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Quality Analysis and Repair of the Visual data stored in cloud

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Abstract— Digital imaging and image-processing technologies have revolutionized the way in which we capture, store, receive, download, view, utilize, and share images. It is highly desirable to have a mechanism to assess the quality of the images that we encounter in our day to day life. The best way to assess the quality of an image is by doing subjective analysis (MOS). But human eye cannot distinguish the minor variations in image content downloaded from cloud. Also, the MOS method is too inconvenient, slow and expensive for practical usage. Here, we propose a natural scene statistic (NSS)-based image quality assessment (IQA) mechanism which operates in the spatial domain. This mechanism uses the scene statistics of normalized luminance coefficients to quantify the 'naturalness' (or lack thereof) in the image due to the presence of distortions.

Keywords— *NSS images , Gaussian Distribution , Luminance, MSCN Coeficients;*

I. Introduction

Today, we have come to expect the ability to instantly share photos online, to send and receive multimedia messages at a moment's notice, and to stream live video across the globe instantaneously. These conveniences are possible because the digital cameras and photo-editing systems used by photographers and artists, the compression and transmission systems used by distributors and network engineers, and the various multimedia and display technologies enjoyed by consumers all have the ability to process images in ways that were unthinkable just 20 years ago.

But despite the innovation and rapid advances in technology and despite the prevalence of higher-definition and more immersive content, one thing has remained constant throughout the digital imaging revolution: the biological hardware used by consumers—the human visual system. Although personal preferences can and do change over time and can and do vary from person to person, the underlying neural circuitry and biological processing strategies have changed very little over measurable human history. As a result, digital processing can alter an image's appearance in ways that humans can reliably and consistently judge to be either detrimental or beneficial to the image's visual quality.

Because of the prevalence of these alterations, a crucial requirement for any system that processes images is a means of assessing the impacts of such alterations on the resulting visual quality. To meet this need, numerous algorithms for image quality assessment (IQA) have been researched and developed over the last several decades. Today, IQA research has emerged as an active sub discipline of image processing, and many of the resulting techniques and algorithms have begun to benefit a wide variety of applications. Variations of IQA algorithms have proved useful for applications such as image and video coding, digital watermarking, unequal error protection, de-noising, image synthesis, and various other areas (e.g., for predicting intelligibility in sign language video).

Quality assessment is a very complicated task, and even full -reference quality assessment methods have only limited success in making accurate quality predictions. To tackle the distortion problem algorithms that are capable of assessing the quality of an image without the need for a reference and without the knowledge of the distortion that affect the image, have to be designed.

II. LITERATURE SURVEY

Existing IQA metrics can be classified into three categories according to the availability of the original image: 1) full-reference IQA; 2) reduced-reference IQA; and 3) no-reference/blind IQA (BIQA). Most IQA algorithms operate in this relative-to-a-reference fashion; these are so-called full-reference algorithms, which take as input a reference image and a processed (usually distorted) image and yield as output either a scalar value denoting the overall visual quality or a spatial map denoting the local quality of each image region.

- FR QA algorithms assume that apart from distorted image whose quality needs to be judged, a pristine reference stimulus is also available to the algorithm to be compared with.
- RR QA algorithms assume that some auxiliary information about the reference stimulus is available to the algorithm, even though the actual reference stimulus itself in unprocurable.
- NR QA algorithms seek to find quality of distorted stimulus with no information about its pristine counterpart. Such an assessment of visual quality, also known with the name of blind image quality assessment, forms the crux of our proposed work.

In absence of any information from pristine image, it may seem that the problem of no reference image quality is impossible. Hence researchers' first addressed the problem of full reference quality, where distorted images are compared with their pristine counterparts. Mean squared error (MSE) between distorted and pristine images being a standard criterion for signal fidelity determination gave a head start. It had nice properties of simplicity, parameter free estimation, inexpensive computation and memorylessness, it being evaluated at each sample independent of other samples. However, it had a strong assumption neglected by image processing community at first; i.e. no spatial relationships exists between samples of the signal. In other words, if we randomly re-order pristine and distorted signals in the exact same way, mean squared error would remain same. This assumption fails critically for images and videos having a well defined structure which makes neighbouring pixels dependent on each other. Hence the most intuitive way was to reduce the dependencies between neighbouring pixels first in both pristine and distorted images before using MSE. Vision community indeed found that human visual system adopt a similar approach of reducing dependencies between neighbouring coefficients. More recently, researchers have begun to develop no-reference and reduced-reference algorithms, which attempt to yield the same quality estimates either by using only the processed/distorted image (no- reference IQA or by using the processed/distorted image and only partial information about the reference image(reduced-reference IQA). All three types of IQA algorithms can perform quite well at predicting quality. Some of today's best-performing full reference algorithms have been shown to generate estimates of quality that correlate highly with human ratings of quality.

