International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2015): 6.391

No Reference Gradient Oriented Image Quality Assessment

Sukhpreet Kaur[1], Jaspreet Singh[2]

[1]Student, Department of Electronics and Communication Engineering, Punjabi University, Patiala, India
b.sukhpreet@gmail.com

[2] Assistant Professor, Department of Electronics and Communication Engineering, Punjabi University, Patiala, India
jas.kaleka@gmail.com

Abstract: ***Image quality assessment plays a ubiquitous role in the applications of image processing. As we are familiar, the digital images are most likely to subject wide range of distortions in the process of preprocessing, compression, storage, transmission, etc. Quality of images can be perceived by using IQA metrics. IQA metrics are of two types: subjective image quality metrics that perform best only in the human visual system and second type of metrics is objective metrics, which are more appropriate than subjective metrics as they are more convenient and less time consuming. In spite of great advancement in the research area, no reference image quality assessment is still a challenging task because of the lack of the reference image. No reference image quality assessment evaluates the perceptual quality of the distorted image without its reference image. Existing BIQA methods mainly focused on the picture quality by breaking down the image insights in DCT, DWT domains. In this paper, we propose a novel no reference image quality assessment method using Laplacian of Gaussian features and Gradient Orientation. Previously gradient orientation is not much explored deeply as the main source of information for image quality assessment. In this paper, we apply the gradient orientation relative to all directions.***

Keywords: No Reference, Full Reference, Image Quality Assessment, Gradient Orientation, Blind Image Quality Assessment, Laplacian of Gaussian

1. Introduction

Pictures and recordings are regularly packed for proficient storage, transmission, which definitely presents a few distortions, for example, blocking and ringing relics. These distortions corrupt visual qualities, and lessen the data legitimacy. To guarantee that the end clients get agreeable experience, it is important to deliver better picture/video quality or to facilitate spare data transmission spending plan by parameter reconfiguration. The perceptual evaluation of the picture plays a vital role in taking decisions regarding image quality assessment. Image quality is the most important index in evaluating the image performance.

Image quality assessment (IQA) calculation uses the factual highlights [1] of normal pictures and mutilations, which can be gathered in spatial area or change space. In the previous decade, a few endeavors have been made to build up some target IQA calculations. The execution of IQA calculations can be further enhanced if picture components are extracted and collaborated with human visual framework system (HVS). A progression of IQA measurements, for example, visual information fidelity (VIF), structural similarity index (SSIM) [2], most apparent distortion (MAD), PSNR-HVS model [3], visual signal to noise ratio, feature similarity index metric (FSIM) [4] have been proposed, which satisfied with human perceptions.

Generally, in order to maintain, control, and improve the quality of digital images, which might be changed during image acquisition, processing (watermarking, enhancement, compression, rendering), noise, blur, fading and image transmission. With the help of image quality assessment methods, any visual degradation and improvement of the image quality can be achieved into a real value. Quality assessment of image content is achieved either by using the subjective tests or through objective metrics. Hence, image quality assessment is classified into two parts which are subjective quality metrics and objective quality metrics. The human vision system is known as subjective quality assessment. By revealing how visual information is processed in the human vision system, psychologists have laid the foundation for the development of image quality assessment methods.

