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No-reference image quality assessment algorithms: A survey

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ABSTRACT

Evaluation of noise content or distortions present in an image is same as assessing the quality of an image. Measurement of such quality index is challenging in the absence of reference image. In this paper, a survey of existing algorithms for no-reference image quality assessment is presented. This survey includes type of noise and distortions covered, techniques and parameters used by these algorithms, databases on which the algorithms are validated and benchmarking of their performance with each other and also with human visual system.

1. Introduction

Estimation of noise content of a signal/image and its subsequent removal is a very important area of research. Till these years, human intelligence was considered to be the only tool for sensing noise in signal/image. However, a few developments in signal processing like transform based statistical tools have generated a ray of hope that noise sensing by machines may become possible. This paper presents a brief review of major published algorithms for no reference noise sensing in an image which is referred to as 'image quality assessment' (IQA). Finally we present a few parameters for image quality assessment.

Quality of an image represents the amount of visual degradations of all types present in an image. Degradations may occur due to presence of noise, blocking artifacts, blurring, fading etc. These degradations are introduced during image acquisition, compression, storage, transmission, decompression, display or even printing. Sensing the degradation at the time of image acquisition can be useful to take counter measure to reduce the degradation while storing the image as a file. In general, sensing quality of an image during various stages of operations may be helpful for appropriate reconstruction. It saves unnecessary application of denoising algorithms. It may also suggest appropriate denoising or processing algorithm to retrieve quality of degraded image. A noise-sensing or IQA algorithm can provide types of distortions present in the image along with levels of degradation which can be used while denoising as shown in Fig. 1.

Overall image quality cannot be evaluated by only a few parameters like brightness, contrast or sharpness which can be mathematically calculated from image pixels. A sharp image can have salt and pepper noise present in it thereby devaluating its quality. A standardized evaluation procedure is required to assess the quality of an image irrespective of the type of distortions present. This evaluation procedure and the results should confirm well with human perception of an image quality.

The simplest way to evaluate the quality of an image is to show it to an expert human observer. However, human perception may be different for each individual. One can tackle this problem by taking multiple views from different individuals and then statistically processing the results. This is called subjective image quality assessment. But it is a very lengthy and imprecise procedure for quality evaluation. Right from selection of observers, their knowledge, expertise, availability, seriousness bias, interpretations everything is subjective and qualitative. Thus an automated system for quantitative evaluation of images is required. The problem can thus be represented as "Quantitative Evaluation of Quality". Obviously this may require a high level of intelligence.

Automated evaluation of image quality by means of machine is referred to as 'Objective Image Quality Assessment'. Objective image quality assessment can be accomplished in three ways,

(a) Full reference image quality assessment (FR-IQA)
(b) Reduced reference image quality assessment (RR-IQA)
(c) No reference image quality assessment (NR-IQA)

Full reference image quality assessment (FR-IQA) refers to assessing the quality of distorted image by comparing with the

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0030-4026/

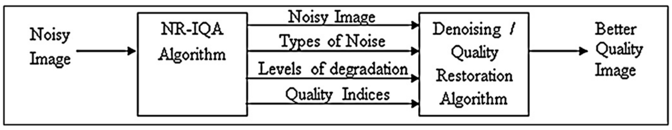

Fig. 1. Application of NR-IQA – image denoising.

original, believed to be undistorted version of same image. The extent of distortion is calculated by measuring the deviation of distorted image from the reference image. Simplest way to measure image quality is by calculating the peak signal to noise ratio (PSNR) however PSNR does not always correlate with human visual perception and image quality [1]. To tackle the limitation of PSNR metric, other parameters were proposed. Parameters which correlate well with human perception include structural similarity index (SSIM) [2], visual information fidelity (VIF) [3], Fast SSIM [4], information fidelity criteria (IFC) [5], Multi-scale Structural Similarity (M-SSIM) [6], four-component weighted structural similarity [7]. These parameters give the extent of deviation of a distorted image from the reference image. The need of reference image for quality evaluation limits the use of these parameters and subsequent quality evaluation algorithms.

Reduced reference image quality assessment (RR-IQA) algorithms are those which use only limited features from reference image instead of complete image to evaluate the quality of distorted image. A training approach can also be used for RR-IQA. RR-IQA methods are mentioned in [8–10]. The limitation of FR-IQA still remains in RR-IQA, i.e., features extracted from reference image are necessary for quality evaluation. In spite of all its limitations, the RR-IQA techniques are widely used in satellite and remotely sensed image quality evaluation.

No reference image quality assessment (NR-IQA) algorithms provide quality of an image without the need of any reference image or its features. The problem of NR-IQA is much tougher than the above two problems. Due to absence of reference image, one needs to model the statistics of reference image, the nature of human visual system and effect of distortions on image statistics in an unsupervised way. It is also very difficult to evaluate the effectiveness of a quality measure with a specific distorted image in absence of a reference image.

