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No-reference image blur index based on singular value curve

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ABSTRACT

We describe a new no-reference blur index for still images based on a singular value curve (SVC). The algorithm is composed of two steps. First, the singular value decomposition is performed on the image to be blur-assessed. Then an image blur index is constructed from the singular value curve. Experimental results obtained on four simulated blur databases and on the Real Blur Image Database show that the proposed SVC algorithm achieves high correlation against human judgments when assessing the blur distortion of images.

1. Introduction

Digital images are being produced in vast numbers as digital cameras and camera-equipped smartphones are becoming very widely used. Many of these images are acquired under less than ideal conditions, often by inexperienced or inexpert users. One very common problem is image blur induced by, for example, camera shake or inaccurate focussing, since users routinely capture many more images than in the film days. Since these images are available for digital analysis, it is highly desirable to be able to assess automatically their perceptual quality. Since it would be very valuable to be able to sort and/or cull the 'good' from the 'bad', in recent years research on no-reference (NR) image blur assessment method has become very active. A variety of no-reference blur indexes have been proposed in the literature. For example, in [1], an image sharpness index is proposed that is based on the notion of just noticeable blur (JNB). The authors of [2] proposed a new sharpness measure utilizing local phase coherence (LPC) evaluated in the complex wavelet transform domain. In [3], the authors presented a no-reference image blur metric which utilizes a probabilistic model to estimate the probability of detecting blur at each edge in the image, where the information is pooled by computing the cumulative probability of blur detection (CPBD). Li et al. [4] proposed a new no-reference blur index for still images that is based on the observation that it can be difficult to distinguish between versions of an image blurred to different degrees (BC).

The singular value decomposition (SVD) method is a flexible image matrix decomposition that has been successfully applied to the full reference (FR) image quality assessment (IQA) problem. Existing FR methods based on SVD can be divided into two categories. One directly uses the singular values to assess image quality. For example, the MSVD algorithm proposed in [5] uses the amount of change of the singular value as the image quality evaluation criteria. The other uses the left and right singular vectors to assess image quality [6]. In our approach, we broaden the SVD IQA idea by analysing the distribution of singular values. A new blind method for assessing image blur severity is developed based on a computed singular value curve.

The remainder of this paper is organized in the following way. Section 2 describes the relationship between blur distortions and the image singular value curve. Section 3 details a new no-reference image blur index that uses a model of the singular value curve. The results of experiments conducted on the five databases are presented and analysed in Section 4. Section 5 concludes the paper.

2. The relationship between blur distortion and singular value curve

Every $m \times n$ real grey scale image A can be decomposed into a product of three matrices, $A = USV^T$, where U and V are orthogonal matrices $U^TU = I$, $V^TV = I$, and $S = \begin{bmatrix} S_r & 0 \\ 0 & 0 \end{bmatrix}, S_1 = (\sigma_1, \sigma_2, \ldots, \sigma_r)$, where r is the rank of A. The diagonal entries of S are the singular

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values of A, S_1 is the singular value vector, the columns of U are the left singular vectors of A, and the columns of V are the right singular vectors of A. This decomposition is the singular value decomposition (SVD) of A.

To explain our idea of SVD-based NR IQA, we arbitrarily selected a source image and its five blurred versions from the CSIQ database [7] and LIVE2 database [8], as shown in Figs. 1 and 3. The degree of blur is sorted in ascending order from images Aa to Ae.

We subjected each of these images to singular value decomposition to obtain singular vectors S_1. A blur-dependent singular value curve is plotted with the singular value along the Y-axis and the index of the singular value vector (the position of the singular value component in the vector) along the X-axis, as shown in Figs. 2 and 4. It can be seen from the singular value curve that the singular values decay exponentially. Note that the curve becomes increasingly steep with larger degree of blur. We plotted the singular value curves of all of the blurred images in the CSIQ database and the LIVE2 database and found that the same law applied.

