ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 5, May 2014

Automatic Multiple Object Tracking System

Vignesh.C[1], Jeyanthi.K[2]

PG scholar, ME-VLSI design, KPR institute of engineering and technology, Coimbatore, India[1]

Assistant professor, Electronics and Communication Engineering, KPR institute of engineering and technology, Coimbatore, India[2]

Abstract: This paper deals with an intelligent image processing method for the video surveillance systems. We propose a technology detecting and tracking multiple moving objects, which can be applied to consumer electronics such as home and business surveillance systems consisting of an internet protocol (IP) camera and a network video recorder (NVR). A real-time surveillance system needs to detect moving objects robustly against noises and environment. So the proposed method uses the red-green-blue (RGB) colour background modelling with a sensitivity parameter to extract moving regions, the morphology to eliminate noises, and the blob-labelling to group moving objects. To track moving objects fast, the proposed method predicts the velocity and the direction of the groups formed by moving objects. Finally, the experiments show that the proposed method has the robustness against the environmental influences and the speed, which are suitable for the real- time surveillance system.

Keywords: multiple moving object tracking, IP camera, NVR, background modelling, morphology, blob-labelling, group tracking.

I. INTRODUCTION

Object tracking is an important problem in computer vision and it has a variety of applications, such as coding, video surveillance, robotics, etc. It has been the focus of considerable research work in the last decades, centered on two mainstream approaches. In the motion-based approach, 2D or 3D motion parameters are estimated for the moving objects in a video sequence. Motion models such as similarity, affine or projective transformations are commonly used. This approach works well when the objects undergo small deformations. However, its efficiency may drastically decrease when there are significant object structure changes, e.g., for non-rigid objects. In the model-based approach, the tracking of the moving objects on a current frame is performed by using the previous frame tracking result as a starting point. The moving objects are then tracked in each video frame by fitting a priori known parameters about the appearance of the objects. Among the model-based tracking methods, active contours have gained popularity in the last few years. With active contours, non-rigid bodies can be tracked thanks to the deformation capacity of the contours. Furthermore, with the advent of the level set formalism, changes in the topology of the objects are automatically handled. Among the tracking methods that used active contours in the past are those that assumed a static background for the video sequence. For example, the authors propose partitioning the difference image between two successive frames of the sequence in order to separate the moving objects from the background. In a fast boundary-based method is proposed for object contour tracking. However, only the edge information is used as a cue for tracking, which makes the method sensitive to noise. Although the method does not require calculation of object motion parameters, it may fail to track objects in the presence of texture, illumination changes and/or occlusions.

The histogram matching efficiency may drastically decrease if the object undergoes intensity variations due to noise or illumination changes. To make active-contour tracking robust to noise. Although this parameterization is realistic for a wide range of objects, it cannot be applied to arbitrary non-rigid objects. In general, the above active-contour methods fall into three main groups. The first of these is related to cluttered backgrounds where the contours may be easily distracted. The second problem is related to texture. Indeed, intensity histograms are generally lacking in texture information, and thus the tracking models may fail if a moving object contains texture or moves over a textured or noisy area. Last, but not least, is the problem of the sensitivity of the tracking models to occlusions: the object may be partially or completely lost if an occlusion occurs. These three problems, which may or may not occur together in a given sequence, can drastically affect the performance of the tracking or even cause it to fail.

The present paper proposes an active-contour method which is capable of tracking moving objects on non-static and cluttered backgrounds and efficiently handling inter-object occlusions. The method combines multiple cues from the image to track the objects. These cues include the colour and texture of the objects, the image edge map and the shape of the objects. The tracking is formulated by minimizing an energy functional which combines region, boundary and shape information about the objects to find their boundaries in all the video frames. The region information is formulated by minimizing the distance between the local and global statistics of the objects and the background. The boundary information is formulated using a multi-band edge detector, which has the role of aligning the object contours with pixels having a high discontinuity in the region information. Finally, the shape information is formulated using the properties of level set contours, and has the role of mitigating distraction of the tracking in cluttered backgrounds and when object occlusions are encountered. In the proposed method, the initialization required is only segmentation of

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 5, May 2014

the objects in the first frame of the sequence. We have successfully applied the method for tracking multiple objects in colour, IR and fused colour-IR video sequences.

