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Contourlet Transform Based Reduced-Reference Image Quality Assessment

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Abstract—**In this paper, we propose a reduced-reference image quality assessment method based on Contourlet transform, due to its properties of multi-resolution, multi-scale, multi-directional and anisotropy. It can capture the image edge profile effectively by using a small number of coefficients. First, we perform three-scale and four-level Contourlet decomposition for the reference and test images. Then we calculate energy eigenvectors on each scale and subsequently obtain the angel of energy eigenvector between the reference and test images. Finally, a weighted summation is used to predict the image quality score. Various experiments based on the LIVE2 database verify the performance of the proposed algorithm, which has high consistency with human visual system.**

Keywords: Reduced-reference Image Quality Assessment; Contourlet Transform; Energy information

I. Introduction

Distortions and artifacts are inevitably introduced in to digital image during image acquisition, compression, transmission, processing and reproduction. Therefore, it is crucial to access the quality of digital images. There are two kinds of image quality assessment (IQA) methods: subjective and objective image quality assessment methods. As accurate it is, the former method is both time-consuming and energy-consuming, and it cannot be embedded into the system to be assessed automatically, so the latter method is comparatively more viable. Objective image quality assessment method can fall into three categories: Full-Reference (FR), No-Reference (NR) and Reduced-Reference (RR). Up until now of the three methods FR is the most developed, RR less developed, and NR the least for it is still in the primary stage and has not formed a complete effective system. Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) are the most frequently used FR image quality assessment methods. The advantages of MSE/PSNR include: (1) the computational complexity is low; (2) the nice mathematical convexity guarantees a closed-form optimization solution. However, many researchers find that the results they get by means of the method do not correspond with those of the subjective assessments made by people. In [1], it explains in detail why MSE/PSNR is not a desirable predicative method.

Later many scholars have improved image quality assessment methods, and put forward a lot of excellent visual perception methods, for example, the structural similarity index method (SSIM) [2] and wavelet domain reduced-reference image quality assessment algorithm based on natural statistical model [3]. Zhang et al. proposed a feature similarity index (FSIM) [4] that applies phase congruency (PC) and gradient magnitude (GM) in color image quality assessment. In practical RR method is better than FR method because RR IQA methods only need a part of the reference image information and it is more likely to be embedded into real-time application system.

Contourlet transform possesses such properties as multi-resolution, local positioning, multi-directional, neighbor boundary sampling and anisotropy, its basis function distribute in multi-scale, multi-directional, with a small amount of coefficients it can effectively capture the image edge profile, which serves as the major feature of image quality, so it corresponds with human visual system, fits in for image quality assessment, whereby this paper uses Contourlet transform to assess image quality.

The rest of paper is organized as follows: Section 2 addresses the Contourlet Transform theory. Section 3 addresses image quality assessment index. Section 4

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addresses the proposed algorithm. Section 5 addresses the experimental results. Section 6 addresses conclusion.

II. Contourlet Transform

Contourlet transform proposed by Do and Vetterli [5], also known as pyramidal directional filter banks (PDFB), is an efficient representation for image geometry structure. It uses Laplacian Pyramid(LP) decomposition to produce multi-resolution images, and then adopt Directional Filter Bank (DFB) to do direction decomposition on different resolution image, as shown in Fig.1 .In Fig.1,first the circle was decomposed to two scales by LP, as shown in up and down of Fig.1,then the first scale(up) was decomposed to two directions and the second scale(down) was decomposed to four directions by DFB, Contourlet transform was finished eventually.

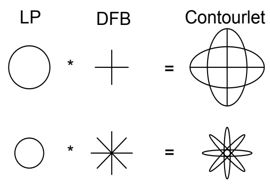

Figure 1. Contourlet Transform Diagram

A. Laplacian Pyramid (LP) Decomposition

Laplacian pyramid decomposition can be used for multi-resolution image analysis. Fig.2 shows the Laplacian pyramid decomposition process, which can be mathematically expressed by:

$$c=Hx,\ p=Gc,\ d=x-p=x-GHx=(1-GH)x \quad (1)$$

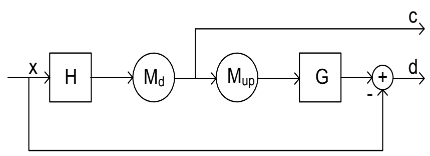

Figure 2. Laplacian Pyramid Decomposition

In Fig.2, LP decomposition uses filter H and down sampling matrix Md to get low pass sub-band (low frequency information) signal c (c = Hx). Then let the low pass sub-band signal c pass the up-sampling matrix Map and synthetic filter G to get forecast signal p (p = Gc). Finally, we can get the difference signal d (d = x - p) (high frequency information) between the original image signal and forecast signal. Apply the process stated above to next layer, we can get multi-resolution images.