This paper provides an extensive review of major NR-IQA algorithms developed so far. This review summarizes the methods used by algorithms, evaluation parameters, distortion types for which they are designed, image databases used for validation and benchmarking of the algorithms with human visual performance.

2. Benchmarking parameters

Different NR-IQA algorithms provide different quality score. So to compare the performance of different NR-IQA algorithms, a common benchmarking system is necessary. Few benchmarking parameters are mentioned as follows.

2.1. Pearson correlation coefficient (PCC)

It is used to measure the dependency between to variables. Its value lies between '−1' and '+1' where value close to '+1' indicates that the two variables have positive correlation and value close to '−1' indicates that the two variables have negative correlation. A very low or zero value implies that the two variables are not correlated. Pearson correlation coefficient (ρ) between two variables 'X' and 'Y', with standard deviation σ_X and σ_Y respectively is shown in (1).

$$\rho = \frac{convariance(X, Y)}{\sigma_X \sigma_Y} \tag{1}$$

The two variables 'X' and 'Y' are the output of NR-IQA algorithm and the actual quality score provided with the database.

2.2. Spearman correlation coefficient (SCC)

Spearman correlation provides the relation between two ranked variables. Its range is from '−1' to '+1' with same interpretation as that of Pearson's correlation coefficient. Spearman correlation coefficient is calculated as shown in (2).

$$\rho = 1 - \frac{6 * \sum d^2}{n(n^2 - 1)} \tag{2}$$

where 'd' is the difference in ranks of two variables 'X' and 'Y'.

2.3. Outlier's ratio (OR)

Outlier's ratio is defined as the percentage of algorithm's output which is beyond twice standard deviation of subjective scores. If there are 'I' images and 'S_i' is the subjective quality score of ith image then mean subjective score (S_m) is calculated as shown in (3).

$$S_m = \frac{1}{I}\sum_{i=1}^{I} S_i \tag{3}$$

The standard deviation of subjective scores (σ_s) is calculated as shown in (4).

$$\sigma_s = \left[\frac{1}{2}\sum_{i=1}^{I}(S_i - S_m)^2\right]^{1/2} \tag{4}$$

Suppose there are 'P' images with individual objective quality score (O_i) such that

$$|O_i - S_i| > 2 * \sigma_s \tag{5}$$

then the outlier's ratio is given by (6)

$$\text{Outlier's ratio} = \frac{P}{I} \tag{6}$$

Outlier's ratio increases if the output of NR-IQA algorithm is not at all in agreement with standard or subjective quality score.

2.4. Root mean square error (RMSE)

Root mean square error (RMSE) is used to measure the pixel wise deviation between two entities. If 'I' and 'I_N' are original and noisy images of size $M \times N$, then the RMSE between these two images is defined as

$$\text{RMSE} = \left[\sum_{n=1}^{N}\sum_{m=1}^{M}\frac{I(m, n) - I_N(m, n)}{MN}\right]^{1/2} \tag{7}$$

3. No-reference image quality assessment algorithms

The NR-IQA algorithms that are developed by researchers are discussed in this section. The algorithms are discussed in the order of their publication.

Marziliano et al. [11] proposed a perceptual blur and ringing metric for images corrupted by distortion caused by JPEG-2000 compression. The method is based on edge detection using Sobel operator. Noise and other subtle edges are removed by applying threshold to gradient image. Edge width per edge is used as a local blur metric. Local blur scores are aggregated to get final blur present in the image. JPEG-2000 images from LIVE database [12] are used for validation of the algorithm. The linear correlation coefficient obtained is 73% and Spearman's correlation coefficient is 81%. This metric is designed only for JPEG-2000 compressed images and tackles only two distortion categories with a low correlation value.

Juan et al. [13] presented a quality metric based on model of human visual system (HVS). It uses the concept of jumping phenomenon of eyes which changes point of fixation. The used HVS model is proposed using fixation point instead of contrast sensitivity function (CSF). Block size of 10×10 is used for computation. The performance of algorithm is compared using PSNR metric. Lena image is used for experimentation. This metric is not validated on any database but only on a few degraded versions of Lena image.

Sheikh and Bovik [14] proposed no-reference image quality metric using natural scene statistics (NSS) of JPEG-2000 compressed images. JPEG-2000 compression disturbs the nonlinear dependencies which are observed in natural images. Wavelet coefficients' magnitudes and magnitudes of linear prediction of coefficients in four sub-bands are used as statistical features. Algorithm is trained using mean opinion score (MOS) provided with LIVE database [12]. Pearson's correlation coefficient obtained is 0.91. This metric is designed only for JPEG-2000 compressed images.