The matrix norm that we deploy is the Frobenious norm (F-norm), which captures image energy:

$$E = \|A\|_F = \|U * S * V^T\|_F = \|S\|_F = \sqrt{\sum_{i=1}^{r} \sigma_i^2} \tag{1}$$

where r is the matrix rank and the σ_i are singular values. Generally, a sharp image will have Frobenious higher energy value than a blurred counterpart of it.

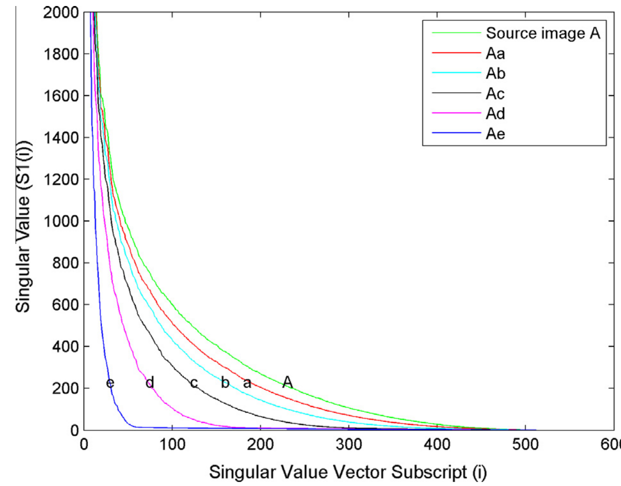

Fig. 2. Singular value curve of Fig. 1.

3. Constructing a no-reference blur index based on a singular value curve

We have found that the shape of the singular value curve of naturalistic images, as exemplified in Figs. 2 and 4, closely resembles an inverse power function. Let $y = S_1(i)$, $x = i$, which we approximate by the following equation

$$y = x^{-q} \tag{2}$$

where y is the singular value $S_1(i)$, and x is the corresponding subscript i of the singular value vector. Because the steepness of the singular value curve corresponds to blur degree, we use q to capture the image blur. Taking logarithms

$$\ln(1/y) = q \ln x \tag{3}$$

and letting $M = \ln(1/y)$, $N = \ln x$, yields

$$M = qN \tag{4}$$

which is a linear equation in the coefficient q which can be solved by linear regression. We use least squares to minimize the residual sum of squares:

$$\min \sum_{i=1}^{r} e_i^2 = \sum_{i=1}^{r} (M_i - qN_i)^2 \tag{5}$$

Setting the derivative of Eq. (3) to zero, we get:

