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Detecting Human Flows on a Road Different from Main Flows

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Abstract: Automatic detection of human flows on a road by a computer vision system is of great importance mainly in surveillance systems, where human flows are observed by a camera and a computer analyzes the videos that the camera provides to detect a person having a different flow of movement, such as a person walking toward a certain direction while most of the people walk in the opposite direction, or a person running in a group of walking people. This paper describes a technique for finding a person having a different behavior or motion from others. The idea of the paper is to classify motion flows (or optical flows) extracted from a video into respective groups having respective directions of the motion by analyzing the motion flows. Experimental results show effectiveness of the proposed technique.

Keywords: Motion detection, abnormal motion, Harris corner detector, L-K tracker, clustering, feature space.

I. INTRODUCTION

In recent years, along with the unceasing intellectualization of video image monitoring technology, the intelligent monitoring technology has gained more and more domestic and foreign merchants' and scholars' recognition and has conducted a series of researches. One of the most challenging tasks in intelligent monitoring technology is the analysis of human motion in crowed scenes and detecting the people who have a deferent motion from others. The detection of an abnormal motion can trigger video transmission and recording, and can be used to attract the attention of a human observer to a particular video channel.

This paper describes a novel technique for finding a person having a different motion from others The idea of the paper is to classify motion flows (or optical flows) extracted from a video into respective groups having respective directions of the motion by analyzing the motion flows. In order to realize this, the Harris corner detector is applied to an initial image frame to extract feature points on the image: The Lucas-Kanade tracker is then applied to the successive frames to detect motion flows on the video: Pyramidal search is considered, if necessary, to detect the motion flows having different flow lengths indicating difference of the motion speed. The obtained motion flows are finally classified into some groups which have respective motion directions or speed.

II. OVERVIEW OF THE ABNORMAL MOTION DETECTION SYSTEM

The process of detecting abnormal motion involves two primary contents: 1) tracking feature points. First, extract feature points from the initial image frame. Then, track the feature points in the next frame to find the motion vector. However, it is impossible to determine whether the motion is normal or abnormal only by the motion vector of the two successive frames.

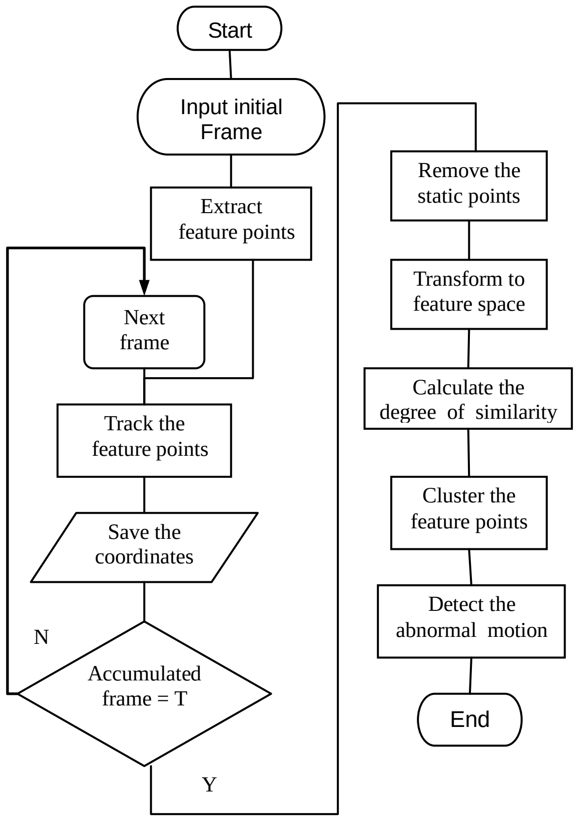


Fig.1. Overview of the proposed abnormal motion detecting method

Therefore, we need to accumulate some image frames from the first frame and store the location of the feature points that are tracked over the entire frames into the coordinate space. 2) Clustering. Remove stationary points from the coordinate space and convert the coordinate space into a feature space. Finally, cluster the feature points to detect abnormal motions. **Fig. 1** shows the overview of the abnormal motion detecting method.

III. METHOD

1. Extracting feature points

Generally, motion vectors are calculated by using the pixel values in the local region around the attracted point. We cannot obtain the right motion vector if texture conditions are poor in this local region. Therefore we need to find an adaptive feature point. In this paper, Harris corner detector, a popular feature point detector, is applied to extract the feature points.

The Harris corner detector is based on the local auto-correlation function of a signal, where the local auto-correlation function measures the local changes of the signal with patches shifted by a small amount in different directions.

