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Visual Analysis and Recognition of Crowd Behavior by Principal Component Analysis

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Abstract — The analysis of the human behavior from video is a wide field of the vision by computer. In this work, we are presenting mainly a new approach and method of detects behavior or abnormal events continuous of crowd in the case of the dangerous situations. These scenes are characterized by the presence of a great number of people in the camera's field of vision. A major problem is the development of an autonomous approach for the management of a great number of anomalies which is almost impossible to carry out by operators. We present in this paper an approach for the anomalies detection, the visual sequences of the video are detected like behavior normal or abnormal based on the measurement and the extraction of the points by the optical flow, then calculations of the distance between the matrices of covariance of the distributions of the vectors of movement calculated on the consecutive reinforcements.

Keywords — Visual analysis, crowd behavior, matrices of covariance, intelligent video surveillance, anomaly.

1. INTRODUCTION

There has been recently an interest within computer vision in the analysis of densely crowded environments. Problems such as segmenting, estimating, and determining the goal of individual's crowd components [1-5], have all been subjects of research. This field of research returns of the video surveillance intelligences, and visual crowd behavior analysis. In many of these, the goal is not so much to analyze normal crowd behavior, but to detect deviations abnormal events.

The approach suggested in this article given in fig.1 differs from the existing approach [6], [7], and [8] by its dynamic of detecting anomalies, in which it makes possible for the detection of anomalies for both cases (case of a group or a single person). It can be divided into three sublevels: the bottom level (the estimate of optical flow), the intermediate level (construction of the model magnitude) and the semantic level (operators notification).

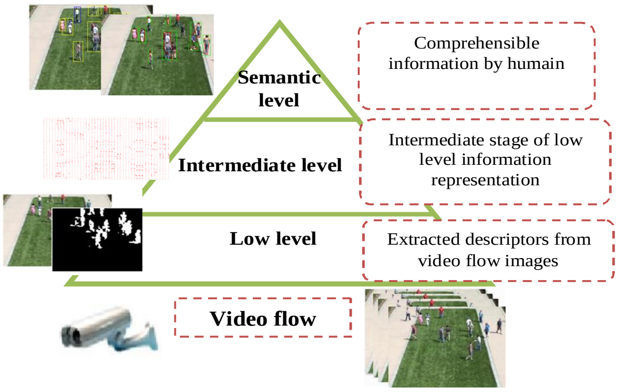


Fig.1. Global illustration for our solution of the crowd behavior analysis.

The remainder of this paper is organized as follows: in section II we present a short background on the various approaches as well as the works related to this field, and section III suggested approach in order to overcome a certain problems encountered in literature. Section IV we present the mathematical formulation new method used in order to detect anomalies of the race type and walk type in a crowded scene. Finally, the results are presented in the section V then, we'll finish by a conclusion and prospects for future work.

2. STATE OF ART

The approaches usually used for the analysis of the crowd behavior in video sequences generally comprise four essential stages: the detection of movement, the segmentation, the classification, and the tracking.

In our work, we propose the use of the detection movement technique by optical flow [9], [10], [11], [12], and [13]. The latter makes it possible to detect groups which move in the same direction and to extract the reasons from movement. The major advantage of this method is that it doesn't need to be modeled [4], because, it consist in detecting the movement by calculation in any point of the image of a mathematical quantity which is a function of the intensity or the color of the whole of the pixels and which is supposed to reflect the importance of the visible movement in the scene. We propose then the segmentation [15] by regrouping of the areas with an aim of providing a more precise cutting of the borders of the areas. Afterward, we propose to use a technique of classification anomalies by measure with a specific threshold. Lastly, we propose the use of the particle filter or KALMAN filter [8] for the tracking which is well adapted to follow disturbed trajectories with abrupt changes of movement.

