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Background Modeling Method based on 3D Shape Reconstruction Technology

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Abstract

In this research, we present a novel dynamic background modeling method based on reconstructed 3D shapes, which can solve background modeling problems of multi-camera in real-time. While 3D shape reconstruction is a popular technology widely used for detecting, tracking or identifying various objects, little effort has been made in applying this useful method to background subtraction. In this work we propose an approach to using 3D shape reconstruction technology to develop a novel decision making mechanism for background image updating. This 3D shape reconstruction based background subtraction method is adaptive to changes in illumination, capable of handling sudden illumination changes as well as complex dynamic scenes efficiently.

Keywords: *background subtraction, intruder detection, 3D shape reconstruction, multi-camera*

1. Introduction

Moving objects detection and segmentation from a video sequence is one of the most essential tasks in object tracking and video surveillance [1-8], [13-15]. A common approach is to use background subtraction, which first builds a statistical background model, then labels the pixels that are unlikely to be generated by this model as foreground. Although a large number of background subtraction methods have been reported in the literature over the past few decades, challenge remains when the scenes to be modeled contain dynamic backgrounds such as waving tree, illumination changes, etc.

In [4], the Gaussian-based methods have an assumption that the pixel color values over time could be modeled by one or multiple Gaussian distributions. In [5], the Local Dependency Histogram (LDH) was proposed, which is computed over the region centered on a pixel, LDH effectively extracts the spatial dependency statistics of the center pixel which contain substantial evidence for labeling the pixel in dynamic scenes. A technique used widely for background subtraction is the adaptive Gaussian mixtures method of [7]. These methods classify each pixel independently, and morphology is used later to create homogenous regions in the segmented image. [8-9] present the Bayesian approach which is an alternative segmentation schema. The background, shadow, and foreground classes are considered to be stochastic processes which generate the observed pixel values according to locally specified distributions. These methods can adapt to changes in illumination slowly, but performs poorly in complex dynamic scenes, and also performs poorly to handle sudden illumination changes. Their performance will notably deteriorate in the presence of dynamic backgrounds such as waving tree, illumination changes, etc.

It is noted that the 3D shape reconstruction technology has been widely used for detecting, tracking or identifying objects successfully, however, to our best knowledge, there has been no public report of using 3D shape reconstruction technology for background subtraction. In this work, we propose a method to build a decision-making unit that is able to judge which part of the background image should be updated immediately and which part of the background image should remain unchanged based on the 3D shape reconstruction technology. It turns out that the proposed background subtraction method is able to adapt to changes in illumination, handle sudden illumination changes, and cope with complex dynamic scenes efficiently.

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2. Background subtraction based on 3D shape reconstruction

The 3D shapes are reconstructed using shape from silhouette (SFS) technique momentarily which is introduced in [10-12]. A 2D example of the visual cone is illustrated in Figure 1. Figure 1 shows different viewpoints C1; C2, which all have a different view at the intruder I, and silhouettes S1; S2, which are gotten using conventional background subtraction. The intersection of the projected silhouettes form is H, H is the visual hull.

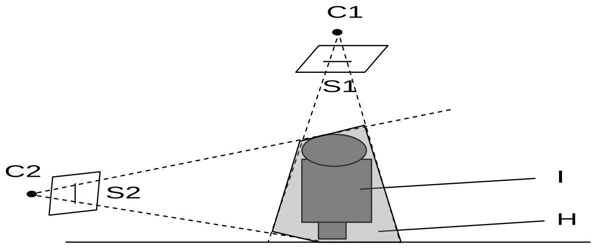

Figure 1. 3D Reconstruction using Shape from Silhouette Method

The key steps proposed in this work are described in what follows. The performance of background subtraction depends mainly on the modeled background images. The adaptive background images are updated timely when the dynamic changes occur in background, and the regions of intruders entering the surveillance area are held unchanged. The adaptive algorithms for background image processing are:

$$
\begin{aligned}
&if \quad (x,y) \in JudgeArea \,\&\, (x,y) \in I_k \\
&\quad B_k(x,y) = B_{k-1}(x,y) \\
&else\ if \quad (x,y) \in JudgeArea \,\&\, (x,y) \in \overline{I}_k \\
&\quad\quad B_k(x,y) = F_k(x,y)
\end{aligned}
$$

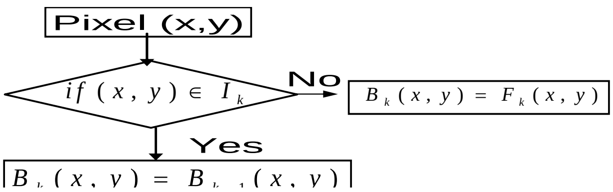

Figure 2. The Flow of Judging the Intruder Segment

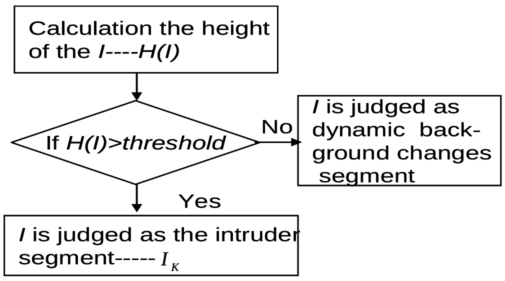

Figure 3. The Flow of Updating the Background Images

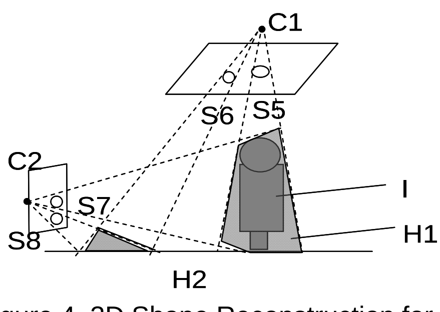

Figure 4. 3D Shape Reconstruction for the Intruder and the Shadow

Here, Judge Area is the common field of view for two cameras, k is the frame number, B is the background image, I is the intruder regions, F is the foreground image.

