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REDUCED-REFERENCE IMAGE QUALITY ASSESSMENT

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Abstract

Image quality assessment (IQA) has been recognized as an effective and efficient way to predict the visual quality of distorted images. Various wavelet transforms based methods are used to extract singularity structures, but they fail to explicitly extract the image geometric information, e.g., lines and curves. In this paper we develop a novel framework for IQA to mimic the human visual system (HVS) by incorporating the merits from multiscale geometric analysis (MGA), contrast sensitivity function (CSF), and the Weber's law of just noticeable difference (JND). MGA can be used for decomposition of image and feature extraction.CSF is used to balance the MGA decomposed coefficients via a weighting scheme. JND is introduced to produce a noticeable variation in sensory experience. After this the normalized histogram is constructed for both reference and distorted image. Both sender side and receiver side is applied to extract the normalized histogram of the reference image and distorted image respectively. Then both the histograms are compared for the image quality assessment.

Keywords

Reduced-reference (RR), Multiscale geometric analysis(MGA),Contrast sensitivity Function(CSF)

I. INTRODUCTION

Image Quality Assessment (IQA) has always been an integral part of image processing. Many different approaches for IQA with different density have been developed in the last decade. Digital images are subject to a variety of distortions during compression, transmission, processing, and reproduction. In order to maintain, control and possibly enhance the quality of the image and video data being delivered, it is important for data management system (network video servers) to be able to identify and quantify quality degradations on the fly. [1] Image QA methods can be classified as subjective and objective methods. The first approaches to image quality evaluation are subjective quality testing which is based on observers that evaluate image quality. These tests are time consuming, expensive and have a very strict definition of observational conditions. The second approaches are the objective image quality testing based on mathematical calculations and also based on test targets or algorithms. Test-target measurements are tedious and require a controlled laboratory environment. Algorithm metrics can be divided into three groups: full-reference (FR), reduced-reference (RR) and no-reference (NR). This classification is related to the availability of reference images. Over the years, a number of researchers have contributed significant research in the design of full reference image quality assessment algorithms, claiming to have made headway in their respective domains. FR metrics cannot be applied to the computation of image quality captured by digital cameras because pixel-wise reference images are missing. FR metrics are applicable for applications such as filtering or compression where an original image has been processed and the output does not differ in terms of scale, rotation or geometrical distortion. NR metrics are applicable only when the distortion type is known and the distortion space is low-dimensional. NR metrics are often used to measure a single artifact, such as blockiness, blurriness or motion in video. For example, many NR sharpness metrics interpret graininess or noise as edges or some other image structure. In addition, NR metrics are often highly image content specific. Understanding image content is a difficult task for computational methods. The published methods are still too unreliable for random natural images. RR metrics provide a tradeoff between NR and FR metrics. An RR metric does not require full access to the reference image; it only needs a set of extracted features. With the aid of RR features, it is possible to avoid problems associated with image content dependencies and multi-dimensional distortion space. In addition, RR metrics can be invariant to scale, orientation or geometrical differences.

II. LITERATURE REVIEW AND RELATED WORK

Extensive research has been done in the area of image quality assessment. Various methods are used to obtain the quality of the received image at the receiver side as that of the original image at the sender side.To obtain the structural similarity Wang et al[38] proposed method known as structural similarity[SSIM]based on the degradation of structural information. As SSIM only considers the local correlation in an image, so detected features are not enough for precise IQA. Thus this method is not efficient for image quality assessment and also fail for full-reference metric as it required original image as reference. After that Wang *et al.* [2] proposed the wavelet-domain natural image statistic metric (WNISM), which achieves promising performance for image visual perception quality evaluation. Although WNISM achieves promising performance it fails to consider the statistical correlations of wavelet coefficients in different subbands and the visual response characteristics of the mammalian cortical simple cells. This problem is resolved by using reduced-reference image quality assessment method in which we are using multiscale geometric analysis[MGA] to decompose original or reference image to obtain the extracted feature of image.

III. ANALYSIS OF PROBLEM

RR metrics provide a tradeoff between NR and FR metrics.For FR metric Mean Squared Error (MSE) and Peak Signal To Noise Ratio (PSNR)has been used as a quality metric from a very long time, because of its simplicity. But because of having a very poor correlation with human perception [1] this method is not in agreement. Progress on no reference metric , however, has been very slow. One approach is to devise NR algorithms for a specific type of distortion only[4], [6]. This approach can be refined by assuming that the distorted image is subjected to a set of possible distortions known a priori. Training based NR metric techniques have resulted in algorithms that perform at least as well as mean squared error, which has the benefit of a reference image [7]. In [8], blind image quality assessment indices that measure the anisotropy in the distorted image through the Renyi entropy are introduced. To avoid this problem we are providind the partial information about the reference , which can be used along with the distorted image to predict quality. This paradigm is known as reduced reference (RR) QA, which may or may not require knowledge of the distortion type.

