Foreground Detection Robust Against Cast Shadows in Outdoor Daytime Environment

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Abstract. This paper proposes a novel foreground detection method which estimates the color changes in shadow regions by using a solar spectral model. In conventional method, since it is assumed that only brightness changes from background in shadow regions, shadow regions are extracted falsely as foreground in the case where color in the shadow region also changes in outdoor daytime environment. The proposed method estimates the color changes in shadow regions by calculating colors of direct and ambient illuminance which radiate to the captured scene using a solar spectral model. By estimating the color changes, the proposed method can robustly distinguish foreground and shadow regions in outdoor daytime environment. Experimental results demonstrate that the proposed method successfully estimates the changes of background color in shadow regions and improves F-measure of foreground detection compared with the conventional methods.

Keywords: Video surveillance · Background subtraction · Solar spectral model · Foreground detection · Shadow detection

1 Introduction

Recently, video surveillance for outdoor purpose has attracted attention due to the fear of terrorism and violent criminals. In a surveillance system, operators catch occurrences of crimes or suspicious behaviors from captured images. To achieve a high security surveillance system and comfortable operations, it is quite expected that image recognition techniques assist the operators by automatically recognizing target objects in real-time and with high accuracy.

Background subtraction is widely used for extracting foreground regions as the first step for object recognition [9]. The background subtraction conducts a comparison between a captured image and a background image data and extracts regions which have differences as foreground. The size and shape of each foreground region are utilized as cues for an identification of objects such as "human" or "vehicle". One of the general problems of the background subtraction is that cast shadows on background are also detected as foreground.

To solve this problem, background subtraction with shadow detection which enables to divide the extracted foreground regions into the actual foreground regions

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and shadow regions are studied [10][12]. These methods try to detect the shadow regions by setting a constraint about change of chromaticity of shadow regions or by installing a physical illumination condition model which enables to predict the color change of shadow regions. However, the conventional methods are insufficient for applying to outdoor daytime environment. There are two kinds of illuminant in daylight scene; one is a direct illumination of the sun and another is an ambient illumination such as sky. These illuminant colors are different, and the strength and the color of each illuminant changes constantly according to the time and the weather condition. Therefore, the change in background color caused by shadows also fluctuates variously.

In this paper, we propose foreground detection method which is applicable to outdoor daytime environment, suppressing the affection of cast shadows. The proposed method utilizes a solar spectral model which can describe the illuminant color of both of direct and ambient illuminations in the daylight scene and extracts foreground regions by estimating the color change of background regions caused by cast shadows.

The rest of the paper is organized as follows. In the next section, we review related works and explain its problems. We describe the proposed method in Section 3. We detail some experimental results in Section 4. Finally we conclude the paper in Section 5.

2 Related Work

It is well known that cast shadows on background tend to be extracted as foreground and it causes inaccurate object detection and decrease of tracking performance. Therefore, detecting cast shadows from the extracted foreground regions has become an important step for realizing robust tracking system and has been widely studied [10][12].

The most famous approach for the cast shadow detection is chromaticity based approach. This approach uses an assumption that regions under shadow become darker but their chromaticity does not change significantly. Various color space are used to evaluate the chromaticity, for example normalized RGB [2], HSV [3] and c1c2c3 [13]. The main advantage of this approach is its easiness of implementation. However, this approach is not effective since the assumption does not match to daylight conditions. In daylight conditions, there are two kinds of illuminant, a direct illumination of the sun and an ambient illumination such as sky, which have different illuminant colors. Since regions in a sunny place are irradiated by these two illuminant lights and the cast shadows are generated by obstructions of the direct illumination light, the chromaticity of the shadow regions changes significantly.