$$\sum_{i=1}^{r} 2(M_i - qN_i)(-N_i) = 0 \tag{6}$$

So the coefficient q can be obtained as

$$q = \frac{\sum_{i=1}^{r} N_i M_i}{\sum_{i=1}^{r} N_i^2} \tag{7}$$

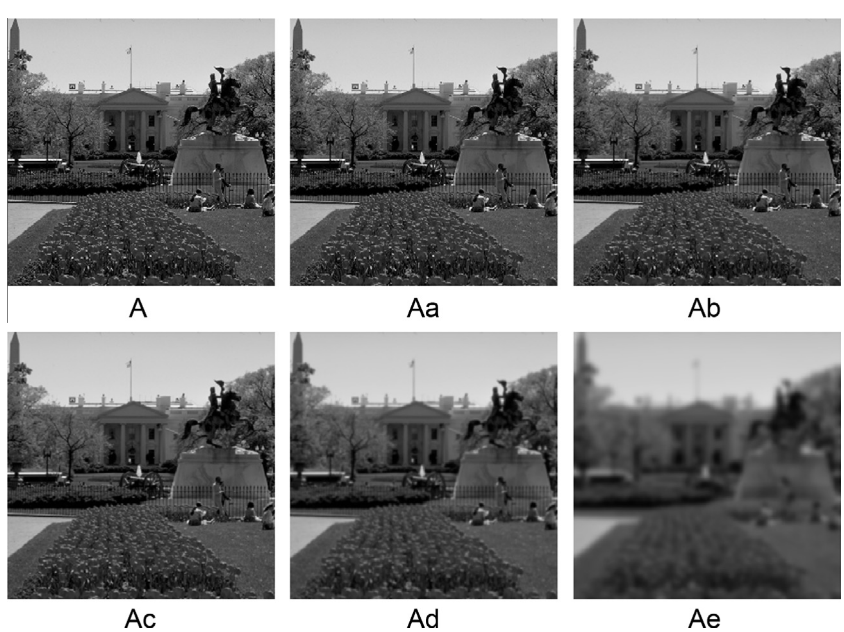

Fig. 1. Source image A and its five increasingly blurred versions in CSIQ database, the degree of blur is sorted in ascending order from images Aa to Ae.

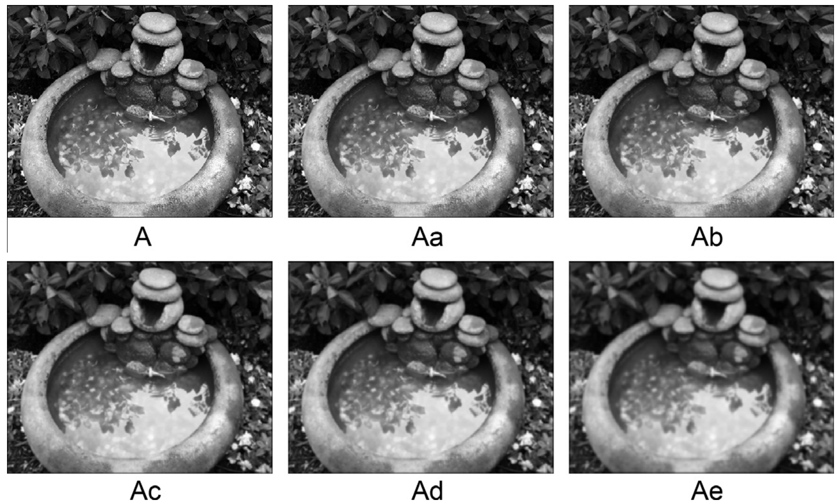

Fig. 3. Source image A and its five increasingly blurred versions in LIVE2 database, the degree of blur is sorted in ascending order from images Aa to Ae.

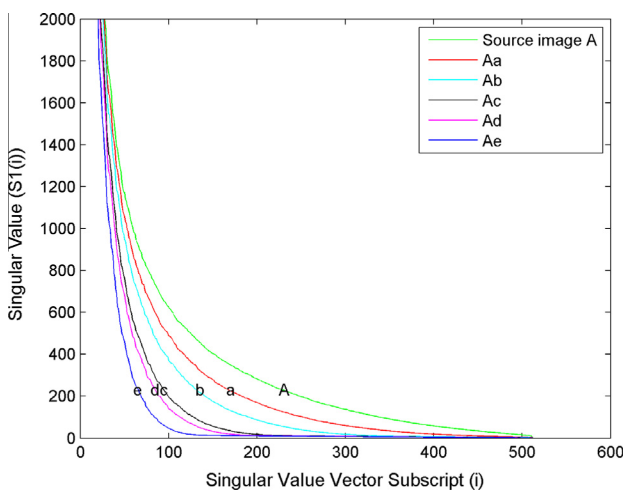

Fig. 4. Singular value curve of Fig. 3.

or

$$q = \frac{\sum_{i=1}^{r} \ln i \ln(1/S_1(i))}{\sum_{i=1}^{r} \ln i \ln i} \tag{8}$$

When the singular values are small, the singular value curves of different blurred images become harder to discriminate, so we only use larger singular values to assess the blur degree. Hence define the blurred image quality index as

$$BlurPred = \frac{\sum_{i=1}^{r} \ln i \ln(1/S_1(i))}{\sum_{i=1}^{r} \ln i \ln i}, S_1(i) > c \tag{9}$$

where S_1 is the singular value vector, i is the subscript of the singular value vector, and c is a threshold value, which is determined by the result of the following experiment.

