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Advance Approach in Image Quality Assessment

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Abstract- Most of the digital images are subject to a wide variety of distortions during acquisition, processing, compression, storage, transmission and reproduction. Most of which may result in a degradation of visual quality. For applications in which images are ultimately to be viewed by human beings, the only appropriate method of quantifying visual image quality is through subjective evaluation. However, subjective evaluation is inconvenient, time-consuming and expensive. The objective of this paper to present different image quality assessment (IQA) methods to develop quantitative measures that can automatically predict perceived image quality.

Keywords- Image Quality Assessment, Image Quality Measures, Full Reference Image Quality Assessment, No Reference Image Quality Assessment

I. INTRODUCTION

Image quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem.An objective image quality metric can play a variety of roles in image processing applications. It can be used to dynamically monitor and adjust image quality. Eg.a network digital video server can examine the quality of video being transmitted in order to control and allocate streaming resources. It can be used to optimize algorithms and parameter settings of image processing systems. For instance, in a visual communication system, quality metric can assist in optimal design of prefiltering and bit assignment algorithms at the encoder and of optimal reconstruction, error concealment and post- filtering algorithms at the decoder. It can be used to benchmark image processing systems and algorithms. And it can used to decide the given input image for biometric system is real or fake as shown in fig. 1

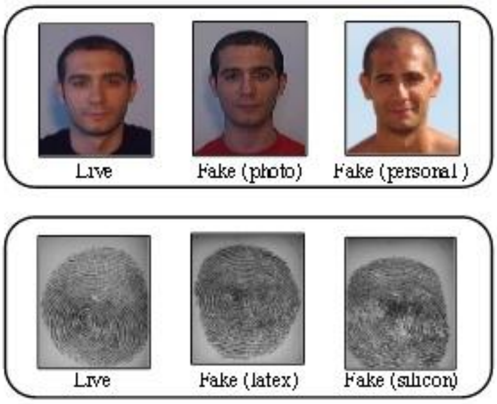

Fig. 1 Image Quality Difference between Real and Fake Image Samples

An image is formed on the image plane of the camera and then measured electronically or chemically to produce the photograph. An image formation process may be described by the ideal pinhole camera model, where only light rays from the depicted scene that pass through the camera aperture can fall on the image plane. In reality, this ideal model is an approximation of image formation process & quality of image may be described in terms of how well camera approximates pinhole model [1].An ideal model of how a camera measures light is that the resulting photograph should represent the amount of light that falls on each point at a certain point in time. This model is an approximate description of the light measurement process of a camera, and image quality is also related to the deviation from this model.

In some cases, the image for which quality should be determined is primarily not the result of a photographic process in camera but the result of storing or transmitting image. An example is a digital image that has been compressed then stored or transmitted & then decompressed it again. Unless a lossless compression method has been used the resulting images is normally not identical to the original image and the deviation from the (ideal) original image is then a measures of quality. By considering a large set of images &determining quality measure for each of them anstatistical methods can be used to determine an overall quality measure of the compression method.In a digital camera, the resulting image quality depends on all three factors mentioned above: how much the image formation process of the camera deviates from the pinhole model, the quality of image measurement process & the coding artifacts that are introduced in the image produced by the camera which is typically by the JPEG coding method.

Image quality has been successfully used in previous works for image manipulation detection and steganalysis in the forensic field. To a certain cases, many spoofing attacks, especially those which involve taking picture of a facial image displayed in a 2D device (e.g., spoofing attacks with printed iris or face images), may be considered as a type of image manipulations which can be effectively detected as shown in the present research works by use of different quality features. In addition to the previous studies in the forensic area,different features measuring trait specific quality properties have already been used for liveness detection purposes in fingerprint and iris applications. However, even though these two works give a solid basis to the use of image quality as a protection method in biometric systems, none of them are general. For instance, measuring the ridge & valley may be a good parameter to detect certain fingerprint spoofs but it cannot be used in iris detection. The amount of occlusion of the eye is valid as an iris anti-spoofing mechanism but it will has little use in fake fingerprint detection system. These same reasoning can be applied now to the vast majority of the liveness detection methods found in the state of the art. Although all of them represent very valuable works which bring insight into the difficult problem of spoofing detection, they fail to generalize to the different problem as they are usually designed to work on one specific modality & in many cases also to detect one specific type of spoofing attack. Human observers very often refer to the “different appearance” of real and fake samples to distinguish between them. The different metrics and methods designed for IQA intend to estimate in an objective and reliable way the perceived appearance of images by humans.

In this paper we present different image quality assessment methods. These methods are widely used while deciding the quality of image. In section II we analyze certain factors which are affects on quality of image while deciding it to be real or fake. In section III we analyze mostly used image quality assessment factors which are based on the factors in section II.

II. FACTORS AFFECTS ON IQA

A. *Distortion-*

It is an aberration that causes straight lines to curve. Distortion tends to be noticeable in low cost cameras, including cell phones (mobiles phones), and low cost DSLR lenses. It is usually very easy to see in wide angle photos. It can be corrected inan software.

B. *Contrast-*

It is also known as gamma, is the slope of the tone reproduction curve in a log-log space. High contrast usually involves loss of detail,loss of dynamic range, or clipping, in highlights or shadows.

