as

$$\mathrm{MSE} = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y)-g(x,y)]^2 \quad (1)$$

where $f(x,y)$ and $g(x, y)$ are the reference and distorted images respectively of size MxN pixels. The advantage of this metrics is its simplicity, but has poor correlation with subjective test results.

3.3.2 Peak signal to noise ratio (PSNR)

This method also compares the reference image and the distorted image on a pixel by pixel basis and calculates the PSNR as follows [16].

$$\mathrm{PSNR}=10\log\left(\frac{(2^B-1)^2}{\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[f(x,y)-g(x,y)]^2}\right)\mathrm{dB}. \quad (2)$$

Eqn.(2) can be written as

$$\mathrm{PSNR}=10\log\left(\frac{(2^B-1)^2}{\mathrm{MSE}}\right)\ \mathrm{dB}. \quad (3)$$

The parameter B is the number of bits per pixel of the image. The main disadvantage of PSNR is the poor correlation with HVS.

3.3.3 Noise quality measure (NQM)

In this method, a degraded image is modeled as an original image subjected to linear frequency distortion and additive noise injection [17]. The psychophysical effects of frequency distortion and noise injection are independent and NQM deals with the noise injection. While computing the NQM, the aspects such as variation in contrast sensitivity with distance, image dimensions and spatial frequency; variation in the local luminance mean; contrast interaction between spatial frequencies and contrast masking effects are considered. The degraded image is processed with a restoration algorithm which results in an image with linear distortion and additive noise. The original image is also processed with the same restoration algorithm, the result of which is an image with linear distortion. NQM is usually expressed in dB and computed as

Journal of Theoretical and Applied Information Technology
10th July 2014. Vol. 65 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$NQM = 10\log_{10}\left(\frac{\sum_x\sum_y f^2(x,y)}{\sum_x\sum_y\left(f(x,y)-g(x,y)\right)^2}\right)dB \quad (4)$$

where f(x,y) and g(x,y) are the model restored image and the restored degraded image respectively. The correlation of the results with subjective tests is better than PSNR.

3.3.4 Universal quality index (UQI)

This algorithm was proposed by Zhou Wang *et al.* in 2002 [18], [19]. It computes the quality index of the distorted image as:

$$Q = \frac{4\sigma_{fg}\bar{f}\bar{g}}{(\sigma_f^2+\sigma_g^2)[(\bar{f})^2+(\bar{g})^2]} \quad (5)$$

where $\bar{f}$ and $\bar{g}$ are the mean luminance, σ_f and σ_g are the standard deviations of the original and distorted images f and g respectively. σ_{fg} represents the linear correlation between the images f and g. The value of Q lies between -1 and +1. The best value of Q is 1 when f=g. This index indicates the loss of correlation, luminance distortion and contrast distortion. Normally, the overall value of Q is calculated for a window of convenient size and the mean value is computed as the quality index. The universal quality index calculated as above had shown better correlation with respect to subjective tests.

3.3.5 IQA based on SSIM

Natural images are highly structured and their pixel values exhibit strong dependencies. The structural similarity index SSIM [20] is an IQA algorithm based on these structural dependencies with in an image. The human visual system is highly adapted to extract structural information from the viewing field. The SSIM algorithm separates the luminance component l(f,g), contrast component c(f,g) and the structural component s(f,g) from the reference image (f) and the distorted image (g) and compares these components. SSIM index is calculated as

$$SSIM(f,g) = [l(f,g)]^{\alpha}.[c(f,g)]^{\beta}.[s(f,g)]^{\gamma} \quad (6)$$

where $\alpha>0$, $\beta>0$ and $\gamma>0$ are constants used to adjust the relative importance of the three comparisons. The luminous, contrast and structural components are computed as follows.

$$l(f,g) = \frac{2\mu_f\mu_g+C_1}{\mu_f^2+\mu_g^2+C_1} \quad (7)$$

$$c(f,g) = \frac{2\sigma_f\sigma_g+C_2}{\sigma_f^2+\sigma_g^2+C_2} \quad (8)$$

$$s(f,g) = \frac{\sigma_{fg}+C_3}{\sigma_f\sigma_g+C_3} \quad (9)$$

The parameters μ_f, σ_f and μ_g, σ_g are the mean and standard deviations of images f and g respectively. The parameter σ_{fg} is calculated as

