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SVD FILTER BASED MULTISCALE APPROACH FOR IMAGE QUALITY ASSESSMENT

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ABSTRACT

Automatic assessment of image quality in accordance with the human visual system (HVS) finds application in various image processing tasks. In the last decade, a substantial proliferation in image quality assessment (IQA) based on structural similarity has been observed. The structural information estimation includes statistical values (mean, variance, and correlation), gradient information, Harris response and singular values. In this paper, we propose a multiscale image quality metric which exploits the properties of Singular Value Decomposition (SVD) to get approximate pyramid structure for its use in IQA. The proposed multiscale metric has been extensively evaluated in the LIVE database and CSIQ database. Experiments have been carried out on the effective number of scales used as well as on the effective proportion of different scales required for the metric. The proposed metric achieves competitive performance with the structural similarity based state-of-the-art methods.

Index Terms— Image Quality Assessment (IQA), Structural Similarity, Singular Value Decomposition (SVD), Pyramid Structure.

1. INTRODUCTION

Image quality assessment algorithms are developed to find a common ground between the human perception and machine's evaluation of image quality. These algorithms aim to develop metrics that will be able to replace the subjective evaluation of images by human observers. However, subjective assessment is time consuming as well as expensive and it cannot be utilized in real time. On the contrary, objective image quality metrics are able to predict quality automatically. Automatic evaluation of the perceived image quality finds application for parameter tuning and benchmarking in various image processing related areas such as image acquisition, image compression, image fusion, image watermarking, image restoration and enhancement. In all of these applications above, human perception of the visible distortions acted as a measure of image quality. Any metric developed for image quality assessment is therefore subjected to test of its correlation with human perception. The better the correlation, the better the metric. The state-of-the-art IQA algorithms are of three types: Full Reference (FR), Reduced Reference (RR) and No Reference (NR). These names are according to the availability of the original/reference image with which the sample image is compared to. For FR, the original high quality image is available. In case of RR, partial information about the original is given and NR algorithms do not need any reference image. Under FR, the current state-of-the-art algorithms explore the structural similarity between the images to predict the image quality.

In this paper, a new approach based on multiscale SVD filter is proposed to determine FR image quality. At first, by using the SVD filter, approximate descriptions of the original and distorted images are obtained in different scales. After this, the structural similarity between two pyramidal structures is calculated to get the final value of the metric. The method being multiscale in nature, the optimum number of scales has been decided experimentally. Also, the relative contributions of the scales in shaping the metric is crucial and this problem has been analyzed experimentally.

The rest of the paper is arranged as follows. Earlier works related with the proposed method are discussed in section 2. Section 3 covers the details about the proposed method. The experimental results are discussed in section 4. Section 5 concludes the paper.

2. RELATED WORKS

The state-of-the-art metrics for finding structural similarity are discussed in this section.

2.1. Structural Similarity based IQA Metrics

Structural SIMilarity index (SSIM) was proposed by Wang et al. [1]. This is the basic metric which introduced the concept of structural similarity. Various modifications and enhancements have followed this metric [2, 3] thereby increasing its effectiveness. Structural Similarity based metric work under the assumption that HVS, in course of time, has developed the capability to derive the structural information from a scene. The pixels in a natural image have strong spatial dependencies carrying continuous structures in it. Considering the corresponding blocks from two images, the internal dependencies of the blocks can be analyzed. In [1], luminance, contrast and structure comparisons in a moving window/block are used to explore pixel interdependence to get the quality. Let I_1 and I_2 be two grayscale images to be compared and (x_1,y_1) be any pixel location selected from both of the images. Also, let w_1

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and w_2 be two blocks of size $m \times n$ selected from I_1 and I_2 respectively and convolved with Gaussian filter [1], considering (x_1,y_1) as the center. A luminance comparison L image is formed such that $L(x_1$,$y_1)$ can be calculated as

$$L(x_1, y_1) = \frac{2\mu_{w_1}\mu_{w_2} + C_1}{\mu_{w_1}^2 + \mu_{w_2}^2 + C_1}. \quad (1)$$