III. REVIEW OF STATE OF THE ART METHODS

Quality Assessment Based on DCT: Michele Saad, Alan C. Bovik, Christophe Charrier developed a method called BLIINDS1 to effectively assess quality in natural scene statistics (NSS). The algorithm relies on discrete cosine transform for feature extraction. The histogram pattern of undistorted and distorted images shows a major difference. Anush Krishna Moorthy and Alan C. Bovik in 2011 devised a method for blind image quality assessment using wavelet transform coefficients (DIIVINE). Here a loose wavelet transform is applied on to the image and the scalespace-orientation of the image is noted. Here, a probabilistic distortion identification is combined with distortion specific quality score to produce a final quality value for the image. In 2013, Xinbo Gao and Xuelong Li successfully implemented a method of Image Quality Analysis by multiple Kernel Learning . This paper uses the secondary and tertiary properties of wavelet transform to get the features of NSS images. Another assessment algorithm using Deep Learning was developed recently by Weilong Hou and Xinbo Gao,-This paper investigates how to blindly evaluate the visual quality of an image by learning rules from linguistic descriptions.. The exponential decay characteristic of wavelet coefficients are used here to represent the image. Furthermore, the exponential decay is less dependent on particular image content and is therefore suitable for constructing a universal BIQA method.

IV. QUALITY ASSESSMENT IN NATURAL IMAGES

Most of the existing quality assessment methods concentrate mapping the image domain from spatial to another and doing processing on that. We are concentrating and processing in spatial domain since we think that the visual cortex of human beings respond well in spatial domain. The normalized luminance value of the image offers a good knowledge about the amount of distortion happened to the image and also the amount of naturalness presented in the image under consideration. In this paper, we examine the quality of an NSS image by inspecting the normalized luminance value. Opinion-unaware[8] methods do not need human subjective scores for training and thus the practical applicability of such methods are more compared to opinion aware quality assessment methods.

The inspiration for creating such a model is based on the fact that NSS images possess some statistical properties and the amount of distortion happened to the image can be found by collecting together this variations from original distribution.

We then demonstrate how the statistical features obtained from the image can represent quality and that the representation confirms well with human perception of quality.

- *Finding the normalized luminance :*

Given a (possibly distorted) image, we compute locally normalized luminances via local mean subtraction and divisive normalization. Ruderman observed that applying a local *non-linear* operation to log-contrast luminances to remove local mean displacements from zero log-contrast and to normalize the local variance of the log-contrast has a de-correlating effect. Such an operation may be applied to a given intensity image *I (i, j)* to produce:

$$\bar{I}(i,j) = \frac{I(i,j) - \mu(i,j)}{\sigma(i,j) + C} \qquad (1)$$

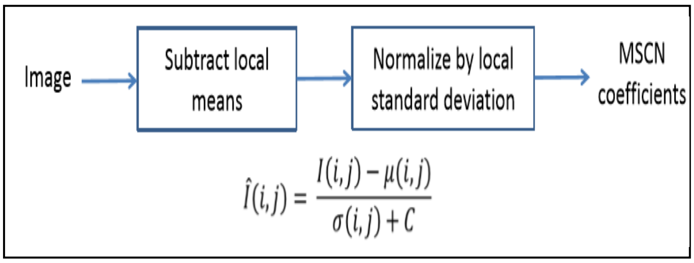
Where I and j are spatial indices and i=1,2,..M and n=1,2,…N. μ(i,j) represents the mean and is taken as

$$\mu(i,j) = \sum_{k=-K}^{K} \sum_{l=-L}^{L} w_{k,l}\, I_{k,l}(i,j) \qquad (2)$$

Variance , σ(i ,j) is obtained as

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} . \sum_{l=-L}^{L} w_{k,l} I_{k,l}(i,j) - \mu(i,j)2} \qquad (3)$$

- Where $w = \{w_{k,l} \mid k = -K, \ldots, K, l = -L, \ldots L\}$ is a 2D circularly-symmetric Gaussian weighting function. In our implementation, K and L are taken as 3[8].



