Image Quality Assessment Employing RMS Contrast and Histogram Similarity

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Abstract: *This paper presents a new approach for evaluating image quality. The method is based on the histogram similarity computation between images and is organized with assessing quality index factors due to the contributions of correlation coefficient, average luminance distortion and rms contrast measurement. The effectiveness of this proposed RMS Contrast and Histogram Similarity (RCHS) based hybrid quality index has been justified over Lena images under different well known distortions and standard image databases. Experimental results demonstrate that this image quality assessment method performs better than those of widely used image distortion quality metric Mean Squared Error (MSE), Structural SIMilarity (SSIM) and Histogram based Image Quality (HIQ).*

Keywords: *Image quality measures, RMS contrast, histogram similarity, SSIM, HIQ, minkowski distance metric.*

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1. Introduction

Nowadays, image quality evaluation is highly required in image processing. Owing to various processes like acquisition, reproduction, and compression, images are being distorted. To evaluate the distortion level of such images, there is high demand for image quality metrics.

In the recent years, effort has been made to develop general image quality metrics, which can be applied to assess the quality of images. But still it has not been possible to find a generally accepted image quality measure [28, 31, 33, 36].

Image quality is evaluated and assessed largely by subjective or objective assessment methods [34]. The subjective assessment method involves observers to quantify their impressions. The quantification is based on standard scales specified, or the understanding of the observers in justifying the visual effects of the images.

On the contrary, the objective assessment method includes Human Visual System (HVS) features, error statistics, and structural similarity. In the error statistical approach the discrepancies are obtained by comparing the distorted image with the reference image through the designated characteristics, providing some statistical quantities to compute the image quality.

Whereas, HVS approach is implemented taking the advantage of human perspective feelings to develop a physical model and to meet the requirements for human perception. It considers the fact that human eyes generally do not recognize minor distortions and changes in the images, however, these minor changes may cause significant amount of differences as far visual effects are concerned. To analyse image quality various parameters are considered which include sharpness, sensitivity to distortion and edge distortion.

In structural similarity method, images are considered as a group of isolated pixels and it overlooks the statistical analysis of individual pixels.

Accordingly, errors in the visual perception are identified leading to abnormal changes in the quality, which are not similar to human visual perception. The HVS approach does not consider the correlation between pixels, thereby causing vast dissimilarities from the genuine visual characteristics. Even though it has many advantages, however, its channel decomposition algorithm is considered to be very complex [30].

The subjective assessment method is widely used in various fields because its evaluation outcomes are closely related to the application effects. On the other hand, objective assessment methods initiating from video or digital image processing, hardly consider specific tasks. The parameters which are commonly used are the variance, contrast, entropy, kurtosis, edge intensity, average gradient, and sharpness [25, 35].

Recent results have shown that under certain conditions, the quantitative assessment indexes reveal some characteristics of image quality. However, the calculation results of object recognition and information extraction are generally differing very significantly from the practical application effects. The objective assessment outcomes are similar to original reference images, because of full-reference image quality assessment [5, 8].

The Mean Squared Error (MSE) is one of the commonly used image quality assessment metric. It is a simple one and is obtained by averaging the squared intensity differences of the reference image pixels and distorted image pixels, along with Peak Signal-to-Noise Ratio (PSNR). The advantages of this method are:

1. Physically meaningful.
2. Simple to calculate.
3. Are mathematically convenient in terms of optimization [31].

But they are not considered suitable to the perceived visual quality [10, 11, 17, 26, 27, 29]. Efforts have been made to develop quality assessment methods having the advantages of known characteristics of the HVS. The most of these models have proposed the modification of the MSE, so that errors are detected in accordance with their visibility.

Objective performance assessment is one of the challenging issues due to the various application requirements and generally there is no clearly defined ground-truth. Generally, fusion algorithms have been evaluated on the basis of comparison of experimental results with an idle composite image as a reference [15, 21, 23]. MSE based metrics are very commonly employed for these comparisons [19].

Although the MSE is the most common objective criterion, its variants do not correlate completely with subjective quality measures.

In this paper, a novel image quality assessment algorithm is proposed. This algorithm utilizes index factors due to the contributions of correlation coefficient, average luminance distortion, rms contrast and histogram similarity metric. This quality measure is based on SSIM index proposed in [31]. Experimental results demonstrate that the proposed RMS Contrast and Histogram Similarity (RCHS) based hybrid quality index metric performs significantly better than the commonly used image distortion quality metric MSE, and more or less better than those of Structural SIMilarity (SSIM) and Histogram based Image Quality (HIQ).