II. DETECTING MOVING OBJECTS

This section deals with the procedure of detecting moving objects from the input image. The procedure consists of the extraction stage based on RGB Background Modelling (BM) and morphology, and the grouping stage based on blob-labelling.

A .Feature Tracking and Region Tracking

Potential foreground features are identified based on non-membership of the dominant background motion using RANSAC. After this, they are spatially clustered by performing a Delaunay triangulation on the set of feature points and subsequently isolated from the non-background points as follows: clusters of features are spatially grouped by disconnecting any edges connecting background points with non-background points, then performing a graph-based connected component analysis to identify isolated sub graphs. Alpha hulls of these sub graphs form envelopes surrounding spatially isolated feature sets, which can be used to identify sets of image pixels.

The object shape from an alpha hull can be extracted using gradient-based edge detection techniques. However, gradient information is typically susceptible to noise or even textured image regions. Therefore, we propose two approaches of increasing computational intensity and accuracy that statistically estimate the foreground from the potential mixture of foreground and background enveloped by an alpha hull. The first approach, i.e., referred to here as single background– foreground boosting (SB–FB), estimates the foreground using a single foreground–background model, which assumes that the tracked object possesses different photometric properties from any part of the background immediately surrounding the object. This assumption is sufficient for a sparse-in-time shape estimation technique, where the object being tracked will be different sufficiently (photometrical) from the background.

In general, the extraction of moving regions from sequential images is carried out by using BM. This kind of BM involves the loss of image information compared with the color BM using RGB and hue-saturation-intensity (HSI) colour space models. Fig. 1 depicts the extracted result of moving regions by gray-scale BM, which shows the image information is excessively attenuated.

Fig 1 Extraction of moving region by gray scale

B. Grouping Moving Objects

The tracking performance deteriorates when each moving object extracted by RGB BM and morphology is tracked individually because the extracted moving regions may be hidden by obstacles as shown in the dotted box and be confused with something in similar colours as shown in the solid box. In addition, the individual tracking of neighbouring or overlapping objects requires a lot of computational capacity and may cause misidentification. The group tracking is used to prevent the aforementioned problems of the individual tracking. Before tracking the groups, a grouping scheme is required to classify moving objects into several groups. The 4-directional blob-labelling is employed to group moving objects, which is suitable for the real-time system because it is implemented easily and needs low computational cost.

C.MB-FB

The nonlocal (but object specific) approach described above is sufficient for many situations, particularly when a sparse-in-time shape extraction approach is required. However, some parts of a tracked object will often possess similar photometric properties in comparison with the background that immediately surrounds the object. A more localized approach described here identifies the localized probabilistic differences between the background and the foreground. This is done by estimating the foreground from the foreground–background mixture in local regions surrounding the tracked object. The local and global shape extraction techniques. The local regions are defined here with centers on the boundary of the alpha shape by circular regions with radii given by twice the distance to the closest point on the medial axis of the alpha shape.

D. Shape Memory for Object Tracking

Prior shape information is particularly useful in active-contour models to reduce the likelihood of the active contour deforming to unlikely configurations of shape. However, the prior shape information is difficult to obtain without manually segmenting and preparing suitable templates to be used for statistical modelling.

However, continually including every tracked shape in the shape memory (from the shape-based active contour) is a potentially hazardous process as errors in object shape are likely to propagate into the object tracking process. If this occurs, the shape memory is likely to become dominated by non-relevant shapes, resulting in a degeneration of the shape memory. To prevent this, a more selective shape memory can be designed. Some observations regarding the object tracking process in relation to a more useful shape memory are the following.

1. At the start of object tracking, we have a somewhat (but limited) representative shape memory of the object being tracked.
2. At any time instance, shapes recently included in the shape memory are likely to be representative of the object being tracked recently.
3. Shapes found to be repeatedly similar to the object being tracked may continue to be similar to the shape of the object being tracked.
4. Some observed shapes may never be similar to a future object shape.