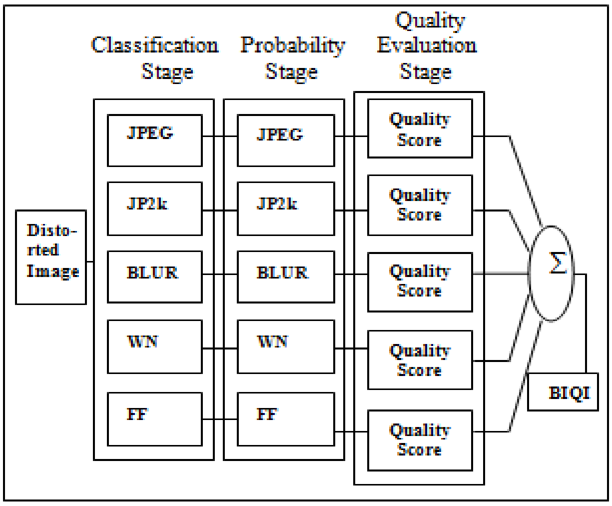


Figure 1: Image Quality Assessment process

Despite of rapid advancement in technology image quality assessment is still a challenging task. Client experience about picture quality can be surveyed by subjective or objective strategies. For subjective assessment, it is required to assemble the human visual perceptions; however, it is cumbersome and inapplicable in real time situations. On the other side, objective score is figured out from a planned calculation with quick execution speed, and its outcomes ought to be reliable with subjective assessment.

Furthermore, objective metrics are classified into three types: (1) Full Reference (FR) metrics in which reference image is available for comparing the test image; (2) Reduced Reference (RR) metrics in which partial reference is available for comparing the test image; (3) No Reference (NR) metrics in which no reference image is available for comparing the test image. That's why no reference image quality metric is more challenging one than the other two categories. A no reference image quality assessment, such as the one explored in this work, does not demand that any original image be present or even exist. A no-reference (NR) image quality assessment is also known as blind image quality assessment. Astonishingly such a technique of IQA is more abundantly utilized in real-world situations than the full-reference image. Such instances include, among others, monitoring image transitions and video broadcasting signals or instantly determining the visual quality of photos snapped with cameras.

NR IQA can likewise be utilized to control the post-preparing to enhance the quality of the decoded pictures. For these applications, the proposed calculation is equipped because of its higher execution speed and exactness.

