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Non-distortion-specific no-reference image quality assessment: A survey

Redzuan Abdul Manap [a,b,d], Ling Shao [a,c,*]

[a] College of Electronic and Information Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, China
[b] Department of Electronic and Electrical Engineering, the University of Sheffield, Sheffield S1 3JD, UK
[c] Department of Computer Science and Digital Technologies, Northumbria University, Newcastle upon Tyne NE1 8ST, UK
[d] Department of Electronic and Computer Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, Durian Tunggal, Melaka 76100, Malaysia

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ABSTRACT

Over the last two decades, there has been a surge of interest in the research of image quality assessment due to its wide applicability to many domains. In general, the aim of image quality assessment algorithms is to evaluate the perceptual quality of an image using an objective index which should be highly consistent with the human subjective index. The objective image quality assessment algorithms can be classified into three main classes: full-reference, reduced-reference, and no-reference. While full-reference and reduced-reference algorithms require full information or partial information of the reference image respectively, no reference information is required for no-reference algorithms. Consequently, a no-reference (or blind) image quality assessment algorithm is highly preferred in cases where the availability of any reference information is implausible. In this paper, a survey of the recent no-reference image quality algorithms, specifically for non-distortion-specific cases, is provided in the first half of this paper. Two major approaches in designing the non-distortion-specific no-reference algorithms, namely natural scene statistics-based and learning-based, are studied. In the second half of this paper, their performance and limitations are discussed before current research trends addressing the limitations are presented. Finally, possible future research directions are proposed towards the end of this paper.

1. Introduction

Due to tremendous growth and near-ubiquitous presence of digital images, it is becoming essential to have efficient and reliable methods to assess the quality of these images. Today, image quality assessment (IQA) has become a crucial aspect in various computer vision and image processing applications such as image acquisition, transmission, restoration and enhancement [66,67], image search and retrieval [25,26,46,78,79,86], image recognition [77,115,116] as well as image tagging [87]. For examples, parameters of image transmission systems may have been fine-tuned to reflect the quality of the transmitted image, image quality can be utilized to rank images in image retrieval systems and image quality measures can be used in image processing algorithms for evaluation purposes [109]. In measuring the quality of an image, a human

* Corresponding author at: College of Electronic and Information Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, China, and Department of Computer Science and Digital Technologies, Northumbria University, Newcastle upon Tyne NE1 8ST, UK. Tel.: +44 (0)191 349 5220.

E-mail address: ling.shao@ieee.org (L. Shao).

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can easily give the subjective score to the observed image. However, embedding such a mechanism into computer vision or image processing systems is a difficult task. Therefore, an IQA method that can automatically provide an objective measurement which is consistent with human subjective results is highly desired.

Depending on the volume of information available about the reference image, objective IQA algorithms can be classified into three categories: full-reference (FR) IQA, reduced-reference (RR) IQA and no-reference (NR) IQA [54], which is also known as blind IQA. In FR-IQA algorithms, full information of the reference image is needed to predict the quality of degraded or distorted images. The simplest approach in implementing an FR-IQA algorithm is by measuring local pixel-wise disparity between reference and distorted images, then collapsing these measurements into a scalar representing the total or global quality metric of the distorted image. Mean squared error (MSE) and peak signal-to-noise ratio (PSNR) are the most extensively used quality metrics in this case. However, it is generally known that they do not correlate well with subjective quality measures [21,89]. Consequently, a large variation of more advanced FR-IQA algorithms have been proposed ranging from quality estimation based on the human visual system (HVS) to quality estimation based on image structure and image statistics.

Primary visual cortex (V1) computational neural models have been employed by most HVS-based FR-IQA algorithms. Three key stages exist in these models [6]: (1) frequency-based decomposition to model initial linear responses of visual neurons, (2) gain control adjustment taking into account non-linearity of the decomposition coefficients and (3) summation of responses to estimate the quality. Visual signal-to-noise ratio (VSNR) [7] and most apparent distortion (MAD) [38] algorithms are well known examples of HVS-based methods.

