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No-reference Image Quality Assessment Based on JND Model and NSCT

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***Abstract*—Considering the image distortion and the masking effect of human visual system, the Just Noticeable Distortion (JND) model is used to construct the model based on the Sigmoid function, using the Just Noticeable Distortion threshold and the absolute value of the pixel change of the image to correct the distorted image and make it conform to the perception effect of the human eye. Then, the mutual information (MI) between relatives' coefficients and father-son coefficients of Nonsubsampled Contourlet Transform(NSCT) directional subbands is calculated as a statistical feature to describe the correlation between these coefficients. Finally, the structural similarity index (SSIM) between relatives coefficients and father-son coefficients of NSCT directional bands is calculated, which is used as a statistical feature to describe the structural information of images. An no-reference image quality assessment (NR-IQA) model is constructed to evaluate image quality. The simulation experiment on LIVE image quality assessment database shows that it can better evaluate the image quality of the distorted image, and accurately capture the edge contour information and texture details of the image, which is better optimized than other algorithms.**

Keywords—no reference image quality assessment; just noticeable distortion; mutual information; nonsubsampled contourlet transform

I. INTRODUCTION

The image quality assessment is particularly important in image processing fields[1].In general, the image quality evaluation methods include three categories: full reference (FR) image quality assessment，reduce reference(RF) image quality assessment and no reference(NF) image quality assessment [2]. Usually, the former two need prior information of the images or need the reference images, but it is limited in practice, so the third one, the NR method, is more desirable and practical in real applications. But how to accurately assess the quality of distorted images without reference images is a challenging problem.

Currently, there are two main types of NR image assessment methods, one is the distortion specified method and the other is the general purpose assessment mothod. Saad proposed dividing DCT and extracting the parameters of Gauss distribution model in frequency band and direction band as quality evaluation features [3]. Moorthy extracted the steerable pyramid wavelet coefficients to give a two-order image quality evaluation model[4];Liu used the asymmetric generalized GGD (AGGD) model to fit the Curvelet subband coefficients, and then used the subband coefficient energy as the feature and NR-IQA[5];Lu used prediction and reference coefficients combined with histograms to capture nonlinear correlation between Contourlet coefficients to evaluate images[6];Lou Bin used the natural image transform domain Contourlet transform domain sub-band mean linear correlation, which is the high frequency sub-band of the low frequency subband mean prediction distortion under true conditions, and uses the difference between them to calculate image distortion[7].

The above wavelet transform, Curvelet transform and Contourlet transform will produce certain overlap effect on the signal spectrum, and can't express the edge effect well. Therefore, based on the above methods, this paper proposes a Nonsubsampled Contourlet Transform (NSCT) combined with JND correction model, which can better correct the distortion image and accurately capture the edge information and texture information in the image. The mutual information (MI) and structural similarity index (SSIM) between subband and parent band coefficients of NSCT are used as feature indices, and support vector machine (SVM) is used to establish NR-IQA model and image distortion type recognition model. The results are well illustrated in the LIVE image quality evaluation database experimental simulation, and the method of this paper has achieved ideal results.

II. CORRECTION OF DISTORTED IMAGE BASED ON JND MODEL

The degree of image distortion is within the JND threshold, which is invisible to the human eye and has little or no effect on image similarity evaluation. Conversely, the amount of image distortion exceeds the JND threshold [8], which has a large impact on the evaluation of image similarity. The JND model is used to establish the preprocessing filter, and the distortion image is filtered and preprocessed to remove the distortion that the human eye cannot perceive. Only the visible distortion is preserved and subjective perception is more suitable [9]. The process is as follows:

Step 1: Calculate the visual threshold T of each pixel in the original image X.

Step2: In order to make the image quality evaluation more in line with the subjective perception of the human eye, each pixel of the distorted image Y is corrected.

$$\mathrm{Y(i,j)} = \mathrm{X(i,j)} \cdot 1\{|D(i,j)| \le T(i,j)\} + \left[Y(i,j) - sign\left(D(i,j) \cdot \lambda(i,j) \cdot T(i,j)\right)\right] \cdot 1\{|D(i,j)| > T(i,j)\} \quad (1)$$

In(1) : $1(.)$is an indicative function;$(.)$ is an absolute value; Y' is a distortion image after correction; an error $D(i,j) = X(i,j) - Y(i,j)$; sign$(.)$ is a symbol function; $\lambda(i,j) \geq 0$ is a penalty factor.

