An Image Quality Assessment Algorithm Based on Feature Selection

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Abstract. Image Quality Assessment(IQA) is of fundamental importance to numerous imaging and video processing applications. For most of the applications, the perceptual meaningful measure is the one which can automatically assess the quality of images or videos in a perceptually consistent manner. However, most commonly used IQA metrics are not consistent well with the human judgments of image quality. Recently, the SSIM metric which takes people's visual characteristics into consideration performs much better than the traditional PSNR/MSE. But the defects of it still exit on some specific kinds of distortions. A new algorithm of IQA based on feature selection is proposed in this paper. Local gradient entropy and phase congruency are added to the SSIM framework. Through in-depth feature selection and definition plus better pooling strategy, this algorithm performs much better in LIVE datasets.

Keywords: Image Quality Assessment, feature selection, phase congruency, local gradient entropy.

1 Introduction

With the rapid tremendous development of digital imaging and video processing, such as acquisition, compression, transmission, reproduction, enhancement, restoration and so on, the increasing importance of Image Quality Assessment(IQA) comes out, so does the need for the research in IQA. IQA aims to evaluate the fidelity or the intelligibility of an image. It can be used in many applications[1], for instance, in image processing field, it is important to evaluate the performance of the amounts of algorithms according to the IQA measure, besides, the result may assist the researcher to obtain the optimal design of the mathematical model and the optimal parameter.

According to the availability of the reference image in computing a perceptually relevant score, IQA indices can be classified into 3 categories[3], full reference(FR), no reference(NR)[4-6], reduced-reference quality assessment(RR). In this paper, we focused on the FR methods.

In the signal and image processing literature, the most common and conventional IQA indices are straightforward methods, such as the peak-signal-to-noise ratio(PSNR), the root-mean-squared error(RMSE). Although they are simple to get, it

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has been widely acknowledged that that are not always in agreement with the subjective fidelity ratings because they operate directly on the intensity of the image[7]. Thus great efforts have been made to predict the human visual quality that take advantage of known characteristic of the human visual system(HVS)[8]. Modeling of the HVS has been regarded as the most suitable paradigm for achieving better results. Through computing the different sensitivity of the HVS, the error between the test image and reference image will be obtained. NQM[9] and VSNR[10] are two representative algorithm following this kind of paradigm. At the same time, Wang and Bovik[1] proposed a structural similarity index(SSIM) based on the hypothesis that the HVS is highly developed for extracting structural information from the visual scene.By measuring the loss of structure in the image, we can obtain the quality rating. This research is said to be a milestone in the research of the FR IQA models, changing the focus from error measurement to structural similarity. From then a new point of view is elicited into this field. A lot of research has been done to improve the performance of it[11, 12]. The multi-scale extension of SSIM produces better results than its single-scale[13].

It is true that the SSIM contributes a lot in the develop of the IQA, but further analysis shows out the SSIM failed to evaluate the quality of blurred image or the Gaussian noise image[14] and it is not sensitive enough to the edge of change in the image. In this paper, a new way to address the problem is introduced here. Under the SSIM framework, we introduce two new features to it to improve its performance. One is the local gradient entropy, it is computed from the gradient map which represents the edge of the image, and it can indicate the region of the interest at some point. The other is the phase congruency, it is a contrast invariant and can represent the structure of the image properly, combined with the contrast information, a quality map can be reached. At the pooling stage, the gradient entropy is used again as the weight function to improve the pooling strategy.

The rest of this paper is organized as follows: Section 2 discusses the feature selection procedures, and the detail implementation of the proposed method, section 3 shows the experimental results and the associated discussion, section 4 concludes the paper.

2 Feature Based Image Quality Assessment

Image quality assessment aims at evaluate the fidelity of the image. And it is indeed difficult to compare with the reference image directly by computer. Through feature selection, we can obtain the good description of an image. and then through the comparison of the features, we get the final evaluation.

2.1 Feature Selection

In the design of the algorithm of IQA, one of the key issue that should be handled properly must be what kinds of features can be used. So the feature selection problem comes out.

