No Reference Gradient Oriented Image Quality Assessment

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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.

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](image)

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] Explored 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 amplitudes 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

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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-excision execution as differentiated and the most standard IQA approaches. Tongfeng Sun et al. [14] proposed a no-execution as differentiated and the most standard IQA approaches. Tongfeng Sun et al. [14] proposed a no-execution as differentiated and the most standard IQA approaches.

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](image)

**Figure 3:** Testing image I.

Its GM map can be processed as

$$ G_I = \sqrt{I \otimes h_x^2 + I \otimes h_y^2 + I \otimes h_z^2} $$

(1)

Where “$$ \otimes $$” denotes linear convolution and $$ h_d, d \in \{x, y, z\}, $$ Gaussian filter applied across the horizontal, vertical and diagonal directions.

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

(2)

Where

$$ g(x, y, z | \sigma) = \frac{1}{2 \pi \sigma^2} \exp \left( -\frac{x^2 + y^2 + z^2}{2\sigma^2} \right) $$

is gaussian function with scale parameter $$ \sigma $$.

LOG map of an image I can be processed as

$$ L_I = 1 \otimes h_{LOG}. $$

(3)

Where

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

(4)

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:

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

(5)

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

$$ N_i(i, j) = \sqrt{\sum_{i \in \alpha_i} \alpha_i(l, k) E_i^2(l, k)} $$

(6)

The normalized GM and LOG features are given as:

$$ \overline{G_I} = \frac{G_I}{N_i + \epsilon} $$

(7)

$$ \overline{L_I} = \frac{L_I}{N_i + \epsilon} $$

(8)
Scores (DMOS/MOS) are typically recorded to portray how subjective image databases. Differential Mean Opinion Score (DMOS) is a standard quality score with which the output of various NR-IQA calculations is to be compared. 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 has 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. 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 o(k, l) are produced by a Gaussian part with scale parameter 2σ. The average value of GM and LOG in LIVE database is taken 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.

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].

Figure 5: (a) Normalized GM feature maps; (b) Normalized LOG feature maps.
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 \((C, \gamma)\) 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 \((C, \gamma)\) 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 M1, M2, M3 models before and after modification.

<table>
<thead>
<tr>
<th>Image</th>
<th>Prediction Scores before modification</th>
<th>Prediction Scores after modification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jpeg 1</td>
<td>M1: 98.8418, M2: 91.0881, M3: 41.4298</td>
<td>M1: 42.309, M2: 95.4079, M3: 78.4805</td>
</tr>
<tr>
<td>Jpeg 2</td>
<td>M1: 94.7303, M2: 89.0694, M3: 65.1988</td>
<td>M1: 47.8443, M2: 92.9631, M3: 100.7082</td>
</tr>
<tr>
<td>Jp2k 25</td>
<td>M1: 82.9768, M2: 89.1527, M3: 73.9973</td>
<td>M1: 77.4910, M2: 91.8997, M3: 96.5003</td>
</tr>
</tbody>
</table>

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.

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References


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