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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (15): 3349-3352, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.3349.3352

No Reference Image Quality Assessment Method for Blurred Image

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Abstract: Considering that many no reference image quality assessment methods cannot give better assessment results for blurred images, this study proposes a no-reference image quality assessment method which has better assessment results. The method firstly extracts texture and structure features of a blurred image and then calculates its texture similarity and structural similarity. Finally, with these texture similarity and structural similarity as the input factors, the subjective assessment value DMOS provided by LIVE database as the output factor, a [2 9 1] Back-Propagation (BP) neural network prediction model is built. The experimental results show that the prediction model is stable and the differences between subjective assessment values and prediction results are small. Their Correlation Coefficients are all above 0.9.

Key words: No reference image quality assessment, the texture similarity, the structural similarity, back-propagation neural network, forecast

INTRODUCTION

No reference image quality assessment method (Zhou *et al*., 2008) directly uses distorted image to evaluate the quality of image without any reference. Currently, no reference image quality assessment method is based on the types of distortion. Fuzzy distortion (Xie *et al*., 2010) is one of the most important factors for lowering the quality of image/video. It can control the quality of the image processing system with quantizing fuzzy distortion and the system will be improve and robust.

The study proposes a no-reference image quality assessment method based on the texture and structure features of blurred image. Based on the fact (Zhang *et al*., 2012) that there is a high difference between a sharp image and its blurred version in texture feature and a low difference between a fuzzy image and its blurred version in texture feature. This method firstly extracts texture feature of image and calculates texture similarity as a measure of the local information of image. Because the texture similarity cannot represent the global feature of the image, this study extracts the structure feature of image and calculates structural similarity as a measure of the global information of image. And then a [2 9 1] Back-Propagation (BP) neural network model (Fan *et al*., 2011) is established with texture similarity and structural similarity as the input factors to forecast the objective evaluation value of image. Experiments indicate that the prediction results show stability, accuracy and consistency, it is superior to the Peak Signal to Noise Ratio (PSNR) and the structure similarity (SSIM) .

A NO-REFERENCE IMAGE QUALITY ASSESSMENT FOR BLURRED IMAGE

Measure of texture similarity: Texture feature reflects a visual characteristic of the homogeneity phenomenon of image and it is a common intrinsic characteristic of the surface of the object. There are many texture feature extraction algorithms, such as a method of texture feature extraction based on gray level co-occurrence matrix, a method of texture feature extraction based on fourier transform,a method of texture feature extraction based on wavelet transform and a method of texture feature extraction based on gabor wavelets. Because of the complexity of the texture, one method of texture feature extraction is difficult to extract the texture feature effectively. It is good to combine these methods to extract the texture features effectively. The author proposes a method of using GLCM and wavelet transformation to extract the texture feature of image.

Texture Feature Extraction Based on Gray Level Co-occurrence Matrix Gray level co-occurrence matrix is the classic method of second order statistics for analysis image texture features. This method firstly utilizes gray

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scale spatial correlation of image textures and the direction and distance of image pixels to calculate the gray level co-occurrence matrix, then extracts meaningful statistics from the matrix. These meaningful statistics are image texture features that we want to obtain. Reference Literature (Baraldi and Parmiggiani, 1995; Haralick *et al*., 1973) proposed 14 methods to calculate the statistics of image texture features based on gray level co-occurrence matrix. But if fact, it will cause a large calculation and redundancy if all the statistics are calculated. The study selects energy, correlation, entropy and moment of inertia to represent the texture of image. Distance is equal to 1 and the direction selects 0, 45, 90 and 135°. At the same time, the gray levels of the original images is compressed to 16 for reducing the calculation. At the last, it calculates the four directions means and standard deviation as the ultimate texture feature vector.

Texture feature extraction based on wavelet transformation: Wavelet transform is a time-frequency analysis method. It has a ability of denoting local signal characteristics in frequency domain and time domain and describes the texture features of images in different scales.

The study firstly selects the bior4.4 wavelet making four layer wavelet decomposing for gaussian blurred images of LIVE image database and then extracts means and variance of each image of wavelet decomposition as the texture feature. It will eventually get a 26- dimensional feature vector.

