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A Review Paper on Single Frame Super-Resolution and Image Quality Assessment

Trupti Kadam[1], Anil Gavade[2]

[1]Dept. Electronics and Communication Engg, Gogte Institute of Technology Belgavi, India
[2] Dept. Electronics and Communication Engg, Gogte Institute of Technology Belgavi, India

Abstract*— Image quality assessment plays very important role in different image processing applications such as image enhancement, image compression, image restoration, image acquisition and other fields. Image quality assessment is necessary because images may contain different types of noise like blur, noise, contrast change, etc. Image quality assessment researchers face many problems when designing a model of Human Visual System which can deal with natural images. The latest progress on developing automatic IQA methods that can predict subjective quality of visual signals is exhilarating. For example, a handful of objective IQA measures have been shown to significantly and consistently outperform the widely adopted mean squared error (MSE) and peak signal-to-noise-ratio (PSNR) in terms of correlations with subjective quality evaluations. In this paper we have reviewed some papers based on IQA. There have been increasing number of super-resolution(SR) algorithm proposed recently to create high-resolution(HR) images from low-resolution(LR) images. A great deal of effort has been made in recent years to develop objective image quality metrics that correlate well with perceived human quality measurement or subjective methods. We have tried to find some advantages of them by studying it.

***Index Terms*—Image quality assessment (IQA), mean squared error (MSE), peak signal-to-noise-ratio (PSNR), super-resolution(SR), low-resolution(LR),**

I. INTRODUCTION

Quality is defined as the measure of excellence. Quality word is used in our daily life like image quality, picture quality, video quality, color quality. ISO defined the image quality as a overall merit or excellence of an image as a perceived by the observers. Image quality is defined by the yendrikhovskji as a compromise between color realism and color discrimination. Image quality assessment can be defined as to assess or to measure the quality of an image in accordance or in reference to the original image. For example, in image compression, if the captured image contains distortions then it would not match with the original image that is stored in the dataset. So, finding the quality of the image in those areas is very necessary. Usually subjective rating methods are used for calculating the quality of the image. In this subjective rating, Observers rated the image quality. The images are given to the experts. Based on the time requirements available, they give scores to the image. Subjective results can provide accurate results, but it is time consuming and also a costly process. This is the reason for the development of objective image quality assessment algorithms (IQA) that will predict the quality of the image automatically. According to the availability of the original reference image, the objective methods are classified into full reference, reduced reference and no reference.

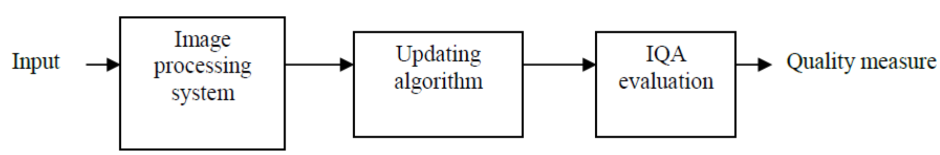

Fig.1 Block diagram for IQA [1]

