



PEOPLE DETECTION FOR VISUAL SURVEILLANCE

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ABSTRACT

Visual surveillance is a very active research area in computer vision thanks to the rapidly increasing number of surveillance cameras that leads to a strong demand for automatic processing methods for their output. The scientific challenge is to devise and implement automatic systems able to detect and track moving objects, and interpret their activities and behaviors. The need is strongly felt world-wide, not only by private companies, but also by governments and public institutions, with the aim of increasing people safety and services efficiency. Our focus here is on the detection phase of a general visual surveillance system using static cameras.

Detection of moving objects in video streams is the first relevant step of information extraction in many computer vision applications. We propose an approach based on self organization through artificial neural networks, widely applied in human image processing systems and more generally in cognitive science. The proposed approach can handle scenes containing moving backgrounds, gradual illumination variations and camouflage, has no bootstrapping limitations, can include into the background model shadows cast by moving objects, and achieves robust detection for different types of videos taken with stationary cameras.

1.INTRODUCTION

Human body motion analysis is an important technology which modern bio-mechanics combines with computer vision and has been widely used in intelligent control, human computer interaction, motion analysis and virtual reality and other fields. In which the moving human body detection is the most important part of the human body motion analysis, the purpose is to detect the moving human body from the background image in video sequences, and for the follow-up treatment such as the target classification, the human body tracking and behavior understanding, its effective detection plays a very important role. Currently, methods used in moving object detection are mainly the frame subtraction method, the background subtraction method and the optical flow method. Frame subtraction method is through the difference between two consecutive images to determine the presence of moving objects. Its calculation is simple and easy to implement. For a variety of dynamic environments, it has strong adaptability, but it is generally difficult to obtain a complete outline of moving object, liable to appear the empty phenomenon, as a result the detection of moving object is not accurate. Optical flow method is to calculate the image optical flow field, and do clustering processing according to the optical flow distribution characteristics of Image. This method can get the complete movement information and detect the moving object.

II. BACKGROUND SUBTRACTION METHOD

The background subtraction method is the common method of motion detection. It is a technology that uses the difference of the current image and the background image to detect the motion region[9], and it is generally able to provide data included object information. The key of this method lies in the initialization and update of the background image. The effectiveness of both will affect the accuracy of test results. Therefore, this paper uses an effective method to initialize the background, and update the background in real time.

A. Background image initialization

There are many ways to obtain the initial background image.



Fig 1) Initialization of background image

For example, with the first frame as the background directly, or the average pixel brightness of the first few frames as the background or using a backgrOlmd image sequences without the prospect of moving objects to estimate the background model parameters and so on.

Among these methods, the time average method is the most commonly used method of the establishment of an initial background.

However, this method cannot deal with the background image (especially the region of frequent movement) which has the shadow problems. While the method of taking the median from continuous

multi-frame can resolve this problem simply and effectively. So the median method is selected in this paper to initialize the background. Expression is as follow

$$B_{init}(x, y) = \underset{k}{\text{median}} f_k(x, y) \quad k = 1, 2, \dots, n \quad (1)$$

Where B_{init} is the initial backgrOlmd, n is the total number of frames selected.

B. Background Update

For the background model can better adapt to light changes, the background needs to be updated in real time, so as to accurately extract the moving object. In this paper, the update algorithm is as follows:

In detection of the moving object, the pixels judged as belonging to the moving object maintain the original background gray values, not be updated. For the pixels which are judged to be the background, we update the background model according to following rules:

$$B_{k+1}(x, y) = \beta B_k(x, y) + (1 - \beta) F_k(x, y) \quad (2)$$

As the camera is fixed, the background model can remain relatively stable in the long period of time. Using this method can effectively avoid the unexpected phenomenon of the background, such as the sudden appearance of something in the background which is not included in the original background. Moreover by the update of pixel gray value of the background, the impact brought by light, weather and other changes in the external environment can be effectively adapted.

III MOVING OBJECT DETECTION

A. Moving Object Extraction

After the background image $B(x, y)$ is obtained, subtract the background image $B(x, y)$ from the current frame $F_k(x, y)$.

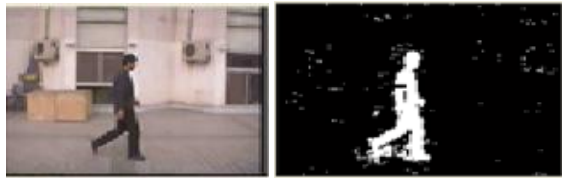


Fig. 2. (a) Typical scene to be processed. (b) Binary foreground image after background subtraction for (a).

