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Detecting Anomalies in Surveillance Videos with Spatio-Temporal Features

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Abstract **- One of the purposes of video surveillance systems is to detect anomalies which are unexpected situations at a certain location or at a frame. Anomalies can be related to motion or appearance according to its spatial position. In this paper, we propose an anomaly detection system based on spatio-temporal features. Features from Accelerated Segment Test (FAST) is used for detection of corners location. Optical Flow magnitude and orientation of these points is used as spatio-temporal features. A grid is**

to the frames to neutralize the effect of proximity to the camera. Normal patterns are clustered with an unsupervised neural network so called Self-Organizing Maps (SOM). In test videos if extracted features cannot model with normal clusters, associated grid cell will be marked as anomaly

Keywords **- Video Surveillance, Anomaly Detection, Features from Accelerated Segment Test (FAST), Optical Flow, Self-Organizing Maps (SOM)**

I. INTRODUCTION

THE widespread use of cameras and security requirements have increased the interest in surveillance videos which have large volumes of data to analyze. Therefore, traditional human-focused surveillance systems have been transformed into the automatic systems which can detect anomalies unassisted. Anomalies can be described as unexpected patterns, situations, things which are not trivial to model. Thus, in the literature normal patterns are modelled via training data [1] or statistical approaches are used [2] to model abnormal patterns.

First step of modelling normal patterns is extracting features from videos. There are two main approaches in the literature [3] : I) extracting features from pixels of image [4], [5] . II) target based methods [6], [7] . Also there exists some studies which use an hybrid structure of both approaches [8]. After extracting features, there are several methods to model them like Hidden Markov Model (HMM) [9], Markov Random Field (MRF)[10], Latent Dirichlet Allocation (LDA) model [11] , Mixture Of Dynamic Textures (MDT) [12].

In this study, we propose a low-level feature extraction by using image pixel values to avoid occlusions and tracking. Moreover, we combine motion and appearance features by using optical flow histograms according to corner points which detected by FAST method. Normal patterns are clustered with SOM. In the next section we will further discuss our proposed method.

II. PROPOSED METHOD

The overview of our method is illustrated in Figure 1.

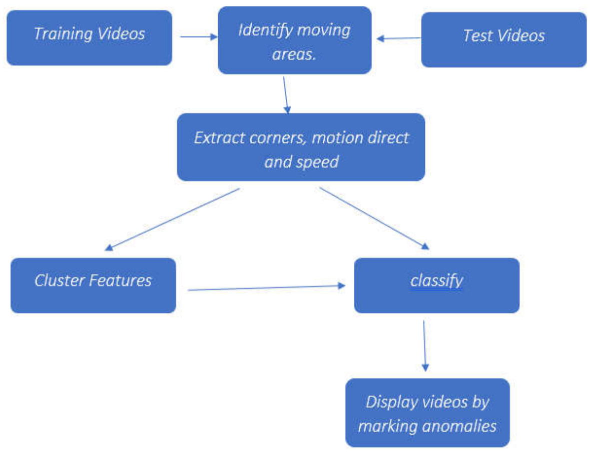

Figure 1. The overview of proposed method.

There are four main phases in our method; identify moving areas, extract features, cluster features and classify. We use non-overlapping grids of video frames as seen in Figure 2.

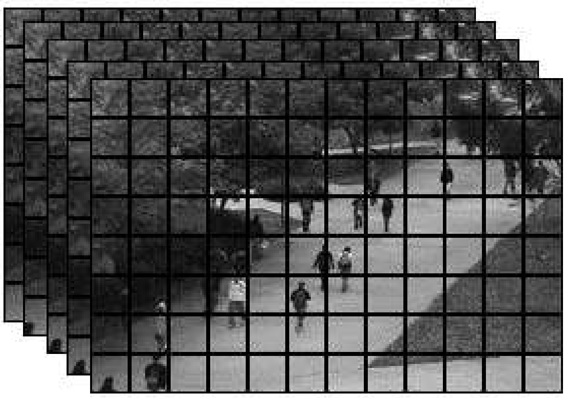

Figure 2. Grid view of frames.

The first step is identifying moving areas, for reducing running time. Motionless areas are eliminating with a basic frame difference method. Pixels that are below the threshold value, are considered to be 0 and the others are 1, shown in Figure 3. Median filter was used for avoiding noise as shown in Figure 4.

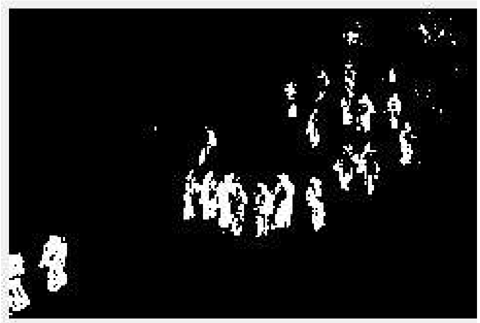

Figure 3: Difference of two frames

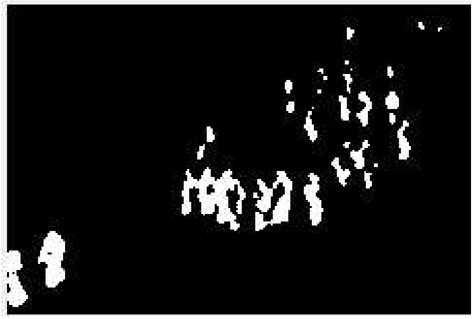

Figure 4: Difference of two frames with median filter

The second step is extracting features. To detect corner points Features from Accelerated Segment Test (FAST) is used [13][14]. Then motion direct and speed are calculated with optical flow method [15] at corner points. In a grid cell with detected corner point, optical flow histograms are computed according to orientation of motion vector. Features are created with a 8-bin histogram for each grid cell.