The remaining part of this paper is organized as follows. Section 2 briefly describes Related Works.

Section 3 discusses on SSIM Index. In section 4, the proposed RMS RCHS based hybrid quality measure is presented. Two important features like rms contrast based assessment and histogram similarity based assessment are also discussed in this section.

Section 5 presents the experimental results and performance. Comparison of the experimental results of various image quality assessment models against Lena image and a large set of database of compressed images are furnished. Finally, section 6 draws the overall conclusions of this paper.

2. Related Works

A substantial amount of research works have been published in literature on image quality assessment.

Such performance measures are not including the ground-truth knowledge. Mutual information has been employed for assessing fusion performance [32]. In [22] an image fusion based metric has been proposed that assessed the relative amount of edge information being transferred from the input image to the composite image. Saad *et al.* [24] have developed a index BLind Image Integrity Notator using DCT Statistics (BLIINDS). Image quality is predicted based on observing the statistics of local discrete cosine transform coefficients. The main disadvantage of this method is that it requires some training. Wang *et al.* [31] have introduced an alternative approach for quality evaluation, called Structural SIMilarity (SSIM) index, based on the degradation of structural information. Yalman [33] has developed a HIQ index. Chen [7] and Chen and Blum [8] has developed a histogram equalization-based contrast enhancement technique for image quality assessment.

Nakarnae *et al.* [19] have performed a computer graphic based assessment for realistic images determining the basic color of the environment and comparing monotone colors against other color models. They employed human feelings to numerous images and subjective preferences. Motwakel and Shaout [18] have proposed a method to analyse fingerprint image quality using fuzzy logic. Kovaleski and Oliveira [13] have established a reverse tone mapping function for images, employing a bilateral filter and edge preservation strategy. Their method is organized by producing piecewise smooth brightness enhancement function with sharp illumination discontinuities. Their approach, nevertheless, suffers from contrast distortion and is prone to visible artefacts. Li *et al.* [16] have proposed an image quality assessment method based on edge information and singular value decomposition. Since the edge information was extracted by Sobel operator, the performance was not consistent with the subjective quality measure. Lee and Park [14] have developed an objective assessment method for perceptual image quality of tone mapped images. Betrabet and Bhogayta [1] have proposed an edge based structure similarity index metric.

3. Structural SIMilarity (SSIM) Index

A digital image whose quality is being assessed can be thought of as a sum of an undistorted reference image and an error signal. Wang *et al.* [31] have developed a structural similarity quality assessment from the perspective of image formation.

Let us start presenting the image quality assessment that was introduced by Wang *et al.* [31].

Given two images $f(x, y)$ and $g(x, y)$ of size $X \times Y$, let μ_f represent the mean of f, let σ^2 and σ_{fg} be the variance of f and covariance of f,g, respectively, i.e.,

$$\mu_f = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1} f(x,y) \qquad (1)$$

$$\sigma_f^2 = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\{f(x,y)-\mu_f\}^2 \qquad (2)$$

$$\sigma_{fg} = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\{f(x,y)-\mu_f\}\{g(x,y)-\mu_g\} \qquad (3)$$

Define

$$Q_0 = \frac{4\sigma_{fg}\mu_f\mu_g}{(\mu_f^2+\mu_g^2)(\sigma_f^2+\sigma_g^2)} \qquad (4)$$

Which can be decomposed as,

$$Q_0 = \frac{\sigma_{fg}}{\sigma_f\sigma_g}\times\frac{2\mu_f\mu_g}{(\mu_f^2+\mu_g^2)}\times\frac{2\sigma_f\sigma_g}{(\sigma_f^2+\sigma_g^2)} \qquad (5)$$

Wang and Bovik referred Q_0 as an image quality index and used it to quantify the structural distortion between images $f(x, y)$ and $g(x, y)$ In fact, the value $Q_0=Q_0(f, g)$ is a measure for the similarity between images f and g and takes values in the range [0,1]. The first component in Equation (5) implies the correlation coefficient between f and g. The second component corresponds to average luminance distortion with a dynamic range of [0, 1] (nonnegative mean values were assumed). The last component in Equation (5) corresponds to a contrast distortion and also within the range of [0, 1]. If f and g are identical then maximum value of $Q_0=1$ is achieved.

