Journal of Visual Communication and Image Representation 50 (2018) 145–158

Contents lists available at ScienceDirect

Journal of Visual Communication and Image Representation

journal homepage: www.elsevier.com/locate/jvci

Blind image sharpness assessment based on local contrast map statistics☆

Goran Gvozden*, Sonja Grgic, Mislav Grgic

Department of Wireless Communications, Faculty of Electrical Engineering and Computing, University of Zagreb, Unska 3/XII, 10000 Zagreb, Croatia

A R T I C L E I N F O

Keywords:
No-reference
Image quality assessment
Contrast
Percentile
Dynamic range
Wavelet

A B S T R A C T

This paper presents a fast blind image sharpness/blurriness assessment model (BISHARP) which operates in spatial and transform domain. The proposed model generates local contrast image maps by computing the root-mean-squared values for each image pixel within a defined size of local neighborhood. The resulting local contrast maps are then transformed into the wavelet domain where the reduction of high frequency content is evaluated in the presence of varying blur strengths. It was found that percentile values computed from sorted, level-shifted, high-frequency wavelet coefficients can serve as reliable image sharpness/blurriness estimators. Furthermore, it was found that higher dynamic range of contrast maps significantly improves model performance. The results of validation performed on seven image databases showed a very high correlation with perceptual scores. Due to low computational requirements the proposed model can be easily utilized in real-world image processing applications.

1. Introduction

A modern information society is overwhelmed with huge amounts of visual content being generated, stored and shared on a daily basis. Each processing phase, from image recording to reproduction, introduces various distortions which can lead to reduced visual experience. One of such distortions, closely related to the loss of visual acuity, limited contrast sensitivity and perceived image sharpness is blur [1]. In certain cases, the blur distortion can question the performance of a human or artificial visual system [2]. On the other side, in certain areas of image processing, the introduction of artificial blur can bring a more realistic virtual environment as well as enhanced visual experience [3]. Methods capable to detect, estimate or classify various types of blur distortion have received increasing attention in the field of image segmentation [4], blur estimation [5,6], sharpness assessment [7] and deblurring [8]. Regardless of the application, an efficient computational model capable to quantify the blur distortion and thus, estimate the image sharpness, can certainly optimize the quality of proliferating visual services.

The human visual system (HVS) is the most reliable estimator of image sharpness; however, the complex and time-consuming evaluation process makes it inapplicable in the real-world image processing environment [9]. The solution to this problem lies in the objective models capable to automatically estimate image sharpness [10]. This objective assessment ecosystem consists of full-reference (FR), reduced reference (RR) and no-reference (NR) methods where differentiation is based on the availability of reference or undistorted image [11]. Unlike FR and RR methods, no-reference or blind image assessment methods predict the image sharpness without the need for reference image. Accordingly, the NR methods are the most interesting due to their applicability in real-time visual systems where reference images are rarely accessible [12].

The early work in blind image sharpness assessment was mainly performed in the spatial domain. It was based on measurement of edge widths [13] where additional improvements were achieved by using perceptual features based on just noticeable blur (JNB) [14] and cumulative probability of blur detection (CPBD) [15]. Bahrami and Kot [16] estimate sharpness by measuring the spread of maximum local variation (MLV) coefficients. In [17] authors use the local Michelson contrast and energy map elements in an autoregressive (AR) space. Additional gains were demonstrated using the general-purpose image quality assessment (IQA) methods based on neural networks [18,19] and machine learning [20]. In [21] image sharpness is measured using the block energy of sparse coefficients normalized with block variances. Li et al. [22] exploit the Tchebichef moments computed from the image gradient maps, while authors in [23,24] take the Singular Value Decomposition (SVD) approach to assess the image sharpness. The sharpness methods in transform domain observe the statistics and energy information of Discrete Cosine Transform (DCT) coefficients to quantify the strength of blur distortion [25,26]. Some authors observe and parameterize Steerable Pyramid Wavelet Transform (SPWT) coefficient distributions in order to extract the statistics and form a feature

☆ This paper has been recommended for acceptance by Zicheng Liu.

* Corresponding author.
E-mail address: goran.gvozden@fer.hr (G. Gvozden).

https://doi.org/10.1016/j.jvcir.2017.11.017
Received 27 July 2017; Received in revised form 15 October 2017; Accepted 19 November 2017
Available online 21 November 2017
1047-3203/

vector relevant for sharpness assessment [27]. Authors in [28–30] observe the local phase coherence of an image to measure the blurriness. In [31], authors proposed a sharpness index expressed as a weighted sum of sub-band log-energies computed in a multi-scale Discrete Wavelet Domain (DWT). Finally, hybrid methods observe and combine the blur features extracted from the spatial and transform domain [32]. Li et al. [33] employ sharpness features extracted from multi-scale spatial/frequency domains in combination with the machine learning model, while Zhang et al. [34] use NSS based features with learned multivariate Gaussian model to measure other image distortions as well.

