No-reference Image Quality Assessment Approach by Compressed Sensing and Mixture of Generalized Gaussian Distributions

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Abstract. This paper proposed a new no-reference image quality assessment approach based on compressed sensing and mixture of generalized Gaussian distribution (GGD). The image is processed by compressed sensing at first, then sparse coefficients of compressed sensing are modeled by mixture of GGD. The parameter of mixture of GGD is estimated by the parameter estimation approach and the feature vector is formed by combining the parameter of mixture of GGD. The feature vector is fed to the support vector machine for training and testing. Experiments result shows that our approach has good performance for image quality assessment.

Introduction

Image quality assessment (IQA) is a challenging problem in the area of image processing. It is widely used in video coding and computer vision. IQA approach can be divided into subjective IQA and objective IQA approaches. Subjective IQA approaches try to evaluate the image quality by human beings, and objective IQA approaches evaluate the image quality by some sepical algorithm. The most reliable approach is the subjective IQA, however, the subjective IQA is time-consuming and inconvenient. Therefore it needs to develop the objective IQA which can predict the image quality scores automatically.

A lot of objective IQA approaches have been proposed for image quality assessment. Those approaches can be divided into three sorts: full-reference IQA, reduced-reference IQA and no-reference IQA. Full-reference IQA uses the complete information of reference image to evaluate the image quality. Reduced-reference IQA uses part information of reference image and no-reference IQA do not use any information of reference image at all. For full-reference IQA, there are a lot of mature approaches. For example, MSE or PSNR are often used for simpleness and convenience. However, MSE or PSNR is not aligned with the human visual character. Wang [1] proposes an IQA approach based on structural information which named SSIM (structural similarity index). However, for no-reference IQA, there are still considerable rooms for improvement. Wang [2] have introduced blockiness effect for JPEG compressed image. Mittal [3] proposed an image quality assessment approach in space domain, which uses the mean subtracted contrast normalized (MSCN) coefficients as the feature tfor IQA. Marziliano [6] introduced the parameter to measure the ringing and blur effect. Ye [7] developed a no-reference IQA using the visual codebooks, which uses the gabor transform for IQA.

This paper proposes a new no-reference IQA based on compressed sensing and mixture of GGD. The image is divided into several blocks and each block is processed by compressed sensing approach. The coefficients of compressed sensing are modeled by mixture of GGD and the parameters of mixture of GGD are determined by parameter estimating method. This paper is organized as follows: Section II introduced our image quality assessment approach based on compressed sensing and mixture of GGD. Experimental results are shown in Section III. Finally, there are conclusions in Section IV.

Compressed Sensing and Mixture of GGD

The proposed approach is based on the assumption that sparse coefficients of compressed sensing contain the distorted information of the image. According to the theory of compressed sensing, the original signal can be restored by the sparse coefficients, so the sparse coefficients contains all the information of the distorted image, which includes the information of original image and the distortion. The sparse coefficients can be modeled by the mixture of generalized Gaussian distribution, and the parameters of mixture of GGD can be estimated as the feature of the image. The objective image quality scores can be predicted by using the feature of the image. The flow of proposed approach is as follows: the image is divided into several blocks at first, then each block is processed by compressed sensing to get the sparse coefficients of the block. After that, the histogram of sparse coefficients of every block of the image is modeled by mixture of GGD. The parameter of mixture of GGD is combined into feature vector and the feature vector is fed into support vector machine for training and testing.

A. Compressed Sensing of the Image

There is sparse character in human visual system according to a lot of research, and sparse representation contains a lot of information of the signal. Sparse representation is widely used in object recognition and sparse coding. In this paper, sparse representation of the image is used for image quality assessment. Assume the image patch $x \in R^{N\times N}$ is transformed into $N^2\times 1$ vector y, the sparse representation of y by using the dictionary D is obtained by the following l_0 norm optimization problem:

$$\hat{a} = \arg\min_{a}\left\{\left\|y - Da\right\|_2^2 + l\left|a\right|_0\right\} \tag{1}$$

This l_0 norm problem is NP-hard and can be transformed into l_1 norm problem. The l_1 norm optimization problem is as follows:

$$\hat{a} = \arg\min_{a}\left\{\left\|y - Da\right\|_2^2 + l\left|a\right|_1\right\} \tag{2}$$

This l_1 norm problem can be solved by Orthogonal Matching Pursuit (OMP) approach and the dictionary D can be learned by KSVD method, which is the joint optimization problem as follows:

$$\min_{D,X}\left\|Y - DX\right\|_2^2 \quad \textit{subject to} \left\|x_i\right\|_0 \le T_0 \tag{3}$$

Where, Y is the dictionary training data matrix, X is the sparse vector and T_0 is the constraint constant of sparsity. The above dictionary learning process can be divided into two steps: sparse coding step and dictionary learning step. During sparse coding step, OMP is used to find the sparsest representation of Y while the dictionary D is fixed. During dictionary training process, the dictionary D is updated while sparse vector X is fixed.

B. Mixture of Generalized Gaussian Model

Mixture of generalized Gaussian distribution is widely used in modeling the wavelet coefficients of the image. In this paper, mixture of GGD is used for modeling the sparse coefficients of the image. The univariate generalized Gaussian distribution is defined as follows:

$$p\left(x\middle|a,b,g\right) = \frac{g\sqrt{\dfrac{\Gamma\left(\left(3/g\right)\right)}{\Gamma\left(\left(1/g\right)\right)}}}{2b\Gamma\left(1/g\right)}\exp\left(-A\left(b\right)\left(\left|\frac{x-a}{b}\right|^{b}\right)\right) \tag{4}$$

Where, a is the mean value, b is the standard deviation and g is the shape parameter. $\Gamma(\cdot)$ is the gamma function and $A(b) = \left[\Gamma(3/b) / \ \Gamma(13/b)\right]^{b/2}$. The mixture of GGD is the mixture of univariate GGD distribution, it is as follows:

$$p\left(x|q\right)=\sum_{i=1}^{K}w_i p\left(x|a_i,b_i,g_i\right) \quad (5)$$

Where, w_i is the mixture parameter of the ith component of the mixture of GGD. a_i, b_i and g_i is the mean value, standard deviation and shape parameter of the ith component.