Since image signals are generally non-stationary, it is appropriate to measure the number Q_0 over local regions and then combine the different results into a single measure. In [31] the authors propose to use a sliding window approach: starting from the top-left corner of the two images f and g, a sliding window of fixed size moves pixel by pixel over the entire image until the bottom-right corner is reached. For each window w, the local quality index $Q_0\ (f,g|w)$ is computed for the values $f\ (x, y)$ and $g\ (x, y)$, where pixels (x, y) lie in the sliding window w. Finally, the overall image quality index Q_0 is computed by averaging all local quality indices:

$$Q_0(f,g) = \frac{1}{|W|}\sum_{w\in W} Q_0(f,g|w) \qquad (6)$$

Where W is the family of all windows and $|W|$ is the cardinality of W.

Betrabet and Bhogayta [1] have compared their quality index with existing image measures, such as the MSE as well as with subjective measures. They concluded that the new index outperforms the MSE, and they also believed that this was due to the index's ability of measuring structural distortions, in contrast to the MSE which is highly sensitive to the energy of errors.

4. RMS Contrast and Histogram Similarity (RCHS) based Hybrid Quality Index

This research exploits the Wang-Bovik image quality index Q_0 in Equation (5) to define a quality measure for images. The proposed method includes two index terms:

1) rms contrast based image quality factor.
2) Histogram similarity based quality factor.

4.1. RMS Contrast based Image Quality Factor

The basic perceptual attribute of an image is contrast and this is also the measurement of the human visual system sensitivity. Its role is significant in visual processing of computer displays. So far most of the literatures address the image quality assessment with different contrast and illumination, in different lighting conditions. To achieve a meaningful and efficient representation, this research focuses on rms (root mean square) contrast based quality assessment.

The rms contrast metric is equivalent to the standard deviation of luminance [3, 4, 20]. Thus the rms contrast of images $f(x, y)$ and $g(x, y)$ can be expressed by the following equations:

$$f_{rms} = \left[\frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\{f(x,y)-\mu_f\}^2\right]^{1/2} \qquad (7)$$

$$g_{rms} = \left[\frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\{g(x,y)-\mu_g\}^2\right]^{1/2} \qquad (8)$$

Where $f\ (x, y)$ and $g\ (x, y)$ are the normalized grey-level values such that $0<f\ (x,y),\ g\ (x,y)<1$ and μ_f, μ_g are their mean normalized grey levels. According to this definition, images taken at different illumination conditions will have the same contrast if their rms contrasts are equal [3]. The rms contrast does not depend on spatial frequency of the image or the spatial spreading of contrast in the image.

The factor for quality measurement using rms contrast term, varying in the range [0,1] (0 is worst and 1 is best), is expressed by the following Equation:

$$Q_{rms} = 1 - \frac{|f_{rms}-g_{rms}|}{f_{rms}+g_{rms}} \qquad (9)$$

4.2. Histogram Similarity based Quality Factor

A histogram is a graph of the frequency distribution of grey levels of an image. It can provide information related to the brightness and contrast of an image [2].

It is presented as a bar graph of the number of occurrences of a pixel value versus pixel values. The pixel grey levels are plotted along the x-axis and the number of occurrences for each grey level is plotted in the y-axis. Obviously, images which are dark have histograms with more pixel distributions towards the dark side (left-hand side), whereas images which are bright have more pixel distributions towards the bright side (right-hand side) of the histogram.

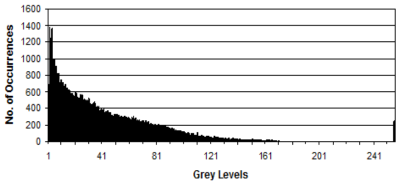
The histogram of an image having grey levels in the range [0, L-1] is defined as a discrete function $h(m_i)= n_i$, where m_i is the i-th grey level and n_i is the number of pixels in the image with grey level m_i. Therefore, the plot of $h(m_i) = n_i$ versus m_i represents the histogram of the image. Figure 1 illustrates four basic types of images: dark, bright, low contrast and high contrast; and their corresponding histograms, respectively.

The probability of occurrence of grey level m_i in the image can be expresses as [12]:

$$p(m_i)=\frac{n_i}{n}, \quad i=0,1,2,\ldots,L-1 \tag{10}$$

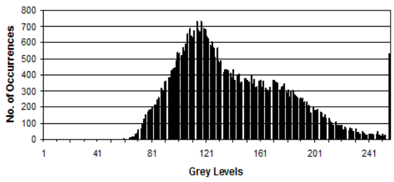
Where n is the total number of pixels in the image, n_i is the number of pixels that have grey level m_i, and L is the total number of possible grey levels in the image.

a) Dark image.



