Demo: Video-Surveillance application with Self-Organizing Maps

Mohamed Dahmane and Jean Meunier
DIRO, Université de Montréal, CP 6128, Succursale Centre-Ville,
2920 Chemin de la tour, Montréal, Québec, Canada, H3C 3J7
{dahmanem,meunier}@iro.umontreal.ca

Abstract - **In this demo, we present an approach for video surveillance detection of abnormal events based on target trajectory analysis. The methodology follows a typical modular form : Detection→Tracking→Recognition. The detection step is based on the color constancy principle and uses an adaptive background subtraction technique with a shadow elimination model. The target tracking involves a direct and inverse matrix matching process. In the recognition stage we consider local motion properties (flow vectors), and more global ones expressed by elliptic Fourier descriptors. From these temporal trajectory characterizations, two Kohonen maps allow to distinguish normal behavior from abnormal or suspicious ones. The classification results show a 94.6 % correct recognition rate with video sequences taken by a low cost webcam. The system runs at a $12Hz$ absolute minimum video acquisition frequency, providing essentially real-time analysis.**

Keywords: Video Surveillance, Motion Detection, Space-Time Trajectory, Elliptic Fourier Descriptors, Self-Organizing Map.

1 Introduction

Automated video surveillance is important in : crime prevention, cecurity, patient monitoring etc.
Such applications need a robust model with a capacity to work in an autonomous way. The goal is to detect unusual situations while minimizing false alarm. In what follows, we present the steps involved in the process : (**a**) moving object (MVO) detection, (**b**) tracking and (**c**) normal/abnormal event recognition.

2 Moving object detection

Detection of MVO is a critical part, when the segmentation process is severely altered by : changes due to the light fluctuations and shadows delimitation. To mitigate these inconveniences we propose a 3-stages background subtraction algorithm :

Background model : The principle of the detection algorithm is inspired by a nonparametric statistical technique [5]. Two informational criteria are used *Brightness distortion* and *Chromatic distortion*

Background subtraction : The potential foreground candidate pixels are those which intensity differences are above a maximum inter-frame absolute difference. Foreground pixels with a reasonable darkening level and a weak chromatic distortion, below a certain threshold, are considered as shadow.

Background maintenance : To keep the system functional as long as possible in the case of dynamic scenes, a periodic maintenance of the background image is computed.

3 Tracking

The tracking algorithm which is based on a direct and inverse matrix matching procedure [3], supervises the temporal evolution of bouding boxes such as *Entering*, *leaving*, *blob correspondence* and special events like *merging*, *splitting* which need additional information (colour distribution). After a splitting event, a pair of blobs maximizing the similarity criteria are considered as corresponding to the same person.

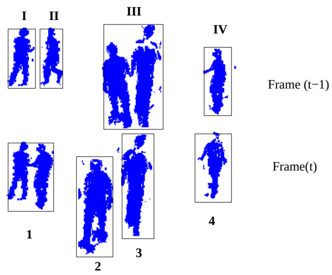


Figure 1: temporal evolution of Bouding boxes.

4 Trajectory monitoring

The information recorded during tracking is a set of centroid points allowing to define each object trajectory locally and globally [1].

Local features : Smoothed flow vector $SF = [s(x), s(y), s(dx), s(dy)]$ where s is a smoothing temporal filter, x, y, dx and dy are positions and displacements of the target.

Global aspect : For a P points trajectory a numerical encoding is performed with the three first elliptic Fourier descriptors harmonics (EFD) [4].

Trajectory monitoring which uses two Kohonen topological maps, is based on the hypothesis that situations at risk imply a deviation from a set of usual behaviours:

Training phase : Two SOMs are used to map respectively local properties (SF) and the global properties (EFD)

Operating phase (surveillance) : If the distance between the current characteristic vector and the nearest winning neuron exceeds a threshold then the vector is said to be not recognized (*alarm*).

5 Experimental results

For evaluating the system, video sequences with a 320×240 pixels resolution were taken, using a QuickCam-Pro 4000 webcam installed on the first floor of the André-Aisenstadt building of the University of Montreal in such a way as to overlook a part of the ground floor hall. All the programs were compiled using Visual Studio C++ 6.0. The acquisition, compression and streaming are realized by using the Logitech SDK [2].
The training data consists of 30 normal trajectories containing 1757 points generated at $2Hz$. The testing set includes 18 usual and 19 unusual trajectories. The recognition unit uses two Kohonen maps:

SOM	dim.	inputs
Local context	30x30	$SF{=}[s(x),s(y),s(\dot{x}),s(\dot{y})]$
Global context	25x25	$[(a_n,b_n,c_n,d_n)_{n=1\ldots3}]$

Table 1: Parameters of both SOMs.

The obtained results are summarized in the following table:

	Classification result	
Sequences	**Normal**	**Abnormal**
Normal	17	1
Abnormal	1	18

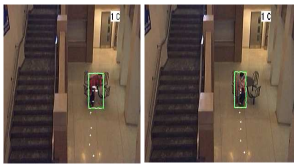
Table 2: Confusion Matrix.

Normal scenarios correctly recognized : The percentage of well classified trajectories (Figure 4) (94.6%) conveys a rather good description quality of the "normal" scenario set, with regard to the limited number of training prototypes (30).

False detection : The false detections are generally due to the sensibility of the EFD features to periodic movements (blobs too close together and intermittent blobs merges and splitting).

Unusual scenarios classified as normal : The false positive (5.3%) detections are due to finer movements not well described by our method (Figure 2).

Atypical behavior correctly recognized : Except for the previous justified cases, all other trajectories were correctly recognized (Figure 5).



(a) Abnormal (b) Normal

Figure 2: Case of omission requiring a higher resolution or a more realistic simulation. The bounding box stays green.

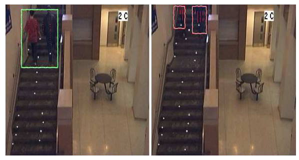
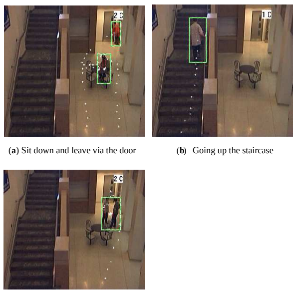
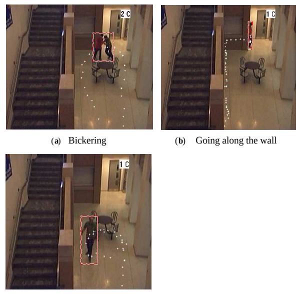


Figure 3: Case of a sequence presenting false alarms. The bounding boxes sometimes switch to red due to abnormal periodic motions.



(a) Sit down and leave via the door (b) Going up the staircase (c) Standing still and discussing

Figure 4: Usual scenarios correctly recognized. The bounding boxes remain green (normal).



(a) Bickering (b) Going along the wall (c) Turn in round

Figure 5: Examples of atypical behavior correctly detected. The bounding box turns red.

References

[1] Dahmane M. and Meunier J. Real-Time Video Surveillance with Self-Organizing Maps. *CRV*, pages 136–143, 2005.

[2] Downloadable at: . `http://www.logitech.com/pub/developer/quickcam/qcsdk.exe`.

[3] Fuentes L.M. and Velastin S.A. People Tracking in Surveillance Applications. *PETS*, 2001.

[4] Kuhl F.P. and Giardina C.R. Elliptic Fourier Features of a Closed Contour. *CGIP*, 18:236–258, 1982.

[5] Prati A. & al. Detecting moving shadows: algorithms and evaluation. *IEEE Tran. on PAMI*, 25(7):918 – 923, 2003.