Technique For Blind Image Processing Using BIQI

Parul Satsangi Department of ECE MIT,Moradaba d, India parulsatsangi8 @gmail.com1

Sagar Tandon Department of ECE MIT,Moradaba d, India sagar.brisk@g mail.com2

Prashant Kr. Yadav Department of ECE MIT,Moradaba d, India pky.prashant@ gmail.com3

Priyal Diwakar Department of ECE MIT,Moradaba d, India priyalplak@gm ail.com4

Sanjay Kumar Department of ECE MIT,Moradaba d, India skysanju@gmail. com5

***Abstract*-In almost every economic sector there is considerable concern regarding the reliable and efficient methods for assessing the quality of visual information in form of images and video. In field of image quality assessment Full-reference image quality assessment (FR-IQA) methods give a satisfactory level of performance because of high correlations with human subjective judgments of visual quality. These methods require a reference signal to compare the test signal. In many applications the reference signal is not available to perform a comparison. This strictly limits the application domain of FR-IQA algorithms and points up the need for reliable blind/NR-IQA algorithms. A new two step framework for no-reference image quality assessment based on Natural scene statistics (NSS) is described which outperforms PSNR-the method of FR-IQA. The new framework for blind image processing is described using blind image quality assessment (BIQI).**

Index terms– Generalized Gaussian Distribution (GGD), Natural Scene Statistics (NSS) , No Reference Image Quality Assessment (NR-IQA), Distorted Image Statistics(DIS), Support Vector Machine(SVM)

I. INTRODUCTION

Recent year have witnessed dramatically increased interest and demand for accurate, easy to use and practical image quality assessment (IQA) tools that can be used to evaluate, control and improve the perceptual quality of image. A number of successful algorithms have been developed that can predict subjective visual quality of distorted image. The goal of objective image and video quality assessment research is to supply quality metrics that can predict perceived image and video quality automatically. A good image quality assessment technique is one that can operate with little or no reference signal information.

When the unspoilt signals are fully available such methods are known as Full reference quality assessment methods, but in practical real world such methods are not of much use as reference signal are not available at receiver side. Conventional Full Reference Image Quality Assessment methods calculate pixel-wise distances peak signal-to-noise ratio (PSNR) and mean square error (MSE) between a distorted image and the corresponding reference image. Full-reference image quality assessment (FR-IQA) methods give a satisfactory level of performance because of high correlations with human subjective judgments of visual quality. A number of successful FR-IQA algorithms have been established but the need of availability of reference image limits their application domain. In today's era the main focus of research is on developing such algorithms that do not depend or depend very less on information from any reference signal. Major contribution towards this goal is of no reference image quality assessment techniques that refer to develop algorithms that seeks to predict the quality of distorted image without the knowledge of pristine reference images and that correlates highly with human perception of quality.

Existing approaches to NR-IQA [1] research can be categorized into three categories 1) Distortion-specific approach: This type of algorithms generally assumes that distortions affecting the image are known. Examples of such NR-IQA algorithms [2], are which computes blockiness measure [3] and [4], which estimate blur, and [5] and [6] which measure ringing effects. 2) Feature extraction and learning approach: In this approach features are extracted from the image and algorithm is trained to distinguish distorted and undistorted image as used in BLIINDS [1]. 3) Natural scene statistics (NSS) approach: This approach relies on how the statistics of images change as distortions are introduced to them. It assumes that natural or undistorted images occupy a subspace of the entire space of possible images, and then seeks to find a distance from the distorted image to the subspace of natural images as described in [8].

Based on NSS approach a two step general purpose framework for designing No reference image quality indices Blind image quality index (BIQI) is

ISBN: 9788175157538

proposed in [9]. In this GGD (Generalized Gaussian distribution) NSS models in wavelet domain are used to create a holistic NR IQA algorithm with very consistent performance. This method is complementary to BLIINDS[1] since it seeks to determine what distortions afflict in image by computing likelihood that each distortion is present; these are used to weight multiple distortion specific algorithm scores derived from NSS models. The two steps comprises of image distortion classification based on a measure of how the NSS are modified, followed step of quality assessment, using an algorithm specific to the decided distortion.

