FISBLIM: A FIVE-STEP BLIND METRIC FOR QUALITY ASSESSMENT OF MULTIPLY DISTORTED IMAGES

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ABSTRACT

The last decade has seen a surge of interest in the research of image quality assessment (IQA). Many successful quality metrics, such as structural similarity index (SSIM) are reportedly to achieve very high accuracy for various kinds of image distortions. However, in practice, multiple image distortions tend to occur together and this leads difficulty to previous works of IQA including SSIM and variations. This problem is even more difficult for no-reference or blind quality assessment. To answer this challenge, this paper proposes a new FIve-Step BLInd Metric (FISBLIM) for quality assessment of multiply distorted images. The algorithm is built upon several common image processing blocks to simulate the image perceiving process of the human visual system (HVS). The FISBLIM method is not training based and the performance is robust and not database-dependent. Experimental results on the newly released LIVE multiply distorted image quality database demonstrate the effectiveness of FISBLIM as compared with mainstream full-reference and no-reference image quality metrics.

Index Terms— Image quality assessment (IQA), blind, multiply distorted images, JPEG, noise estimation, image denoising, blur metric

1. INTRODUCTION

Image quality assessment (IQA) has tremendous values in theory research and engineering application. For instance, IQA can be used to measure and optimize various algorithms in computer vision and image processing, such as image compression, restoration, denoising and enhancement. In the past, peak signal-to-noise ratio (PSNR) prevailed for a time, and it had been regarded as the best image quality metric until the emergence of structural similarity index (SSIM) [1]. Based on the hypothesis that the perception of human visual system (HVS) is highly suitable for extracting structural information from an image, SSIM obtains better performance than traditional PSNR on LIVE database [2]. Since then, an increasing number of researchers have realized the poor correlation of PSNR with human judgment of image quality and the significance of development of valid image quality metrics.

Present study of IQA is generally classified into two categories, namely the familiar subjective assessment and objective assessment. According to a series of suggestions given by VQEG, such as ITU-R BT.500 [3], several image quality databases and subjective mean opinion scores (MOSs) were released in the past decade. In the meantime, thousands of image quality metrics based on various effective models have been proposed. Especially in the field of full-reference (FR) IQA, existing algorithms have contributed to extremely high performance in terms of the correlation between the subjective MOS scores and the objective quality predictions [4, 5, 6, 7, 8, 9, 10, 11, 12]. The other two types of reduced-reference (RR) and no-reference (NR) IQA methods also attain very inspiring prediction accuracy [13, 14, 15, 16, 17, 18, 19].

Despite many powerful IQA methods, most of them are only adapted for singly distorted images. In the real applications, images are usually contaminated by more than one distortion category. Aiming at this problem, a new LIVE multiply distorted image quality database [20] released two groups of multiply distorted images, involving blur followed by JPEG and blur followed by noise, and their associated subjective quality scores. To carefully read the details of the subjective test condition in [20], it can be simply found that these multiply distorted images are produced by adding different levels of noise/JPEG to blurred images. So, by simulating the process of HVS to multiply distorted images, this paper proposes a new FIve-Step BLInd Metric (FISBLIM) for quality assessment of multiply distorted images. Our approach consists of five parts, i.e., the known scale invariant based noise estimator (SINE) [21], block-matching and 3D filtering (BM3D) [22], blur metric [23], JPEG metric [24], and a HVS based fusion model. In brief, the noise of the input image is computed as a prior, followed by possible denoising operation according to its estimated noise value. Then, the input image (or its denoised version) is assessed by blur and JPEG metrics independently. As a consequence, the prediction score of FISBLIM will be obtained through effectively combining the estimated results of noise, blur and JPEG.

