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PERSON COUNTING SYSTEM USING EFV SEGMENTATION AND FUZZY LOGIC

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Abstract

The paper presents an efficient and reliable approach to automatic people segmentation, tracking and counting, used in surveillance systems. The initial novel background extraction algorithm uses an improved mode algorithm to obtain the static and novel fuzzy background subtraction approach regions for background subtraction. We also develop a complete framework to evaluate a new edge flow vector based segmentation processes. Tracking segmented people is a dynamic cluster assignment problem between two consecutive frames, and it is solved by a fuzzy-based rule system for tracking and people counting and is applied to people surveillance. Experimental results suggest that the proposed method can achieve good results in both counting accuracy and execution speed.

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Keywords: People counting; People Segmentation; Mode Background extraction; Background Subtraction; People tracking.

1. Introduction

Background subtraction techniques mostly detect motion in many real-time vision surveillance applications. These approaches consider differences between the incoming and background images to detect foreground objects. Background subtraction speed and accuracy depend on the result of the background extraction algorithm. If there is a scene (frame) without any moving object in the image sequences, it can be a background frame a "pure"

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background image. However, in the real world, there is hardly to get a "pure" background image because of non-stationary objects in the background(like waving trees etc.). In such systems, as in many other applications, extracting a pure background image from videos that include moving objects is critical.

Foreground segmentation is the first step in many computer vision applications. The segmentation of foreground regions for human detection is usually obtained by calculating the differences between the current frame and the background image. If the additional accuracy provided by pixel-wise approaches is not warranted[1,2], block-wise.Analysing a video scene is difficult because many persons occlude each other. We must segment occluded persons to count and identify each person in the scene. Most edge detection methods work on the assumption that an edge occurs where there is a discontinuity in the intensity function or a steep intensity gradient in the image. Gradient-based edge-detection methods, including those developed by Sobel, Prewitt and Hildreth, and Canny, are sensitive to variations in image illumination, blurring, and magnification[3]. Important attributes for edge detectors when tracking people include the accuracy of the detected edges, continuation (lack of boundary fragmentation), and the presence of spurious edges.

Object tracking in image processing is usually based on a reference image or properties of the objects[5]. In many vision surveillance applications, moving targets cast shadows that make accurately detecting them a challenge. Moving shadows can cause object merging, object shape distortion, and even object losses (due to a shadow cast over another object). Moving-shadow detection is thus critical for accurate object detection in vision surveillance applications. Rossi and Bozzoli[6] successfully used moving blobs to track and count people crossing the field of view of a vertically mounted camera. In a different approach using blobs, Bregler[7] represented each pixel in each motion image by its optical flow characteristics.

The proposed system contains several steps:

- Background extraction: using an improved mode algorithm to get a pure background.
- Background subtraction: using a fuzzy-based background subtraction algorithm, the foreground is separated from the background and forms a foreground mask.
- Occlusion detection: using morphological analysis, the system detects blobs that are suspected of having more than one in them.
- Segmentation: using an effective segmentation technique based on an edge field computed directly from the images. The flow field can be computed from various image features, including colour, texture and intensity edges. We also propose a new edge function that is more precise than the commonly used gradient magnitude inverse for localising edges, based on the scalar potential of the edge flow field.
- Tracking: we propose a novel human motion detection algorithm that uses a fuzzy rule-based classification scheme on moving blob regions.

The rest of the paper is organised as follows: Section 2 describes related works, and Section 3 describes proposed system models for object tracking. Section 4 shows Experimental Results. Finally, Section 5 gives the conclusion.

2. Related work

Due to its pervasiveness in various contexts, background subtraction has been the focus of much research[8,9,10]. Haritaoglu et al.[4] use a background subtraction model built from order statistics of background values during a training period to implement a statistical colour background algorithm.

Researchers have proposed edge-based foreground segmentations[11] that use colour information or both colour and gradient information[12]. The Wallflower algorithm aims to solve many problems in background maintenance, including varying lighting conditions, by developing a three-level system: pixel-, region- and frame-level. There has been considerable recent work on region-based segmentation: Paragios *et al.* [13] proposed supervised texture segmentation by combining both region- and edge-based terms, and Zhu *et al*[14] designed a multiband image segmentation algorithm by minimising a generalised .Taj *et al.*[15] evaluate a detection and tracking algorithm that uses a statistical background model and graph matching. Brown *et al.*[16] present a novel method to evaluate background subtraction and tracking performance. With the emerging use of fuzzy logic in various applications, fuzzy-based classification schemes [17] have also yielded better accuracy rates than conventional shape- [18] techniques.

