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No-reference image quality assessment using statistical wavelet-packet features[☆,☆☆]

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ABSTRACT

In this paper an efficient no-reference (NR) image quality assessment (IQA) method is presented based on the statistical features of subband coefficients in the wavelet-packet domain. The proposed method is based on the hypothesis that potential distortions may alter the statistical characteristics of natural un-distorted images. Hence, by characterizing the statistical properties of a given distorted image one can identify the distortion and its strength in the distorted image. For this purpose, several statistical features of a given gray-scale image as well as the magnitude of its gradient and its Laplacian are extracted in the wavelet-packet domain. The extracted features are then mapped to quality scores within a two-stage quality assessment framework. The proposed method is general-purpose, and is able to assess the image quality across various distortion categories. Experimental results indicate that the proposed method achieves high accuracy in image quality prediction as compared to several prominent and state-of-the-art full-reference and no-reference IQA methods.

1. Introduction

With the rapid proliferation of digital images in our daily life, image quality assessment (IQA) has become very important in a wide variety of different practical applications such as digital imaging, image compression, transmission, enhancement, and restoration. Degradation of digital images is often inevitable due to image acquisition, transmission, and compression. Because of these processes, various image distortions such as blur, noise, blocking artifacts, ringing, oversaturation, etc. may be produced in the obtained images.

To goal of IQA is to measure how much the perceived quality of a given digital image has been degraded by potential distortions. This is accomplished by assigning a quality score to the image for representing its perceived quality. The quality score can be estimated either subjectively by human ratings or objectively through automatic computer algorithms. Since subjective IQA methods rely on human observers, they are not always readily available, especially in real-time scenarios. They are also slow and costly. On the other hand, objective IQA methods are readily and routinely available in different applications. They are automatic and fast, and do not have the limitations of the subjective methods. Therefore, they can easily be utilized to quantitatively measure the image quality in a wide variety of applications.

In the past decades, various objective IQA methods have been developed in the literature [1,3,13,14,20,21,23]. Based on the availability of a reference image (i.e. an original distortion-free image), the objective IQA methods are classified into three classes: full reference (FR) [13,20,23], reduced reference (RR) [22], and no reference (NR) [8,10]. In FR methods, the original un-distorted image is provided along with the distorted image whose quality is to be assessed. In RR approaches, some additional information about the original un-distorted image is provided along with the distorted image, either by a separate auxiliary channel or by embedding some information (e.g. a watermark) in the distorted image. In NR (blind) methods, only the distorted image is provided, and the method must predict the image quality only based on the given distorted image without having any knowledge or information about the original un-distorted image. Hence, designing NR methods is very challenging as compared to FR and RR methods.

It is widely known that natural distortion-free images possess specific statistical properties, and distortions may change these properties. Based on this idea, natural scene statistic (NSS) models [17] have been developed to capture such statistical properties, and

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using such models a number of NSS-based FR and NR IQA methods have been developed [9,10].

In this paper, we propose a NSS-based NR IQA method for gray-scale images, which is capable of assessing the quality of a distorted image across multiple distortion categories in a modular manner. In the proposed method, a wavelet packet decomposition (WPD) [2] is first applied on a given image. A number of statistical features are then computed from all the obtained subbands of the given image and the magnitude of its gradient and its Laplacian. A two-stage framework for NR image quality assessment proposed in [9,10] is then employed to compute a quality score for the given image using the extracted features. Experimental results on two popular IQA databases indicate that the image quality scores produced by the proposed method correlate well with human perception and that the proposed method is competitive with several FR IQA methods as well various state-of-the-art NR IQA methods.

It must be pointed out that there are some existing NSS-based NR IQA methods like DIVINE [10] that use statistical features of wavelet subbands. However, to the best of our knowledge, our proposed method is the first that uses wavelet packet features for NR IQA. Note that wavelet packets are an overcomplete generalization of standard orthonormal wavelets in which, unlike the standard wavelets, both the low- and high-frequency components of each level of decomposition are recursively decomposed, thus constructing a tree structured multiband extension of the standard wavelet transform. Hence, WPD allows us to capture the statistical characteristics of a given image more accurately. Moreover, it is known that standard wavelets are ill-suited to represent oscillatory patterns (i.e. signals with strong stationary highpass components) such as rapid variations of intensity in complex textures while wavelet packets have a better ability to represent such patterns [2,7], thus increasing the applicability of the proposed method to a wider range of natural images.