$$\sigma_{fg} = \frac{1}{N-1}\sum_{i=1}^{N}(f_i-\mu_f)(g_i-\mu_g) \quad (10)$$

The constant C_1, C_2 and C_3 are included to avoid instability when $(\mu_f^2+\mu_g^2)$, $(\sigma_f^2+\sigma_g^2)$ or $\sigma_f\sigma_g$ are very close to zero. These values are selected such that $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$. K_1 and K_2 are constants such that $K_1 \ll 1$, $K_2 \ll 1$ and L is the dynamic range of the pixel values (L=255 for 8-bit gray scale images). The equation for SSIM can be simplified by putting $\alpha = \beta = \gamma = 1$. The value of C_3 is normally taken as $C_2/2$. SSIM in its simplified form can be written as

$$SSIM(f,g) = \frac{(2\mu_f\mu_g+C_1)(2\sigma_{fg}+C_2)}{(\mu_f^2+\mu_g^2+C_1)(\sigma_f^2+\sigma_g^2+C_2)} \quad (11)$$

The main advantage of SSIM is that it has a good correlation with the subjective test results over a wide range of distortion types. However, it fails to give a satisfactory correlation with HVS in the case of blurred images [21]. SSIM and its variants are superior to other algorithms such as MSE, SNR and PSNR. This is because SSIM treats image degradations as structural changes and it mimics the HVS to certain extend.

3.3.6 Multi-scale SSIM (MS-SSIM)

This is an improved version of SSIM. For an M-stage MS-SSIM index, the procedure involves M iterations. During each iteration, the reference and distorted images pass through a low pass filter, down sample the filtered image by a factor 2 and the contrast and structural comparisons are done. This process is repeated for M-1 times until we get the stage M. After the M^{th} stage, the luminance comparison is done as $l_M(f,g)$ along with $c_M(f,g)$ and $s_M(f,g)$. Finally the M-stage MS-SSIM is calculated as follows [22].

$$MS-SSIM(f,g) = [l_M(f,g)]^{\alpha_M}.\prod_{j=1}^{M}[c_j(f,g)]^{\beta_j}[s_j(f,g)]^{\gamma_j} \quad (12)$$

The parameters α_M, β_j and γ_j are used to adjust the relative importance of different factors. The MS-SSIM has better quality prediction accuracy compared to single stage SSIM, but the computational complexity is high.

Journal of Theoretical and Applied Information Technology
10th July 2014. Vol. 65 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.3.7 Gradient based structural similarity (GSSIM)

Human eye is very sensitive to edge and contour information of an image. GSSIM is an improved version of SSIM where the contrast and structure comparisons c(f,g) and s(f,g) of SSIM are replaced by the gradient based contrast and structure comparisons $c_g(f,g)$ and $s_g(f,g)$ respectively [21]. Sobel operator is used to generate the gradient map of the images. $c_g(f,g)$ and $s_g(f,g)$ are computed in the same way as c(f,g) and s(f,g) with the difference that the gradient maps of the reference and distorted images are used instead of the original images. GSSIM shows better performance over SSIM especially for blurred images.

3.3.8 Information fidelity criteria (IFC)

This method is based on the amount of visual information present in the image using natural scene statistics (NSS) model. Natural images show strong statistical relation between their pixels. Distortions in the image disturb these relations and make them un-natural. In IFC, the fidelity of the image is measured using natural scene models in conjunction with distortion models [23]. The reference image is modeled as an NSS in the wavelet domain. The distortion model is expressed as an attenuation and additive Gaussian noise model in the wavelet domain. The fidelity criterion between the source and distorted images is the mutual information shared by them.

3.3.9 Visual information fidelity (VIF)

This method is similar to the IFC method described above. It is based on the amount of information shared by the reference and distorted images (i.e. mutual information). The visual quality of the distorted image is strongly related to relative information present in the distorted image. The distortion is considered as the loss of image information and this is used to calculate the IQA metrics. The source image is modeled as a NSS model using Gaussian scale mixture (GSM) in the wavelet domain. The distortion model is described as a signal attenuation and additive noise model in the wavelet domain. The VIF metrics have shown improved performance over many of the existing FR_IQA algorithms [24]. However, the main disadvantage of VIF is its computational complexity.

3.3.10 Quality index based on local variance (QILV)

This method is based on the assumption that a great amount of structural information of an image is coded in its local variance distribution [25]. In this procedure, the local variance of the image is calculated using a weighted neighborhood. The mean and standard deviation of the local variance are calculated for both the images. Finally, the covariance of the local variance of the reference and distorted images are also calculated. The quality index QILV is calculated using a similar method as the SSIM with the difference that the mean and standard deviations of the local variance are used instead of mean and standard deviation of the pixel values. Similarly, instead of the covariance of the pixel values, the covariance of the local variance of both images is used for computation. This algorithm performs better than SSIM especially in the case of a blurred image.

