SISI Metric: Image Quality Assessment from Edge Information based on Local Polynomial Approximation Model

K.Rajkumar, V.Alamelumangai

Abstract: ***The quality assessment of an image plays an important in image processing application systems. Smoothness is one of the most determining factors in the perceptual assessment of image quality. In order to easily and rapidly forecast the image quality, Smoothness and Sharpness computation plays a vital role in the optimal design image processing algorithms. This paper introduces a novel image quality index, Sensed Image Smoothness Index (SISI) that defines the image quality irrespective of the noise. The high quality images are acquired from the public repository, Computation Visual Cognition laboratory that composes of natural scenery images. The acquired images are added by three different noises, namely gaussian, poisson and Heteroscadiscity at different levels and then removed by Local Polynomial Approximation (LPA) model that define the local and global features of an image. With the global features, the SISI metric is designed under multiple thresholds. Initially, the edge oriented information is retrieved from the denoised image. Relied upon the weighting coefficient, the developed SISI metric depicts the accurate information for achieving better image quality. It is evident from the results that the proposed model achieves better explicability of an image.***

Index Terms: ***Quality assessment, Smoothing, Natural scenery images, Local Polynomial Approximation and Multiple thresholds.***

I. INTRODUCTION

With the recent developments in digital imaging system along with internet services, the digital images become a part of our daily life. The users can find tremendous amount of images from variant sources like facebook, flicker, google etc. Depending on the level of noise, blur illumination and pose, the quality of an image is depicted. In some cases, the sources of the distorted image can be found and thus blindly evaluating the quality of the distorted image. The blind assessing of the image quality becomes an important study. At present, the blind image quality assessment is classified into two groups, namely, a) distortion specific methods and b) distortion independent methods [1]. The distortion specific methods analyses the image quality by the given artifacts, whereas the distortion independent methods analyses in general purpose BIQA, which is a cumbersome task. The block diagram of IQA is given in Fig.1. In the communication of digital image's lifecycle, the images may be degraded due to variant facts. These degraded data leads to the loss of information and thus the quality of the image is worsened. The issue of quality assessment on visual information originated in image/ video processing that comprises of Image Compression, Image Transmission and Image Retrieval [2]. Though there are several ways to communicate the images, still the technologies lacks in preventing the image distortion. The image processing techniques like acquisition, compression, digitization, transmission, storage etc lead to the image distortion. Thus, the distortions determination in an image is an important process to validate the quality of the images to the above listed applications.

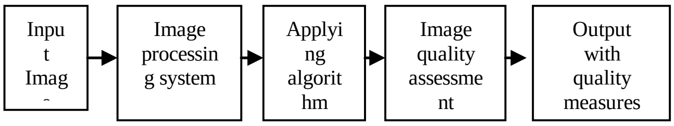

Fig.1. Block diagram of IQA

The images may degrade its quality due to low visual information; capture settings like lighting, exposure, aperture, sensitivity and limitation of lens. If these settings are not processed properly, an unsatisfactory result is obtained. When the image quality is reflexively predicted, the quality of the image can be easily analysed. Several analyses are done on the Image Quality Assessment that sorted into three groups: a) Full Reference- Image Quality Assessment b) Reduced Reference- Image Quality Assessment c) No reference- Image Quality Assessment. Fundamentally, the image quality is analyzed into two ways: a) Subjective quality and b) Objective quality. With the advent of Mean Opinion Score (MOS) [3] value by the humans, the subjective quality is measured. And, by the use of algorithms the objective score is analyzed. The image analysis using no-reference is a challenging task. Without the use of reference image and details about distorted image, the quality assessments of an image are troublesome task. The purpose of the NR-IQA is to design computational model that discovers the quality of the images with reference to human scores or any subjective measures. Three regression models are designed for feature extraction process. The weighted metric is used for measuring the quality of the images.

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The contributions made in this paper are:

a) Smoothing information of an image play a vital role in Image Quality Assessment (IQA).
b) The acquired images are of high quality which composes of natural scenery images.
c) Image Denoising and Image Quality Index (IQI) are important step in our research model.
d) Developed Local Polynomial Approximation (LPA) which discovers the local and global features of the denoised images.
e) Designed novel metric, Sensed Image Smoothness Index (SISI) which intelligently describes the quality of an image.