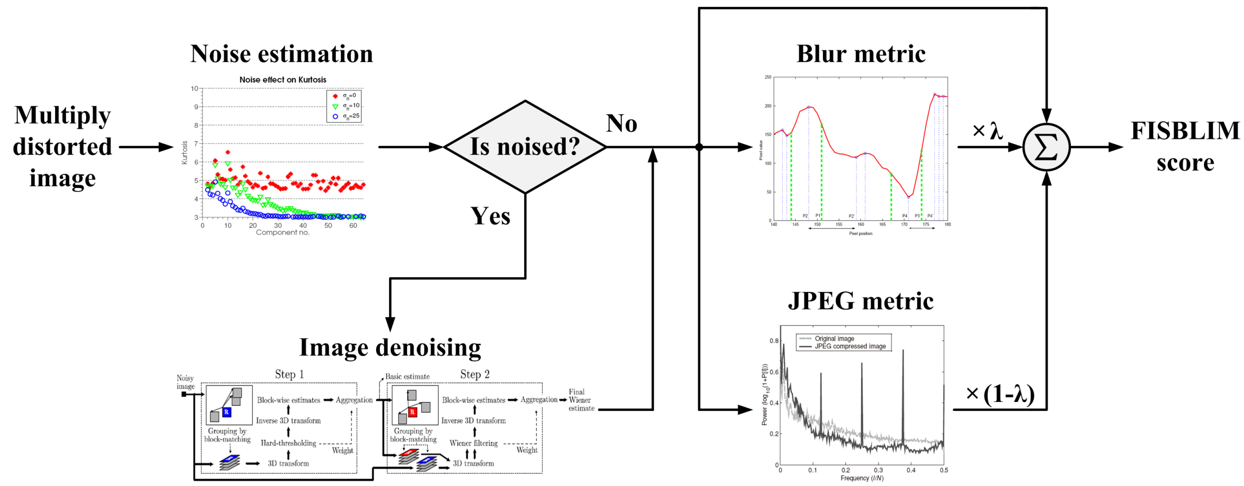

Fig. 1. The illustration of primary flowchart of the proposed FISBLIM algorithm.

The remainder of this paper is organized as follows. Section 2 introduces the proposed FISBLIM algorithm. In Section 3, experimental results using the newly released LIVE multiply distorted image quality database [20] are reported and analyzed. Finally, Section 4 concludes this paper.

2. THE PREDICTION MODEL

As mentioned earlier, the proposed FISBLIM method is not strongly dependent on the training of a large number of features extracted from the distorted image, but is implemented according to a five-step model: SINE, BM3D, Blur metric, JPEG metric, and a HVS related fusion model. Fig. 1 presents the primary flowchart of FISBLIM, which is designed based on an assumption of the perception of HVS to multiply distorted images as follows. When watching a multiply distorted image, the observer will be aware of noise at once, for the reason that HVS can be approximated by a band-pass filter, and it is very sensitive to noise [25]. After perceiving the noise level, if the image is noised, the viewer will denoise the image by adaptively restoring the pixels contaminated by noise, similar to the basic idea of [22]. Then, the blur distortion and JPEG compression are separately perceived by the observer. Notice that HVS can automatically judge the existence of blur and JPEG. In the end, the multiply distorted image quality can be obtained by an appropriate integration of estimated values of noise, blur and JPEG.

2.1. Noise estimation

It has been found in SINE [21] that the kurtosis value seems to be invariant in various scales for an original natural image, while the phenomenon of scale invariance will be deteriorated by the added noise. For an original image X, the kurtosis of its noisy image Y can be expressed as a function of kurtosis and variance of X and the variance of noise:

$$\kappa_Y = \frac{\kappa_X(\alpha) - 3}{(1 + \frac{\sigma_N^2}{\sigma_X^2})^2} + 3 \tag{1}$$

where κ_X and κ_Y are the kurtosis values of X and Y, and σ_X and σ_N indicate the variance values of X and the added noise N. Next, the noise level of Y (namely $\{\sigma_N^2\}_{opt}$) will be calculated by minimizing:

$$\{\sigma_N^2\}_{opt} = \arg\min_{\kappa_X, \sigma_N^2} \sum_{i=2}^{N^2} \left| \frac{\kappa_X - 3}{(1 + \frac{\sigma_N^2}{\sigma_{Y_i}^2 - \sigma_N^2})^2} + 3 - \kappa_{Y_i} \right|. \tag{2}$$

where $\sigma_{Y_i}^2$ and κ_{Y_i} are computed from a response image that is generated by convolving the image Y with each filter from the $N \times N$ DCT basis.

2.2. Image denoising

If the multiply distorted image is noised, it will be denoised first. The BM3D method [22] is adopted here for image denoising. Its main steps are summarized as follows.