Distortion image statistics (DIS) can be used as distortion-specific signature to classify particular image distortion [15].This approach is used to develop the general purpose framework for IQA. Once such classification is achieved using DIS, it is as if the algorithm is aware of the distortion. The algorithm can then deploy a distortion-specific IQA algorithm.

II. PREDICTION MODEL

It consists of 2 stages that will describe the overall process. The basic structure for NR-IQA is shown in figure.

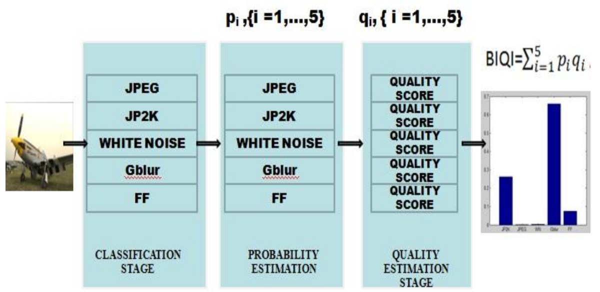


Fig.1.Image quality assessment process.

First the distorted image is taken and the type of distortion that is present in the image is specified by the set of algorithm. Five types of distortion that are taken in consideration are JPEG, JPEG2000 (JP2K), white noise (WN), Gaussian Blur (GB) & Fast Fading (FF). Distorted images are taken from LIVE IQA database[20]. It should be noted that it is not necessary that there should be only one type of distortion present in a image, in some cases there can be many type of distortion in a single image too. A multiclass SVM [22] with a radial-basis function (RBF) kernel is used to classify a given image into one of five distortion categories. The amount of distortion present within the image is predicted by the probability estimation which is provided by the Support Vector Machine (SVM). For each type of distortion, that is present in the image, a probability is estimated and measured p_i, {i=1…5}.

In the second stage the quality of image along each of these distortions is measured. The quality scores for each i.e. JPEG, JP2K, WN, GB & FF distortions are denoted by q_i, {i=1…5}. Blind Image Quality Indices (BIQI) = $\sum_{i=1}^{5} p_i q_i$ is the total probability-quality summation which denotes the quality of the image that is under processing.

These two stages, when combined as described above, form an implementation of the above framework. After the framework is described the statistics of image affected by the distortion are used to evaluate the quality of distorted image.

III. DISTORTED IMAGE STATISTICS

An image is taken is subjected to wavelet transform over three scales and three orientation using the daubechies 9/7 wavelet basis. These wavelet bases have been successfully used for image compression [10] ,texture analysis [11] and for other purposes. Wavelet transform is preferred as it captures both for frequency and time location. In NSS, there exist many models for the marginal distributions of sub-band coefficients [13]. One simple model for these coefficients is the generalized Gaussian model has been used as a feature in this approach of two-stage NR-IQA algorithm that parameterizes the sub band coefficient. The univariate generalized Gaussian density is given by

$$\phi(\xi|\square, \square, \square) = \square \varepsilon^{-(\square |\xi-\square|)^{\square}} \qquad (1)$$

where μ is the mean, γ is the shape parameter, and α and β are the normalizing and scale parameters given by

$$\frac{\quad}{\quad} \qquad (2)$$

$$-\sqrt{\frac{\quad}{\quad}} \qquad (3)$$

where σ is the standard deviation and Γ denotes the gamma function given by

$$\square\,(\zeta) = \int_0^\infty \tau^{\zeta-1} \varepsilon^{-\tau} \delta\tau \qquad (4)$$

This family of distributions includes the Gaussian distribution (β = 2, γ=2) and the Laplacian distribution (β = 1, γ=1). As $\beta \rightarrow \infty$, the distribution converges to a uniform distribution The below figure shows the varying level of shape parameter γ.

