Computer Vision and Image Understanding 117 (2013) 1589–1597

Contents lists available at ScienceDirect

Computer Vision and Image Understanding

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

A novel background subtraction method based on color invariants ☆

Hong Zhou, Yiru Chen *, Rong Feng

Department of Instrument Science and Engineering, Zhejiang University, Zhouyiqing Building 410, Zhejiang University Yuquan Campus, West Lake District, Hangzhou 310027, China

ARTICLE INFO

Article history:
Received 9 June 2012
Accepted 23 July 2013
Available online 2 August 2013

Keywords:
Background subtraction
Color invariants
Color similarity
Illumination change
Indoor environments

ABSTRACT

This paper discusses the problem of segmenting foreground objects precisely in surveillance video images when foreground moving objects and the still backgrounds have the similar color parts. Motivated by the studies in color constancy, the notion of color invariants is introduced to realize integrated segmentation in color similar situations. Color invariants, which are derived from a physical model, are used as descriptors of image. Then a simple background subtraction method using the color invariants is performed to examine the effectiveness of color invariants in color similar situations. The experimental results demonstrated that the color invariants based method performed well in various situations of color similarity and also was robust to environmental illumination change. Moreover, the color invariants based method achieved higher accuracy and efficiency of background subtraction compared with other existing algorithms in practical real-time surveillance video images of indoor environments.

1. Introduction

Background subtraction is a fundamental issue of computer vision, which aims to segment foreground moving objects from images by parameters or descriptors so that the pixels residing in the foreground or background can be effectively differentiated. In some specific applications, background subtraction is demanded to exactly segment the foreground moving object from the background without apertures or discontinuities in segmentation. However in many common situations (e.g., the similar color of foreground moving objects and background, the abrupt change of illumination intensity), it is unable to realize the integrated object segmentation with background subtraction algorithm [1,2].

In order to overcome the problems of apertures and discontinuities in segmentation, researchers [3–6] tried to improve the robustness of background subtraction algorithm for the illumination changes. Nevertheless, few researches worked on the apertures and discontinuities from the view of color model used by images [7]. Intuitively, the color discriminative ability of background algorithm is basically related to the way of representing colors in the image. RGB, the default color model generated by the surveillance camera, is an additive color model, which is formed by adding three basic colors with different proportions to reproduce a band of color arrays to represent colors in image. Since the formation of RGB color model is simple, it is widely used in the electronic devices [8]. Hence, most background subtraction algorithms used in the intelligence surveillance systems are directly processing images based on RGB color model, such as the GMM [9], Codebook [10], and etc. The GMM algorithm is one of the most prevalent background subtraction algorithms. Nonetheless, experiments proved that the GMM algorithm did not perform well when there were shadows; i.e., shadows were usually viewed as foreground objects by the GMM algorithm. This indicates the fact that the GMM algorithm is sensitive to the illumination intensity change. Funt et al. [12] confirmed in his research that the normalization of RGB values could eliminate the effect of illumination intensity. However, once the RGB value is normalized, images' color values in the dark area become unstable [13]. The codebook algorithm uses the color distance to describe colors in order to make the best use of illumination intensity [10]. Although, theoretically, this method makes the algorithm independent of abrupt illumination change and discriminative to color similarity, it works poorly in practice [14].

To get the full use of color information, the HSI color model is proposed, which is more intuitive and perceptual with human eyes compared with the RGB color model. In HSI color model, the intensity and chroma information are defined separately, this is better to cope with the color similarity as well as the illumination change. Unfortunately, the HSI color model is an unstable color model; i.e. when the color saturation is low, the *H* value changes randomly. As a result, HSI color model is unsuitable to the background subtraction algorithm.

Luke et al. [11] proposed the YCrCbCg and HSv color models to improve the stability of the illumination change. The algorithm based on the YCrCbCg and HSv color models works well for various

☆ This paper has been recommended for acceptance by J.-O. Eklundh.

* Corresponding author. Present address: Zhouyiqing Building 410, Zhejiang University Yuquan Campus, West Lake District, Hangzhou 310027, China. Fax: +86 0571 87953661.