It can be seen from the equation that when the absolute error is smaller than the JND value, the corrected distortion image is the same as the pixel value of the original image. Since the distortion area is easily noticed by the human eye, the subjective evaluation quality of the corresponding image is degraded. Therefore, when the absolute error is larger than the JND value, the distortion image depends on the error and the JND value, increases the error, and reduces the image quality evaluation value.

The penalty factor $\lambda(i,j)$ plays an important role in image quality evaluation, and $\lambda(i,j)$ is related to the perceptual error $R(j,j) = |D(i,j)/T(i,j)|$ of each pixel of the image. This paper designs $R(i,j)$ as a Sigmoid function, expressed as:

$$\lambda(i,j) = \frac{1}{1+exp(-R(i,j))} \tag{2}$$

Passing the relationship can be seen that the penalty factor gradually approaches 1 as the perceptual error increases, which indicates that the influence of the visibility error increases. Distorted images corrected with JND are more in line with human visual characteristics and can also optimize IQA performance.

III. ESTABLISHMENT OF EVALUATION MODEL

A. *MI statistical Characteristics of NSCT Subband Coefficient Correlation*

Mutual Information (MI) is an important concept in information theory and is often used to describe the correlation between two event systems or the amount of information contained. For the MI (A, B) between images A and B can be defined as:

$$\mathrm{MI}(A,B) = \mathrm{H}(A) + \mathrm{H}(B) - \mathrm{H}(A,B) \tag{3}$$

In the formula (3), H(A) and H(B) are the entropy H (A, B) of the images A and B, respectively, and the joint entropy of the images A and B. The entropy can be calculated by the edge probability density function.

For the entropy of the image, the calculation expression is as follows:

$$p_i = h_i/(\textstyle\sum_{i=1}^{N-1} h_i), \mathrm{H}(Y) = -\textstyle\sum_{i=0}^{N-1} p_i \, log p_i \tag{4}$$

h_i denotes that the gray value in the image Y is the total number of i pixels, N is the total number of gray levels, and Pi represents the probability of occurrence of the gray level i. Joint entropy is the representation of two variables. The joint entropy for the two images can obviously be derived using a histogram.

Because the correlation between the relative coefficient and the subband coefficient is strong, and the NSCT decomposition can effectively improve the evaluation effect in two scales, this paper performs two scale NSCT decomposition on the image, and each scale is decomposed into 8 detail directions. A total of 24 MI statistical features were extracted between the corresponding relative coefficient and the father-son coefficient. Figure 1 shows "Monarch" and its JP2K, JPEG, WN, Gblur and FF five kinds of distorted images in the LIVE image quality evaluation database [10], and Figure 2 shows the NSCT sub-band relative coefficient and the inter-sub-coefficient MI in the image of Figure 1. Statistical Features.

FIGURE I. NATURAL DISTORTION-FREE IMAGE "MONARCH" AND ITS VARIOUS DISTORTED IMAGES IN THE LIVE DATABASE

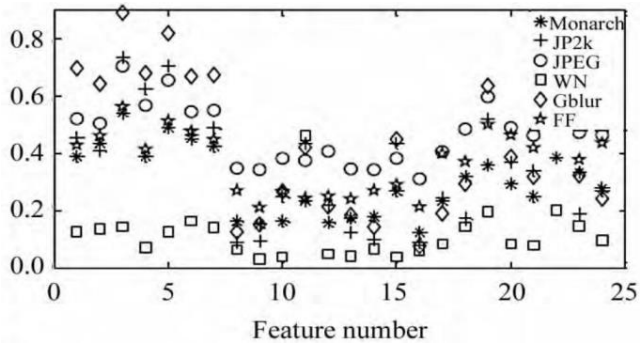

FIGURE II. THE MI STATISTICAL FEATURES OF THE IMAGE IN FIGURE 1.