ISBN: 9788175157538

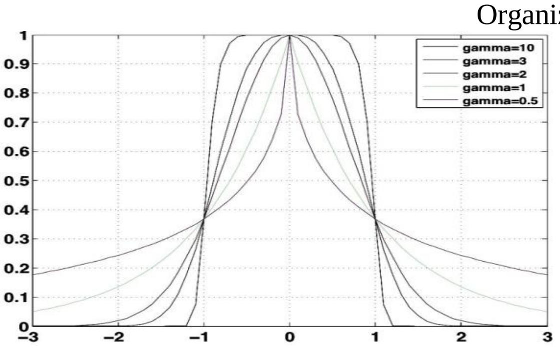


Fig.2. Generalized Gaussian Distribution at Varying Gamma Parameter Values.

Wavelet bases act as band-pass filters, the responses are zero-mean and 2 parameters (σ^2 & γ) are left for each subband thus forming an 18D vector f_i (3scales X 3 orientation X 2 parameters) which act as the representative feature vector for the image. Support vector machine (SVM) is used as classifier in which classification is made using f_i as feature vector to classify image distortion wise (JPEG, JPEG2000, WN, Blur, and FF). SVMs are preferred over other classifiers since they perform well in high-dimensional spaces, avoid over-fitting and have good generalization capabilities. Two step framework uses multiclass SVM with radial basis function given by $C(f(x), y) = \max(1 - f(x)y, 0)$ which gives 0 for a correctly signed assignment and a linear penalty for misclassification. Where $C(f(x), y)$ is Hinge Loss function [16] which take x as image which gives 0 for a correctly signed assignment and a linear penalty for misclassification. There are two parameters to be set in the SVM (C & γ) [14] these are set using 5-fold cross validation on the training set of images.

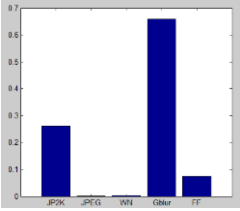
After the classification quality index is computed by using support vector regression. The model produced by SVR depends only on a subset of the training data, because the cost function for building the model ignores any training data close to the model prediction. This regression provides a score representative of quality of image which correlates well with human perception. Finally, each SVM constructed for QA requires a set of parameters (C, γ, v) to be determined. As before for C , γ a 5-fold cross-validation on the training set is used to select these parameters. v is the default value (0.5).

IV. RESULTS

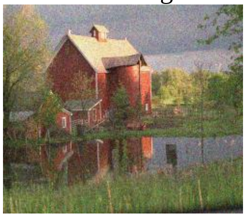
To demonstrate performance of BIQI algorithm, we use the LIVE image quality assessment database [16]. It consists of 29 reference images. Total 808 distorted images along with the associated differential mean opinion score (DMOS) is available. DMOS is representative of the perceived quality of the image and was computed from subjective scores of over 29 subjects in a large scale study. Few figures are shown below as example of how BIQI algorithm gives the class probabilities:

Distorted Image: Gblur Class Probabilities

a.



Distorted Image: WN Class Probabilities



b.

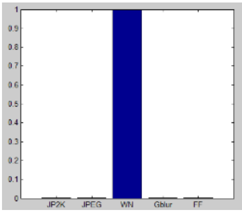


Fig.3. BIQI operation (a) & (b)Classification probabilities for the images.

Scatter plots (for each of the distortion sets as well as for the entire LIVE IQA Database) of the predicted DMOS using BIQI versus subjective DMOS on the test sets are shown in Figs. 4-6.

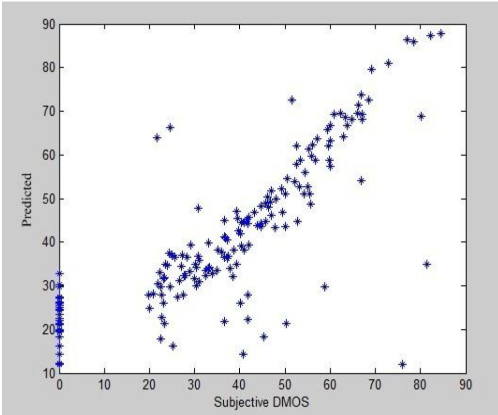


Fig.4. Predicted versus subjective DMOS on the GBlur database subset.