E-mail addresses: zhouh@mail.bme.zju.edu.cn (H. Zhou), chenyiru@zju.edu.cn (Y. Chen).

1077-3142/$ - see front matter
http://dx.doi.org/10.1016/j.cviu.2013.07.008

kinds of indoor environments, but it still unable to process the image under the color similarity situation.

The color models used in the above mentioned algorithms describe image colors only with color spectral information, but without consideration of color spatial structure in image. The color of an object is not only a function of surface reflectance, but also a function of both the illumination spectrum and the sensing device [15]. Thus, it is necessary to consider the formation of color image as the combination of the image surface reflectance, ambient illumination and the photographing device. Therefore, it is assumed that a color model which integrates the color spectral information and spatial configuration will be more precise to describe colors in image.

Geusebroek et al. [16,18] analyzed that the formation of colors in image was an integrated process of spectrum energy distribution in the spatial dimension at certain spectral scale-space and spatial scale-space. Then the Kubelka–Munk theory was adopted to model the formation of the color in term of physical basis, which integrated the color spectral information and spatial content to describe color [17]. The color invariants were derived from the Kubelka–Munk theoretic model, which were invariable to illumination changes and had excellent color discriminative capability in theory.

In this paper, the color invariants are applied as descriptor for background subtraction method. The indoor environments are selected as the tentative environments. A background subtraction method based on a novel descriptor consist of color invariants is proposed. Experiments and results demonstrate that the proposed method realizes precise background–foreground segmentation in different color similarity situations and it has the robustness to illumination change. The method also achieves a high true-positive segmentation accuracy and runtime efficiency.

The rest of this paper is organized as follows: Section 2 introduces the color invariant descriptors. In Section 3, the framework of background subtraction method based on color invariants is described. Section 4 presents the experiments and the results that examine the foreground segmenting capability and efficiency of the proposed method in different color similarity situations and its robustness to illumination.

2. Color invariant descriptors

Color is an effective cue to discriminate objects in images. However, the general color models only use the color spectral information and its color representation for color spectrum is not as sophisticated as the color reflected light spectrum for human eyes. Therefore, in order to describe colors in a more discriminatively way, it is necessary not only to use the color spectral energy distribution coding color information, but also the spatial configuration of color [18]. The Kubelka–Munk theory as defined in Eq. (1) is established based on a physical model in term of spectral and spatial dimension of color [16]. Parameters with properties independent of illumination intensity and viewpoint are defined as the color invariants.

$$E(\lambda,\vec{x}) = e(\lambda,\vec{x})(1-\rho_f(\vec{x}))^2 R_\infty(\lambda,\vec{x}) + e(\lambda,\vec{x})\rho_f(\vec{x}) \quad (1)$$

where $\vec{x}$ denotes the position in the image plane, λ denotes the wavelength, $e(\lambda,\vec{x})$ denotes the illumination spectrum, $\rho_f(\vec{x})$ denotes the Fresnel reflectance at $\vec{x}$, and $R_\infty(\lambda,\vec{x})$ denotes the material reflectivity. The set of color invariants derives from the Kubelka–Munk theory are shown in Table 1. In Table 1, C.I. is short for color invariant and the corresponding column lists the names of the defined color invariants. The second column is the definitions of each color invariant. The third and the forth columns give out the conditions and physical models from which the color invariants derived.

Table 1
Definition, condition and physical model formula of color invariants.

C.I.	Definition	Conditions	Physical model formula
H	$\frac{E_\lambda}{E_{\lambda\lambda}}$	Equal energy but uneven illumination	$E(\lambda,x) = i(x)\{\rho_f(x) + (1-\rho_f(x))^2 R_\infty(\lambda,x)\}$
W	$\frac{E_x}{E}$	Equal energy but uneven illumination on matte, dull surface and planar objects	$E(\lambda,x) = iR_\infty(\lambda,x)$
C	$\frac{E_\lambda}{E}$	Equal energy but uneven illumination on matte, dull surface	$E(\lambda,x) = i(x)R_\infty(\lambda,x)$
U	$\frac{E_{\lambda x}E - E_\lambda E_x}{E^2}$	Uniform object	$E = e(\lambda,x)\{\rho_f + (1-\rho_f)^2 R_\infty(\lambda)\}$
N	$\frac{E_{\lambda x}E - E_\lambda E_x}{E^2}$	Uneven illumination	$E = e(\lambda)i(x)R_\infty(\lambda,x)$