- Local Entropy of the Gradient Image

The gradient of image is a traditional topic in image processing. Image is always been seen as a 2-dimensional dispersed function, so to image $I(x, y)$, the gradient of it can be expressed as equation(1):

$$\begin{aligned} dx(i,j) &= I(i+1,j) - I(i,j) \\ dy(i,j) &= I(i,j+1) - I(i,j) \end{aligned} \tag{1}$$

In application, the gradient operators can be expressed by convolution masks. There are many kinds of gradient operators at present[15]. we choose the commonly used Sobel Operator as the convolution mask due to its simplicity and efficiency, as a dispersed difference operator, it is always been used to compute the gradient of the luminance of image efficiently.

Suppose $M_i \times N_i$ is a part of the whole gradient map naming as Ψ_i, then the local entropy of the gradient image can be expressed as equation(2).

$$GE(\Psi_i) = -\sum_{j=0}^{L-1} p_j \log p_j \tag{2}$$

Where $p_j = \dfrac{n_j}{M_j \times N_j}$ means the probability of the gray scale j in Ψ_i, L is the amount of the total gray scale, n_j indicates the total amount of the gray scale j in Ψ_i, $M_i \times N_i$ indicates the size of the image, and $GE(\Psi_i)$ is the local gradient entropy of this part of image.

The gradient image and the local gradient entropy image can be seen in Fig.1. The value of the gradient entropy will be larger if the area located in the place where there are more details or the change of the contrast is sharper. On the contrary, the area has less details, or smoother edges will have smaller gradient entropy.

a)Original Image b)Gradient Image c)Gradient Entropy Image

Fig. 1. The Entropy Image

- Phase Congruency

It has been proved that the phase information can represent the feature of image quite well[16, 17]. When an image is decomposed into Fourier Field, the magnitude part of the image characterizes the amount of the frequency of the image, it contains the contrast information of the image. For a specific image, it will turn to be much softer if there are many dark points on the magnitude map, while it will be much more sharp if the points on the magnitude map turn to be bright. The phase part of the image indicates the position of the specific frequency component, it contains much of the texture information. In order to show the typicality of the two features, we reconstruct the image using each of them. It can be seen clearly that the reconstruction image(Fig.2(b)) from the phase has much more details than it from the magnitude.

The phase congruency postulates that features can be detected at points where the Fourier components are maximal in phase[18]. The phase congruency refers to the phase similarity of each frequency component in every position. As a dimensionless quantity, the value of it has nothing to do with the change of the luminance and contrast. Physiology experiments have confirmed that the human visual system is very sensitive to the place where phase information consistently with each other[19]. So we can use it to represent the structure of the images.

To obtain the quantity, first execute the image filter convolution with a 2-dimensional Log Gabor filter. Then compute it using the 1-dimensional signal phase consistency model based on local energy. This model greatly simplifies the computation of the phase congruency. The 2D log-Gabor function has the transfer function like equation (3).

(a) The Reconstruction Image using the Magnitude Map

(b) The Reconstruction Image using the Phase Map

(c) Phase Congruency Map

Fig. 2. The Phase Image

$$G_2(\omega,\theta) = exp(-\frac{(log(\omega/\omega_0))^2}{2\sigma_r^2}) \cdot exp(-\frac{-(\theta-\theta_j)^2}{2\sigma_\theta^2}) \quad (3)$$

Convolving the filer with the image, the responses at each point can be divided into a pair of even-symmetric and odd-symmetric.

$$[e_n(x), o_n(x)] = I(x) * G \quad (4)$$

Then the local amplitude on scale n is :

$$A_n(x) = \sqrt{e_n(x)^2 + o_n(x)^2} \tag{5}$$

The local energy will be:

$$E(x) = \sqrt{(\sum_n F_n(x))^2 + (\sum_n H_n(x))^2} \tag{6}$$

Where $F(x)$ is the sum of the even-symmetric part of the response. And $H(x)$ is the sum of the odd-symmetric of all the response. Then the phase congruency is defined as:

$$PC(x) = E(x) \Big/ (\varepsilon + \sum_n A_n(x)) \tag{7}$$

Fig.2(c)shows the phase congruency map of the original image, the most of the details in the original image can be seen in it, which validly prove the efficiency of the phase congruency as a feature .

