A No-reference Blur Image Quality Assessment Algorithm Based on Wavelet Singular Value Decomposition

Xiao-sheng HUANG¹, Si-si FU¹,*, Yi-qin CAO¹ and Jie SONG¹
¹School of Software, East China Jiaotong University, Nanchang, 330013, China
*Corresponding author

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Abstract. A simple and effective no reference blur image quality assessment algorithm based on wavelet high frequency singular value decomposition is proposed. As the different wavelet high frequency sub-bands in the same level are highly structural correlation, and the degree of correlation would be weaken as the degree of blur distortion strengthen. The proposed method decomposes the images by wavelet transform firstly. Then the singular value decomposition is used for different high frequency sub-bands to get their singular value vectors, which we used to represent their structural information. Thirdly the angles between different sub-bands singular value vectors are computed, which reflects their degree of correlation. Finally the sum of angles is used as the last objective assessment index. Compared to the traditional methods, the proposed algorithm is more efficient and practical as it does not need to train or create a reference image. Experimental results show its good effectiveness and performance on LIVE2, CSIQ and TID2013 databases.

Introduction

Nowadays digital images are widely used in various applications. But how to assess the quality of images objectively and effectively still remains a challenge [1]. Based on the availability of reference images, with which the distorted image is to be compared, objective image quality assessment (IQA) approaches can be classified into: full-reference (FR), no-reference (NR) and reduced-reference (RR) approaches. As the reference image is not available, no-reference approach is more widely used and has been the research hot spot in image quality assessment[2].

The proposed method is a NR IQA method assumed to a blurry image. In this field, Rony Ferzli, etc[3] presented a perceptual-based no-reference objective image sharpness/blurriness metric by integrating the concept of just noticeable blur into a probability summation model. Xie Xiaofu, etc[4] introduced an no-reference structural sharpness(NRSS) method for quality evaluation of blurred images by constructing a reference image by a low-pass filter. Considering the human visual system, Yin Ying, etc[5] compute the blur value of image by producing a reference image through Gauss low-pass filter transformation and combining the singular value decomposition(SVD) and generalized regression neural network model techniques. These methods can be roughly reduced into two categories. The first category methods construct a reference image through some sort of filtering process and then evaluates the quality by comparing the difference between the before and after filtered image, such as in literature[4,5]. The second category methods firstly make some transformation to the image to get the feature information, and then predict image quality score by some kinds of machine learning models. The above two category methods needs either to construct a reference image or to train and learn with the opinion quality score by machine learning to predict the image quality, these will undoubtedly increase the computing cost and accordingly decrease the practicality of the algorithms.

A simple and effective no reference blur image quality assessment algorithm based on wavelet high frequency singular value decomposition is proposed, which does not need to train or create a reference image. It can be designed to achieve accuracy close to that of the complex methods.
The Correlation of the Natural Image Wavelet High Frequency

Normally natural images have high sharpness, clear texture and other natural properties, its different directional sub-bands in the same scale through wavelet decomposition have strong correlation, especially at the structure of the image edges. A motivating example is shown in figure 1(b)-(f), which represents the 4-level wavelet decomposition of the “parrots” original image and its different blur distorted images. It also gives each image’s mean Person correlation coefficient among the three outermost layer high frequency wavelet coefficients. Note that the figure 1(b), the different high frequency sub-bands in the same scale of the original undistorted image has the similar structure and the Person correlation coefficient $\rho$ is the largest, the figure 1(e)-(f) are images distorted with different blur degree. The structures of their three high frequency sub-bands in the same scale are great different and the $\rho$ would be reduced with the increase in the standard deviation $\sigma$ of the Gaussian function (distortion degree deepening). Therefore, this paper uses the SVD to obtain the singular value vectors of the image high frequency sub-bands which represent their structural information, and then compute their difference which is considered as the last objective quality index.

![Figure 1](image_url)

Figure 1. the wavelet decomposition of the original image and the blur distorted images.

Proposed Method

Singular Value Decomposition of the Image

The singular value decomposition is a numerical algorithm for matrix diagonalization. The specific SVD is defined as follows, the matrix $A \in \mathbb{R}^{m \times n}$, there exists an orthogonal matrix (or unitary matrix) $U \in \mathbb{R}^{m \times m}$ and $V \in \mathbb{R}^{n \times n}$, so that $A$ can be expressed by the follow formula:

$$A = U S V^T$$

(1)

Where the matrix $S = \begin{bmatrix} S_2 & 0 \\ 0 & 0 \end{bmatrix}$, $S_2 = \text{diag}(\delta_1, \delta_2, \ldots, \delta_k)$, the diagonal entries $\delta_1 \geq \delta_2 \geq \ldots \geq \delta_k \geq 0$, $k=\text{rank}(A)$, the matrix $U$ is the left-singular value matrix and its column vector is the left-singular value vector of $A$; the matrix $V$ is the right-singular value matrix and its column vector is the right-singular value vector of $A$. The diagonal entries of $S_2$ are known as the singular values of $A$ [7].