1. Obtain the basic estimate.
   (a) Block-wise estimates. For each block in the noisy image, use block-matching to find the locations of the blocks, which are similar to the currently processed one. Then, apply a 3D transform to attenuate the noise by hard-thresholding its transform spectrum. Eventually, invert the 3D transform to produce estimates of all grouped blocks.
   (b) Aggregation. Compute the basic estimate by a weighted average of obtained block-wise estimates.
2. Obtain the final estimate by using the basic estimate to further improve the grouping and to preform collaborative Wiener filtering.

(a) Block-wise estimates. For each block in the basic estimate, use block-matching to find the locations of the blocks, which are similar to the currently processed one, so as to form a pair of 3D arrays (groups). One is from the noisy image, and the other is from the basic estimate. Next, apply a 3D transform on this couple of 3D arrays and perform 3D Wiener filtering using the energy spectra of the basic estimate. Eventually, invert the 3D transform to produce estimates of all grouped blocks.

(b) Aggregation. Compute the final estimate by a weighted average of obtained block-wise estimates.

2.3. Blur metric

So far, we have obtained a noiseless or denoised image. Other two possible distortion types will be measured in subsequent steps. One is a classical blind blur metric proposed by Pina *et al*. [23], and the other is an improved version of high-performance no-reference JPEG metric [24]. The blur algorithm is operated based on the utilization of an edge detector as a prior, in order to find vertical/horizontal edges in an image. Next, each row/column of the image is scanned. For pixels corresponding to an edge location, the start and end positions of the edge are defined as the local extrema locations closest to the edge. The edge width is then measured by the difference between the end and start positions, and is identified as the local blur measure for this edge location. At last, the global blur measure for the whole image is gained by computing the mean value of the local blur values over all the edge locations.

2.4. JPEG metric

For JPEG compression, blurring and blocking artifacts occur due to the coarse quantization to 8×8 independent coding blocks. The blurring effect is mainly introduced from the loss of high frequency DCT coefficients while the blocking effect occurs due to the discontinuity at block boundaries. This JPEG metric is defined in four steps: First, blockiness is estimated as the average differences across block boundaries:

$$B_h = \frac{1}{M(\lfloor N/8 \rfloor - 1)} \sum\nolimits_{i=1}^{M} \sum\nolimits_{j=1}^{\lfloor N/8 \rfloor - 1} |d_h(i, 8j)|; \quad (3)$$

Second, the average absolute difference between in-block image samples is calculated as follows:

$$A_h = \frac{1}{7}\left[\frac{1}{M(N-1)} \sum\nolimits_{i=1}^{M} \sum\nolimits_{j=1}^{N-1} |d_h(i,j)| - B_h\right]; \quad (4)$$

Third, the horizontal zero crossing rate can be computed by

$$Z_h = \frac{1}{M(N-2)} \sum\nolimits_{i=1}^{M} \sum\nolimits_{j=1}^{N-2} z_h(m,n); \quad (5)$$

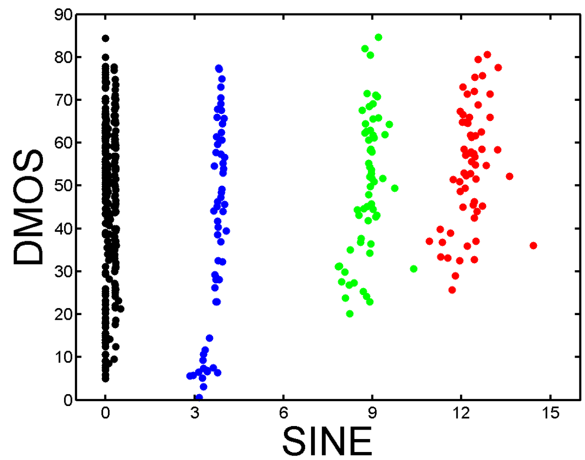

Fig. 2. Scatter plots of differential MOS (DMOS) vs. SINE [21] on LIVE multiply distorted database. Red, green, blue and black scatter plots represent four various levels of noise.