For a small shift [u, v], we have bilinear approximation as follows;

$$E(u,v) \cong [u,v] \ \ M \ \begin{bmatrix} u \\ v \end{bmatrix} \tag{1}$$

where M is a 2×2 matrix of the following form computed from image derivatives;

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \tag{2}$$

The Harris measure of a corner is defined by

$$R = \det M - k\left(\operatorname{trace} M\right)^2 \tag{3}$$

where

$$\begin{aligned} \det M &= \lambda_1 \lambda_2 \\ \operatorname{trace} M &= \lambda_1 + \lambda_2 \end{aligned} \tag{4}$$

where λ_1 and λ_2 are the eigenvalues of the matrix M.

Find the points with large corner response function R (R>threshold), and take the points of local maxima of R. **Fig. 2** shows the image of extracted feature points.

2. Tracking feature points

The Lucas-Kanade tracker, one of the most well-known feature points tracking algorithms is employed in the proposed method.

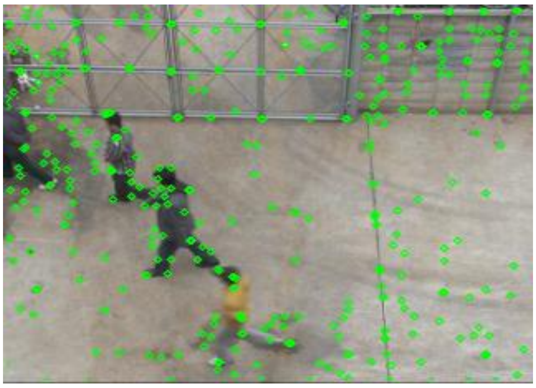


Fig.2. Feature points extraction

The L-K algorithm relies only on local information that is derived from some small windows surrounding each of the points of interest. Based on the condition, we can get the final expression in the form of

$$\boldsymbol{d} = (A^T A)^{-1} A^T \boldsymbol{b} \tag{5}$$

where

$$A = \begin{bmatrix} I_x(\boldsymbol{x}_1,t) & \cdots & I_x(\boldsymbol{x}_n,t) \\ I_y(\boldsymbol{x}_1,t) & \cdots & I_y(\boldsymbol{x}_n,t) \end{bmatrix}^T \tag{6}$$

The disadvantage of using small local windows in Lucas-Kanade algorithm is that large motions can move points outside of the local window and thus become impossible for the algorithm to find them. This problem led to the development of the pyramidal L-K algorithm, which starts tracking from the highest level of an image pyramid and working down to lower levels. Tracking over image pyramids allows large motion to be caught by local windows. **Fig. 3** shows the image of motion vectors.

Fig.3. Motion vectors

3. Creating the feature space

Since it is difficult to detect an abnormal motion only by the motion vectors between successive frames, we need to accumulate some frames from the first frame.

The feature points are tracked over the entire frames and their location information is stored into a coordinate space. Suppose that a feature point n (n=0,1,2,…,N-1) is tracked through T image frames and its position on the frame t (t=0,1,2,…,T-1) is denoted by ($x_t^{(n)}$, $y_t^{(n)}$). We then define a sequence of T coordinates of the feature point by the following form;

$$\begin{aligned} X_0 &= \left[x_0^{(0)}, y_0^{(0)}, x_1^{(0)}, y_1^{(0)}, \ldots, x_{T-1}^{(0)}, y_{T-1}^{(0)}\right] \\ X_1 &= \left[x_0^{(1)}, y_0^{(1)}, x_1^{(1)}, y_1^{(1)}, \ldots, x_{T-1}^{(1)}, y_{T-1}^{(1)}\right] \\ &\vdots \\ X_{N-1} &= \left[x_0^{(N-1)}, y_0^{(N-1)}, x_1^{(N-1)}, y_1^{(N-1)}, \ldots, x_{T-1}^{(N-1)}, y_{T-1}^{(N-1)}\right] \end{aligned} \quad (7)$$

Fig. 4 shows the tracking result throughout the T frames.

However, the movement cannot be known only by the position information of points in the coordinate space. Therefore the coordinate space is converted to three kinds of feature space such as velocity (8), velocity magnitude (9), and velocity orientation (10).