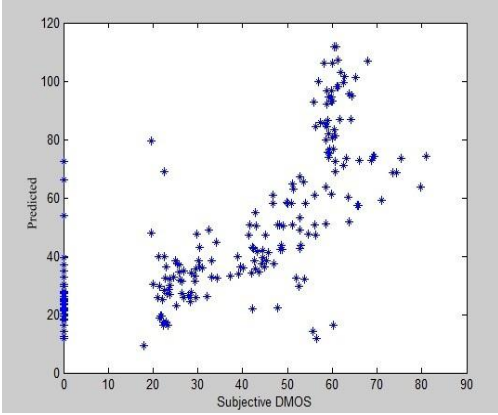


Fig.5. Predicted versus subjective DMOS on the JPEG database subset.

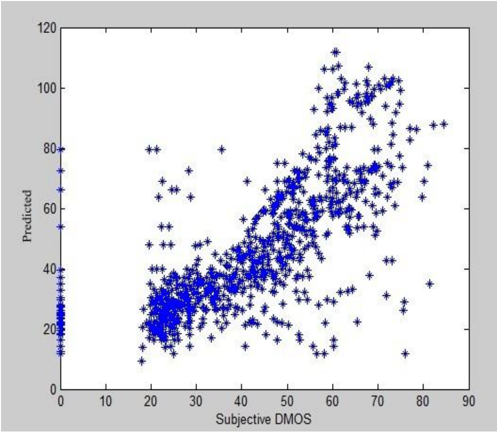


Fig.6. Predicted versus subjective DMOS on the entire LIVE IQA database Subset.

TABLE I.
Median Spearman's Rank Ordered Correlation Coefficient (SROCC) & Median Linear Correlation Coefficient (LCC) Between Algorithm and DMOS on LIVE IQA Database

	SROCC			LCC		
LIVE subset	SSIM	PSNR	BIQI	SSIM	PSNR	BIQI
JPEG2000	0.949	0.865	0.855	0.940	0.864	0.808
JPEG	0.966	0.888	0.785	0.941	0.886	0.901
WN	0.964	0.979	0.971	0.979	0.978	0.953
G Blur	0.931	0.788	0.910	0.891	0.782	0.829
FF	0.941	0.866	0.762	0.942	0.887	0.732
ALL	0.918	0.866	0.819	0.900	0.863	0.820

It is obvious that BIQI performs well in terms of correlation with human perception; and is competitive with the full-reference PSNR across distortion types. Table I lists the (median of the) LCC and (median of the) SROCC values of SSIM, BIQI and PSNR for each distortion type and across all distortions.

This is a remarkable result, as it shows that algorithms that operate without any reference information can offer performance competitive with the predominant IQA algorithm. A probability weighted summation is used to compute the final BIQI score, hence, the performance of each of the QA modules are dependent on each other. Again, the performance of BIQI is competitive with that of full-reference PSNR. It can be noticed that even though BIQI performs competitively with (and in some cases beats) PSNR across all of these measures.

CONCLUSION

In this paper a two step framework for no reference blind image quality assessment using Distorted image statistics (DIS) which is an extension of natural scene statistics(NSS) is described .This framework is unique as it assesses the quality of an image without any knowledge of source distortion. DIS is used to generate the signature of distortion which is used as the means of classification of images distortion wise. This distortion classification is

These exhibit nice properties: a nearly linear relationship against DMOS, tight clustering, and a roughly uniform density along each axis.

combined with the evaluated quality of image to produce Blind image quality index (BIQI).

REFERENCES

[1] Michele A. Saad,A.C.Bovik and Christophe Charrier" A DCT Statistics Based Blind Image Quality Index" IEEE Signal Processing Letters, Vol. 17, No. 6, June 2010.