Another approach for the detection is learning based approach, which predicts the color change of shadow regions based on an illumination model of the scene. This approach can represent the color change of shadow regions in daylight conditions and can successfully detect the cast shadows when the illumination property of the scene which represents direct and ambient illuminant colors is correctly given. This approach has a difficulty to conduct appropriate setting of the illumination property. In recent years, several methods try to estimate the illumination properties or the specific color appearances of shadows which are the best fit to the captured scene using machine learning [5]. However, in daylight scene, the strength and the color of the direct and the ambient illumination changes constantly according to the time and the weather condition. So their estimated illumination color properties become invalid unless the learning process is repeated again and again, which takes high computational cost. Furthermore, the learning process needs data sets in stable illuminant condition which is sometimes difficult to obtain in actual daylight scenes. The other approaches use regional texture correlations [7][11] and discriminate target regions as shadow if the texture correlation between the target region and background is high.

There is another approach which uses geometrical properties such as sizes and shapes of the shadows [4]. However, this approach lacks versatility since the performance strongly depends on the feature of target objects and background.

We propose foreground detection method robust against cast shadows outdoor daytime environment.

3 Proposed Method

3.1 The Concept of the Proposed Method

The proposed method detects foreground regions suppressing the affection of cast shadows by estimating the color changes in background. Since colors of cast shadows changes in outdoor daytime environment it is difficult to estimate the regions of shadows. The proposed method estimates these color changes in background using spectrums of direct and ambient illuminants calculated by a solar spectral model [6] and enables to distinguish the foreground regions and the shadow regions.

3.2 Solar Spectral Model

A solar spectral model by Bird and Riordan [1] is a physics based simulation model to represent a daylight spectrum at the earth's surface under cloudless condition. In this model, the diffusion and the attenuation of sunlight passing through the atmosphere under cloudless condition are simulated and spectral power distributions of the direct illumination and the ambient illumination are calculated. In order to calculate the spectral power distributions, solar zenith angle and atmospheric conditions of the scene are needed. Since the affection by the atmospheric conditions such as water vapor, air pressure, turbidity and aerosol is much less than the solar zenith angle, a daylight spectrum is estimated with the solar zenith angle and a priori determined constant parameters of atmospheric conditions under a clear sky. The solar zenith angle is determined by the date of the year, the time of the day, and the latitude and the longitude of the place, which can be easily obtained in actual operations.

The solar spectral model is extended by Kaneko et al. to apply under weather conditions from clear sky to cloudy [6]. This model takes the behavior of light passing through clouds into consideration and represents a daylight spectrum under cloudy condition as a linear combination of the direct and the ambient illuminant spectrum under cloudless condition. Their experimental results show that their model can successfully represent daylight spectrum in cloudless, cloudy and shady conditions in the range of the wavelength from 350nm to 1000nm which includes visible wavelength.

Based on the model, illuminant colors of direct and ambient light in a captured scene L_d and L_a are represented by using the illuminant colors of direct and ambient light under the cloudless condition I_d and I_a as follows:

$$L_d^c = m\, I_d^c, \quad L_a^c = nI_d^c + l\, I_a^c \tag{1}$$

where c denote color channels in RGB color space and m, n, and l is coefficient parameters which describe the intensity of each illuminant. The illuminant colors I_d and I_a are obtained from the spectral power distributions of the direct and the ambient illumination by applying color matching functions.

3.3 Color Change Model in Background

Changes of color in shadow regions are estimated using the direct and ambient illuminance color by solar spectral model. By estimating the changes of background color, possible background colors are obtained. The changes of background color are described as followed. By using direct and ambient illuminant colors L_d^c and L_a^c, color information of background B^c is represented by

$$B^c = r^c(L_d^c + L_a^c) = r^c\left((m+n)I_d^c + lI_a^c\right) \tag{2}$$

where r is the surface reflectance.

