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An algorithm for measurement of quality of image

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Abstract

This paper, start by providing an overview of the measurement of quality of image. There are various objective methods which can measure the quality of the image. The paper providing an idea which can measure the error between the actual image and reference image. And can calculate the quality of image.

Keywords—

- Error Sensitivity Function
- Perceptual Quality
- Image Quality
- Structural Similarity
- Measurement of Quality

I. INTRODUCTION

Various images are subject to variety of distortion when they are processed, compressed, stored and transmitted. In these applications we can process the images. The only correct method to quantify the image is through subjective evaluation.
The subjective evaluation is usually time consuming, inconvenient and complex. For a computer based educational system to provide such attention, it must reason about the reference image and actual image. The goal of research in objective image quality assessment is to develop quantitative measures that can automatically predict perceived image quality. An objective image quality metric can play a variety of roles in image processing applications. First, it can be used to dynamically monitor and adjust image quality. For example, a network digital video server can examine the quality of video being transmitted in order to control and allocate streaming resources. Second, it can be used too optimize algorithms and parameter settings of image processing

II. Image Quality Assessment Based on Error

An image signal whose quality is being evaluated can be thought of as a sum of an undistorted reference signal and an error signal. A widely adopted assumption is that the loss of perceptual quality is directly related to the visibility of the error signal. The simplest implementation of this concept is the MSE, which objectively quantifies the strength of the error signal. But two distorted images with the same MSE may have very different types of errors, some of which are much more visible than others. Most perceptual image quality assessment approaches proposed in the literature attempt to weight different aspects of the error signal according to their visibility, as determined by psychophysical measurements in humans or physiological measurements in animals.

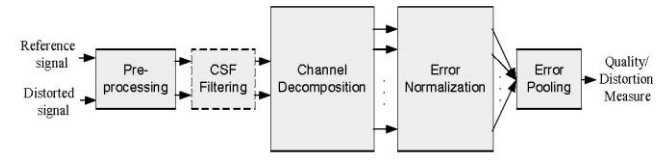

Fig. 1 Interaction of components in measurement of quality of image

A. Pre-Processing

Fig. 1 illustrates a generic image quality assessment framework based on error sensitivity. Most perceptual quality assessment models can be described with a similar diagram, although they dicer in detail. The stages of the diagram are as follows: Pre-processing. This stage typically performs a variety of basic operations to eliminate known distortions from the images being compared. First, the distorted and reference signals are properly scaled and aligned. Second, the signal might be transformed into a colour space (e.g., [14]) that is more appropriate for the HVS. Third, quality assessment metrics may need to convert the digital pixel values stored in the computer memory into luminance values of pixels on the display device through point wise nonlinear transformations. Fourth, a low-pass filter simulating the points spread function of the eye optics may be applied. Finally, the reference and the distorted images may be modified using an nonlinear point operation to simulate light adaptation Pedagogical Model.

B. CSF Filtering

CSF Filtering. The contrast sensitivity function (CSF) describes the sensitivity of the HVS to divergent spatial and temporal frequencies that are present in the visual stimulus. Some image quality metrics include a stage that weights the signal according to this function (typically implemented using a linear filter that approximates the fre- system, a quality metric can assist in the optimal design of pre filtering and bit assignment algorithms at the encoder and of optimal reconstruction, error concealment and post filtering algorithms at the decoder. Third, it can be used to benchmark image processing systems and algorithms. Objective image quality metrics can be classified according to the availability of an original (distortion-free) image, with which the distorted image is to be compared. Most existing approaches are known as full-reference, meaning that a complete reference image is assumed to be known. In many practical applications, however, the reference image is not available, and a no-reference or "blind" quality assessment approach is desirable. In a third type of method, the reference image is only partially available, in the form of a set of extracted features made available as side information to help evaluate the quality of the distorted image. This is referred to as reduced-reference quality assessment. This paper focuses on full-reference image quality assessment.

C. Channel Decomposition

Channel Decomposition. The images are typically separated into sub bands (commonly called "channels" in the psychophysics literature) that are selective for spatial and temporal frequency as well as orientation. While some quality assessment methods implement sophisticated channel decompositions that are believed to be closely related to the neural networks.