As can be seen from Fig.2, the NSCT subband relative coefficient and the MI between the father and son coefficients of the JP2K, JPEG, Gblur, and FF distortion type images are significantly larger than the undistorted image "Monarch", especially the Gblur distortion type. The reason for this phenomenon is that the four types of distortions all produce blurring effects, Moreover, the Gblur distortion type is the most serious, the MI between the sub-bands is also the largest; the MI of the NSCT subband coefficients of the WN distortion type is significantly smaller than the undistorted image "Monarch", mainly because the Gaussian noise is mainly high-frequency components. Moreover, it is random, which greatly changes the NSCT direction subband coefficient of the corresponding image, so that the correlation between the subband coefficients is significantly weakened, and the MI is correspondingly reduced.

It can be seen that the NSCT subband relative coefficient and the MI between the father and son coefficients of different distortion type images have significant differences. This is because different distortion types change the MI statistics

between these subbands in different ways. Therefore, the image NSCT subband relative coefficient and the MI between the father and son coefficients can be selected as the NSS features of image quality evaluation, and the influence of distortion on image correlation is characterized.

B. SSIM Statistical Characteristics of NSCT Subband Coefficients

Natural images have a strong structure and there is a strong correlation between pixels. The human eye first extracts the structural information of the image when observing the image, and evaluates the quality of the degraded image based on the structural information; Furthermore, SSIM describes the high structural correlation of the image, and SSIM includes comparison of brightness comparison, contrast comparison and structural information [11]. Let X, Y be the reference image and the degraded image respectively, then the SSIM between them is defined as:

$$\mathrm{SSIM(X,Y)} = \left(l(X,Y)\right)^{\alpha} \cdot \left(c(X,Y)\right)^{\beta} \cdot \left(s(X,Y)\right)^{\gamma} \quad (5)$$

In the formula (5), l (x, y), c (x, y), and s (x, y) are brightness comparison, contrast comparison, and structural information comparison, respectively.

l (X, Y), c (X, Y) and s (X, Y) are defined as:

$$\mathrm{l(X,Y)} = \frac{2\mu_X\mu_Y + C_1}{u_X^2 + u_Y^2 + C_1},\ \mathrm{c(X,Y)} = \frac{2\sigma_X\sigma_Y + C_2}{\sigma_X^2 + \sigma_Y^2 + C_2},$$

$$\mathrm{s(X,Y)} = \frac{\sigma_{XY} + C_3}{\sigma_X^2 + \sigma_Y^2 + C_3} \quad (6)$$

μ_X, μ_Y is the mean value of X, Y; σ_X^2, σ_Y^2 is the standard deviation of X, Y, and σ_{XY} is the covariance of X and Y.

In this paper, SSIM is used to extract the NSCT subband relative coefficient and the structure information s (X, Y) between the father and son coefficients, and use these structural information as the characteristics of image quality evaluation. Similar to the extracted MI statistical features, the statistical features of the structural information extracted after the image NSCT is decomposed beyond two scales can't effectively improve the image quality evaluation effect [12]. Therefore, the statistical characteristics of the structural information between the relative coefficient and the father-son coefficient are extracted in the same scale and direction, and the total number of features is 24, as shown in Table 1.

TABLE I. FEATURE EXTRACTION DESCRIPTION

Feature	Feature description	Computing method
$f_1 - f_8$	Correlation between NSCT relative coefficients in 1st scale	Compute *MI* between NSCT relative coefficients in 1st scale
$f_9 - f_{16}$	Correlation between NSCT relative coefficients in 2nd scale	Compute *MI* between NSCT relative coefficients in 2nd scale
$f_{17} - f_{24}$	Correlation between NSCT coefficients and its parent coefficients	Compute *MI* between NSCT coefficients and its parent coefficients
$f_{25} - f_{32}$	Structure information between NSCT relative coefficients in 1st scale	Compute *SSIM* between NSCT relative coefficients in 1st scale
$f_{33} - f_{40}$	Structure information between NSCT relative coefficients in 2nd scale	Compute *SSIM* between NSCT relative coefficients in 2nd scale
$f_{41} - f_{48}$	Structure information between NSCT coefficients and its parent coefficients	Compute *SSIM* between NSCT coefficients and its parent coefficients

Fig.3 is a statistical feature of the NSCT subband relative coefficient and the structural information between the father and son coefficients of the image in Fig.3.