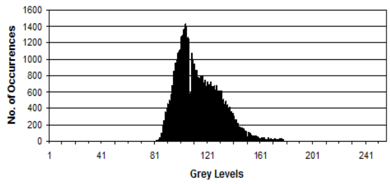
b) Histogram of (a).

c) Bright image.



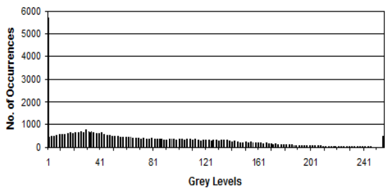
d) Histogram of (c).

e) Low contrast image.



f) Histogram of (e).

g) High contrast image.



h) Histogram of (g).

Figure 1. Four basic types of images and their histograms.

Let $h_f =\{h_f^i \mid i=0,1,2,\ldots,L-1\}$ and $h_g =\{h_g^i \mid i=0,1,2,\ldots,L-1\}$ be the frequencies of the occurrences of grey levels of the two images $f(x,y)$ and $g(x,y)$ of size $X\times Y$, respectively. The similarity between image $f(x,y)$ and $g(x,y)$ is calculated on the basis of Minkowski-form vector distance metric from their histograms. The generalized Minkowski-form distance metric (L_M norm) for similarity computation is given by [6, 9]:

$$S_{fg}=d_M(h_f,h_g)=\left(\sum_{i=0}^{L-1}\left|h_f^i-h_g^i\right|^M\right)^{\frac{1}{M}} \tag{11}$$

Where N is the dimension of the vectors h_f and h_g and h_f^i, h_g^i are the i-th element of h_f and h_g respectively. Three special cases of the L_M metric are of particular interest, namely, $M=1,2$, and ∞ (this research has chosen empirically the value M=2). Then, the factor for quality measurement due to histogram contribution is expressed using the following Equation:

$$Q_h=1-\frac{S_{fg}}{2MN} \tag{12}$$

Since the upper limit due to the histogram change is $2\times X\times Y$, the range of the factor is [0, 1]. The best value 1 is achieved if and only if $h_f = h_g$.

Thus considering the overall parameters due to correlation coefficient, average luminance distortion, rms contrast and histogram similarity, the quality index is expressed by the following equation:

$$Q_0=\frac{\sigma_{fg}}{\sigma_f\sigma_g}\times\frac{2\mu_f\mu_g}{(\mu_f^2+\mu_g^2)}\times Q_{rms}\times Q_h \tag{13}$$

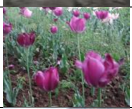
5. Experimental Results and Performance

In order to justify the effective performance of this proposed approach several experiments were conducted using different image databases with various types of 400 images. The experiments were carried out on an Intel® Core™ i5 CPU with 2.70 GHz PC. The programs for experimentation were developed using Visual C++. A snapshot of the graphical interface for image quality evaluation process is shown in Figure 2.

Figure 2. Snapshot of the image quality evaluation software interface.

The image quality assessment results for a few randomly selected images from the image database are furnished in Table 1.

Table 1. Quality measures for different types of images.

Test image	SSIM	HIQ	RCHS
	0.98	0.92	0.88
	0.99	0.93	0.91
	0.99	0.91	0.89
	0.99	0.90	0.89
	0.92	0.91	0.81
	0.92	0.89	0.77
	0.99	0.92	0.89
	0.95	0.92	0.84
	0.99	0.93	0.91
	0.93	0.93	0.80

Evaluation of "Lena" images were done by comparing some sample images downloaded from the Laboratory for Image and Video Engineering (LIVE) [2], as shown in Figure 3. They were tuned with all well-known distortions to yield the same MSE values relative to the original image, except for the JPEG compressed image. The MSE, SSIM, HQI and RCHS results are furnished in Table 2. The MSE results for Figures 3-b, 3-c, 3-d, and 3-e, are same, which implies that the added distortions have the same effect on them.

This reveals the fact that the MSE parameter does not merely enable distinguishing for all probable cases between the original image and test image. It exhibits a very poor performance in terms of a numeric quality measure. The proposed Rms Contrast and Histogram Similarity (RCHS) based hybrid quality index metric performs better than those of the widely used image distortion quality metric Mean Squared Error (MSE), SSIM and HIQ.

a) Original "Lena" image. b) Contrast stretched image. c) Blurred image.

d) Gaussian noise. e) Salt and Pepper noise. f) JPEG Compressed image.