In the shadow region, it is assumed that direct light is occluded by the object and decays, so color information of shadow region B_{sh}^c is represented by

$$B_{sh}^c = r^c(\alpha L_d^c + L_a^c) = r^c\left((\alpha m+n)I_d^c + lI_a^c\right) \tag{3}$$

where α is the parameter which represents the intensity of occluded direct light in the captured scene.

$$B_{sh}^c = \frac{(\alpha m+n)I_d^c + lI_a^c}{(m+n)I_d^c + lI_a^c} B^c = \frac{qI_d^c + I_a^c}{pI_d^c + I_a^c} B^c \tag{4}$$

where

$$p = \frac{m+n}{l}, q = \frac{\alpha m+n}{l}. \tag{5}$$

B_{sh}^c is the possible shadow colors which varies according to parameters p and q. By minimizing the color difference between B_{sh}^c and color information in captured image J^c, shadow color is estimated uniquely. Then energy function E defined as followed must be minimized for parameters p and q.

$$E = \textstyle\sum_c (J^c - B_{sh}^c)^2 \tag{6}$$

where J^c represents the color information of input image. By minimizing E, p and q are determined and shadow color B_{sh}^c in the equation (4) is estimated uniquely.

3.4 Extract Foreground Region

Foreground likelihood for each pixel is calculated from the matching rate with the color change model. The estimated background color represents the changed color information of a pixel if its behavior follows the color changes in background (shadow). So foreground likelihood becomes high if the difference between the color information of the pixel and that of estimated background is large.

The proposed method can extract only foreground regions by using these features. To extract foreground regions, some threshold need to be set and if the foreground likelihood is higher than the threshold it is extracted as foreground region. Threshold is needed to be set appropriately to extract foreground but to suppress shadow.

3.5 The Overview of the Proposed Method

In proposed method, foreground regions are extracted by estimating the background color changes using solar spectral model. Fig. 1 shows the overall flow of the proposed method. First, from the date and position of the captured scene, spectral of direct and ambient illuminants are derived by using solar spectral model. Next, change of color information from input background image by the shadow in the captured scene is estimated from captured image and input background image. By using estimated background, foreground likelihood is calculated. As a result, foreground regions (object regions) can be extracted which have the property whose color information is highly different from that of estimated background.

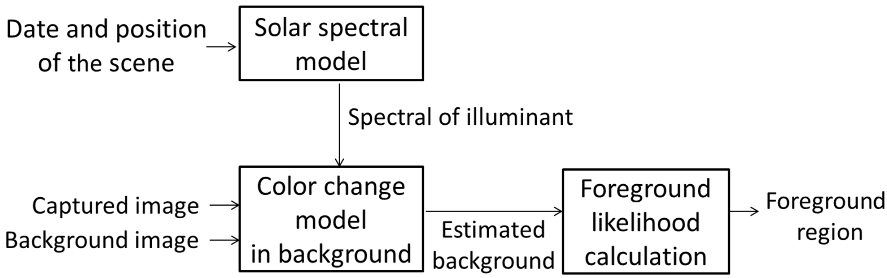


Fig. 1. Flow of the proposed method

4 Evaluations

4.1 Evaluation of Color Change Model

In the first experiment, the validity of the proposed color change model in background is confirmed compared with the model used in the chromaticity based method [3].

Fig. 2 shows the model of the chromaticity based method in RGB color space. Red line represents the possible colors of shadow. If the target pixel color is close to the line, the pixel is discriminated as shadow. In the shadow pixel, the distance between the pixel value and estimated shadow color value represents the model error of chromaticity based method. And the intersection point with the possible shadow color line (red line) and perpendicular line drawn from the pixel color point to the red line can be considered as estimated shadow color point. By using estimated shadow color C_{sh}, the model error of the chromaticity based method E_C is represented as followed.

$$E_C = \sum_c (J^c - C_{sh}^c)^2 \tag{7}$$

where J^c is corresponding pixel value of input image in shadow region.

Fig. 3 shows the proposed color change model in RGB color space. Red curved surface represents the possible colors of shadow. The target pixel color is also discriminated as shadow if the color point is close to the curved surface. The intersection point with curved surface and perpendicular line drawn from the pixel color point is the estimated background color point and the model error of the proposed method is represented by E in equation (6).