Meanwhile, an assumption that a good quality image has structure which is similar to the original image is exploited in image structure-based FR-IQA. By measuring changes in a local image's structure, such as luminance, contrast, phase or gradient, the quality of the image can be estimated. Examples of established image structure-based FR-IQA quality metrics include universal image quality index (UQI) [88], structural similarity index (SSIM) [91], multi-scale SSIM (MS-SSIM) [95], complex wavelet SSIM (CW-SSIM) [62], feature similarity index (FSIM) [112], edge strength SSIM (ESSIM) [113], hybrid phase congruency IQA (IQA-HPC) [11], visual gradient similarity (VGS) [117] and matching pursuit based metric (MP_Q) [28].

The third approach, image statistics-based, is based on statistical measures and often supplemented by machine learning techniques. Information fidelity criterion (IFC) [71], visual information fidelity (VIF) [65,69], singular value decomposition (SVD) [73] and machine learning image quality measure (MLIQM) [9] are the examples of current FR-IQA algorithms for this approach.

In contrast to FR-IQA algorithms, only parts of the reference image information are necessary for RR-IQA algorithms. A minimal set of reference image parameters are extracted and then used with the distorted image to predict image quality. Generally, the RR-IQA algorithms can be categorized into three groups. The first RR-IQA group is based on the image source models. These models often capture low-level statistical properties of natural images in transform domains such as discrete wavelet transform (DWT) [42,58,94,96] or discrete cosine transform (DCT) [47]. The second RR-IQA algorithms class is aligned to capture image distortions. Sufficient information of the distortion process undergone by the images such as standard image or video compression is required by the algorithms in [12,24,36,97] to estimate the images' quality. The final category of RR-IQA algorithms is based on the image receiver models where the physiological and/or psychophysical vision studies models are utilized [4,5].

Higher correlation with subjective assessment of image quality is achieved by the above-mentioned algorithms when full or partial information of the reference image is available. However, in many situations, the availability of any reference information may be implausible. For example, in quality of service (QoS) monitoring of the image content transmitted over different types of network, the original signals are often not available at the middle or the end parts in the network. In photo and film restoration application, it is possible that a degraded print is the only available record of a photo or a film. In such cases, an NR-IQA algorithm is highly desired.

The objective of the NR-IQA algorithms is to estimate the quality of distorted images with respect to subjective perceptual measures without having to use any reference images. In general, these algorithms can be further classified into two categories: distortion-specific (DS) and non-distortion-specific (NDS), depending on the prior knowledge of the distortion type. Distortion that affects the image is assumed to be known in the DS NR-IQA, where it is quantified in isolation of other factors. For example, the quality of JPEG2000 compressed images is estimated by algorithms in [43,63,70,110,111] while JPEG compressed images' quality estimation is proposed in [2,3,16,22,61,93]. In addition, the quality of an image distorted by blocking artifacts is predicted in [56,83,90,98,102] whereas the effect of blur and noise is studied in [10,14,15,17,34,54,103]. Unfortunately, application domains of the algorithms might be limited by this assumption. Multiple types of distortion may present in the distorted image, thus universal or generic NR-IQA algorithms which are responsive to multiple distortions are preferred in real-world applications.

In contrast to DS NR-IQA, the prior knowledge of distortion type is not considered by NDS NR-IQA algorithms. Instead, the quality score is given through assumption that the image to be assessed has similar distortion type to those in the training database. Most of the NDS NR-IQA algorithms are designed to follow one of these two approaches: (1) natural scene statistics (NSS) based approach and (2) learning or training based approach. Towards this end, the general classification of IQA algorithms can be illustrated as in Fig. 1.

This paper is meant to provide a survey of the recent advances in IQA, specifically for NDS NR-IQA algorithms. The organization of this paper is as follows. Several established NDS NR-IQA algorithms based on NSS techniques are first described in Section 2. Previous approaches based on learning techniques in designing NDS NR-IQA algorithms are then studied in