D. Error Normalization

The error (difference) between the decomposed reference and distorted signals in each channel calculated and normalized according to a certain masking model, which takes into account the fact that the presence of one image component will decrease the visibility of another image component that is proximate in spatial or temporal location, spatial frequency, or orientation. The normalization mechanism weights the error signal in a channel by a space-varying visibility threshold [26]. The visibility threshold at each point is calculated based on the energy of the reference and/or distorted coefficients in a neighbourhood (which may include coefficients from within a spatial neighbourhood of the same channel as well as other channels) and the base-sensitivity for that channel. The normalization process is intended to convert the error into units of just noticeable difference.

E .Error Pooling

The final stage of all quality metrics must combine the normalized error signals over the spatial extent of the image, and across the different channels, into a single value. For most quality assessment methods, pooling takes the form of a Minkowski norm.

Limitations:

The underlying principle of the error-sensitivity approach is that perceptual quality is best estimated by quantifying the visibility of errors. This is essentially accomplished by simulating the functional properties of early stages of the HVS, as characterized by both psychophysical and physiological experiments. Although this bottom-up approach to the problem has found nearly universal acceptance, it is important to recognize its limitations. In particular, the HVS is a complex and highly non-linear system, but most models of early vision are based on linear or quasi-linear operators that have been characterized using restricted and simplistic stimuli. Thus, error-sensitivity approaches must rely on a number of strong assumptions and generalizations. These have been noted by many previous authors, and we provide only a brief summary here.

These systems provide problems for the learner to solve without trying to connect those problems to a real world situation and are designed to teach abstract knowledge that can be transferred to multiple problem solving situations.

Problems of measurement of quality of image

The Quality Definition Problem. The most fundamental problem with the traditional approach is the definition of image quality. In particular, it is not clear that error visibility should be equated with loss of quality, as some distortions may be clearly visible but not so objectionable. An obvious example would be multiplication of the image intensities by a global scale factor. The study in [29] also suggested that the correlation between image fidelity and image quality is only moderate.

The Suprathreshold Problem. The psychophysical experiments that underlie many error sensitivity models are specifically designed to estimate the threshold at which stimulus is just barely visible. These measured threshold values are then used to define visual error sensitivity measures, such as the CSF and various masking effects. However, very few psychophysical studies indicate whether such near-threshold models can be generalized to characterize perceptual distortions significantly larger than threshold levels, as is the case in a majority of image processing situations. In the suprathreshold range, can the relative visual distortions between different channels be normalized using the visibility thresholds? Recent efforts have been made to incorporate suprathreshold psychophysics for analysing image distortions.

The Natural Image Complexity Problem. Most psychophysical experiments are conducted using relatively simple patterns, such as spots, bars, or sinusoidal gratings. For example, the CSF is typically obtained from threshold experiments using global sinusoidal images. The masking phenomena are usually characterized using a superposition of two (or perhaps a few) different patterns. But all such patterns are much simpler than real world images, which can be thought of as a superposition of a much larger number of simple patterns. Can the models for the interactions between a few simple patterns generalize to evaluate interactions between tens or hundreds of patterns? Is this limited number of simple-stimulus experiments sufficient to build a model that can predict the visual quality of system which has an explanation planning component that uses a substantial domain knowledge base to construct answers to student queries in the domain of electrical circuits.

These classifications are really points along a continuum, and serve as good rules of thumb rather than skill, and hence cognitive in nature. However, the emphasis of this system is also knowledge based and involves generating explanations and using general pedagogical tactics for generating feedback. Generally, tutors that teach procedural skills use a cognitive task analysis of expert behaviour, while tutors that teach concepts and frameworks use a larger knowledge base and place more emphasis on communication to be effective during instruction.

II. NEW PHILOSHIPY

In previous algorithm we have seen that this can calculate the quality of image. But in this case the MSE of all the images is almost same. But this new algorithm will calculate the quality of image and gives the best image quality. This will calculate the quality of image in the case of the distortion. This will calculate the quality of image in the noise. This algorithm the error in the quality of image if picture is not clear.

These Results are in agreement with visual quality of the corresponding images. Although we cannot define some clear criterion for subjective quality assessment, human observer can intuitively feel when distorted image is more or less close to the reference image. Most human observers would agree with the rankings given by the proposed quality measure and in that sense these results are very reasonable.