The paper is unionized as follows: Section II describes the prior works; Section III describes proposed work; Section IV presents the experimental results and analysis and concludes in Section V.

II. LITERATURE SURVEY

The previous Blind IQA models dealt with certain kind of distorted images to predict the quality of the images. Distortion specific models declined the visual quality of the images in terms of patch boundaries. In recent years, a general design for NR-IQA is explored. The author in [4] suggested a group of evaluation metrics to recover visual quality of the images like sharpness, random and structured noise. Using the similar metrics, Gabarda and Cristobal suggested the use of anisotropies. A visual codebook is formed by extracting local appearance from Gabor filter model. Each vector is associated with an image patch that connects the DMOS assigned scores. Packet loss [5] is found in the image patches. This model incurred high computational complexity.

Then, the study is focused on feature extraction models. Feature extraction relied on the nature image statistics, distortion texture statistics and blur/noise statistics. It collectively contain ensemble of learning models with those features. The advents of Curvelet, wavelet and cosine transforms are studied in [6]. The above discussed models worked on different sorts of distorted images. Yet, it restricted to define the new distorted images. The Natural Scene Statistics (NSS) database was studied in Full –Reference (FR) [7] [8] [9], Reduced- Reference (RR) [10] and No-Reference (NR) [11, 12 and 13] algorithms, to measure the visual characteristics of an image. The output obtained from the NSS followed simple Quality Assessment (QA) algorithms. The Distortion Identification based Image Integrity and Verity Evaluation (DIIVINE) used to evaluate the NSS coefficient model that involves two step frameworks. The DIIVINE model performed better in LIVE IQA database [14] in terms of Structural Similarity (SSIM) index. A similar model was developed named, BLind Image Notator (BLINDS) that obtains the features of Discrete Cosine Transform (DCT). The features of an image are computed and that forms as a block of DCT coefficients to predict the quality of an image. It fall under the class of single stage algorithm, it performed better in the No-Reference IQA. Both the algorithm failed to deliver in real-time applications.

The practices of polynomial functionalities in Image Processing System (IPS) have been studied. In the preceding years, it was widely applicable to Medical Image Processing Systems (MIPS) [15]. The medical images are studied in two steps, resampling and interpolation methods. Hybrid methods are suggested by [16]. They suggested statistical evaluation of 26 image quality measures. Depending upon the information, it was classified into several groups. Developed Distortion and Noise Quality Measure (NQM) were measured for restoration techniques. They also depicted the spatial frequency like local luminance, contrast effect and contrast masking. Yet, the information loss is higher. In [17], SSIM was improved using multiscale model that computed the overall SSIM values. Since the images are observed from multiscale analysis, the structural information is preserved. Another metric, information fidelity criterion that defines the difference between reference and distorted images are calculated. Similar metric was studied using gaussian mixture model which depicts visual information fidelity.

In [18], Visual Signal to Noise Ratio (VSNR) was studied with the baseline of wavelet transform. This process assisted better objective analysis score. The author in [19] studied about the perceptual quality assessment of images. In specific to, binocular characteristics of the images are analyzed. It was analyzed on five databases which yielded better performance. Statistical based quality modelling was developed using local correlation that extracted the relevant features and then computed quality score. Discrete Cosine Transform (DCT) [20] was applied on the reduced reference image modeling that measured the differences of spatial properties. It was further extended to fractal dimension.

. The author in [21] studied about application specific approach for smart cameras which improved the robustness of the image quality algorithm. In [22], they developed two-steps frameworks for natural scene statistics image that computed the blind image quality index. Each distortion in an image portrays some unique quality features. The computed BIQI score was not applicable to the practical possibility. The study was further extended to the JPEG images. The serious drawback is on feature extraction models [23]. By enhancing the contrast features such as gradient magnitude and Laplacian of gaussian response of an image, the objective quality was explored [24]. Database used for validation is the LIVE database [25]. They further have developed an NR-IQA model which is highly training free and distorted image have certain latent characteristics which are different from those of original image/ natural image.