4. Experimental results and analysis

4.1. Databases and metrics for comparison

Performance of the proposed blur index was evaluated on five blur image databases (CSIQ [7], LIVE2 [8], TID2008 [9], IVC [10]) and Real Blur Image Database (RBID) [11]. The characteristics of these five databases are summarized in Table 1.

Two commonly used performance metrics were employed to evaluate the competing IQA methods. The first is the Spearman rank-order correlation coefficient (SROCC), which can assess the prediction monotonicity of an IQA method. This metric operates on the ranked data points and ignores the relative distances between data points. The second metric is the Pearson linear correlation coefficient (CC) between MOS and the objective scores after nonlinear regression. For the nonlinear regression, we used the following mapping function:

$$Quality\ (\alpha) = \beta_1 * (0.5 - 1/(1 + \exp(\beta_2 * (\alpha - \beta_3)))) + \beta_4 * \alpha + \beta_5 \tag{10}$$

where α is the score obtained from the objective metric, and β_k with $k = 1, 2, 3, 4, 5$ are parameters. The fitting, i.e., determination of parameters in [12], is done by the nonlinear regression over dataset.

4.2. Image blocking

Singular value decomposition is a factorization of a real or complex matrix, whose computational complexity is O(N^3). If the image size is large, it could be too time-consuming. In order to improve the efficiency of the algorithm, in our implementation we partitioned the image into blocks, and use the mean values of the obtained quality indices from each block to compute the image quality. The smaller the block size, the less the time involved in each calculating SVD, but more blocks implies more transforms. Hence the size of the blocks must be considered with respect to both SVD complexity as a function of block size and with respect to the block cardinality. In our simulations, the block size was set to 512×512.

Table 1
Benchmark test databases for IQA.

Database	Source images	Types	Blurred images	Observers
LIVE2	29	Colour	145	161
TID2008	25	Colour	100	838
CSIQ	30	Colour	150	35
IVC	10	Colour	20	15
RBID	–	Colour	585	10–20

Table 2
Comparison of performance for different c values on LIVE2, TID2008, CSIQ and IVC databases.

c	Measure	LIVE2	TID2008	CSIQ	IVC
0	SROCC	0.8881	0.8449	0.8680	0.9007
	CC	0.8837	0.8189	0.9109	0.9124
30	SROCC	0.9410	0.9084	0.9155	0.5207
	CC	0.9337	0.8834	0.9495	0.6950
50	SROCC	**0.9528**	**0.9089**	**0.9167**	**0.7841**
	CC	**0.9596**	**0.9319**	**0.9433**	**0.8540**
70	SROCC	0.9514	0.8986	0.9046	0.8661
	CC	0.9520	0.9339	0.9353	0.9091
90	SROCC	0.9478	0.8941	0.8933	0.8962
	CC	0.9513	0.9513	0.9295	0.9249

The best results are highlighted in bold.

Table 3
Performance comparison of no-reference blur image quality assessment models with $c = 50$ on the LIVE2, TID2008, CSIQ and IVC databases.

Measure	Model	LIVE2	TID2008	CSIQ	IVC
SROCC	JNB [1]	0.8368	0.7045	0.7625	0.7722
	LPC [2]	0.9368	0.8030	0.8931	0.9022
	CPBD [3]	0.9437	0.8406	0.8790	0.8404
	BC [4]	0.9375	0.8154	0.8963	**0.9029**
	BlurPred	**0.9528**	**0.9089**	**0.9167**	0.7841
CC	JNB [1]	0.8390	0.7171	0.8572	0.7992
	LPC [2]	0.9239	0.8113	0.8856	**0.9718**
	CPBD [3]	0.9107	0.8316	0.8743	0.8865
	BC [4]	0.9478	0.8547	0.9347	0.9404
	BlurPred	**0.9506**	**0.9319**	**0.9433**	0.8540

The best results are highlighted in bold.

Table 4
Performance comparison of various no-reference blur image quality assessment models on the Real Blur Image Database.