Here μ_{w_1} and μ_{w_2} denote the mean values of the blocks w_1 and w_2 respectively and C_1 is a constant. Also a contrast comparison image C and a structure comparison image S are calculated as

$$C(x_1, y_1) = \frac{2\sigma_{w_1}\sigma_{w_2} + C_2}{\sigma_{w_1}^2 + \sigma_{w_2}^2 + C_2}, \quad (2)$$

$$S(x_1, y_1) = \frac{\sigma_{w_{12}} + C_3}{\sigma_{w_1}\sigma_{w_2} + C_3}. \quad (3)$$

Here, σ_{w_1} and σ_{w_1} denote the standard deviation of the blocks w_1 and w_2 respectively with $\sigma_{w_{12}}$ as their correlation coefficient. C_1, C_2 and C_3 are constants included to avoid any instability caused when the denominator is very close to zero. The SSIM index map between I_1 and I_2 is defined as

$$SSIM(x_1, y_1) = [L(x_1, y_1)]^{\alpha}[C(x_1, y_1)]^{\beta}[S(x_1, y_1)]^{\gamma}. \quad (4)$$

Here, α, β and γ are the weights of the luminance, contrast and structure comparison images respectively. The mean of the SSIM index map is used as the similarity measure for the two images. The metric holds the property of being symmetric, being bounded by the upper limit 1 and is equal to 1 iff $I_1 = I_2$ which is referred as *Unique Maximum* [1]. The blocks extracted are overlapping ones and the border of the index map (depending on m and n) is excluded while calculating the mean. Further details about SSIM are given in [1]. Gradient-based Structural SIMilarity metric (GSSIM) [3] is similar to finding SSIM, with the only difference that SSIM is calculated between the gradient images obtained from the distorted and high quality images.

2.2. SVD based Approach for Structural Similarity

Singular Value Decomposition [4] is a way of factoring matrices into a series of linear approximations that expose the underlying structure of the matrix. Let X be a real (complex) matrix of order $m \times n$. The singular value decomposition (SVD) of X is the factorization

$$X = U * S * V^T \quad (5)$$

where U and V are *orthogonal (unitary)* matrices whereas S is a diagonal matrix whose entries are arranged in non-increasing fashion. The matrices U, V and S are the *left singular vectors*, *right singular vectors* and *singular values* respectively, associated with matrix X. A singular value decomposition (SVD) based approach, called M-SVD, is proposed in [5] for assessing structural similarity. The method works on the chrominance channel of the images. Blocks w_1 and w_2 of size $m \times m$ are extracted from same locations of the images I_1 and I_2. The blocks extracted from the images are non-overlapping ones. The SVD is applied on w_1 and w_2 to obtain the singular values in S_1 and S_2. The elements on the principal diagonal of S_1 and S_2 are copied in the arrays sv_{1j} and sv_{2j} respectively, where j corresponds to the j^{th} block. Since there are m singular values, the Euclidean distance between sv_{1j} and sv_{2j} for the j^{th} block is obtained by

$$D_j = \left[\sum_{i=1}^{m}(sv_{1j} - sv_{2j})^2\right]^{\frac{1}{2}}. \quad (6)$$

If there are total number of K non-overlapping blocks of size $m \times m$, M-SVD can be defined as

$$M - SVD = \frac{\sum_{j=1}^{K} |D_j - D_{median}|^2}{K}. \quad (7)$$

Here D_{median} is the median of distances D_j obtained from each block. This metric is symmetric and unbounded. This method provided good results for different distortion types [5].

2.3. Multiscale SSIM

MSSSIM was proposed by Wang et al. in [2]. SSIM, which is a single scale method, was modified to multiscale, so that the viewing distance and display resolution which affect human perception, can be embedded in MSSSIM. Also, a method to find the proportion in which different scales affect the human perception was introduced in this paper. The distorted and original images are iteratively downsampled by a factor of 2. From the downsampled image, at each iteration i, the contrast and the structure comparison images C and S are calculated as mentioned in section 2.1. The luminance comparison image is calculated at the final iteration only. Let the scale of original image be denoted by 1 and the highest scale be P. If mean of the luminance comparison image at scale P is L_P and those of contrast and structure comparison images at scale P are C_P and S_P respectively, the MSSSIM is defined as

$$MSSSIM = (L_P)^{\alpha_P} \prod_{k=1}^{P} (C_k)^{\beta_k}(S_k)^{\gamma_k}. \quad (8)$$

Here, α_P, β_k and γ_k are relative proportions of importance in each scale. For MSSSIM, $\alpha_k = \beta_k = \gamma_k$ is considered and their values were determined experimentally. For P scales, P weights were used. Also, $\sum_{k=1}^{P} \gamma_k = 1$ was maintained for normalization of the parameters across all scales.