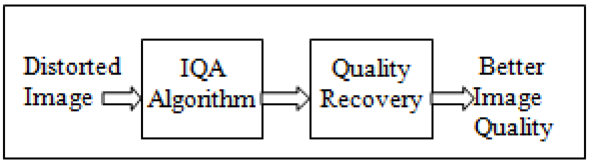


Figure 2: No Reference Image Quality Assessment

2. Related Work

No Reference Image Quality Assessment models usually include two stages : feature extraction and feature learning based quality evaluation. The evaluations of these strategies depend on both the perceptual significance of the extracted components and on the procedure of feature learning. Characteristic scene insights (NSS) models, for example, the Gaussian features model has been appearing to be both perceptually pertinent and exceptionally consistent descriptors of regular pictures. Xue W et al. [5] Explrored a novel BIQA model that uses the joint statistics of two sorts of generally utilized features: 1) gradient magnitude (GM) and 2) Laplacian of Gaussian (LOG). They used a versatile strategy to joint standardize the GM and LOG and illustrated that the standardized GM and LOG highlights had alluring properties. The proposed model is broadly assessed on three extensive scale benchmark databases. Zhang et al. [6] explored a novel no-reference image quality evaluation technique by presenting three types of picture distortions, including noise, obscure degree and blocking impacts. First of all, the standard deviation of image noise is assessed by changing the medium of wavelet estimation. Additionally, the dark level of an image is evaluated by checking edge pixel centers. Thirdly, blocking effect is addressed by characteristics of picture pixel pieces. Finally, the assessment model is set up by joining these three mutilation sorts. They got the weighting coefficients by joining the differential mean conclusion scores (DMOS) gave in the LIVE IQA database. Saha A. et al. [7] proposed another approach to manage outwardly weakened picture quality evaluation (BIQA), requiring no arrangement, in the perspective of scales and works by surveying the overall complexity of the faulty picture separated at different scales with the request picture at an interesting determination. The approach relied upon on the limit of the trademark pictures to indicate redundant information over various scales. Ci Wang et al. [8] proposed an outwardly impeded/no-reference (NR) procedure for picture quality assessment (IQA) of the photos compacted in discrete cosine change (DCT) region. Right when a photo is measured by the assistant closeness (SSIM), two vacillations, i.e. mean power and change of the photo, are used as components. They moreover proposed machine learning based figuring to gage quantization racket considering picture content. Differentiated and front line computations, the proposed IQA is more heuristic and profitable. They watched that the proposed, figuring (gave no reference picture) achieved comparable ampleness to some full reference (FR) systems. Indrajit De et al. [9] proposed a non-selective, no-reference picture quality evaluation (NR-IQA) system by combining manual visual perception of individuals in naming quality class imprints to the photos. Using a fleecy method of reasoning methodology, they considered information theoretic entropies of ostensibly striking areas of pictures as components and study nature of the photos using etymological qualities. They had taken a course of action of getting ready pictures fitting in with five particular pre-doled out quality class names for determining impression of precariousness (FOU) contrasting with each class. Jingwei Guan et al. [10] showed a no-reference target dark metric in light of edge model (EMBM) to address the photo dark assessment issue. The parametric edge model is considered to depict and recognize edges, which can offer synchronous width and separation estimation for each edge pixel. With the pixel-flexible width and separation estimations, the probability of perceiving dark at edge pixels can be determined. They examined using the exceptional edge pixels to emulate the dark examination in the Human Visual System (HVS).. Shuigen Wang et al. [11] proposed a Blind Noisy Image Quality Assessment model using Kurtosis (BNIQAK). They found that there exists a noteworthy differentiation between the transports of Discrete Wavelet Transform (DWT) coefficients of typical pictures and uproarious pictures: (1) for customary pictures, their scatterings are sharp with high peakedness and slight tail; (2) for boisterous pictures, the shapes are much compliment with lower peakedness and heavier tail. Kurtosis could gage and separate the probability dispersals of disorderly pictures with various noise levels. Also, the kurtosis estimations of DWT coefficients are enduring to fluctuate repeat channels. Qingbo Wu et al. [12] proposed a novel NR-IQA procedure that addresses the issues by displaying the multi-space assistant information and piecewise backslide. The essential motivation of their methodology relied on upon two core interests. Firstly, they developed another adjacent picture representation which expels the essential picture information from both the spatial-repeat and spatial regions. Additionally, they developed a gainful piecewise backslide methodology to get the adjacent allotment of the component space. Lixiong Liu et al. [13] researched slant presentation as an insightful wellspring of information for a photo quality evaluation. They adjusted this by mulling over the quality noteworthiness of the relative incline presentation, viz., the edge acquaintance with deference to the include. They similarly sent a relative slant, size segment that speaks to a perceptual covering and utilized an Ada Boosting back-spread (BP) neural framework to diagram picture components to picture quality. The theory of the Ada Boosting BP neural framework results in a capable and solid quality gauge model. The new model, called Oriented Gradients Image Quality Assessment (OG-IQA), seemed to pass on outstandingly engaged picture quality pre-expression execution as differentiated and the most standard IQA approaches. Tongfeng Sun et al. [14] proposed a no-reference picture quality evaluation in perspective of slant histogram response (GHR). The GHR is the slant histogram assortment of a photo object under an area change. A test picture is spoiled to a tumult picture and a dark picture, which are taken as two picture objects, through pre-taking care of in the metric. Each photo article applies to an area change as a thing data, and its GHR as an article yield is expelled in multi scale space. The two GHRs made an overall part vector and are mapped to a photo quality score. The metric is researched achievable for the quality evaluation of the photos changed from mixed bending, however the sorts of these photos are avoided in the readiness database.

3. Proposed Methodology

As talked about in the introduction area, GM and LOG elements are essential components that are normally used to shape picture semantic structures. As we will see, they are moreover solid components to foresee picture neighborhood quality. In this part, we demonstrate how the joint insights of GM and LOG can be adjusted to the BIQA perceptions.

3.1 Gradient Magnitude and Laplacian of Gaussian

Luminance discontinuities pass on the greater part of the basic data of a characteristic picture, and they can be adequately distinguished from the reactions of the GM and LOG operators. LOG and GM operators offer normal property that they are registered utilizing isotropic diverse operators without any support. LOG manages focus encompassed profile and symmetrically touchy to force changes overall introduction where as GM alludes most extreme power in any case introduction. Let I be an image.