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With the advancement in today's computer systems, large number of computational problems can be easily solved by implementing the most complex algorithms. Thus, making the work easier. Advances in the digital imaging technology recently, and also the computational speed, networking across wide areas as well as in the storage capacity have resulted in the increased number of digital images, both in terms of still and video. As the digital images are being captured, stored, transmitted, and displayed in various devices, there is a need to maintain image quality. The end user of these various images, in large number of applications, is human observers. The terms image quality and image fidelity is used synonymously, i.e. how close an image is to a given original or reference image. Image Quality Assessment (IQA) plays a fundamental role in the design and evaluation of imaging and image processing systems. Quality Assessment (QA) algorithms can be used to systematically evaluate the performance of different image compression algorithms that attempt to minimize the number of bits required for storage of an image, while maintaining sufficiently high quality of an image. Subjective evaluations are accepted to be the most effective and can be relied on, although quite complicated and expensive, way to assess image quality. Objective IQA measures aim to predict perceived image/video quality by human subjects, which are the ultimate receivers in most image processing applications. Usually one of the images is the reference which is considered to be “original,” “perfect,” or “uncorrupted.” The second image has been modified or distorted in some sense. The output of the QA algorithm is often a number that represents A number of successful algorithms have been created that can predict subjective visual quality of a distorted image. IQA measures can be classified into full-reference (FR), reduced reference (RR), and no-reference (NR) methods. FR measure require full access to the reference image, while NR methods assume completely no access to the reference. RR methods provide a compromise in between, where only partial information in the form of RR features extracted from the reference image is available in assessing the quality of the distorted image. IQA measures may also be categorized into application-specific or general-purpose methods. The former only applies to some specific application where the types of distortion are often known and fixed, e.g., JPEG compression. The latter is employed in general application, where one may encounter diverse types and levels of image distortions. Several algorithms, including the structural similarity index (SSIM) and its derivatives, and the visual information fidelity (VIF), significantly outperformed PSNR and MSE in a series of tests based on large-scale subject-rated independent image databases. On the other hand, there is also an abundant menu of unresolved IQA problems left for future studies, including the following: General-purpose RR and NR IQA where the types of image distortions are unavailable, is still at an immature stage. Method for effective IQA of texture images are still lacking. There have not been good solution for cross-resolution for cross-dynamic range and IQA, where the reference image is available but has a different dynamic range of intensity levels or a different spatial resolution from the image being assessed. IQA for image signals with extended dimensions creates many challenging research problems, which include video, color, multi-spectrum, hyper-spectrum, stereo, multi-view and 3D volume IQA. IQA algorithms that can be used for evaluating segmentation, half-toning and fusion algorithms are lacking.

II. LITERATURE REVIEW

Zhou Wang and Qiang Li [33] aims at testing the hypothesis that when viewing an natural image, the optimal perceptual weighs pooling should be proportional to local information content, which can be estimated in units of bits using advanced statistical models of natural images. algorithm is proposed to achieve SSIM- optimal compromise in combining the input & sparse dictionary reconstructed images. The results show that the proposed method outperforms and provides better visual quality than the corresponding least-square based method. Yang Gao et al. [20] Introduce series of novel image classification algorithm based on CW-SSIM and use handwritten digit recognition and face recognition as eg for demonstration. Mohammad Rostami et al. [15] They show to minimize the complexity through reducing the number of the lens lets while compensating sensing. Also, they provide empirical proof that the above simplification & its associated solution scheme result in image reconstruction. Abdul Rehman and Zhou Wang [27] propose an RR-IQA method by estimating the structural similarity index(SSIM), which is a widely used full-reference (FR) image quality measure shown to be good indicator of perceptual image quality. Nima Nikvand and Zhou Wang [22] there work is motivated by the normalized information distance [NID] measure that has been shown to be valid and universal distance metric application to similarity measurement of any two objects. Yuming Fang et al. [18] A simple but effective method for no reference quality assessment of contrast image based on NSS approach is proposed. Shiqi Wang et al. [7] A novel local patch-based objective quality method is proposed that uses an adaptive representation of local patch structure, which allows us to decompose any image into its mean intensity, signal strength & signal structure and then evaluate their perceptual distortions in different ways. Jiheng Wang et al. [9] A database is build that contains both single-view & symmetrically and asymmetrically stereoscopic images. Kede Ma et al. [6] They proposed a C2G structural similarity index which evaluates the luminance, contrast & structural similarities between the reference color image and C2G converted image. Hojatollah and Zhou Wang [8] The proposed method adopts a NSS framework, where image quality degradation is gauged by the deviation of its statistical features from the NSS models trained upon high-quality natural images. Rania Hassen et al. [12] They proposed. The method is based on 3 factors of fused image quality:1) contrast preservation. 2) Sharpness. 3) Structure preservation. The real data set and subjective scores were used to verify the performance for the current method, which outperforms the existing measures. Wei Zhang et al. [5] proposed an exhaustive statistical evaluation is conducted to justify the added value of computational saliency in objective image quality assessment, using 20 state-of-art saliency models & 12 best known IQMs.