3. PROPOSED METHOD

3.1. SVD based filter

Let X be a matrix with u_i and v_i as the columns of its singular vectors U and V respectively. Then, the SVD of X, given by Eqn. 5, can also be represented in truncated form as

$$X = \sum_{i=1}^{r} s_i u_i v_i^T \quad (9)$$

where s_i are the diagonal elements of S and $r \leq min(m, n)$ is the rank of matrix X. From Eqn. 9, it is clear that any matrix can be represented as a linear combination of the basis ($u_i\ v_i^T$). It is also obvious that the basis depends on the matrix X which makes SVD a unique representation of its own kind. The largest singular value captures almost only signal information whereas the smallest ones contain almost only noise [6]. Therefore, the representation of the matrix X corresponding to largest singular value is nothing but the approximate version of the original matrix with less noise.

Being inspired with this idea, an SVD based approximate filter which also has a pyramid structure is explored in this paper. The computation of SVD based filter corresponds to the following steps.

1. Segment X into non-overlapping blocks of size 2×2 and arrange each block into a 4×1 vector by stacking columns to form the matrix X_1 of size $4 \times (mn/4)$.
2. Generate corresponding centered matrix i.e. $\overline{X}_1$ followed by the scatter matrix (T_1) of size 4×4 by
$$T_1 = \overline{X}_1 \overline{X}_1^T \tag{10}$$
3. Let U_1 be the matrix of eigenvectors which diagonalize the scatter matrix T_1 i.e. $U_1^T T_1 U_1 = S_1^2$, where $S_1^2 = diag(s_1(1)^2, s_1(2)^2, s_1(3)^2, s_1(4)^2)$ contains the squares of singular values of $\overline{X}_1$ arranged in descending order of their values.
4. Construct a feature vector of length $mn/4$ corresponding to largest singular value ($s_1(1)$) as
$$F_V = U_1(:, 1)^T \overline{X}_1 \tag{11}$$

The feature vector F_V is constructed with the help of first column vector of U_1 which corresponds to largest singular value of $\overline{X}_1$. Therefore, it represents the approximate version (say X_A) of matrix X. X_A is obtained by simply stacking feature vector into an array with raster-scan manner. The size of X_A is $m/2 \times n/2$ since the length of F_V is $mn/4$. Hence, the approximate version X_A is the approximate downsampled version of X [6]. The above procedure is applied repeatedly on approximate version to realize the pyramid structure till desired level, each of which is called scale. Figure 1 shows the pyramid structure obtained by SVD based approximate filter. The image of scale 1 represents the original image and image of scale 2 is the downsampled filtered version of the original. Images of scale 3 and 4 are obtained by applying the SVD filter recursively on the image of scale 2.

3.2. IQA metric using SVD based filter

In the proposed method, a pair of original and distorted images is subjected to the SVD filter iteratively for P scales. So $(P - 1)$ images which gradually diminish in size by a factor of 4 are obtained from original and distorted images each. The contrast comparison image and its mean (C_j) along with the structure comparison and its mean (S_j) are obtained in each scale j from the corresponding filtered images. The luminance comparison image is calculated in the final scale only and therefore its mean (L_P) is obtained at scale P only. Thus, there are two types of blocks involved. The downsampling process involving SVD based filter uses block size 2×2 whereas the contrast, structure and luminance comparison images are calculated with block size 11×11. The final metric is then calculated according to Eqn. 8. Henceforth, the metric is named as SVD Filter based Similarity Index (SFIndex). SFIndex, therefore inherits the property of being bounded, symmetric and having unique maximum, from MSSSIM, unlike the other SVD based IQA metric M-SVD. The maximum value taken by SFIndex is 1 and that is obtained for a perfect match with the reference/original image. As the quality of the distorted image goes down, SFIndex decreases.

