ISSN No: 2456-2156

No-Reference Image Quality Assessment Based on MLBP Using Distortion Aggravation

Lakshmi Suresh
CSE Department
The Oxford College of Engineering Bangalore, Karnataka, India

Abstract:- The use of imaging devices obtain massively large amount of images every day and the Internet makes sharing of these images easier and faster. Digital images are undergoes distortions as it goes through the whole procedure like acquisition, storage, transmission, processing and compression. This makes image quality assessment important in modern systems. According to the availability of original undistorted image, the IQA metric can be classified into three categories, the Full-Reference (FR), Reduced Reference (RR) and blind/no-reference (NR) IQA. Traditional blind image quality assessments predict the quality from a whole distorted image directly. In this paper, multiple pseudo reference images (MPRIs) for NR-IQA is introduced initially by distortion aggravation. For that, the distorted images are subjected to various types of commonly encountered distortions and for each type, five different levels of distortions is added. Later modified local binary patterns(MLBP) features are extracted to describe the similarities between the distorted image and the MPRIs. These similarities metrics are used for estimating the quality of the image using SVM. More similar to a particular pseudo reference image indicates closer to the quality to this PRI. The influence on image content can be reduced by the availability of the created MPRIs. Also the image quality can be inferred more accurately and consistently.

Keywords:- *Blind/No-Reference Image Quality Estimation (BIQA/NR-IQA), Full-Reference IQA (FR-IQA), Image Quality Estimation (IQA), Natural Scene Images (NSI), Reduced Reference IQA (RR IQA), Screen Content Images (SCI).*

I.INTRODUCTION

The advancement of innovations in transmission technology and network technology helped different media sources applications and services for broadcasting. Majority of their service providers expect greater and better level of experience from end users. Yet how the QoE can be measured and strengthened turns into a pressing question. Consumers are extremely sensitive to the trouble of viewing experiences such as blurred, unclear images. Once the images are exposed to various processes such as transmission, processing, compression, chances of the images being corrupted occur. The deterioration affects an image's naturalness. Thus, extracting features from distorted image becomes really tough for later analysis. Evaluation of image quality is one of the key techniques used in applications for image processing. This is because in applications where image is the principal information medium, the quality of an image is very important. IQA is the method for determining the original image quality of a distorted image. One can easily deploy this blind IQA system. Also this leads to distortion detection and quantification which helps to enhance and monitor the distorted image. Different quality assessment methods for images are used for prediction of the quality of image. Such IQA methodologies can be divided into two according to the availability of reference image. Quality of the image can be assessed either in a subjective or objective manner. Subjective methods can estimate the image quality based on the human viewer's perceptual experience regarding the image's attributes. But analytical approaches, based on statistical models, predict the image quality. The subjective methods are costly because they require a large number of human viewers and are therefore not applicable in real-time applications. The purpose of the methods of estimating image Dept. of Computer Science & Engineering, VJCET 1NR-IQA Based on MLBP using Distortion Aggravation quality is thus to develop methods for objective evaluation that are also compatible with the subjective methods. The image created can be distorted as it is exposed to multiple processes such as compression, transmission, etc., by which image would be affected due to other distortions.

A. *Types of IQA*

The IQA method, as described above, is of two types; subjective and objective. The objective IQA approach can be classified based on certain factors such as; the availability of the original image, based on where it is applied, when the HVS simulation is used for quality evaluation etc. Thus the different objective methods are;

1. *Full-Reference methods*

The image quality is estimated using the details already available on the reference image. It can also be called fidelity, because it appears as a contrast between two images. Through this process the divergence of the distorted image from the image is actually measured in its pure state. That method is straightforward.

2. *Reduced-Reference methods*

Partial knowledge about the reference image is available here for the consistency estimation. And that partial information is used for quality assurance comparison with the original image.

3. Blind/No-Reference methods

This NR-IQA measure is used for estimating the image's quality where the knowledge of the original images is inaccessible in advance. The accuracy of the distorted image will be measured because this is the only information available at hand . This means that the pure image would not be used as the reference image in the NR-IQA system and that the distorted image itself will be used to determine the quality. In the case of applications in real world, it can be very difficult to obtain reference image as a source for determining the quality of the original images. Despite of this, NR-IQA methods are widely used for output prediction, and these methods are simpler to implement than other methods.