3. System Architecture

Fig. 1 gives the block diagram of the proposed system for people segmentation, tracking and counting. The main goal of people group tracking is tracking people in unconstrained and cluttered environments as they form groups at low frame rate, interact and part from the group in presence of occultation. The proposed algorithm contains two steps: foreground segmentation and tracking. At foreground segmentation, to simplify the problem, we assume that the camera is stationary and the background model is static. The first step of the algorithm is background subtraction, which, in our setup, is performed on a block level. For high frame rate sequences, the adjacent frame subtraction method is used, as the motion change between consecutive frames is small. This method eliminates the stationary background, leaving only the desired motion regions.

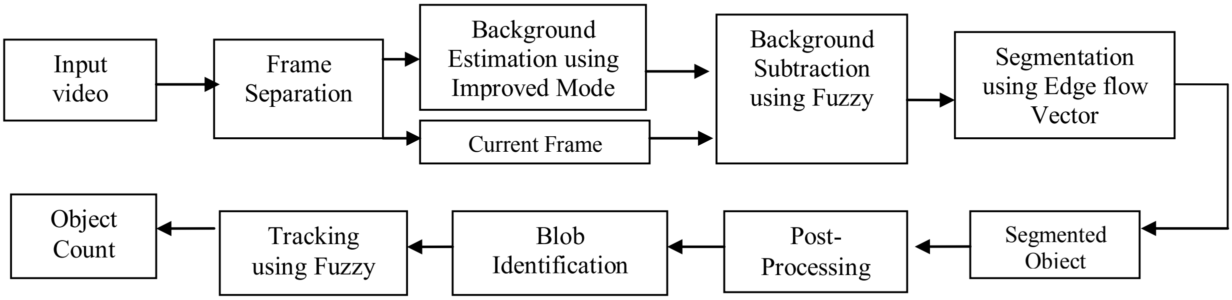


Fig. 1. Proposed method

3.1. Background Estimation

The background estimation must be dynamic, meaning that the background image must be updated. This is important for a good people counting algorithm. For example, if the people counting system is placed in the entrance of one building, some little and slow modifications occur during the day and can affect the people counting algorithm (more particularly, the background difference algorithm). In fact, the sun's light intensity changes throughout the day, or some objects could be removed from or added to the work scene. If the background estimation is never recomputed, the algorithm always detects variations. Before launching the background estimation, the algorithm must be obtain initial 20 frame as background model followed by pixel are update in current image are compare with background model. If changes in current image are less than the threshold, the pixel can be updated in background model or else mark it has foreground. After few seconds background estimation model is invoked. In this method, there is no motion in the field of the video camera during this moment. If it detects no motion, the reference image (background image) is updated; if there is motion, the background image is not updated and tries to be updated in the next background estimation.

We propose a novel background extraction algorithm based on an improved mode algorithm to obtain the static background regions. Employing these approaches seeks to obtain a clean static background reference image and apply it to background subtraction.To eliminate deficiencies of the mode algorithm, this paper improves the mode algorithm after locating its source of inaccuracy. The frame differences method separates pixels into two classifications, unchanging background and moving objects, and calculates the unchanged background pixels using the mode algorithm. This method can eliminate the deficiency in the mode method. The computing formula of the new method is the following:

$$BG(x,y)=mode(B_{t-N}(x,y)*\alpha_{t-N}, B_{t-N+1}(x,y)*\alpha_{t-N+1}, B_{t-N+2}(x,y)*\alpha_{t-N+2},\ldots,B_{t-2}(x,y)*\alpha_{t-2}, B_{t-1}(x,y)*\alpha_{t-1})$$

$$If\ \alpha_n=\begin{cases}1 & if BW_n(x,y)=0\\ 0 & otherwise\end{cases}$$

(1)

Here constant Alpha α can be identify by using binaryzation of an image ($BW_n(x, y)$). To get binary image, First calculate distance between current frame and previous frame that can compare with threshold value. If it is less than mark as background or else mark as moving object.

$$BW_n(x, y) = \begin{cases} 0 \equiv background & if D(x, y) < T \\ 1 \equiv moving\ object & otherwise \end{cases}$$

After binaryzation of image, if the pixel value BW is 0 then alpha value is 1 or otherwise alpha value is 0. Based on this condition values substitute in improved mode algorithms to get better background estimation.

