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Image Quality Assessment Method Based On Statistics of Pixel Value Difference And Local Variance Similarity

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Abstract. This paper mainly presents a new image quality assessment method using statistics of pixel value difference (SPVD). Based on the statistics of pixel value difference of images with different quality, the method introduces the concept of membership function, which combines objective numerical values with human's subjective feelings. But the SPVD method ignores image structural information. To overcome this limitation, this paper further combines SPVD with local variance similarity (LVS) method and puts forward SPVD-LVS method. Experimental results show that this method works well in combining advantages of SPVD and LVS and comparing to MSE, PSNR and LVS, the assessment results of SPVD-LVS method correspond to human's subjective feelings better.

Keywords: local variance, pixel value difference, membership function, subjective feelings

1. Introduction

Currently there are two main assessment methods of image quality: subjective assessment and objective assessment. Subjective assessment is a laborious and time-consuming method and not suitable in practical use, in which every observer assess the image and then we calculate the weighted mean [1]. Objective assessment is the present study focus in which we use errors between the reconstructed image and the original image such as mean square error(MSE) and peak signal to noise ratio (PSNR) to assess the reconstructed image. In recent years researchers have put forward assessment methods based on human vision system (HVS) whose assessment results satisfy subjective judgment further. For example, Wang, Z. et al (2004) puts forward a method based on structural similarity (SSIM) [2], Aja-Fernandez, S. et al (2006) put forward a method similar to SSIM to compare the local variance between two images and thus compare the structural similarity between them [3], and Wang, Y. et al (2008) put forwards a method based on SSIM and local variance [4]. The methods used by Aja-Fernandez, S. et al (2006) and Wang, Y. et al (2008) can provide detailed structural information of the image, but they're insufficiently sensitive to errors. Based on statistics of pixel value difference (SPVD) and local variance similarity (LVS, which represents image structural information), this paper comes up with a new error sensitive image quality assessment method.

2. A New Assessment Method Of Image Quality Based On Statistics Of Pixel Value Difference（SPVD）

Among traditional assessment methods, MSE and PSNR are both based on the pixel value difference between two images. They are simple, intuitional and strict, but the results are often not in accord with human's objective feelings because they only represent the overall difference between two images but cannot represent the local information [5]. Obviously treating the pixels in the image in the same way cannot represent characteristics of human vision [6]. As for this problem, this paper puts forward a new method based on statistics of pixel value difference, in which we process each pixel separately and consider their influence to the overall quality of the image separately and introduce the concept of membership function to combine

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objective numerical values with man's subjective feelings to simulate human visual system and ascribe different weights to six levels of the pixel value difference so that the assessment result conform to the human visual characteristic.

Subtracting two images pixel by pixel, we get the gray difference matrix $Diff(i, j)$. Then we can give each value in the difference matrix a weight ω_i to indicate its influence on image quality. Based on human visual characteristic and some tests, we can make some assumptions. First, pixels with no gray difference has no influence on image quality, their weights are set to 0; pixels with gray difference larger than 50 have significant influence on image quality, their weights are set to 1 (the exact thresholds may change in different situations). Second, the relation curve between gray difference and image quality approximates S-type: between 0 and 30, as the gray difference increases, the growth largens but between 30 and 50, the growth lessens.

To combine all the hypothesis talked above, we can use S-Shape membership function(Figure 1) to represent the weight of each gray difference which can be used to represent every pixel's influence on image quality. Suppose that the quality of the original image is 1, there are M levels of the gray difference matrix and one gray level has proportion of $\rho_i = n_i / N \, (0 \le i \le M)$ if it has n_i pixels in N(the total number) pixels and we get the assessment method based on statistics of pixel value difference (SPVD) which is represented in Formula (1).

$$SPVD = 1 - \sum_{n=1}^{M} \omega_n \rho_n \tag{1}$$

where ω_n is the weight of each level of gray difference in difference matrix that is computed by membership function.