Finally, the image quality prediction is given by

$$Q_J = \kappa_1 + \kappa_2 \cdot (B_J)^{\theta_1} \cdot (A_J)^{\theta_2} \cdot (Z_J)^{\theta_3} \quad (6)$$

where

$$B_J = \frac{B_h + B_v}{2},\ A_J = \frac{A_h + A_v}{2},\ Z_J = \frac{Z_h + Z_v}{2}, \quad (7)$$

B_v, A_v and Z_v are the vertical features applying similar methods like B_h, A_h and Z_h, and $\{\kappa_1, \kappa_2, \theta_1, \theta_2, \theta_3\}$ are the model parameters to be determined.

2.5. A fusion model based on HVS

The proposed fusion model is a linear combination of weighted measures of noise, blur and JPEG:

$$FISBLIM = \alpha \cdot Q_N + \beta \cdot \lambda \cdot Q_B + (1-\lambda) \cdot Q_J \quad (8)$$

where α, β, λ are model parameters, and Q_N, Q_B, Q_J are objective quality predictions for noise, blur, JPEG.

Note, the newly released LIVE multiply distorted image quality database [20] involves two groups of multiply distorted images, namely blur&JPEG images and blur&noise images. It has been mentioned that HVS will directly perceive and depart noise from an image that is possibly distorted by noise, blur and JPEG. In other words, the measure of noise is comparatively independent of the other two distortion categories. As a matter of fact, SINE is immune to the influence of blur and JPEG when estimating noise. As shown in Fig. 2, all the images in [20] with the four various levels of noise are represented by red, green, blue and black scatter plots, proving that the noise estimation of SINE is rarely affected by blur distortion and JPEG compression. Accordingly, we directly applies the weighted Q_N in Eq. 8.

For blur and JPEG, HVS can easily distinguish them from each other, but it is still a difficult work for computer. In this

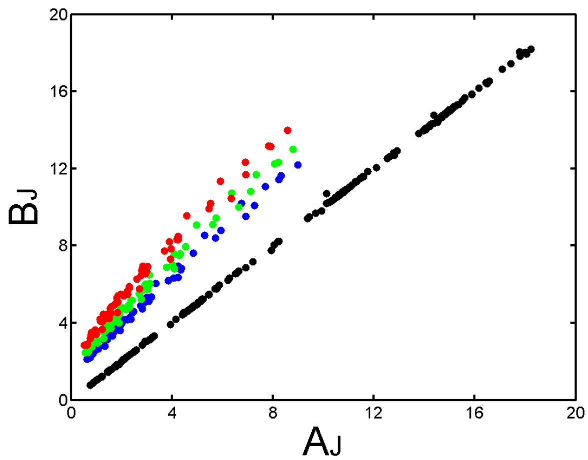

Fig. 3. Scatter plots of $\mathrm{B_J}$ vs. $\mathrm{A_J}$ on LIVE multiply distorted database. Red, green, blue and black scatter plots correspond to four different degrees of JPEG compression.

work, by carefully comparing Eq. 3 and Eq. 4, we find that the ratio of B_h and A_J can validly separate the JPEG and JPEG&blur images from other images. More specifically, B_J is actually computing the mean of $|d_h|$ and $|d_v|$ values located in the edge of all the blocks, while A_J is performing for the 6×6 interior part. It is not difficult to conjecture that B_J is nearly equal to A_J for a big and clear image, and contrarily, B_J is larger than A_J for a JPEG or JPEG&blur image. Fig. 3 displays the relationship between B_J and A_J for all the multiply distorted images in [20]. Among them, red, green, blue and black scatter plots indicate four different levels of JPEG compression.

Notice that the blur metric [23] is highly influenced by blockiness, because its basic idea is to measure the spread of the edges in an image. Considering the fact that A_J and Z_J are proposed to measure blur, we therefore only adopt Q_J with updated newer values of $\{\kappa_1, \kappa_2, \theta_1, \theta_2, \theta_3\}$ to predict the qualities of JPEG and JPEG&blur images. The parameter λ that manipulates the choice of using blur metric or JPEG metric is defined by

$$\lambda = \begin{cases} 0 & \text{if} \quad B_J/A_J \geq thr \\ 1 & \text{otherwise} \end{cases}. \tag{9}$$

where thr is set as an empirical value of 1.5. As shown in Fig. 1, JPEG metric will be only applied if $B_J/A_J \geq thr$ is satisfied, or else blur metric will be just employed.