Steps for New Model:-

1. Given the reference image f(m,n), distorted image p(m,n), width, height and number of pixels of the input images and viewing distance, compute images x(m,n) and y(m,n) using the described model of HVS.
2. Compute the average correlation coefficient as the average value of locally computed correlation coefficients between images x(m,n) and y(m,n).
3. Compute the average correlation coefficient as the average value of locally computed correlation coefficients between images x(m,n) and e(m,n).
4. Compute Image Quality as MSE of frequency domain coefficients obtained after some transform (DFT, DCT etc)
5. Find the Image Quality Measure.

Lena Image with Various Type of Distortion:-

Fig. 2 Lena Image with Impulsive Salt Paper Noise

Fig. 3 Lena Image with Additive White Noise

Fig. 4 Lena Image with Blurring

III. FUTURE WORK

In this section, we are representing the only the measurement of image quality and we are discussing the various algorithms that represent the measurement of quality of image.

In this paper, we have summarized the traditional approach to image quality assessment based on error sensitivity, and have enumerated its limitations. We have proposed the use of structural similarity as an alternative 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. The decorrelation problem when one chooses to use a Minkowski metric for spatially pooling errors, one is implicitly assuming that errors at different locations are statistically independent. This would be true if the processing prior to the pooling eliminated dependencies in the input signals. Empirically, however, this is not the case for linear channel decomposition methods such as the wavelet transform. It has been shown that a strong dependency exists between intra- and inter-channel wavelet coefficients of natural images. In fact, state-of-the-art wavelet image compression techniques achieve their success by exploiting this strong dependency. Psychophysically, various visual masking models have been used to account for the interactions between coefficients. Statistically, it has been shown that a well-designed nonlinear gain control model, in which parameters are optimized to reduce dependencies rather than for fitting data from masking experiments, can greatly reduce the dependencies of the transform coefficients, it is shown that Optimal design of transformation and masking models can reduce both statistical and perceptual dependencies. It remains to be seen how much these models can improve the performance of the current quality assessment algorithms.
The Cognitive Interaction Problem. It is widely known that cognitive understanding and interactive visual processing (e.g., eye movements) influence the perceived quality of images. For example, a human observer will give different quality scores to the same image if s/he is provided with different instructions. Prior information regarding the image content, or attention and fixation, may also affect the evaluation of the image quality. But most image quality metrics do not consider these effects, as they are difficult to quantify and not well understood. Confused, another student may be able to help without relying for assistance.

The simplest and most widely used full-reference quality metric is the mean squared error (MSE), computed by averaging the squared intensity differences of distorted and reference image pixels, along with the related quantity of peak signal-to-noise ratio (PSNR). These are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization. But they are not very well matched to perceived visual quality (e.g., [1]–[9]). In the last three decades, a great deal of effort has gone into the development of quality assessment methods that take advantage of known characteristics of the human visual system (HVS). The majority of the proposed perceptual quality assessment models have followed a strategy of modifying the MSE measure so that errors are penalized in accordance with their visibility. Section II summarizes this type of error-sensitivity approach and discusses its difficulties and limitations. In Section III, we describe a new paradigm for quality assessment, based on the hypothesis that the HVS is highly adapted for extracting structural information. As a specific example, we develop a measure of structural similarity that compares local patterns of pixel intensities that have been normalized for luminance and contrast. In Section IV, we compare the test results of different quality assessment models against a large set of subjective ratings gathered for a database of 344 images compressed with JPEG and JPEG2000.

IV. CONCLUSIONS

An algorithm for image quality assessment has been described. The algorithm uses a simple HVS model, which is used to process input images. CSF used in this model is not fixed; it has one user-defined parameter, which controls attenuation at high frequencies. This way it is possible to get better results than in the case when CSF with fixed parameters is used. This is due to the fact that HVS treats very differently high frequency components present in the original image than those of noise. Two processed images are used to compute average correlation coefficient, which measures the degree of linear relationship between two images. This way we take into account structural similarity between two images, which is ignored by MSE-based measures. Finally, image quality measure is computed as the average correlation coefficient between two input images modified by the average correlation coefficient between original image and error image. This way we differentiate between random and signal dependant distortion, which have different impact on a human observer.

Future research in this area should focus on finding better models for brightness perception, which will include characteristics of display device. Another possible improvement is creating a CSF, which models HVS more accurately.

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