If the pixel difference is greater than the set threshold T , then determines that the pixels appear in the moving object, otherwise, as the background pixels. The moving object can be detected after threshold operation. Its expression is as follows:

$$D_k(x, y) = \begin{cases} 1 & |F_k(x, y) - B_{k-1}(x, y)| > T \\ 0 & \text{others} \end{cases} \quad (3)$$

Where $D_k(x, y)$ is the binary image of differential results. T is gray-scale threshold, its size determines the accuracy of object identification. As in the algorithm T is a fixed value, only for an ideal situation, is not suitable for complex environment with lighting changes.

Therefore, this paper proposes the dynamic threshold method, we dynamically changes the threshold value according to the lighting changes of the two images obtained.

C. Extraction of Moving Human Body

After median filtering and morphological operations, some accurate edge regions will be got, but the region belongs to the moving human body could not be determined. Through observation, we can find out that when moving object appears, shadow will appear in some regions of the scene.



Fig 3. Foreground image after foreground mask

The presence of shadow will affect the accurate extraction of the moving object. By analyzing the characteristics of motion detection, we combine the projection operator with the previous methods. Based on the results of the methods above, adopting the method of combining vertical with horizontal projection to detect the height of the motion region. This can eliminate the impact of the shadow to a certain degree. Then we analyze the vertical projection value and set the threshold value (Determined by experience) to remove the pseudo-local maximum value and the pseudo-local minimum value of the vertical projection to determine the number and width of the body in the motion region, we will get the moving human body with precise edge. This article assumes that people in the scene are all in upright-walking state.

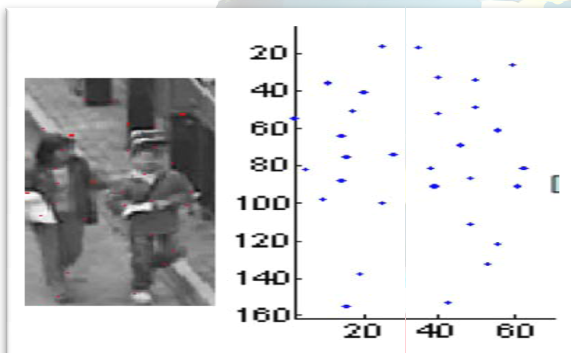
Human body detection is to identify the corresponding part of human from the moving region. But the extracted moving region may correspond to different moving objects, such as pedestrians, vehicles and other such birds, floating clouds, the swaying tree and other moving objects. Hence we use the shape features of motion regions to further determine whether the moving object is a human being. Judging criteria are as follows: (1) The object area is larger than the set threshold (2) The aspect ratio of the object region should conform to the set ratio. If these two conditions are met, the moving object is the moving human body, or is not a human body.

D. Individual Detection

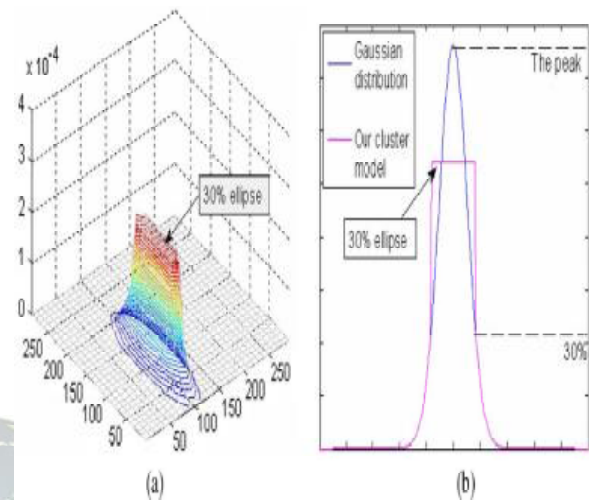
The methods based on foreground pixels can estimate the number of people easily, but they cannot provide any information on the location of each person. Individual detection is important for subsequent video processing. This section introduces a simple method for detecting individuals in such situation. Since the image has a low resolution (a frontal human closest to the camera is only about 15 pixels wide in our test), human detection methods based on edges or gradients in the image will not work effectively. The methods based on segmenting foreground blobs do not require a high resolution.

However, getting an accurate foreground contour for images with stationary people is almost impossible, as shown in Fig. 2. As mentioned in the previous section, a closing operation can extract most areas occupied by human beings from a foreground image. The new image could be used as a rough foreground mask.

To avoid the dependence on accurate foreground extraction, some corner-like feature points will be extracted from the whole image. After being filtered with the foreground mask, most feature points from the background will be filtered out while points from human beings remain. The key step for human detection is to cluster these feature points with some prior knowledge of human size. The details of this method will be introduced in the following sections.