The third step is clustering. Features are clustered using an unsupervised artificial neural network, Self-Organizing Maps (SOM) [16]. SOM is a well-known artificial neural network, which produces low dimensional projection of high dimensional data [17]. The forth step is classifying. Test videos are classified according to clusters. Grid cells are marked as anomalies, if they do not match any of the clusters.

III. EXPERIMENTAL RESULTS

The proposed system is tested in UCSD Peds1 dataset [18]. The features, obtained from the training videos are modeled with SOM to create clusters that model normal conditions for each cell. In the test videos, features are also calculated for each cell to check whether they are included in the relevant clusters. Some samples of detected anomalies as chart and biker in pedestrian walkways and a person in the grass, are shown in Figure 5.

Figure 5: Sample of marked anomalies at video frames

IV. CONCLUSION

In this paper, an anomaly detection system is proposed, and test results are shown visually. To combine motion and appearance features, optical flow histogram is used at corner points which detected by FAST method. Normal patterns are clustered with SOM. Detected anomalies are shown to user as marked. As future work, feature extracting method will be improved and system will be tested on other datasets.

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REFERENCES

[1] M. Sabokrou, M. Fayyaz, M. Fathy, and R. Klette, "Deep-Cascade: Cascading 3D Deep Neural Networks for Fast Anomaly Detection and Localization in Crowded Scenes," *IEEE Trans. Image Process.*, vol. 26, no. 4, pp. 1992–2004, Apr. 2017.

[2] V. Saligrama and Z. Chen, "Video anomaly detection based on local statistical aggregates," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 2112–2119, 2012.

[3] A. A. Sodemann, M. P. Ross, and B. J. Borghetti, "A Review of Anomaly Detection in Automated Surveillance," *IEEE Trans. Syst. Man, Cybern. Part C (Applications Rev.*, vol. 42, no. 6, pp. 1257–1272, Nov. 2012.

[4] A. M. R. R. Bandara, L. Ranathunga, and N. A. Abdullah, "A feature clustering approach based on Histogram of Oriented Optical Flow and superpixels," *2015 IEEE 10th Int. Conf. Ind. Inf. Syst. ICIIS 2015 - Conf. Proc.*, no. 12, pp. 480–484, 2016.

[5] R. V. H. M. Colque, C. Caetano, M. T. L. de Andrade, and W. R. Schwartz, "Histograms of Optical Flow Orientation and Magnitude and Entropy to Detect Anomalous Events in Videos," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 27, no. 3, pp. 673–682, Mar. 2017.

[6] M. J. V Leach, E. P. Sparks, and N. M. Robertson, "Contextual anomaly detection in crowded surveillance scenes," *Pattern Recognit. Lett.*, vol. 44, pp. 71–79, 2014.

[7] C. Li, Z. Han, Q. Ye, and J. Jiao, "Visual abnormal behavior detection based on trajectory sparse reconstruction analysis," *Neurocomputing*, vol. 119, pp. 94–100, 2013.

[8] A. Surana, A. Nakhmani, and A. Tannenbaum, "Anomaly Detection in Videos : A Dynamical Systems Approach JJRfi J Pinside (X I," pp. 6489–6495, 2013.

[9] J. Snoek, J. Hoey, L. Stewart, R. S. Zemel, and A. Mihailidis, "Automated detection of unusual events on stairs," *Image Vis. Comput.*, vol. 27, no. 1–2, pp. 153–166, 2009.

[10] J. Kim and K. Grauman, "Observe locally, infer globally: A space-time MRF for detecting abnormal activities with incremental updates," *2009 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work. CVPR Work. 2009*, no. June, pp. 2921–2928, 2009.

[11] S. Kwak and H. Byun, "Detection of dominant flow and abnormal events in surveillance video," *Opt. Eng.*, vol. 50, no. 2, p. 027202, 2011.

[12] V. Mahadevan, W. Li, V. Bhalodia, and N. Vasconcelos, "Anomaly detection in crowded scenes," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 1975–1981, 2010.

[13] E. Rosten, R. Porter, and T. Drummond, "Faster and better: A machine learning approach to corner detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 1, pp. 105–119, 2010.

[14] H. Fradi and J. L. Dugelay, "Spatial and temporal variations of feature tracks for crowd behavior analysis," *J. Multimodal User Interfaces*, vol. 10, no. 4, pp. 307–317, 2016.

[15] B. K. P. Horn and B. G. Schunck, "Determining optical flow," *Artif. Intell.*, vol. 17, no. 1–3, pp. 185–203, 1981.

[16] T. Kohonen, "Self-organized formation of topologically correct feature maps," *Biol. Cybern.*, vol. 43, no. 1, pp. 59–69, 1982.

[17] T. Kohonen, *MATLAB Implementations and Applications of the Self-Organizing Map.* Unigrafia Oy, Helsinki, Finland, 2014.

[18] "UCSD Anomaly Detection Dataset." [Online]. Available: http://www.svcl.ucsd.edu/projects/anomaly/dataset.htm.