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Analysis of Weibull Statistic Features Impact on Image Degradation Measurement

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ABSTRACT-The traditional concept of quality of service (QoS) which focuses on network performance (*e.g.* packet loss, throughput, and transmission delay), recently has been grown towards the modern concept of quality of experience (QoE). This reflects all user practice including accessing and service provided. In order to maintain the required QoE, it's necessary for the service provider to recognize and measure image degradation. This study provides different features in order to assess degraded image quality blindly depending on Weibull statistics. Also, it presents a comparison analysis to give the more performing one. The introduced features are originated from the gist of natural scenes (NS) using Weibull distribution of Log-derivatives. These measuring features were collected through both sharper and rich edging regions of the images. Besides, Weibull features were developed by maximum likelihood estimation (MLE) parameters to improve the quality assessment. LIVE database used to calibrate the proposed features achievement. Experiments prove Weibull statistics the best among popular full-reference peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) methods. Also, they show Weibull features extracted by means of sharper regions are the best when assess the prediction monotonicity. While applying the prediction accuracy evaluation come up with a good performs when taking the improved Weibull features via sharper regions.

Keywords: *measuring feature, image degradation, Features Measuring.*

المستخلص - المفهوم التقليدي لجودة الخدمة (QoS) والذي يهتم بأداء الشبكة (فقد الحزم، الإنتاجية، تأخير الانتشار...الخ) مؤخرا تطور للفهم الحديث لجودة الخبرة (QoE). هذا يعكس كل أنشطة المستخدم بما فيها النفاذ والخدمات المقدمة. من أجل المحافظةعلى QoEالمطلوبة، من المهم لمقدم الخدمة أن يتعرف على مدى اضمحلال الأشارة ويقيسه. هذه الدراسة تقترح سمات مختلفة لتقييم جودة الصورة المضمحلة بدون مرجععتمادا على أحصائيات ويبل Weibull statistics. أيضا تعطى الدراسة تحليل مقارنة لمعرفةأكثر هذه السمات أداءً. السمات المقدمة تم ابتدارها من لب المشاهد الطبيعية باستخدام مشتقات توزيع ويبل اللوغاريثمية. سمات القياسهذه تم جمعها خلال كل من المنطقتين الغنية بالحواف والاكثر وضوحا. بجانب ذلك، تم تطعيم سمات ويبل بمعاملات تقدير الاحتمال الأعظم (MLE) لتحسين تقييم الجودة. لمعرفة أداء السمات المقترحة، تمت معايرتها باستخدام قاعدة بيانات LIVE. أثبتت التجارب بأن احصائيات ويبل هي الأفضل من بين خوارزميات كل من نسبة ذروة الإشارة - الى- الضوضاء (PSNR)، والتشابه الهيكلي (SSIM)كاملتي المرجع. كذلك أوضحت أن سمات ويبل المستخلصة عن طريق المناطق الاكثر وضوحا هي الأفضل عند أعمال تقييم رتابة التنبؤ prediction monotonicity. بينما تطبيقتقييم دقة التنبؤ prediction accuracy يأتي بنتائج أفضل عند أخذ سمات ويبل المحسنة عن طريق المناطق الاكثر وضوحا.

1.Introduction

The traditional concept of quality of service (QoS) which focuses on network performance (e.g. packet loss, throughput, and transmission delay), recently has been grown towards the modern concept of quality of experience (QoE).

This reflects all user practice including accessing and service provided. In order to maintain the required QoE, it's necessary for the service provider to recognize and measure the quality of image degradation. Basically, Quantifying the image is done by humans because they are the ultimate judges. But their judgment is impractical where its subjective and consumes time. Thus, automatic measurement of image quality required which it is objective assessment.

Objective assessment classified as: no-reference NR (blind assessment), reduced reference (RR) and full reference (FR). Assessing image quality depending on original image done by the FR models. The mode which extracts some of the reference image features is RR model. Full or even partial of the original image may not be available when assessing the image under study. In existence of reference images, its purification can be also uncertain. So, the only available choice is NR image quality assessment (IQA) method [1-3]. As an example, when assessing the quality of a de-noising algorithm on a real-world database the perfect noise-free image is not available.