IV. REDUCED-REFERENCE METRIC

As in the RR metric we are providing the partial or side information about the reference image this information usually consists of relevant features extracted from the original media which are transmitted and compared with the analogous features extracted from the degraded media. The side information consists of two distinct types of measurements: spatial measurement extracted from the frames edges, and temporal measurements extracted from frames differences. The following figure [5]shows the framework used for reduced reference image quality assessment metric. In which at the sender side first feature extraction is take place and then this partial or side information is send along the channel. At the receiver side distorted image and extracted features are compared by using RR quality analysis method. For the feature extraction from the original media first we have to decompose the image for this purpose we are using the Multiscale Geometric Analysis framework.

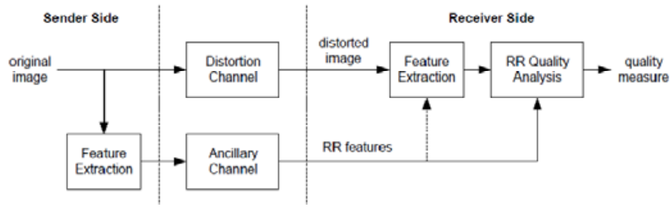

Fig.1 Reduced reference image quality assessment metric

V. MULTISCALE GEOMETRIC ANALYSIS FRAMEWORK(MGA)

MGA is such a framework for optimally representing high-dimensional function. It is developed, enhanced, formed and perfected in signal processing, computer vision, machine learning, and statistics. MGA can detect, organize, represent, and manipulate data, e.g., edges, which nominally span a high-dimensional space but contain important features approximately concentrated on lower dimensional subsets, e.g., curves. MGA can be utilized to a large variety of applications, e.g., medical imaging, object categorization, and image compression. For IQA, we need to find MGA transforms, which perform excellently for reference image reconstruction, have perfect perception of orientation, are computationally tractable, and are sparse and effective for image representation. Among all requirements for IQA, effective representation of visual information is especially important. MGA contain a series of transform such as curvelet, bandelet, contourlet transforms. It capture the characteristics of image, e.g., lines, curves, cuneiforms and the contour of object are considered for image decomposition ,feature extraction and also analyze and approximate geometric structure while providing near optimal sparse representations. The image sparse representation means we can represent the image by a small number of components, so little visual changes of the image will affect these components significantly. Therefore, sparse representations can be well utilized for IQA. In this paper, we develop a novel framework for IQA by applying MGA transforms to decompose both the images at sender and receiver side and extract effective features. After decomposition and extraction of feature of the original image it sends to receiver side along distortion and ancillary channel. CSF masking is utilized to balance subbands coefficients in different scales obtained by the MGA transform. CSF [3] measures how sensitive we are to the various frequencies of visual stimuli. JND produces a noticeable variation in sensory experience. It measures the minimum amount, by which stimulus intensity must be changed to produce a noticeable variation in the sensory experience . After this histogram is constructed for image representation at both the sender and receiver side , each bin of the histogram corresponds to the amount of visual sensitive coefficients of a selected subband, and finally the normalization step is applied to the histogram. The quality of a distorted image is measured by comparing the normalized histogram of the distorted image and that of the reference image.

VI. APPLICATIONS

i. Low Data Rate:

By using wavelet, bandelet, and curvelet transforms in the proposed framework for RR IQA have low data rates for representing features of the reference image with different distortions. This metric needs a very low amount of data (lower than 8 bytes) to be able to compute the quality scores. The results show a high correlation between the metric scores and the human judgement and a better quality range than well-known metrics like PSNR

ii. General purpose**:**

A number of different transforms, e.g., wavelet, curvelet, bandelet, contourlet, WBCT and HWD, for image decomposition can be applied in the proposed framework for IQA. All these transforms can work well for different image distortions .

iii. Sound effectiveness**:**

The proposed framework has good consistency with subjective perception values and the objective assessment results can well reflect the visual quality of images

VII. CONCLUSION

. In this paper, a reduced-reference image quality assessment framework is proposed by incorporating merits of multiscale geometry analysis (MGA), contrast sensitivity function (CSF), and the Weber's law of *just noticeable difference* (JND). In comparing with existing image quality assessment approaches, the proposed one has strong links with the human visual system (HVS). In this framework we are using various transforms along with MGA for the decomposition of image and feature extraction .CSF is utilized to balance magnitude of coefficients obtained by MGA to mimic nonlinearities of HVS, and JND is utilized to produce a noticeable variation in sensory experience. In this framework, images are represented by normalized histograms, which correspond to visually sensitive coefficients. The quality of a distorted image is measured by comparing the normalized histogram of the distorted image and that of the reference image.

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