NATURAL SCENE STATISTICS APPROACH FOR NO REFERENCE IMAGE QUALITY ASSESSMENT

Vrushali S. Mandgaonkar*

Charudatta V. Kulkarni*

Abstract:

A no reference image quality assessment algorithm based on natural scene statistical approach in DCT domain is presented. The aim is to predict the quality of image without any reference. No reference image quality assessment is technically difficult. The parameters used for training are NSS based features in DCT domain. Prediction model used is the regression model of SVM. The extracted features are used for training of the prediction model and the quality of the test image is assessed. The features used shows high correlation with the subjective score.

Keywords:No Reference Image Quality assessment, Natural Scene Statistics,Discrete Cosine Transform.

* Department of Electronics and Telecomm, MITCOE, University of Pune, Pune, India

I. INTRODUCTION

With the advancement of digital imaging, there has been a tremendous growth in using digital images for representing and communicating information. In such an environment, it is critical to have good image quality assessment methods to help maintain, control and enhance the quality of the digital images. The goal of objective image quality assessment (IQA) is to build a computational model that can accurately predict the quality of digital images with respect to human perception or other measures of interest.

Based on the availability of reference images, objective IQA approaches can be classified into: full-reference (FR), no-reference (NR) and reduced-reference (RR) approaches. Most widely used Image quality algorithms are SSIM[1] and MS-SSIM[2] full reference approach. This paper addresses the most challenging category of objective IQA methods – NR-IQA, which evaluates the quality of digital images without access to reference images. NR-IQA has long been considered as one of the most difficult problems in image analysis. Speed is an important issue for NR-IQA systems since NR-IQA measures are often used in real-time imaging or communication systems. Previous works on NR-IQA have focused primarily on natural scene image and image quality is defined with respect to human perception. Presently, NR-IQA algorithms generally follow one of three trends: 1) distortion-specific approaches. These employ a specific distortion model to drive an objective algorithm to predict a subjective quality score. These algorithms quantify one or more distortions such as blockiness, blur [or ringing] and score the image accordingly; 2) training based approaches: these train a model to predict the image quality score based on a number of features extracted from the image and 3) natural scene statistics (NSS) approaches: these rely on the hypothesis that images of the natural world (i.e., distortion-free images) occupy a small subspace of the space of all possible images and seek to find a distance between the test image and the subspace of natural images. The algorithm used is a fast single-stage framework that relies on a statistical model of local discrete cosine transform (DCT) coefficients It uses a regression SVM model to predict quality scores after a set of features is extracted from an image. For feature extraction, a generalized NSS based model of local DCT coefficients is estimated.

II. OVERVIEW

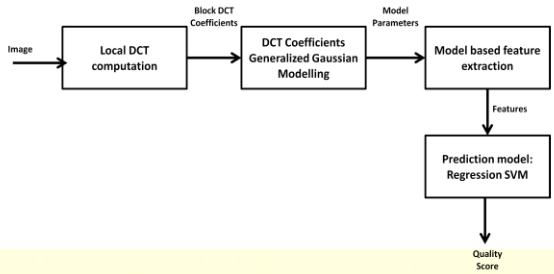

Fig 1 Overview of the algorithm

The framework of the given approach is as described in Fig. 1. 2-D DCT coefficients are computed for the given image as a first stage. Here the image is partitioned into equally sized nxn blocks, called as local image patches, then local 2-D DCT is computed on each of the blocks. The coefficients are extracted from the local image patches in the spatial domain. This DCT decomposition is accomplished across spatial scales. In the second stage a generalized Gaussian density model is applied to each block of DCT coefficients, as well as for specific partitions within each block.

The DCT block partitions that are used are described. The DCT block is partitioned directionally (as shown in Fig. 3) across three orientations. This is done to capture directional information from the local image patches. A generalized Gaussian fit is derived for each of the oriented sub regions of DCT coefficients. A further configuration for the DCT block partition is as shown in Fig. 2. The DCT blocks are partitioned along three radial frequency sub bands. The upper, middle, and lower partitions represent the low-frequency, mid frequency, and high-frequency DCT sub bands, respectively. A generalized Gaussian fit is derived for each of the radial DCT coefficient sub regions as well.

The third stage of the algorithm computes the parameters of the derived generalized Gaussian model. These features are used to predict image quality scores.

The final stage of the algorithm is prediction model that predicts the quality score for the image.

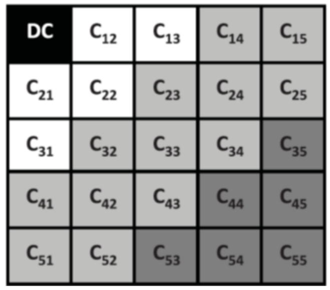

Fig 2 DCT coefficients along radial frequencies

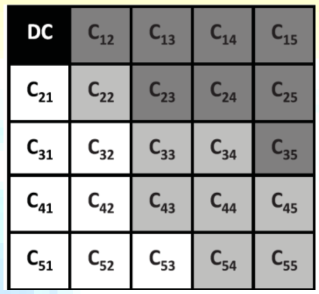

Fig 3 DCT coefficients collected along three orientations.