A grey image could be expressed by a two-dimensional matrix, we can use SVD to decompose an image luminance matrix. The image singular value vector contains its main structural information. If we eliminate the singular value vector, the image quality would be changed greatly, as shown in
SVD can effectively extract the structural information of images, the literature [9] verified the method based on SVD that can still exhibit its good evaluation criteria when the image occurs translation, rotation and other geometric transformations. The proposed approach acquires the image wavelet high frequency singular value vectors by the SVD, and the last image quality index is the sum of the difference among the three vectors.

**Image Quality Assessment Algorithm Based on HFSVD**

The proposed method adopts the literature[9] which calculated the angle of the singular value vectors for reflecting their relevance. If they have strong correlation, the angle would tend to 0 degree, or tend to 90 degree for the weak correlation. The larger the angle the poorer quality is. The proposed algorithm based on HFSVD is divided into four parts as follows in detail:

1. Decomposing the blur image by Harr single level wavelet transform to get three high frequency sub-bands: the Vertical sub-band $I^v$, the Horizontal sub-band $I^h$ and the Diagonal sub-band $I^d$.
2. Using SVD to get the three singular value vectors of the different high frequency sub-bands: the singular value vector of the vertical sub-band $S^v$, the singular value vector of the horizontal sub-band $S^h$ and the singular value vector of the diagonal sub-band $S^d$.
3. Using the follow formula(2) to compute the angles among the three singular value vectors of the different high frequency sub-bands: the angle between the vertical sub-band and the horizontal sub-band $\text{Angle}(S^v, S^h)$, the angle between the vertical sub-band and the diagonal sub-band $\text{Angle}(S^v, S^d)$, the angle between the horizontal sub-band and the diagonal sub-band $\text{Angle}(S^h, S^d)$. The matrix $V$ and the matrix $\tilde{V}$ are the column vectors.. $k=\min(\text{rank}(V),\text{rank}(\tilde{V}))$.

$$\text{Angle}(V, \tilde{V}) = \arccos \frac{\sum_{i=1}^{k}(V_i \times \tilde{V}_i)}{\sqrt{\sum_{i=1}^{k}(V_i \times V_i) \times \sum_{i=1}^{k}(\tilde{V}_i \times \tilde{V}_i)}}$$

(2)

4. The last objective evaluation index based on HFSVD is the sum of the angles among the three singular value vectors: $\text{HFSVD} = \sum_{i \neq j} \text{Angle}(S^i, S^j)$, where the $i,j \in \{v, h, d\}$.

**Experimental Analysis and Discussion**

The proposed algorithm uses three common image databases to evaluate the performance: the LIVE2 database[10], the CSIQ database[11] and the TID2013 database[12]. After testing the HFSVD algorithm, the scatter plots of the subjective value versus objective value are shown in Figure 3. It shows the proposed objective evaluation have good consist with the subjective evaluation.
In order to analysis the performance of the proposed method compared with some algorithms of the references, we use the logistic function of Eq. (3) to regress the objective HFSVD value with the subjective value. It concludes five regression parameters, the x is built up by objective HFSVD value.

\[
\text{Quality}(x) = \beta_1 \left( 1 - \frac{1}{1+\exp(\beta_2(x-\beta_3))} \right) + \beta_4 x + \beta_5
\]

(3)

It uses two universal criterions to evaluate the performance of the HFSVD algorithm, after the nonlinear regression, the Correlation Coefficient (CC) and the Spearman Rank Order Correlation Coefficient (SROCC), the value of them are ranged from 0 to 1. Table 1 gives the detail performance of the HFSVD algorithm and some algorithm of references.

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<tbody>
<tr>
<td>LIVE2</td>
<td>0.7876</td>
<td>0.8189</td>
<td>0.9375</td>
<td>0.9478</td>
<td>0.9604</td>
<td>0.9337</td>
<td>0.8418</td>
<td>0.7906</td>
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<td>0.7625</td>
<td>0.8572</td>
<td>0.8963</td>
<td>0.9347</td>
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</tr>
<tr>
<td>TID2013</td>
<td>0.6667</td>
<td>0.6567</td>
<td>0.8154</td>
<td>0.8547</td>
<td>0.8228</td>
<td>0.8158</td>
<td>0.6923</td>
<td>0.6852</td>
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It shows only the proposed method and the literature[3] don’t need to train or create reference images. Although the performance of HFSVD algorithm is slightly weaker than the literature[5] and literature[8], but they all need training which are time-consuming and computational complexity. The best performance literature [8] also needs to create the reference images. By the test, the proposed method running one second can evaluate about five 768*512 resolution images on the Matlab of Core2 Duo CPU. The proposed HFSVD algorithm is simple and convenient to apply.

Summary

A simple and effective no reference blur image quality assessment algorithm is proposed in this paper which is based on wavelet HFSVD to solve the problem that traditional methods are complicated and high computation. As for a wavelet decomposed image, its different high frequency sub-bands in the same level are highly structural correlation, and the degree of correlation would be weaken as the degree of blur distortion strengthen. The method uses SVD to obtain structural information of the three different high frequency singular value vectors and by evaluating the correlation of these vectors to obtain the last image quality index. By testing on three databases, the simulation results show the HFSVD has good consist with the subjective evaluation. Due to it does not need training or creating the reference image, the proposed HFSVD algorithm is more effective and convenient, and visibly has good practicality. However, the blur distortion is just one of type distortion, how to evaluate other type distortions (like JPEG images, white noise images, etc.) effectively is the future work.

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