In this work, we use totally content-independent training and testing sets to obtain the optimal values of parameters. The training set includes 360 images (about 80%) derived from 12 reference images, and the testing set contains the rest 90 images (about 20%). Model parameters obtained with all test images are $\kappa_1 = -1303.74$, $\kappa_2 = 1097.02$, $\theta_1 = 347.74$, $\theta_2 = 83.67$, $\theta_3 = -638.81$, $\alpha = 3.1442$, $\beta = 6.6897$.

3. EXPERIMENTAL RESULTS

As suggested by VQEG [26], this paper further applies nonlinear regression with a four-parameter logistic function to attain mappings of the scores of PSNR, SSIM [1], SSIM' [27], MS-SSIM, VIF, MAD, IW-SSIM, DIIVINE [16], BLIINDS-II [17], BRISQUE [18], and the proposed FISBLIM methods to subjective differential MOSs (DMOSs):

$$Quality(x) = \frac{\phi_1 - \phi_2}{1 + e^{(-(x-\phi_3)/\phi_4)}} + \phi_2 \tag{10}$$

where x indicates the input score, $Quality(x)$ is the mapped score, and ϕ_1 to ϕ_4 are free parameters to be confirmed during the curve fitting process.

Pearson linear correlation coefficient (PLCC), Spearman rank-order correlation coefficient (SROCC), and Root mean-squared error (RMSE) are commonly used performance metrics according to the suggestion of VQEG [26]. In this research, we employ them to evaluate the prediction accuracy of the proposed FISBLIM metric and the other ten FR and NR IQA methods on newly released LIVE multiply distorted image quality database. Table 1-3 tabulate their performance results, and three scatter plots of DMOS vs. FISBLIM on the whole image database and two image data sets are displayed in Fig. 4-6, respectively. Obviously, our FISBLIM algorithm has achieved better result than mainstream NR IQA metrics, and has comparable performance as compared with popular FR IQA approaches.

Furthermore, we want to emphasize here that FISBLIM is not dependent on the training of numerous features, but is designed based on the simulation of the perception of HVS to multiply distorted images. That is to say, our FISBLIM

Table 1. Pearson linear correlation coefficient (PLCC), Spearman rank-order correlation coefficient (SROCC), and Root mean-squared error (RMSE) values (after nonlinear regression) of PSNR, SSIM [1], SSIM' [27], MS-SSIM, VIF, MAD, IW-SSIM, DIIVINE, BLIINDS-II, BRISQUE and the proposed FISBLIM methods on blur&JPEG image data set.

Blur&JPEG image data set			
Full-Reference Metric	PLCC	SROCC	RMSE
PSNR	0.8525	0.7786	10.034
SSIM [1]	0.7981	0.7443	12.478
SSIM' [27]	0.8949	0.8488	8.6657
MS-SSIM	0.8862	0.8421	9.2217
VIF	0.9182	0.8788	7.6479
MAD	0.9195	0.8906	7.5536
IW-SSIM	0.9149	0.8700	7.8177
No-Reference Metric	PLCC	SROCC	RMSE
DIIVINE	0.7627	0.7080	12.565
BLIINDS-II	0.5641	0.6114	16.407
BRISQUE	0.8645	0.7930	13.024
FISBLIM	0.8920	0.8583	8.7352

algorithm is a general model for multiply distorted images, and the higher performance will be gained by replacing one or some composition parts in our flowchart with other more powerful models.

4. CONCLUSION

In this paper, we propose a new FISBLIM metric by simulating the process of human visual perception to multiply distorted images. Experimental results on the newly released LIVE

Table 2. Pearson linear correlation coefficient (PLCC), Spearman rank-order correlation coefficient (SROCC), and Root mean-squared error (RMSE) values (after nonlinear regression) of PSNR, SSIM [1], SSIM' [27], MS-SSIM, VIF, MAD, IW-SSIM, DIIVINE, BLIINDS-II, BRISQUE and the proposed FISBLIM methods on blur&noise image data set.