3.3.11 Visual signal to noise ratio (VSNR)

VSNR is a wavelet based approach in which the metrics is calculated in two stages [26]. In the first stage, the contrast threshold for the detection of distortions in the image is determined using wavelet based models of visual masking and visual summation to check if the distortions are visible. If the distortions are below the threshold of detection, the distorted image is considered as of perfect fidelity (VSNR=∞). If it is above the threshold of detection, the second stage of computation is applied. In this stage low-level visual property of perceived contrast and the mid-level visual property of global precedence are used to calculate the VSNR using multi-scale wavelet decomposition. The attraction of VSNR is its correlation with HVS and computational simplicity.

3.3.12 IQA based on edge and contrast similarity ECSM

This method is based on the assumption that the perceived quality of a distorted image has a strong dependency on the edges. A distorted image with very close similarity in its edges with the original image gives very good perceptual quality for the human visual system. Similarly, contrast similarity is another important parameter that represents the quality of a distorted image. Therefore, in ECSM, the edge similarity ESM and the contrast similarity CSM are combined [27].

$$\mathrm{ECSM} = (\mathrm{ESM})^{\alpha}.(\mathrm{CSM})^{\beta} \quad (13)$$

Journal of Theoretical and Applied Information Technology
10th July 2014. Vol. 65 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Values of α and β are selected such that α > 0 and β >0 in order to adjust the relative importance of these parameters and for simplicity, they can be made equal to unity. The value of ECSM lies between 0 and 1, zero for very poor quality and 1 for the highest quality. It was shown that the performance of ECSM was better than PSNR, MSE and SSIM.

3.3.13 IQA based on LU factorization (MLU)

This method was proposed by H.-S. Han *et al* [28]. LU factorization is done on the reference and distorted images block by block with typical block size of 8x8 and a 2-D distortion map is made. The images are converted in to gray scale images before factorization. From the distortion map as obtained above, the MLU metric is calculated. The performance of this algorithm is better than PSNR and SSIM for the LIVE database.

3.3.14 Most apparent distortion (MAD)

In this algorithm, two separate strategies are used to compute the distortions, on images having near threshold distortions (detection based strategy) and images having clearly visible distortions (appearance based strategy). In the case of high quality images, the image is most apparent, and thus the HVS attempts to look for distortions. In the second case, the distortions are most apparent, and thus the HVS attempts to look for the image's subject matter. The distortions in the above two cases are calculated using visual detection model and image appearance model respectively. Local luminance and contrast masking are used to estimate distortion in the first case where as changes in the local statistics of spatial-frequency components are used to estimate distortions in the second case. Finally, the above two perceived distortion measures are combined into a single estimate of overall perceived distortion [29].

3.3.15 Visual importance pooling for SSIM

These algorithms are used to improve the SSIM by incorporating the visual importance of different regions of an image. The hypothesis is that certain regions in an image are visually more important than others. Hence region-of-interest based quality assessment can improve the performance of SSIM. The three improved versions of SSIM under this category are Fixation-SSIM (F-SSIM), Percentile-SSIM (P-SSIM) and PF-SSIM which is a combination of these two. By applying this method it has been shown that the correlation of SSIM with respect to the subjective test results has been improved [30].

3.3.16 Content partitioned SSIM (4- SSIM)

This is an improved version of SSIM or MS-SSIM where the image is segmented in to four categories of regions such as changed edges, preserved edges, textures and smooth regions. Weights are applied to the SSIM values over these regions. The weighted SSIM values are pooled to get a single index for image quality. Depending upon whether SSIM, MS-SSIM, G-SSIM or MS-G-SSIM are used, the different content partitioned quality indices namely 4-SSIM, 4-MS-SSIM, 4-G-SSIM or 4-MS-G-SSIM are obtained. The test results have shown improved consistency with human subjective tests compared to G-SSIM or MS-G-SSIM [31].

3.3.17 Feature based IQA using RIESZ transforms

This algorithm abbreviated as RFSIM [32] is based on the assumption that perceptible image degradations will induce corresponding changes in image low level features at key locations. In this algorithm, the Riesz transform features are compared at key locations between the distorted image and the reference image to calculate the RFSIM index. The Canny operator is used to create a mask to mark the key locations of the image. The low-level features are extracted using the 1st order and 2nd order Riesz transforms and the coefficients which are inside the feature mask are taken for IQA calculation. RFSIM showed better consistency with subjective test results for TID2008 database.