Figure 3: Testing image I.

Its GM map can be processed as

$$G_I = \sqrt{[I\otimes h_x]^2+[I\otimes h_y]^2+[I\otimes h_{z1}]^2+[I\otimes h_{z2}]^2} \quad (1)$$

Where "⊗" denotes linear convolution and h_d, d € {x, y, z1, z2}, Gaussian filter applied across the horizontal, vertical and diagonal directions.

$$h_d(x,y,z1,z2|\sigma) = \frac{\partial}{\partial d} g(x,y,z1,z2)$$
$$= -\frac{1}{2\pi\sigma^2}\frac{d}{\sigma^2}\exp\left(-\frac{x^2+y^2+z1^2+z2}{2\sigma^2}\right)^{d\in\{x,y,z1,z2\}} \quad (2)$$

Where

$g(x,y,z1,z2|\sigma)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{x^2+y^2+z1^2+z2^2}{2\sigma^2}\right)$ is gaussian function with scale parameter σ.

LOG map of an image I can be processed as

$$L_I = \mathrm{I}\otimes \mathrm{h}_{\mathrm{LOG}}, \quad (3)$$

Where

$$L_{LOG}(x,y|\sigma) = \frac{\partial^2}{\partial x^2}g(x,y|\sigma)+\frac{\partial^2}{\partial y^2}g(x,y|\sigma) \quad (4)$$
$$= \frac{1}{2\pi\sigma^2}\frac{x^2+y^2-2\sigma^2}{\sigma^4}\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right).$$

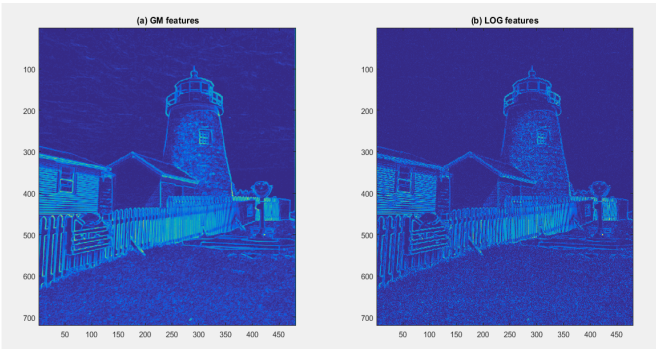


Figure 4: (a) GM features; (b) LOG features.

3.2 Joint Normalization of GM and LOG

GM and LOG operators are firmly identified by the perceptual nature of regular pictures henceforth and an assumed distortion is likewise added to the accepted format values. The performance may shift based upon the operators. GM and LOG administrators could evacuate a noteworthy sum of picture spatial redundancies, while certain relationships between neighboring pixels will remain. The GM and LOG features can be jointly normalized as:

$$F_I(i,j) = \sqrt{G_I^2(i,j)+L_I^2(i,j)} \quad (5)$$

The Normalization factor on each pixel (i, j) is computed as:

$$N_I(i,j) = \sqrt{\sum\sum_{(l,k)\in\Omega_{i,j}}\omega(l,k)F_I^2(l,k)} \quad (6)$$

The normalized GM and LOG features are given as:

$$\overline{G_I} = G_I/(N_I+\epsilon) \quad (7)$$
$$\overline{L_I} = L_I/(N_I+\epsilon) \quad (8)$$