III. PROPOSED METHODOLOGY

A. Motivation

Speed is an important factor for NR-IQA systems, as of NR-IQA images are widely used in real time imaging or communication systems. It is limited to support highly expensive image transforms applications. The previous algorithms CORNIA and BRISQUE have significantly applied with higher accuracy rate but information loss is high. By using a compact set of image interpolation algorithm, our method can further facilitate the accuracy of image processing systems. Conventional image quality measures developed for natural scene images may not work well in terms of smoothness analysis. Building a NR-IQA system that can be adapted to images with different characteristics is a cumbersome issue. Edge Information is more important for image analysis and interpretation. Most of the spatial domain techniques examine the regions around the image edges that are influenced by smoothing or smearing effect under blurred images.

B. Proposed model

In this work, we develop a novel metric, coined as Sensed Image Smoothness Index (SISI) that defines the smoothness in an image for its quality analysis. The SISI make use of spatial domain images which outperforms by using enhanced edge computational models. In addition, the gradient of the edges have also analyzed that models using local gradient information in view of smoothness. Our proposed method is computationally rapid and easily evaluates the properties of the Human Visual System (HVS). Several researchers have found that the human eyes are very sensitive to the image edge and contrast. The objective of the study is to introduce a novel SISI metric that depicts the smoothness quality of image using edge oriented information. Generally, there is a high correlation between red, green and blue channels of natural images and its relevance to define the edges. By accurately defining the local information of an image, the edge can be computed, smoothly. The proposed algorithm contains the following steps:

1) Noise generation:

Noise generation is an important step in the image processing systems. The collected quality images are applied to three types of noises, namely, Gaussian noise, Poisson Noise and Heteroscedasticity with four variant noise levels.

2) Gaussian Noise:

Gaussian noise is the type of noise evenly distributed to the signal. Each pixel contain sum of true pixel value and random Gaussian distributed noise value. This type of noise degrades the illumination details of an image. It is given as follows:

$$p(z) = \frac{1}{\sqrt{2\prod\sigma}} e^{-(z-\mu)^2/2\sigma^2} \qquad (3.1)$$

Where P(z) is the Gaussian noise in image; μ and σ are the mean and standard deviation respectively.

3) Poisson Noise:

Poisson noise is the noise that depicts the statistical errors due to finite particles. It is also known as photon noise that randomly works on the probability distribution model. It is given as follows:

$$P(f_{(pi)}) = k = \frac{\gamma^k e_i^{-\gamma}}{k!} \qquad (3.2)$$

Where k is the pixel information and γ is the number of photons per unit time.

4) Heteroscedastic noise:

It describes the linear relation between expectation and variance of a pixel by correcting the gamma. It is given as follows:

$$x_i \sim N\left(\mu_{x_i}, a\mu_{x_i} + b\right) \quad (3.3)$$

Where x_i indicates the raw pixel and μ_x indicates the expectation of the random variable x.

5) Image Denoising:

Image denoising is the second step of our proposed algorithm which eliminates the added noise in an image using local polynomial approximation model. Assume an image I with denoising operator on filtering parameter F_p. Thus, image divergence is given as:

$$I - D_{F_p} I \quad (3.4)$$

The primary objective of the denoising model is not to interpolate the non- noisy images. Since the image with better quality is also prone to the noise, image denoising plays a vital role in image quality assessment system. The main aim of the LPA is to specify the region of the extracted pixel to its local neighborhood structure of the pixel. In this work, the neighborhood pixels supposed to be homogeneous color and edge properties. By doing so, it helps to achieve better edge pixels analysis for a wider range of points. A row of pixel data is created for devising the local fluctuations of pixels. Thus, the pixel X is computed as:

$$\mu^{(F_P)} = \sum_{j=1}^{F_P} g_j^{F_P} I(X + (j-1)\theta_i) \quad (3.5)$$

Where $g^{(Fp)}$ is the Convolutional kernel with the window size. In relevance to center pixel X, the pixel weights j=1...F_p. Then, the local content is retrieved by adjusting the window size with filtering parameter. The local standard deviation is given as follows:

$$\sigma_\mu(F_p) = \sigma \left\| g^{(F_P)} \right\| \quad (3.6)$$

Then, each pixel at direction θ_i at different polynomials is given as:

$$D_{F_p} = \left[\mu^{F_p} - \tau\sigma_{\mu(F_p)}, \mu^{F_p} + \tau\sigma_{\mu(F_p)}\right] \quad (3.7)$$

Where τ>0 depicts the global parameter that checks tolerance of noise. Finally, we have obtained the denoised image.