2.2 Feature Based Image Quality Assessment

Getting these four features, then, come to the problem of how to use it in IQA. An traditional way of this problem is to compare the features in the test image with the reference image, and then combine them into one evaluation image, and the last step is to gather the map into one index. The index is the last result that can be used to assess the quality of the reference image.

According to the SSIM, the commonly used similarity measure function has the following form.

$$s = \frac{2xy + C}{x^2 + y^2 + C} \tag{8}$$

So the similarity measure for the reference image and the test image is defined as:

$$S_{GE}(x, y) = \frac{2GE_x GE_y + C}{GE_x{}^2 + GE_y{}^2 + C} \tag{9}$$

$$S_{PC}(x, y) = \frac{2PC_x PC_y + C}{PC_x{}^2 + PC_y{}^2 + C} \tag{10}$$

$$S_l(x,y)=\frac{2\mu_x\mu_y+C}{\mu_x^2+\mu_y^2+C} \tag{11}$$

$$S_c(x,y)=\frac{2\sigma_x\sigma_y+C}{\sigma_x^2+\sigma_x^2+C} \tag{12}$$

Then the feature based image quality assessment can be obtained as equation :

$$S(x,y)=[S_{GE}]^{\alpha}\bullet[S_{PC}]^{\beta}\bullet[S_l]^{\gamma}\bullet[S_c]^{\tau} \tag{13}$$

The $S(x,y)$ at each point is obtained so that the overall similarity between the two image has been obtained. Considering that the aggregation strategy will influence the result of the index very much and that different locations have different contribution to the quality of the image, we use the gradient entropy information to weight the importance of the $S(x,y)$ in the overall similarity between the two image. It can be comprehended easily that the edge in the image convey much more crucial visual information than the locations in the smooth area and people pay much more attention to it. So the feature based image quality assessment index is defined as:

$$index=\frac{\sum_{(x,y)\in I}S(x,y)\bullet GE(x,y)}{\sum_{(x,y)\in I}GE(x,y)} \tag{14}$$

Where the I is the whole image, $S(x,y)$.is the quality map just obtained , and GE is the local gradient entropy as the weight function.

3 Experimental Results

In order to evaluate the performance of the algorithm we proposed, some experiments have been done on the LIVE(Laboratory for Image & Video Engineering) dataset. we go for the LIVE Image Quality dataset for in-depth discussion[20]. The LIVE dataset has 779 images in total, 29 reference images, each containing about 30 distortion images. These distortions cover a broad range of the image impairments and a broad range of quality, by containing 5 types of distortion, JPEG2000, JPEG, white noise, Gaussian blur, and simulated fast fading Rayleigh channel and different levels of distortion from imperceptible levels to high levels of impairment. The perceptual score of these images is obtained by 25000 individual human quality judgments removing outlier subjects and scores and compensating for the bias across reference images and subjects.

We design the algorithm to approximate the visual effect of the human eye, so the closer the better. Thus, we use the Spearman rank-order correlation coefficient(SROCC), the Kendall rank-order correlation coefficient(KROCC) and the

Pearson product-moment correlation coefficient(PLCC) between the objective and subjective scores to measure the correlation between them. The Pearson correlation coefficient is defined as the covariance of the two product of their standard deviations. The Spearman correlation is the Pearson correlation coefficient between the ranked variables while the Kendall correlation is a non-parametric hypothesis test. All of them can be used to test for statistical dependence or the association between two measured quantities. The higher the value is, the closer the quantities get, and the better the algorithm is.

First, we test the algorithm on each of the different types of distortions(as shown in Fig.3), and compare the performance of it with PSNR and MSSIM, the related results are listed in Table 1. From the results, we can see that our algorithm can perform well when the PSNR cannot distinguish between the distortions.