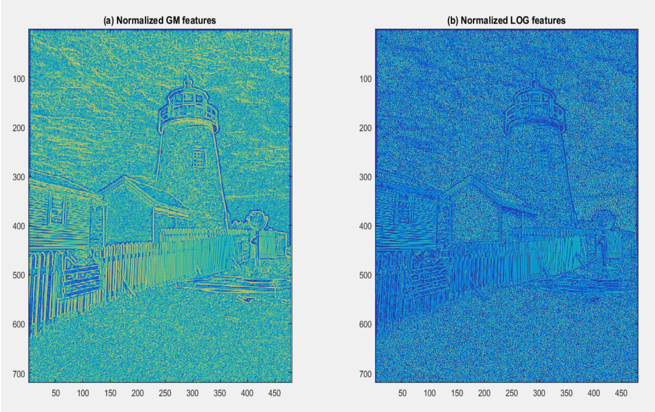


Figure 5: (a) Normalized GM feature maps; (b) Normalized LOG feature maps.

3.3 Marginal Distribution of GM and LOG

The marginal probability function of $\overline{G}_I$ denoted by N_G and of $\overline{L}_I$ by N_L.

$$N_G = \sum_{n=1}^{N} K_{m,n} \tag{9}$$

$$N_L = \sum_{m=1}^{M} K_{m,n} \tag{10}$$

3.4 Independency Distributions

3.4.1 Independency Distribution of GM on LOG

It is denoted by I_G and given as:

$$I_G = \frac{1}{N}\sum_{n=1}^{N}\frac{P(N_G, N_L)}{P(N_L)} \tag{11}$$

3.4.2 Independency Distribution of LOG on GM

It is denoted by I_L and given as:

$$I_L = \frac{1}{M}\sum_{m=1}^{M}\frac{P(N_L, N_G)}{P(N_G)} \tag{12}$$

3.5 Prediction Model Learning

In prediction model learning, we use three prediction models, i.e. regression models denoted by M1, M2 and M3. To evaluate more effective statistical features we learn different models using different sets of features.

In the first model, M1, only marginal distribution N_G and N_L for learning the prediction score. In the second model, M2, only dependency measures I_G and I_L are used. And in the third model, M3, both the marginal distribution and the dependency measures are used to learn the model.

To learn such regression models Support Vector Regression (SVR) is widely used.

4. Results and Discussion

4.1 Image Databases and Evaluation Protocols

For evaluating the performance of regression models we use subjective image databases. Differential Mean Opinion Scores (DMOS/MOS) are typically recorded to portray how intently the predicted picture quality scores by a BIQA model connect with human judgments. A few subjective picture quality assessment databases have been set up in the IQA group. The three biggest and generally broadly utilized ones: the LIVE database [15], the CSIQ database [16] and the TID2008 database [17].

Here we use LIVE database. Laboratory for Image and Video Engineering (LIVE) [18] is a standard database which contains an arrangement of pictures used to check and approve the picture quality appraisal algorithms by giving diverse arrangements of standard pictures and their comparing distorted pictures. The database contains both sorts of pictures, reference and its twisted variants. Lab for Image and Video Engineering (LIVE) database is a standard picture database. The LIVE database had been produced at the University of Texas at Austin, USA, and it contains reference pictures and twisted pictures in 24-bpp shading BMP design at various picture resolutions going from 634 × 438 pixels to 768 × 512 pixels. It includes an arrangement of reference pictures consolidated in a separate envelope alongside various organizers of various kinds of mutilation with distinctive contorting level. There are 29 distinctive reference pictures utilized as a part of this database. Every reference picture is distorted by 5 distinctive sorts of twisting also, every sort of twisting is debased with various distorted level. Henceforth complete 779 pictures are accessible in this database. The types of distortions involved in this database are : JPEG2000 compression distortion (175 images), JPEG compression distortion (169 images), Fast fading distortion (145 images), Gaussian blur distortion (145 images), White noise distortion (145 images).

The database is furnished with a MATLAB record which contains the Differential Mean Opinion Score (DMOS) of every picture presented in the database. DMOS is the mean of value scores given by various human onlookers. This score is considered as a standard quality score with which yield of various NR-IQA calculations is to be thought about.

