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Estimation of light source colours for light pollution assessment☆

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ABSTRACT

The concept of the smart city raised several technological and scientific issues including light pollution. There are various negative impacts of light pollution on economy, ecology, and heath. This paper deals with the census of the colour of light emitted by lamps used in a city environment. To this end, we derive a light bulb colour estimator based on Bayesian reasoning, directional data, and image formation model in which the usual concept of reflectance is not used. All choices we made are devoted to designing an algorithm which can be run almost in real-time. Experimental results show the effectiveness of the proposed approach.

1. Introduction

By analogy to sound, garbage, and chemical products, excessive or misdirected artificial light is a consequence of human activities yielding numerous negative impacts on individuals, on the ecosystems, on astronomy, and on energy consumption. Among these negative impacts, some examples are sleep disruption, hormonal disruption, cancer, unsafe driving, energy waste, and the lethal effects on insects (Falchi et al., 2011; Hori et al., 2014; International Dark Sky Association, 2010). That's why it is qualified by light pollution. The light pollution is mainly studied in astronomy and remote sensing for the characterization of sky glow and the identification of street lamps by using digital cameras, solar cells, SQM sensors, or other remote sensors (Alamús et al., 2017; Aubé et al., 2005; Conci, 2013; Elvidge et al., 2010; Flanders, 2006; Kruse and Elvidge, 2011; Sánchez de Miguel, 2015; Zotti, 2007). The proposed procedures are more suitable for global measures of light intensity such as the light sphere above the city. They cannot meet all the needs of smart cities such as public health, well being, local control of pollution, and the management of energy consumption. For that, one can consider updating of the geographical city map by adding a layer of information about visible lamps in the street such as their spatial position, their intensity, and the colour of emitted light. We argue that such a map can be drawn by processing colour images of areas that include light bulbs, acquired overnight in the visible spectrum. The cameras placed on a satellite or a plane are unusable because lamps can be directed towards the ground or they can be hidden by trees and buildings. The camera can be placed close to the ground. To the best of our knowledge, this approach has not previously been implemented. In addition to light intensity, light colour is also a pollutant. As evidence, at night the blue hue disturbs humans, because it affects their biological clock (Falchi et al., 2011). It is harmful to insects such as larvae, mosquitoes, and some flies (Hori et al., 2014). In computer vision, several methods are available for estimating illuminants (Hordley, 2006; Lakehal and Ziou, 2016). An illuminant is the colour of the light estimated from a colour image. In the art, most existing methods for estimating an illuminant were derived by using, explicitly or implicitly, a reflectance-based image formation model such as the dichromatic reflectance model (Hordley, 2006; Lakehal and Ziou, 2016). They are mature, but most of them are time-consuming and designed to estimate a global illuminant (Lakehal and Ziou, 2016). However, in the target application, the physical features of the lamp or the reflectance of its surrounding area are irrelevant because what interests us is the light as it is seen by an observer with a normal vision. Moreover, in one image there may be several light bulbs. Therefore, that a global illuminant estimator is unusable.

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In this paper, we propose the use of a specific image formation model for light source and a probabilistic model for the estimation of the light colour emitted by lamps. From images acquired overnight by a digital camera, the normalized colour of light is considered as directional data on sphere sampled from von Mises-Fisher probability density function (pdf). The illuminant is a parameter of the pdf estimated by using empirical Bayesian reasoning over directional data. Note that, to the best of our knowledge, colour image processing acquired by an off-the-shelf camera seems never been used before to characterize the light pollution by measuring colours of light emitted by lamps and therefore we propose here the first approach. The next section is devoted to the image formation model of light bulbs used to derive the empirical Bayesian model for light estimation which is explained in Section 3. The algorithm validation is described in section 4.

2. Image formation model

In urban areas, different sources of light pollution exist, including vehicles, traffic lights, floor lamps, billboards, indoor lights, door lamps, and logos. The images of these light sources are acquired at night by using a digital colour camera operating on the visible spectrum (See Fig. 1). The images must be acquired during a moderate turbidity so that the shift of light colour caused by the medium (e.g. dense fog, smoke) is reduced.

Several existing algorithms for the illuminant estimation have been suggested (Hordley, 2006; Lakehal et al., 2017; Lakehal and Ziou, 2016; Shafer, 1985; Toro et al., 2005; van de Weijer et al., 2007). Most of them are: 1) mature because the accuracy obtained through the use of available data collections, is high; 2) global because only one illuminant is estimated for the whole image; 3) time consuming. The implementation of local illuminant estimators when the scene is illuminated by several sources is challenging and few have been proposed (Lakehal et al., 2017). Both existing local and global estimators are intended to estimate the illuminant in the case of the reflectance-based image formation model; the light falling on the camera sensor is reflected by objects. The commonly used features to estimate the illuminant are colour vectors, chromaticities, and the logarithm of relative chromaticities (Drew et al., 2014; Hordley, 2006). Instead of using all pixels, the selection of bright ones only leads to an improvement in accuracy (Drew et al., 2014; Joze et al., 2012; Lakehal and Ziou, 2016).