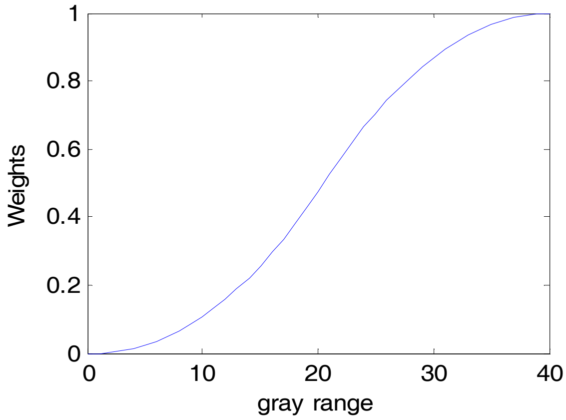

Figure 1: S-Shape membership function

To simplify calculation, gray difference is classified into 6 levels: A(1-10), B(10-20), C(20-30), D（30-40）, E(40-50) and F(>50)(these levels are divided to simplify calculation, the thresholds and number of classes change in difference situations). Count the number of pixels N_k in each level. Divide the number by the total pixel number and get the proportion of a class ρ_k. Then Formula (1) is simplified as Formula (2).

$$SPVD = 1 - \sum_{k=1}^{6} \omega_k \rho_k \tag{2}$$

The weight ω_k is computed by membership function showed in Formula (3). To build up membership function, level A, B, C are merged into one class and level D, E, F are merged into another class, and weight changes linearly inside each class.

$$\omega_k = \begin{cases} 0, & Diff(i,j) = a \\ 2 \cdot (\dfrac{Diff(i,j) - c}{c - a})^2, & a < Diff(i,j) \le b \\ 1 - 2 \cdot (\dfrac{Diff(i,j) - c}{c - a})^2, & b < Diff(i,j) \le c \\ 1, & Diff(i,j) > c \end{cases} \tag{3}$$

where a=0,b=20,c=50.

Figure 2 shows a set of images order by subjective assessment results from high to low, Figure 2-(a) has highest quality and Figure 2-(i) has lowest quality in subjective assessment.

Figure 2: Test image. Figure 2-(a) is the original image, Figure 2-(b) and Figure 2-(g) are the images added with 2% and 4.8% of Gaussian noise, Figure 2-(c) and Figure 2-(f) are the compressed JPG2000 images with compression ratio of 50% and 80%, Figure 2-(d) and Figure 2-(h) are blurred images with ambiguity of 0.5 and 1.9, Figure 2-(e) is the image formed after the value of each pixel of the original image added by 30, and Figure 2-(i) is the image formed after the original image singular value decomposed and only keep the first 8 columns.

Image quality assessment results of figure 2 using MSE, PSNR and SPVD are listed in Table 1.

Table 1: Comparison of assessment results between MSE, PSNR and SPVD

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
MSE	0	10.7931	8.4741	4.3260	204.0545	22.0205	41.8626	20.7175	48.6789
PSNR	INF	37.7993	38.8499	41.7699	25.0333	34.7025	31.9125	34.9674	31.2574
SPVD	1.0000	0.9468	0.9467	0.9395	0.5645	0.9210	0.8830	0.8370	0.7606

From Table 1 we can see that SPVD generated better assessment results than MSE and PSNR do: SPVD gives low mark to Figure 2-(i) which is in serious distortion. But we also notice that any of the methods doesn't have ideal assessment result with Figure 2-(e), which may be caused by the fact that all the three methods are based on gray difference in corresponding pixels, and thus are sensitive to noise. SPVD method can't represent structural information well although it considers human visual characteristics. Some more work need to be done to overcome the limitation of SPVD.

3. Comparison between SPVD and LVS

As mentioned above, SPVD cannot take structural information into account when assessing images. To overcome this limitation, we can combine SPVD with another assessment method that focus on structural information to get an improved assessment method. Wang, Y. et al (2008) mentioned that the details and structural information of images lie in the high frequency components to which human eyes are sensitive. The local variance of images equals to the details of the images so we can analyze the details as well as the structural information of images by analyzing the local variance [4]. Then it presents an image quality assessment method that takes structural information into account by computing local variance called LVS.

This part of the paper will first compare the advantages and disadvantages of LVS and SPVD, then combine LVS and SPVD together and present an improved method.

Conduct LVS on images in Figure 2, and comparison between LVS result and SPVD results are shown in Table 2.

Table 2: Comparison of LVS and SPVD results on Figure 2

	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
LVS	1.0000	0.9946	0.9853	0.9736	0.9707	0.9574	0.8857	0.8267	0.8487
SPVD	1.0000	0.9468	0.9467	0.9395	0.5645	0.9210	0.8830	0.8370	0.7606

From Table 2, we can see that LVS's assessment result on fuzzy image is relatively low, and that the result to Figure 2-(i) is even higher than Figure 2-(h) but in fact Figure 2-(i) has been singular value decomposed and is in serious distortion, which means assessment using LVS goes against man's subjective feelings in some situations. But the SPVD method is much too sensitive to blurred images and not that sensitive to noise.