The introduction should briefly place the study in a broad context and highlight why it is important. It should define the purpose of the work and its significance. The current state of the research field should be carefully reviewed and key publications cited. Please highlight controversial and diverging hypotheses when necessary. Finally, briefly mention the main aim of the work and highlight the principal conclusions. As far as possible, please keep the introduction comprehensible to scientists outside your particular field of research. References should be numbered in order of appearance and indicated by a numeral or numerals in square brackets—e.g., [1] or [2,3], or [4–6]. See the end of the document for further details on references.

II.LITERATURE SURVEY

The work presented in [1] is mainly used for estimating the quality of the image that are distorted by blur and noise artifacts. This model used continuous wavelets transform for the quality estimation where Mexican hat function is used as the mother wavelet. The histogram of the CWT coefficients are computed and the histogram patterns are analyzed for distinguishing the distortion found in the image whether it is a blurred image, or a natural image or, a noisy image. The spread of the histogram is used for this. The mean and the standard deviation of the spread is computed and the value of these terms reflects the quality measure of the image. According to [1], the image has good quality if the mean value and standard deviation is 128 and 64 respectively. This technique only considers blur and noise as the distortions.

The work proposed in [2] mainly focused on three kinds of images; NSI,CGI, and SCI. A database that consist of these three kinds of images is constructed which is named as Cross-Content-Type (CCT) and the method uses this database as the input source. Features from the images are extracted, especially corner and edge features. This is because corners and edges of the image are the features that are affected more due to distortions. By using an adaptive weighting strategy, these features are integrated. And finally the overall quality of the image is evaluated from this value. If any specific color distortions occur when the distortion is not restricted to compression, then the method needs improvement.

The system described in [3] deals with a method that estimate the quality of the image that is contrast distorted. This method performs the quality evaluation in both local and in global manner. For local details, the predictable components of the image are removed and the unpredictable components are retained. Entropy of the optimum areas from the image that are selected using saliency detection technique are then computed. Similarly for global details, the entropy is computed. The entropy supposes that the uniformly distributed histogram, u gives maximum information. The histogram, h is alike to u has the largest global information. Combining the local and global information yields the overall quality score. But this method does not consider the effect of display devices on the image as the quality can be greatly influenced by the gamma function.

The paper [4] is based on a convolution neural network. It mainly process HDR images. The network has three parts; E-net, P-net and a Mixing function. The E-net portion quantifies the change in the statistics in the distorted image. The P-net portion computes the Perceptual Resistance which represents the difficulty in the viewing experience of the viewer to perceive the error. And finally the Mixing function combines the calculated error and the perceptual resistance for generating the quality score. But since it uses a CNN in which each layer uses the result from the previous layer for it processing, it takes more time. And so the execution speed is slower. Also by predicting higher errors it underestimates the perceptual distortions.

The proposed work [5] uses the concept of pseudo reference image generated from the distorted image. These PRIs can be generated by applying distortions to the distorted image itself. Based on the distortion already in the distorted image, new distortion is applied. If the image is blurred image, then it is re-blurred to generate its PRIs. Similarly if the image is noisy, then a certain intensity of noise is again applied to the distorted image for generated PRIs. Thus these PRIs are generated using distortion specific quality metric. Using this metric, a general purpose PRI based quality metric is modelled using which the quality of the image can be evaluated. For that, the distortion is first identified and then performs the distortion specific quality assessment.

The work proposed in [6] is a technique that estimates the quality of the image that is degraded either by a single type of distortion or by multiple distortions. Here the distortion is identified initially. Then the distortion parameters are calculated using which quality mapping is performed and overall quality is computed. But this method considers only three distortions. And it uses most-apparent strategy for combining the different distortion types and their quality results into a single value. Since the method performs the quality estimation of multiply distorted image, it not only needs to consider the joint effect of the distortions but also need to consider the effects of each distortion to each other.

The proposed method in [7] is proposed for considering three types of visual perception such as image distortion, depth perception and binocular perception. Here a disparity search algorithm is first developed based on the Gaussian average structural similarity which is robust. The distortion is measured by utilizing the characteristics of Laplace distribution and BNB based quality metric. Then features are extracted specific to each visual perception factors above mentioned. And the weight map, rivalry map, depth map and cyclopean images are generated. And finally using machine learning the features extracted from the image is mapped to image quality value. Since the image used by this method is a stereoscopic image, it is difficult to perform the 3D-IQA for the lack of understanding of 3D visual perception. Also it is much more difficult for quality assessment of the stereoscopic images when it is applied with asymmetric distortions.