The statement of the problem here is different, because of the used image formation model. Indeed, let us consider a light bulb at night. In this case, the light pollution model involves several physics phenomena and parameters. A complete physics model is provided in the papers (Kocifaj, 2007, 2008). Considering the assumption we made before and the use of a camera without any additional measuring devices, we propose an appearance-based model where implementation is easier. Negative effects caused by simplifications will be compensated by statistical reasoning. The light falling on the camera sensor has two origins. The first, considered a degradation source, is the global light caused by the hemispherical sky source such as the sky glow. The second origin is the direct illumination caused by the light emitted by a bulb, travelling across the medium formed by suspended particles, and falling on the camera sensor. Therefore, the image formation model is a linear combination of both the direct and indirect illumination. More precisely, the latter can be seen as a light emitted by the sky hemisphere $L(q,\lambda)$ modulated by the scattering function $\beta(q,\lambda)$, where λ is the wavelength and q the position in the image. The former is also the product of the emission from a punctual light source $C(\lambda)$ and modulated by the scattering function $\alpha(q,\lambda)$. The image formation model of the k^{th} colour band by a camera having a spectral sensitivity $s_k()$ on the visible spectrum interval $\mathscr{V}$ can be written as:

$$I_k(q) = \int_{\mathscr{V}} (\alpha_k(q,\lambda)C(\lambda) + \beta_k(q,\lambda)L(q,\lambda))s_k(\lambda)d\lambda \tag{1}$$

Adding the camera's point spread function to this model does not cause any change in the proposed approach. It affects the functions which depend on q but does not affect $s_k()$. Assuming that $\alpha_k()$ and $\beta_k()$ are continuous with respect to λ as well as $C(\lambda)s_k(\lambda)$ and $L(q,\lambda)s_k(\lambda)$ are integrable on $\mathscr{V}$, so according to the mean value theorem (Smoryski, 2017), there exists wavelength λ_0 such that:

$$I_k(q,\lambda_0) = \alpha_k(q,\lambda_0)c_k + L_k(q,\lambda_0) \tag{2}$$

where the illuminant is the vector c of components $c_k = \int_{\mathscr{V}} C(\lambda)s_k(\lambda)d\lambda$, $k = 1,2,3$ and $L_k(q,\lambda_0) = \beta_k(q,\lambda_0)\int_{\mathscr{V}} L(q,\lambda)s_k(\lambda)d\lambda$. According to Eq. (2) two observations can be made. First, the estimation of the illuminant requires the knowledge of the image, the background light, and the scattering due to the medium between the lamp and the camera. If the background light does not change in the acquired image, then a differentiation operator D applied to this image allows for neglect of the second term in eq. (2); i.e. $D(I_k(q,\lambda_0))\simeq D(\alpha_k(q,\lambda_0))c_k$. However, if $D(\alpha_k(q,\lambda_0))$ is too small, the estimation of c_k will be noisy. Second, if $\alpha_k(q,\lambda_0)$ and $L_k(q,\lambda_0)$ are spatially variants, then the illuminant c depends on the pixel position q. However, there is one illuminant for a light bulb, invariant to noise in the image, and physically realizable. To fulfill these requirements, the illuminant can be estimated by marginalization over q such as

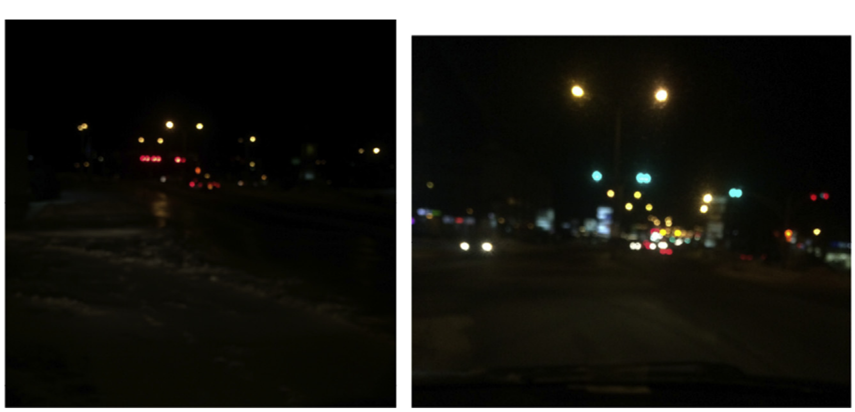

Fig. 1. Example of images of light sources.