III. IMAGE QUALITY METRICS

2.1 Structural similarity index measure (SSIM)

The Structural similarity index measures follows that a measure of structural information change can provide a good approximation to perceived image distortion. The SSIM compares local patterns of pixel intensities that have been normalized such as luminance and contrast. It is an improved version of traditional methods like PSNR and MSE. The SSIM index is a decimal value between 0 and 1. A value of 0 would mean zero correlation with the original image, and 1 means the exact same image

Symmetry: S (x, y) = S (y, x)
Boundedness: S (x, y) <= 1
Unique maximum: S (x, y) = 1 if and only if x = y (in
discrete representations xi = yi, for all i = 1, 2,…………..,N)
SSIM can be calculated using,

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

2.2 PSNR

The Peak Signal to Noise Ratio is one of the most widely used metrics until now due to its computational simplicity. Mathematically, PSNR is represented as:

$$PSNR = 10\log_{10}\frac{L^2}{MSE}$$

2.3 MSE

It means mean squared difference between the original image and distorted image. The mathematical definition for MSE is: Where a is the pixel value at position (i, j) in the original image and bij is the pixel value at the distorted image.

$$MSE = 1/(M * N)\sum_{i=1}^{M}\sum_{j=1}^{N}(a_{ij} - b_{ij})^2$$

2.4 Image Fidelity

The image fidelity - how closely the image represents the real source distribution - depends not only on the thermal noise but also on other errors in the data, such as amplitude, phase, and pointing errors, and also on imaging artifacts.

2.5 Structural Content

The structural content measure used to compare two images in a number of small image patches the images have in common. The patches to be compared are chosen using 2D continuous wavelet which acts as a low level corner detector. The large value of structural content SC means that image is poor quality,

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$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(B_{ij})^2}$$

2.6 Normalized Cross-Correlation

Normalized cross correlation is a measure of similarity of two waveforms as a function of the time lag applied to one of them. The cross correlation is similar in nature to the convolution of two functions.

$$NCC = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{(A_{ij} * B_{ij})}{{A_{ij}}^2}$$

2.7 Entropy

Entropy is used to evaluate the information quantity contained in an image. The higher value of entropy implies that the fused image is better than the reference image. Entropy is defined as,

$$E = -\sum_{i=0}^{L-1} pi \log_2 pj$$

2.8 Maximum Difference

Difference between any two pixels such that the larger pixel appears after the smallest pixel. The large value of maximum difference means that image is poor in quality.

$$MD = Max(|A_{ij} - B_{ij}|)$$

i=1, 2….m;
j=1, 2…. n;

IV. IQA ALGORITHMS

3.1 Full Reference Image Quality Assessment (FR-IQA)

Here distorted image is compared with the original or undistorted version of that image. Which is usually captured using a high-quality device.

Sheikh and Bovik [2, 3] proposed a frame work known as information fidelity criterion (IFC). In this, Gray Scale Model (GSM) model is used. Fidelity criterion is nothing but the mutual information between reference image and distorted image. IFC was later enhanced to the Visual Information Fidelity (VIF).VIF models the natural images in the wavelet domain using Gaussian scale mixtures (GSMs).

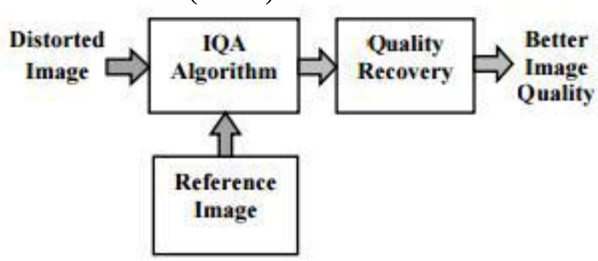

Figure 2 Full reference image quality assessment

Images and videos that are taken from natural environment by using high quality capturing devices operating in visual spectrum are classified as natural scenes. VIF algorithm consists of three components: source model, distortion model, and HVS model. But VIF is very complex for computation Chandler and hemami [4, 5] presented a Visual Signal to Noise Ratio (VSNR). VSNR is related to wavelet transform in which metric calculated in two stages. Feng shao et al. [6, 7] proposed Perceptual FR-IQA of Stereoscopic Images by taking into account Binocular Visual Characteristics. In their further research they introduced a stereoscopic images based new FR-IQA by

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learning binocular reception properties. Their experiment results achieved high consistency validates using five 3D-IQA databases.

