Volume 3, Issue 3, March 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

An Algorithm for Measurement of Quality of Image

Poonam Dabas[1],
[1]Assistant Professor,
U.I.E.T. KurukshetraUniversity,
Kurukshetra, Haryana, INDIA

Priya Soni[2]
[2]Research Scholar,
U.I.E.T, Kurukshetra University,
Kurukshetra, Haryana, INDIA

Abstract: - ***There are objective methods for assessing image quality. These methods can the visibility of errors between a distorted image and a reference image using a variety of known properties of the human visual system. Under the assumption that human visual perception is highly adapted for extracting structural information from a scene, we introduce an alternative frame work for quality assessment based on the degradation of some Model. As a specific example of this concept, we develop a HVS Model and demonstrate its promise through a set of intuitive examples, as well as comparison to both subjective ratings and state-of-the-art objective methods on a database of images compressed with Contrast Sensitivity function.***

Keywords—Error sensitivity, human visual system (HVS) image coding, image quality assessment finite impulse response (FIR).

I. INTRODUCTION

Methods for image quality assessment can be divided into two groups: subjective and objective. The only subjective measure is mean opinion score (MOS) where quality of an image is judged by several individuals and then the men value of their scores is used as the measure. Since human observer is ultimate receiver of the information contained in an image, this is the best way to assess image quality. Objective measures try to assess image quality and express it as a number. The goal in developing objective (quantitative) measures is to find the one that correlates well with image quality as perceived by human visual system (HVS). These measures are used to assess performance of different algorithms for image enhancement and coding. Quality measures can also be used to optimize image processing algorithms. For example in image coding the goal is to represent images with as few bits as possible with the minimal loss of image quality. Quality measure is used as a criterion in a sense that the bits that contribute more significantly to the used quality measure are coded first. In this the measurement of quality can be calculated as index of image. This will check whether the actual image can be obtained after distortion. In distortion the image can be calculated as mean squared error. There are various measure elements of the quality of image in the measurement of image. This paper presents various techniques to measure Image quality assessment. The rest of the paper is organized as follows. Section 2 presents Overview of Image Quality Measure. Section 3 discusses the HVS model with their properties. Section 4 presents the various techniques used for the Image Quality Assessment and finally Section 5 presents our conclusions.

II. OVERVIEW OF IMAGE QUALITY MEASURES

In this case distorted image with smaller MSE will be perceived closer to the original image than the one with greater MSE. However, when we use images with different types of degradation MSE does not produce results that correlate well with subjective quality assessment. Images with different types of degradations with the same MSE values can have very different subjective visual qualities.It is assumed here that input image is degraded by two sources of degradation: linear distortion (for example as a result of filtering) and additive noise. In the first step linear distortion and additive noise are separated and then two quality measures are computed: distortion measure and noise quality measure. Distortion measure is computed using discrete Fourier transform (DFT) coefficients of the original image and original image distorted by linear distortion only. Noise quality measure is computed using the original image degraded by linear distortion and noise and the original image degraded by linear distortion only. These two images are decomposed into sub bands using a system of filters and perceptual threshold is computed for every sub band and every spatial location. If the difference between the two images is below the perceptual threshold it is not considered visible and that difference is ignored, otherwise the difference is taken into account. Finally, noise quality measure is compute as SNR of the modified input images, which contain only visible difference between the two images. This approach requires as input not only two images but also the algorithm that causes linear distortion and produces two numbers, which assess image quality.

III. HVS MODEL

Most of these algorithms are trying to model the following two properties of HVS: perceived brightness, frequency response of HVS (contrast sensitivity function) we mention:

Brightness perception: Digital images are represented using a finite number of intensity levels. For example, gray scale images with 8 bits/pixel are represented by 256 intensity levels, where 0 corresponds to the darkest level and 255 corresponds to the brightest level. Intensities between these two extremes represent various shades of gray level. Brightness perceived by HVS is not a linear function of intensity represented by integers from 0 to 255. This can be shown by the following experiment. First we create an image which consists of uniform background of intensity I and a small square in the center of intensity I+ I, and then we repeat this for different values of background intensity I while keeping I constant. When the background intensity is very low (for example I=10) or very high (I=240) the difference in perceived brightness is between the background and the center square is smaller than in the case when the background intensity is in the mid range (I=125). Since the intensity difference between the background and the center square is the same in each case, perceived brightness must be a nonlinear function of intensity. In other words equal increases in intensity do not correspond to equal increases in perceived brightness. This phenomenon is well known but it is very difficult to model it because we do not know how to measure perceived brightness. Usually, this is modeled by transforming input intensities by some nonlinear function, such as logarithmic or cube root function. If we denote perceived brightness by B and input intensity by I, then by using logarithmic function they are related as:

$B = K \log I$

Where K is a constant. This is known as Weber's law and is cited in many books on image processing (for example [4] and [8]). The second formula, which is used in [9], is obtained using cube root function:

$B = K (I)$ 0. 33

***Contrast sensitivity function*:** It describes the frequency response of HVS. HVS is not equally sensitive to all spatial frequencies, which can be shown by the following experiment. First we design a 2-D filter, which will approximately have the following magnitude frequency response:

(4) H (f) =f1+f2

(5) S (f) =H (f) +B

In the last formula f1and f2 are normalized frequencies, taking values between -0.5 and 0.5. Therefore, the values for f1 and f2 must be between 0 and 0.707. This filter cannot be realized exactly but it can be numerically approximated by creating a finite impulse response (FIR) filter using frequency sampling method FIR filter obtained by this method will have the same magnitude frequency response as the ideal filter at given points in the frequency plane. Magnitude frequency response of the ideal filter and the obtained FIR filter are for f =0.35 and f =0.4. Then we generate white Gaussian noise and filter it by the FIR filter obtained using the described procedure. This filtered noise is added to the original Lena image for various values of f and f. Each time the filtered noise is scaled so that its standard deviation is 10. We get the sequence of images. All images in the sequence are corrupted by the noise with the same variance, but the noise is not equally visible in each image. It is equal to one at the frequency where the sensitivity is maximal and everywhere else is less than one.

IV. VARIOUS MEASURE OF IMAGE QUALITY ASSESSMENT

The various techniques or measure differentiates between the random and signal-dependant distortion, which have different effects on human observer are described below:

RRIQA (Reduced-reference image quality assessment) algorithm: The algorithm using statistical features extracted from a divisive normalization-based image representation. We demonstrate that such a DNT (*Domain Statistics of Distorted Images)* image representation has simultaneous perceptual and statistical relevance and its statistical Properties are significantly changed under different types of image distortions. These properties make it well-suited for the development of RRIQA algorithms. Experimental verifications with publicly-accessible subject-rated image databases suggest that this new image representation leads to improved performance in the evaluation of image quality.

Algorithm for image quality assessment: It provided an algorithm for image quality assessment has been presented. First, reasons for disagreement between MSE-based and subjective visual quality evaluation have been identified. Then a new quality measure has been defined. The proposed measure takes into account two HVS properties: nonlinear relationship between intensity and perceived brightness and presence of spatial filtering in HVS. This measure is based on average value of locally computed correlation coefficients, which is more closely related to the way in which human observer determines quality of an image than MSE. Finally, this value is modified by average value of locally computed correlation coefficients between original image and error image. This way the proposed measure differentiates between random and signal-dependant distortion, which have different effects on human observer. Proposed image quality measure performs reasonably well. The examples presented here demonstrate that this measure ranks images according to their visual quality in cases when MSE-based measures fail to do that. However, subjective evaluation is still the best way for image quality assessment. HVS is more sophisticated than any mathematically defined image quality measure.

Iris image quality assessment: Iris image quality assessment is an important part that can never be neglected in iris recognition system. In this paper, we first segmented pupil using the least square method. Then, a novel multiple step algorithms was proposed for the defocused image and the occlusion image of eyelid and eyelashes, which only needed to process three local areas of the iris image and largely reduced the computational complexity. Experiments illustrated that the proposed algorithm is fast and efficient. The average processing time was 0.0308s/frame, which fully met the real-time iris recognition system. Iris recognition is one of the most reliable methods of biometrics personal identification. Poor quality iris image will be rejected by recognition system, which will result in the failure of recognition. Therefore iris image quality assessment is very essential to the iris recognition system. In this paper, a multiple step algorithm of iris image quality assessment is proposed to distinguish two kinds of poor quality images, i.e. defocus and occlusion.