Another difference of the proposed method with the previous wavelet-based methods is that in the proposed method the statistics are gathered not only from the subband coefficients of the distorted image, but also from the subband coefficients of the magnitude of its gradient and its Laplacian. Note that the gradient and the Laplacian of an image carry important information about the structure of the image, and they are sensitive to noise and other distortions, and that is the reason for using them in the proposed method.

The organization of this paper is as follows. In Section 2, prominent previous works on FR and NR IQA are briefly reviewed. The proposed method is then presented in Section 3. The experimental results are given in Section 4, followed by conclusions in Section 5.

2. Related works

In the literature several FR and NR IQA methods have been proposed. The most popular and widely-used objective FR IQA metrics include the peak signal-to-noise ratio (PSNR) and the mean squared error (MSE). These methods operate directly on the intensity values of the image, but they do not correlate well with the subjective fidelity ratings. The reason is that these methods do not consider any properties of the human visual system (HVS). On the other hand, there are methods that are designed based on the HVS properties or attempt to mimic it. These include the very popular structural similarity (SSIM) index [20], the information fidelity criterion (IFC) [14], and the visual information fidelity (VIF) metric [13].

SSIM works based on the hypothesis that HVS is highly sensitive to the loss of structure in the image. Hence, to measure the perceived image quality, SSIM measures the structural similarity between a distorted image and its related reference image. In IFC the information shared between the distorted and reference images is measured and used for IQA in an information-theoretic framework. VIF is an extension of IFC in which HVS is modeled as a simple channel that introduces additive noise in the wavelet domain. Using this model, VIF quantifies the Shannon information that is shared between the reference and the distorted images relative to the information contained in the reference image itself.

The prominent NR IQA methods include BIQI [9], DIVINE [10], BLINDS-II [12], BRISQUE [8], and SSEQ [5]. BIQI is a two-step framework for NR IQA, which involves distortion classification and distortion-specific quality assessment, and it uses several NSS features. The DIVINE index is an extension of BIQI in which a series of NSS features in the wavelet domain are used to predict image quality, and it achieves excellent performance. BLIINDS-II extracts NSS features in the block-based DCT domain using a fast single-stage quality assessment framework. The BRISQUE index provides a low-complexity NR IQA method in which several features are extracted in the spatial domain, and it shows very good performance for image quality prediction. SSEQ utilizes spatial and spectral entropy features from a distorted image in the block-based DCT domain to predict the image quality in a two-stage framework. Experimental results showed that SSEQ achieves high accuracy as compared to several state-of-the-art NR IQA methods.

The above mentioned NR-IQA methods are able to assess the image quality across various distortion categories, similar to the method proposed here. However, there are some NR IQA methods that are distortion-specific and target a certain distortion category such as compression or blur. The examples are the methods proposed in [4,6,18].

3. Proposed method

In this section, we propose a method to estimate the subjective quality of a given gray-scale distorted image in a no-reference manner. The proposed method consists of three steps. In the first step, the magnitude of the gradient and the Laplacian of the given distorted image are first computed. These two additional images serve as the first and second derivative of the given distorted image, respectively. The gradient and Laplacian of an image carry important information about the edges and the structure of the image, and as they are derivative operators, they are very sensitive to noise and other similar distortions. Hence, characterizing their statistical properties may help identify distortions better. In the second step, a wavelet-packet decomposition pyramid is applied to the distorted image, as well as its first and second derivative images, and a number of statistical features are extracted from all the subband coefficients of each of the three images. In the third step, the extracted features are fed to a distortion classifier as well as a number of regression modules to estimate a quality score for the given distorted image. The details of each step are elaborated in the next sections. A flowchart of the proposed method is shown in Fig. 1.

3.1. Wavelet-packet decomposition

Consider a distorted gray-scale image $\mathbf{I}$. Our goal is to quantify the subjective quality of $\mathbf{I}$ without having a reference image. For this purpose, the magnitude of the gradient and also the Laplacian of $\mathbf{I}$ are first computed as $\mathbf{G}$ and $\mathbf{L}$, respectively. For computing the gradient information, we used the Scharr gradient operator whose horizontal and vertical components, $\mathbf{G}_x$ and $\mathbf{G}_y$, are defined as:

$$\mathbf{G}_x = \frac{1}{16}\begin{bmatrix} 3 & 0 & -3 \\ 10 & 0 & -10 \\ 3 & 0 & -3 \end{bmatrix}, \quad \mathbf{G}_y = \frac{1}{16}\begin{bmatrix} 3 & 10 & 3 \\ 0 & 0 & 0 \\ -3 & -10 & -3 \end{bmatrix}. \tag{1}$$

Other possible gradient operators such as Sobel and Prewitt can also be used here but in our experiments we found that the Scharr