Babu et al. [15] presented an IQA model for JPEG compressed images. This model uses growing and pruning radial basis function (GAP-RBF) [16] for image quality evaluation. The HVS features used are edge amplitude, edge length, background activity and background luminance. Background activity refers to amount of high frequency components and background luminance refers to the amount of brightness. Relation between HVS features and MOS are modeled using GAP-RBF network. This network uses sequential learning without modifying past learning so it needs less memory and less computation. In JPEG compression, blocking artifacts occur at boundaries of 8×8 blocks so same block size is used for patch wise operation. JPEG compressed images from LIVE database [12] are used for validation. 154 images are used for training and 79 images are used for testing. The RMSE between mean opinion score (MOS) and predicted quality score is 0.57. MOS is the average subjective quality score of an image. This metric is designed only for JPEG compressed images.

Marais and Steyn [17] proposed a blur identification metric based on variation of spectral subtraction method which uses power spectrum surface of revolution. This method is useful while differentiating between in-focus and out-of-focus blur. Blur is modeled by a uniform point spread function with a 2D circular support. The algorithm is tested on 210 images which are obtained by degrading 5 remote sensing images. This metric is used only for quality evaluation of blurred images and is not validated on any standard database.

Gabarda and Cristóbal [18] used anisotropy as a measure of image quality. Anisotropy means having different properties in different directions. Generalized Renyi entropy [19] and the normalized Pseudo-Wigner distribution (PWD) is used to calculate directional entropy of an image. Variance of expected entropy is taken as an indicator of anisotropy. Eight point window is used for Renyi entropy calculation. Images from LIVE database [12] are used for validation. Standard benchmarking parameters are not used to demonstrate the performance of this algorithm.

Sazzad et al. [20] proposed a NR-IQA algorithm for JPEG-2000 compressed images in spatial domain. This method uses pixel distortion and edge information for quality evaluation. Pixel distortion is measured using standard deviation of central pixel in a 5×5 neighborhood with partial overlap. Edge information is inferred using zero crossing rate in horizontal and vertical direction. Pixel distortion and edge information are combined as mentioned in [21]. LIVE database [12] is used for validation of which, 50% images are used for training and remaining 50% are used for testing. Achieved Pearson's correlation coefficient, Spearman's correlation coefficient and outlier ratio are 0.93, 0.99 and 0.0396 respectively. This metric is designed for quality evaluation of only JPEG-2000 compressed images.

Brandao and Queluz [22] proposed a new method for image quality assessment. The method uses natural scene statistics (NSS) of discrete cosine transform (DCT) whose distribution is modeled by Laplacian probability density function [23]. A distribution parameter is specified for a particular frequency pair. Images from LIVE database [12] is used for testing and validation. Pearson's correlation coefficient and Spearman's correlation coefficient achieved by this technique are 0.973 and 0.978 respectively. This method is trained and tested on only JPEG coded images from LIVE database. Performance of the algorithm on other image distortions is not mentioned.

Zhai et al. [24] introduced a measure to estimate blockiness in block DCT coded images. Blockiness refers to pixel distortion caused at block boundaries during encoding of an image. Blockiness caused by quantization is mapped by block discontinuity. A noticeable blockiness map (NBM) is obtained from luminance and texture masking. Luminance masking is measured as luminance difference between neighboring blocks and texture masking is computed using neighboring blocks directional properties. The algorithm is validated on LIVE [12] and IRCCyN/IVC [25] databases. Achieved Pearson's and Spearman's correlation coefficients on IRCCyN/IVC JPEG database are 0.9688 and 0.9629. Pearson's and Spearman's correlation coefficients on LIVE JPEG database are 0.9621 and 0.9087 respectively. As this metric is designed for blockiness estimation, it can be used only for JPEG and JPEG-2000 compressed images.

Suresh et al. [26] proposed a machine learning approach for NR-IQA of JPEG coded images. HVS features such as edge amplitude, edge length, background activity and background luminance are used. These features along with MOS of images are fed to extreme machine learning (ELM) [27] algorithm to obtain a functional relationship. 154 and 79 images are used for training and testing respectively. RMSE between mean opinion score (MOS) and proposed method's output is obtained as 0.70. As this is a training based approach, quality assessment of images distorted with unknown distortion type is unpredictable.

Ferzli and Karam [28] presented a sharpness metric based on concept of just noticeable blur (JNB). JNB comes from just noticeable difference (JND) [29] and is the minimum difference in intensity value relative to background that is noticeable. JNB is the minimum perceivable blur around an edge given a higher contrast than a JND. Standard deviation corresponding to JNB threshold is calculated using subjective evaluation. Subjective scores are obtained from the LIVE database [12]. For validation, images corrupted by Gaussian blur and JPEG-2000 compression are used. Achieved Pearson's and Spearman's correlation for Gaussian blur distortion is 0.932 and 0.936 respectively. Pearson's and Spearman's correlation for JPEG-2000 compressed images is 0.881 and 0.873 respectively. This method targets only sharpness as a parameter for image quality evaluation and is validated on blurred and JPEG-2000 compressed images.