Model	JNB [1]	LPC [2]	CPBD [3]	BC [4]	MFNNC [12]	*BlurPred*
SROCC	0.1409	0.3534	0.2558	0.3622	**0.5600**	0.4817
CC	0.0471	0.3625	0.2620	0.3777	**0.5600**	0.4519

The best results are highlighted in bold.

4.3. Determination of threshold c

In order to find an appropriate value for the threshold c, we used several values of c in formula (7) and compared the obtained results, which are shown in Table 2. As can be seen from Table 2, the accuracy of the blur index is improved by introducing a threshold. However, performance is robust over a wide range of values of c, so we can use any value between 50 and 90. In the following experiments we use 50 as the value of c.

4.4. Test on five blur databases

We also compared our blur index with four current top no-reference blur indices [1–4] on the four blur databases and on the Real Blur Image Database [11]. The experimental results are shown in Tables 3 and 4. The experimental results of the MFNNC blur index [12] on the Real Blur Image Database are also shown in Table 4.

Table 3 compares the performance of the blur index in terms of SROCC and CC on the four image databases. It can be seen that the proposed method delivers better performance than JNB, LPC and CPBD. But on the IVC database its results are a little inferior to that of BC. Fig. 5 further suggests that blur index is consistent with human subjective judgments. Table 4 reveals that the proposed method and the MFNNC blur index achieve the best performance on the Real Blur Image Database. However, our proposed index has a lower computational complexity and the virtue of conceptual simplicity.

Table 5
The values of γ and *BlurPred* of Fig. 3.

Image	*s*	*a*	*b*	*c*	*d*	*e*
γ	0	0.5625	0.8489	1.4505	1.7083	2.5104
BlurPred	−1.0506	−1.1008	−1.1881	−1.3370	−1.3951	−1.5315

4.5. Standard deviation γ and BlurPred

Fig. 3 are blurred images in LIVE2 database, whose R, G, and B components were filtered using a circularly-symmetric 2-D Gaussian kernel of standard deviation γ. The greater the value of standard deviation γ, the greater the blur. The values of γ are given in Table 5. The values of *BlurPred* are calculated using formula (7). Fig. 6 is plot of γ versus *BlurPred*. This can be seen from Fig. 6: γ and *BlurPred* have a reciprocal relationship.

4.6. Running time

Speed is an important factor regarding the value of an NR IQA method since in many practical applications it is necessary to judge the quality of an image in real-time. We implemented our method on a PC running Windows 7 Enterprise with a single 2.7 GHz Intel Core i7 CPU and 4 Gbytes of main memory. The version of MATLAB is R2008b. The benchmark used is the CSIQ database which include 150 blurred images. Table 6 summarizes the run time of the test

