A Novel Technique for Colour Image Quality Assessment by Structural Similarity

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***Abstract* - The main aim of this paper is to provide a practical solution for automatic image quality assessment in various application where only use partial information about the original reference image is accessible. Use of the RR-IQA method find the structural similarity index(SSIM).We extract statistical features use of a multiscale multiorientation divisive normalization transform and distortion measure by structural similarity index. The interesting linear relationship between FR SSIM measure and the image distortion type is fixed then RR estimate is use. Image distortion type is measure by DNT. We use the six image database to test the proposed RR-SSIM method, most correlations with SSIM and subjective quality. Finally we introduce the great idea of partially repairing an image using RR features and use in satellite and medical images in application.**

***Keywords*— Image repairing, reduced reference image quality assessment(RR-IQA) , Divisive normalization statistics, structural similarity.**

I. Introduction

The field of image and video processing generally deals with signals that are meant for human consumption, such as images or videos over the Internet. An image or video may go through many stages of processing before being presented to a human observer, and each stage of processing may introduce distortions that could reduce the quality of the final display. For example, images and videos are acquired by camera devices that may introduce distortions due to optics, sensor noise, color calibration, exposure control, camera motion etc. After acquisition, the image or video may further be processed by a compression algorithm that reduce the bandwidth requirements for storage or transmission. Such compression algorithms are generally designed to achieve greater savings in bandwidth by letting certain distortions happen to the signal. Similarly, bit errors, which occur while an image is being transmitted over a channel or (rarely) when it is stored, also tend to introduce distortions. Finally, the display device used to render the final output may introduce some of its own distortion, such as low reproduction resolution, bad calibration etc. The amount of distortion that each of these stages could add depends mostly on economics and/or physical limitations of the devices.

One is obviously interested in being able to measure the quality of an image or video, and to gauge the distortion that has been added to it during different stages. One obvious way of determining the quality of an image or video is to solicit opinion from human observers. After all, these signals are meant for human consumption. However, such a method is not feasible not only due to the shear number of images and videos that are "out there" but also because we want to be able to embed quality measurement techniques into the very algorithms that process images and videos, so that their output quality may be maximized for a given set of resources.

The goal of research in *objective* image quality assessment is to develop quantitative measures that can automatically predict perceived image quality. Generally speaking, an objective image quality metric can play an important role in a broad range of applications, such as image acquisition, compression, communication, displaying, printing, restoration, enhancement, analysis and watermarking. First, it can be used to dynamically *monitor* and adjust image quality. Second, it can be used to *optimize* algorithms and parameter settings of image processing systems. Third, it can be used to *benchmark* image processing systems and algorithms.

In short, objective quality measurement (as opposed to subjective quality assessment by human observers) seeks to determine the quality of images or videos algorithmically. The goal of objective quality assessment (QA) research is to design algorithms whose quality prediction is in good agreement with subjective scores from human observers.

Image and video QA algorithms may be classified into three broad categories:

Full-Reference (FR) QA methods, in which the QA algorithm has access to a 'perfect version' of the image or video against which it can compare a 'distorted version'. The 'perfect version' generally comes from a high-quality acquisition device, before it is distorted by, say, compression artifacts and transmission errors. However, the reference image or video generally requires much more resources than the distorted version, and hence FR QA is generally only used as a *tool* for designing image and video processing algorithms for in-lab testing, and cannot be deployed as an *application*.

No-Reference (NR) QA methods, in which the QA algorithm has access only to the distorted signal and must estimate the quality of the signal without any knowledge of the 'perfect version'. Since NR methods do not require any reference information, they can be used in any application where a quality measurement is required. However, the price paid for this flexibility is in terms of the ability of the algorithm to make accurate quality predictions, or a limited scope of the NR QA algorithm (such as NR QA for JPEG images only etc.).

Reduced-Reference (RR) QA methods, in which partial information regarding the 'perfect version' is available. A side-channel (called an RR channel) exists through which some information regarding the reference can be made available to the QA algorithm. RR QA algorithms use this partial reference information to judge the quality of the distorted signal.

In the extreme, when the rate is enough to fully reconstruct the reference, RR-IQA converges to FR-IQA. The performance gap betweenRR-IQA and FR-IQA may be reduced by selecting RR features that are efficient, perceptually relevant, and sensitive to various kinds of distortions. In addition, since the RR features provide information about what the "correct" image is supposed to look like, they may also be used as side information to repair the received distorted image, as illustrated in fig.1.

