Average Difference (AD):
AD is simply the average of difference between the reference signal and the test image and it is given by the equation.

$$\text{AD}=1/\text{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j))$$

Mean Absolute Error (MAE):
MAE is average of absolute difference between the reference signal and test image. It is given by the equation.

$$\text{MAE}= 1/\text{MN} \sum_{i=1}^{M}\sum_{j=1}^{N} |x(i,j)-y(i,j)|$$

B. Structural Similarity Measures

Although being very convenient and widely used, the aforementioned image quality metrics based on error sensitivity present several problems which are evidenced by their mismatch with subjective human-based quality scoring systems.Among Structural Similarity Index Measure (**SSIM**), has the simplest formulation and has gained widespread popularity in a broad range of practical applications.

In this method measuring the similarity between two images, here we measure image quality based on an initial uncompressed or distortion-free image as reference. It compares two images using information about luminous, contrast and structure. SSIM metric is designed to improve on traditional methods like PSNR and MSE and this is calculated on various windows of an image. The measure between two windows x and y of common size N×N is given as follows:

$$\text{SSIM}(x, y) = \{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)\}/ \{(\mu_x^2 + \mu_y^2 + C_1)(\sigma x2 + \sigma_y^2 + C_2)\}$$

Where µx is average of x, µy is average of y, σx, σy are standard deviation between the original and processed images pixels, respectively.C1, C2 are positive constant chosen empirically to avoid the instability of measure. SSIM is a decimal value between (-1, 1).

C. Information Theoretic Measures

The goal is to relate the visual quality of the test image to the amount of information shared between the test and the reference signals, or more precisely, the mutual information between them. In this measure the Visual Information Fidelity (VIF) is used which is based on the informationtheoretic perspective of IQA

The VIF metric measures the quality fidelity as the ratio between the total informationideally extracted by the brain from the whole distorted image and the total information conveyed within the complete reference image.This metric relies on the assumption that natural images of perfect quality, in the absence of any distortions pass through the human visual system (HVS) of an observer before entering the brain, which extracts cognitive information from it. For distorted images, it is hypothesized that the reference signal has passed through another "distortion channel"before entering the HVS. The VIF measure is derived from the ratio of two mutual information quantities: the mutual information between the input and the output of the HVSchannel when no distortion channel is present (i.e., referenceimage information) and the mutual information between the input of the distortion channel and the output of the HVS channel for the test image. Therefore, to compute the VIF metric, the entire reference image is required as quality is assessed on a global basis.

5. No-Reference Image Quality Assessment

A. Distortion-specific approaches

Thefinal quality measure is computed according to a model trained on clean images and on images affected by this particular distortion. Two of these measures have been included in the biometric protection method.

The JPEG Quality Index (JQI):
This method evaluates the quality in images affected by the usual block artifacts found in many compression algorithms running at lowbit rates such as the JPEG

The High-Low Frequency Index (HLFI):
This method is inspired by previous work which considered local gradients as a blind metric to detect blur and noise. Similarly, the HLFI feature is sensitive to the sharpness of the image by computing the difference between the power in the lower and upper frequencies of the Fourier Spectrum.

B. Training-based approaches

In this approach features are extracted from the image and algorithm is trained to distinguish distorted and undistorted image as used in BLIINDS

Blind Image Quality Index (BIQI) follows a two-stage framework in which the individual measures of different distortion-specific experts are combined to generate one global quality score.

C. Natural Scene Statistic approaches

This approach relies on how the statistics of images change as distortions are introduced to them. It assumes that natural or undistorted images occupy a subspace of the entire space of possible images, and then seeks to find a distance from the distorted image (which supposedly lies outside of that subspace) to the subspace of natural images

This approach is followed by the Natural Image
Quality Evaluator (NIQE):
Completely blind image quality analyzer based on the construction of a quality aware collection of statistical features (derived from a corpus of natural undistorted images) related to a multivariate Gaussiannatural scene statistical model.

6. Reduced Reference (Rr) Models

A RR image quality assessment method based on Roberts cross derivative or wavelet domain model of statistic of natural image is possible. The Roberts cross derivative can be used to extract geometric features of an image, which are applied in HVS perception.

Another method is based on wavelet domain RRIQA using natural image statistics model. This method of RRIQA implements the Kullback-Leibler distance between the marginal PDFs of wavelet coefficients of the original reference and distorted images as an image distortion measure.

7. Conclusion

In this paper we discussed about the various approaches used to evaluate the quality of an image. The experimental results demonstrate that the MSE and PSNR methods are simple and are easy to implement but it does not correlate highly with human awareness. Quality assessment algorithms are desirable to monitor the quality for real time applications. Subjective methods are difficult to implement in real time schemes, so objective approaches are more involved in current years. But correct and effective IQA measures help to improve their applicability in real time applications.

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