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No-reference blur image quality measure based on multiplicative multiresolution decomposition

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ABSTRACT

A new approach for analyzing the blur effect on real images is proposed. This approach is based on the Multiplicative Multi-resolution Decomposition MMD. From MMD image-content analysis, a blind image quality measure dedicated to blur is then derived. The proposed measure has been applied on Gaussian-blurred and JPEG2000-compressed images from the LIVE, TID and IVC databases. The performance of the proposed measure is evaluated and compared with some referenced image quality metrics. The experimental results measured in terms of correlation with the subjective assessment of the images, demonstrate the efficiency of the proposed image quality measure in predicting the amount of blur.

1. Introduction

The blur is considered as one of the most studied distortions affecting image quality. It manifests itself as a loss of sharpness around edges and a decrease of visibility of fine details. This annoying degradation results from different causes. The isotropic blur effect may result from a defocus, whereas the blur due to motion appears as directional smear and contrast attenuation across contours. In microscopy blur may be due to different drifts or mechanical instabilities. The blur is often modeled through the PSF (Point Spread Function) using Linear Shift-invariant Systems theory. Many methods based on LSS theory for estimating the blur PSF without referring to the original image have been then proposed [1,17,36]. The blur could be also estimated by comparing the original images with the degraded ones using some image quality metrics. However, in many real-world applications, such as traditional television broadcast, Live Streaming and video-streaming, the original images are mostly not available. Hence, for these applications, No-Reference (NR) image quality measures are highly needed. Discriminating between image features and impairments is often ambiguous, so, quality assessment without a reference is a challenging task. However, human observer is able to discriminate between some blur effects. For example, motion produces a directional blur on the acquired images. But blur due to low pass filtering for noise reduction may appear as the blur due to lossy compression or defocusing. In this work we propose a quantitative analysis of the blur effect and propose a blurriness measure that does not make any assumption on the origin of the blur.

There are mainly two approaches for detecting and estimating the blur on images. One approach is based on the modeling of the blur effect on the image features. The second approach consists in analyzing the effect on the Human Visual System HVS [15,16,40]. Several no reference objective metrics were proposed in the literature [11]. The most known approaches are based on the analysis of the transform coefficients, such as DCT [29] or wavelet transform coefficients [2,14] or on the analysis of the edges. These approaches are based on the fact that the blur is intrinsically due to the attenuation of spatial high frequencies, which commonly occurs during image filtering or data compression. Many blur estimation methods have been proposed in the literature [4,9,12,19,25]. In contrast to other existing sharpness metrics, the metric proposed in [9] performs well under low to moderate SNR since the noise is reduced across wavelet scales. However, these approaches do not make any difference between the blur caused by compression and the one due to the image acquisition conditions.

HVS-based methods tempt to analyze the perceptual effect of the blur on the human observer. The modeling of the blur as perceived by the HVS allows to derive an objective measure directly related to the sharpness of edges and some salient features. Since edges and fine details are the most affected components by blur,

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many of the blur estimation methods are mainly based on the detection of these features. Therefore edge detection is a common step in most blurred image quality measures and several approaches have been proposed [4,5]. A blur metric defined in the spatial domain generally relies on measuring the spread of edges in an image, since blur is perceptually apparent along edges or in textured regions.

The methods described in [4,20,21,26] are performed into two main steps: edge detection and contour analysis. In the method proposed in [26] the parameters of the blur metric are tuned according to some subjective tests. Therefore, this blur measure is dependent on the test images. Furthermore, it is time consuming since it requires a search procedure to localize the extrema.

Many methods based on the modeling of the Human Visual System HVS for image analysis and processing have been proposed. One of the most studied characteristics of the HSV is its limitation to distinguish details or object on a uniform background. The notion of "just noticeable difference " (JND) [24] has been introduced in Weber-features experiment to measure the limitation of the HSV to perceive a target on a uniform background. Recently, the "just noticeable Blur" (JNB) [11] has been introduced to quantify the blurriness perception. A perceptual sharpness metric based on measured JNB and probability summation over space, which takes into account the response of the HVS to sharpness at different contrast levels, has been introduced in [11]. It provides a relative prediction of the relation sharpness/blurriness of images. Most of the aforementioned existing metrics tend to underestimate the amount of blurriness due to the fact that, at significantly high blur levels, many of the image details and edges are wiped out, which should affect the performance of the edge-based no-reference sharpness metric.

Although many interesting works on NR blur metrics have been done, there is still room for improvement. Of particular interest to this work, is to prospect new ways for analysis and assess the blurriness effect in relation with image intrinsic information modeling by using a Multiplicative Multi-resolution Decomposition [31,32] called MMD. Thus to analyze blur effect, we propose to model blurred transitions and study the polyphase components' ratio evolution close to transitions and through multi-resolution analysis.