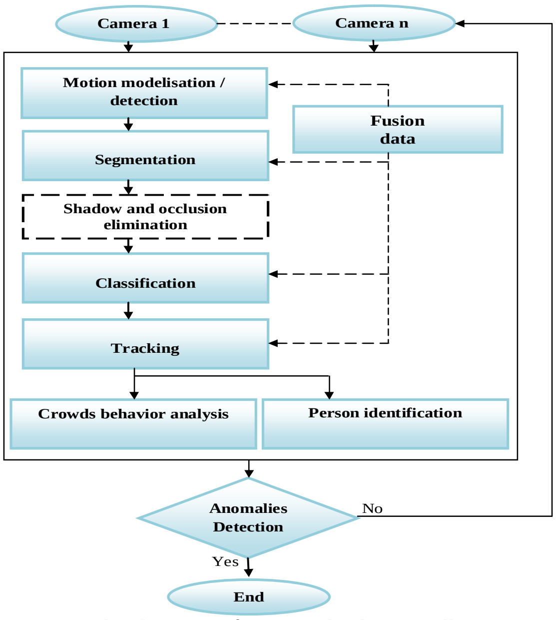


Fig.2. General architecture of automated video surveillance system.

After the state of the art we proposed gathered in the flow chart of the fig.2. The first stage consists in acquiring the image to be treated by the means of a camera. After that, we carried out detection by the optical flow; segmentation of the movements, and classification, this last represents the new approach for the detection of abnormalities in very dense scenes while being based on the speed of the individuals and that of the group. The various anomalies are detected measure with a specific threshold. The next stage is the tracking of the abnormalities. Finally a test is carried out in order to enable us to extract some comprehensible information "detection crowd behavior normal and abnormal".

3. Approach Description

Our approach presented in this section detects abnormal events principally from unidirectional flow of crowd. The video frames are labeled normal or abnormal based on the distance measure between covariance matrices of the distributions of the optical flow vectors computed on consecutive frames. These flow vectors are the result of tracking a set of features points discovered by the optical flow detector applied on each frame. This region is produced by background subtraction to form a two dimensional histogram of motion called motion heat map.

A simple flow diagram of the proposed framework has been shown in fig.3. The approach is characterized by optical flow patterns of human behaviors followed by some statistical treatments, to detect abnormal events mainly in onward crowd flow.

We have constructed covariance matrix (CM) using the extracted spatiotemporal knowledge of optical flow. A CM is merely collection of several variance-covariances in the form of a square matrix. We have computed the dissimilarity as a distance measure between two consecutive CMs. We have studied the normalized distance measure to differentiate normal or abnormal frame based on a defined value (label) called threshold.

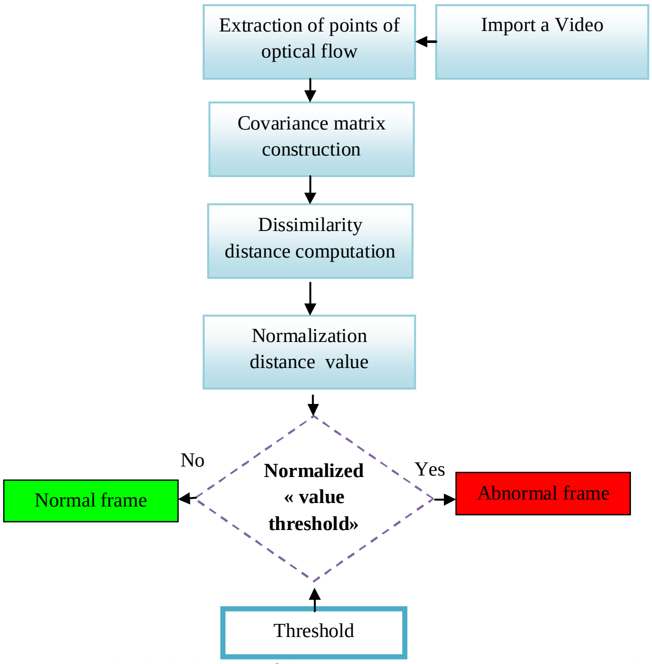


Fig.3. General Block diagram of the proposed Covariance Matrix approach.

