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Histogram modelling-based no reference blur quality measure

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ABSTRACT

Blurring is a common artefact detrimental to the image quality. It affects especially edges and texture features that represent high frequency components of an image. The purpose of this paper is to propose a simple, fast, and faithful measure able to blindly assess blur amount in images. The main idea turns on analysing the frequency response at the multiresolution transitions. To achieve that, the histogram of the *discrete cosine transform* coefficients of the edge map is modelled by using an exponential probability density function (pdf). Tests revealed that the steepness of the pdf depends on the blur amount, hence, it is used as a cue to characterize the blur effect. Comprehensive testing demonstrates good consistency of the proposed measure with subjective quality scores as well as satisfactory performance when compared with representative state-of-the-art blind blur quality measures.

1. Introduction

Over the past decade, we have witnessed a proliferation of artificial visual systems including acquisition, processing, and display. The quality of the image has become a criterion for choosing one technology among others. This strengthened the developments of methodologies and algorithms for image quality assessment (IQA).

There exist mainly two categories of IQA techniques subjective and objective. The subjective evaluation is implicit. Indeed, human observers are asked to deliver a quality score according to a specific scale in some specific conditions [1]. The obtained scores are analysed and used to define a quality score. Subjective scores have the advantage of being reliable since the human visual system (HVS) still is the most accurate mechanism used for quality evaluation. However, the approach is infeasible in real-time applications because of the human in the loop. To overcome such limit, objective measures are highly required. In this case, an algorithm is used to substitute psychovisual experiments.

In order to define an objective quality measure, prior knowledge about the original image (a reference) may be required. In this case, we talk about full reference (FR) or reduced reference (RR) measures depending on, the total or the partial use of the reference image. When the reference image is not available, we talk about no reference (NR) measures, called also *blind* [2]. In this case, to assess the quality, only the distorted image content is used. The NR IQA measures are highly desirable when a reference image is not available or expensive to obtain. Owing to its intrinsic difficulty, the issue of NR quality measures is challenging indeed and remains largely unexplored. Note that most existing NR quality measures are dedicated to a specific distortion [2]. Fortunately, the distortion process is often known in real applications and the task of developing distortion-specific NR quality measures is of practical importance.

In this work, we develop a NR objective IQA measure dedicated especially to blurring artefact. Blur commonly occurs in compression or filtering process where high frequency components are attenuated [3,4]. Although intensive research has been carried out in the field of IQA [4,5], the issue of NR measures still is challenging and many questions still are open [6,7]. The proposed quality measure fulfils the following three requirements:

- Achieving the trade-off simplicity/accuracy: The proposed quality metric has to be easy to reproduce while delivering satisfying scores.
- Normalization: The proposed measure has to be normalized to make it easy the interpretation of the obtained scores.
- Generalization: The proposed measure has to generalize well on different existing blur image collections

Among the variety of existing works, some measures are simple to reproduce while delivering low correlation scores [8]–[9]. To improve the scores, two strategies are introduced, classification-based and HVS

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properties-based measures. The first category requires a learning step and more importantly, it does not generalize well to the non learned cases [10]–[11]. Moreover, the statistics of natural scenes form the feature space used by some of them for learning [11]–[12]. Nevertheless, these characteristics are useful only on a subset of images, natural images, and useless for manmade and indoor scenes. The other category of methods propose to mimic the HVS by modelling some of its features [13]–[14]. However, modelling some of HSV features can be computationally heavy and difficult to reproduce such as the Visual Difference Predictor [15]. Furthermore, the HSV still is not totally understood.

To assess the blur effect, high frequency components are generally analysed either in the spatial [16,17] or a transform domain [18–20]. We are planning to use the frequency domain. Low frequencies means that pixel values are changing slowly over space, while high frequencies means that pixel values are abruptly changing in space. Thus, high frequency coefficients contain information about edges and texture. In a blurred image, the number and the persistence of edge pixels, or their contrast through resolutions, depends on the blur intensity. This postulate is at the basis of the quality measure we propose. The intent is to model the histogram of the multiresolution DCT coefficients using an adequate probability density function (pdf). The proposed blur measure is related on the pdf steepness. The generalization of proposed blur quality measure on six blur image collections reveals its advantage of being objective, blind, simple, fast, and faithful. Moreover, it does not consider any assumption about the origin of blur (acquisition, processing, or transmission).

The next section details the proposed approach. Experimental results and analysis are described in Section 3. The last section concludes this work pointing out some issues.