Image fusion: An improved algorithm for the image fusion, and synthetically evaluates the quality by the subjective assessment method and the objective assessment method. The assessment results show that our proposed algorithm can fuse the images information in better performance. It is noted that the factors that can affect the performance of image fusion are too much. Moreover, the type of images can also affect the fusion quality. Thus, we need to make further verification for the more types of images. This improved discrete wavelet framework based image fusion algorithm, after studying the principles and characteristics of the discrete wavelet framework. The improvement is the careful consideration of the high frequency sub band image region characteristic. The algorithms can efficiently synthesis the useful information of the each source image retrieved from the multi sensor. The multi focus image fusion experiment and medical image fusion experiment can verify that our proposed algorithm has the effectiveness in the image fusion. On the other side, the quality assessment of the image fusion, and summarize and quantitatively analysis the performance of algorithms proposed in the paper.

***Visual component detection and supervised machine learning*:** A new approach for image quality assessment based on visual component detection and supervised machine learning. Our preliminary based only on face detection and face based quality modeling yielded encouraging results. However, more work needs to be done in area such object detection; feature selection and machine to better establish this method. Image quality assessment is an area of intense contemporary research interest, but a majority of algorithms described in the literature require the use of an original image as a reference. Although this is useful in applications such as compression there are other applications where quality assessment is desirable but a reference image is not available. a new image quality assessment algorithm that does not rely on reference images.

***Error-sensitivity*:** An efficient method proposed the use of structural similarity as an alternative motivating principle for the design of image quality measures. To demonstrate our structural similarity concept, we developed an SSIM index and showed that it compares favorably with other methods in accounting for our experimental measurements of subjective quality of JPEG2000 compressed images. Although the proposed SSIM index method is motivated from substantially different design principles, we see it as complementary to the traditional approach. Careful analysis shows that both the SSIM index and several recently developed divisive-normalization based masking models exhibit input-dependent behavior in measuring signal distortion.

Analyze SSIM Index: The main objective of this project was to analyze SSIM Index in terms of compressed image quality. It explained why MSE is a poor metric for the image quality assessment systems. In this project also tried to compare the compressed image quality of SSIM with VIF. By simulating MSE, SSIM and VIF and tried to obtain results, which I showed in the previous slides. Image is altered with different distortions, each adjusted to yield nearly identical MSE relative to the original image. Despite this, the images can be seen to have drastically different perceptual quality. Only VIF has the ability to predict the visual image quality that has been enhanced by a contrast enhancement operation. For the JPEG compression, quality factor, compression ratio and MSSIM are related with each other. So as quality factor increases compression ratio decreases and so MSSIM increases.

A great progress in image quality assessment (IQA): A great progress has been achieved in algorithms about image quality assessment (IQA). Several IQA algorithms have been put forward with high correlation with human perception. However, these algorithms can perform even better. In this paper, one strategy is proposed based on region of interest (ROI) in which some alternation on structure similarity (SSIM) are made to enhance the correlation with human perception. In addition, experimental results are demonstrated to highlight the improvement. It is known that traditional image quality assessment (IQA) method is mean square error (MSE). Unfortunately, the obvious drawback of MSE is its inability to reflect human visual system (HVS). Due to its shortcoming, many researchers have been searching better IQA algorithms.

The local dependency property: It proposed the local dependency property of natural images and the influences of distortions on it. Based on these observations, we develop two universal NR-IQA metrics. Both of these two metrics are in good consistency with the human perception, and perform better than the predominant NR-IQA metrics and some classical full reference metrics, across various distortions. This verifies the feasibility of constructing versatile blind quality evaluation metrics based on local dependency characteristic using the global scheme or the two-step scheme. However, the proposed metrics cannot perform as well as the state-of-the-art universal NR and FR quality indexes over the entire database, and their effectiveness for the other types of distortions has not been verified.

***Reduced-reference image quality assessment framework*:** A reduced-reference image quality assessment framework is proposed by incorporating merits of *multiscale geometry Analysis* (MGA), *contrast sensitivity function* (CSF), and the Weber's law of *just noticeable difference* (JND). In comparing with existing image quality assessment approaches, the proposed one has strong links with the *human visual system* (HVS): sparse image representation is utilized to mimic the multichannel structure of HVS, CSF is utilized to balance magnitude of coefficients obtained by MGA to mimic nonlinearities of HVS, and JND is utilized to produce a noticeable variation in sensory experience. In this framework, images are represented by normalized histograms, which correspond to visually sensitive coefficients.