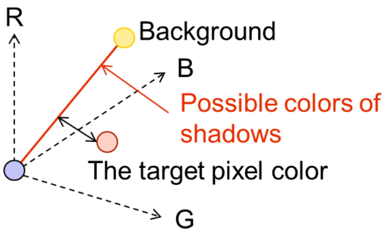


Fig. 2. Possible shadow colors under the chromaticity based method

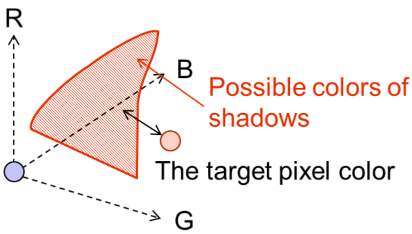


Fig. 3. Possible shadow colors under the proposed method

The experiment conducted in outdoor daytime environment and on three types of ground, lawn, artificial lawn and asphalt. Fig. 4 shows captured images and the model errors of the chromaticity based method E_C and the proposed method E calculated using the shadow pixels. Horizontal axis represents $\mathrm{imgV}/\mathrm{bgV}$, where

$$\mathrm{imgV} = \mathrm{R} + \mathrm{G} + \mathrm{B} \tag{8}$$

for each shadow pixel in input image and bgV is also the sum value of RGB of corresponding pixel in background image. Vertical axis represents the value of the model errors and red dots and blue dots represent E and E_C of each pixel in shadow region respectively. From Fig. 4 it is obvious that proposed method has the smaller model error compared to the chromaticity based method and it is confirmed that the color change model used in the proposed is valid to estimate the color changes occurred in shadow regions. In Fig. 4 (b), the shadow region is much darker than background and model errors in some shadow pixels are large. This means that if shadows become quite dark, it doesn't match the proposed color change model because the proposed model assumes that ambient illuminance doesn't attenuate even in shadow regions. So if not only direct illuminant but ambient illuminant is considerably occluded by the object, the colors in the shadow region tend not to follow the proposed color change model. In spite of this feature, the model errors are small compared with the chromaticity based method. If this feature will be solved in the future work, the performance of estimating the color changes in shadow regions can be much more improved.

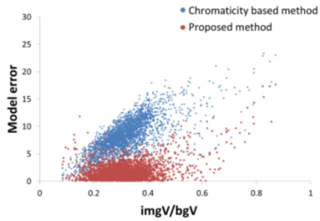
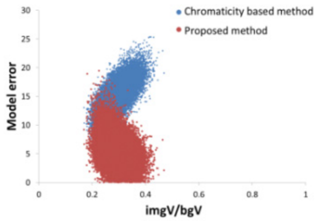
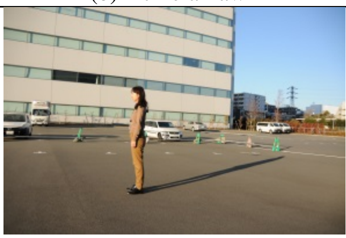
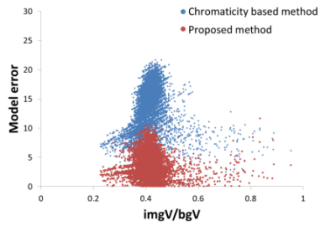
Input image	The model errors for shadow pixels
 (a)Lawn	
 (b)Artificial lawn	
 (c)Asphalt	

Fig. 4. Model errors in shadow pixels from captured images

4.2 Evaluation of Foreground Region Detection Performance

Other experiments were conducted to evaluate the performance of detecting foreground region by the proposed model and compare with the conventional methods, the chromaticity based method [3] and two texture based methods [7][11]. In the conventional based methods, at first it needs to extract the region which includes both foreground and shadow regions. Then extracted regions were analyzed and distinguished to foreground and shadow regions. As mentioned in the survey research by Sanin et al. [12], it is difficult to make masks manually for evaluation which include foreground and shadow regions because the boundary of shadows is ambiguous. So we first applied the background subtraction technique by using a Gaussian mixture model (GMM) of OpenCV 2.0 to extract foreground and shadow regions as Sanin et al. have done in their survey. To evaluate the chromaticity based method and the texture based method, we used the open source codes by them[1].