Our goal is to build an efficient blind computational model capable to: identify the blur distortion signature, quantify the level of distortion, and estimate the perceived image sharpness/blurriness. We observe the influence of isotropic blur on local contrast statistics in the spatial and frequency domain as well as its implications on perceived image sharpness/blurriness. Contrast has been used as a constituent feature in many IQA models. As part of the structural similarity paradigm, the local standard deviation based contrast was used within full reference models operating in single-scale [35] and multi-scale spatial domain [36]. In the blind image assessment environment, changes in contrast were accounted by measuring the total [32] or maximum local variation in image intensities [16]. The gradient magnitudes (GM) and Laplacian of Gaussian (LOG) responses were also successfully employed as local spatial contrast features in [37]. Some authors use locally computed Michaelson contrast in the autoregressive space [17], while others observe the transform domain to extract DCT [38] or DWT [39] based local contrast features.

Our model builds upon the perceptual contrast sensitivity mechanism which has a fundamental role in the visual information processing, especially in terms of discrimination of spatial and temporal patterns falling onto the retina. We use the local root-mean-square

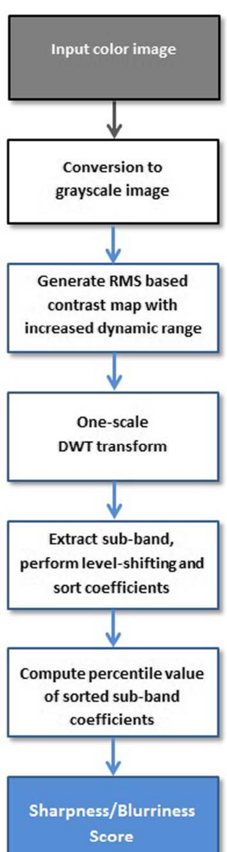

Fig. 1. Flowchart of the proposed BISHARP model.

(RMS) contrast measure, to generate contrast image maps and capture the intensity variations across the image [40,41]. Unlike previous approaches, we introduce the concept of increased dynamic range. By increasing the dynamic range of generated contrast maps the performance of proposed model is significantly improved. Furthermore, we extended our approach into the high frequency discrete wavelet space due to the well-known fact that high frequency image components are attenuated by blur [42]. Here, the level-shifting operation, performed on decomposed wavelet coefficients, is introduced to further enhance the model performance. The computed statistical parameters – in our case percentile values – are defined as perceptually significant image sharpness/blurriness features. The proposed model demonstrates very high correlation with perceptual scores. If processing time in combination with prediction accuracy across all tested databases is taken into consideration, the proposed method outperforms other state-of-the-art image sharpness metrics. These findings were validated as part of an extensive performance evaluation, which involved seven publicly available blur databases.

The following section describes the proposed algorithm. In Section 3 the results of performance evaluation are given along with short description of databases and performance attributes used for model validation. Additionally, a thorough evaluation of the proposed sharpness measure is presented including results of correlation analysis, hypothesis testing and computational complexity. In Section 4, the paper ends with the concluding remarks and future work.

2. Image sharpness assessment model

HVS encodes only relative luminance values based on its intrinsic light adaptation mechanism [43]. The processing of visual information is performed using a nonlinear function where only values that show 1% change in luminance are being registered and coded. This capability expressed as the contrast sensitivity represents one of the fundamental attributes of visual perception. Moreover, the perceptual response to an image strongly depends on image contrast ratio which is commonly defined as the ratio between the maximum and minimum luma[1] values [44]. In the context of image quality assessment the contrast is found to be inextricably related to image sharpness where images with higher contrast ratios are perceived as sharper [39]. Hence, observing and quantifying the changes in contrast can contribute to reliable sharpness/blurriness estimation [36,45]. Next, we explain how local contrast is computed, integrated and utilized within our sharpness model.

2.1. Blind image sharpness estimation framework

The proposed BISHARP model incorporates processing in the spatial and wavelet transform domain. The flowchart of the proposed model is shown in Fig. 1. It is a fast and straightforward process where an image being tested for sharpness is first converted to grayscale domain. Then, the local contrast map is generated computing the root mean square values in local pixel neighborhood. The generated map is transformed to frequency domain using one-scale discrete wavelet transform. Extracted sub-band coefficients are sorted and level-shifted by the maximum value found in a negative valued wavelet coefficients pool. The computed percentile value of the resulting, level-shifted wavelet coefficients distribution represents the final image sharpness score. Below, we present the 5-step framework designed to compute the image sharpness measure.

2.1.1. Conversion to grayscale image

Step 1. The first step is conversion from color *R′G′B′* to grayscale

[1] Luma is defined as a weighted sum of tristimulus R′G′B′ values obtained after processing the linear RGB values with nonlinear gamma function. Gamma function is an approximation of the perceptual response to luminance.