The work described in [8] is used for the assessing the quality of stereoscopic images that are either singly or multiply distorted. This is done by employing a taskdriven and modality-specific MB-LVP by characterizing with the underlying MRF and BRF properties of visual cortex. Given a stereoscopic input image, the feature encoding is performed using the learned MB-LVP which results in the monocular and binocular responses. All these results are combined and obtain the final monocular and binocular features for quality regression. As the effect of image distortions, depth perception etc. need to addressed simultaneously, the 3D-IQA methods faces more challenges. Also since the methods follows learning of NR-IQA framework that requires subjective ratings, it is always expensive and large labour consumption.

The paper presented in [9] deals with four elements for quality estimation of SCI. the first element is regarding the image complexities. The second element is used for measuring the statistical degradation of image for its original state by using local mean and variance maps. the third element measure the global brightness and surface quality using sample mean and skewness respectively. And the fourth element measures the picture details by measuring sharpness loss and blocking. A total of 15 features are extracted from each input image and they are converted to the overall quality score. Since the SCI present different complexities than NSI, deeper CNN network is required for accurate quality estimation.

The work [10] is proposed for measuring the quality of SCI using new method called HR-feature fusion. This technique is used for fusing the characteristics of local Dept. of Computer Science & Engineering, VJCET 26NR-IQA Based on MLBP using Distortion Aggravation and global SCI region. For this the SCI is categorized into two patches; SEPes, which are regions that contain text, graphics, high frequency components and non-SEPes which are remaining portions of SCI other than SEPes. After the segementation of SCI into SEPes and non-SEPes, features are extracted. Both local features from the SEPes and global features from the entire SCI are extracted. By incorporating these local and global features, visual quality of SCI is predicted. Since it does not consider different visual perception features of SEPs and non-SEPs, shows relatively poor performance in CC distortions.

III.SYSTEM DESIGN

There are various approaches for estimating the quality of the image from the experiments being carried out in the field of quality estimation. From this, the methods for quality estimation conducted using the pseudo reference images are very unusual. Most of the work such as [11] uses distortions added to the image to create pseudo-reference images are JPEG compression, blur, and noise. Those PRIs are used for quality assurance compared with the distorted image [11].

The method being proposed uses the idea of multiple pseudo-reference images to estimate the image quality. The Figure 1 shows the proposed system for quality evaluation of no-reference images using MPRIs and MLBP extraction process.

These MPRIs are created by applying various kinds of distortions to the images. Many forms of distortion aggravation can be used to quantify the objects that blocking, noising, ringing and blurring.

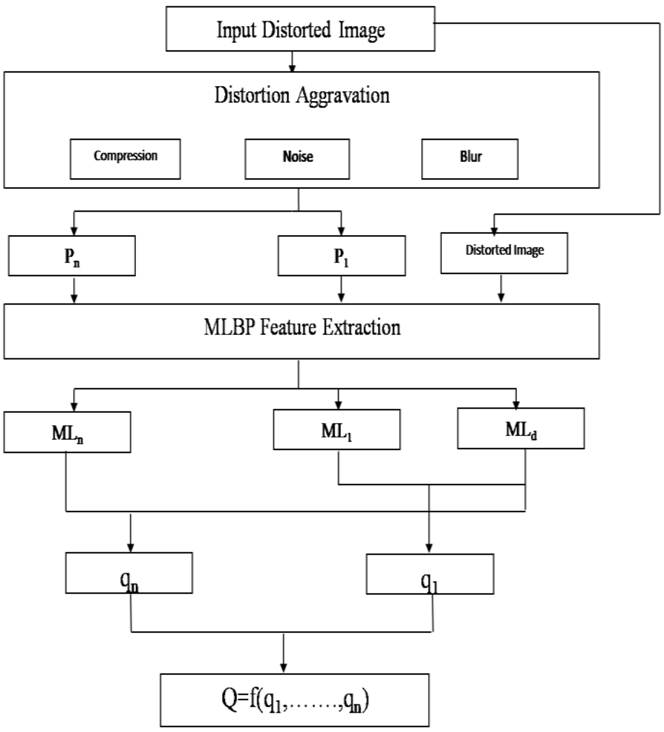


Fig.1. Proposed System for Blind Image Quality Estimation

Then, like the FR IQA method, from the image which is distorted, features are extracted and MPRIs using MLBP feature extraction approach and their similarities of the MPRIs from its original distorted image is compared. More comparable to a given PRI denotes closer to its quality.