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 5, May 2014

5. Computer memory and processing power are finite. These observations enable us to build shape memory online that prioritizes recently observed and recently similar object shapes.

Therefore, the definition of the shape memory can be extended to include variables for each object shape. These variables are which are the time when it was generated, the time when it was last used, and a count of the number of times an object shape has been recalled for use in the tracking framework, respectively. This last discrete frequency variable is incremented if the currently tracked object shape is similar to a past observed shape.

III. RESULTS AND DISCUSSION

The proposed detecting-tracking method is implemented as shown in Fig. The 33Mbit IP camera provides the input image with 704*x* 480 pixels. The surveillance image is transmitted through Internet, and the consumer PC with 2.66GHz CPU and 4GB RAM is used for the image signal processing and the proposed algorithm.

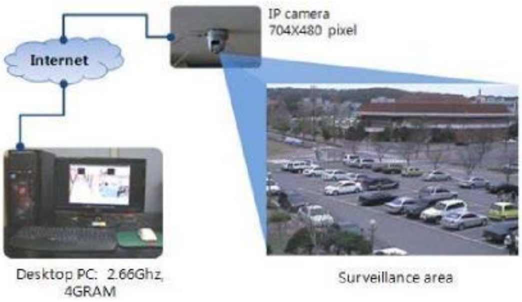
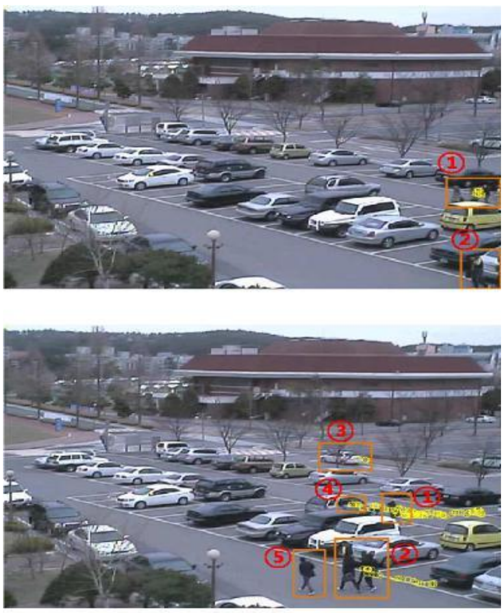


Fig 2 Experimental setup

A. System Implementation

The proposed algorithm consists of two parts of detecting the moving objects and tracking them. The detecting stage is performed through the extraction of moving objects by RGB BM, the elimination of noises by morphology, and grouping the objects by blob-labelling as shown in the left box of Fig



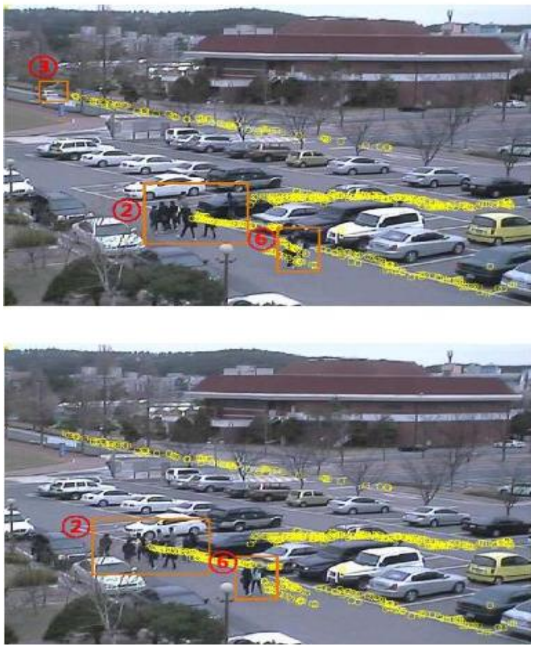


Fig 3 Resulting image of the proposed method

And the tracking stage is activated when a moving object is detected. As shown in the right box of Fig, the tracking stage uses the geometric information of groups such as the previous position *IG*, the variation *IGD*, the predicted position *PG*, and the current position *CG*. In sequential frames, the groups at the shortest Euclidean distance are recognized as the same ones. Finally, newly appearing and disappearing groups are identified by comparing the number of groups in each frame.

