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Gradient-based no-reference image blur assessment using extreme learning machine

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ABSTRACT

The increasing number of demanding consumer digital multimedia applications has boosted interest in no-reference (NR) image quality assessment (IQA). In this paper, we propose a perceptual NR blur evaluation method using a new machine learning technique, i.e., extreme learning machine (ELM). The proposed metric, Blind Image Blur quality Evaluator (BIBE), exploits scene statistics of gradient magnitudes to model the properties of blurred images, and then the underlying blur features are derived by fitting gradient magnitudes distribution. The resultant feature is finally mapped into an associated quality score using ELM. As subjective evaluation scores by human beings are integrated into training, machine learning techniques can predict image quality more accurately than those traditional methods. Compared with other learning techniques such as support vector machine (SVM), ELM has better learning performance and faster learning speed. Experimental results on public databases show that the proposed BIBE correlates well with human perceived blurriness, and outperforms the state-of-the-art specific NR blur evaluation metrics as well as generic NR IQA methods. Moreover, the application of automatic focusing system for digital cameras further confirms the capability of BIBE.

1. Introduction

With the rapid development of digital techniques, multimedia content has become a very popular means of entertainment and communication, such as high definition television (HDTV), streaming Internet protocol TV (IPTV), and websites like Youtube, Facebook and Flickr. An enormous amount of visual data is making its way to consumers. This phenomenon has resulted in great advances in multimedia acquisition, compression, transmission, enhancement, and reproduction, etc. However, impairments generally exist along visual signal processing and communication. The visibility of these impairments has a drastic effect on the Quality of Experience of the consumers. Hence, image quality assessment (IQA) techniques are in great demand for measuring the perceived quality of the multimedia content [1].

Since human visual system (HVS) is the ultimate receiver of sensory information in many cases, subjective quality assessment is the most reliable way to measure image quality. Nevertheless, subjective quality evaluation suffers from high cost, heavy complexity, and infeasibility to be used in real-time applications. Thus, it is necessary to develop objective quality metrics.

According to the availability of reference information, there is a general agreement that objective quality assessment metrics can be categorized into full-reference (FR), reduced-reference (RR), and no-reference (NR) methods [2]. To evaluate the quality of distorted images, FR metrics utilize the information of original reference image, RR ones use some features extracted from the original images, while NR methods do not require any reference information, and are the most useful techniques in applications where the original image is not available. However, on the other hand, NR metrics designing is quite challenging since the corresponding reference information cannot be exploited for the gauging of distorted image quality.

Unlike FR IQA, where a reference image is available to be used for the evaluation of most distortion types, NR IQA approaches generally aim to capture one or few distortions, e.g., blur, white noise, blockiness, since different distortions have distinct properties and it is difficult to use the same features to model all distortion types. In this paper, we mainly concentrate on NR blur assessment, which is one of the most important issues needed to be tackled in many applications, such as image acquisition and compression [3].

Recently, a number of NR blur evaluation models have been proposed in the literature, including pixel-based ones, statistical properties based ones, transform-based and gradient-based ones. In

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[4,5], local kurtosis is used in the frequency domain for measuring sharpness, since the kurtosis is inversely proportional to the sharpness of edge. Ong et al. [6] and Marziliano et al. [7] measured blurriness by analyzing the spread of edges. DCT coefficients and Wavelet coefficients are employed for blur estimation in [8–11].

In [12], Ferzli et al. analyzed that the aforementioned existing blur metrics cannot well predict the blurriness in images with different contents, and they proposed a blur assessment method by integrating the concept of just noticeable blur into a probability summation model. The metric proposed in [12] is able to predict the amount of blurriness in images with different contents, but it does not correlate well with images having nonuniform saliency content. Sadaka et al. [13] tried to improve the performance of [12] by incorporating a visual attention model, such that the areas in the images which are most likely noticed by humans are given more weight than others. Hassen et al. [14] proposed a multiscale sharpness metric based on the local phase coherence (LPC) of complex wavelet coefficients. In [15], Karam et al. developed a probabilistic model to assess image blur by adopting the cumulative probability of blur detection. Liang et al. [16] and Yan et al. [17] developed their blur algorithms based on the histogram of gradient profile variance and gradient profile sharpness, respectively.

However, most of the metrics mentioned above have limitations in both feature extraction and feature mapping. Therefore, it is emergent to develop more accurate feature extractors and reasonable mapping algorithms.

In this paper, we propose an NR metric (BIBE) for blurriness assessment using image gradient and extreme learning machine (ELM). The contributions are in threefold:

(1) A generalized Gaussian distribution is exploited to model the properties of gradient magnitudes of blurred and original images, and the estimated parameters of the gradient distribution are employed as features. As shown in Fig. 1, the gradient distributions of blur and distortion-free images are different in shape, and one can easily observe that the distinction of them is obvious. And therefore, the proposed feature is expected to accurately represent the characteristics of blurriness.