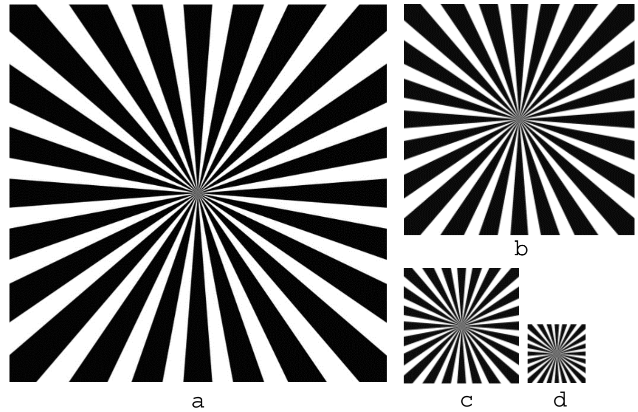

Fig. 1. Pyramid structure obtained by SVD based filter: (a), (b), (c) and (d) represent the filtered images at scale 1, 2, 3 and 4 resp.

4. EXPERIMENTAL RESULTS

The experiments have been carried out in two databases using different number of scales for the image decomposition. Also, interesting test results are found by varying the relative importance of different scales in building the metric. A comparative study of the proposed metric with the traditional and state-of-the-art methods has been made to strengthen the analysis.

4.1. Databases Involved and Performance Measures

The experiments have been carried out in the LIVE database [7, 8] and CSIQ Database [9]. LIVE database consists of 982 images (including hidden reference images). There are 29 original high quality images and they were distorted using the five techniques: JPEG2000 compression (JPEG2K), JPEG compression (JPEG), White Noise (Wh.Noise), Gaussian Blur (Blur) and transmission over a simulated fast-fading Rayleigh Channel (Fastfading). CSIQ Database has 30 high quality original images. 6 types of distortion techniques were applied at 4-5 different levels.

The distortion techniques used are: JPEG2K, JPEG, Additive White Gaussian Noise (AWGN), Additive Pink Gaussian Noise (APGN), Blur and Global Contrast decrements (CONTRAST). 866 distorted images are presented in the CSIQ database. Both of the databases have subjective quality scores from human observers and the human viewer ratings are reported in the form of Differential Mean Opinion Score (DMOS). The performance of the proposed metric is at first evaluated using Spearman's Rank Order Correlation Coefficient (SROCC) and Kendall's Rank Correlation Coefficient (KRCC). Then a logistic transform is applied to the quality scores given by the metric to bring them at par with the DMOS values. The logistic function used here is a five parameter function defined in [7]. After applying the logistic function, the predicted scores are compared with the DMOS values using Pearson's Linear Correlation Coefficient (LCC), Mean Absolute Prediction Error (MAE) and Root Mean Square (RMS). The definitions for SROCC, KRCC, LCC, MAE and RMS are all standard. SROCC and KRCC stand for prediction monotonicity and LCC is a measure of prediction accuracy ; the higher they are, the better the IQA values are suited to the HVS. MAE and RMS are measures of error; the lower they are, the closer the IQA values are related to DMOS values after logistic regression.

Table 1. Performance of SFIndex in LIVE Database for different scales

	Sc	SROCC	KRCC	LCC	MAE	RMS
JPEG2K	5	0.9477	0.7939	0.9531	3.9399	4.9082
	4	0.9477	0.7937	0.9532	3.9333	4.9017
	3	0.9496	0.7973	0.9542	3.8724	4.8506
	2	0.9512	0.7990	0.9552	3.8161	4.7963
JPEG	5	0.9015	0.7313	0.9335	4.0873	5.7833
	4	0.9023	0.7318	0.9341	4.0832	5.7568
	3	0.9052	0.7353	0.9366	3.9975	5.6480
	2	0.9090	0.7410	0.9404	3.7951	5.4791
Wh.Noise	5	0.9422	0.7898	0.9678	3.2419	4.0174
	4	0.9427	0.7910	0.9682	3.2340	3.9893
	3	0.9460	0.7950	0.9700	3.1818	3.8779
	2	0.9555	0.8174	0.9758	2.8272	3.4874
Blur	5	0.9618	0.8289	0.9666	3.3745	4.0303
	4	0.9626	0.8303	0.9671	3.3423	4.0011
	3	0.9623	0.8297	0.9661	3.3819	4.0608
	2	0.9593	0.8220	0.9579	3.6833	4.5175
Fastfading	5	0.9521	0.8234	0.9527	3.4125	5.0207
	4	0.9532	0.8247	0.9536	3.4051	4.9741
	3	0.9517	0.8188	0.9522	3.4708	5.0473
	2	0.9501	0.8107	0.9495	3.5859	5.1782