The regression model of SVM maximizes the probability that the image has a certain quality score given the model-based features extracted from the image.

III. GENERALIZED GAUSSIAN MODEL

The non-DCT coefficients are modeled as GGD by fitting each block DCT histogram with the best-fitting GGD function. Each block is also divided into sub-blocks designed to capture the radial frequency and orientation behavior, and the histogram fit is done on each of these sub-blocks as well. In this way, the estimated NSS model parameters are used to create all features that are used The univariate generalized Gaussian density is given by

$$f(x|\alpha, \beta, \gamma) = \alpha e-(\beta|x-\mu|)\gamma \qquad (1)$$

Where μ is the mean, γ is the shape parameter, and α and β are the normalizing and scale parameters

IV. DCT BASED FEATURES

The performance of any IQA model is a function of the representativeness of the features that are used for quality score prediction. In other words, the prediction is only as good as the choice of features extracted. This motivates us to design features representative of human visual perception of quality Consequently, the features are defined which are representative of image structure, and whose statistics are observed to change with image distortions. The structural information1 in natural images may loosely be described as smoothness, texture, and edge information composed by local spatial frequencies that constructively and destructively interfere over scales to produce the spatial structure in natural scenes. Feature extraction is performed in the local frequency (DCT) domain. The main motivation behind feature extraction in the DCT domain is the observation that the statistics of DCT coefficients change with the degree and type of image distortion. Another advantage is computational convenience: optimized DCT-specific platforms and fast algorithms for DCT computation can ease computation.

V. NSS BASED FEATURES

Only very simple parametric features are extracted from the fit to the GGD NSS model: the GGD shape parameter b, coefficient of variation (CoV), the ratios of energy between the radial frequency bands, Orientation Model-Based features

A. GGD shape parameter

A generalized Gaussian model is applied to each block of the non-DC DCT coefficients excluding DC coefficient as it does not convey any structural information of image and it neither increases nor decreases performance in presence of image distortion.

B. Coefficient of Frequency Variation

Coefficient of frequency variation feature is given by

$$\zeta = \frac{\sigma|X|}{\mu|X|} \qquad (2)$$

C. Energy Subband Ratio Measure

Image distortions often modify the local spectral signatures of an image in ways that make them dissimilar to the spectral signatures of pristine images. To measure this, local DCT energy–subband ratio measure is defined

$$E_n = \sigma_n^2$$

The ratio of energy is calculated as

$$Rn = \frac{|En - \frac{1}{n-1}\sum j < n\, Ej|}{En + \frac{1}{n-1}\sum j < n\, Ej}$$

Rn is calculate for n=2,3.

D. Orientation Model-Based Feature

Image distortions often modify local orientation energy in an unnatural manner To capture directional information in the image that may correlate with changes in human subjective impressions of quality, we model the block DCT coefficients along three orientations. A generalized Gaussian model is fitted to the coefficients for each partition of block. and ζ is obtained from the model histogram fits for each orientation. The variance of ζ is computed along each of the three orientations.

	G 10%	G 100%	Z 10%	Z 100%	R 10%	R 100%	O 10%	O 100%
JPEG2000	0.8891	0.6532	0.8936	0.8800	0.8707	0.9143	0.8620	0.8836
JPEG	0.7832	0.7095	0.7922	0.1011	0.6162	0.4376	0.8273	0.7725
WN	0.9587	0.9500	0.9530	0.9569	0.9618	0.9538	0.9568	0.9514
GBLUR	0.8463	0.2075	0.8491	0.7704	0.7784	0.5333	0.8964	0.8874
FASTFADING	0.8067	0.4785	0.8119	0.8095	0.7915	0.7083	0.8459	0.8532

Table I SROCC between DMOS and features 10% and 100%

Table I reports the SROCC scores between the LIVE IQA Database DMOS scores and the pooled highest 10% and 100% averaged feature values, respectively, using 5×5blocks.

VI. PREDICTION MODEL

The regression model of SVM is used for prediction. The features are extracted for training set of 120 images for all 5 types of distortion. Let Xi=[x1,x2,x3…xm] be the vector of features extracted from the image, where i is the index of the image being assessed, and m be the number of pooled features that are extracted. Additionally, let DMOSi be the subjective DMOS associated with the image i . We model the distribution of the pair (Xi,DMOSi). The SVM is trained on LIVE IQA database.

VII. RESULT

The LIVE IQA[5] database is used which contains 29 reference images, each impaired by many levels of five distortion types: JPEG2000, JPEG, white noise, Gaussian blur, and fast-fading channel distortions. The total number of distorted images (excluding the 29 reference images) is 779. 80% of the LIVE IQA database content was chosen for training, and the remaining 20% for testing.

The model based-features were extracted. Total 8 features are extracted i.e. 4 features for 2 pooling methods: 10 percentile and 100 percentile pooling. These features shows good correlation with DMOS as shown in table I.

VIII. CONCLUSION

The given algorithm uses a small number of computationally convenient DCT-domain features.The algorithm can be easily trained to achieve excellent predictive performance using a simple probabilistic prediction model. The method correlates highly with human visual judgments of quality.

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