$$\begin{aligned} \mathbf{V}_0 &= \left[v_x^{(0)}, v_y^{(0)}\right] = \left[x_{T-1}^{(0)} - x_0^{(0)}, y_{T-1}^{(0)} - y_0^{(0)}\right] \\ \mathbf{V}_1 &= \left[v_x^{(1)}, v_y^{(1)}\right] = \left[x_{T-1}^{(1)} - x_0^{(1)}, y_{T-1}^{(1)} - y_0^{(1)}\right] \\ &\vdots \\ \mathbf{V}_N &= \left[v_x^{(N)}, v_y^{(N)}\right] = \left[x_{T-1}^{(N)} - x_0^{(N)}, y_{T-1}^{(N)} - y_0^{(N)}\right] \end{aligned} \quad (8)$$

$$\begin{aligned} |\mathbf{V}_0| &= \sqrt{(x_{T-1}^{(0)} - x_0^{(0)})^2 + (y_{T-1}^{(0)} - y_0^{(0)})^2} \\ |\mathbf{V}_1| &= \sqrt{(x_{T-1}^{(1)} - x_0^{(1)})^2 + (y_{T-1}^{(1)} - y_0^{(1)})^2} \\ &\vdots \\ |\mathbf{V}_N| &= \sqrt{(x_{T-1}^{(N)} - x_0^{(N)})^2 + (y_{T-1}^{(N)} - y_0^{(N)})^2} \end{aligned} \quad (9)$$

$$\begin{aligned} \theta_0 &= \arctan\left(\frac{y_{T-1}^{(0)} - y_0^{(0)}}{x_{T-1}^{(0)} - x_0^{(0)}}\right) \\ \theta_1 &= \arctan\left(\frac{y_{T-1}^{(1)} - y_0^{(1)}}{x_{T-1}^{(1)} - x_0^{(1)}}\right) \\ &\vdots \\ \theta_N &= \arctan\left(\frac{y_{T-1}^{(N)} - y_0^{(N)}}{x_{T-1}^{(N)} - x_0^{(N)}}\right) \end{aligned} \quad (10)$$

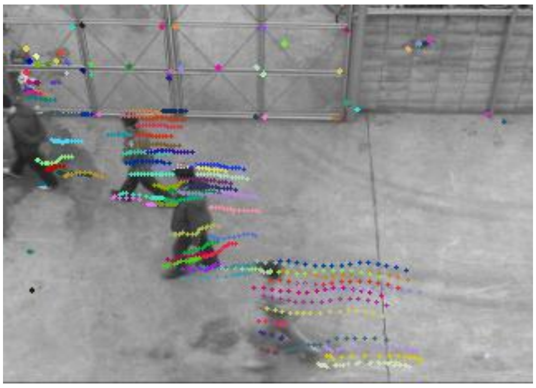


Fig.4. Tracking result throughout T frames

3. Detecting an abnormal motion

The flow chart of clustering is shown in **Fig. 5**, where d_{ij} and Th are defined as follows;

$$d_{ij} = \mathrm{SSD}\,(s_j, s_i) \quad (11)$$

$$\begin{aligned} Th &= \alpha(\max - \min) + \min \equiv \gamma \\ \alpha &= 0.001 \end{aligned} \quad (12)$$

The similarity of the features with respect to the feature points are calculated among them. This

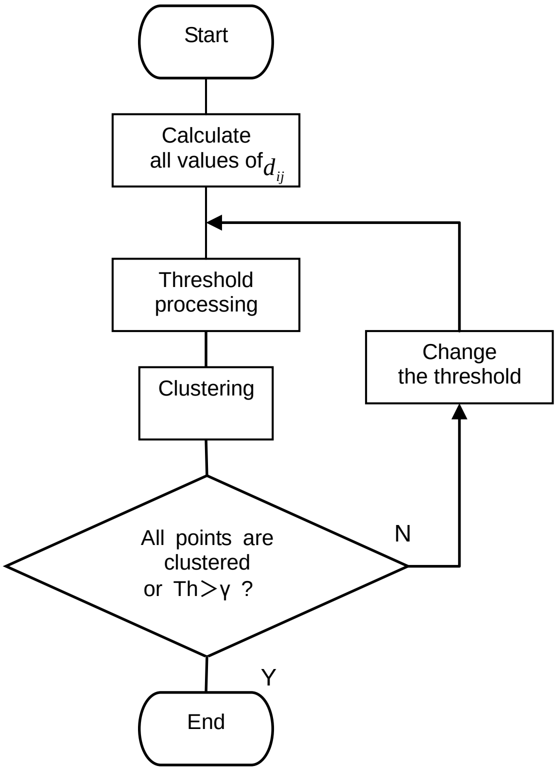


Fig.5. Flow chart of clustering

similarity is clustered by threshold processing. At first, the threshold is set strictly. The threshold is adjusted so as to cluster all the points or larger than γ. Look-up table is used in the clustering process. After clustering, count the number (n) of feature points clustered in each class. The class that satisfies the following condition, $n \leq$ total number of points $\times R$ %, is defined as an abnormal motion.

IV. EXPERIMENTS AND CONCLUSIONS

The abnormal motion detection algorithm proposed here was successfully tested on various outdoor scenes. **Fig. 6** shows the final result.