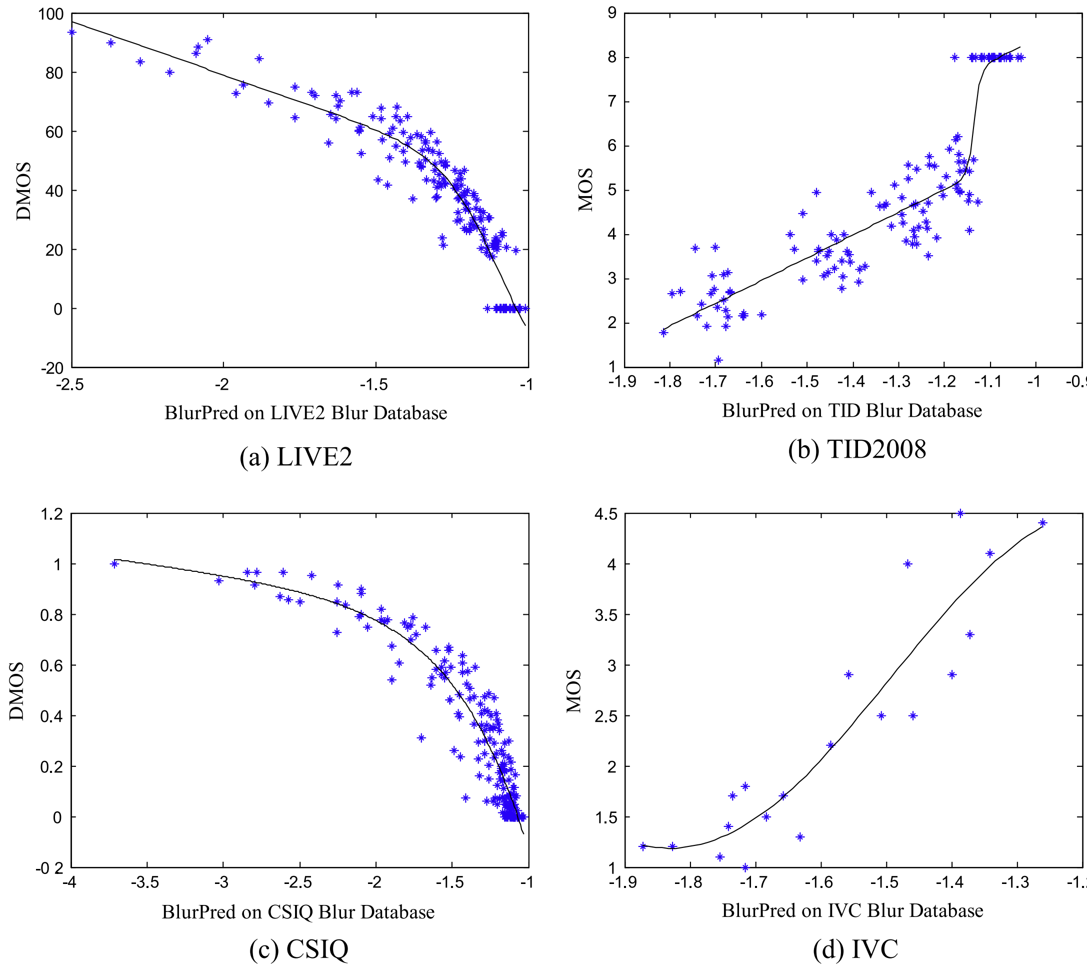

Fig. 5. Plot of predicted objective scores versus DMOS from (a) LIVE2, (b) TID2008, (c) CSIQ and (d) IVC image quality database.

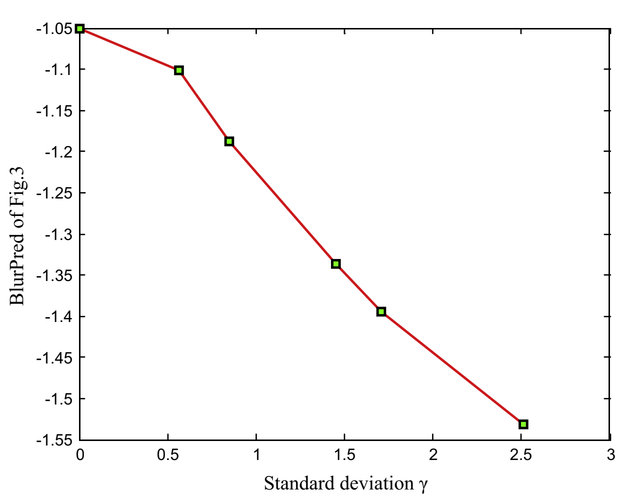

Fig. 6. Plot of γ versus *BlurPred* of Fig. 3.

Table 6
The total number of seconds on CSIQ blur database.

Model	JNB[1]	LPC[2]	CPBD[3]	BC[4]	*BlurPred*
Runtime (s)	91.49	266.40s	109.23	176.23	25.16

stage of all competing methods. LPC is the slowest, while SVC is the fastest (requiring only 0.1677s per image).

5. Conclusions

We have presented a no-reference image blur index based on a model of the image singular value curve. The solid performance of this no-reference image blur index that uses a singular value curve in an efficient manner suggests that it is well-suited for real-time applications.

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