V. CONCLUSION

An algorithm for image quality assessment has been described. The algorithm uses a simple HVS model, which is used to process input images. CSF used in this model is not fixed; it has one user-defined parameter, which controls attenuation at high frequencies. This way it is possible to get better results than in the case when CSF with fixed parameters is used. This is due to the fact that HVS treats very differently high frequency components present in the original image than those of noise. Two processed images are used to compute average correlation coefficient, which measures the degree of linear relationship between two images. This way we take into account structural similarity between two images, which is ignored by MSE-based measures. Finally, image quality measure is computed as the average correlation coefficient between two input images modified by the average correlation coefficient between original image and error image. This way we differentiate between random and signal dependant distortion, which have different impact on a human observer.Various methods and techniques used for measures of Image Quality Assessment such as RRIQA, Iris Image Quality Assessment, Image Fusin and many other measures along with their advantages and drawbacks are also discussed.

REFERENCES

[1] Z. Wang and Qiang Li "Reduced-reference image quality assessment (RRIQA) using Divisive Normalization-Based Image Representation" VOL. 3, NO. 2, APRIL 2009.

[2] Z. Wang and A. C. Bovik, *Modern Image Quality Assessment*. SanRafael, CA: Morgan & Claypool, Mar. 2006.

[3] N. Damera-Venkata, T. D. Kite, W. S. Geisler, B. L. Evans, and A.C. Bovik, "Image quality assessment based on a degradation model,"*IEEE Trans. Image Process.*, vol. 9, no. 4, pp. 636–650, Apr. 2000.

[4] E. C. Larson and D. M. Chandler, "Most apparent distortion: Full-reference image quality assessment and the role of strategy," *J. Electron. Imag.*, vol. 19, no. 1, pp. 1–21, 2010.

[5] Goran Ivkovic and Ravi Sankar "AN ALGORITHM FOR IMAGE QUALITY ASSESSMENT" at 2004 IEEE.

[6] Songnan Li, *IEEE*, Fan Zhang, Lin Ma, and King Ngi Ngan "Image Quality Assessment by Separately Evaluating Detail Losses and Additive Impairments" VOL. 13, NO. 5, OCTOBER 2011.

[7] Chunlei Shi and Longxu Jin "A Fast and Efficient Multiple Step Algorithm of Iris Image Quality Assessment" V2- 2010 2nd International Conference on Future Computer and Communication.

[8] T. Mansfield, G.Kelly, D. Chandler and J. Kane, Biometric Product Testing Final Report, issue 1.0, National Physical Laboratory of UK, 2001.

[9] J. Daugman, "How Iris Recognition Works," IEEE Transactions on Circuits and Systems for Video Technology, vol. 2, pp. 21-30, 2004.

[10] Yijian Pei, Jiang Yu, Huayu Zhou and Guanghui Cai "The Improved Wavelet Transform Based Image Fusion Algorithm and The Quality Assessment" 2010 3rd International Congress on Image and Signal Processing.

[11] Huitno Luo "A TRAINING-BASED NO-REFERENCE IMAGE QUALITY ASSESSMENT ALGORITHM" 2004 International Conference on image Processing (ICIP).

[12] Z. Wang et al.. "No-reference perceptual quality assessment of JPEG compressed images," in *ICIP'OZ.*

[13] H. Sheikh et al. "Blind quality assessment for JPEG2000 compressed images:' in *Asilomar Conf'O2*.

[14] N. B. Nil1 and B. H. Bouzas. "Objectivc image quality measure derived from digital image power spectm" *Optical Engineering.* vol. 31, pp. 813-825. 1992

[15] Zhou Wang, Alan Conrad Bovik, Hamid Rahim Sheikh and Eero P. Simoncelli "Image Quality Assessment: From Error Visibility to Structural Similarity" IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 13, NO. 4, APRIL 2004.

[16] B. Girod, "What's wrong with mean-squared error," in *Digital Images and Human Vision*, A. B. Watson, Ed. Cambridge, MA: MIT Press,1993, pp. 207–220.

[17] P. C. Teo and D. J. Heeger, "Perceptual image distortion," in *Proc. SPIE*,vol. 2179, 1994, pp. 127–141.