3.1. Motion vectors extraction

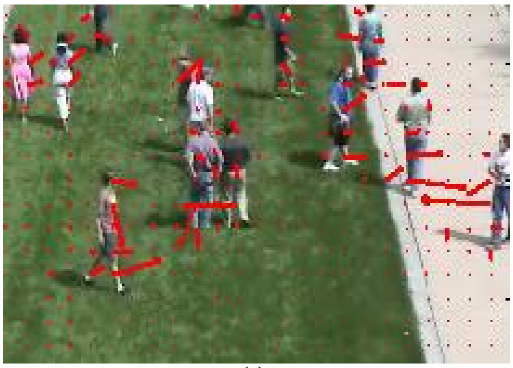
The investigated crowd activities are characterized by movement of people. The examination of motion dynamics of crowd is based on the so called motion vectors obtained by the methods optical flow which is applied to each pair of subsequent video frames.

Applying optical flow returns a set of motion vectors in the form:

$$V_{i,t} = (x_{i,t}, y_{i,t}, m_{i,t}, \theta_{i,t}) \quad (1)$$

Where "$V_{i,t}$" is the motion vector "i" at frame "t", represented by the feature point at the coordinate $(x_{i,t}, y_{i,t})$, the magnitude "$m_{i,t}$" and the orientation angle "$\theta_{i,t}$".

The goal of optical flow technique is to compute an approximation to the 2D motion field, a projection of the 3D velocities of surface points onto the imaging surface, from spatiotemporal patterns of images intensity. An example of optical flow vectors produced by the feature tracker shown in images on Fig. 4.


(a)

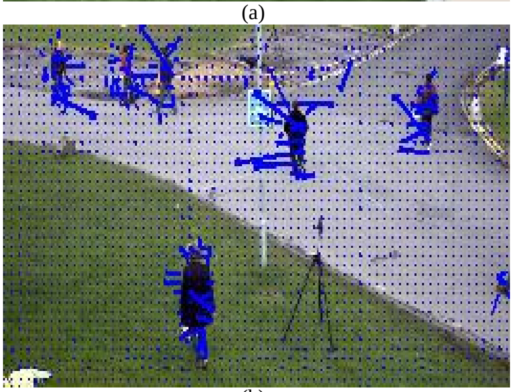

(b)

Fig.4. Optical flow vectors in (a) and (b) illustration.

Optical flow estimation step, we have used the pyramidal implementation of optical flow algorithm. Once we define the video, we track those features over the next frames using the above combination feature tracker of Kanade-Lucas-Shi-Tomasi [9], [10], [11], [12], and [13]. An example of optical flow vectors produced by the feature tracker shown in the right image on fig.4. After matching features between frames, we can consider that the result is a set of vectors $V_k(j)$ of n elements over time :

$$V_k(j) = \begin{bmatrix} x_1 & y_1 & v_1 & \alpha_1 \\ x_2 & y_2 & v_2 & \alpha_2 \\ x_3 & y_3 & v_3 & \alpha_3 \\ . & . & . & . \\ . & . & . & . \\ x_i & y_i & v_i & \alpha_i \\ . & . & . & . \\ . & . & . & . \\ x_n & y_n & v_n & \alpha_n \end{bmatrix} \quad (2)$$

Where $k = 1, 2, 3, \ldots n,\ i \epsilon k, j\ 2\ \{x, y, v, \alpha\}$, and :

$x_i \rightarrow$ x - Coordinate of any feature element i,

$y_i \rightarrow$ y - Coordinate of the i,

$v_i \rightarrow$ Velocity v of the i,

$\alpha_i \rightarrow$ Moving direction a of the i.

Images in fig.4 gives evidence of the set of vectors obtained by optical flow feature tracking in two different situations. The image in fig.5 divulges an orderly vector flow. This step also allows removal of static and noise features. Static features are the features that move less than two pixels. Noise features are the isolated features that have a big angle and distance difference with their near neighbors due to tracking calculation errors.