$q=\{w_1,a_1,b_1,g_1,...,w_K,a_K,b_K,g_K\}$.

Given the data sample $c=\{x_1,x_2,...,x_N\}$ and the number of the components of mixture of GGD K, the expectation maximization (EM) method is used for estimating the parameter as follows:

$$w_i=\frac{1}{K}\sum_{i=1}^{K}p\left(q_i|x_j\right) \quad (6)$$

$$a_i=\frac{\sum_{i=1}^{K}p\left(q_k|x_i\right)\left|x_j-a_i\right|^{b_i-2}x_j}{\sum_{i=1}^{K}p\left(q_k|x_i\right)\left|x_j-a_i\right|^{b_i-2}} \quad (7)$$

$$s_i=\left[\frac{b_iA\left(b_i\right)\sum_{i=1}^{n}p\left(q_k|x_i\right\}\left|x_i-m_k\right|^{b_k-2}x_i\right)}{\sum_{i=1}^{n}p\left(q_k|x_i\right\}\left|x_i-m_k\right|^{b_k-2}x_i\right)}\right] \quad (8)$$

$$b_k=b_k-\left\{\frac{\partial^2\log p\left(c|q\right)}{\partial b_k^2}\right\}^{-1}\frac{\partial\log p\left(c|q\right)}{\partial b_k} \quad (9)$$

The flow of estimating the parameter of mixture of GGD is as follows: for different number of the components K $\left(K_{\min}\le K\le K_{\max}\right)$, the parameter w_i, a_i, s_i and b_k is determined by expectation maximization (EM) method.

IQA Approach Based on Compressed Sensing and Mixture of GGD

In previous work, the generalized Gaussian distribution is used to model the histogram of DCT coefficients[2]. However, histograms of DCT coefficients often have multi-peak characteristics. The generalized Gaussian distribution is a single-peak function and can not model the histogram of DCT coefficients properly. The mixture of generalized Gaussian distribution has mutiple peaks and can model the histogram of DCT coefficients properly. Therefore, we use the mixture of generalized Gaussian distribution to model the histogram of DCT coefficients of the image.

The flow of our approach is as follows: The input image is divided into $N\times N$ patches and each patch is used for KSVD(kernel singular value decomposition) dictionary training to obtain the dictionary. After that, each patch is processed to get the sparse decomposition by using the dictionary trainned by the KSVD dictionary learning approach, the histogram of sparse coefficients of the trainning or testing image are modeled by mixture of GGD and the parameter of mixture of GGD is estimated by parameter estimating approach. The feature vectors are formed by combining parameters of mixture of GGD. The feature vector is fed into support vector regression machine to predict the MOS value of the input image. For training the SVR (support vector regression machine), the feature vector of the training image and the MOS value is fed into SVR machine for training the SVR.

Implementation Result and Experiments

The LIVE (Laboratory for Image and Video Engineering) image quality assessment database [7, 8, 9] is used to evaluate the performance of our approach. The LIVE IQA database has 29 reference image and 779 distorted image with five types, which are JPEG2000 Compression (JPEG2K), JPEG

Compression (JPEG), White Noise (WN), Gaussian Blur (GB) and Fast Fading (FF). The LIVE IQA database is divided into two parts: training image and testing image. The degraded version of 24 reference images are used for training, and the degraded version of remaining 5 reference images are used for testing.

The Spearman rank order correlation coefficient (SRCC) and Pearson linear correlation coefficient (PLCC) are used to evaluate the performance of different algorithms. Two other approaches which are PSNR and MS-SSIM are used to compare with our approach. The detailed result is shown in Table I. According to table II, the proposed approach is superior than the PSNR approach by evaluating the SRCC and PLCC coefficients between the distorted image and the reference image in testing image database.

Table I. Spearman Rank Order Correlation Coefficient of Different Algorithm (aligned DMOS)

	JP2K	JPEG	WN	GB	FF	ALL
PSNR	0.8954	0.8809	0.9854	0.7823	0.8907	0.8755
SSIM	0.9613	0.9754	0.9748	0.9474	0.9537	0.9478
Proposed IQA	0.9632	0.9643	0.9732	0.9635	0.9422	0.9517

Table II. Pearson Correlation Coefficient of Different Algorithm (aligned DMOS)

	JP2K	JPEG	WN	GB	FF	ALL
PSNR	0.8769	0.8674	0.9294	0.7746	0.8760	0.8591
SSIM	0.8845	0.9268	0.9560	0.8820	0.9349	0.8959
Proposed IQA	0.9042	0.9321	0.9532	0.8702	0.8421	0.8932

Conclusions

A new no-reference image quality assessment approach based on compressed sensing is proposed to evaluate the objective image quality score of the image. The image is divided into blocks and each block is processed by compressed sensing at first, then sparse coefficients of image blocks are modeled by mixture of GGD. The parameter of mixture of GGD is estimated by the parameter estimation approach and the feature vector is formed by combining the parameter of mixture of GGD. The feature vector is fed to the support vector machine for training and testing. Experiment results show that our approach has good performance for no-reference image quality assessment..

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