C. *Noise-*

It is a random variation of image density which is visible as grain in film and pixel level variations in digital images. Typical noise reduction (NR) software reduces the visibility of noise by smoothing the given image, excluding areas near to the contrast boundaries.

D. *Sharpness-*

It determines the amount of detail an image can convey. System sharpness are affected by the lens design & manufacturing quality,focal length, aperture and distance from the image center and sensor. In the field, sharpness is affected by camera, focus accuracy & the atmospheric disturbances (thermal effects and aerosols).

E. *Dynamic Range-*

It is the range of light levels a camera can capture, usually measured in f-stops, EV (exposure value), or zones (all factors of two in exposure). It is closely related to noise i.e. high noise implies low dynamic range.

F. *Artifacts-*

Software especially operations performed during RAW conversion can cause significant visual artifacts, including data compression & transmission losses (e.g. Low quality JPEG), over sharpening "halos" and loss of fine & low contrast detail.

III. IQA METHODS

There are several techniques that can be measured objectively and automatically evaluated by a computer program. Therefore, they can be classified into full-reference (FR) methods and no-reference (NR) methods. In FR image quality assessment methods, the test image quality is evaluated by comparing it with a reference image that is assumed to have perfect quality. NR image quality assessment methods try to assess the quality of an image without any reference to the original one.

A. *FR (Full-Reference) Image Quality Measures[2]*

Full-reference (FR) IQA methods rely on the availability of a clean undistorted reference image to estimate the quality of the test sample. The input grey-scale image I (of size N × M) is filtered with a low-pass Gaussian kernel in order to generate a smoothed version Ĩ. Then, the quality between both images (I and Ĩ) is computed according to the corresponding full-reference IQA metric. Here we use-

1) *Pixel Difference measures:*
   It finds the difference between pixels of image
   Eg. Mean Squared Error, Peak Signal to Noise Ratio [6], and Signal to Noise Ratio [5]
2) *Correlation-based measures:*
   It finds similarity between two images
   Eg. Normalized Cross-Correlation
3) *Edge-based measures:*
   It find two dimension features such as corners in image. Since the structural distortion of an image is tightlylinked with its edge degradation, here it considers edge-related quality measures
   Eg. Total Edge Difference
4) *Spectral distance measures:*
   It uses Fourier transform to find spectral related feature
   Eg. Spectral Magnitude Error
5) *Structural Similarity Measures:*
   It is based on hypothesis that the human visual system is highly adapted for extracting structural information from the viewing field. Therefore, distortions in an image that come from variations in lighting such as contrast or brightness changes (nonstructural distortions), should be treated differently from structural ones.
   Eg. Structural Similarity Index Measure
6) *Gradient based measures:*
   Gradients convey important visual information which can be of great use for quality assessment. Many of the distortions that can affect an image are reflected by a change in its gradient. Therefore, using such information, structural and contrast changes can be effectively captured
   Eg. Gradient Magnitude Error, Gradient Phase Error
7) *Information Theoretic Measures:*
   The core idea behind these approaches is that an image source communicates to a receiver through a channel that limits the amount of information that could flow through it, thereby introducing distortions. 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. Under this general framework, image quality measures based on information fidelity exploit the (in some cases imprecise) relationship between statistical image information and visual quality
   Eg. Visual Information Fidelity, Reduced Reference Entropic Difference index

B. NR (No-Reference) Image Quality Measures[2]

Automatic no-reference image quality assessment (NR-IQA) algorithms try to handle the very complex and challenging problem of assessing the visual quality [3] of images, in the absence of a reference. Here we use-

1) *Distortion-specific approaches:*
   It relay on visual quality loss by specific distortionThese techniques rely on previously acquired knowledge about the type of visual quality loss caused by a specific distortion. The final 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 proposed in the present work.The JPEG Quality Index (JQI), which evaluates the quality in images affected by the usual block artifacts found in many compression algorithms running at low bit rates such as the JPEG.
   Eg. JPEG Quality Index
2) *Training-based approaches:*
   Here model is trained using clean and distorted images the quality score is computed based on a number of features extracted from the test image and related to the general model
   Eg. Blind Image Quality Index
3) *Natural Scene Statistic approaches:*
   These blind IQA techniques use apriori knowledge taken from natural scene distortion-free images to train the initial model (i.e., no distorted images are used). The rationale behind thistrend relies on the hypothesis that undistorted images of the natural world present certainregular properties which fall within a certain subspace of all possible images. If quantified appropriately, deviations from the regularity of natural statistics can help to evaluate the perceptual quality of an image
   Eg. Natural Image Quality Evaluator

IV. CONCLUSIONS

Image quality assessment is the very important approach for finding the quality of an image. It has vast application in various area likedynamically monitor and adjust image quality, visual communication system, network digital video server can examine the quality of video being transmitted, to benchmark image processing systems, biometric system to detect fake or real input image etc. Introduction to new image quality measure will surely increase the accuracy of image quality assessment approach. The challenge to such assessment is to deal with the different quality factor for an image on the basis of which we can assessing quality of image. The more we concentrate on quality factors, the more result accuracy is there. The futuristic approach in image quality assessment is to find image quality with less and optimized algorithmic way which will give result as fast as blinking eye lids.

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