ISSN No: 2456-2156

IV.IMPLEMENTATION

A. Language Used

Python is one of the popular programming language which is easy to pick up. It has efficient high-level data structures, and also a simple but strong, object-oriented programming approach. The elegant syntax and dynamic typing along with its interpreted nature of this language makes it a perfect language for scripting and for fast application development on most platforms in various areas. It supports both functional and formal methods of programming, and OOP. It can be used as a scripting language, or it can be compiled to byte-code for broad application construction. It provides dynamic data types of very high level and supports the dynamic type check. This allows automated sorting of the garbage. Simple to integrate with C , C++, COM, ActiveX, CORBA, and Java.

B. Dataset

The dataset used in this methodology which includes three mainstream NSI QA databses are LIVE [12], TID2013 [13],CSIQ [14]. But most of the images are taken from LIVE which is used for testing.

C. Modules

1. Distortion Aggravation

Different types of aggravation of distortion are applied on the image, and five levels are added for each type. Wavelet compression, Gaussian blur, Salt and Pepper noise and White noise are the widely implemented distortions in this approach. Wavelet compression[12] is used here to calculate the effects of blocking in the image. The compression of wavelets functions as follows; (a) The image is read and is applied with 2D DWT using daubechies wavelet. (b) Then the standard deviation is calculated. This STD is considered as the threshold. (c) Compression can be done by ignoring the approximation coefficients from the wavelet coefficients that are below the threshold (t = STD). (d) The compressed image can be obtained by reconstruction of the image by performing the inverse transform. Various orthogonal daubechies wavelets from db1-db10 can be used to apply various degrees of compression. Compression here is achieved using the orthogonal db1-db5 wavelets. For blurring effect Gaussian blur is applied to the image. To get its MPRIs say Pbi the image is distorted. Use different Gaussian filter to blur the image. The Gaussian filter is chosen based on the size of the window. As for each distortion five rates are applied, five different Gaussian filters are used for five different window sizes. The image is blurred by using the convolution operator with the picture and the Gaussian filter as its parameters. For noise effect, white noise and salt and pepper noise are added to the image. For this the noise values are applied to the image.

2. MLBP Feature Extraction

MLBP is an amended version of the extraction technique for LBP features. This technique is pretty quicker than approach to LBP. The image extracted using MLBP will also be unique in characteristics. These features have better features too. The properties of the image are minimized to just four values. Therefore, using MLBP than LBP is still feasible. To extract features, you must first get the original image as in [13]. If the image is a color image, change it from 3 dimensional to 2 dimensional. Retrieve the number of rows and columns of the matrix. Using this threshold value then calculate two parameters say a and b, which are used to calculate a third parameter, say c. Its value is added to the Features Array finally with four values in the function array which are the MLBP features. Compared to other extraction methods for the LBP feature, MLBP is more efficient due to its speed-up factor. The MLBP feature can be susceptible to changes in the original image.

3. Similarity Calculation

The similarity of the original image with its distorted image is calculated to predict image quality. For that, it defines the overlap between the original image and the distorted image. It is from this overlap that the similarity is calculated and in turn its quality. The standard is calculated based upon the rating ranking. High q score means bad quality because the MPRIs describe poor image quality.

4. Quality Prediction

All the similarity scores of both the original image and its distorted images are concatenated together to form a feature vector, say q. This vector contains features describing the effects of image blurring, noise, and compression. Because the distortions in the practical application are unknown and the portion of the distortion effect is not understood either, through training, the feature vector q is integrated into a final quality score. Here Support Vector Machine (SVM) is used for this testing and training. The quality feature, say f, and the quality label, say Q, of the image is used for the testing. The quality of the test image can be estimated using the quality feature after the training process.