B. Directional Filter Bank

After LP decomposition, we can get the high frequency information of different direction by using the Direction Filter Bank (DFB), DFB includes two modules: double-channels Quincunx filter bank and shearing operation. The Quincunx filter has two levels, where the first level decomposition outputs vertical directional sub-band and horizontal directional sub-band. The second level decomposes y0 into y00 and y01, and decomposes y1 into y10 and y11. From the third level, we first do shear operation, and then use Quincunx filter. The third level DFB decomposition of y00 and y01 can be divided into two types according to the upper channel 0 and the down channel 1. The upper channel uses Type-1 decomposition, the down channel uses the Type-2 decomposition. The y10 and y11 also have two DFB decomposition forms, which are similar to the y00 and y01.

The relationship between the number of image decomposition levels and the number directional sub-bands is M=N2, where N is the number of decomposition levels on each scale, M is the No. of obtained sub-bands on each scale.

III. Image Quality Evaluation Index

Take the famous zoneplate picture, as an example (Fig.3). We do 3-scale Contourlet decomposition to it and subsequently 4-level directional decomposition on each scale. Thus, we can get 16 different directional sub-bands on each scale, as shown in Fig.4. We define the sum of squared coefficients to be the sub band energy: $Eng = \sum_{i=1}^{M}\sum_{j=1}^{N} C(i,j)^2$, where C (i, j) is the sub band coefficient of row i column j, M and N is the resolution of the scale images respectively. Then, we can get the energy feature vector of each scale sub band $Eng_{vector}(k)$:

$$Eng_v(k)=ln\big(Eng(k)\big) \qquad k=1,2,\cdots,16 \qquad (2)$$

where k is the k-th directional sub band.

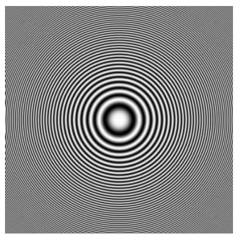

Figure 3. 6zoneplate

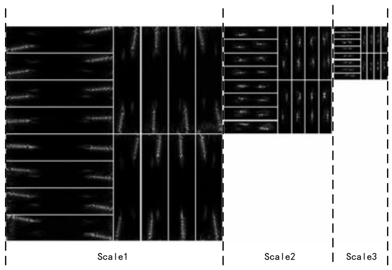

Figure 4. Contourlet Decomposition for zoneplate

The angle between two images' energy vectors can be used to measure the similarity of them:

$$\theta = \arccos \frac{\langle Eng_v X, Eng_v Y \rangle}{\sqrt{\langle Eng_v X, Eng_v X \rangle} * \sqrt{\langle Eng_v Y, Eng_v Y \rangle}} \tag{3}$$

Where <x, y> is the dot product. EngvectorX and EngvectorY are 16 dimensional energy feature vectors of reference image and distortion image respectively.

If the angle between the distortion image energy feature vector and the reference image energy feature vector is smaller, the distortion image quality is better. According to this principle, we define the image quality evaluation by using the angle between the energy feature vectors of reference image and distortion image on each scale:

$$QENG = w_1 * \theta_1 + w_2 * \theta_2 + w_3 * \theta_3 \tag{4}$$

Where $\vec{w}$ is the weight of each scale, and $\vec{\theta}$ is the energy feature vector angles between the reference image and distortion image on scale1, scale2 and scale3, they are calculated by formula (3), and w_1 , w_2 and w_3 respectively is weight on each scale.

IV. Reduced-Reference Image Quality Evaluation Algorithm Based on Contourlet Transform

The proposed Contourlet transform based Reduced-Reference image quality evaluation algorithm can be summarized follows:

Step 1: Apply 3 scale 4 level Contourlet decomposition for distortion image and the corresponding reference image, and get 16 different directional sub band on each scale.

Step 2: Calculate energy feature vectors $Eng_v(k)$ on each scale for the distortion image and reference image respectively.

Step 3: Calculate the energy feature vector angles θ_1,θ_2 and θ_3 between the distortion image and reference image on each scale by using (3) respectively.

Step 4: Calculate the image quality value QENG by using $\vec{w} = [0.1,0.2,0.7]$.

V. Evaluations

A. The Experiment Database and Evaluation Index

To validate the effectiveness of proposed algorithm, we test it on the LIVE Image Quality

Assessment Database Release2(LIVE2) from the University of Texas [6]. The LIVE2 database has 5 kinds of distortion type images, including Fast Fading image, Blur image, JPEG compression image, JP2K compression image and Noise image, as shown in table 1. It provides "subjective Difference score", Difference Mean Opinion Scores (DMOS), for all distortion images, which describes the difference between subjective score (Mean Opinion Scores, MOS) and full score 100 (namely DMOS = 100 - MOS). Thus, the bigger DMOS is, the poorer image quality is.