Distortion-specific NR IQA [4-9] are aware about the distortion categories and they represent most existing NR IQA methods. Application of such algorithms is limited by these specifications. Non-distortion-specific are general distortion NR IQA algorithms. Building of such algorithms are by acquiring a collection of distorted images. Then the images are registered by their human scores. These IQA algorithms are opinion aware (OA) [10-12].

If the IQA algorithms are not trained on databases of human judgments of distorted images they are opinion unaware (OU) algorithms [13]. The availability of the images under study is uncertain, so between OU models there are models called distortion unaware (DU) models [14]. In this study a model using Weibull distribution of Log-derivative features of natural scenes for no-reference image quality measurement is introduced. The effective features developed in the model are gathered from gist of image based on edges and sharper regions. This claim is supported by the fact human eye is sensitivity to information carried by edge and contour of an image. Also, image's structure has a large amount of data included in their edges and contours. This information is enough for the scene to be grasped by the human eye [15]. The sharper an image the better is its quality as claimed by Punit and Damon [16]. Moreover, more heavily weight judgments of image quality given from the sharp image regions [14].

All the parameters: prediction accuracy, algorithmic and micro-architectural efficiency are improved in this study. In contrast to many researches which ignore the two last parameters [17,18]. Weibull contrast statistics contains a great visual information [19]. Also, they can characterize a uniform texture of various natural scenes [20]. Besides they used by Fabian and Erhardt to detect the defect in textures [21].

The aims of this study refer to, multimedia content delivered over communication networks pass throughout a lot of processing phases before provided to a human consumer. The quality of the last display may be affected by one or more of these phases in the form of distortions.

The economics and/or physical limitations of the devices are the main factors that mostly determine the distortion contribution of each of these stages. Technically, it is important to gauge the distortion that has been added during different stages and then measure the visual contents quality. The image quality assessment algorithms are built to estimate image distortion content and measure how it degraded. The proper features selected from the images cooperate significantly in constructing these algorithms and measuring its quality.

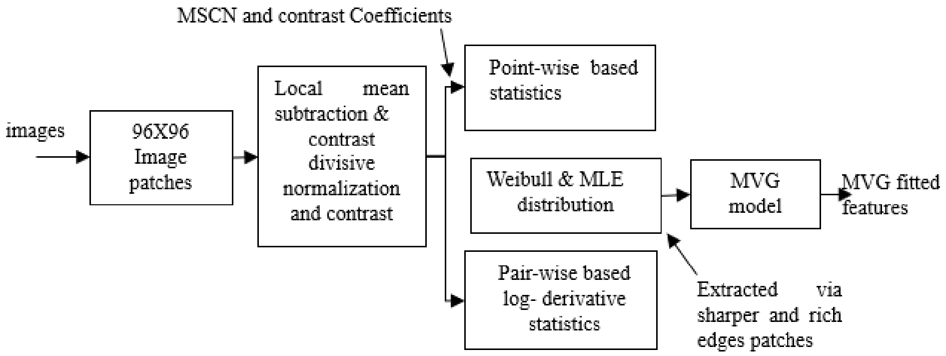

Figure1: The model block diagram for the three features categories extraction.

After building a robust model, this study aims to collect three features categories, analyze them, and see the competent one through examine their performance.

2. Material and Method

The developed natural features are low level features. These are created of locally normalized luminance. Also contrast values have been added. for single pixels, point wise statistics modeled the features. For the relation of adjacent pixels, the approach gets the log-derivative based on pair wise statistics. the features that match patches with both rich of edges and sharper were gathered individually. Then the gathered features were fit to Multivariate Gaussian Model (MVG).

The model gauges the distance between MVG of the distorted and pristine (natural). How is the measured distance, it assigned as the distorted image quality score. Figure 1 shows the model block diagram for the three features categories extraction.