Wu et al. [30] proposed a method for assessing the amount of blur present in an image. The method uses Sobel operator for edge detection and then applies Radon transform to locate line features. The line spread function and point spread function are calculated from the located line features. For validation, 13 natural world images are blurred with standard blur levels and then used for testing the algorithm. Effect of increasing image blur on the output of algorithm is used to estimate the performance of algorithm. This metric is designed only for quality assessment of blurred images.

Suthaharan [31] presented a metric for measurement of blocking artifacts caused by block coding in images. It uses the multi-neural channel aspect of HVS. In this, the primary edges and undistorted edges are estimated and edges caused by block compression are filtered out. The filtered edges give an estimate of blocking artifact. JPEG compressed images from LIVE database [12] are used for validation of algorithm. Pearson's correlation coefficient value of 0.91 is obtained. As this metric estimates strength of the blocking artifacts, it is used for quality evaluation of JPEG and JPEG-2000 compressed images only.

Lu et al. [32] proposed a contourlet transform based natural scene statistics (NSS) model for image quality assessment. The statistics of contourlet coefficients are described by a joint distribution function. An image is decomposed in multi-scale and directional sub-bands using contourlet transform. The algorithm is trained using statistics of images from LIVE database [12]. Same database is used for validation and the Pearson's correlation coefficient is found to be 0.8271. Though the overall performance of algorithms is acceptable but the correlation for JPEG compressed images is very low, i.e. 0.5810.

Liu et al. [33] introduced a metric to measure perceived ringing artifact. In this method, bilateral filtering is used to smooth edges which do not contribute to perceivable ringing. These edges are obtained by Canny edge detector, skeletonizing, edge linking, noise removal and line segment labeling. An extracted perceptual edge map obtained from line segments is used to select edges around which perceivable ringing can occur. Images from "Kodak lossless true color image suit" are used for validation. Pearson's and Spearman's correlation coefficients obtained are 0.868 and 0.85 respectively. This metric can be used for quality evaluation of images which are distorted by ringing artifact only.

Moorthy and Bovik [34] presented a two step framework for image quality assessment. The algorithm is named as blind image quality index (BIQI). This method first estimates the presence of set of distortions and then makes a probability weighted summation to give a quality score. Wavelet transform [35] over three scales and three orientations is applied to obtain sub-band coefficients. These coefficients are parameterized using a generalized Gaussian distribution. Feature vectors obtained from sub-band coefficients are fed to a support vector machine (SVM) [36] for classification of different distortion types. LIVE database [12] is used for training and testing of this algorithm. Pearson's correlation coefficient, Spearman's correlation coefficient and RMSE are obtained as 0.8205, 0.8195 and 15.6223 respectively. This algorithm performs well only for distortion types on which the algorithm is trained.

Saad et al. [37] proposed BLind Image Integrity Notator using DCT Statistics (BLIINDS) algorithm. It uses discrete cosine transform (DCT) to extract contrast and structural features from an image. Contrast is obtained from average value of DCT coefficients of 17×17 size patches. Kurtosis of same size patches is used to obtain DCT based structural features. The algorithm is trained and tested on LIVE database [12]. Spearman's correlation coefficient is obtained as 0.7996. This is a training based algorithm and is not benchmarked using Pearson's correlations coefficient.

Zhang and Le [38] introduced a quality metric for images coded by JPEG-2000 compression. It uses the monotonically changing pixel activity along horizontal and vertical directions. The distortion in the monotonicity is considered as degradation. JPEG-2000 compressed images from LIVE database [12] are used for validation of algorithm. Achieved Pearson's correlation and Spearman's correlation coefficient are 0.928 and 0.919. This metric is designed only for JPEG-2000 compressed images and is not generalized.

Liang et al. [39] presented a measure for assessing the quality of JPEG-2000 compressed images. This quality metric is designed by combination of a blur and a ringing metric. Blur metric uses the gradient profile along edges along with the just noticeable difference (JND) [29]. Ringing metric is characterized by local variance in a small neighborhood region. Weighted Minkowski summation is used to combine the two metrics, i.e., blur metric (M_{blur}) and ringing metric (M_{ringing}) as shown in (8).

$$\text{Quality score} = (a \cdot M_{\text{blur}}^p + b \cdot M_{\text{ringing}}^p)^{1/p} \quad (8)$$

The optimum values for Minkowski parameters are 0.85, 0.15 and 3 for 'a', 'b' and 'p' respectively. JPEG-2000 compressed images from LIVE database [12] and TID dataset [40] are used for validation. Achieved Pearson's and Spearman's correlations on LIVE database are 0.947 and 0.912 respectively. Pearson's and Spearman's correlation on TID dataset are 0.911 and 0.902 respectively. This metric is specifically designed for quality evaluation of only JPEG-2000 compressed images.