Texture similarity: At first, the study extracts texture feature of 174 gaussian blurred images from LIVE database based on gray level co-occurrence matrix and wavelet transform to get a 34-dimensional feature vector. Second, this study is to blur the 174 gaussian blurred images with a low-pass filter and to extract texture feature of the image with a low-pass filter. Experiments show that it is the most effective that the low-pass filter choose median filter and the window size of the filter is 9×9. The last is to compute the euclidean distance between the feature vector from gaussian blurred image and the feature vector from gaussian blurred image with a low-pass filter as the texture similarity. The texture similarity is defined as in the following equation:

$$D(X,Y)=\sqrt{\sum_{i=1}^{d}(X(i)-Y(i))^2} \quad i=1,2,\cdots,34 \tag{1}$$

where, X and Y are the feature vectors from gaussian blurred image and the feature vector from gaussian blurred image with a low-pass filter and i is defined the dimensions of the vector.

Measure of structural similarity: The structural information is a measure of the global information of image. The change of structural information reflects a approximation from the visual perception of distorted image. The measure of Structural Similarity is a modification of SSIM (Wang *et al*., 2004):

- Blurring the 174 gaussian blurred images with the median filter to get the corresponding secondary fuzzy images
- Splitting the blurred image and the blurred image with the median filter into 8×8 block,and calculating structural similarity SSIM(x, y) between image block x from blurred image and image block y form the same location of blurred images with the median filter.
- Calculating the average structural similarity S of image blocks as the structural similarity of the whole image:

$$S=\frac{1}{M}\sum_{j=1}^{M}SSIM(x_j,y_j) \tag{2}$$

where, M is the number of image block, j = 1, 2,..., M.

Establishment of the BP neural network prediction model: The bp neural network is a feed forward hierarchical network structure composed of a large number of neurons with nonlinear mapping capability. And it can solve a series of complex nonlinear problems.

The study establishes a [2 9 1] Back-Propagation (BP) neural network prediction model with texture similarity and structural similarity as the input factors and the subjective evaluation value provided the LIVE database as the output factor. The selection of the number of nodes in hidden layer is determined by the empirical equation:

$$N=\sqrt{n+m}+a \tag{3}$$

where, m and n are the number of input nodes and the number of output nodes and the value of a is a number between 1-10. Experiments indicate that there is a minimum error between the predicted value and the output sample when the number of nodes in hidden layer is 9. Parameter values in the bp neural network is shown in Table 1.

In conclusion, the flow chart of the study algorithm is shown in Fig. 1.

EXPERIMENTAL RESULTS AND ANALYSIS

Images of the simulation experiment come from gaussian blurred images in the LIVE database established

Table 1: Parameter values in the bp neural network

Transfer function of hidden layer neurons	Transfer function of output layer neurons	Network training function	Cycle times	Training error	Learning rate
Tansig	Logsig	Trainlm	5000	0.01	0.05