Observations have shown that these normalized luminance values depicts a unit Gaussian distribution in the absence of any distortion for NSS images. These normalized luminance values are also termed as Mean Subtracted Contrast Normalized values (MSCN)[1].Our experiments are based on the theory that the MSCN coefficients have characteristic statistical properties that are changed by the presence of distortion, and that quantifying these changes will make it possible to predict the type of distortion affecting an image as well as its perceptual quality. In order to visualize how the MSCN coefficient distributions vary as a function of distortion, the coefficient values were plotted for an undistorted pristine image and on a distorted low quality image. The MSCN coefficients clearly shows the distinction between a good quality undistorted natural image and a low quality distorted image (Fig 1).The shape of the curve is perfecty Gaussian for an undistorted NSS image and is exhibiting variations its distorted version. For each type of distortion the shape of the curve changes in its own characteristic way.

The Fig 4 shows that MSCN coefficients follow Gaussian[5] like signatures for natural scene Images. Also, we are more interested in finding how distortions affect this pristine image signature and if unique characteristic signature exists for each kind of distortion(Refer fig 3) . Above figure(fig 4) shows 5 kinds of different distortions[4] which span the set of distortions considered in LIVE database - JPEG2000 (JP2K) compression, JPEG compression, additive white noise (WN), Gaussian Blur (blur) and a Rayleigh fading channel labelled fast fading (FF).

By analysing the MSCN coefficients, it is clear that each of the different kinds of distortion affect the shape of the curve in a different way. The shape parameter α controls the 'shape' of the distribution while $\boldsymbol{\sigma^2}$ control the variance. The shape parameter α also denotes the rate of decay: the smaller α, the more peaked is the distribution, and the larger α, the flatter is the distribution, so it is also called as the decay rate. For NSS images, there exists a statistical relationship between neighbouring pixels and these dependencies gets disturbed in the presence of distortion.

By analysing shape of the curve, the type of distortion and the amount of distortion can be the quantized[6][7]. Suppose we know the distortion affecting the image repair action can be done to rectify or reduce the distortion. Popular methods like denoising , deblurring , deblocking or deringing can be applied(fig 5).

Fig1 shows undistorted original NSS image and (b) and(c) its two Low Quality distorted version (by high and medium white noise distortion)

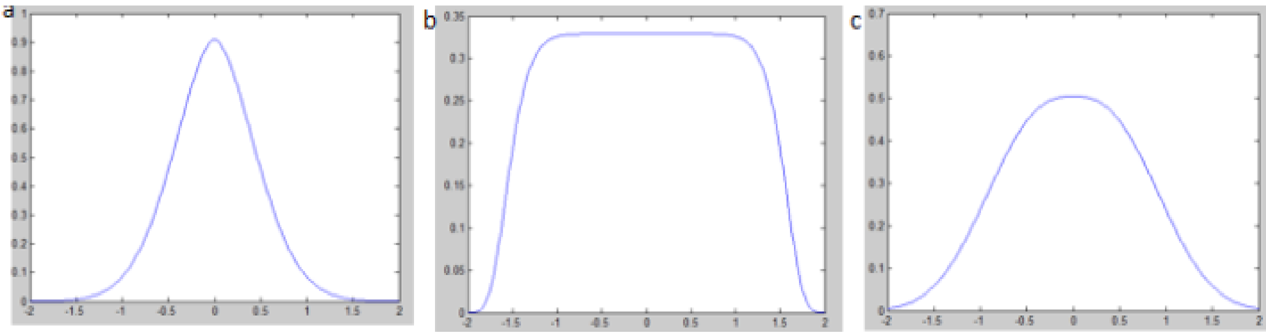


Fig 2(a),(b)and (c) shows the distribution of MSCN coefficients of Fig 1(a),(b) and(c). Even though fig 1(a) and(c) does not show much difference in human perception, the MSCN coefficients clearly shows the distortion difference by means of difference in shape.