Normalized luminance, contrast coefficients, and their log-derivatives

The image-indicated by $I(i,j)$ has been divided in to patches. Each of patches has a size of 96 × 96. Then equation (3) is used to calculate the contrast of distorted and pristine images. This done for all the patches. The same procedure followed to compute the normalized luminance (MSCN)$\hat{I}(i,j)$ (1) [22].

$$\hat{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + 1} \qquad (1)$$

Where $i \in \{1,2,\ldots,M\}$and$j \in \{1,2,\ldots,N\}\}$ are spatial domain indices, M and $N$are the dimensions of the image. The local mean and local contrast are shown in (2) and (3) respectively.

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} I(i+k, j+l) \qquad (2)$$

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l} \left[I(i+k, j+l) - \mu(i,j) \right]^2} \qquad (3)$$

The 2D circularly-symmetric Gaussian weighting function, w, is:

$$\mathrm{w} = \{\mathrm{w_{k,l}} | \mathrm{k} = -\mathrm{K}, \ldots, \mathrm{K}, \mathrm{l} = -\mathrm{L}, \ldots, \mathrm{L}\}$$

This function is sampled out to three standard deviations($K = L = 3$)and rescaled to unit volume.

Features are calculated through coefficients of (1) and (3) for each patch. The features extraction done using log-derivative statistics [23]. To acquire the log-derivatives (5-6), (4) is used. This to create new image sub-band J .

$$J(i,j) = \log\left(\hat{I}(i,j) + \varepsilon\right) \qquad (4)$$

To prevent $I(i,j)$from being zero, ε is taken to be 0.1.The equations (5-6) include horizontal, vertical, main-diagonal, secondary-diagonal, and combined-diagonal.

$$J_x(i,j) = J(i,j+1) - J(i,j) \qquad (5)$$

$$J_y(i,j) = J(i+1,j) - J(i,j) \qquad (6)$$

$$J_{xy}(i,j) = J(i+1, j+1) - J(i,j) \quad (7)$$

$$J_{yx}(i,j) = J(i+1, j-1) - J(i,j) \quad (8)$$

$$J_{xandy}(i,j) = J(i,j) + J(i+1, j+1) - J(i, j+1) - J(i+1, j) \quad (9)$$

Any deformation happens to the original image due to distortion can be investigated by applying coefficients of (1) and (5-6) [10, 24].

The Extracted Features

The model carefully selects various categories of features which were extracted using statistical approach that can facilitate efficient and rapid extraction of a scene's gist. The features are initiated using Weibull distribution of Log-derivative. Besides, the Weibull features developed by maximum likelihood estimation parameters to improve the quality evaluation.

Thus, as will be explained in the following sections, the features are categorized into; Weibull statistics based on sharper regions, improved Weibull statistics based on sharper regions, and Weibull statistics based on edging regions. To examine the effect of the gathering technique on these measuring features, they were collected through both sharper and rich edging regions of the images.

Weibull Statistics Based Features of Sharper Regions:

The Weibull distribution (10) models the MSCN (1), contrast (3) coefficients, and the five log-derivatives in (5-9). It useful to represent These features in multi-scale behavior. In this model they calculate at two scales using low pass filter then down sampling by two. The spatial domain is the platform of extracting all features. The gathering process includes only features involved in the sharper patches.

$$f(x;\lambda,\gamma,\mu) = \begin{cases} \frac{\gamma}{\lambda}\left(\frac{x-\mu}{\lambda}\right)^{\gamma-1} e^{-\left(\frac{x-\mu}{\lambda}\right)^{\gamma}} & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (10)$$

Where λ, γ, and μ are the scale parameter, the shape parameter, and the origin of the contrast distribution respectively. The parameter μ close to zero for natural images which is the case in this model [21].

To quantify degraded image, it's better to consider the features of sharper and rich edge as suggested by [14,15,25].

