The International Journal of Engineering and Science (IJES)
|| Volume || 13 || Issue || 6 || Pages || PP 01-06 || 2024 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

Fast Motion Detection in a Crowd based on Shift Histogram

Panca Mudjirahardjo, Nurussa'adah, Rahmadwati, Angger Abdul Razak
Dept. of Electrical Engineering, Faculty of Engineering, Brawijaya University, Indonesia
Corresponding Author: panca@ub.ac.id

ABSTRACT
We present a fast motion detection technique in a dynamic background as an abnormal motion based on a motion history image (MHI). Since a camera view is usually not in perpendicular with motion direction, the velocity of motion is not uniform spatially. Instead of object detection directly from an image, we divide an image into several blocks. Then we calculate the probability that a block(s) contains a fast motion by using parameters of a shifting histogram. A shifting histogram is created based on a MHI. The performance of the proposed method is experimentally shown.

KEYWORDS;- *Abnormal motion, motion history image, shifting histogram.*

Date of Submission: 26-05-2024 Date of acceptance: 07-06-2024

I. INTRODUCTION

In recent years, abnormal motion detection has attracted great research attention in computer vision. Most current surveillance systems only provide *reactive* security by enabling the analysis of events after the event has already occurred — what is really needed by the security community is *proactive* security to help prevent future attacks.

Many approaches on video event analysis are based on the object trajectories extracted from the video. The abnormal events can be detected through a prior learning of normal events or without a learning process by analyzing the trajectory result directly [1-10].

Jiang et al. [1] used spatial and temporal context and performed frequency-based analysis to detect anomalous video events. The normal observation is modeled by a hidden Markov model (HMM). This research detected the anomalous car trajectory on the road from top view. Kiryati, et al. [2] recognized an abnormal human behavior from high camera view. Before the detection phase, they included the training phase for normal condition. Baranwal, et al. [3] detected an abnormal motion indoors and in a static background environment. They trained various motions using radial basis functions networks (RFBN). Bobick, et al. [4] used clustering of motion based on similarity measurement of a feature space. They detected an abnormal motion, especially in a different direction case, from high camera view.

Different from the previous researches [1-4], our camera view is lower than them. In this paper, we propose a fast motion detection in a dynamic environment with a camera view not in perpendicular with motion direction, as an abnormal motion among walking motion. We capture outdoor scenes from a 2 meter or more high position, as shown in **Figure 1**. Due to the camera view not in perpendicular with motion direction, motion velocity in the image is not uniform spatially.

Some researches [11-17] have detected fast human motion as an abnormal motion in occlusive environment successfully. However, the human movement was in perpendicular with a camera view. They failed to detect an abnormal motion when a motion occurs toward or near a camera. The method [5] should be improved with the point.

Figure 1. Scenes for experiments

To avoid a failure as in [5], we need to analyze part by part of an image. So we divide an image into several blocks. In [5] the detector relies only on the feature points generated by Harris corner detector and their tracking results obtained by Lucas-Kanade tracker, and some of them are noise. Then the method [5] will lose the motion information in some blocks.

The method proposed in this paper requires no foreground segmentation, no motion recognition and no object detection. We analyze the object's velocity through trajectory of a motion history image (MHI).

II. THE OVERVIEW OF THE PROPOSED METHOD

Fast motion detection needs some velocity data. In this paper, we provide velocity data from a motion history image (MHI). To avoid foreground segmentation, which is a difficult task in an occlusive environment, we separate an image into several blocks and evaluate them. So the detection framework is to calculate the probability that a block (or some blocks) contains a fast motion rather than object detection.