To evaluate impartially, we should use some classical database such as Hallway, Highway series, Campus, Room CAVIAR, etc. But our model needs latitude, longitude and time corresponding to the captured images to use solar spectral model. Also our model can only apply to the outdoor environment. From above reasons, we cannot use the well-used database and alternatively we used the images captured by ourselves which latitude, longitude and time is known.

Fig. 5 and Fig. 6 show examples of results of foreground region detection. In Fig 5 and Fig 6, (a)input captured image, (b)input background image, (c)ground truth of foreground region, (d)result image by chromaticity based method [3], (e)result image by the small region texture based method [7], (f)result image by large region texture based method [11], (g)estimated background image by the proposed method and (h)result image by proposed method are shown.

From these results it is confirmed that the proposed method detected foreground regions successfully compared with the chromaticity based method [3] and the texture based methods [7][11]. The chromaticity based method and the texture based methods detected some shadow pixels as foreground falsely, also some foreground pixels were not detected successfully. Fig. 5 demonstrated that shadows on the flat ground like asphalt can be easily estimated by both the conventional and the proposed methods. But it is shown by Fig. 6 shadows on complicated textured ground like lawns are difficult to discriminate by the conventional methods. The proposed method handled both types of ground and extracted only foreground regions robustly.

Another evaluation was conducted to confirm the numerical improvement of the foreground region detection. In the evaluation images of fifteen scenes whose date, time, place and illuminant condition are different. Table 1 shows the average precision, recall and F-measure of the proposed method, the chromaticity based method and the texture based methods, compared with the ground truth of foreground regions. From this result, it is demonstrated that F-measure of the proposed method is the highest in four methods and confirmed that the proposed method achieved the highest foreground detection performance.

The precision of the proposed method is highest and it means the proposed method successfully suppressed cast shadows and excluded them from foreground regions. But the recall of the proposed method was lowest in four methods and the conventional methods achieved high recall. This is because the conventional methods