The MVG density (11) models the features obtained by (10).The last process gives the rich representation of these features [14].

$$f_X(x_1,\ldots,x_k) = \frac{1}{(2\pi)^{k/2}|\Sigma|^{1/2}} \times exp(-\frac{1}{2}(x-\upsilon)^T\Sigma^{-1}(x-\upsilon)) \quad (11)$$

Where,$x_1,\ldots,x_k$,are the features. The mean and covariance matrix of the MVG model are υ and ∑ respectively.

Improved Weibull Statistics-Based Features of Sharper Regions:

Again, the Weibull distribution (10) models the MSCN (1) and the five log-derivatives in (5-9), by this step 12 features are available. Beside pure Weibull parameters, maximum likelihood estimation (MLE) also added for improvement causes. The pure Weibull and the MLE parameters collectively are measuring features. Now the total model features are 24 by gaining12 MLE features 24 overalls. the model uses two scales, as discussed above, this process leads to a set of 48 features. All features fitted with an MVG density (11). Here also the gathering process includes only the features involved in the sharper patches.

Weibull Statistics Features Based on Rich Edges Regions:

Weibull distribution (10) models the MSCN (1) and contrast coefficients (3), and their five log-derivatives through using edging patches. Each of MSCN and contrast coefficients provides two features and their five derivatives provide 20 extra features with a total of 24 features. The two scales process adds 24 more features giving 48 overalls. Again, spatial domain is the platform of extracting all features in this model. Fitting all features using (11) gives their rich representation.

Natural Scene Statistic Model

Flickr and the Berkeley are natural scene image database [26]. The main model selects 125 natural images to form natural scene statistic (NSS) model. The NSS model summarized in the flowing steps:

- Each patch divided to sub-patches of 6×6 size.
- In each sub-patch only sharper and edge feature are selected (called effective sub-patches).
- Only effective sub-patches contributed into their main patches.
- Then the effective sub-patches of each patch were computed.
- Patches that had an effective sub-patch greater than 75% selected.
- The features corresponding to the selected patches were gathered.
- The features of NSS extracted using the three categories discussed above in section (3.2).
- These features were fitted to MVG model (11).
- Equation (12) used to compute the quality according to the above steps.

$$D(\upsilon_1,\upsilon_2,\Sigma_1,\Sigma_2)=\sqrt{(\upsilon_1-\upsilon_2)^T\left(\frac{\Sigma_1+\Sigma_2}{2}\right)^{-1}(\upsilon_1-\upsilon_2)} \quad (12)$$

The mean vectors and covariance matrices of the NSS MVG and the tested image MVG models are υ_1,υ_2 and $\sum_1,\sum_2$ respectively.

3. Testing and Calibration

LIVE (Laboratory for Image and Video Engineering) IQA database [27] is used to calibrate the proposed algorithms and do performance analysis and comparison. There is a lot database used to Calibration IQA algorithms. LIVE which contains 29 reference images and 779 distorted ones is the most common database. The 779 distorted images of LIVE database are classified into JPEG compression, JPEG2000 (JPEG2K) compression, Gaussian blur (Gblur), fast fading (FF), and additive white Gaussian noise (WN).

Two common parameters used in the field of IQA to evaluate and test the calibrated images which are Spearman's rank ordered correlation coefficient (SROCC) and Pearson's linear correlation coefficient (PLCC). The first parameter used to assess the prediction monotonicity while the second for prediction monotonicity,

Before calculating PLCC, maximizing the correlations between subjective and objective scores needed. This done by passing the last scores through a function called logistic non-linear function [28]. The parameters of this function found numerically using 'fminsearch' (a function in MATLAB optimization toolbox).

4. Results and Discussion

This section discusses and analyze performance of the obtained results. The plots of Figures 2 and (3) obtained when the all features gathered through the same techniques, *e.g.* sharper regions. The Figures show a comparison of SROCC and PLCC when extracting features using pure Weibull and Weibull with MLE through sharper regions respectively.