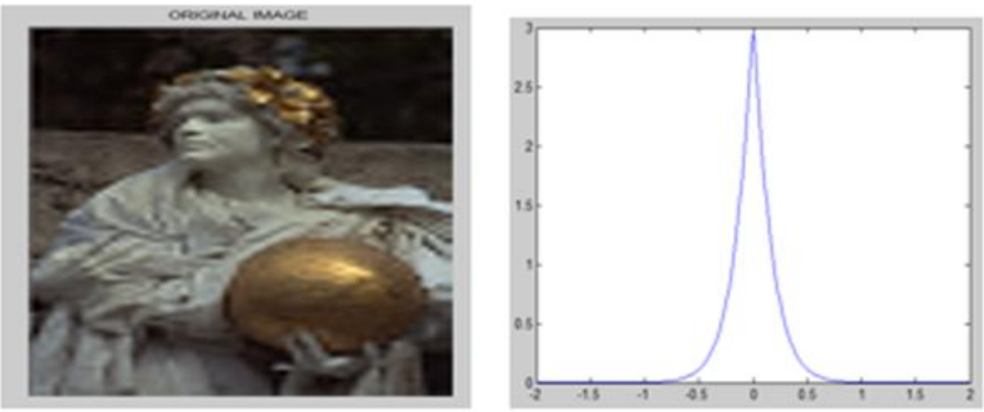


Fig 3(c) and 3(d) shows Low Quality –FF(Rayleigh fast-fading) distorted image and its MSCN coefficient.

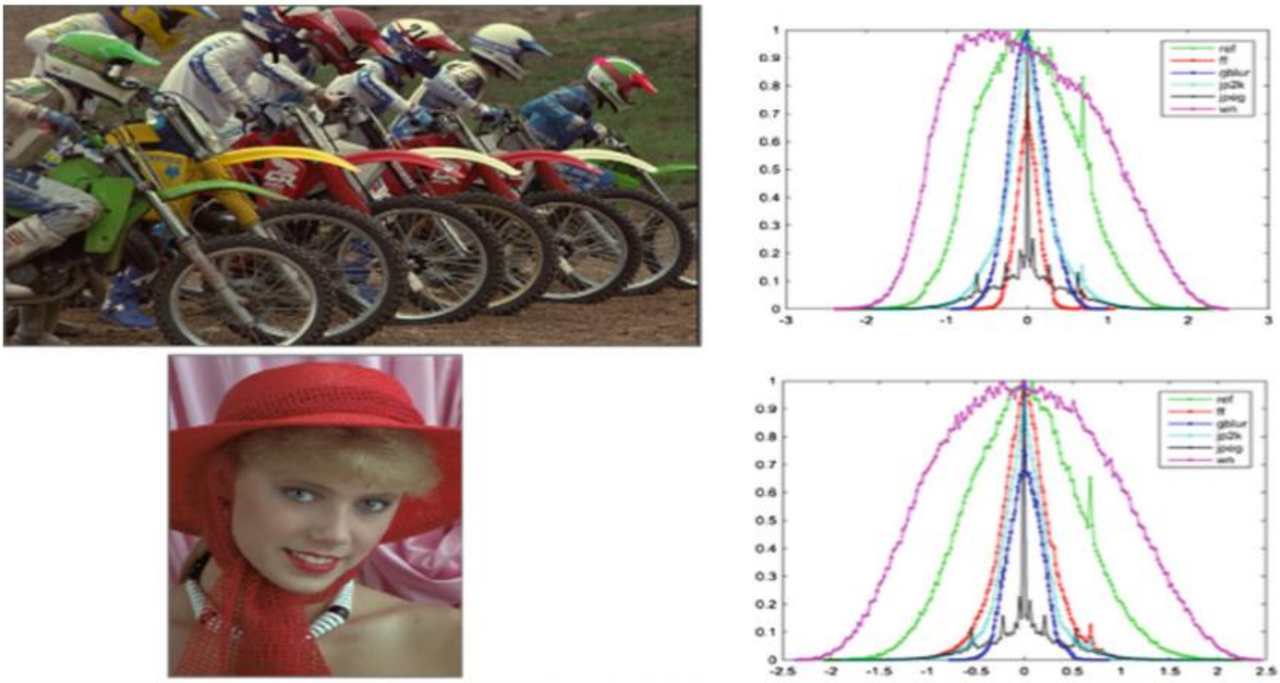


Fig 4. Empirical histograms of the MSCN coefficients of two random reference images from LIVE database and their distorted versions.