4.2 Implementation Summary

While processing the GM and LOG feature maps, the scale parameter σ of the channels hx, hy, hz1 and hz2 should be set. We set σ to a little esteem 0.5 with the goal that fine picture points of interest can be caught in the GM and LOG highlight maps. In the JAN procedure, the weights ω(k, l) are produced by a Gaussian part with scale parameter 2σ. The average value of GM and LOG in LIVE database is taken 2.5 as default value.

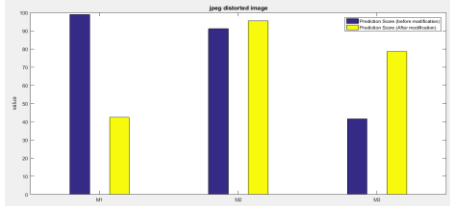
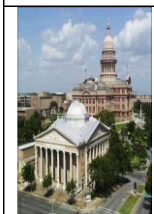
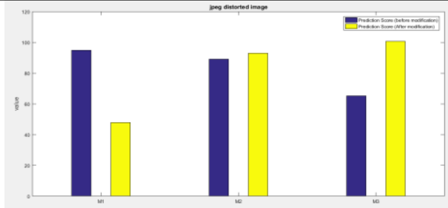
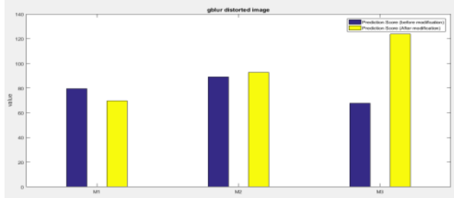
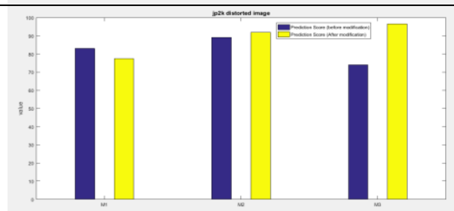
Here we use Spearman rank order correlation coefficient in order to evaluate the performance and measure the correlation between regression models and the subjective DMOS scores.

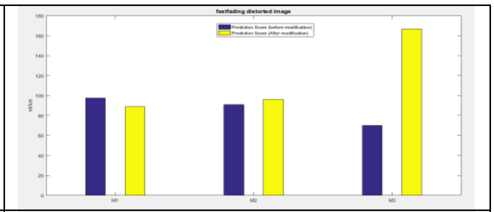
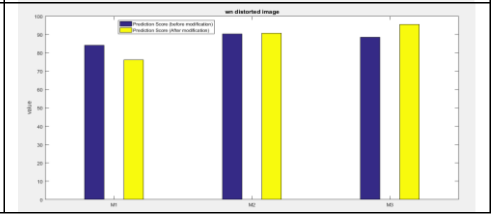
While utilizing the SVR, the SVR parameters (C, γ) should be set in order to learn regression models. We have done a cross approval test to choose the estimations of (C, γ). LIVE database is divided into non overlapped sets, i.e. the preparing set and the test set. We arbitrarily chosen 80% of the reference pictures (and their noisy versions) as the preparation set and the rest 20% as the test set. In this way, we guaranteed that there was no substance overlapped between the preparation set and the test set. This generally speaking train-test technique was repeated over 1000 times, and the middle results were accounted for execution assessment. The (C, γ) values conveying the best mean result were picked as the parameter. In this whole process the third model M3 shows the best SRC result on the LIVE database. The ideal (C, γ) parameters we observed for the three proposed models M1, M2 and M3 are (65536, 2), (1024, 8) and (16384, 2) on the LIVE database respectively.

4.3 Performance

Among the proposed three models, although the models, M1 and M2 perform well while the model M3 performs the best results. As it is clear model M3 consists of both marginal distributions and dependency measures. So model M3 is superior to other models in the given database. Spearman coefficient correlation is utilized for extracting the prediction scores of all the three models M1, M2 and M3. The database is furnished with a MATLAB record which contains the Differential Mean Opinion Score (DMOS) of every picture presented in the database which is used to compare the outcome results. The given table 1 shows the comparison of the three proposed models on different test images of different distortions before and after modification.