Figure 3. Comparison of the "Lena" images having different types of distortions.

Table 2. Statistics of quality measures (MSE, SSIM, HQI and RCHS) for Lena image having different types of distortions.

Test image	Distortion type	MSE	SSIM	HIQ	RCHS
Figure 4-b	Contrast stretching	225	0.964	0.510	0.585
Figure 4-c	Blurring	225	0.946	0.907	0.825
Figure 4-d	Additive Gaussian	225	0.953	0.800	0.823
Figure 4-e	Impulsive Salt & Pepper	225	0.952	0.975	0.932
Figure 4-f	JPEG Compression	215	0.954	0.211	0.214

6. Conclusions

So far, we have not come across any image quality metric that can predict the subjective judgments of the quality of an image. In fact, designing quality measurement algorithms without any reference image, is itself a challenging task. Existing methods for image quality assessment without any reference are not feasible without having any knowledge of the type of image distortion. This paper addresses a new rms contrast and histogram similarity based hybrid image quality index. It outperforms the MSE substantially under different types of distortions (jpeg, blurring, noise environments) and it is evident from experimental results. It also exhibits better performance than SSIM and HIQ measures, which are two prominent fidelity-based image quality assessments. This method can be employed to statistically distinguish any test images corrupted by noise or affected by different types of distortions.

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References

[1] Betrabet S. and Bhogayta C., "Structural Similarity Based Image Quality Assessment Using Full Reference Method," *International Journal of Scientific Engineering and Technology*, vol. 4, no. 4, pp. 252-255, 2015.

[2] Bhuiyan A., Ampornaramveth V., Muto S., and Ueno H., "On Tracking of Eye for Human-Robot Interface," *International Journal of Robotics and Automation*, vol. 19, no. 1, pp. 42-54, 2004.

[3] Bhuiyan A. and Liu C., "Intelligent Vision System for Human-Robot Interface," *International Journal of Computer, Electrical, Automation, Control and Information Engineering*, vol. 1, no. 4, pp. 862-868, 2007.

[4] Bhuiyan A., Liu C., and Ueno H., "On Pose Estimation for Human-Robot Symbiosis," *International Journal of Advanced Robotic Systems*, vol. 5, no. 1, pp. 19-30, 2008.

[5] Carnec M., Callet P., and Barba D., "Objective Quality Assessment of Color Images Based on A Generic Perceptual Reduced Reference," *Signal Processing: Image Communication*, vol. 23, no. 4, pp. 239-256, 2008.

[6] Celik T., "Two-Dimensional Histogram Equalization and Contrast Enhancement," *Pattern Recognition*, vol. 45, no. 10, pp. 3810-3824, 2012.

[7] Chen S., "A Histogram Equalization-Based Contrast Enhancement Technique for Image Quality Assessment," *Digital Signal Processing*, vol. 22, no. 4, pp. 640-647, 2012.

[8] Chen Y. and Blum R., "A New Automated Quality Assessment Algorithm for Image Fusion," *Image and Vision Computing*, vol. 27, no. 10, pp. 1421-1432, 2009.

[9] Colombo C. and Bimbo A., "Color-Induced Image Representation and Retrieval," *Pattern Recognition*, vol. 32, no. 10, pp. 1685-1695, 1999.

[10] Eskicioglu A. and Fisher P., "Image Quality Measures and their Performance," *IEEE Transactions on Communications*, vol. 43, no. 12, pp. 2959-2965, 1995.

[11] Eskicioglu A. and Fisher P., "A survey of Quality Measures for Gray Scale Image Compression," *in Proceedings of the Workshop on Space and Earth Science Data Compression*, San Diego, pp. 304, 1993.

[12] Gonzalez R. and Woods R., *Digital Image Processing*, Prentice Hall, 2008.

[13] Kovaleski R. and Oliveira M., "High-Quality Brightness Enhancement Functions for Real-Time Reverse Tone Mapping," *The Visual Computer*, vol. 25, pp. 539-547, 2009.

[14] Lee J. and Park R., "Image Quality Assessment of Tone Mappled Images," *International Journal of Computer Graphics and Animation*, vol. 5, no. 2, pp. 9-20, 2015.

[15] Li H., Manjunath B., and Mitra S., "Multisensor Image Fusion using the Wavelet Transform," *Graphical Models and Image Processing*, vol. 57, no. 3, pp. 235-245, 1995.