V.RESULTS

The image is applied with different distortion like wavelet compression, Gaussian blur, white noise and salt and pepper noise. The result of various distortion are shown below;

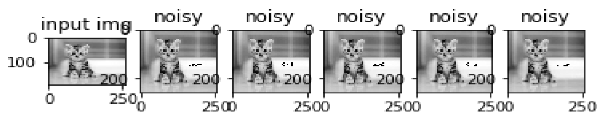


Fig.2. Distortion by adding white noise

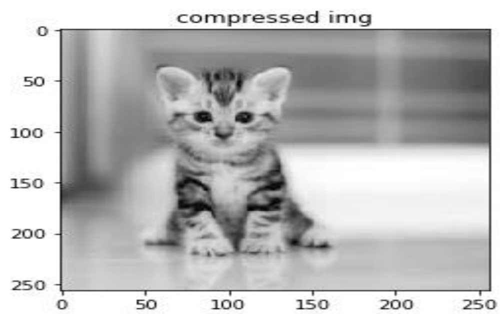


Fig.3. Distortion by wavelet compression

ISSN No: 2456-2156

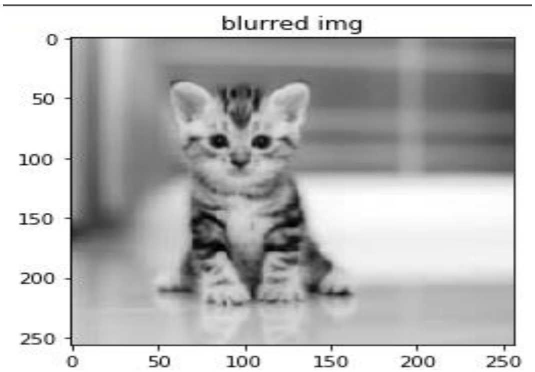


Fig.4. Distortions by Gaussian blur

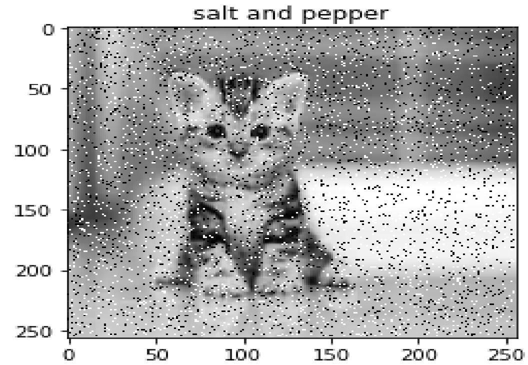
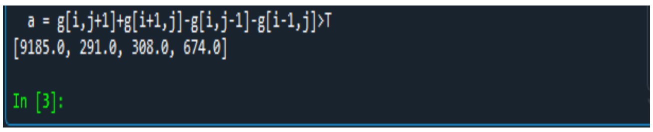


Fig.5. Distortion by adding salt and pepper noise

After these distortion applied on the image, multiple pseudo reference images are obtained. From these MPRIs and original image, MLBP features are extracted. There will be four unique values as shown figure 6;

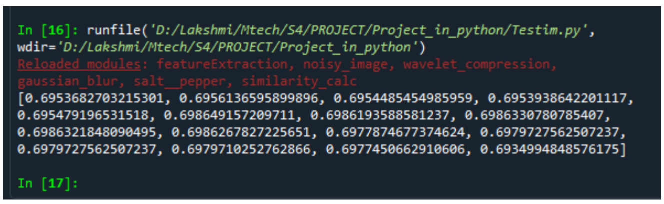


```
 a = g[i,j+1]+g[i+1,j]-g[i,j-1]-g[i-1,j]>T
[9185.0, 291.0, 308.0, 674.0]

In [3]:
```

Fig.6. Output of MLBP feature extraction

The similarity between the original image and its distorted images are calculated. This similarity is considered as its quality value as shown in figure 7.

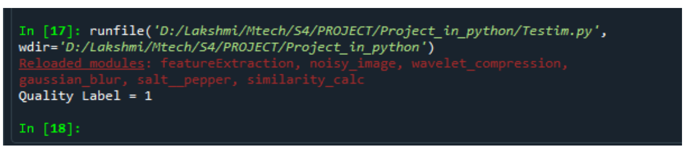


```
In [16]: runfile('D:/Lakshmi/Mtech/S4/PROJECT/Project_in_python/Testim.py',
wdir='D:/Lakshmi/Mtech/S4/PROJECT/Project_in_python')
Reloaded modules: featureExtraction, noisy_image, wavelet_compression,
gaussian_blur, salt__pepper, similarity_calc
[0.6953682703215301, 0.6956136595899896, 0.6954485454985959, 0.6953938642201117,
0.695479196531518, 0.698649157209711, 0.6986193588581237, 0.6986330780785407,
0.6986321848090495, 0.6986267827225651, 0.6977874677374624, 0.6979727562507237,
0.6979727562507237, 0.6979710252762866, 0.6977450662910606, 0.6934994848576175]

In [17]:
```