3.3.18 IQA based on information content weighting

This method is based on the hypothesis that when viewing natural images, the optimal perceptual weights for pooling should be proportional to the local information content. In this case the local quality or distortion is measured and the same is pooled with the information content as the weighting parameter. In the first stage, the local quality/distortion measurement is done in a similar manner as MSE, PSNR or SSIM. The information content weighting is then applied to compute the new quality metrics such as IW-MSE (information weighted MSE), IW-PSNR or IW-SSIM [33]. The authors have shown that there has been significant improvement in the predicted quality by applying this method on MSE, PSNR and SSIM.

3.3.19 Feature similarity index (FSIM)

FSIM is based on the theory that HVS understands an image based on its low level features such as edges, and a good IQA metric could be obtained by comparing these low level features [34]. At

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

points of high phase congruency of the Fourier waves of different frequencies of the image, highly informative features can be extracted. FSIM utilizes this property of the Fourier transform of images for quality assessment. In FSIM, the phase congruency (PC) and the image gradient magnitude (GM) are computed for the quality assessment of the distorted image with respect to the reference image. The PC of the image is computed using the response of a 2-D log-Gabor function. The GM is calculated as $G = \sqrt{G_x^2 + G_y^2}$ where G_x and G_y are the partial derivatives of the image along the x and y directions. The gradient operator used was Scharr which gave better performance compared to Sobel or Prewitt operators. The performances of the FSIM and FSIMc (for color images) were superior over SSIM and MS-SSIM for a variety of image databases.

3.3.20 IQA based on detail losses and additive impairment

This method computes quality metric by separately evaluating detail losses and additive impairment [35]. Detail losses are the losses of useful visual information which affect the content visibility in the distorted image. Additive impairment is the redundant visual information present in the distorted image, but not in the original image such as blocky artifacts in a JPEG image. The original and the distorted images are decomposed in to their wavelet coefficients and the detail losses and additive impairments are separated. The quality index is calculated by combining the detail loss measure and the additive impairment measure.

3.3.21 IQA based on multi-channel regional mutual information (MRMI)

This algorithm proposed by Jing Li et al [36] uses the regional mutual information (RMI) to evaluate the difference between the distorted image and the reference image. The image is decomposed into different frequencies using wavelet transform. The RMI values are calculated on these decomposed components. Multi-channel RMI is calculated by weighted sum of all RMIs. The effectiveness of this algorithm is better than PSNR and SSIM for distortion types Gaussian Blur, JPEG, JPEG2K and White Noise.

3.3.22 Perceptual image quality assessment (PIQA)

This is an improved version of SSIM. In this method, the luminance, contrast and structural comparison measures are done as in the case of SSIM. However, in the structural comparison, the structural orientation is utilized to measure the structural similarity [37]. The contrast comparison measure is done in the contourlet domain. The performance of the PIQA algorithm has been better than the other FR-IQA algorithms such as MSE, PSNR and SSIM for most of the distortion types.

3.3.23 IQA based on spectral residual (SR-SIM)

This method is based on spectral residual visual saliency (SRVS). The hypothesis behind this approach is that an image's perceived quality is related to its visual saliency map. In this method, the Visual Saliency (VS) is calculated for the reference and distorted images based on Spectral Residual. The Gradient Modulus (GM) is calculated using the Scharr operator. The local values for SR-SIM is calculated using the two components namely SRVS and GM using the relation $S(x) = S_v(x).[G_v(x)]^{\alpha}$ where $S_v(x)$ and $G_v(x)$ are the local values for SRVS and GM and α is a parameter used to adjust the relative strength of these components. After obtaining the local values for S(x), the global value is calculated by applying suitable pooling mechanisms [38]. The overall performance of this algorithm was superior to most of the existing FR-IQA algorithms for the LIVE, CSIQ and TID 2008 image data bases.

3.3.24 Edge strength similarity (ESSIM)

It is based on the fact that HVS is more sensitive to the direction showing stronger edge strength. Any directional high pass filters can be used to define the edge strength. Different gradient operators such as Sobel, Prewitt or Scharr can be used to extract the edge strength. The edge strength are calculated in the horizontal-vertical direction and in the diagonal direction. The maximum of these two values is taken as the edge strength at any point. The ESSIM index is defined as [39]

$$ESSIM(f,g) = \frac{1}{N}\sum_{i=1}^{N} \frac{2E(f,i)E(g,i)+C}{(E(f,i))^2+(E(g,i))^2+C} \quad (14)$$

where f and g are the reference and distorted images, N is the total no. of pixels in f or g, E(f,i) and E(g,i) are the edge strength at pixel "i" of images f and g respectively. C is a scaling parameter such that $C= (BL)^2$ where B is a constant and L is the dynamic range of edge strength. It has been shown that the ESSIM has good correlation with HVS.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3.3.25 IQA using histogram of oriented gradients (HOGM)