4.2. Effect of using Different Number of Scales

The proposed method is a multiscale method. Therefore, the number scales (Sc) needs to be determined. For this purpose, the relative importance of scales or weights are kept constant for 5 scales and these weights are given in [2]. Since we are varying the number of scales from 2 to 5 here, the weights should be normalized. For $i \in [2, 3, 4, 5]$ scales, first i weights are chosen out of 5 and normalized by dividing each of them with their sum-total upto i weights. The results for different types of distortions in LIVE Database are summarized in Table 1. As observed from the results, the choice of 5 scales is not optimum for all distortions. In LIVE database, for less scales, better performance of the SFIndex is achieved for JPEG2K, JPEG and Wh.Noise. As the number of scales are increased, finer details are lost more. But finer details are suppressed to a larger extent than coarse scales for these image coding techniques [2]; hence more scales may not contribute for the better performance of the metric. Since, the SVD based filter selects the eigenvector corresponding to the largest singular value, most of the noise get filtered out in the process. The more the number of scales, the higher is the reduction of noise. And therefore, for JPEG2K, JPEG and WN, the approximate images are more similar at higher scales. For Blur and Fastfading, best results are obtained by using more scales. These distortions affect the finer scales but due to frequency spreading imposed by them, lower frequency components are affected as well. Hence, at larger scales, the images look dissimilar and higher scales contribute in the better performance of the metric. So, best of the metric is brought out at higher scales for Blur and Fastfading. The test results for different scales in CSIQ database is given in Table 2. We observe that for images in CSIQ database, a similar trend is followed by the metric for JPEG. Also AWGN and APGN are random noises and hence the metric performs better at lower scales for them. Blur is best perceived at higher scales. However, for global contrast decrement the performance across different number of scales is quite similar.

4.3. Effect of using Different Set of Weights across the Scales

The trend of the values of relative importance of scales or weights as mentioned in [2] is similar to a bell shaped curve which implies that the weights may be modeled using a Gaussian/Normal distribution. This fact inspired us to use normally distributed weights as a measure of the relative importance across scales. The results for LIVE database reported in the Table 3 represent the scores for normalized uniform weights across all scales as well as for the weights according to Gaussian distributions with variance σ^2 ranging from 1 to 5. As the variance of the weights increases, the weights become more uniform. Therefore, the evaluations of SFIndex with normalized uniform weights and with variance 5 are similar. In LIVE database, except for images having Gaussian Blur as distortion, the correlation (both LCC and SROCC) increases as σ^2 is increased. Only for the Gaussian Blur, a significant improvement is observed for small variance (= 1) of weights. Similar phenomena is observed with our experiments in CSIQ database. These experiments, therefore in-

Table 2. Performance of SFIndex in CSIQ Database for different scales

	Sc	SROCC	KRCC	LCC	MAE	RMS
JPEG2K	5	0.9629	0.8366	0.9760	5.1797	6.8781
	4	0.9633	0.8374	0.9766	5.0932	6.7919
	3	0.9631	0.8346	0.9762	5.1452	6.8504
	2	0.9608	0.8272	0.9732	5.4377	7.2678
JPEG	5	0.9543	0.8090	0.9736	5.2017	6.9999
	4	0.9555	0.8111	0.9745	5.0983	6.8704
	3	0.9574	0.8169	0.9765	4.8645	6.5983
	2	0.9594	0.8220	0.9812	4.3860	5.9065
AWGN	5	0.9065	0.7242	0.9054	5.5465	7.1272
	4	0.9085	0.7260	0.9072	5.5134	7.0628
	3	0.9107	0.7360	0.9097	5.4002	6.9729
	2	0.9235	0.7557	0.9227	4.8644	6.4825
APGN	5	0.8823	0.6934	0.8950	8.1283	10.0960
	4	0.8922	0.7082	0.9034	7.7478	9.7060
	3	0.9057	0.7272	0.9143	7.2526	9.1686
	2	0.9233	0.7585	0.9330	6.4866	8.1496
Blur	5	0.9726	0.8496	0.9702	5.2172	6.9420
	4	0.9723	0.8493	0.9698	5.2223	6.9838
	3	0.9705	0.8446	0.9662	5.4172	7.3981
	2	0.9635	0.8296	0.9538	6.0169	8.6600
Contrast	5	0.9548	0.8203	0.9619	3.6176	4.6000
	4	0.9553	0.8209	0.9617	3.6320	4.6168
	3	0.9547	0.8192	0.9611	3.6563	4.6555
	2	0.9543	0.8186	0.9602	3.7015	4.7050