Fig.7. Output of similarity calculation

These similarity values of original image and all of its distorted images are concatenated into a quality vector which is shown in figure 8.



```
In [17]: runfile('D:/Lakshmi/Mtech/S4/PROJECT/Project_in_python/Testim.py',
wdir='D:/Lakshmi/Mtech/S4/PROJECT/Project_in_python')
Reloaded modules: featureExtraction, noisy_image, wavelet_compression,
gaussian_blur, salt__pepper, similarity_calc
Quality Label = 1

In [18]:
```

Fig.8. Output of quality prediction by SVM

The accuracy score is plotted based on training score and cross-validation score as shown in figure 9. The graph is plotted for various values of the kernel parameter with training scores and cross validation scores of an SVM. The graph is straight for median values of gamma. Here for any training set, the score is same which means the classifier is performing fairly well. Training score higher than validation score means the model will be a better fit to data.

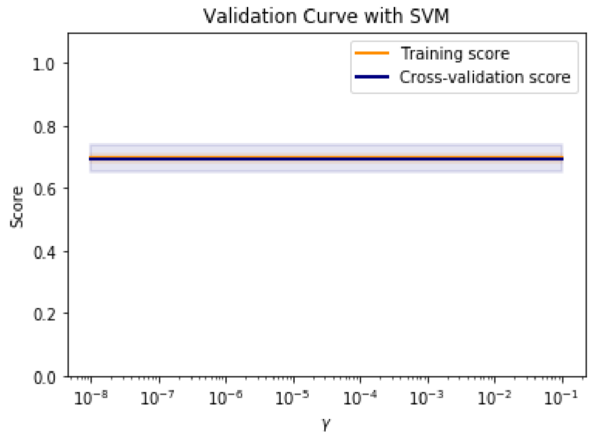


Fig.9. Graphical representation of accuracy score against cross validation score

Performance of the model shows how much time was required to train the model for each training sizes which is shown in figure 10. That is, it is the variation of the score with time. The fit time used in the x-axis is the time spent for fitting in seconds only if the return value is true.

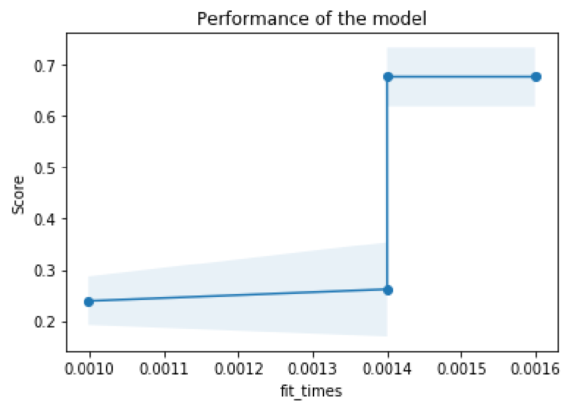


Fig.10. Figure 10. Graphical representation of performance of the model

VI. CONCLUSION

Image Quality Estimation has become one of the essential processes in image processing, because good image quality is often a better communication tool. In the proposed approach, NR-IQA is applied more, because the reference image of the original image is not always available in real-world applications. The researchers have developed different NR-IQA approaches. The method proposed uses multiple pseudo-reference image concepts for estimating the output. The MPRIs themselves are created from the distorted image. Previous papers find JPEG compression to be one of the distortions added to producing MPRI on the distorted image.

The proposed method uses another form of compression, called wavelet-based compression. It is for avoiding lossy compression methods which causes loss of image quality during the reconstruction process. The proposed approach uses MLBP extraction feature technique as it improves the classifier's speed and accuracy. The system increases efficiency over the current models. It is also robust and compatible with previous approaches as it predicts the output by comparing the pairs of images and decreases the influence of the content of images.