Cohen and Yitzhaky [41] proposed a metric to measure blur and noise impact on images. The image is modeled by Fourier transform, blurring point spread function and additive noise. Noise distortion is computed in both spatial and frequency domain. In spatial domain, 10×10 size patches are subjected to variance calculation and in frequency domain, image power spectrum is used. Effect of increasing Gaussian noise variance and defocusing blur diameter on output of proposed metric is observed for validation. This method is tested on 75 natural monochrome images [42] but a correlation parameter is not provided for performance comparison with other algorithms.

Ciancio et al. [43] introduced an algorithm for blur assessment using multi-feature classifier. Outputs of multiple algorithms which include frequency domain metric [44], spatial domain metric [45], perceptual blur metric [11] and HVS based metric [46] are given to a classifier. Other features provided to the classifier are Local Phase Coherence using wavelet transform, mean brightness level, variance of HVS frequency responses [47] and depth of contrast. The classifier generates an input–output map using a training dataset. Pearson's and Spearman's correlation for real blur images is 0.564 and 0.56 respectively. Real blur is difficult to model so the correlation value is low. Pearson's and Spearman's correlation for simulated blur is 0.748 and 0.744 respectively. Inclusion of real blur images for validation authenticates the performance of this algorithm though the correlation is low.

Zhang et al. [48] presented a kurtosis based quality metric for JPEG-2000 compressed images. 1D kurtosis calculated in DCT domain is used as a quality indicator. Kurtosis represents the deviation of the probability distribution from normal distribution and is measured as forth central moment. Kurtosis increases as blurring increases. JPEG-2000 images from LIVE database [12] are used for validation of algorithm. Pearson's and Spearman's correlation coefficient is obtained as 0.922 and 0.915 respectively. This metric is designed only for JPEG-2000 compressed images and uses blur as the sole parameter for quality evaluation.

Li et al. [49] proposed general regression neural network based approach for image quality assessment. Phase congruency image [50], entropy of phase congruency image and gradient of the distorted image are used as features. These features and differential mean opinion score (DMOS) i.e., subjective image rating are fed to the neural network to obtain a relationship. LIVE database [12] is used for validation purpose. Pearson's correlation, Spearman's correlation coefficient and RMSE are obtained as 0.8374, 0.8268 and 8.7495 respectively. The correlation values for this metric are low as compared to other algorithms.

Chen and Bovik [51] introduced a blur assessment metric based on natural scene statistics (NSS) model and wavelet decomposition. A support vector machine (SVM) [52] classifier is used to measure distance between image gradient statistics and NSS.

Sum of horizontal and vertical responses in the high band of wavelet decomposition is used to produce a detail distortion map of image. Quality score is the function of distance given by SVM and wavelet decomposition response. The algorithm is validated on LIVE database and the Spearman's correlation coefficient is obtained as 0.9352. Pearson's correlation coefficient is not used for benchmarking of this metric and distortion caused only due to blurring is considered for quality assessment.

Shen et al. [53] presented an image quality assessment algorithm for noisy, blurry, JPEG-2000 and JPEG compressed images. The algorithm is based on hybrid of curvelet, wavelet and cosine transform. It uses the property of natural images which occupy well defined clusters in the transformed space. Image characteristics are expressed by probability distribution of logarithm of the magnitude of curvelet coefficients. Curvelet transform is replaced by wavelet transform and DCT and the same procedure is applied to extract image characteristics. Pearson's correlation coefficient obtained on LIVE database [12] is 0.921. Effect of distortions on statistics of three different transforms is studied in this paper.

Narvekar and Karam [54] proposed a blur assessment metric for images. It is based on cumulative probability of blur detection (CPBD). In this method, the image is first divided into 64×64 size patches, depending on edge information, the block is classified as edge or non-edge block. Probability of detecting blur in edge pixel is measured as presented in [28]. Normalized histogram of blur detection probabilities is obtained which provides the probability density function. The algorithm is validated on LIVE database [12], TID2008 database [40], IRCCyN/IVC [25] and MICT [55] database. Images distorted by Gaussian blur and JPEG-2000 compression are considered for evaluation. Exhaustive validation results yield a set of correlation coefficients, RMSE, Outlier's Ratio is presented in Table 1. As this metric estimates presence of blur, it cannot be used for images with other distortion types.

Zhang et al. [56] used structural activity for image quality assessment. Structural activity is the property which changes predictably either in spatial or frequency domain, whose variations can imply that there is a change in structural information of an image. Direction spread is used as a local structural activity indicator and a multi-stage median filter based approach is used for structural strength estimation. LIVE database [12] is used for validation purpose. Pearson's and Spearman's correlation coefficient is obtained as 0.9315 and 0.9217 respectively.