3.2 Reduced Reference Image Quality Assessment (RR-IQA)

In this method, the reference image is partially available which helps to evaluate quality of distorted image. Figure 3 describe the method RR-IQA,

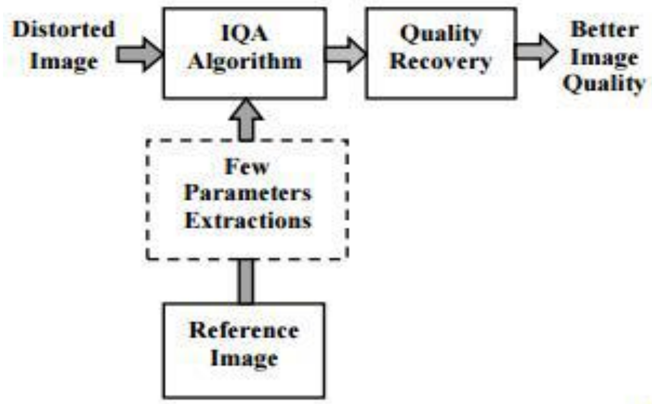

Figure 3 Reduced reference image quality assessment

Jinjan et al. [8, 9] developed a Reduced-Reference Image Quality Assessment based on visual information fidelity. They have proposed an index and used 30 bit data and achieve high consistency with human perception. Redi et al. [10] used descriptors based on color correlogram. They have analysed the alternations between the color distributions of an image for RR-IQA. Rehman and Zhou [11] proposed an RRIQA method with the estimation of SSIM, which is mostly utilized by FR-IQA. Soundarajan and bovic [12] studied the problem of RRIQA with respect to changes in image data which are measure between reference and natural image approximation of distorted image. Lin et al. [13, 14] proposed an RR-IQA by statically modelling the DCT distribution. Experimental analysis determines that only a small number of reduced reference parameters are sufficient to estimate the image quality. Xu et al. [15] introduced an approach for RRIQA which measures the differences of spatial arrangement between the reference image and distorted image in terms of spatial regularity measured by fractal dimension. Proposed method was evaluated on seven publically available benchmarking databases.

2.3 No reference image quality assessment (NR-IAQ)

Generally, this method is known as blind image quality assessment as the reference image is absent. This is most difficult task as it evaluates the quality of an image without reference image. It may be less accurate but more realistic the research problem.

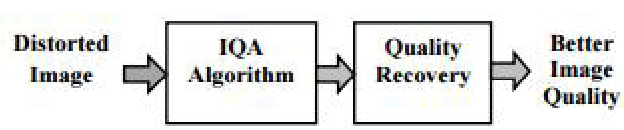

Figure 4 No reference image quality assessment.

Liu et al. [16] proposed an NRIQA metric for perceived ringing artifacts. For this analysis, Kodak lossless true color image database was used as validation database. Jing Zang and Le [17, 18] presented a new non reference quality

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metric for JPEG 2000 images. It overcomes the limitations imposed by feature extraction of distorted images. It is uses changing pixel activity along horizontal and vertical directions. This metric is used only for JPEG-2000 compressed images. Chao feng et al. [19, 20] proposed BIQA using a general regression neural network in which they expand some features: a) mean value congruency of image, b) entropy of phase congruency image, c) entropy of distorted image d) gradient of distorted image. Here they evaluated Image quality by approximating the function relationship between these features and subjective Mean Opinion Score (MOS) by using LIVE database for training and testing purpose. BIQA is further developed by Xue et al. [28] in which, they proposed a novel BIQA model that utilizes the joint statistics of two types of commonly used local contrast features: (1) the Gradient Magnitude (GM) map and (2) the Laplacian of Gaussian (LOG) response. Morthy and Bovic[29] further introduced an algorithm named as Distortion Identification based Image Verity and Integrity Evaluation (DIIVINE). Evaluation did in two stages, distortion identification and distortion specific quality analysis. For validation of this algorithm they used LIVE and TID2008 databases.
The performance analysis of various image quality assessment algorithms is presented in Table1.