1 http://arma.sourceforge.net/shadows/

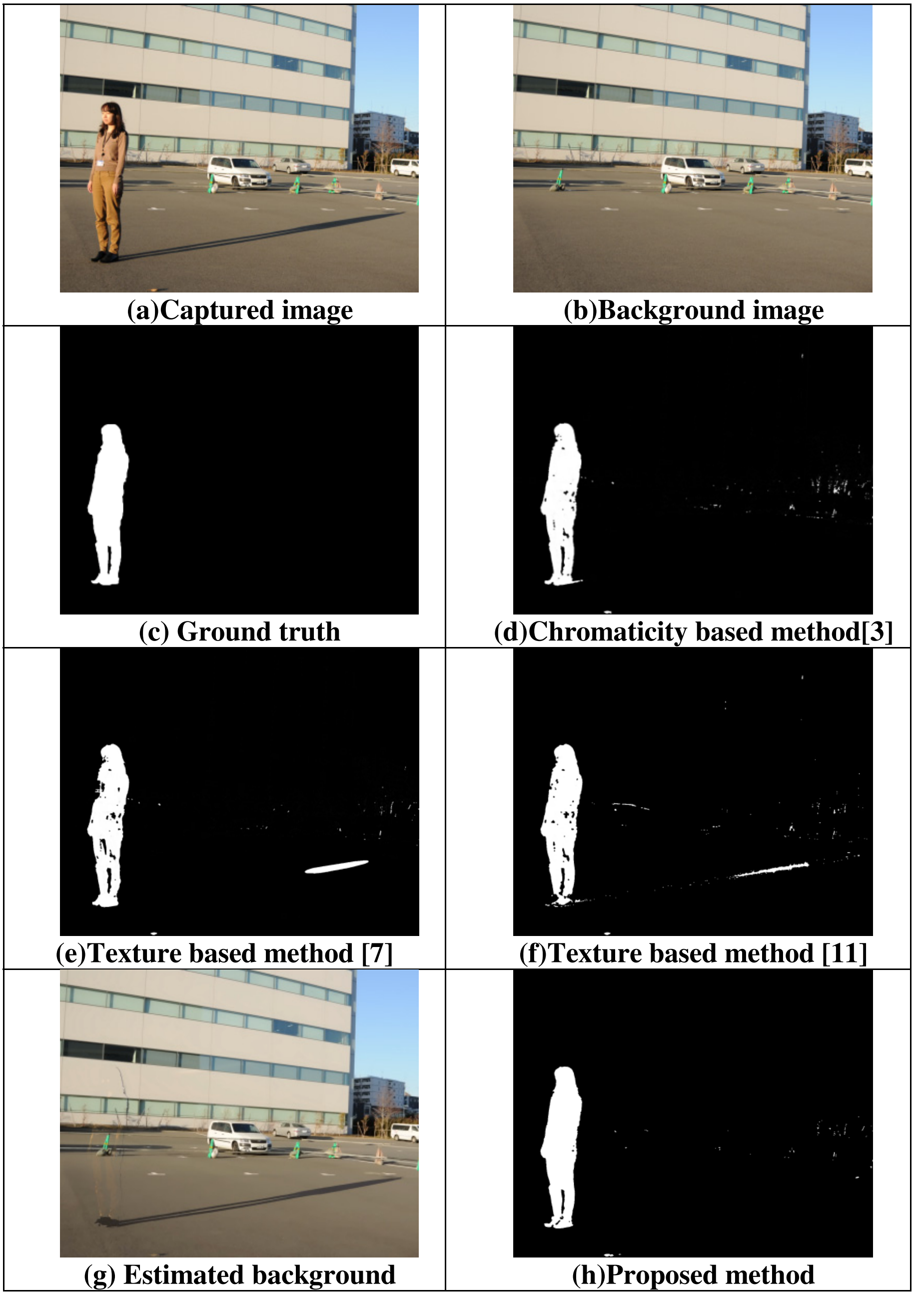


Fig. 5. Results of detected foreground regions

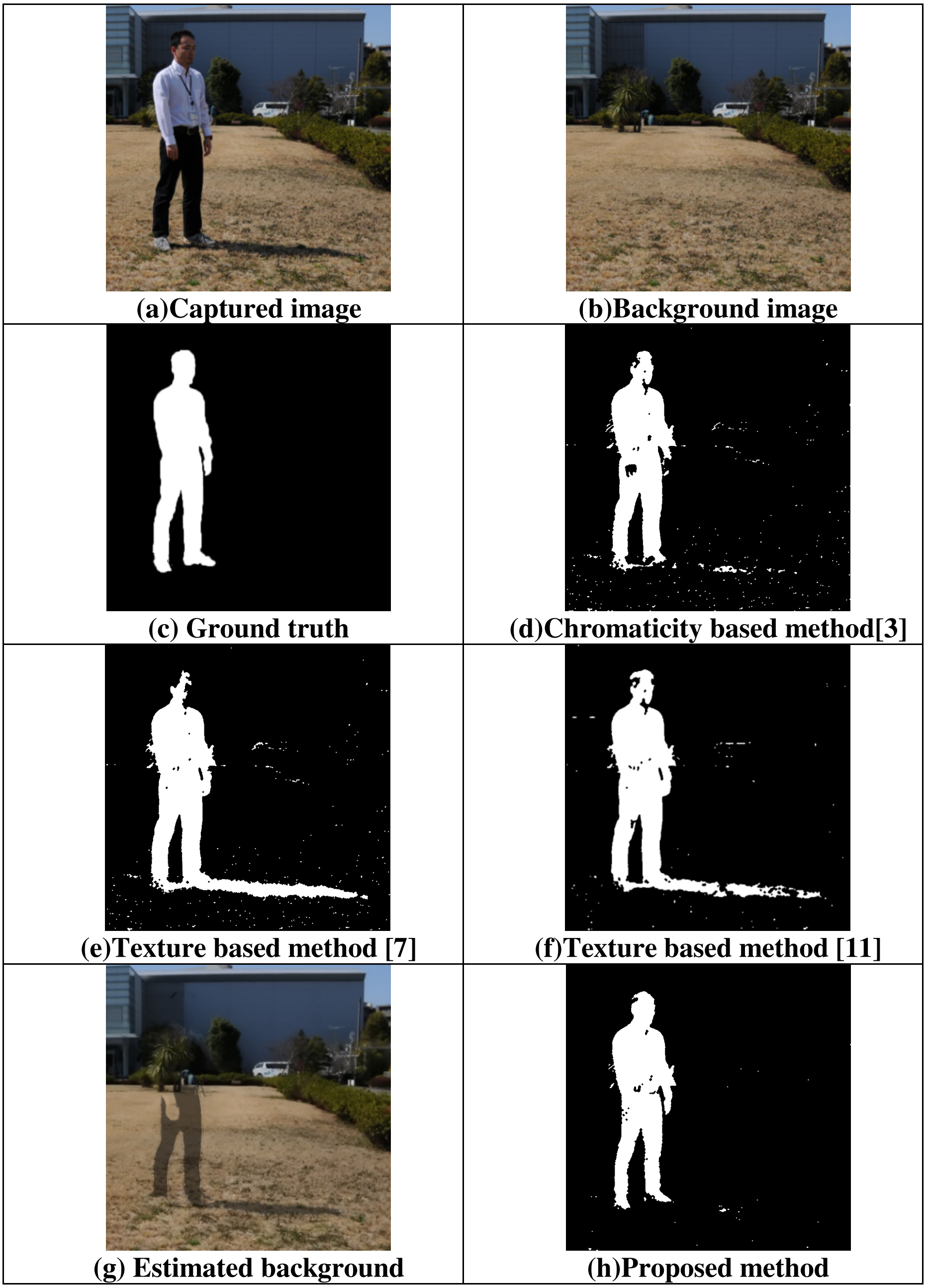


Fig. 6. Results of detected foreground regions

Table 1. Evaluation results of foreground detection

	Precision	Recall	F-measure
Chromaticity based method[3]	0.4386	0.7625	0.5370
Texture based method [7]	0.3907	0.8874	0.5183
Texture based method [11]	0.5044	0.8691	0.6242
Proposed method	0.8100	0.6859	0.6863

extracted not only foreground but also background components such as shadows caused by illuminant changes. So the extracted regions were much larger than ground truth foreground. We tested many parameters to improve this phenomenon but it didn't work well. The extracted regions included ground truth foreground so the recall became high, but the precision become low. Conversely the proposed method could exclude extra background components from extracted foreground regions but it became difficult to include ground truth foreground in extracted region perfectly, so the recall became low. There is still room for discuss to decide which to emphasize precision or recall, but it can be said that the proposed method has the highest performance in foreground detection because it achieved the highest F-measure.

5 Conclusion

We proposed the foreground detection method which estimates the color changes in shadow regions using solar spectral model. The proposed method detects foreground region robustly against cast shadows in outdoor daytime environment by estimating the color changes in background using the direct and ambient spectral which fluctuate variously. Evaluation result demonstrated that the proposed color change model in shadow region is accurate compared with conventional only chromaticity based model. Also from accuracy evaluation, it was confirmed that the proposed method improved foreground detection performance compared with the conventional methods.

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