6) Sensed Image Smoothness Index:

Sensed Image Smoothness Index (SISI) is the novel metric designed in this step. With reference to denoised image, the novel metric is generated. Since edge of an image depicts lot of tiny contents of an image, we have also employed edge detections with multi-threshold values. An optimal threshold value is being chosen from the set of obtained thresholds.

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Generally, it is noted that HVS observes clear information when the threshold is high and vice versa. Hence, a multiple-threshold is designed for our proposed work to retrieve information of low and high quality images. The proposed steps are as follows:

a) Let the set of thresholds be Ts of an image I, as CannyEdgDet (I, t) where t is the optimal threshold.

b) Let $B^{(t)}$ be the optimal edge value of given threshold t.

c) Let $B^{(t)}_{plain}$ and $B^{(t)}_{Denoise}$ be the binary edge of the plain images and denoise images in which 0 indicates non-edge point and 1 indicates edge point.

d) The computed edges are constrained to:

$$B^{(t)}(i,j) = \begin{cases} 1 - \frac{|plain(i,j) - Denoise\ (i,j)|}{m} & \text{if } B^{(t)}_{plain}(i,j) \wedge B^{(t)}_{denoise}(i,j) = 1; \\ 0 & \text{otherwise} \end{cases} \quad (3.8)$$

Where m is the adjustment of luminance ranges from [0,255].

e) The similarity of the edge is detected as follows:

$$E(Plain, Denoise) = \frac{N(B^{(t)}_{Plain})}{N(B^{(t)}_{Denoise})} \quad (3.9)$$

Where N is the non-zero elements of the images.

f) Since threshold t assists for better decision, the improved canny edge detection with different threshold are [0.0, 0.1], [0.1, 0.2] and [0.2, 0.3]. It is observed that high discontinuity points will depict stronger edge information for Human Visual System (HVS).

Finally, the smoothness index between plain and denoised image are computed as follows:

$$SISI\ (I_{plain}, I_{Denoise}) = \rho\ E\ (I_{plain}, I_{Denoise}) + (1-\rho)\ \tau^{i}_{j} \quad (3.10)$$

Where $\rho = 1 - a(2^{E(plain,denoise)} - 1)\ ;a \in (0,0.5)$

$\tau^{i}_{j} \in 1$ is the weighting coefficient of an indexed edge.

The framed formula is of three folds,

i) In HVS, edge information dictates the accurate information to visual perception than the textural features.

ii) The contribution of edge information presents stronger perceptual system.

iii) The deviation between noise and denoise should not vary too sensitively. Because gradient information indicates the image quality.

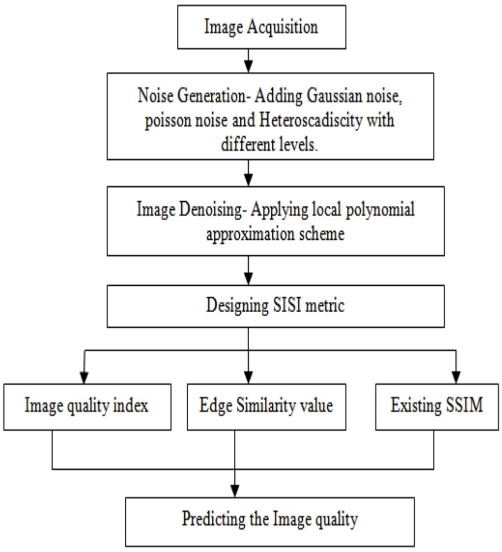

Fig.2 Proposed workflow

IV. Experimental Results

This section depicts the experimental results of our proposed algorithm. The dataset is obtained from the well-reputed repository, Computation Visual Cognition laboratory. This database contains 8 datasets, namely, coast, forest, highway, inside city, mountain, open country, street and tall building in which each contain more than 300 images. The sample images are placed in fig.3.