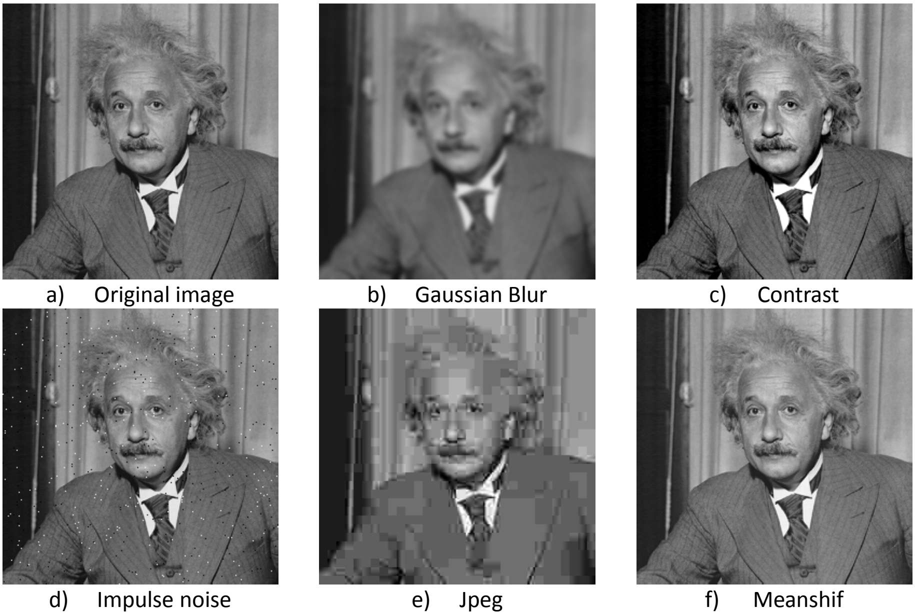

Fig. 3. The Images for testing

Table 1. Performance comparison on specific distortion

Distortion type	PSNR	MSSIM	Our algorithm
Blur	26.5499	0.6940	0.6046
Contrast	26.5406	0.9133	0.8789
Impulse	26.5490	0.8396	0.8610
JPG	26.6094	0.6624	0.5439
Meanbshift	26.5473	0.9884	0.9859

Second, we test the algorithm on the entire datasets. Table 2 lists the SROCC and KROCC results of the algorithm we proposed, the PSNR and the MSSIM index on the entire datasets. As shown in the table, our algorithm has the highest coefficient, and is most relevant to the subject scores of the three. Fig.4 shows the scatter plot of each of the algorithm, it is obvious too that our algorithm is more convergent and linear than the rest of the algorithm. Both of them prove that the algorithm we proposed is competitive in state-of –art indices.

Table 2. Performance comparision of IQA metrics

Correlation coefficient	*PSNR*	*MSSIM*	*Our algorithm*
SROCC	0.8730	0.9226	0.9468
KROCC	0.6801	0.7474	0.7959
PLCC	0.8435	0.8072	0.8628

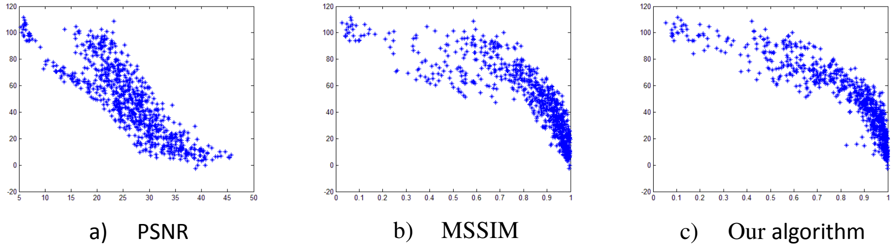

Fig. 4. Scatter plots of the IQA method over the subject ones

4 Conclusion

In this paper, a new algorithm of evaluating the quality of image is proposed. We showed that through more in-depth feature selection plus complex pooling strategy, the performance of SSIM can be greatly improved. Three kind of features are used in our algorithm, local gradient entropy, phase congruency and the contrast information. The local gradient entropy is utilized to extract the edge information. It is then be aggregated to the final metric. Considering the fact that people pay more attention to the structure of the image, the phase congruency is utilized to extract the structural information instead of the original method of calculating. Taking into account that the visual sensitivity is paid more attention to the local edge information, we use the local gradient entropy again as the weight function to improve the pooling strategy. The experimental results on the LIVE datasets show that our algorithm does improve the performance a lot.

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