dicate that the images having blur are handled in a different fashion by the HVS. For blur, the maximum impact and best performance come from the scales at the higher range.

4.4. Comparative Study

A comparative study of the proposed method with other methods is presented here. The proposed method is compared against 5 well-known methods used to find structural similarity: Peak Signal-to Noise Ratio (PSNR), SSIM [1], GSSIM [3], MSSSIM [2], Harris Response Quality Measure(HRQM) [10] and M-SVD [5]. The LCC scores for 5 types of metrics and different types of distortions are presented for LIVE database in Table 5. For, individual distortions, SFIndex has been calculated with 5 scales and weights with $\sigma^2 = 5$ except for Gaussian Blur where weights are with variance $\sigma^2 = 1$. The parameter σ is chosen according to the best performance of SFIndex with individual distortion types. The proposed metric achieves improved performance over state-of-the-art methods in JPEG2K, Gaussian Blur and Fastfading and Contrast. However, a good performance with individual distortion types not necessarily ensure the same across all distortions. Overall comparison across all distortions has been shown for both of the databases and that has been found using number of scales $Sc = 2$. The comparison of SFIndex in CSIQ database is also shown in Table 5. The proposed method performs better than state-of-the-art methods for blur and global contrast decrement. In case of random noise, MSSSIM and PSNR are found to be better predictors of image quality compared to the proposed metric. This is because the SVD approximate filter considers the largest singular values which are less sensitive to noise and so the metric cannot deliver its best for random noise. In both of the databases, SFIndex achieves better prediction accuracy across all distortions.

Table 3. Performance of SFIndex in LIVE Database for different weights

	Weights	SROCC	KRCC	LCC	MAE	RMS
JPEG2K	Equal	0.9544	0.8070	0.9576	3.7591	4.6648
	$\sigma^2 = 1$	0.9462	0.7906	0.9520	3.9750	4.9634
	$\sigma^2 = 2$	0.9527	0.8056	0.9571	3.7898	4.6965
	$\sigma^2 = 3$	0.9538	0.8061	0.9575	3.7709	4.6727
	$\sigma^2 = 4$	0.9537	0.8061	0.9576	3.7657	4.6679
	$\sigma^2 = 5$	0.9545	0.8074	0.9577	3.7637	4.6661
JPEG	Equal	0.9124	0.7484	0.9411	3.7494	5.4454
	$\sigma^2 = 1$	0.8996	0.7276	0.9319	4.1556	5.8474
	$\sigma^2 = 2$	0.9092	0.7446	0.9398	3.8204	5.4993
	$\sigma^2 = 3$	0.9102	0.7459	0.9407	3.7742	5.4664
	$\sigma^2 = 4$	0.9115	0.7477	0.9409	3.7612	5.4532
	$\sigma^2 = 5$	0.9119	0.7485	0.9410	3.7558	5.4543
Wh.Noise	Equal	0.9541	0.8148	0.9759	2.8178	3.4850
	$\sigma^2 = 1$	0.9409	0.7862	0.9662	3.3174	4.1146
	$\sigma^2 = 2$	0.9504	0.8065	0.9736	2.9428	3.6437
	$\sigma^2 = 3$	0.9526	0.8115	0.9749	2.8724	3.5538
	$\sigma^2 = 4$	0.9532	0.8130	0.9753	2.8480	3.5232
	$\sigma^2 = 5$	0.9532	0.8134	0.9756	2.8372	3.5093
Blur	Equal	0.9514	0.8063	0.9540	3.8725	4.7112
	$\sigma^2 = 1$	0.9616	0.8282	0.9674	3.3410	3.9859
	$\sigma^2 = 2$	0.9553	0.8130	0.9590	3.6978	4.4561
	$\sigma^2 = 3$	0.9525	0.8080	0.9564	3.7924	4.5921
	$\sigma^2 = 4$	0.9523	0.8077	0.9554	3.8273	4.6433
	$\sigma^2 = 5$	0.9521	0.8075	0.9550	3.8436	4.6675
Fastfading	Equal	0.9582	0.8284	0.9605	3.2283	4.5865
	$\sigma^2 = 1$	0.9490	0.8178	0.9508	3.4735	5.1250
	$\sigma^2 = 2$	0.9571	0.8289	0.9589	3.2301	4.6802
	$\sigma^2 = 3$	0.9579	0.8287	0.9598	3.2188	4.6262
	$\sigma^2 = 4$	0.9577	0.8276	0.9601	3.2221	4.6076
	$\sigma^2 = 5$	0.9578	0.8274	0.9603	3.2241	4.5988