Moorthy and Bovik [57] proposed Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE) index. DIIVINE is based on the hypothesis that statistical properties of images change in presence of distortions. In this algorithm, the distorted image is subjected to Wavelet decomposition to obtain band pass responses. The wavelet decomposition employed a steerable pyramid [58] over two scales (1,2) and six orientations (0°, 30°, 60°, 90°, 120°, 150°). The extracted sub-band coefficients are then used to extract statistical features. The algorithm is validated on LIVE database [12] and TID2008 dataset [40]. Pearson's correlation, Spearman's correlation coefficient and RMSE on LIVE database are obtained as 0.917, 0.916 and 10.90 respectively. Spearman's correlation coefficient on TID2008 dataset is 0.889. Spearman correlation coefficient on LIVE and TID2008 datasets are close to 0.9 indicating the consistency of this index.

Lee and Park [59] presented a method to measure strength of blocking artifacts in block coded images. It is observed that high frequency components are present at boundaries of image blocks which have blocking artifacts. This blocking artifacts cause pixel luminance to change abruptly at block boundaries. In this method, pixel luminance change across block boundaries is used as an indicator of blockiness. JPEG coded images from LIVE database [12] are used for validation. Pearson's and Spearman's correlation coefficient is obtained as 0.9847 and 0.9764 respectively. This metric is designed only for images distorted by blocking artifact and is validated only on JPEG coded images from LIVE database.

Mittal et al. [60] introduced a training free model for image quality assessment. Mean subtracted contrast normalized coefficients (MSCN) are used to form a feature vector. Feature vectors are calculated for all image patches of size 64×64 with 8×8 overlap. The obtained feature vectors are clustered into 400 visual words using K-means clustering algorithm. Model fitting procedure is used to attain latent quality factors in test image. Pearson's and Spearman's correlation coefficient for LIVE database [12] is obtained as 0.79 and 0.80 respectively. The correlation coefficients obtained for this metric are low as compared to other algorithms.

Ye and Doermann [61] proposed an image quality metric based on visual codebook. Codebook means collection of specific features which specify quality of an image. It uses Gabor filtering [62] in five frequencies and four orientations on image patches of size 8×8. Mean and variance of filtered output is used to form a feature vector. K-means clustering is used to form 200 clusters corresponding to each image. Images from LIVE database [12] are utilized to construct the codebook. Pearson's and Spearman's correlation coefficient for LIVE database [12] is obtained as 0.928 and 0.930 respectively. Pearson's and Spearman's correlation coefficient for CSIQ dataset [63] is obtained as 0.908 and 0.884 respectively. Correlation coefficients on LIVE and CSIQ databases are nearly same which indicate the consistency of this metric.

Saad et al. [64] utilized a natural scene statistics (NSS) model of discrete cosine transform (DCT) coefficients for evaluation of image quality. The method relies on Bayesian inference model. Gaussian density model is applied to DCT coefficients of 5×5 patches. A function of derived Gaussian model is obtained in the form of a simple Bayesian model that predicts quality. Pearson's and Spearman's correlation coefficient for LIVE database [12] is obtained as 0.9302 and 0.9306 respectively. This is a training based approach so the algorithm performs well only on distortion on which it is trained.

Mittal et al. [65] proposed Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE), as an image quality metric in spatial domain. This algorithm uses locally normalized luminance [66], i.e., mean subtracted contrast normalized (MSCN) image (I') and is calculated as shown in (9).

$$I'(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + 1} \tag{9}$$

where 'I' is the intensity image, 'μ' and 'σ' are the mean and standard deviation in a 3×3 window. It further applies a generalized Gaussian distribution to obtain distorted image statistics which tend to show change in coefficients distribution in presence of distortion. Pearson's and Spearman's correlation coefficient for LIVE database [12] is obtained as 0.9424 and 0.9395 respectively. Spearman's correlation coefficient for TID2008 dataset [40] is obtained as 0.896. The algorithm is benchmarked on two databases with consistent results.

Mittal et al. [67] proposed natural image quality evaluator (NIQE), an image quality metric in spatial domain based on natural scene statistics (NSS) model. In this method, the image is first subjected to local mean removal and divisive normalization. Local mean deviation is then calculated. Image quality is estimated by the distance between multi-variate Gaussian fit of NSS features of test images and that of natural images. Pearson's and Spearman's correlation coefficient for LIVE database [12] is obtained as 0.9147 and 0.9135 respectively. It is training based approach and can be applied only on distorted images for which it is trained.

Huang et al. [68] presented a local image variance based approach to measure block homogeneity. An adaptive method is

Table 1
Various algorithms for no-reference image quality assessment.