Analysis above indicates that in some situations, the results of SPVD may violate human's subjective feelings, this is mainly caused by not taking structural information and structural similarity into account. On the other hand LVS works well in assessing structural information, but it assesses noise added images too high and assesses fuzzy images too low. This may cause inaccuracy when assessing these two kinds of images. Based on the analysis on characteristics of LVS and SPVD above, it can be found that both these two methods focus on some aspects of image quality but cannot do well in some other aspects, and their strengths and weaknesses are complementary. Based on these characteristics, we can use the product of SPVD and LVS as the indicator of image quality(Formula (4)), and the new method is called SPVD-LVS.

$$SPVD - LVS = SPVD \bullet LVS \tag{4}$$

4. Tests on Images

To verify the effect of the new method, we conducted a series of experiments on image quality assessment database (release 2) provided by Laboratory for Image & Video Engineering in University of Texas at Austin [7]. The database provides five kinds of distorted images including JPEG, JPEG2000, white noise, Gaussian blur and fast fading. Difference Mean Opinion Score (DMOS) is also provided as subjective data. DMOS has a range of 0 to 100 and low value of DMOS indicates high image quality [8].

According to VQEG's Final report [9], there exists a non-linear relationship between objective data and subjective data. To test the quality of assessments, first, a logistic function is generated for each method to map objective data to subjective scale. The function is a cubic polynomial, and it is constrained to be monotonic in the range of x. The form of logistic function is shown as Formula (5):

$$DMOSp = ax^3 + bx^2 + cx + d \tag{5}$$

Where a, b, c, d are coefficients obtained by fitting the function to data.

Figure 5 presents scatter plot of objective data and subjective data as well as the non-linear fitting function, where the results of the objective methods are on the horizontal axis, the results of the subjective methods are on the vertical axis, the red line represents the fitted curve using the Formula (6), and the better the fitted curve fits the data, the better the assessment method is.

To compare image quality assessment performance, we performed LVS (Figure 3),MSE(Figure 4), PSNR(Figure 5), SPVD(Figure 6) and LVS-SPVD(Figure 7) separately on JPG2000 compressed images, blurred images and images with Gaussian white noise. The results are presented in Table 4, where CC stands for correlation coefficient, MAE for mean average error, and RMSE for root mean square error. A good assessment model has high CC and low MAE and RMSE.