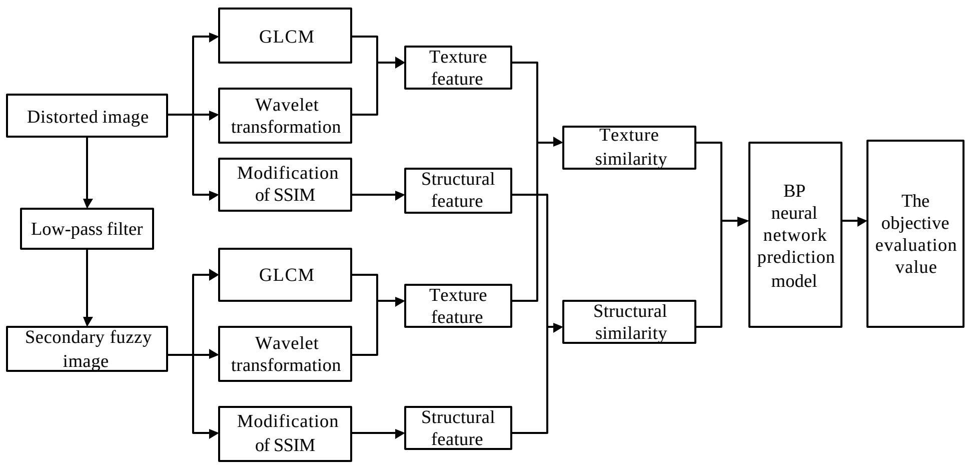

Fig. 1: Flow chart of the study algorithm

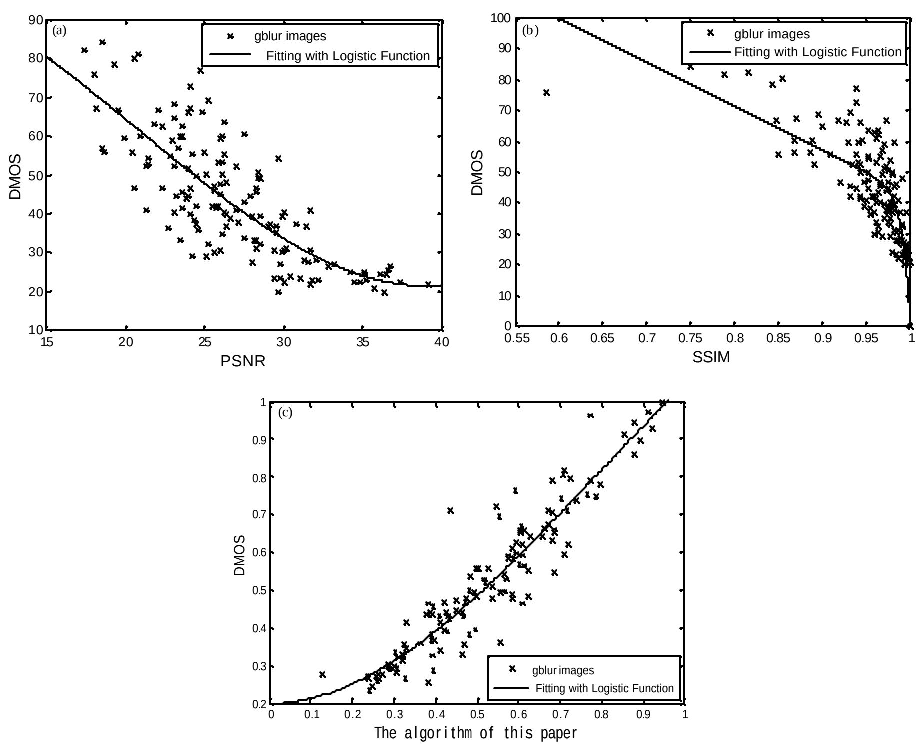

Fig. 2(a-c): Scatter plot of the different algorithm (a) PSNR, (b) SSIM and (c) Algorithm of this study

by The University of Texas. This database contains 145 gauss blurred images and 29 original images and the subjective evaluation value of the images. In order to facilitate the prediction of back-propagation neural network model and calculation, the subjective evaluation values are normalized to 0-1 range and images are converted into gray images and the size of these images are compressed to 512×512. Figure 2 is the scatter plot

Table 2: Value of evaluation index from the different algorithm

Method	CC	SROCC	MSE	RMAE	OR
PSNR	0.7750	0.7835	8.0028	9.9367	0.0575
SSIM	0.8241	0.8148	7.0940	8.9057	0.0517
The method of this study	0.9182	0.9147	6.5827	8.0747	0.0517

between the objective evaluation value and the subjective evaluation value. The PSNR and SSIM which are the classic reference image quality assessment method are comparison experiment. Table 2 is the value of evaluation index from the different method.

It is obvious that the fitting degree between the objective evaluation value of this study and the subjective evaluation value is higher than the PSNR and SSIM from the Fig. 2. And the method of this study is better than the PSNR and SSIM in the value of evaluation index from the Table 2. The value of evaluation index in Table 2 shows that the study has a better accuracy, consistency and monotonicity compared with the PSNR and SSIM .

CONCLUSION

The study makes full use of the local texture feature and the global structural feature of the image. Experiments show that the method of the study is superior to the PSNR and SSIM which are the classic reference image quality assessment method for blurred image. The method does not need information of the original image and is more suitable for practical application. The research direction of the next step is to make the method suitable for no reference image quality assessment of other types of distorted image.

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