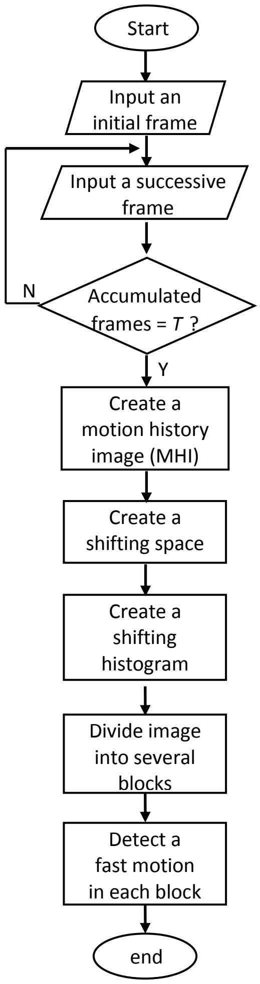

Figure 2. Overview of the proposed fast motion detection method in a dynamic background

We describe the proposed method in the following:

There are two main processes in the proposed method. The first one is to create a *shifting histogram*. A shifting histogram provides four parameters; the maximum shift (max_S), average shift (avg_S), mode of shifting ($mode_S$) and spreading width of the histogram (SW_S). Finally, we detect a fast motion in the dynamic background by using those parameters of the histograms.

To create a shifting histogram, we do the following steps. Firstly, we create a motion history image [6]. Then we calculate the shifting object horizontally corresponding to the change of pixel intensity.

The quantity value to determine if a block(s) contains a fast motion is SW_V, SW_S, $avg_V - mode_V$ and $avg_S - mode_S$. **Figure 2** depicts the overview of the proposed method.

III. METHOD

3.1. Creating a Motion History Image (MHI)

In our research, another idea, object shifting, is employed. To calculate the object shifting, we use a motion history image (MHI) [6].

Motion History Image is a view-specific representation of movement, where movement is defined as the motion over time. MHI, as the name implies, keeps track of the motion history, i.e., representing how the motion is moving along a certain period of time. It is very famous and well-established motion representation strategy since many years. The MHI is represented as a frame-based temporal template for human motion. In generating a MHI, the temporal information is specified by the pixel intensity. Let H_τ (x,y,t) be the pixel intensity function of the temporal history of motion at a particular point (x,y) on an image. The function is defined as shown in Eq.(3).

$$H_\tau(x,y,t) = \begin{cases} \tau & \text{if } D(x,y,t) = 1 \\ \max(0, H(x,y,t-1)-1) & \text{otherwise} \end{cases} \tag{3}$$

Here, $D(x,y,t)$ is a difference image in a binarized form constructed from successive frame difference.

The function H_τ (x,y,t) returns a scalar value. According to the function, the more recently moving pixels are brighter than the past moving pixels in the generated MHI. In Eq.(3), τ is taken as the temporal extent which is critical to define. But for the flexibility of the value of τ, it can be taken as the maximum gray level pixel value 255 or the maximum number of frames defining a motion. An example of a MHI is shown in **Figure 3**.

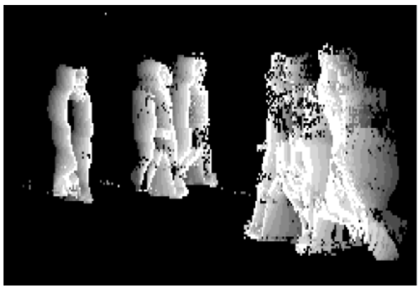

Figure 3. An example of a MHI

3.2. Creating a shifting space and shifting histogram

To get an information of object motion from a MHI, we need to convert it into a shifting space. A shifting space is numerical representation of a MHI. We have two directions, to the left and to the right: So we have two shifting spaces. To make each shifting space, we need to scan each direction. In the first scan, we put an increasing digit, if the gray scale value at the neighborhood is more than the current pixel. In the second scan, in opposite direction, we put a maximum digit between the current pixel and the neighborhood. **Figure 4** depicts the calculation of a shifting space of MHI to the right.

Based on the data of the shifting space, we calculate the frequency of shifting occurrence. Then we create a shifting histogram and get max_S, avg_S, $mode_S$ and SW_S as in **Figure 5**.