3.2. Background Subtraction

In the proposed adaptive background modelling and classification scheme, we use image data from the past frames to compute the joint image distribution to build a background model. The main contribution of this paper is a methodology to detach moving objects. Detaching objects from the adaptive background is a challenging task because of the lack of automated reasoning about what is or is not a target object, as evidenced in a video sequence.

In this case, we could employ sophisticated object recognition and identification algorithms. However, these algorithms are often computationally intensive and not robust in a dynamic environment. Our scheme is based on a fuzzy logic inference system, which fuses multiple information sources together for decision making. Suppose we are working on frame *n*, and the object in frame *n* – 1 has been correctly extracted. Let the foreground image region in frame *n* be *O n*, which might contain the human body and moving objects. Our fuzzy logic inference system is based on the following observations:

If an image block in *O n belongs* to the object, it should have a high possibility of finding a good match in *O n* – 1. We use the sum of absolute difference (SAD) to measure the matching "goodness".

(1) If many blocks in its neighbourhood have good matches in *O n* – 1, it is highly possible that this block also belongs to the object.
(2) If this block is far from the predicted position of the object centroid, the possibility that this block belongs to the object is low. Based on these observations, we extract the following feature variables from each block in *O n*.
(3) SAD in motion matching. For each block in *O n*, we find its best match in frame *n* – 1.
(4) The SAD between this block and its best match form the first feature variable. The distance between the new block and the predicted object centroid.

According to the above rules, if an object is recognised as foreground, using the fuzzy inference system to detach moving objects erodes the object due to misclassification. We propose binaryzation fuzzy background subtraction after passing morphological operations and neighbourhood information to the image to repair these missing parts. Morphological operations are performed on the motion image.

3.3 Segmentation

People segmentation is a difficult problem in image analysis. The segmentation of people based solely on appearance is difficult because of the variability of their shapes. Image segmentation in general remains an unsolved problem; however, the problem becomes more tractable when we have a sequence of images with moving objects. Moving objects can be separated from the background and each other more easily using their motion information. The main idea presented in this section is an effective segmentation technique based on an edge field computed directly from the images. The flow field can be computed from various image features, including colour, texture and intensity edges. This method first identifies a flow direction at each pixel location that points to the closest boundary. It then detects locations that encounter two opposite directions of the edge flow. Because any image attributes, including colour, texture, or their combination, can be used to compute the edge energy and flow direction, this scheme provides a general framework for integrating different image features for boundary detection. The Edge Flow method utilises a predictive coding model to identify and integrate the direction

of change in image attributes, including colour, texture, and phase discontinuities, at each image location.
At the end, a region merging algorithm merges similar regions based on a measurement that evaluates the region colour and texture feature distances, region sizes, and the percentage of the original boundary between two neighbouring regions. This algorithm sequentially reduces the total number of regions each time by checking whether the user's preferred number has been approached to the best extent.