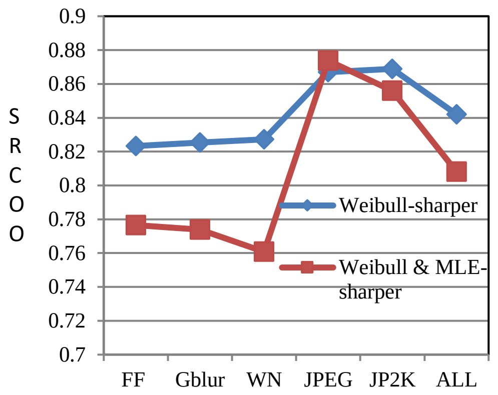

Figure 2: Comparison of SRCC when extracting features using Weibull and improved Weibull (Weibull & MLE) through sharper regions.

Figures 2 indicates pure Weibull features better when assess the prediction monotonicity, which is 0.84 for the overall (average of the SROCC for all distortions). While applying the prediction accuracy evaluation come up with a good performance when developing Weibull features with MLE as verified by Figure 3, which is 0.86 for the overall average of the PLCC for all distortions.

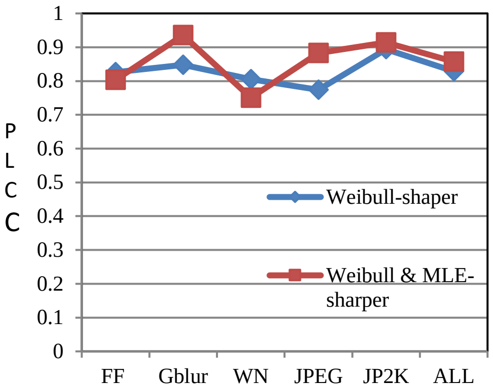

Figure 3: Comparison of PLCC using Weibull and improved Weibull (Weibull & MLE) through sharper regions.

Figures 4 and 5, investigate the behavior of the three features categories, regard the different two gathering techniques. A comparison of SROCC and PLCC when the measuring features are pure Weibull and Weibull with MLE (improved Weibull) of sharper regions and pure Weibull of edging regions. Figures still proves pure Weibull sharper regions is the outperforming features when assessing the prediction monotonicity with 0.84 overall.

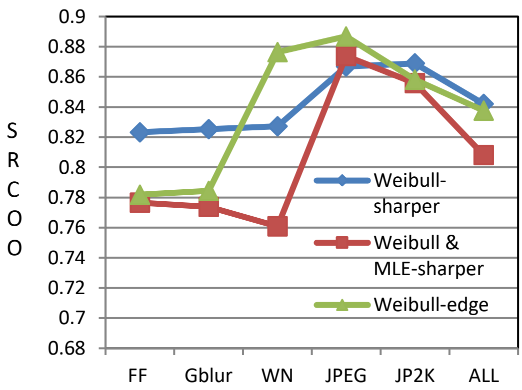

Figure 4: Comparison of SRCOO using Weibull, improved Weibull (Weibull & MLE), and edging Weibull feature.

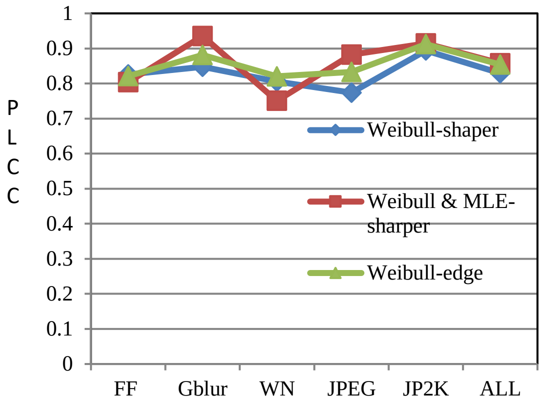

Figure 5: Comparison of PLCC using Weibull, improved Weibull (Weibull & MLE), and edging Weibull feature.