Based on the underlying design philosophy, existing RR-IQA algorithms may be loosely classified into three categories.The first type of methods are primarily built upon models of the image *source*. Since the reference image is not available in the deterministic sense, these models are often statistical that capture *a priori* the low-level statistical properties of natural images. The model parameters provide a highly efficient way to summarize the image information, and thus these methods often lead to RR-IQA algorithms with low RR data rate. the marginal distribution of wavelet subband coefficients is modeled using a generalized Gaussian density (GDD) function, and GGD model parameters are used as RR features are employed to quantify the variations of marginal distributions in the distorted image. The model was further improved in reference by employing a nonlinear divisive normalization transform (DNT) after the linear wavelet decomposition, which resulted in enhanced quality prediction performance, especially when images with different distortion types are mixed together. The second category of RR-IQA methods are oriented to capture image *distortions*. These methods provide useful and straightforward solutions when we have sufficient knowledge about the distortion process that the images underwent, e.g., standard image or video compression. The limitation of such approaches is in their generalization capability. Generally, it is inappropriate to apply these methods beyond the distortions they are designed to capture. The third category of RR-IQA algorithms are based on models of the image *receiver* [i.e., the hierarchical visualisation system (HVS)], where computational models from physiological and/or psychophysical vision studies may be employed. These methods have demonstrated good performance for JPEG and JPEG2000 compression. Among the three classes of RR-IQA approaches, the first and third ones, i.e., methods based on modeling the image source and the receiver, have more potential to be extended for general-purpose applications because the statistical and perceptual features being employed are not restricted to any specific distortion process. There are also interesting conceptual connections between these two types of approaches, because it is a general belief in biological vision science that the HVS is highly tuned for efficient statistical encoding of the natural visual environment.

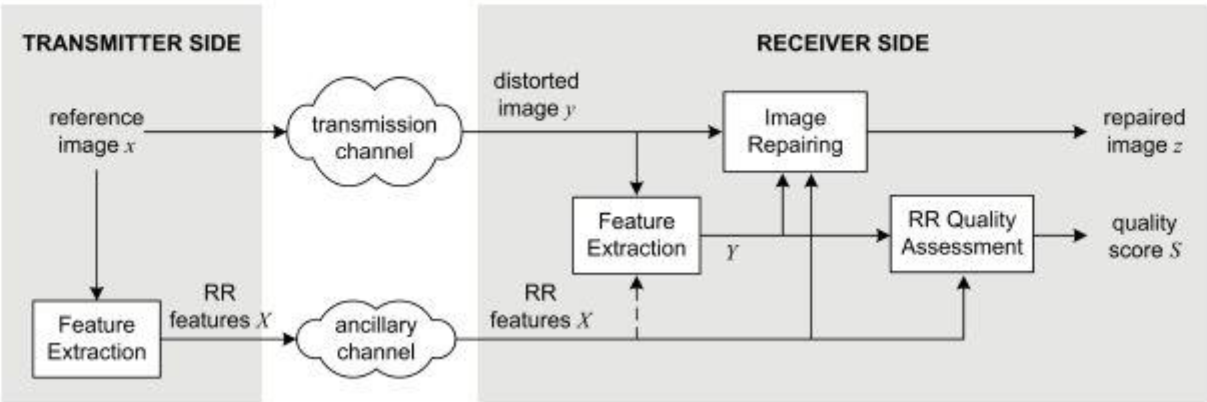

Fig. 1 General framework for the deployment of RR-IQA systems with image repairing capability.

II RR-SSIM ESTIMATION

The proposed RR-SSIM estimation algorithm starts with a feature extraction process of the reference image based on a multiscale multiorientation DNT. Divisive normalization was found to be an effective mechanism to account for many neuronal behaviors in biological perceptual systems. It also provides a useful model to describe the psychophysical visual masking effect. DNT is typically applied after a multiscale linear transform (loosely referred to as wavelet transform) that decomposes the image into transform coefficients representing localized structures in space, frequency (scale), and orientation. The DNT-domain representation of the image is then calculated by dividing each coefficient by a local energy measure based on its neighboring coefficients. It was found that the histogram of DNT coefficients within a wavelet subband can often be well fitted with a zero-mean Gaussian density function, which is a one-parameter function that allows efficient summarization of the statistics of the reference image.