The rest of the paper is organized as follows: blurred transitions are modeled and analyzed through multi-resolution analysis in Section 2. Then Section 3, introduces the Multiplicative Multi-resolution Decomposition. Section 4 describes the new no-reference blur quality metric. Section 5 presents the performance evaluation of the proposed method in terms of computational complexity and consistency with the subjective judgment by using LIVE, TID2008 and IVC databases. Finally, the last section is devoted to conclusion and some potential perspectives.

2. Blur analysis

The blur effect on an image could be analyzed in both the spatial or spatial-frequency domains or even in the joint space/spatial-frequency domain [3]. In the space domain the blur manifests itself as a reduction of sharpness around edges and fine details. One way for estimating the blur effect in the spatial domain is then to measure the spread of the signal around edges using some models based on the gradient measure [4,20,21,26]. In the frequency domain, the blur could be estimated by analyzing its impact on the high frequency components. Indeed, the blur distortion affects fine details and sharp transitions; this results in a decrease of the energy of high spectral components. By measuring the decrease of the energy in the frequency domain one can estimate the amount of blur [6]. Another way for characterizing the blur effect is to express the observed image using a deterministic model. One of the most used models is to consider the observed blurred image as the result of convolving the original unaltered version with the Impulse Response of a low pass filter [27]. The blur amount is then estimated through the filter parameters. Following this approach, in [8,13], the authors consider the standard deviation of the Gaussian IR as the unknown to be determined leading to estimate the strength of the blurring caused by defocusing. These methods tend to define areas with details as the sharper areas. This is not always the case since area with very few details may also look sharp. Here, we consider the underlined blurred image model to demonstrate the relevance of the multiplicative multi-resolution transform. The idea is then to model, at first, the blur effect at transitions and then, to develop suitable tools to quantify it.

To analyze the blur effect in an image I of size $K \times M$, consider the k^ith row $x(n) = I(k,n)$ with $n = 1,\dots,M$, filtered by a one-dimensional low pass filter defined through its impulse response IR. Let us consider h this IR of length $L+1$ with $L = 2p \quad p \in \mathbb{N}$. The filtered version $x_L(n)$ could be expressed as the convolution of the original signal with h as follows:

$$x_L(n) = \sum_{l=-\frac{L}{2}}^{\frac{L}{2}} h(l)x(n+l) \tag{1}$$

Here, as an alternative to Gaussian filter we use the 1D binomial filter defined through the finite impulse response (FIR) as done in [6]. The FIR of the filter is given by:

$$h(l) = \frac{1}{2^L}\sum_{m=0}^{L} C_L^m \delta\left(l + \left(\frac{L}{2} - m\right)\right) \tag{2}$$

with $l = -\frac{L}{2},\dots,\frac{L}{2}$. Eq. (1) could be rewritten as follows:

$$x_L(n) = \frac{1}{2^L}\sum_{m=0}^{L} C_L^m x\left(n - m + \frac{L}{2}\right) \tag{3}$$

where $C_L^m = \frac{L!}{(L-m)!m!}$.

We introduce the polyphase decomposition [37,39] which is a powerful tool for the representation of nonlinear filter banks and especially those based on the multiplicative representation.

Let us consider a signal $x(n)$. The polyphase decomposition of order N of a signal $x(n)$ involves subdividing the signal into N sub-signals $x_l(n)$ defined by (4) and illustrated in Fig. 1.

The polyphase component $x_l(n)$ is the signal $x(n)$ advanced by l and decimated by N.

$$x_l(n) = x(nN + l), \quad l \in [0 : N-1] \tag{4}$$

Let us consider $N = 2$. Thus, the polyphase components are given by:

$$\begin{aligned} x_0(n) &= x(2n) \\ x_1(n) &= x(2n+1) \end{aligned} \tag{5}$$

and those corresponding to the filtered signal are expressed as follows:

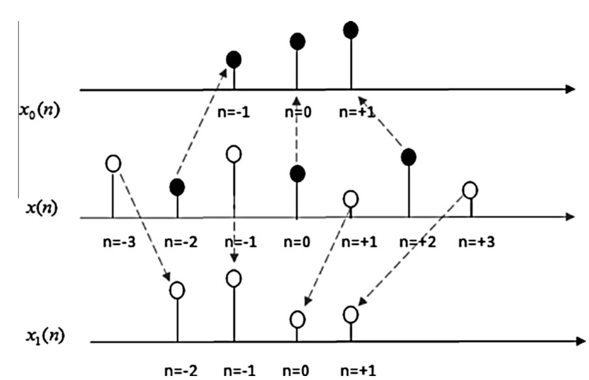

Fig. 1. Illustration of polyphase components $x_l(n)$ for $N = 2$.