5. CONCLUSION AND FUTURE WORKS

We have proposed an SVD filter based mutliscale IQA metric. The performance of the proposed method has been evaluated in the LIVE and CSIQ database and have shown to demonstrate better results for blur, fastfading and global contrast decrement. Also, experiments regarding the optimum number of scales and relative importance of scales have clearly demarcated blur as a special kind of distortion that needs to be handled differently. Future work involves the modification of this method for better performance with images having random noise as well.

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6. REFERENCES

[1] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: From error visibility to structural similarity,” *IEEE Trans. Image Processing*, vol. 13, no. 4, pp. 600–612, 2004.

[2] Z. Wang, E. P. Simoncelli, and A. C. Bovik, “Multi-scale structural similarity for image quality assessment,” in *IEEE Asilomar Conf. on Signals, Systems, and Computers*, 2003, pp. 1398–1402.

[3] G.-H. Chen, C.-L. Yang, and S.-L. Xie, “Gradient-based structural similarity for image quality assessment,” in *Int. Conf.on Image Processing*, 2006, pp. 2929–2932.

[4] G. H. Golub and C. F. V. Loan, “Matrix computations,” *John Hopkins University Press*, 1996.

[5] A. Shnayderman, A. Gusev, and A. M. Eskicioglu, “An svd-based grayscale image quality measure for local and global assessment,” *IEEE Trans. Image Processing*, vol. 15, pp. 422–429, 2006.

[6] R. Kakarala and P. Ogunbona, “Signal analysis using a multiresolution form of the singular value decomposition,” *IEEE Trans. Image Processing*, vol. 10, pp. 724–735, 2001.

[7] H. R. Sheikh, M. F. Sabir, and A. C. Bovik, “A statistical evaluation of recent full reference image quality assessment algorithms,” *IEEE Trans. Image Processing*, vol. 15, pp. 3440–3451, 2006.

[8] H. R. Sheikh, Z. Wang, L. Cormack, and A. C. Bovik, “Live image quality assessment database release 2,” *http://live.ece.utexas.edu/research/quality*.

[9] E. C. Larson and D. M. Chandler, “Most apparent distortion: full-reference image quality assessment and the role of strategy,” *Journal of Electronic Imaging*, vol. 19, pp. 011006, 2010.

[10] D.-O Kim and R.-H. Park, “New image quality metric using the harris response,” *IEEE Signal Processing Letters*, vol. 16, pp. 616–619, 2009.