Table 1. Performances of IQA algorithms

Technique	Algorithms	Performance
Full Reference Image Quality Assessment	MSE PSNR	Widely utilized but has poor correlativeness.
	NQM UQI SSIM MS-SSIM IFC VIF VSNR	It is good as that of FR-IQA. But required whole knowledge of the image. Quite complex in the computational point of view
Reduced-Reference Image Quality Assessment	Application orient	It required prior and sufficient knowledge about distortions of the image. It compensates in between FR and NR approaches in terms of quality prediction accuracy
Non-Reference Image Quality Assessment	BIQI BLIND BLIND II BRISQUE DIVINE	Meets desired expectation with least available knowledge. It gives better correlative data score as compared to previous techniques.

V. CONCLUSION

Image quality is an attribute of an image which measures subjective and objective image degradations after performing the comparison with the ideal or perfect image/s. Image may be distorted by different degradations like blurring, fading, frequency distortion, noise and blocking artefacts. Image quality assessment has many challenges due to distortions in images. Researchers are trying to develop various methods to assess the quality of an image. Each method has its own advantages and disadvantages. In real time applications, precise and efficient IQA methods help to assess and report the image quality in application like an aerial image, MRI, CT scan images. In this paper, we have summarized the state-of-the-art techniques, challenges and databases for Image Quality Assessment. Although FR-IQA based techniques have good consistency, there are still some issues to be explored in the future. For example, we can review the new image representation technique to reduce the number of feature extraction

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parameters needed for IQA metrics and also, we can propose the technique which can evaluate the quality of the image using no-reference image quality assessment.