TABLE I. LIVE2 Image Database

Distortion type	Distortion mages	Source Images
FastFading	145	29
Blur	145	29
JPEG	175	29
JP2K	169	29
Noise	145	29

We choose two common objective parameters as our evaluation index: Correlation Coefficient (CC) under the condition of nonlinear regression and Spearman Rank Correlation Coefficient (SROCC). CC and SROCC are the linear correlations between objective quality and subjective quality under the nonlinear regression conditions. The higher the value is, the better the correlation of objective evaluation method and subjective quality is. SROCC and CC are between 0 and 1. The closer to 1 their value is, the better the performance is. CC value is calculated by nonlinear regression function of five parameters $\{\beta_1, \beta_2, \beta_3, \beta_4, \beta_5\}$in literature [6-7]:

$$Quality(x) = \beta_1 logistic(\beta_2, (x - \beta_3)) + \beta_4 x + \beta_5 \tag{5}$$

$$\text{logistic}(\tau, x) = \frac{1}{2} - \frac{1}{1+\exp(\tau x)} \tag{6}$$

B. Analysis of Experimental Results

Our proposed algorithm was compared to several state-of-the-art RR-IQA and FR-IQA metrics, including WNRS [3], SSIM [2], SUMMER [7], CEQI [8], and VCGS [9], whose original source code are available online. The experimental results have two parts: CC and SROCC value comparison of different algorithms and DMOS value of different distortion types by using the proposed algorithm, as shown in table 2.

TABLE II. COMPARISON OF DIFFERENT ALGORITHMS ON LIVE2 DATABASE

Measure	Model	FastFading	Blur	JPEG	JP2K	Noise
CC	WNRS	0.9263	0.8883	0.8760	0.9245	0.8898
	SSIM	0.9492	0.8741	0.9297	0.9368	0.9793
	SUMMER	0.9663	0.9683	0.9560	0.9545	0.9698
	CEQI	0.9572	0.9702	0.9623	0.9345	0.9645
	VCGS	0.9567	0.9781	0.9687	0.9676	0.9723
	proposed (RR)	**0.9706**	**0.9612**	**0.9789**	**0.9689**	**0.9436**
SROCC	WNRS (RR)	0.9229	0.9147	0.8508	0.9205	0.8702
	SSIM（FR）	0.9411	0.8943	0.9107	0.9317	0.9629
	SUMMER	0.9512	0.9678	0.9534	0.9598	0.9665
	CEQI	0.9634	0.9711	0.9656	0.9456	0.9678
	VCGS [69]	0.9556	0.9638	0.9707	0.9621	0.9764
	proposed (RR)	**0.9637**	**0.9710**	**0.9658**	**0.9479**	**0.9660**

In Table 2, CC and SROCC are the correlation coefficient used to measure the performance of image quality evaluation algorithms. The value is between 0 and 1. If it is close to 1, the image quality evaluation index is highly correlated with DMOS, and the performance of image quality evaluation is better. It can be seen from Table 2 that the proposed algorithm has best evaluation index on all 5 kinds of distortion type images. The index value is stable and suitable for all kind of distortion. For full reference algorithms, the performance of the proposed algorithm is slightly less than the rothers for noise distortion type. But it performs better in blur distortion type, JPEG distortion type and JP2K distortion type. Also, the proposed algorithm has high consistency with the human visual system.

In addition, the proposed algorithm is a kind of reduced reference image quality evaluation method. Compared with full reference image quality assessment algorithm, we only need a part of the information of images. Furthermore, the proposed algorithm has advantages including transport easily, easy to be embedded into real-time application system and suit for practical application.

VI. CONCLUSION

The main function of Contourlet transform is multi-scale and multi-directional distribution with the characteristics of multi-resolution, locality and directionality. Therefore, a small number of coefficients can effectively capture the edge contour of the image, conforming to the characteristics of human vision and suitable for image quality evaluation. The image is decomposed by 3 scale and 4 level Contourlet, the included angle of energy eigenvectors of each scale is calculated, and the weighted sum is carried out to obtain the image quality evaluation standard QENG in this paper. The smaller QEBG value is, the better image quality is. The experiment results show that the algorithm has good performance, and is more superior performance than other literature algorithm. No reference image quality evaluation method will be the future research direction, which extracts image quality characteristics based on Contourlet transform.

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