REFERENCES

[1] Bouaynaya.N and Schonfeld.D, “A complete system for head tracking using motion-based particle filter and randomly perturbed active contour,” in Proc. SPIE—IVCP, San Jose, CA, Mar. 2005, vol. 5685, pp. 864–873.

[2] Chiverton.J, Mirmehdi.M, and Xie.X, “On-line learning of shape information for object segmentation and tracking,” in Proc. Brit. Mach. Vis. Conf., 2009, pp. 1–11.

[3] Cremers.D, “Dynamical statistical shape priors for level set based tracking,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 8, pp. 1262–1273, Aug. 2006.

[4] Dambreville.S, Rathi.Y, and Tannenbaum.A, “A framework for image segmentation using shape models and kernel space shape priors,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 30, no. 8, pp. 1385–1399, Aug. 2008.

[5] DeLaTorre.F and Black.M, “A framework for robust subspace learning,” Int. J. Comput. Vis., vol. 54, no. 1–3, pp. 117–142, Aug./Sep. 2003.

[6] Fussenegger.M, Roth.P, Bischof.H, Deriche.R, and Pinz.A, “A level set framework using a new incremental, robust active shape model for object segmentation and tracking,” Image Vis. Comput., vol. 27, no. 8, pp. 1157–1168, Jul. 2009.

[7] Gai.J and Stevenson.R, “Studentized dynamical system for robust object tracking,” IEEE Trans. Image Process., vol. 20, no. 1, pp. 186–199, Jan. 2011.

[8] Nummiaro.K, Koller-Meier.E, and Gool.L, “Object tracking with an adaptive color-based particle filter,” in Proc. 24th DAGMSymp. Pattern Recognit., 2002, pp. 353–360.

[9] Pan.P and Schonfeld.D, “Visual tracking using high-order particle filtering,” IEEE Signal Process. Lett., vol. 18, no. 1, pp. 51–54, Jan. 2011.

[10] Ross.D, Lim.J, Lin.R, and Yang.M, “Incremental learning for robust visual tracking,” Int. J. Comp. Vis., vol. 77, no. 1–3, pp. 125–141, May 2008.

ISSN (Online) 2321 – 2004
ISSN (Print) 2321 – 5526

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN ELECTRICAL, ELECTRONICS, INSTRUMENTATION AND CONTROL ENGINEERING
Vol. 2, Issue 5, May 2014

[11] Skoˇcaj.D and Leonardis.A, "Weighted and robust incremental method for subspace learning," in Proc. IEEE Int. Conf. Comput. Vis., 2003, vol. 2, pp. 1494–1501.
[12] Smith.S and Brady.J, "ASSET-2: Real-time motion segmentation and shape tracking," IEEE Trans. Pattern Anal. Mach. Intell., vol. 17, no. 8, pp. 814–820, Aug. 1995.
[13] Tu.J, Tao.H, and Huang.T, "Online updating appearance generative mixture model for meanshift tracking," Mach. Vis. Appl., vol. 20, no. 3, pp. 163–173, Feb. 2009.
[14] Yezzi.A and Soatto.S, "Deformotion: Deforming motion, shape average and the joint registration and approximation of structures in images," Int. J. Comput. Vis., vol. 53, no. 2, pp. 153–167, 2003.
[15] Yilmaz.A, Li.X, and Shah.M, "Contour-based object tracking with occlusion handling in video acquired using mobile cameras," IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 11, pp. 1531,2004.

BIOGRAPHY

Jeyanthi.k is a Assistant Professor of the Department of Electronics and Communication Engineering, KPR Institute of Engineering and Technology, Coimbatore, 641 407 .She received Bachelor's degree in Electronics and Communication Engineering from Mahendra Engineering College in 2004 and Master's degree in Communication Systems from Mahendra Engineering College in 2010. She is a very interested in image processing & soft computing and has worked in this field more than 9 years. She has published more than 5 papers in International Journals & Presented 12 Papers in International/National Conferences. Her recent research interests include: ultrasonic diagnosis and intervene treatment for Early Detection of Breast Cancer.