[16] Li J., Wang C., Li M. and Guo P., "An Image Quality Assessment Algorithm on the Basis of Edge Information and Singular Value Decomposition," *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 8, no. 6, pp. 283-288, 2015.

[17] Moorthy A. and Bovik A., "A Two-Step Framework for Constructing Blind Image Quality Indices," *IEEE Signal Processing Letters*, vol. 17, no. 5, pp. 513-516, 2010.

[18] Motwakel A. and Shaout A., "Fingerprint Image Quality Fuzzy System," *The International Arab Journal of Information Technology*, vol. 13, no. 1A, pp. 171-177, 2016.

[19] Nakarnae E., Kaneda K., Harada K., Miwa T., Nishita T., and Saiki R., "Reliability of Computer Graphic Images for Visual Assessment," *The Visual Computer*, vol. 7, no. 2-3, pp. 138-148, 1991.

[20] Peli E., "Contrast in Complex Images," *Journal of Optical Society*, vol. 7, no. 10, pp. 2032-2040, 1990.

[21] Piella G., "A General Framework for Multiresolution Image Fusion: From Pixels to Regions," *Information Fusion*, vol. 4, no. 4, pp. 259-280, 2003.

[22] Qu G., Zhang D., and Yan P., "Information Measure for Performance of Image Fusion," *Electronic Letters*, vol. 38, no. 7, pp. 313-315, 2002.

[23] Rockinger O., "Image Sequence Fusion Using A Shift Invariant Wavelet Transform," *in Proceedings of International Conference Image Processing*, Santa Barbara, pp. 288-291, 1997.

[24] Saad M., Bovik A., and Charrier C., "A DCT Statistics-Based Blind Image Quality Index," *IEEE Signal Processing Letters*, vol. 17, no. 6, pp. 583-586, 2010.

[25] Seghir Z. and Hachou F., "Edge-region Information Measure Based on Deformed and Displaced Pixel for Image Quality Assessment," *Signal Processing Image Communication*, vol. 26, no. 8, pp. 534-549, 2011.

[26] Sheikh H. and Bovik A., "Image Information and Visual Quality," *IEEE Transactions on Image Processing*, vol. 15, no. 2, pp. 430-444, 2006.

[27] Teo P. and Heeger D., "Perceptual Image Distortion," *in Proceedings of 1st International Conference on Image Processing*, Austin, pp. 127-141, 1994.

[28] Wang Z. and Bovik A., "A Universal Image Quality Index," *IEEE Signal Processing Letters*, vol. 9, no. 3, pp. 81-84, 2002.

[29] Wang Z. and Bovik A., "Mean Squared Error: Love it or Leave it?-A new Look at Signal Fidelity Measures," *IEEE Signal Processing Magazine*, vol. 26, no. 1, pp. 98-117, 2009.

[30] Wang Z., Bovik A., and Lu L., "Why Is Image Quality Assessment So Difficult," *in Proceedings of IEEE International Conference on Acoustics Speech and Signal Processing*, Orlando, pp. 3313-3316, 2002.

[31] Wang Z., Bovik A., Sheikh H., and Simoncelli E., "Image Quality Assessment: From Error Visibility to Structural Similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600-612, 2004.

[32] Xydeas C. and Petrovic V., "Objective Pixel-Level Image Fusion Performance Measure," *Architectures, Algorithms and Applications*, Orlando, pp. 88-99, 2000.

[33] Yalman Y., "A Histogram based Image Quality Index," *Electrical Review*, vol. 88, no. 7, pp. 126-129, 2012.

[34] Yuan T., Zheng X., Hu X., Zhou W., and Wang W., "A Method for the Evaluation of Image Quality According to the Recognition Effectiveness of Objects in the Optical Remote Sensing Image Using Machine Learning Algorithm," *PLOS Journal*, vol. 9, no. 1, pp. 1-7, 2014.

[35] Zhang J. and Lee T., "Kurtosis-based No-Reference Quality Assessment of JPEG2000 Images," *Signal Processing Image Communication*, vol. 26, no. 1, pp.13-23, 2011.

[36] Zhang Q., Eagleson R., and Peter T., "High-Quality Cardiac Image Dynamic Visualization with Feature Enhancement and Virtual Surgical Tool Inclusion," *The Visual Computer*, vol. 25, no. 11, pp. 1019-1035, 2009.

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