Fig.3: (a) coast (b) forest (c) highway (d) inside city (e) mountain and (f) open country.

Though, the acquired images are of high quality, the noises are added to the images in order to effectively determine the quality of an image. The table 1 dictates the level of noise settings to an image. In our work, we have analyzed three metrics, namely, SISI, proposed SSIM and existing SSIM. Generally, SSIM depicts the structural information from a scene for the perceptual quality that ranges from 0 to 1. Our proposed SSIM computed from edge based structural information which provides better perceptual systems. It is evident from the results that our proposed SSIM performs better than existing SSIM. The obtained SISI metric yields greater than 1 which depicts better perceptual quality.

The table 1 dictates the noise level used for analysis purpose. Table 2 -4 depicts the performance analysis of poisson noise, gaussian noise and Heteroscadiscity noise The threshold value SSIM and SISI value is set to above 1.It is inferred from the tables that the proposed model exhibits better outcome than the existing models.

TABLE: 1 IMAGE PREPROCESSING- NOISE GENERATION

Noise type	*Level 1*	*Level 2*	*Level 3*	*Level 4*
Gaussian noise	12.75	9.2	4.2	0.5
Poisson noise	0.1	0.7	0.9	1.2
Heteroscadiscity	20	10	5	0.5

TABLE 2: PERFORMANCE ANALYSIS FOR POISSON NOISE

Noise level	Image details	SISI	Proposed SSIM	Existing SSIM
12.75	Coast	1.235378	0.999101	0.918949
	Forest	1.578622	0.994951	0.75687
	Highway	1.355561	0.998482	0.830316
	Inside city	1.199361	0.998173	0.900314
	Mountain	1.285559	0.998372	0.888535
	Open country	1.548578	0.99565	0.722036
9.2	Coast	1.186205	0.999231	0.937066
	Forest	1.469949	0.995579	0.799039
	Highway	1.310501	0.998685	0.860366
	Inside city	1.128525	0.998691	0.931111
	Mountain	1.184948	0.998772	0.916038
	Open country	1.443791	0.99622	0.760761
4.2	Coast	1.078582	0.999523	0.960324
	Forest	1.33314	0.99657	0.857992
	Highway	1.099746	0.99929	0.909842
	Inside city	1.018888	0.999488	0.968707
	Mountain	1.036233	0.999291	0.952512
	Open country	1.308897	0.997099	0.820328
0.5	Coast	1.031043	0.999671	0.970982
	Forest	1.281375	0.997042	0.880392
	Highway	1.048348	0.99958	0.950615
	Inside city	0.995717	0.999777	0.986311
	Mountain	0.969538	0.999626	0.969969
	Open country	1.240619	0.997616	0.842191

TABLE 3: PERFORMANCE ANALYSIS OF GAUSSIAN NOISE

Noise level	Image details	SISI	Proposed SSIM	Existing SSIM
0.1	Coast	1.676508	0.995634	0.618059
	Forest	1.158306	0.995723	0.680922
	Highway	1.297289	0.99638	0.639428
	Inside city	1.187107	0.99701	0.71119
	Mountain	1.633554	0.997318	0.69011
	Open country	1.372961	0.995315	0.619651
0.7	Coast	1.480584	0.996992	0.797329
	Forest	1.010789	0.998273	0.902912
	Highway	1.169935	0.997939	0.830119
	Inside city	1.089809	0.998534	0.894626
	Mountain	1.251586	0.998383	0.875426
	Open country	1.086101	0.997521	0.829418
0.9	Coast	1.356429	1.314347	1.314347
	Forest	1.003323	0.998439	0.914139

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	Highway	1.169935	0.997939	0.830119
	Inside city	1.016314	0.999059	0.880937
	Mountain	1.171581	0.998489	0.888574
	Open country	1.050637	0.997855	0.845379
1.2	Coast	1.314347	0.815772	0.997376
	Forest	1.003323	0.998588	0.923086
	Highway	1.099914	0.998366	0.860861
	Inside city	1.037994	0.998959	0.920483
	Mountain	1.171581	0.998661	0.899462
	Open country	1.015442	0.99805	0.86045