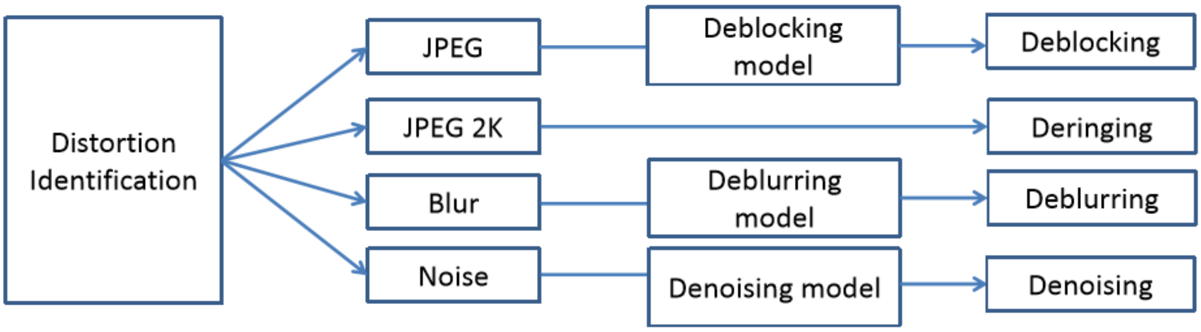


Fig 5. A model showing repair in distorted NSS Images

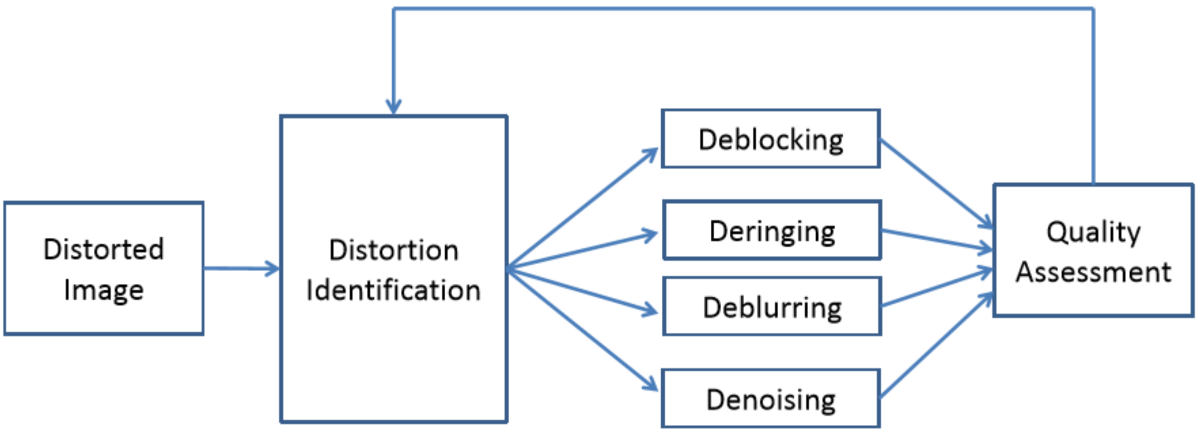


Fig 6. A model showing iterative deblurring method in distorted NSS images

Often one kind of repair creates other distortions, eg. denoising leads to blur[5]. Hence, iteratively repair the image by identifying distortion type after each iteration(fig 6). Continue iterating until quality drops after a particular iteration when compared with the previous iteration.

CONCLUSION

In this paper, we have proposed a method for analyzing the quality of the images which are captured or downloaded from the internet. The structural difference in NSS images works as the base concept of comparison. This helps in a revolutionary development since enormous applications need huge amount of good quality visual content and this method ensures quality of the received or downloaded content. The result of the proposed work is comparable with human judgment and that shows the versatility of the application. The proposed method also shares light on repair mechanism to reduce the effect of distortion.

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