REFERENCES

[1]. P. Joshi and S. Prakash, "Continuous Wavelet Transform Based No-Reference Image Quality Assessment for Blur and Noise Distortions," IEEE Access, vol. 6, no. c, pp. 33871–33882, 2018.
[2]. X. Min, K. Ma, K. Gu, G. Zhai, Z. Wang, and W. Lin, "Unified Blind Quality Assessment of Compressed Natural, Graphic, and Screen Content Images," IEEE Trans. Image Process., vol. 26, no. 11, pp. 5462–5474, 2017.
[3]. K. Gu, W. Lin, G. Zhai, X. Yang, W. Zhang, and C. W. Chen, "No-Reference Quality Metric of Contrast-Distorted Images Based on Information Maximization," IEEE Trans. Cybern., vol. 47, no. 12, pp. 4559–4565, 2017.
[4]. N. K. Kottayil, G. Valenzise, F. Dufaux, and I. Cheng, "Blind quality estimation by disentangling perceptual and noisy features in high dynamic range images," IEEE Trans. Image Process., vol. 27, no. 3, pp. 1512–1525, 2018.
[5]. X. Min, K. Gu, G. Zhai, J. Liu, X. Yang, and C. W. Chen, "Blind Quality Assessment Based on Pseudo-Reference Image," IEEE Trans. Multimed., vol. 20, no. 8, pp. 2049–2062, 2018.
[6]. Y. Zhang and D. M. Chandler, "Opinion-Unaware Blind Quality Assessment of Multiply and Singly Distorted Images via Distortion Parameter Estimation," IEEE Trans. Image Process., vol. 27, no. 11, pp. 5433–5448, 2018.
[7]. L. Shen, R. Fang, Y. Yao, X. Geng, and D. Wu, "No-Reference Stereoscopic Image Quality Assessment Based on Image Distortion and Stereo Perceptual Information," IEEE Trans. Emerg. Top. Comput. Intell., vol. 3, no. 1, pp. 59–72, 2018. vNR-IQA Based on MLBP using Distortion Aggravation
[8]. Q. Jiang, F. Shao, W. Gao, Z. Chen, G. Jiang, and Y. S. Ho, "Unified NoReference Quality Assessment of Singly and Multiply Distorted Stereoscopic Images," IEEE Trans. Image Process., vol. 28, no. 4, pp. 1866–1881, 2019.
[9]. K. Gu, J. Zhou, J. F. Qiao, G. Zhai, W. Lin, and A. C. Bovik, "No-Reference Quality Assessment of Screen Content Pictures," IEEE Trans. Image Process., vol. 26, no. 8, pp. 4005–4018, 2017.
[10]. L. Zheng, L. Shen, J. Chen, P. An, and J. Luo, "No-Reference Quality Assessment for Screen Content Images Based on Hybrid Region Features Fusion," IEEE Trans. Multimed., vol. 21, no. 8, pp. 2057–2070, 2019.
[11]. Xiongkuo Min, Guangtao Zhai, Ke Gu, Yutao Liu, and Xiaokang Yang, "Blind Image Quality Estimation via Distortion Aggravation", vol. 64 , no. 2 , 2018.
[12]. H. R. Sheikh, Z. Wang, L. Cormack, and A. C. Bovik. LIVE Image Quality Assessment Database Release 2. Accessed: Mar. 22, 2014. [Online]. Available: http://live.ece.utexas.edu/research/quality
[13]. E. C. Larson and D. M. Chandler, "Most apparent distortion: Fullreference image quality assessment and the role of strategy," J. Electron. Imag., vol. 19, no. 1, 2010, Art. no. 011006
[14]. N. Ponomarenko et al., "Image database TID2013: Peculiarities, results and perspectives," Signal Process. Image Commun., vol. 30, pp. 57–77, Jan. 2015.
[15]. E. C. Larson and D. M. Chandler, "Most Apparent Distortion: Full-Reference Image Quality Assessment and the Role of Strategy," Journal of Electronic Imaging, 19 (1), March 2010.
[16]. Nedhal Mohammad Al-Shereefi," Image Compression Using Wavelet Transform ," Journal of Babylon University/Pure and Applied Sciences no. 4 vol.21, 2013.
[17]. Bilal Zahran, Jamil Al-Azzeh, Ziad Alqadi, Mohd–Ashraf Alzoghoul, Saleh Khawatreh, " A Modified Lbp Method To Extract Features From Color Images," Journal of Theoretical and Applied Information Technology, 31st May 2018. vol.96. no 10. Dept. of Computer Science & Engineering, VJCET viNR-IQA Based on MLBP using Distortion Aggravation
[18]. Xiongkuo Min, Guangtao Zhai, Ke Gu, Yutao Liu and Xiaokang Yang, "Blind Image Quality Estimation via Distortion Aggravation," IEEE Trans. Broadcasting vol. 64, no. 2, pp. 508-517, 2018