Blur&noise image data set			
Full-Reference Metric	PLCC	SROCC	RMSE
PSNR	0.8170	0.7674	10.773
SSIM [1]	0.7542	0.7022	13.228
SSIM' [27]	0.8945	0.8760	8.4746
MS-SSIM	0.8889	0.8646	8.9526
VIF	0.8801	0.8807	8.9053
MAD	0.8683	0.8376	9.2769
IW-SSIM	0.9101	0.8933	7.8248
No-Reference Metric	PLCC	SROCC	RMSE
DIIVINE	0.6846	0.6020	13.724
BLIINDS-II	0.1302	0.0360	18.835
BRISQUE	0.3693	0.2992	18.180
FISBLIM	0.8725	0.8548	9.2158

Table 3. Pearson linear correlation coefficient (PLCC), Spearman rank-order correlation coefficient (SROCC), and Root mean-squared error (RMSE) values (after nonlinear regression) of PSNR, SSIM [1], SSIM' [27], MS-SSIM, VIF, MAD, IW-SSIM, DIIVINE, BLIINDS-II, BRISQUE and the proposed FISBLIM methods on LIVE multiply distorted image database.

LIVE multiply distorted image database			
Full-Reference Metric	PLCC	SROCC	RMSE
PSNR	0.8349	0.7766	10.410
SSIM [1]	0.7333	0.6459	12.859
SSIM' [27]	0.8914	0.8604	8.5707
MS-SSIM	0.8770	0.8392	9.0881
VIF	0.8985	0.8823	8.3005
MAD	0.8944	0.8646	8.4593
IW-SSIM	0.9105	0.8836	7.8212
No-Reference Metric	PLCC	SROCC	RMSE
DIIVINE	0.7183	0.6563	13.157
BLIINDS-II	0.3574	0.2548	17.663
BRISQUE	0.5485	0.5017	15.813
FISBLIM	0.8801	0.8568	8.9787

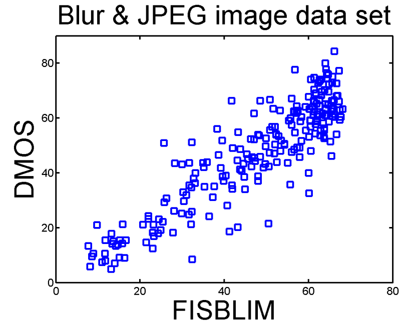

Fig. 4. Scatter plots of DMOS vs. FISBLIM on the blur&JPEG image data set.

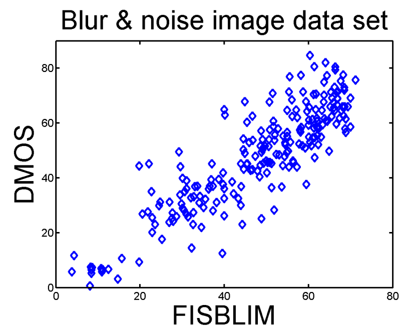

Fig. 5. Scatter plots of DMOS vs. FISBLIM on the blur&noise image data set.

multiply distorted image quality database and its two image data sets, namely blur&JPEG images and blur&noise images, are provided to confirm the effectiveness of our FISBLIM method as compared with mainstream no-reference and full-reference image quality metrics.

Note, the proposed FISBLIM algorithm is a universal model. Instead of four approaches used in this paper, more valid noise, denoising, blur, JPEG metrics will make our IQA method achieve higher performance. Besides, it is worth mentioning that FISBLIM works effectively for images simultaneously contaminated by two distortion types. Due to the fact that FISBLIM is developed based on some features of HVS, we have a reason to believe that its improved version is probably available for predicting the quality of three multiply distorted images. So, our future work will be devoted to the study of IQA on three or more multiply distorted images.

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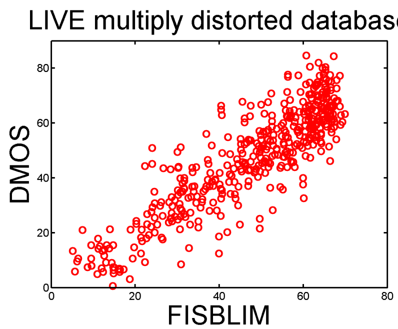

Fig. 6. Scatter plots of DMOS vs. FISBLIM on the whole LIVE multiply distorted database.

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