(2) Unlike those SVM-based metrics (e.g., the work in [3]), an emerging learning technique, i.e., ELM [18–22], is utilized for feature mapping. Compared with SVM, ELM tends to have better generalization performance and faster learning speed with smaller norm weights and fewer neuron nodes, and these properties have been theoretically proven in [18,19]. Moreover, compared with other traditional feature mapping methods (e.g., linear combination in [6,16,17]), by using ELM for feature mapping, subjective evaluation scores of human beings are integrated into the trained model, and thus the obtained metric is more consistent with human perception.

(3) To further demonstrate the capability and applicability of proposed metric, a BIBE-based automatic focusing framework is established for digital cameras, by detecting the blurriness of captured images. Defocusing of cameras always results in image blurriness, and BIBE can be utilized for the assessment of blur artifacts in the images, and thus focal distance can be accordingly adjusted based on the BIBE results.

The rest of this paper is organized as follows: Section 2 presents the discussion of related works. In Section 3, we provide detailed introduction on the proposed BIBE, including feature extraction and feature mapping. In Section 4, substantial experimental results and related analysis are demonstrated. Section 5 introduces an application of the proposed BIBE, while Section 6 gives the conclusion.

2. Related works

In the proposed work, we develop an NR blur IQA metric (BIBE) in two different aspects: (1) employing a generalized Gaussian model to fit image gradient magnitudes and using the resultant model parameters as image features, and (2) using ELM for feature mapping and metric establishment. In this section, the relevant existing works are reviewed in both feature extraction and mapping to clarify the novelties of the proposed BIBE.

Ong et al. [6] proposed a blurred image quality metric by measuring the average extent of the slope's spread of an edge in the opposing gradients' directions. This method involves the following four steps: (1) gradients' direction detection; (2) edge detection; (3) edge-spread measuring; and (4) image quality prediction by a linear formula. It is a good attempt to exploit gradient for no-reference blurriness assessment, however, it also suffers from some drawbacks, such as inaccuracy of edge detection, high requirement of accurate measurement of edge width, and the ad-hoc feature mapping means (linear function).

In [16], Liang et al. considered that sharpest edges can reflect blur artifacts in JPEG2000 coded images, and moreover, the gradient profiles are capable of measuring the degree of blurriness. They proposed a method to calculate the gradient profile sharpness of image edge along horizontal and/or vertical directions, and the resulting sharpness is fused with a simple linear summation. In [17], Yan et al. followed the idea of Liang et al. [16] and used the sharpest edges for blur assessment. They built a triangle model to represent edge gradient profiles, and extracted features from the distribution histogram of gradient profile sharpness. Both approaches in [16,17] are based upon the assumption that sharpest edges are able to accurately reflect blurriness, and use linear prediction functions for feature mapping but without theoretical proofs [23].

Chen et al. [3] proposed a blur metric (named QS-SVM) by measuring the distance between the gradient statistics of a distorted image and its corresponding natural scene. The QS-SVM classifies the training images into two groups (i.e., sharp images and blurred images, respectively), using a probabilistic SVM classification model. However, it uses the entire gradient histogram as a feature, which results in a fairly high-dimension feature vector. Furthermore, the classification of "sharp" and "blurred" images seems some rough lacking of theoretical analysis by applying probabilistic SVM [17].

In [24], Suresh et al. utilized edge amplitude, edge length, background activity and background luminance as image features and used a *k*-fold selection ELM (KS-ELM) for the NR IQA modelling. The KS-ELM is actually n random k-fold training with original ELM, which results in roughly n times computational complexity but similar training accuracy of ELM.

In this work, we propose an NR metric (BIBE) for blur assessment using image gradient and ELM. The detailed technical descriptions will be presented in the following sections.

3. Proposed algorithm

In this section, we are to present a detailed description of the proposed approach BIBE. The algorithm diagram is shown in Fig. 2. We can see that the gradient magnitudes of input image are first computed by a Prewitt filter (3×3 in size), and the resultant gradient magnitudes distribution can be modeled by a generalized Gaussian function. The fitted function parameters (such as shape and scale parameters) are then used to form a 16-dimension feature vector to represent the properties of image content. The feature vector is finally mapped into a quality score using the ELM.

3.1. Gradient magnitude computation

As illustrated in Fig. 2, gradients are first computed for input images. For digital images, image gradient at each pixel is a 2D vector with the components given by the derivatives in horizontal and vertical directions. The magnitude is defined as the root mean