TABLE 4: PERFORMANCE ANALYSIS OF HETEROSCADISCITY NOISE

Noise level	Image details	SISI	Proposed SSIM	Existing SSIM
20	Coast	2.054804	0.994518	0.609919
	Forest	1.148433	0.996006	0.693709
	Highway	1.527892	0.997674	0.673629
	Inside city	1.327713	0.996571	0.704159
	Mountain	1.601732	0.997365	0.712073
	Open country	1.571839	0.994649	0.602925
10	Coast	1.949711	0.995131	0.678396
	Forest	1.071231	0.997204	0.814517
	Highway	1.493257	0.997981	0.743346
	Inside city	1.193935	0.998112	0.786616
	Mountain	1.498355	0.99772	0.786272
	Open country	1.31663	0.996007	0.717424
5	Coast	1.771879	0.995594	0.720715
	Forest	1.031511	0.997814	0.870283
	Highway	1.372725	0.99822	0.782505
	Inside city	1.139855	0.998404	0.831223
	Mountain	1.402844	0.997911	0.824195
	Open country	1.157004	0.997047	0.785013
0.5	Coast	1.549226	0.996274	0.767163
	Forest	1.004312	0.998369	0.911087
	Highway	1.321147	0.998476	0.821445
	Inside city	1.091316	0.99875	0.87135
	Mountain	1.291167	0.998183	0.859075
	Open country	1.053858	0.99783	0.838028

V. CONCLUSION

Image Quality Assessment plays a vital role in the image processing applications such as enhancement, restoration, compression and other domain. Discovery of image quality is still a daunting task due to inappropriate image details like contrast, luminance, saturation etc. In this paper, we have designed a novel metric named, Sensed Image Smoothness Index (SISI) that depicts the image quality irrespective of the noise addition/ removal. Edge is the most vital process of describing the images. The novel metric is designed from two phases, image denoising and edge information analysis. Initially, four levels of noise settings are analyzed for three sorts of noises, namely, Gaussian noise, Poisson noise and Heteroscadiscity. In image denoising phase, the generated noise is eliminated by Local Polynomial Approximation (LPA). The primary objective of the denoising model is not to interpolate the non- noisy images. With the assistance of filtering parameter and convolution kernel, the denoised image is preserved. Once after obtaining the denoised image, the edge information is predicted under multiple thresholds.

Atlast, the smoothness index is designed between plain image and denoised image. Experimental analysis is carried out in public repository, Computational Visual Cognition laboratory which proves that our proposed metric elegantly describes the image quality. It is evident from the results that proposed SSIM yields better performance than the prior SSIM.