Foreground Mask: The foreground mask is obtained from the foreground pixel image after a closing operation. With an appropriate structuring element, the foreground image after a closing operation can cover almost all the areas occupied by human beings while cutting most of the cluttered background. The size of the structuring element is related to the density of scattered foreground pixels from the stationary people in the image. After filtering with the foreground mask, almost all feature points from the background will be removed. The remaining feature points are mainly from human contours and different clothing. Hence, human detection is formulated as a problem of clustering these feature points.



Postprocessing: After the EM clustering step, some postprocessing operations need to be performed. a) The EM clustering results may contain some redundant ellipses. The feature points falling in these redundant ellipses are also included in other ellipses. It is sufficient evidence from the feature points. In our test, the candidate ellipses are checked one by one and the redundant ellipses removed. b) A very simple occlusion analysis is performed in this step.

In our evaluations, “occlusion” is simply defined as a 30% overlap of two ellipses.

IV. BACKGROUND MODELLING

Although there are many algorithms for background subtraction, they all follow a general pattern of processing which includes pre-processing, background subtraction, post processing.

Pre-processing

Firstly, video frames captured from a camera are input to the background subtractor. Pre-processing stages are used for filtration and to change the raw input video to a processable format.



Background subtraction

The main problem of the background subtraction approach to moving object detection is its extreme sensitivity to dynamic scene changes due to lighting and extraneous events. Although these are usually detected, they leave behind “holes” where the newly exposed background imagery differs from the known background model (ghosts). While the background model eventually adapts to these “holes,” they generate false alarms for a short period of time. Therefore, it is highly desirable to construct an approach to motion detection based on a background model that automatically adapts to changes in a self-organizing manner and without *a priori* knowledge.

We propose to adopt a biologically inspired problem-solving method based on visual attention mechanisms. The aim is to obtain the objects that keep the user attention in accordance with a set of predefined features, including gray level, motion and shape features.

Based on the learnt background model through a map of motion and stationary patterns, our algorithm can detect motion and selectively update the background model. Specifically, a novel neural mapping method is proposed to use a whole trajectory incrementally in time fed as an input to the network. This makes the network structure much simpler and the learning process much more efficient.

Therefore, the network behaves as a competitive neural network that implements a winner take-all function with an associated mechanism, that modifies the local synaptic plasticity of the neurons, allowing learning to be restricted spatially to the local neighbourhood of the most active neurons. For each color pixel, consider a neuronal map consisting of $n \times n$ weight vectors. Each incoming sample is mapped to the weight vector that is closest according to a suitable distance measure, and the weight vectors in its neighbourhood are updated.

Post processing

Background modelling then uses the observed video frame to calculate and update the background model that is representative of the scene without any objects of interest. Foreground detection is where the pixels that show a significant difference to those in the background model are flagged as foreground. Data validation is used to examine the found objects of interest and to eliminate any false matches. A foreground mask can then be output in which pixels are assigned as foreground or background. Christo Ananth et al. [3] proposed a method in which the minimization is performed in a sequential manner by the fusion move algorithm that uses the QPBO min-cut algorithm. Multi-shape GCs are proven to be more beneficial than single-shape GCs. Hence, the segmentation methods are validated by calculating statistical measures. The false positive (FP) is reduced and sensitivity and specificity improved by multiple MTANN.

The foreground detection stage can be described as a binary classification problem whereby each pixel in an image is assigned a label to the class of foreground or background. Formally, for every pixel p in image I , a label p_l is assigned where $I \in \{0, 1\}$ where 0 = background and 1 = foreground. After this mask is obtained background pixels are usually set to white or black to allow focus on the foreground object. Many background subtraction algorithms reduce down to the simple subtraction of the pixel in the expected background image from the pixel in the observed image and any significant change indicates that an object of interest has been identified. One of the most popular decision rules is to threshold this simple subtraction Simple Decision Rules.

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CONCLUSION

The scenario analyzed in this paper is quite common in public areas. Yet, little research has been carried out in such scenes. In this paper, foreground pixels from both moving people and near stationary people have been considered to estimate their number. After a closing operation over foreground pixels, one can observe a linear relationship between the number of people and foreground pixels. The best estimation results, with a 10% average error, were achieved when both foreground pixels and based foreground pixels are learned in a neural network.

The application of methods based on segmenting the foreground has been extended to detection of people who are moving only slightly. This new cluster model has been shown to be more accurate in both counting and detection than the Gaussian model.

In the future, texture inside the foreground region can be used as another input for the neural network. This addition will be an extension of the present paper.

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