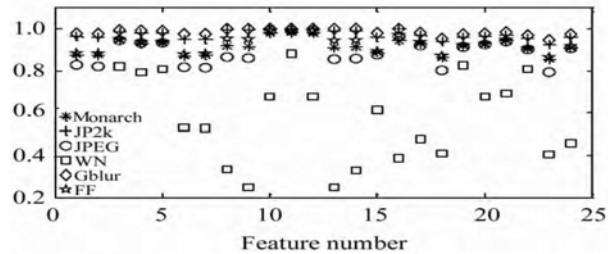

FIGURE III. FIGURE 1 STATISTICAL CHARACTERISTICS OF THE STRUCTURAL INFORMATION OF THE IMAGE

IV. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

Support Vector Machine (SVM) is a theory of prediction and classification in statistics. It has many advantages in small sample, nonlinear and high-dimensional pattern recognition. Therefore, SVM is used to construct NR combining MI statistical features and SSIM statistical features.NR -IQA model (abbreviated as MISSIM), mainly developed by the Dr. Lin Zhiren and other design LIBSVM-3.14 toolkit [13]. In this paper, the image quality evaluation model uses epsilon-SVR, and the kernel function uses a radial basis function.

A. Comparison of Algorithm Performance Indicators

In order to make a fair comparison with the current mainstream no-reference image quality assessment methods MIQA, CBIQ, BLINDS-II, DIIVINE, CurveletQA, the same test methods as these documents are used. The LIVE IQA database is randomly divided into no repeated training image sets and test image sets, accounting for 80% and 20% respectively; the performance of various algorithms is tested separately, and 1000 times are repeated, and the median value of 1000 test results is selected as the algorithm. The results were evaluated and the SROCC and Pearson linear correlation coefficients (PLCC) and (SROCC) between the objective evaluation results of these algorithms and DMOS were calculated separately. The performance indicators of each evaluation method are shown in Table 2 and Table 3.

TABLE II. 1000 ITERATIONS TEST EACH EVALUATION METHOD SROCC VALUE

Type	Algorithm	JP2k	JPEG	WN	Gblur	FF	All
FF-IQA	*PSNR*	0.8646	0.8831	0.9410	0.7515	0.8736	0.8636
	SSIM	0.9389	0.9466	0.9635	0.9046	0.9393	0.9129
NR-IQA	MIQA[8]	0.9408	0.9259	0.9828	0.9572	0.8800	0.9333
	CBIQ[9]	0.8935	0.9418	0.9582	0.9324	0.8727	0.8954
	BLIINDS-Ⅱ[10]	0.9323	0.9331	0.9463	0.8912	0.8519	0.9124
	DIIVINE[11]	0.9123	0.9208	0.9818	0.9373	0.8694	0.9250
	CurveletQA[13]	0.9367	0.9117	0.9876	0.9650	0.9005	0.9303
	MISSIM	0.9208	0.9205	0.9807	0.9468	0.9128	0.9316

TABLE III. 1000 ITERATIONS TEST THE PLCC VALUE OF EACH EVALUATION METHOD

Type	Algorithm	JP2k	JPEG	WN	Gblur	FF	All
FF-IQA	*PSNR*	0.8762	0.9029	0.9173	0.7801	0.8795	0.8592
	SSIM	0.9405	0.9462	0.9824	0.9004	0.9514	0.9066
NR-IQA	MIQA[8]	0.9405	0.9276	0.9802	0.9515	0.8917	0.9232
	CBIQ[9]	0.8898	0.9454	0.9533	0.9338	0.8951	0.8955
	BLIINDS-Ⅱ[10]	0.9386	0.9426	0.9635	0.8994	0.8790	0.9164
	DIIVINE[11]	0.9233	0.9347	0.9867	0.9370	0.8916	0.9270
	CurveletQA[13]	0.9465	0.9280	0.9887	0.9694	0.9186	0.9328
	MISSIM	0.9384	0.9395	0.9869	0.9581	0.9306	0.9329

It can be seen from Table 2 and Table 3 that the overall performance of the proposed image quality evaluation method MISSIM is comparable to the current mainstream algorithm CurveletQA, and is superior to the PSNR, SSIM and CBIQ, MIQA, DIIVINE without reference evaluation algorithm. And BILINDS-II.