Ref.	Parameters used	PCC	SCC	RMSE	OR	Database	Distortion tackled
[11]	Edge width	73%	81%	–	–	LIVE JPEG-2000	Blur, JPEG-2000
[13]	HVS model	–	–	–	–	Lena image	Multiple
[14]	Wavelet transform	0.91	–	8.54	–	LIVE JPEG-2000	JPEG-2000
[15]	HVS model	–	–	0.57	–	LIVE JPEG	JPEG
[17]	PSF for blur	–	–	–	–		Blur
[18]	Renyi entropy	–	–	–	–	LIVE	Multiple
[20]	Standard deviation of pixels	0.93	0.99	–	0.03	LIVE JPEG-2000	JPEG-2000
[22]	NSS of DCT coefficients	0.97	0.97	–	–	LIVE	Multiple
[24]	Luminance and texture features	0.96	0.96	–	–	IRCCyN/IVC	JPEG
		0.96	0.90	–	–	LIVE JPEG	
[26]	HVS features	–	–	0.7	–	LIVE JPEG	JPEG
[28]	JNB	0.93	0.93	0.46	0.41	LIVE G.Blur	Blur
		0.88	0.87	0.39	0.47	LIVE JPEG-2000	
[30]	Radon transform	–	–	–	–	13 real blur images	Blur
[31]	Edges	0.91	–	–	–	LIVE JPEG	Blockiness
[32]	Contourlet transform	0.82	0.73	14.10	–	LIVE	Multiple
[33]	Edge map	0.86	0.85	–	–	Kodak lossless true color image suite	Ringing
[34]	Wavelet transform	0.82	0.81	15.62		LIVE	Multiple
[37]	DCT	–	0.79	–	–	LIVE	Multiple
[38]	Pixel activity	0.92	0.91	6.04	0.03	LIVE JPEG-2000	JPEG-2000
[39]	JND for blur, Local variance for ringing	0.94	0.91	7.5	1.32%	LIVE JPEG-2000	JPEG-2000
		0.91	0.90	0.81	–	LIVE G.Blur	
		0.92	0.94	8.2	–	TID2008	
[41]	Fourier transform and PSF	–	–	–	–	G.Noise corrupted images	Blur, G.Noise
[43]	Wavelet transform and neural network	0.56	0.56	–	–	Real blur	Blur
		0.74	0.74	–	–	Simulated blur	
[48]	1D DCT Kurtosis	0.92	0.91	9.90	0.62	LIVE JPEG-2000	JPEG-2000
[49]	Phase congruency	0.83	0.82	8.74	–	LIVE	Multiple
[51]	NSS and wavelet transform		0.93		–	LIVE	Multiple
[53]	Hybrid of curvelet, wavelet and DCT	0.92	–	–	–	LIVE	Multiple
[54]	Cumulative probability of blur detection (CPBD)	0.91	0.94	8.98	0.16	LIVE G.Blur	Blur
		0.88	0.88	11.42	0.32	LIVE JPEG-2000	
		0.83	0.84	0.64	–	TID2008 G.Blur	
		0.92	0.92	0.74	–	TID2008 JPEG-2000	
		0.88	0.84	0.66	–	IRCCyN/IVC G.Blur	
		0.77	0.78	0.86	–	IRCCyN/IVC JPEG-2000	
		0.78	0.78	0.82	0.14	MICT JPEG-2000	
[56]	Median filter	0.93	0.92	–	–	LIVE	Multiple
[57]	Wavelet transform	0.91	0.91	10.9	–	LIVE	Multiple
		–	0.88	–	–	TID2008	
[59]	Luminance change across blocks	0.98	0.97	–	–	LIVE JPEG-2000	Blockiness
[60]	Locally normalized luminance	0.79	0.8	–	–	LIVE	Multiple
[61]	Gabor filtering	0.92	0.93	–	–	LIVE	Multiple
		0.90	0.88	–	–	CSIQ	
[64]	NSS model of DCT coefficients	0.93	0.93	–	–	LIVE	Multiple
[65]	Divisive normalization	0.94	0.93	–	–	LIVE	Multiple
		–	0.89	–	–	TID2008	
[67]	NSS in spatial domain	0.91	0.91	–	–	LIVE	Multiple
[68]	Local variance	–	0.96	–	–	LIVE	Multiple
[69]	Mean subtracted contrast normalized coefficients	0.88	0.90	–	–	LIVE	Multiple
[70]	Gabor filter	0.89	0.88	7.24	–	LIVE 3D	Natural Stereo pairs
[72]	Multiplicative multi-resolution decomposition	–	0.92	–	–	LIVE	Blur
		0.90	0.89	–	–	TID2008	
		0.91	0.89	–	–	IVC	

used to select image blocks for noise statistics estimation. Variance of selected blocks is used as an estimate for noise statistics. LIVE database [12] images are used for validation and the Spearman's correlation coefficient is obtained as 0.9616. Pearson's correlation coefficient is not used to benchmark this metric.

Jiao et al. [69] introduced a low computation image quality assessment metric in spatial domain. This method uses the mean subtracted contrast normalized (MSCN) coefficients [65] for log-energy computation. Log energy of each block of size 96×96 is calculated as shown in (10).

$$E = \log_{10}\left(1 + \frac{1}{96 \times 96}\sum\nolimits_{i,j} I'^{2}(i,j)\right) \tag{10}$$

Variance of MSCN coefficients is used to measure local contrast Image is divided into 96×96 patches and then operated. Pearson's and Spearman's correlation coefficient for LIVE database [12] is

Table 2
Database for image quality assessment.