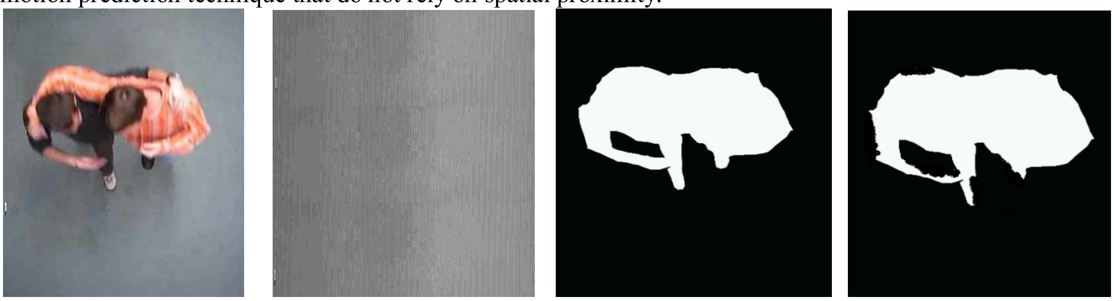
3.4 Tracking

After performing segmentation, another image processing must be launched in the binary image. To track objects, the first step is identifying all objects on the scene and calculating their features. This process is called a Blob Analysis. It consists of analysing the binary image, finding the blobs present and computing statistics for each one. The blob features typically calculated include the area (number of pixels that compose the blob), perimeter, location and blob shape. We present an algorithm that considers occlusions (two objects merge to form a unique blob) and splits (one object splits into several parts).Tracking objects in a video-sequence can be described as follows. If two frames are in succession, it is highly probable that objects identified in the first frame correspond to objects identified in the second frame. Tracking is the identification of this correspondence. Corresponding objects can be more or less translated, and the amount of translation depends on both object speed and frame rate. We can also have objects appearing in only one of the two frames because they enter or leave the scene; furthermore, The challenges associated with people tracking can be caused by people's similarity in shape, colour, size or occlusion by other people or background components.

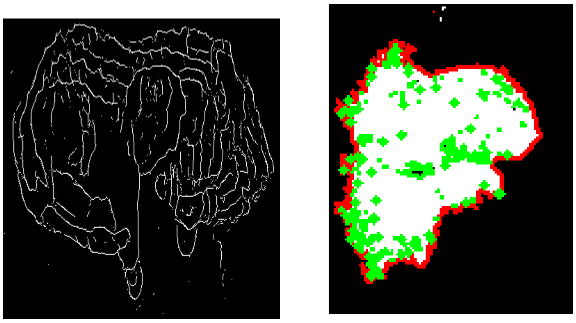
4. Experiment and Analysis

To evaluate the performance of the proposed algorithm, zenithal cameras mounted 3 m above the ground generated indoor colour video sequences. The videos were captured in an office (640 × 480 pixels, 1635 frames, fluorescent light) and in a corridor (320 × 240 pixels, 1500 frames, daylight). We compared the proposed algorithm with the recently published method for people counting by[20]. Table 1 presents the results of this comparison.For validation, we tested the complete system in online human tracking experiments. No dataset is available for testing the complete tracking system because of its dynamic nature. We recorded all experiments to manually extract their ground-truth for performance evaluation. MATLAB was used as the implementation tool.

We implement the fuzzy-based rule for the occulted frame. Based on the accurate human body position prediction, the algorithm uses a large temporal update window size unit in its frames for image blocks inside the bounding box while using a relatively small size for those outside the bounding box. The test cases show the most frequent interaction patterns observed that formerly led to tracking errors. The fuzzy-based system can resolve these cases and continuously track the user's body. We can only compare the performance of the two methods by stating that the improved one gives results, whereas the other did not produce satisfactory results. The second scenario showed an increase in tracking reliability after applying the fuzzy method with a rule set adapted to the specific lighting conditions. The failure rate for critical cases was lower than in conventional tracking. By comparing the two tracking methods, producing numbers that measure the problems we wanted to solve is difficult. The results show that our algorithm can handle and overcome its shortcomings, as it uses a repetitive target detection scheme and motion prediction technique that do not rely on spatial proximity.



(a) (b) (c) (d)



(e) (f)

Fig. 2. Demonstrative results of the processing steps for background estimation, background subtraction, people segmentation, tracking and counting. (a) Original frame (b) Background image generated by our proposed extraction method (c) Ground truth (d) Fuzzy-based background subtraction. (e) Edge flow vector people segmentation (f) Tracked image with occulation

Table 1. Comparison of methods for people counting

	Ground Truth	Barandiaran Et al[19]	Borislav[20]	Proposed
In+Out	11+10	11+9	10+10	11+10

5. Conclusions

This paper presents a novel method for people segmentation, tracking and counting. We proposed a fuzzy-based approach for combining several heuristics in image processing applications. The proposed method uses a fuzzy inference system. The algorithm uses background subtraction and relies solely on the edge flow-based foreground blocks to achieve human segmentation. To handle object extraction challenges in dynamic environments, we fused high-level knowledge and low-level features and developed a fuzzy logic inference system for people tracking. Representative video sequences have been used to evaluate the result. The proposed people counting method is simple yet efficient, and achieves real time performance.

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