2. Proposed blur quality measure (BQM)

The proposed BQM is based on the assumption that blur visual impairment alter mainly high frequencies of an image such as edges and texture. Therefore, to assess the blur amount, we propose to model the histogram of high frequency coefficients using a suitable pdf. The statistical parameter of the pdf is used as a cue to characterize blur effect.

Before providing details about the proposed approach, we will verify first the considered assumption. To achieve that, two blurred images are simulated using a *Gaussian* filter of length 11×11 and a standard deviation value of 3 ($SD = 3$). Obtained images are depicted in Fig. 1. Accordingly, the first image appears to be more blurred compared to the second even if both are blurred using the same filter. Actually, it depends on the image content. The first image contains more edges and texture compared to the second hence the clear appearance of the blur. However, the blur appear to be weak in the second image because few details are present. Thus, the image content seems to be relevant for the perceptual quality evaluation of blurred images. These observations led us to analyse blur effect specially on edges where the human visual system is sensitive to the blur effect. To achieve that, edge analysis is the main step [21]. For a deeper study, edge persistence through resolutions will be tackled.

We will now focus on detailing the proposed quality measure (BQM) used for blur assessment. It is composed of two main steps. First, the multiresolution edge map is constructed and second the high frequency components are analysed to deliver a quality score.

2.1. Edge map construction

The edge map is constructed using the luma component of a test image. Edges are enhanced through the decomposition in the wavelet basis at J resolution levels. For the purpose of edge enhancement, it is useful to interpret the wavelet transform as a multiscale differential operator. Thus, edge enhancement relies on the difference of behaviour along the wavelet scales of the noise in front of the edges. Over resolutions, the noise is progressively smoothed, and it is almost spatially uncorrelated between scales. At each resolution of the two dimensional wavelet transform, three bandpass components are obtained, where each one enhances the discontinuities in a different direction, horizontal $Dh^{(j)}$, vertical $Dv^{(j)}$, and diagonal $Dd^{(j)}$. To construct the edge map $Edge^{(j)}$, at each edge pixel (k, l), only the horizontal and vertical details are considered. Diagonal details are neglected since they mostly represent the redundant features. $Edge^{(j)}$ is constructed as follows.

(a) Blurred image1.

(b) Blurred image2.

Fig. 1. Blur effect on textured and non textured images.

$$Edge^{(j)}(k,l) = \begin{cases} E^{(j)}(k,l) & if \quad E^{(j)}(k,l) > Th^{(j)} \\ 0 & otherwise \end{cases} \tag{1}$$

with

$$E^{(j)}(k,l) = \sqrt{Dh^{2(j)}(k,l) + Dv^{2(j)}(k,l)},\ j \in [1,\ J]. \tag{2}$$

Herein, $E^{(j)}(k,l)$ stands for the detected edge pixel magnitude at the jth resolution level. While evaluating the blur amount at different resolution levels using the *wavelet* transform, it is observed that for a fixed threshold, the edge magnitude decreases with resolutions. This is due to smoothing introduced by the *wavelet* transform filters. Consequently, the thresholding must be adaptive to the resolution level. Indeed, for a given resolution j, we observed that the threshold is proportional to the edge magnitude average. That is:

$$Th^{(j)} = \frac{1}{2^{j-1} N^{(j)} M^{(j)}} \sum_{k=1}^{N^{(j)}} \sum_{l=1}^{M^{(j)}} E^{(j)}(k,l) \tag{3}$$

where $N^{(j)} M^{(j)}$ corresponds to the edge map size at the jth resolution. Thus, while going down in resolutions, the threshold value decreases in order to consider more edge pixels and overcome the wavelet filters smoothing effect.

2.2. Quality measure specifications

Having the edge maps at different resolution levels, we will move to the frequency domain by applying the discrete cosine transform (DCT). The absolute values of the quantized DCT coefficients are only considered. The study is restricted only of the absolute values because the sign of the DCT coefficients is not informative about the degradation caused by the blur. Indeed, in the Fourier domain, the blurred image is equal to the product of the Fourier transform of the sharp image and the Gaussian function. Because the Fourier transform of the Gaussian function is a non negative real function, then, the sign of the DCT coefficients is inferred only from the sharp image and it is independent from the blur. Furthermore, absolute values are quantified to transform the uncountable set of DCT coefficients into a finite set of prescribed values. In the state of the art, the quantization is implemented through linear or non linear transforms [22]. For our purpose, quantization is seen as the process of reducing the precision. In other words, absolute DCT coefficients are quantized by rounding to the nearest integer, other