This method uses the Histogram of Oriented Gradients (HOG) to estimate the gradient similarity and produce the regional weight map with the SSIM index to compute the HOG weighted SSIM. Regions where strong gradient changes occur should have greater visual importance. The HOGM based IQA approach uses the SSIM quality map of reference image and the distorted image. A regional weight map is calculated using the HOG descriptors. The HOGM index is calculated as follows [40].

$$\mathrm{HOGM}(f,g) = \frac{\sum_{i=1}^{P}\sum_{j=1}^{Q} \mathrm{SSIM}(f_{ij},g_{ij}).\omega_{ij}}{\sum_{i=1}^{P}\sum_{j=1}^{Q}\omega_{ij}} \qquad (15)$$

where P, Q are the image dimensions and ω_{ij} is the weight value at pixel (i,j). SSIM(f_{ij},g_{ij}) is the SSIM map at location (i,j). The performance of HOGM was better than SSIM and MS-SSIM at the cost of increased complexity.

4. PERFORMANCE COMPARISON

In the previous sections, the various algorithms for FR-IQA have been discussed. For testing the performance of an algorithm, publically available image data bases are used. These databases consist of a number of reference images and distorted versions of the reference images. The distorted images are classified in to various distortion types such as Gaussian blur, white noise, fast fading, jpeg, jpeg2000, quantization noise, mean shift etc. Each image has undergone subjective tests and the mean opinion score (MOS) or difference mean opinion score (DMOS) are calculated and available with these databases. Examples of such data bases are LIVE data base [41], TID 2008 database [42], CSIQ database [29], IVC database [43], Toyama database [44] and A57 database [27]. In order to evaluate the performance of an algorithm, the objective scores obtained from the algorithm for various images in the database are compared with the subjective scores (MOS or DMOS). The important performance metrics used in IQA are the Spearman rank order correlation coefficient (SROCC) and the Kendall rank order correlation coefficient. These two measure the prediction monotonicity of an IQA metric [45], [46]. The Pearson linear correlation coefficient (PLCC) and the RMS error (RMSE) between MOS and the objective scores after nonlinear regression are the other parameters used for evaluating the performance [47]. The execution time of these algorithms is also an important parameter for selecting a particular algorithm for an application.

Table I shows the performance results of some important FR-IQA algorithms compiled from cited articles.

Table 1: Performance parameters for some FR-IQA Algorithms

Algorithm	SROCC	KROCC	PLCC	RMSE
PSNR	0.8756	0.6865	0.8723	13.3597
NQM	0.9086	0.7413	0.9122	11.1926
UIQ	0.8941	0.7100	0.8987	11.9843
SSIM	0.9479	0.7963	0.9449	8.6188
MS-SSIM	0.9513	0.8045	0.9489	8.6188
GSSIM	0.9448	-	0.9563	6.7652
IFC	0.9259	0.7579	0.9268	10.2643
VIF	0.9636	0.8282	0.9604	7.6137
VSNR	0.9274	0.7616	0.9231	10.505
MAD	0.9438	0.7920	0.9394	9.368
4-SSIM	0.946	-	0.9489	7.3012
4-MS-G-SSIM	0.9626	-	0.9555	6.822
RFSIM	0.9401	0.7816	0.9354	9.6642
IW-SSIM	0.9567	0.8175	0.9522	8.3473
FSIM	0.9634	0.8337	0.9597	7.678
DLAI	0.946	-	0.9360	9.627
PIQA	0.9612	-	0.9655	-
SR-SIM	0.9618	0.8299	0.9553	8.0811
ESSIM	0.9622	0.8397	-	-
HOGM	0.9569	0.8159	0.9529	8.281

5. FUTURE TREDNS

Even though significant progress has been made during the last decade in the field of FR-IQA, there are a lot of challenges before the research community. There is a great need for algorithms which are fast, simple and accurate. PSNR and MSE are computationally simple and researchers are showing increased interest to overcome the limitations associated with them. The principle of structural similarity is being extended to derive a number of new algorithms with improved accuracy. Video Quality Assessment (VQA), IQA of 3-D images and IQA for multimedia contents are some of the areas where significant research is ongoing.

6. CONCLUSION

In this paper we have introduced the concept of IQA and major classification of IQA algorithms followed by a detailed review of some major FR IQA algorithms available today. We have also presented methodologies followed for evaluating

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the performance of FR IQA algorithms and the public databases available for such evaluation. In order to have a comparison, we have presented some performance parameters of selected FR IQA algorithms on LIVE database. We hope that this paper will serve as an introductory review to those who are new to the subject.

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