REFERENCES

[1] Hojatollah Yeganeh, Mohammad Rostami and Zhou Wang, "Objective quality assessment for image super-resolution: A natural scene statistics approach", IEEE Trans Image Processing, 2012.
[2] Anil Gavade and Vijay Rajpurohit, " Multispectral super resolution and image quality assessment comparative analysis", ICCCES-16, 2016.
[3] S Baker and T Kanade, " Limits on super resolution and how to break them". IEEE Trans, on PAMI, 2002.
[4] J. Wang, S. Zhu and Y. Gong, " Resolution enhancement based on learning the sparse association of image patches", Pattern Recognitt. Lett., vol. 31, no. 1, pp. 1-10, Jan 2010.
[5] X Li and M T Orchard "New Edge Directed Interpolation" IEEE Trans Image Processing, 2001.
[6] R Y Tsai and T S Huang, "Multi-frame image restoration and registration" in advances in Computer and Image signal Processing, 1984.
[7] H Chang, D.Y.Yeung and Y Xiong , Super Resolution through Neighbor Embedding, In CVPR , volume 1,2004.
[8] Freeman, W.T., Jones, T.R., Pasztor, E.C.: Example-based super-resolution. IEEE Computer Graphics and Applications 22(2), 56{65 (2002).
[9] K Kim and Y kwon "Example Based Learning for Single Image SR and JPEG Artifact Removal" , MPI-TR, (173), 08.
[10] S C Park and M C Park and M G Kang, "Super Resolution Image Reconstruction: A Technical Overview", IEEE Signal processing Magazine 20(3):21-36, 2003.
[11] Bourke, P., "Bi-cubic Interpolation for Image Scaling", May 2001
[12] Gleicher, M., "A Brief Tutorial on Interpolation for Image Scaling", Dec 1999.
[13] He He and Wan Chi Siu, " Single Image Super Resolution Using Gaussian Process Regression ", Hong Polytechnic University.
[14] S. C. Park, M. K. Park, and M. G. Kang;, "Super-resolution image reconstruction: a technical overview," IEEE Signal Processing Magazine, vol. 20, no. 3, pp. 21–36, 2003.
[15] A. R. Reibman, R. M. Bell, and S. Gray, "Quality assessment for super-resolution image enhancement," in Proc. IEEE Int.Conf. Image Proc., pp. 2017–2020, 2006.
[16] A. R. Reibman and T. Schaper, "Subjective performance evaluation for super-resolution image enhancement," in Second Int. Wkshp on Video Proc. and Qual. Metrics (VPQM'06), 2006.
[17] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," IEEE Trans. Image Proc., vol. 13, pp. 35–44, Apr.2004.
[18] Z. Wang and A. C. Bovik, "Reduced- and no-reference visual quality assessment - the natural scene statistic model approach," IEEE Signal Processing Magazine, vol. 28, pp. 29–40, Nov. 2011.
[19] E. P. Simoncelli and W. T. Freeman, "Steerable pyramid: a flexible architecture for multi-scale derivative computation," in IEEE International Conference on Image Processing, vol. 3, pp. 444–447, 1995.
[20] J. Yang, J. Wright, T. S. Huang, and Y. Ma, "Image super resolution via sparse representation," IEEE Transactions on Image Processing, vol. 19, pp. 2861–2873, 2010.
[21] Z. Wang, H. R. Sheikh, and A. C. Bovik, "No reference perceptual quality assessment of JPEG compressed images," in IEEE International Conference on Image Processing, vol. 1,pp. I/477–I/480, 2002.
[22] X. Li and M. T. Orchard, "New edge-directed interpolation," IEEE Transactions on Image Processing, vol. 10, pp. 1521–1527, 2001.
[23] S. Wang, K. Gu, K. Zeng, Z. Wang and W. Lin, "Objective Quality Assessment and Perceptual Compression of Screen Content Images," accepted as a feature article by *IEEE Computer Graphics and Applications*, to appear 2016.
[24] W. Zhang, A. Borji, Z. Wang, P. Le Callet, and H. Liu, "The application of visual saliency models in objective image quality assessment: A statistical evaluation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 6, pp. 1266-1278, June 2016.
[25] K. Ma, T. Zhao, K. Zeng and Z. Wang, "Objective quality assessment for color-to-gray image conversion," *IEEE Transactions on Image Processing*, vol. 24, no. 12, pp. 4673 – 4685, Dec. 2015.
[26] S. Wang, K. Ma, H. Yeganeh, Z. Wang and W. Lin, "A patch structure representation method for quality assessment of contrast changed images," *IEEE Signal Processing Letters*, vol. 22, no. 12, pp. 2387-2390, Dec. 2015.
[27] H. Yeganeh, M. Rostami and Z. Wang, "Objective quality assessment of interpolated natural images," *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 4651-4663, Nov. 2015.

All Rights Reserved, @IJAREST-2017

[28] Y. Fang, K. Ma, Z. Wang, W. Lin, Z. Fang and G. Zhai, "No-reference quality assessment of contrast-distorted images based on natural scene statistics," *IEEE Signal Processing Letters*, vol. 22, no. 7, pp. 838-842, Jul. 2015.

[29] Y. Fang, K. Zeng, Z. Wang, W. Lin, Z. Fang, and C.-W. Lin, "Objective quality assessment for image retargeting based on structural similarity," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, special issue on *Content-Aware Visual Systems: Analysis Streaming and Retargeting*, vol. 4, no. 1, pp. 95-105, Mar. 2014.

[30] A. Rehman and Z. Wang, "Reduced-reference image quality assessment by structural similarity estimation," *IEEE Transactions on Image Processing*, vol. 21, no. 8, pp. 3378-3389, Aug. 2012.

[31] A. Rehman, M. Rostami, Z. Wang, D. Brunet and E. R. Vrscay, "SSIM-inspired image restoration using sparse representation," *EURASIP Journal on Advances in Signal Processing*, special issue on *Image and Video Quality Improvement Techniques for Emerging Applications*, Jan. 2012.

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