III DNT-DOMAIN STATISTICS OF DISTORTED IMAGES

The strong perceptual and statistical relevance of DNT image representation provides good justifications for the use of DNT for RRIQA. In addition to that, we must also show that the statistics of DNT coefficients are sensitive to various image distortions. To study this, we apply DNT to a set of images with different types of distortions and observe how these distortions alter the statistics of the coefficients in DNT domain. This is demonstrated in Fig. 2, where the histogram of the DNT coefficients of a wavelet subband can be well-fitted with a Gaussian model [Fig.2(a)]. However, when we draw the same Gaussian model together with the histogram of the DNT coefficients computed from Gaussian noise contaminated image [Fig. 2(b)], Gaussian blurred image [Fig. 2(c)], or JPEG compressed image [Fig. 2(d)], significant changes are observed. It is also interesting to see that the way the distribution changes varies with the distortion type. For example, Gaussian noise contamination increases the width of the histogram, but maintains the shape of Gaussian. By contrast, Gaussian blur reduces the width of the histogram and creates a much peakier distribution than Gaussian. These observations are important because our RRIQA algorithm is based on quantifying the variations of DNT-domain image statistics as a measure of image quality degradation.

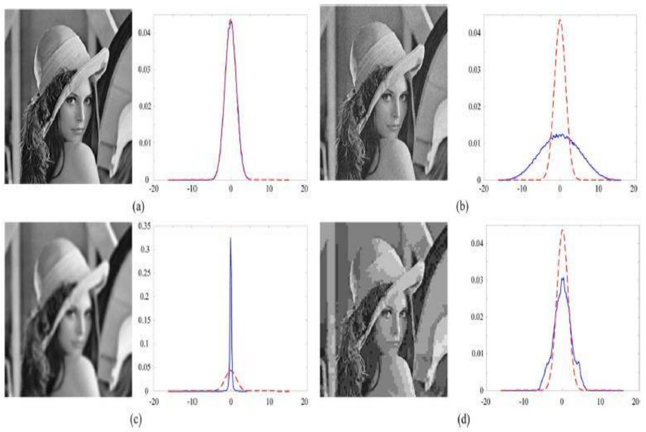

Fig. 2. Histograms of DNT coefficients in a wavelet subband under different types of image distortions. (a) Original "Lena" image. (b) Gaussian noise contaminated image. (c) Gaussian blurred image. (d) JPEG compressed image. Solid curves: histograms of DNT coefficients. Dashed curves: the Gaussian model fitted to the histogram of DNT coefficients in the original image. Significant departures from the Gaussian model is observed in the distorted images (b), (c), and (d).

IV THE STRUCTURAL SIMILARITY (SSIM) INDEX

We construct a specific example of a structural similarity quality measure from the perspective of image formation. we generalize this algorithm, and provide a more extensive set of validation results. The luminance of the surface of an object being observed is the product of the illumination and the reflectance, but the structures of the objects in the scene are independent of the illumination. Consequently, to explore the structural information in an image, we wish to separate the influence of the illumination. We define the structural information in an image as those attributes that represent the structure of objects in the scene, independent of the average luminance and contrast. Since luminance and contrast can vary across a scene, we use the local luminance and contrast for our definition.

The system diagram of the proposed quality assessment system is shown in Fig. 1. Suppose x and y are two nonnegative image signals, which have been aligned with each other (e.g., spatial patches extracted from each image). If we consider one of the signals to have perfect quality, then the similarity measure can serve as a quantitative measurement of the quality of the second signal. The system separates the task of similarity measurement into three comparisons: luminance, contrast and structure. First, the luminance of each signal is compared. Assuming discrete signals, this is estimated as the mean intensity:

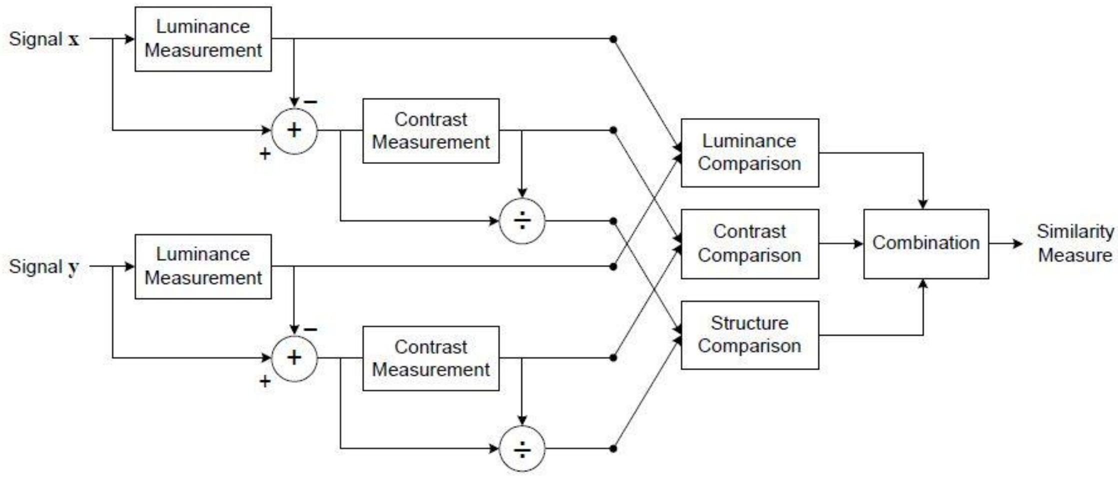

Fig.3 Diagram of the structural similarity (SSIM) measurement system

$$\mathrm{SSIM}(\mathbf{x},\mathbf{y}) = [l(\mathbf{x},\mathbf{y})]^{\alpha} \cdot [c(\mathbf{x},\mathbf{y})]^{\beta} \cdot [s(\mathbf{x},\mathbf{y})$$

where $\alpha > 0$, $\beta > 0$ and $\Gamma > 0$ are parameters used to adjust the relative importance of the three components.

For image quality assessment, it is useful to apply the SSIM index locally rather than globally. First, image statistical features are usually highly spatially non-stationary. Second, image distortions, which may or may not depend on the local image statistics, may also be space-variant. Third, at typical viewing distances, only a local area in the image can be perceived with high resolution by the human observer at one time instance. And finally, localized quality measurement can provide a spatially varying quality map of the image, which delivers more information about the quality degradation of the image and may be useful in some applications

In practice, one usually requires a single overall quality measure of the entire image. We use a mean SSIM(MSSIM) index to evaluate the overall image quality:

V. PERFORMANCE OF IQA MEASURES

1. PLCC after a nonlinear mapping between the subjective and objective scores. For the *i* th image in an image database of size *N*, given its subjective score *oi* [mean opinion score (MOS) or difference of MOS (DMOS) between reference and distorted images] and its raw objective score *ri* , we first apply a nonlinear function to *ri* given by

$$q(r) = a_1 \left\{ \frac{1}{2} - \frac{1}{1 + \exp\left[a_2(r - a_3)\right]} \right\} + a_4 r + a_5$$

where *a*1–*a*5 are model parameters found numerically using a nonlinear regression process in MATLAB optimization toolbox to maximize the correlations between subjective and objective scores. The PLCC value can then be computed as

$$\text{PLCC} = \frac{\sum_i (q_i - \bar{q}) * (o_i - \bar{o})}{\sqrt{\sum_i (q_i - \bar{q})^2 * \sum_i (o_i - \bar{o})^2}}.$$

2. MAE is calculated using the converted objective scores after the nonlinear mapping described above

$$\text{MAE} = \frac{1}{N} \sum |q_i - o_i|.$$

3. Root mean-squared (RMS) error is computed similarly As

$$\text{RMS} = \sqrt{\frac{1}{N} \sum (q_i - o_i)^2}.$$

4. Spearman's rank correlation coefficient (SRCC) is defined as

$$\text{SRCC} = 1 - \frac{6 \sum_{i=1}^{N} d_i^2}{N(N^2 - 1)}$$

   where *di* is the difference between the *i* th image's ranks in subjective and objective evaluations. SRCC is a nonparametric rank-based correlation metric, independent of any monotonic nonlinear mapping between subjective and objective scores.
5. Kendall's rank correlation coefficient (KRCC) is another nonparametric rank correlation metric given by

$$\text{KRCC} = \frac{N_c - N_d}{\frac{1}{2} N(N-1)}$$

   where *Nc* and *Nd* are the number of concordant and discordant pairs in the dataset, respectively.