Table 4. Performance of SFIndex in CSIQ Database for different weights

	Weights	SROCC	KRCC	LCC	MAE	RMS
JPEG2K	Equal	0.9681	0.8441	0.9792	4.9704	6.3989
	$\sigma^2 = 1$	0.9622	0.8350	0.9753	5.2260	6.9725
	$\sigma^2 = 2$	0.9672	0.8439	0.9790	4.9358	6.4415
	$\sigma^2 = 3$	0.9676	0.8439	0.9792	4.9386	6.4014
	$\sigma^2 = 4$	0.9680	0.8442	0.9793	4.9520	6.3968
	$\sigma^2 = 5$	0.9679	0.8439	0.9793	4.9586	6.3964
JPEG	Equal	0.9610	0.8254	0.9811	4.5322	5.9128
	$\sigma^2 = 1$	0.9530	0.8068	0.9715	5.3553	7.2758
	$\sigma^2 = 2$	0.9593	0.8202	0.9790	4.7322	6.2340
	$\sigma^2 = 3$	0.9605	0.8234	0.9802	4.6192	6.0448
	$\sigma^2 = 4$	0.9609	0.8249	0.9806	4.5835	5.9840
	$\sigma^2 = 5$	0.9608	0.8249	0.9808	4.5657	5.9575
AWGN	Equal	0.9299	0.7673	0.9289	4.5724	6.2316
	$\sigma^2 = 1$	0.9053	0.7224	0.9038	5.6241	7.1826
	$\sigma^2 = 2$	0.9250	0.7579	0.9239	4.7858	6.4339
	$\sigma^2 = 3$	0.9276	0.7637	0.9267	4.6530	6.3212
	$\sigma^2 = 4$	0.9292	0.7664	0.9278	4.6171	6.2775
	$\sigma^2 = 5$	0.9293	0.7662	0.9281	4.6009	6.2606
APGN	Equal	0.9090	0.7324	0.9185	7.0990	8.9542
	$\sigma^2 = 1$	0.8659	0.6703	0.8773	8.8769	10.8593
	$\sigma^2 = 2$	0.8968	0.7149	0.9085	7.5372	9.4568
	$\sigma^2 = 3$	0.9031	0.7243	0.9143	7.2860	9.1691
	$\sigma^2 = 4$	0.9061	0.7283	0.9161	7.2039	9.0734
	$\sigma^2 = 5$	0.9067	0.7292	0.9170	7.1652	9.0305
Blur	Equal	0.9696	0.8414	0.9654	5.5433	7.4763
	$\sigma^2 = 1$	0.9729	0.8503	0.9707	5.1733	6.8845
	$\sigma^2 = 2$	0.9719	0.8486	0.9678	5.3837	7.2139
	$\sigma^2 = 3$	0.9708	0.8454	0.9666	5.4695	7.3471
	$\sigma^2 = 4$	0.9705	0.8443	0.9661	5.5003	7.4013
	$\sigma^2 = 5$	0.9702	0.8432	0.9658	5.5155	7.4279
Contrast	Equal	0.9543	0.8192	0.9622	3.7015	4.5837
	$\sigma^2 = 1$	0.9548	0.8192	0.9618	3.6167	4.6074
	$\sigma^2 = 2$	0.9542	0.8185	0.9621	3.6082	4.5891
	$\sigma^2 = 3$	0.9543	0.8192	0.9622	3.6076	4.5859
	$\sigma^2 = 4$	0.9543	0.8189	0.9622	3.6070	4.5849
	$\sigma^2 = 5$	0.9543	0.8192	0.9622	3.6070	4.5845

Table 5. Comparison of Proposed Method with other methods using LCC scores on LIVE and CSIQ Databases

Database	LIVE Database						CSIQ Database						
Methods	JPEG2K	JPEG	Wh.Noise	Blur	Fastfading	All	JPEG2K	JPEG	AWGN	APGN	Blur	Contrast	All
PSNR	0.8875	0.8587	0.9809	0.7840	0.8752	0.9280	0.9467	0.8852	0.9437	**0.9526**	0.9241	0.8887	0.7999
SSIM [1]	0.9365	0.9295	0.9793	0.8740	0.9448	0.9386	0.9177	0.9319	0.9254	0.8937	0.8937	0.7430	0.8144
GSSIM [3]	0.9381	0.9341	0.9591	0.9071	0.9477	0.9562	0.9098	0.9485	0.8516	0.8517	0.8938	0.8220	0.8458
MSSSIM [2]	0.9571	**0.9411**	**0.9843**	0.9565	0.9451	0.9462	0.9776	**0.9823**	**0.9469**	0.9427	0.9657	0.9513	0.8986
HRQM [10]	0.8697	0.8564	0.8525	0.8478	0.9271	0.9376	0.9066	0.9024	0.7957	0.7927	0.9295	0.9308	0.8152
M-SVD [5]	0.9521	0.9127	0.9717	0.8171	0.9273	0.8716	**0.9808**	0.9406	0.9435	0.9077	0.9108	0.8753	0.7750
SFIndex	**0.9577**	0.9410	0.9756	**0.9674**	**0.9603**	**0.9491**	0.9793	0.9808	0.9281	0.9170	**0.9707**	**0.9622**	**0.9040**