B. *Algorithm Complexity*

In NR-IQA, the time taken for general feature extraction is much longer than the time required for classification and regression. Therefore, when comparing the computational complexity of different evaluation methods, this paper only considers the feature extraction process. The MISSIM method extracts features into three steps:1) NSCT decomposition of the image; 2) extracting the statistical features of the NSCT subband relative coefficient and the father and son coefficients; 3) extracting the SSIM statistical characteristics between the NSCT subband relative coefficient and the father and son coefficients. In the computational complexity experiment, all the distorted images with a resolution of 1280×720 in the MDIQA database were selected, and the time consumed by each image in the three steps of extracting features was calculated separately, and the average was taken as the actual cost of each step. Time, and then calculate the percentage of time spent on the three steps, see Table 4.

TABLE IV. PERCENTAGE OF CONSUMPTION TIME IN EACH STAGE OF MISSIM FEATURE EXTRACTION

Step	Percentage of time/%
NSCT decomposition	44.56
Extracting *MI* statistics features from NSCT coefficients	27.40
Extracting structure features from NSCT coefficients	28.04

TABLE V. COMPARISON OF RUNNING TIME OF FIVE KINDS OF NO-REFERENCE IMAGE QUALITY ASSESSMENT ALGORITHMS

NR-IQA algorithm	Time/s
BLIINDS-Ⅱ[10]	308.91
DIIVINE[11]	84.33
CurveletQA[13]	9.41
MISSIM	22.26

V. CONCLUSION

Image distortion and visual masking effects are difficult to evaluate without reference image quality. Considering the consistency of natural statistics and human perception characteristics, Study the correlation between subband coefficients in the NSCT direction, Extracting the correlation and structural similarity between subband and parent band coefficients as statistical features, MI and SSIM, modeling the images corrected in the JND model, Compare the different evaluation effects and distortion type models. The evaluation model has achieved good results, and has a good effect on the non-reference image quality evaluation of the distorted image.

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REFERENCES

[1] Zhou Jingchao, Dai Weiwei, Xiao Baihua.A Review of Image Quality Evaluation

[2] Wang Zhiming. Overview of quality evaluation without reference image[J]. Acta Automatica Sinica,2015,41(06):1062-1079

[3] Saad M, Bovilk A C, Charrier C. Blind image quality assessment: Anatural scene statistics approach in the DCT domain[J].IEEE Transactions on Image Processing,2012 21(8):3339-3352

[4] Moorthy A K, Bovilk A C. Blind image quaility assessment: Anatural scene statistics to perceptual quality[J].IEEE Trans. Image Process,2011,20(12): 3350-3364

[5] Liu L X, Dong H P, Huang H. N0-reference image quality assessment in curvelet domain[J] signal Processing: Image Communication , 2014,29(7):494-505.

[6] Lu W, Zen K, Tao D. No-reference image quality assessment in curvelet domain[J]. Neuro computing,2010,73(4-6):784-794

[7] LOU Bin, ZHAO Wu-Feng, YAN Xiao-Lang. No-reference image quality assessment based on satistical model of natural image[J]. journal of Zhejiang University (Engineering Science),2010,44(2):248-252.

[8] YANG Xiaokang, LIN Weisi, LU Z, Motion-compensated residue preprocessing in video coding based on just-noticeable-distorion profile[J]. IEEE Transaction on Circuits and systems for Video Technology,2005,15(6):742-752.DOI:10.1109/TCSVT.2005.848315

[9] Zhu Xinshan, Yao Siru, Sun Wei, Qian Yongjun, Image Quality Evaluation: Fusion Visual Characteristics and Structural Similarity Index, Journal of Harbin Institute of Technology, 2018, 5

[10] Sheikh H R, Wang Z, Cormack L, Bovik A C. LIVE Image quality assessment database release 2 [Online], available: http://live.ece.utexas.edu/research/quality, February 4, 2015

[11] Wang Z, Bovik A C, Sheikh H R. Image quality assessment: from error visibility to structural similarity [J]. IEEE Transactions on Image Processing, 2004, 13(4): 1-14

[12] LI Junfeng, ZHANG Feiyan, DAI Wenzhan, PAN Haipeng. Evaluation of non-reference image quality based on image correlation and structure information[J]. Optoelectronics· Laser, 2014, 25(12): 2407-2416

[13] Fan R E,chen P H,lin C J,working set selection using second order information for training SVM[J].Journal of Machine Learning Research,2005,6(12):1889-19