Among the above metrics, PLCC, MAE, and RMS are adopted to evaluate prediction accuracy, and SRCC and KRCC are employed to assess prediction monotonicity. A better objective IQA measure should have higher PLCC, SRCC, and KRCC, with lower MAE and RMS values. All these evaluation metrics are adopted from previous IQA studies. Only the distorted images in the six databases were employed in our tests. This avoids several difficulties in computing the evaluation metrics. Specifically, the reference images have infinite peak signal-to-noise-ratio (PSNR) values, making it hard to perform nonlinear regression and compute PLCC, MAE, and MSE values. In addition, since all reference images are assumed to have perfect quality, there are no natural relative ranks between them, resulting in ambiguities when computing SRCC and KRCC metrics.

VI. VALIDATION OF RR-IQA ALGORITHM

Six databases were used to test the proposed algorithm and compare its performance with other IQA algorithms. The databases include.

1. The LIVE database contains seven datasets of 982 subject-rated images, including 779 distorted images with five types of distortions at different distortion levels. The distortion types include: a) JPEG2000 compression (2 sets); b) JPEG compression (2 sets); c) white noise contamination (1 set); d) Gaussian blur (1 set); and e) fast fading channel distortion of JPEG2000 compressed bitstream (1 set). The subjective test was carried out with each dataset individually, and a crosscomparison set that mixes images from all distortion types is then used to align the subject scores across datasets. The alignment process is rather crude, but the aligned subjective scores (all data) are still useful references for testing general-purpose IQA algorithms, for which cross-distortion comparisons are highly desirable.
2. The Cornell-A57 database contains 54 distorted images with six types of distortions: a) quantization of the LH subbands of a five-level discrete wavelet transform, where the subbands were quantized via uniform scalar quantization with step sizes chosen such that the RMS contrast of the distortions was equal; b) additive Gaussian white noise; c) baseline JPEG compression; d) JPEG2000 compression without visual frequency weighting; e) JPEG2000 compression with the dynamic contrast-based quantization algorithm, which applies greater quantization to the fine spatial scales relative to the coarse scales in an attempt to preserve global precedence; and f) blurring by using a Gaussian filter.
3. The IVC database includes 185 distorted images with four types of distortions, which are: a) JPEG compression; b) JPEG2000 compression: c) local adaptive resolution (LAR) coding: and d) blurring.
4. The Toyama-MICT database contains 196 images, including 168 distorted images generated by JPEG and JPEG2000 compression.
5. The Tampere Image database 2008 (TID2008) includes 1700 distorted images with 17 distortion types at four distortion levels. The types of distortions are: a) additive Gaussian noise; b) additive noise in color components more intense than additive noise in the luminance component; c) Spatially correlated noise; d) masked noise; e) high-frequency noise; f) impulse noise; g) quantization noise; h) Gaussian blur; i) image denoising; j) JPEG compression; k) JPEG2000 Compression; l) JPEG transmission errors; m) JPEG2000 transmission Errors, n) Non-eccentricity pattern noise; o) local block-wise distortions of different intensity; p) mean shift (intensity shift); and q) contrast change.
6. The Categorical Image Quality (CSIQ) database contains 866 distorted images of six types of distortions at 4 and 5 distortion levels. The distortion types include JPEG compression, JPEG2000 compression, global contrast decrements, additive pink Gaussian noise, and Gaussian blurring.

VII. SCOPE OF THE WORK

There are many different applications and scopes of the work are as listed below.

1. Automatically give the distortion in the image.
2. Reduced the reference image features.
3. Repair image.
4. Application wise detect the distortion.

VIII. CONCLUSION

The work, presented here can be drawn from the investigations and implementation that have been done so far and it is intended to be of some use in such application.

REFERENCES

[1] Abdul Rehman Zhou Wang ,Reduced-Reference Image Quality Assessment by Structural Similarity Estimation," IEEE Trans.Image Process,AUGUST 2012.

[2] Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, "Image quality assessment: From error visibility to structural similarity," IEEE Trans.Image Process., vol. 13, no. 4, pp. 600–612, Apr. 2004.

[3] Q. Li and Z. Wang, "Reduced-reference image quality assessment using divisive normalization-based image representation," IEEE J. Sel. Topics Signal Process., vol. 3, no. 2, pp. 202–211, Apr. 2009.

[4] H. Sheikh, A. Bovik, and G. Veciana, "An information fidelity criterion for image quality assessment using natural scene statistics," IEEE Trans.Image Process., vol. 14, no. 12, pp. 2117–2128, Dec. 2005.

[5] Z.Wang,"The SSIM index for IQA" http://www.cns.nyu.edu/~lcv/ssim/ .

[6] http://web.njit.edu *for visual information fidelity.*