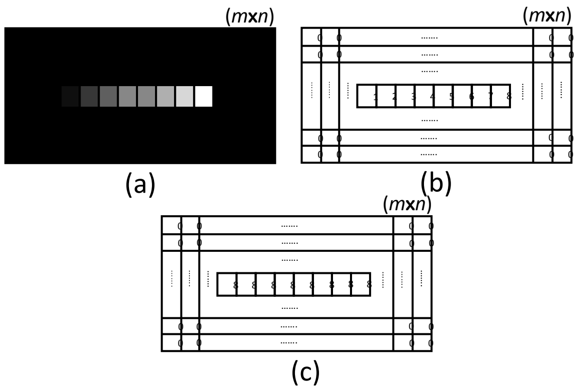

Figure 4. MHI and a shifting space: (a) a MHI to the right, (b) a shifting space after the first scan, (c) a shifting space after the second scan.

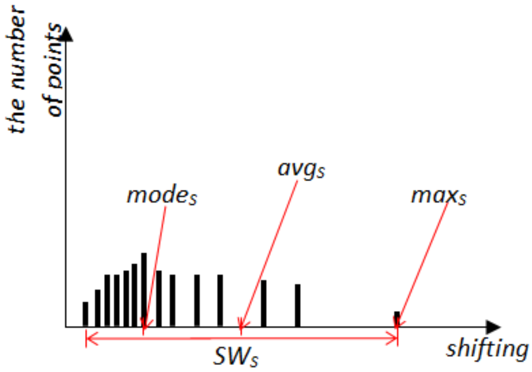

Figure 5. A shifting histogram and its property

3.3. Detecting a fast motion

Instead of object detection directly, we divide an image into several blocks. Then based on parameters of velocity and shifting histogram on each block, we determine whether a block contain a fast motion or not. Let us denote the parameter of SW_V by p_1, the parameter of SW_S by p_2, the parameter of avg_V - $mode_V$ by p_3, and the parameter of $avg_S - mode_S$ by p_4. Then we have,

$$p_1 = \begin{cases} 0 & \text{if } SW_V < th_1 \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

$$p_2 = \begin{cases} 0 & \text{if } SW_S < th_2 \\ 1 & \text{otherwise} \end{cases} \tag{5}$$

$$p_3 = \begin{cases} 0 & \text{if } avg_V - mode_V < th_3 \\ 1 & \text{otherwise} \end{cases} \tag{6}$$

$$p_4 = \begin{cases} 0 & \text{if } avg_S - mode_S < th_4 \\ 1 & \text{otherwise} \end{cases} \tag{7}$$

We also denote the total of the above parameters by p_T defined by

$$p_T = \sum_{i=1}^{4} p_i \tag{8}$$

Then the fast motion in each block is decided when $p_T \geq 3$ is satisfied.

IV. EXPERIMENTAL RESULT

For experiment, we use scenes as shown in **Figure 1**, where many people do normal motion (walking), whereas a person does abnormal motion (running). The video frame rate and the size of an image are 30 fps and 320×180 pixels, respectively. The observation frames consist of 10 successive frames. We divide an image into 16 blocks.

The experimental results are shown in **Figure 6**. We label with red lines when fast motion is detected. For evaluation of the results, let us define *recall*, *precision* and *FPR* by

$$\text{recall} = \frac{TP}{TP+FN} \times 100\% \tag{9}$$

$$\text{precision} = \frac{TP}{TP+FP} \times 100\% \tag{10}$$

$$\text{FPR} = \frac{FP}{FP+TN} \times 100\% \tag{11}$$

Here

TP : fast motion is detected as fast motion,

FN : fast motion is detected as normal motion,
FP : normal motion is detected as fast motion,
TN : normal motion is detected as normal motion.

Then the performance of the proposed method is given numerically in **Table 1**.

Scene	Recall (%)	Precision (%)	FPR (%)
1	83.7	80.5	3.5
2	83.4	81.3	3.7
3	80.6	79.5	4.8
Average	82.6	80.4	4

Table 1. Evaluation of the performance

Figure 6. Performance of fast motion detection from various scenes. A detected person with fast motion is indicated by red block.

V. CONCLUSION

In this paper, we proposed a fast motion detection method in a dynamic background, with camera view not in perpendicular with motion direction. Unlike existent methods, the camera location is not very high from the ground. Instead of object detection and to avoid foreground segmentation, we calculate the probability that a block(s) of image contains a fast motion. An evaluation parameter, given by Eq.(8), to determine if a block(s) contains a fast motion is based on a velocity histogram and a shifting histogram. Experimental results show satisfactory values of recall, 82.6%, and precision, 80.4%, in average.