[2] Z.Wang,A. C. Bovik and B. L. Evans, "Blind measurement of blocking artifacts in images" IEEE Int. Conf. of Image Processing, September 2000, vol. 3, pp. 981-984.

[3] Z. M. Parvez Sazzad, Y. Kawayoke, and Y. Horita, "No-reference image quality assessment for jpeg2000 based on spatial features" Signal Process. Image Commun., vol. 23, no. 4, pp. 257–268, April 2008.

[4] X. Zhu and P. Milanfar, "A no-reference sharpness metric sensitive to blur and noise" International Conference on Quality of Multimedia Experience (QoMEX), 2009.

[5] R. Barland and A. Saadane, "A new reference free approach for the quality assessment of MPEG coded videos" 7th Int. Conf. of advanced Concepts for Intelligent Vision Systems, vol. 3708, pp. 364–371, Sep. 2005.

[6] X. Feng and J. P. Allebach, "Measurement of ringing artifacts in JPEG images" Proceeding of the SPIE, vol. 6076, pp. 74–83, Jan. 2006.

[7] C. Charrier,G. Lebrun and O. Lezoray, "A machine learning-based color image quality metric" Third Eur. Conf. Color Graphics, Imaging and Vision, pp. 251–256, June 2006,

[8] H. R. Sheikh, A. C. Bovik, and L. K. Cormack, "No-reference quality assessment using natural scene statistics: JPEG2000" IEEE Trans. Image Processing, vol. 14, no. 11, pp. 1918–1927, Nov. 2005.

[9] Anush Krishna Moorthy and Alan Conrad Bovik, "A Two-Step Framework for Constructing Blind Image Quality Indices" IEEE signal processing letters, vol. 17, no. 5, may 2010.

[10] T. Brandao and M. P. Queluz, "No-reference quality assessment of H.264/AVC encoded video" IEEE Trans. Circuits Syst. Video Technol., vol. 20, no. 11, pp.1437–1447, Nov. 2010.

[11] D. S. Taubman and M.W. Marcellin, JPEG2000: Image Compression Fundamentals, Standards, and Practice, Kluwer Academic Publishers, 2001.

[12] J. Chen, T.N. Pappas, A. Mojsilovic, and B. Rogowitz, "Adaptive image segmentation based on color and texture" IEEE Intl. Conf. Image Proc., vol. 2, pp. 789–792, 2002.

[13] A. Srivastava, AB Lee, EP Simoncelli, and S.C. Zhu, "On advances in statistical modeling of natural images" J. Math. Imaging Vis., vol. 18, no. 1, pp. 17–33, 2003.

[14] V. Vapnik The Nature of Statistical Learning Theory. Berlin, Germany: Springer Verlag, 2000.

[15] Anush K. Moorthy and Alan C. Bovik, "Statistics of natural image distortions" IEEE Intl. Conf. acoustics speech and signal processing march 2010.

[16] Lectures by Andreas Krause "Advanced Topics in Machine Learning".

[17] H. R. Sheikh, Z. Wang, L. Cormack, and A. C. Bovik, "Blind quality assessment for JPEG2000 compressed

images" Proc. IEEE Asilomar Conf. on Signals, Systems, and Computers, Nov. 2002.

[18] E. P. Simoncelli "Statistical models for images: Compression, restoration and synthesis" Proc. IEEE Asilomar Conf. on Signals, Systems, and Computers, Nov. 1997.

[19] R. W. Buccigrossi and E. P. Simoncelli, "Image compression via joint statistical characterization in the wavelet domain" IEEE Trans. Image Processing, vol. 8, pp. 1688–1701, Dec.1999.

[20] H. R. Sheikh, Z. Wang, L. Cormack, and A. C. Bovik, Live Image Quality Assessment Database Release 2. [Online].Available: http://live.ece.utexas.edu/research/ quality.

[21] Software release of BIQI available online on: http://live.ece.utexas.edu/research/quality/BIQI_release.

[22] LibSVM package for MATLAB, Download from: http://www.csie.ntu.edu.tw/~cjlin/libsvm

ISBN: 9788175157538