The color invariants list in Table 1 are defined in an ideal physical model, i.e. the color invariants are defined in the given dimensional spectrum at an infinitesimal small spatial neighborhood. However, in practice, the spatial-spectral energy distribution is measurable only at a certain spatial extend and a certain bandwidth. According to Florack and Munk [17], the Gaussian function and its derivatives can be used as general probes for the measurement of spatial-spectral differential quotients. Therefore, in order to compute the color invariants in practice, Gaussian color model is adopted as the image color describing model. Gaussian color model is a human perceptual oriented color model which conveys color in term of spectral and spatial structure [18]. Hence, the spectral and spatial parameters in the definitions of color invariants can be calculated in the Gaussian color model.

The spectral parameters of color in Gaussian color model: Let $E(\lambda)$ be the energy distribution of the incident light as defined in Eq. (1), λ denotes wavelength. The observed spectral energy distribution $\widehat{E}(\lambda)$ in Gaussian color model may be approximated by a Taylor expansion at λ_0 with scale σ_λ;

$$\widehat{E}^{\sigma_\lambda}(\lambda) = \widehat{E}^{\lambda_0,\sigma_\lambda} + \lambda\widehat{E}_\lambda^{\lambda_0,\sigma_\lambda} + \frac{1}{2}\lambda^2\widehat{E}_{\lambda\lambda}^{\lambda_0,\sigma_\lambda} + \cdots \quad (2)$$

where $\widehat{E}^{\lambda_0,\sigma_\lambda}$, $\widehat{E}_\lambda^{\lambda_0,\sigma_\lambda}$ and $\widehat{E}_{\lambda\lambda}^{\lambda_0,\sigma_\lambda}$ are the incident light spectral energy distribution parameter with Gaussian aperture weighted at λ_0 with scale σ_λ.

Since the subspace spanned by the human visual system is of dimension 3, the third or higher order Taylor expansion of incident light spectral energy distribution is unobservable by human eyes [18]. Hence, the second order truncated Taylor expansion is sufficient to approximate the spectral energy distribution of color for human visual system. For color image, $\widehat{E}^{\lambda_0,\sigma_\lambda}$, $\widehat{E}_\lambda^{\lambda_0,\sigma_\lambda}$ and $\widehat{E}_{\lambda\lambda}^{\lambda_0,\sigma_\lambda}$ consist of the spectral parameters of Gaussian color model at λ_0 with scale σ_λ.

The spatial parameters of color in Gaussian color model: The energy distribution of incident light at x direction can be expressed as Taylor expansion:

$$\widehat{E}(\lambda,x) = \widehat{E} + \begin{pmatrix} x \\ \lambda \end{pmatrix}^T \begin{bmatrix} \widehat{E}_x \\ \widehat{E}_{\lambda x} \end{bmatrix} + \frac{1}{2}\begin{pmatrix} x \\ \lambda \end{pmatrix}^T \begin{bmatrix} \widehat{E}_{xx} & \widehat{E}_{x\lambda} \\ \widehat{E}_{\lambda x} & \widehat{E}_{\lambda\lambda} \end{bmatrix}\begin{pmatrix} x \\ \lambda \end{pmatrix} + \cdots \quad (3)$$

where

$$\widehat{\mathrm{E}}_{\mathrm{x}^i\lambda^j}(\lambda,\mathrm{x}) = \mathrm{E}(\lambda,\mathrm{x}) * \mathrm{G}_{\mathrm{x}^i\lambda^j}(\lambda,\mathrm{x};\sigma_\lambda,\sigma_\mathrm{x}) \quad (4)$$

Here, $G_{x^i\lambda^j}(\lambda,x;\sigma_\lambda,\sigma_x)$ is the Gaussian spatial-spectral probe.