Table 1: Comparison of MI, M2, M3 models before and after modification.

Image	*Comparison of the three models M1, M2, M3 before and after modification among different types of distorted images.*
	
	
	
	

The given table 2 shows the performance of the three proposed models on different test images of different distortions.

Table 2: Performance Parameters using SVR in LIVE database

Image Type	*Image No.*	*Prediction Model*	*Prediction Score (before modification)*	*Prediction Score (after modification)*
Jpeg	1	M1 M2 M3	98.8418 91.0881 41.4298	42.309 95.4079 78.4805
Jpeg	2	M1 M2 M3	94.7303 89.0694 65.1988	47.8443 92.9631 100.7082
Gblur	4	M1 M2 M3	79.6259 89.0489 67.7533	69.6766 92.7297 123.7352
Jp2k	25	M1 M2 M3	82.9768 89.1527 73.9973	77.4910 91.8997 96.5003
Fast Fading	73	M1 M2 M3	97.4579 90.7715 69.9941	88.8685 95.9994 166.5020
WN	82	M1 M2 M3	84.1972 90.4027 88.4511	76.0727 90.6660 95.5105

5. Conclusion

Existing BIQA models ordinarily break down a picture into diverse frequencies and then extract features to learn the prediction quality model. In this we applied joint adaptive normalization of Gradient Magnitude and Laplacian of Gaussian as it is effective and it improves the performance of BIQA models. It helped to improve the quality, accuracy, distortion, robustness of the image. The previous work does not include the orientation of the gradient model as considering the orientation of high gradient pixels can affect the results. The existed gradient methods use vertical and horizontal gradients, but other directions, i.e. diagonal can also be achieved. Here we made the primary endeavor to utilize GM and LOG components to evaluate superior BIQA. To lighten the impacts of picture distortion varieties, we connected a joint versatile standardization strategy to standardize the GM and LOG highlights and brighten the picture information. Since GM and LOG elements are not autonomous and the connection between them can think about nearby quality expectation common pictures, we proposed a straightforward record, called Independency measures, to gauge the joint measurements of them.

In this paper, we applied gradient magnitude to all directions, i.e. horizontal, vertical and diagonal directions which illustrated better result than the previous work done in his area. The prediction score of all the models is far better than the previous. Although a great research had been done in this field, it is still a challenging area.

6. Acknowledgement

First and foremost, I would like to express my deepest gratitude to my supervisor assistance professor Er. Jaspreet Singh for his esteemed guidance, inspiration and contributions throughout this paper, without whom this paper would not be in its present form. I also thank for his gracious teaching and encouragement through the whole work. I am also very much obliged to all the faculty members and contributors for creating and keeping up the IEEE Latex style documents which have been utilized as a part of readiness of this format. A debt of gratitude is in order for their remarks and advice.

References

[1] A.C. Bovik, Z. Wang, “Modern Image Quality Assessment,” Morgan & Claypool, 2007.

[2] H.R. Sheikh and A.C. Bovik, “Image Information and Visual Quality,” IEEE Transactions on Image Processing, vol. 15, no. 2, pp. 430-444, 2006.

[3] Z. Wang, A.C. Bovik, H.R. Sheikh and E.P. Simoncelli, “Image Quality Assessment: From Error Visibility to Structural Similiarity,” IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600-612, 2004.

[4] L. Zhang, X. Mou, D. Zhang, “FSIM: A Feature Similiarity Index for Quality Assessment,” IEEE Transactions on Image Processing, vol. 20, no. 8, pp. 2378-2386, 2011.

[5] L. Zhang, X. Mou, W. Xue, A.C. Bovik, “Blind Image Quality Assessment using Joint Statistics of Gradient Magnitude and Laplacian Features,” IEEE Transactions on Image Processing, vol. 23, no. 11, pp. 4850-4862, 2014.