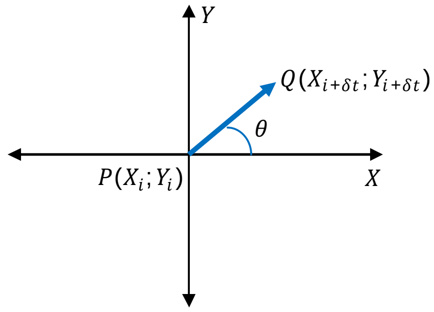


Fig.5. Optical flow vectors and Moving direction θ of a feature i.

Covariance is a statistical measure of correlation of the continual changes from one point or condition to another of two different quantities. In statistics and probability theory, a covariance matrix or dispersion matrix is a matrix of covariances between elements of a random vector. It is the bona fide generalization to higher dimensions of the concept of the variance of a scalar-valued random variable. The diagonal entries of the covariance matrix represent the variance of each feature and the non-diagonal entries represent the covariances. Due to symmetry covariance matrix has only $(m^2 + m)/2$ different values, where m is number of either rows or columns.

We construct a 4x4 CM for representing a video frame using the data obtained in Eq.1 where x_i & y_i as spatial information, and v_i & α_i as temporal information. Assume Cf be a CM for a frame, we define Cf as :

$$v_i = \frac{\delta s_i}{\delta t} = \sqrt{\left(\frac{x_i}{\delta t}\right)^2 + \left(\frac{y_i}{\delta t}\right)^2} \qquad (3)$$

And :

$$\alpha_i = atan\left(\frac{y_i - y_j}{x_i - x_j}\right) \qquad (4)$$

$$Cf = \begin{bmatrix} x & xy & xv & x\alpha \\ yx & y & yv & y\alpha \\ vx & vy & v & v\alpha \\ \alpha x & \alpha y & \alpha v & \alpha \end{bmatrix} \qquad (5)$$

Where diagonal elements x, y, v, and α are variances, and non-diagonal elements are covariances. We compute the $(p, q) - th$ element of the Cf in the following statistical formula.

$$Cf(p,q) = \frac{1}{n-1}\left[\sum_{k=1}^{n} V_k(p)V_k(q) - \frac{1}{n}\sum_{k=1}^{n} V_k(p)\sum_{k=1}^{n} V_k(q)\right] \qquad (6)$$

Where $\{p, q\} \in \{x, y, v, \alpha\}$.

3.2. Covariance Matrices Dissimilarity Computation

Esteem as Cf_t and Cf_{t+1} are two consecutive 4x4 MCs, then the distance measure proposed in [12] to measure the dissimilarity of two covariance matrices can be defined by :

$$d(Cf_t, Cf_{t+1}) = \sqrt{\sum_{k=1}^{4} \log_e^2 \lambda_k(Cf_t, Cf_{t+1})} \qquad (7)$$

Where $\lambda_t(Cf_t, Cf_{t+1})_{t=1\ldots4}$ are four generalized eigenvalues of Cf_t and Cf_{t+1}, computed from $\lambda_t Cf_t x_1 - Cf_{t+1} x_1$ avec $x_1 \neq 0$ are generalized eigenvectors.

3.3. Normalization of Dissimilarity Distances

Now, we wish to transfer each dissimilarity distance measure into a normalized distance value ranges between 0 and 1. Assume that $d(Cf_t, Cf_{t+1})$ be any dissimilarity distance measure between any two consecutive frames f_t and f_{t+1}.

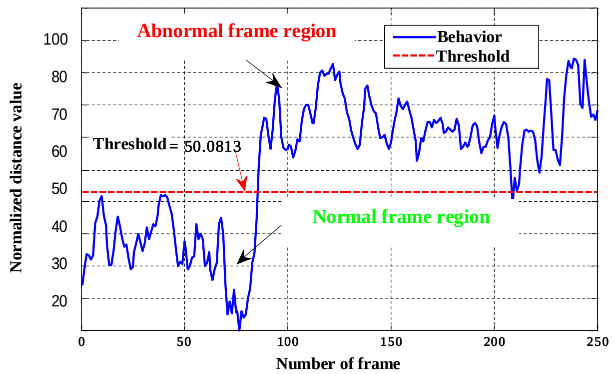
$$Normalized\ Value = \left(1 - \frac{1}{log\ d(Cf_t, Cf_{t+1})}\right) \tag{8}$$