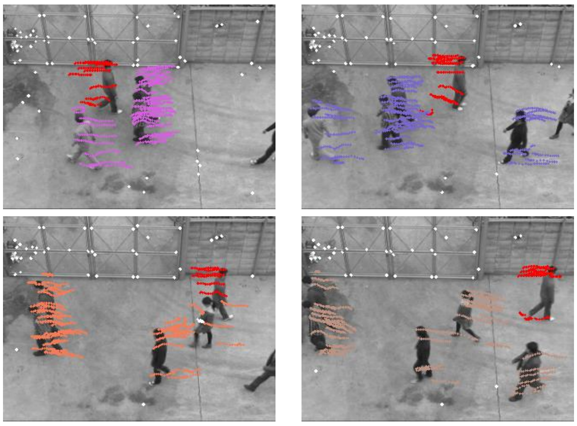
In this paper, we propose a novel technique of abnormal motion detection from the images obtained from a surveillance camera. The Harris corner detector and the pyramidal Lucas-Kanane algorithm are applied to feature tracking and calculation of motion vectors. Then a coordinate space and a feature space are created based on the tracked points coordinates. The feature points are clustered by a Look-up table. Finally abnormal motions are detected based on the clustered points. The future work is to integrate the multiple features in order to improve the accuracy.

REFERENCES

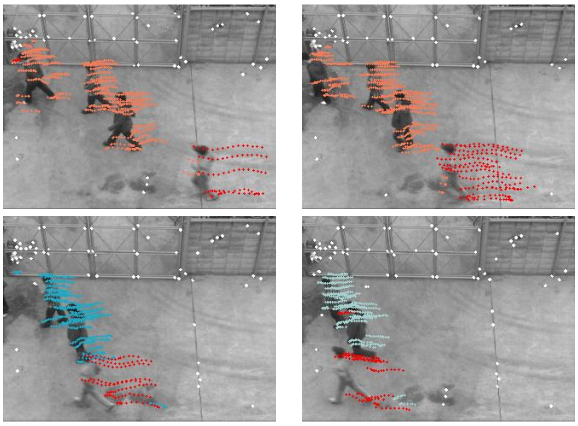
[1] C. Harris, M. Stephens (1988), A combined corner and edge detector, Proc. of the 4th Alvey Vision Conference, pp.147-151.

[2] B. D. Lucas, T. Kanade (1981), An iterative image registration technique with an application to stereo vision", Proc. of the 7th International Joint Conference on Artificial Intelligence, pp.674-679.

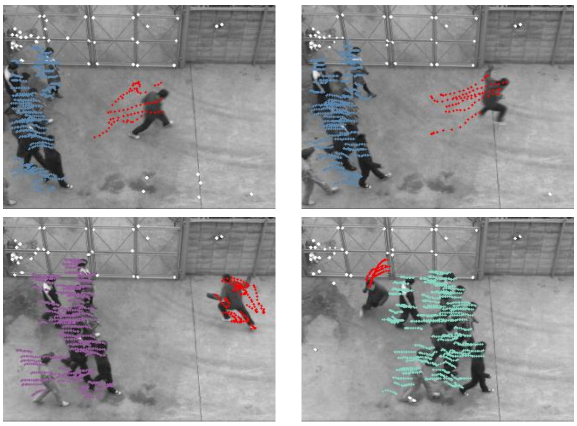
[3] M. A. Fischler, R. C. Bolles (1981), Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography, Communications of the ACM, vol.6, no.24, pp.381-395.



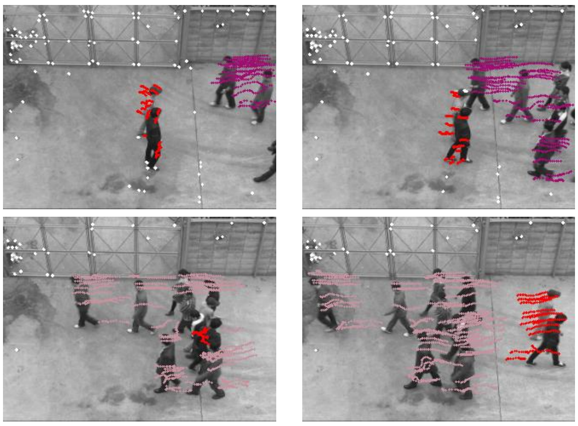
(a)



(b)



(c)



(d)

Fig.6. Performance of abnormal motion detection from various scenes. The red line in the frames shows the abnormal notion of a person having a different motion from others. Time elapses in the order of upper left, upper right, lower left and lower right image.