Database	Distortions covered	Total images
Laboratory for Image & Video Engineering (LIVE) [12]	Reference images	29
	JPEG	169
	JPEG-2000	175
	Gaussian Blur	145
	White noise	145
	Fast fading	145
CSIQ [63]	Reference images	30
	JPEG	150
	JPEG-2000	150
	Global contrast decrements	150
	Additive pink Gaussian noise	150
	Gaussian blurring	150
TID 2008 [40]	17 types of distortions	25 reference + 1700 distorted
IRCCyN/IVC [25]	JPEG, JPEG-2000, LAR (Locally Adaptive Resolution) compression and blur	10 reference + 235 distorted
MICT [55]	JPEG	98
	JPEG-2000	98

obtained as 0.8815 and 0.9027 respectively. As it is a spatial domain metric, its computation time is less.

Chen et al. [70] proposed and image quality assessment model for static stereoscopic images. In this method, a disparity map is generated from stereo image pair and multi-scale Gabor filter responses are obtained. A cyclopean image is integrated from stereo image pair, disparity map and Gabor filter responses. 2D features are extracted from cyclopean image and 3D features are extracted from the estimated disparity map. These features are then fed to a training model used to predict image quality. LIVE 3D database [71] is used to evaluate performance of this method. Pearson's, Spearman's correlation coefficients and RMSE for LIVE 3D database [71] is obtained as 0.895, 0.880 and 7.247 respectively.

Serir et al. [72] presented a blur metric for image quality assessment. The metric uses multiplicative multi-resolution decomposition (MMD) [73] in which the singularities are characterized by ratio of polyphase components. MMD is similar to sub-band decomposition using filter banks. It is a training algorithm and learns from parameters obtained from MMD. The algorithm is validated using LIVE database [12], TID2008 dataset [40] and IRCCyN/IVC database [25]. The details of results are shown in Table 1. This metric is benchmarked on three datasets and the performance indicates its consistency.

4. Image quality assessment databases

Results of a no-reference image quality assessment algorithm should agree well with human perception of image quality. To analyze the performance of NR-IQA, standard image databases are used. These databases are provided with subjective ratings (quality score) of images which are obtained under standard test conditions. The quality score corresponding to each image is also called mean opinion score (MOS) or differential mean opinion score (DMOS). Correlation of NR-IQA algorithm's output and DMOS indicates the performance of that particular algorithm. Details of databases used for validation are presented in Table 2. Information about other databases can be found in [74]. Pearson's correlation and Spearman's correlation coefficient are mainly used to compare the performance of algorithm. Range of both the correlation metrics is from '−1' to '+1' and value close to '−1' or '+1' indicates high correlation in negative or positive direction respectively.

5. Discussion

An overview of discussed algorithms is provided in Table 1. Correlation coefficient values corresponding to the algorithms are close to '1' but none has correlation equal to '1'. Also majority of algorithms target only specific types of distortions. Distortion caused by block coding techniques and blur is a main area of focus so far. This shows the distortion specific nature of algorithms. An ideal algorithm or may be a set of algorithms is expected to perform equally well for all types of distortions. Algorithms are benchmarked using different databases which mainly contain images degraded by limited number of distortions and each image contains only one type of distortion. This may not be the situation in real life. Practical images are frequently degraded by many types of noise, degradations and distortions. Correlation value yield by an algorithm varies with the type of database used for validation and also from image to image. So an algorithm needs to be benchmarked on all major image quality assessment databases mentioned in Table 2. The best algorithm will yield high correlation coefficient values on all the databases

6. Conclusion

To evaluate quality of an image in absence of a reference image is comparatively a complex task that demands intelligence. Knowledge of statistics of natural images, response of human visual system, the effect of distortions on images and also knowledge of the content of images is required for designing better image quality assessment algorithm. Designing of such a system is challenging as human knowledge, perception and inference is difficult to model mathematically. Researchers are trying to mimic human perception using training approaches and statistical parameters. But the techniques still have limitations as the performance of an algorithm is limited by modeling or training. This paper reviews the methods developed for image quality assessment in the absence of reference image with regard to the methods used, distortion nature, testing and validating databases. The algorithms are benchmarked using subjective scores provided with the corresponding database. Information about the databases mainly used for quality assessment and the types of degraded images in the database is summarized. This survey is expected to provide perspective researchers a complete overview of existing NR-IQA algorithms at one place. Fortunately, in many specific practical applications, the statistical model of images, the types of noise or distortion available in the images and their statistical models are available. However, NR-IQA of an image of which statistics are not available and the type of degradation or distortion is totally unknown is really a challenging problem. In practical distorted images, the distortions, degradation, noise of different type may simultaneously affect the image quality. This makes the NR-IQA problem further challenging for study, analysis, research and development.

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