We considered that the characteristic of the state of a collapse situation as a signal of sudden change with a high peak height of duration. If there exists such signal then there is an abnormal event. The decision for normal or abnormal events is to be taken by comparing the calculated and normalized measure with a specific threshold defined by :

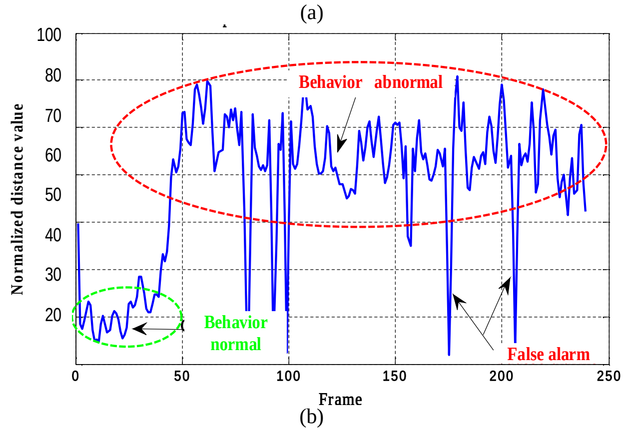
$$T_N = max_{k=1...F}\{N(d(Cf_t, Cf_{t+1}))\}_k \tag{9}$$

4. RESULTS

The proposed approach is based on computing the magnitude of the motion vector which presents the optical flow in the Cartesian frame fig.5. We calculate the dissimilarity of two covariance matrices of each sequence of images, with an aim to determine the running and walking events fig.6. These events can be identified by using the distance measure of the vectors of optical flow. Therefore the principal idea consists of calculating the dissimilarity of two covariance matrices of the movement vectors in each image. A high distance indicates a running event while low distance indicates a walking one.



(a)



(b)

Fig.6. Examples of distance measure of a group of people, (a) situation dangerous, and (b) situation of escalator.

The results of the approach are represented in Fig.7 and 8. In our work, we suppose that the number of people in an occulted group is not limited. The obtained results are encouraging when the automatic detection of anomalies is close to the real time measurement. The approach suggested shows a great robustness against false alarm detection since the automatic detection of anomaly occurs after the real release of the anomaly.

(a)

(b)

Fig. 7. Example 1 of event detected by covariances matrix algorithm in situation dangerous (a- normal behavior, and b- abnormal behavior).

(a)

(b)

Fig.8. Example 2 of event detected by covariances matrix algorithm in situation of escalator (a- normal behavior, and b- abnormal

Our approach presents some advantages as it presents a positive contribution for the detection of the movement in a complex environment. However, it requires the estimation of temporal time for each image bloc and at every moment of the video sequence which makes it very greedy in computing power consumption. And Our approach reached a flow of 6 images per second on an INTEL Pentium 2.16 GHz processor (which can be seen as a weak processor) simulated under MATLAB "R2014a".

In our work, we suppose that the number of people in an occulted group is not limited. Moreover, we compare our results with other methods, such as the function of probabilistic density [15], [16], [17], are obtained results are encouraging when the automatic detection of anomalies is close to the real time measurement.

TABLE I
COMPARE OUR RESULTS WITH OTHER METHODS

Approach detection of anomalies	Situation dangerous	Situation of escalator
Appreach proposed	✓	✓
W. Foerstner and B. Moonen [15]	x	✓

5. Conclusion

As conclusion, we presented our approaches of autonomous vision by computer, to analyze the human behavior starting from the video while basing ourselves on the dissimilarity of two covariance matrices of the movement, speed and orientation. The targeted environments can be in interior or outside. Particularly, we treat the detection of crowd events, where we proposed an approach which allows detecting events in dense scenes using statistical models. Our approach reached a flow of 6 images per second on a lack processor of the mark INTEL Pentium 2.16 GHz, simulated under MATLAB "R2014a". As perspectives, we propose to improve the performances of the method used by introducing a technique of Estimate of the threshold value.

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