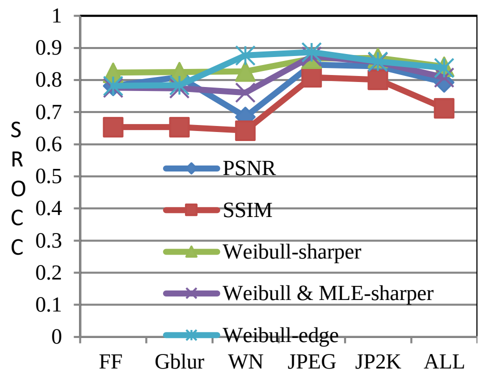

Figure 6: Comparison of SROCC of the proposed features against FR-PSNR and FR-SSIM algorithms.

The features formed by Weibull statistics and MLE obviously are the best when evaluate the prediction accuracy. The improved Weibull features have overall PLCC of 0.86. Figures 6 and 7 show a comparison of SROCC and PLCC for all proposed features against FR-PSNR and FR-SSIM algorithms respectively.

They show the average of SROCC and PLCC for all distortions not only competes the popular full-reference peak signal-to-noise ratio (PSNR) and the structural similarity (SSIM) but also outperforms them. Pure Weibull (sharper) has best performance when assessing SROCC with 0.84, as Figures 6 illustrates. The improved Weibull features obviously appeared when evaluate the prediction accuracy (PLCC) as clearly indicated by (7).

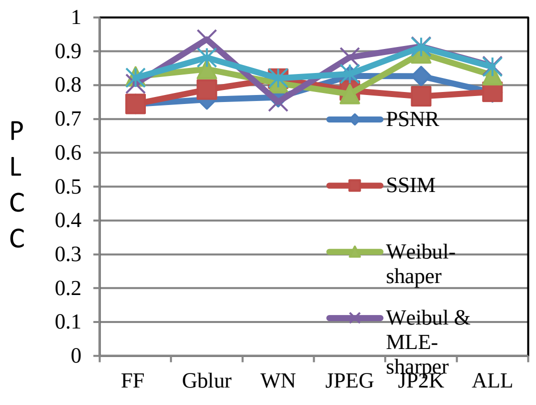

Figure 7: Comparison of PLCC of the proposed features against FR-PSNR and FR-SSIM algorithms.

5. *Conclusions*

The suitable features and the way to gather are significantly affective in measuring degraded image task. In this study, a model for blind NR IQA built and a performance comparison between three Weibull distribution statistics feature categories introduced. Also, two different gathering techniques for the features are analyzed and examined. The features used in this paper obtained in the spatial domain without transformation to DCT, wavelet, or any other domain. Algorithms constructed in spatial domain have fast execution with no complexity. All the introduced features are the best when compared with state-of-the-art algorithms as shown in results section.

References

[1] Sathya Veera Reddy Dendi, Chander Dev, Narayan Kothari, Sumohana S. Channappayya,(2019) "Generating Image Distortion Maps Using Convolutional Autoencoders With Application to No Reference Image Quality Assessment." Signal Processing Letters IEEE, 26, 1.

[2] Jomgyoo Kim, Sanghoon Lee (2017), "Deep Image Quality Assement By Employing FR-IQA." International conference on Image Processing, IEEE, 17-20, Beijing China.

[3] SaifeldeenAbdalmajeed and Jiao Shuhong, (2014), "No-reference image quality assessment algorithm based on Weibull statistics of log-derivatives of natural scenes.", Electronics Letters, 50, 8, 595 – 596.

[4] Wang, Z., A.C. Bovik, H.R. Sheikh and E.P. Simoncelli (2004),"Image quality assessment: From Error visibility to structural similarity." IEEE Trans.13, 600-612,.

[5] Li, X. (2002), "Blind image quality assessment." Proceedings of the IEEE International Conference on Image Processing, Rochester, New York, USA,.

[6] Gabarda, S. and G. Cristobal (2012),"No-reference image quality assessment through the von Mises distribution." J. Opt. Soc. Am. A,29, 2058-2066.

[7] Wang, Z., A.C. Bovik and B.L. Evans (2000), "Blind measurement of blocking artifacts in images." Proceedings of the International Conference on Image Processing, Vancouver.