[6] Luo-yu Zhou, Zheng-bing Zhang, “No-reference Image Quality Assessment Based on Noise, Blurring and Blocking Effect,” Optik – International Journal for Light and Electron Optics, vol. 125, no. 19, pp. 5677-5680, 2014.

[7] A. Saha, Wu, Q.M.J., “Utilizing Image Scale Towards Totally Training Free Blind Image Quality Assessment,” IEEE Transactions on Image Processing, vol. 24, no. 6, pp- 1879-1892, 2015.

[8] Ci Wanga, Minmin Shen, Chen Yao, “No-reference Quality Assessment for DCT-based Compressed Image,” Journal of Visual Communication and Image Representation, vol. 28, pp. 53-59, 2015.

[9] Indrajit Dea, Jaya Silb, “No-reference Image Quality Assessment using Interval Type 2 Fuzzy Sets,” Applied Soft Computing, vol. 30, pp. 441-453, 2015.

[10] Jingwei Guan, Wei Zhang, Jason Gu, Hongliang Ren, “No-reference Blur Assessment Based on Edgee Modeling,” Journal of Visual Communication and Image Representation, vol. 29, pp. 1-7, 2015.

[11] Shuigen Wang, Chenwai Deng, Cheng Li, Xun Liu, Bhaojun Zhao, “Kurtosis-based Blind Noisy Image Quality Assessment in Wavelet Domain,” Systems, Man and Cybemetics (SMC), IEEE International Conference, pp. 1557-1560, 2015.

[12] Qingbo Wu, Hongliang Li, Fanman Meng, King Ngi Ngan, Shuyuan Zhu, “No Reference Image Quality Assessment Metric via Multi-domain Structural Information and Piecewise Regression,” Journal of Visual Communication and Image Representation, vol. 32, pp. 205-216, 2015..

[13] Lixiong Liu, Yi Hua, Qingjie Zhao, Hua Huang, Alan Conrad Bovik, “Blind Image Quality Assessment by Relative Gradient Statistics and Ada Boosting Neural Network,” Signal Processing: Image Communication, vol. 40, pp. 1-15, 2016.

[14] Tonffeng Suna, Shifei Dinga, Wei Chena, Xinzheng Xua, “No Reference Image Quality Assessment Based on Gradient Histogram Response,” Computers and Electrical Engineering Journal, 2016.

[15] H.R. Sheikh, Z. Wang, L. Cormack and A. C. Bovik, “Live Image Quality Assessment Database Release 2,” online available: http://live.ece.utexas.edu/research/quality . [Online]. Available: [Accessed: Sept., 2011].

[16] E.C. Larson and D. M. Chander, “Most Apparent Distortion: Full Reference Image Quality Assessment and The Role of Strategy,” Journal of Electronic Imaging, vol. 19, no. 1, pp. 011006-011021 , 2010.

[17] N. Ponomarenko, V. Lukin, A. Zelensky, K. Egiazarian, M. Carli and F. Battisti, “TID2008-A database for Evaluatiion of Full Reference Visual Quality Assessment Metrics,” Advanced Modern Radio Electron, vol. 10, no. 4, pp. 30-45, 2009.

[18] L.D. Jacobson and H. Wechsler, “Joint Spatial/Spatial-Frequencu Representation,” Signal processing, vol.14, no. 1, pp. 37-68, 1988.

Author Profile

Sukhpreet Kaur received the B.Tech. Degree from Swami Vivekanand Institute of Engineering and Technology, Punjab, India in 2014 and is currently pursuing M.Tech. Degree in Electronics & Communication Engineering from Punjabi University, Patiala Punjab. Her research interests are oriented to image quality assessment and image processing.

Jaspreet Singh received the B.Tech. Degree in 2009 and M.Tech. Degree in 2012. He is currently working as Assistant Professor in the Department of Electronics and Communication Engineering, Punjabi University, Patiala, Punjab, India. His research interests are oriented to digital signal processing and image processing.