As future work, we are going to conduct experiments on the recognition of abnormal motion under stronger occlusion.

REFERENCES

[1] F. Jiang, J. Yuan, S. A. Tsaftaris, A. K. Katsaggelo (2011), "Anomalous video event detection using spatiotemporal context", *Computer Vision and Image Understanding* 115, pp. 323-333.

[2] N. Kiryati, T. R. Raviv, Y. Ivanchenko, S. Rochel (2008), "Real-time abnormal motion detection in surveillance video", *Proc. Int. Conf. on Pattern Recognition,* 2008.

[3] M. Baranwal, M. T. Khan, C. W. De Silva (2011), "Abnormal motion detection in real time using video surveillance and body sensors", *Int. Journal of Information Acquisition.* Vol. 8, No. 2, pp. 103-116.

[4] A. Bobick, J. Davis (2001), "The recognition of human movement using temporal templates", *IEEE Trans. on PAMI*, Vol. 23, No. 3, pp. 257-267.

[5] R. Mehran, A. Oyama, M. Shah. "Abnormal crowd behavior detection using social force model", Proc. of Conf. on Computer Vision and Pattern Recognition (CVPR 2009), pp. 1-8, 2009.

[6] I. Tziakos, A. Cavallaro, L. Q. Xu. "Event monitoring via local motion abnormality detection in non-linear subspace", Journal of Neurocomputing, pp. 1-12, 2009.

[7] Y. Shi, Y. Gao, R. Wang. "Real time abnormal event detection in complicated scenes", Proc. of Int. Conf. on Pattern Recognition, pp. 1-4, 2010.

[8] D. Tran, J. Yuan, D. Forsyth. "Video event detection : from subvolume localization to spatio temporal patch search". IEEE, Trans. on Pattern Analysis and Machine Intelligence, Vol. 36, No. 2, pp. 404-416, 2014.

[9] B. Antic, B. Ommer. "Video parsing for anomaly detection", Proc. of the 13th Int. Conf. on Computer Vision (ICCV'11), pp. 1-8, 2011.

[10] Y. Cong, J. Yuan, J. Liu. "Sparse reconstruction cost for abnormal event detection", Proc. of Computer Vision and Pattern Recognition, pp. 3449-3461, 2011.

[11] X. Cui, Q. Liu, M. Gao, D.N. Metaxas. "Abnormal detection using interaction energy potentials", Proc. of Computer Vision and Pattern Recognition (CVPR), pp. 3161-3167, 2011.

[12] S. Wu, B.E. Moore, M. Shah. "Chaotic invariants of lagrangian particle trajectories for anomaly detection in crowded scenes", Proc. of Computer Vision and Pattern Recognition (CVPR), pp. 1-7, 2010.

[13] E. Ricci, G. Zen, N. Sebe, S. Messelodi. "A prototype learning framework using EMD application to complex scenes analysis", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 35, No. 3, pp. 513-526, 2013.

[14] L. Kratz, K. Nishino. "Anomaly detection in extremely crowded scenes using spatio-temporal motion pattern models", Proc. of Computer Vision and Pattern Recognition (CVPR), pp. 1-8, 2009.

[15] A. Adam, E. Rivlin, I. Shimshoni, D. Reinitz. "Robust real-time unusual event detection using multiple fixed-location monitors" IEEE, Trans. on Pattern Analysis and Machine Intelligence, Vol. 30, No. 3, pp. 555-560, 2008.

[16] S. Saxena, F. Bremond, M. Thonnat, R. Ma. "Crowd behavior recognition for video surveillance", Advanced Concepts for Intelligent , Lecture Notes in Computer Science Volume 5259, pp 970-981, 2008.

[17] J. Kim, K. Grauman. "Observe locally, infer globally: a space-time MRF for detecting abnormal activities with incremental updates". Proc. of the IEEE conf. on Computer Vision and Pattern Recognition, pp. 1-8, 2009.