[8] Bovik, A.C. and S. Liu. (2001), "DCT-domain blind measurement of blocking artifacts in DCT-coded images." Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, Salt Lake City, UT., USA.

[9] Zhang, J., S.H. Ong and T.M. Le. (2011), "Kurtosis-based no-reference quality assessment for JPEG2000 images." Signal Processing Image Communication, 26, 13-23.

[10] Mittal, A., A.K. Moorthy and A.C. Bovik (2012), "No-reference image quality assessment in the spatial domain." IEEE Trans. Image Process.21, 4695-4708.

[11] A. K. Moorthy, and A.C. Bovik (2011), "Blind image quality assessment: From natural scene statistics to perceptual quality." IEEE Trans. Image Proces.20, 3350-3364.

[12] M., Saad, A.C. Bovik and C. Charrier (2012), "Blind image quality assessment: A natural scene statistics approach in the DCT domain" IEEE Trans. Image Process.21, 3339-3352.

[13] A. Mittal, G.S. Muralidhar, J. Ghosh and A.C. Bovik (2011), "Blind image quality assessment without human training using latent quality factors." IEEE Signal Process. Lett.19,75–78,.

[14] A., Mittal, R. Soundararajan and A.C. Bovik

(2013),"Making acompletely blind image quality analyzer." IEEE Signal Process.Lett.20, 209-212,.

[15] Marr D.; E. Hildreth (1980), "Theory of Edge Detection." Proceedings of the Royal Society of London. Series B, Biological Sciences, No. 1167,.

[16] Punit Singh and Damon M. Chandler (2013), "F-MAD: A Feature-Based Extension of the Most Apparent Distortion Algorithm for Image Assessment," in Proc.of SPIE,.

[17] D. M. Chandler (2013), "Seven Challenges in Image Quality Assessment: Past, Present, and Future Research," ISRN Signal Processing,2013, 53.

[18] M., Saad, A.C. Bovik and C. Charrier (2012), "Blind image quality assessment: A natural scene statistics approach in the DCT domain" EEE Trans. Image Process.21, 3339-3352.

[19] Ghebreab, S., A.W.M. Smeulders, H. S. Scholte, and V.A.F. Lamme (2009), "A biologically plausible model for rapid natural scene identification." Proceedings of the International Conference on Advances in Neural Information and Processing Systems, Vancouver, BC, Canada, 629-637.

[20] Geusebroek, J.M. and A.W.M. Smeulders (2005), " A six-stimulus theory for stochastic texture. " Int. J. Comput. Vision, 62, 7-16.

[21] Timm, F. and E. Barth (2011), "Non-parametric texture defect detection using Weibull features." Proceedings of the SPIE 7877, Image Processing: Machine Vision Applications, 7877, San Francisco, USA,.

[22] D. L. Ruderman (1994), "The statistics of natural images Network Comput." Neural Syst., 5, 517–548.

[23] Huang, J. and D. Murnford (1999), "Statistics of natural images and models." Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Fort Collins, CO., USA.

[24] Ghebreab, S., A.W.M. Smeulders, H. S. Scholte, and V.A.F. Lamme (2009),"A biologically plausible model for rapid natural scene identification." Proceedings of the International Conference on Advances in Neural Information and Processing Systems, Vancouver, BC, Canada, .

[25] SaifeldeenAbdalmajeed and Jiao Shuhong (2015), "Using the Natural Scenes' Edges for Assessing Image Quality Blindly and Efficiently," Mathematical Problems in Engineering, 2015, 9 pages.

[26] D., Martin, C. Fowlkes, D. Tal and J. Malik (2001),"A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics." Proceedings of the 8th International Conference on Computer Vision, California University Berkeley, USA.

[27] H.R., Sheikh, Z. Wang, L. Cormack and A.C. Bovik (2005), "LIVE image quality assessment database, Laboratory for Image and Video Engineering, release 2".

[28] H.R., Sheikh, M.F. Sabir and A.C. Bovik (2006), "A statistical evaluation of recent full reference image quality assessment algorithms." IEEE Trans. Image Processing,.15, 3440–3451.