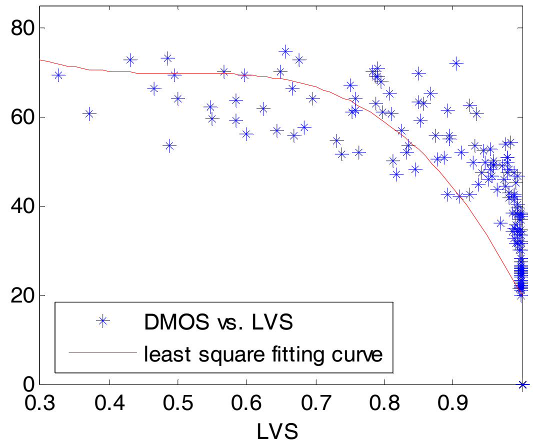

Figure 3

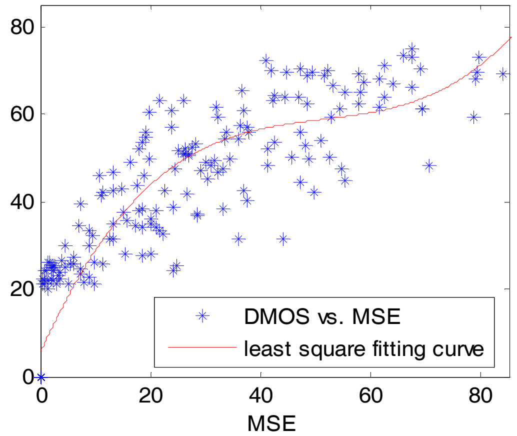

Figure 4

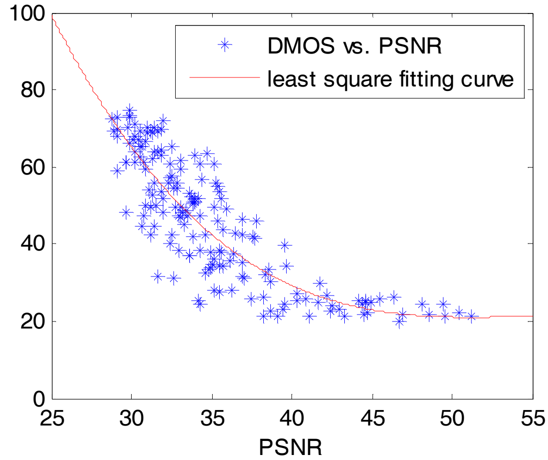

Figure 5

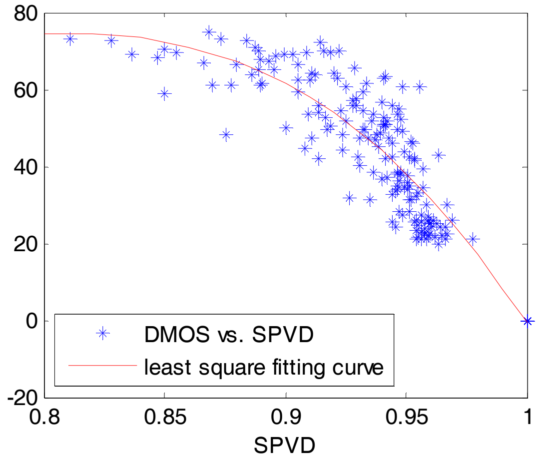

Figure 6

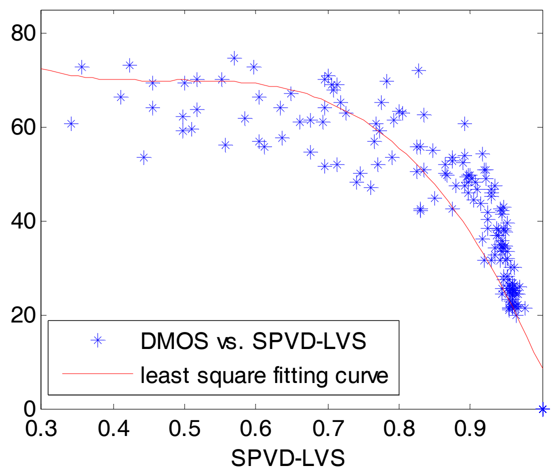

Figure 7

Table 4

jp2k	CC	MAE	RMSE	blur	CC	MAE	RMSE	WN	CC	MAE	RMSE
PSNR	0.85	6.74	8.57		0.63	9.58	12.27		0.94	4.72	5.67
MSE	0.78	9.61	11.41		0.62	9.96	12.51		0.92	5.56	6.70
LVS	0.87	10.11	12.44		0.93	4.49	5.63		0.92	6.55	8.09
SPVD	0.84	7.28	9.25		0.67	9.31	11.81		0.94	4.60	5.65
LVS-SPVD	0.91	6.28	8.16		0.94	4.41	5.51		0.95	5.22	6.26

According to Table 4, SPVD has very good performance on noise added images, with high CC and low MAE and RMSE. On blurred images, SPVD works better than MSE and PSNR, but far more worse than LVS, which takes structural information into account. LVS has relatively higher accuracy on blurred images, but on noise added images, the performance is not that good. The results of LVS-SPVD show that this model works well in combining LVS and SPVD; it has highest CC in all three kinds of images. In the results of noise added image, because of influence of LVS, SPVD-LVS has a little higher MAE and RMSE than SPVD do. Though SPVD-LVS has little influence on SPVD in some situations, it enhanced SPVD in most situations.

5. Conclusion

This paper first put forward a SPVD method based on statistical analysis of pixel value difference. Considering the shortcomings of SPVD and the advantages and disadvantages of LVS, and that SPVD and LVS are complementary, this paper finally comes up with a new assessment method of image quality called LVS-SPVD. And experiments show that the method of this paper represents human visual perception well and considers all kinds of factors affecting the quality of the images, thus it is better than MSE、PSNR and LVS. But the assessment precision depends on how pixel difference values are divided into classes and how the weights are set, so more research need to be done.

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