REFERENCES

1. H. Yu, L. Zhao, and H. Wang, Image denoising using trivariate shrinkage filter in the wavelet domain and joint bilateral filter in the spatial domain. IEEE Transactions on Image Processing, 18, 2364 (2009).
2. P. Liu, F. Huang, G. Li, and Z. Liu, Remote-sensing image denoising using partial differential equations and auxiliary images as priors. IEEE Geoscience and Remote Sensing Letters, 9, 358 (2012).
3. Q. Yuan, L. Zhang, Senior Member, IEEE, and H. Shen, Member, IEEE, Hyper-spectral image denoising employing a spectral–spatial adaptive total variation model. IEEE Transactions on Geoscience and Remote Sensing 50(2012).
4. L. Zhang a, W. Dong, D. Zhang, and G. Shi, Two-stage image denoising by principal component analysis with local pixel grouping. International Journal of Pattern Recognition43, 1531(2010).
5. T. Tasdizen, Principal neighborhood dictionaries for non-local means image denoising. IEEE Transactions on Image Processing 8(2009).
6. Vikas D. Patil and Sachin D. Ruikar, PCA based image enhancement in wavelet domain. International Journal of Engineering Trends and Technology 3(2012).
7. Hari Om and Mantosh Biswas, An improved image denoising method based on wavelet thresholding.Journal of Signal and Information Processing, 3, 109 (2012).
8. T. Tasdizen, Principal components for non-local means image denoising, Electrical and Computer Engineering Department, University of Utah (2008).
9. K. I. Kim, M. O. Franz, and B. Scholkopf, Image modeling based on kernel principal component analysis, Max-planck-Institut für Biologische Kybernetik, Tübingen, Germany(2005).
10. K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, Image denoising with shape-adaptive principal component analysis, Department of Signal Processing, Tampere University of Technology, France (2009).
11. Shashikant Agrawal and Rajkumar Sahu, Wavelet based MRI image denoising using thresholding techniques. International Journal of Science, Engineering and Technology Research 1, 32(2012).
12. C. Li, Y. Diao, H. Ma, and Y. Li, A statistical PCA method for face recognition. Intelligent Information Technology Application 376(2008).
13. K. Gu, M. Liu, G. Zhai, X. Yang, and W. Zhang, “Quality assessment considering viewing distance and image resolution,” IEEE Trans. Broadcast., vol. 61, no. 3, pp. 520–531, Sep. 2015.
14. K. Moorthy and A. C. Bovik, “Blind image quality assessment: From scene statistics to perceptual quality,”IEEE Trans. Image Process., vol. 20, no. 12, pp. 3350–3364, Dec. 2011.
15. M. A. Saad, A. C. Bovik, and C. Charrier, “Blind image qual-ity assessment: A natural scene statistics approach in the DCT do-main,”IEEE Trans. Image Process., vol. 21, no. 8, pp. 3339–3352, Aug. 2012.
16. Mittal, A. K. Moorthy, and A. C. Bovik, “No-reference image quality assessment in the spatial domain,”IEEE Trans. Image Process., vol. 21, no. 12, pp. 4695–4708, Dec. 2012.
17. G. Zhai, X. Wu, X. Yang, W. Lin, and W. Zhang, “A psychovisual quality metric in free-energy principle,”IEEE Trans. Image Process., vol. 21, no. 1, pp. 41–52, Jan. 2012.
18. K. Gu, G. Zhai, X. Yang, and W. Zhang, “A new reduced-reference image quality assessment using structural degradation model,” inProc. IEEE Int. Symp. Circuits Syst., May 2013, pp. 1095–1098.
19. K. Gu, G. Zhai, X. Yang, and W. Zhang, “Using free energy principle for blind image quality assessment,”IEEE Trans. Multimedia, vol. 17, no. 1, pp. 50–63, Jan. 2015.
20. Mittal, R. Soundararajan, and A. C. Bovik, “Making a ‘completely blind’ image quality analyzer,”IEEE Signal Process. Lett., vol. 22, no. 3, pp. 209–212, Mar. 2013.
21. W. Xue, L. Zhang, and X. Mou, “Learning without human scores for blind image quality assessment,” inProc. IEEE Int. Conf. Comput. Vis. Pattern Recog., Jun. 2013, pp. 995–1002.
22. R. Mantiuk, S. J. Daly, K. Myszkowski, and H.-P. Seidel, “Predicting vis-ible differences in high dynamic range images: Model and its calibration,” in Proc. SPIE, Human Vis. Electron. Imaging X, Mar. 2005, vol. 5666, pp. 204–214.
23. R. Mantiuk, K. J. Kim, A. G. Rempel, and W. Heidrich, “HDR-VDP-2: A calibrated visual metric for visibility and quality predic-tions in all luminance conditions,” ACM Trans. Graph., vol. 30, no. 4, pp. 1–13, Jul. 2011.
24. M. Narwaria, R. Mantiuk, M. P. D. Silva, and P. L. Callet, “HDR-VDP-2.2: A calibrated method for objective quality prediction of high-dynamic range and standard images,”J. Electron. Imaging, vol. 24, no. 1, pp. 010501–010501, Jan. 2015.
25. H. Yeganeh and Z. Wang, “Objective quality assessment of tone-mapped images,” IEEE Trans. Image Process., vol. 22, no. 2, pp. 657–667, Feb. 2013.