Figure 2 illustrated the flow of judging the intruder segment, the threshold is chose based on the experience. Figure 3 illustrated the flow of updating the background images. To illustrate this method, consider 3D shapes reconstruction using SFS technique as depicted in Figure 4. I is an intruder entering the surveillance area, the silhouettes in different viewpoints C1, C2 are S5, S7, the reconstructed 3D shape of the intruder I is H1. Because the height of H1 is higher than threshold, the silhouettes S5, S7 are judged as the silhouettes of intruders. In the other hand, H2 is the reconstructed 3D shape of the shadow or illumination changes appearing on the ground, the height of H2 are lower than threshold, then the silhouettes S6, S8 are judged as the dynamic background changes. We separate the background image into following segments: 1), the segments containing the dynamic background changes (such as S6, S8); 2), the segments haven't any changes with existing background image; 3), the segments containing intruders (such as S5, S7). The background images are modeled based on the following rules: The segments containing the dynamic background changes should be updated immediately, and the segments containing intruders shouldn't be update. The areas which are not belonging to the JudgeArea are updated using the conventional method such as Gaussian-based method.

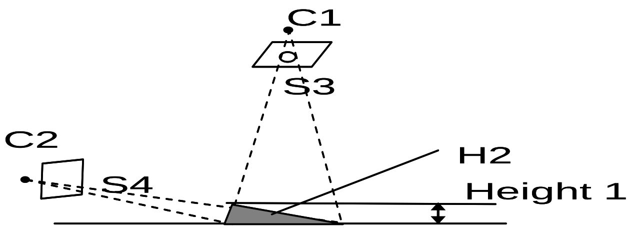

Figure 5. Selecting the Threshold

The threshold is dynamic in our research and selected using the method illustrated in Figure 5. In order to select the threshold for silhouette S3, we assume silhouette S3 is the projection of shadow appearing on the ground in the real world, ignoring the projection on camera C2, 3D shape H2 can be reconstructed. The height of H2 (height1) can be selected as the threshold.

3. Experiment

(a) The background Image (waving tree) (b) The input image (c) The modeled background image

Figure 6. The Examples of the Experiment Results

The test images were manually captured. We selected video sequences of scenes for testing, and a total of 300 images were used for this experiment. These include 220 images of indoor scenes, 80 images of outdoor scenes, all the test images include the intruder or the dynamic background changes simultaneously. There are two types of dynamic background changes in the test images, i.e., sudden illumination changes (Figure 7) and waving tree (Figure 6). The examples of the test images and the result images are illustrated in Figure 6 and Figure 7. We compared with the Gaussian-based methods to demonstrate the efficiency of our proposed method. In this experiment, we define the case that the intruder regions are embedded in the background image mistakenly as false updating, and the case that the dynamic background changes are not embedded in the background timely as miss updating.

Experiment result shows that with the proposed method the false updating rate is 0% and the miss updating rate is 0.67% (2 miss updating images out of 300 images), the reason for the miss updating is that both the labels of dynamic background changes and the labels of intruder are conjoint.

We define the case that the intruder regions are embedded in the background image mistakenly as false updating, and define the case that the dynamic background changes aren't embedded in the background timely as miss updating. Experiment result shows using proposed method, the false updating rate is 0% and the miss updating rate is 0.67% (2 miss updating images), the reason of the miss updating is the labels of dynamic background changes and the labels of intruder are conjoint. For example, as shown in Figure 7(a), since the labels of dynamic background changes and the labels of intruder are conjoint, 3D shape reconstructed contain the part of sudden illumination changes and the part of intruder, the result of the modeled background image is illustrated in Figure 7(c), the region of sudden illumination changes is not embedded in the background timely.

(a) The background Image (sudden illumination changes) (b) The input image (c) The modeled background image

Figure 7. The Examples of the Experiment Results (miss updating)

In order to validate the efficiency of proposed method, we compared the experiment using Gaussian-based methods introduced in [7] with our method. Using Gaussian-based methods, the false updating rate is 5% (15 false images out of 300 images) and the miss updating rate is 3.3 % (10 miss updating images). As shown from the experimental results, the efficiency of proposed method is better than the conventional method observably, it is because the propose method can handle the dynamic background changes such as sudden illumination changes timely and correctly.

4. Conclusion

In this work we presented a novel dynamic background subtraction method, in which the 3D shapes are reconstructed using shapes from silhouette technique momentarily. The experimental results demonstrated the efficiency of the proposed algorithms.

Ackbowlegment

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