Motion pattern analysis using partial trajectories for abnormal movement detection in crowded scenes

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A motion pattern analysis method for abnormal movement detection is introduced. It analyses motion patterns and detects abnormal movement using partial trajectories, which can be obtained in crowded scenes and are more effective than local motion. In addition, the proposed method is able to deal with noisy data, which is a major cause of false alarms. The experimental results from real-world traffic scene datasets show that the proposed method improves on previous, local motion-based methods.

Introduction: Intelligent video surveillance aims to support human operators during real-time abnormal event detection (e.g. left luggage, intrusion, loitering) and the associated statistical analysis, such as motion pattern (main path, dominant flow) detection or semantic region (exit zone, entry zone) detection. This popular research topic has seen a number of different approaches introduced in recent years, although most of them use only two feature types: trajectories and local motion.

The trajectory is the path of a moving object. Many previous studies have used this for the analysis of motion patterns, because it is the most effective feature. Saleemi *et al.* [1] presented a novel method to model and learn traffic patterns using trajectories, and their approach exhibited a good performance in detecting anomalies. They regard a tracking error as an outlier. However, this is not appropriate in crowded scenes, such as an urban area. Object tracking in crowded scenes is not simple owing to the frequent occlusion that occurs.

The general approach to avoiding the occlusion problem is to use local motion (such as optical flows) instead of the object trajectory. Wang *et al.* [2] proposed an unsupervised framework to model activities and interactions in crowded and complicated scenes using local motion as a low-level feature. The local motion in a crowded scene can be obtained, but owing to the short motion length, a complicated model, such as a hierarchical Bayesian model, is required for accurate analysis.

In this Letter, we propose a motion pattern analysis method for abnormal movement detection. The proposed method uses partial trajectories. These are easily obtained from crowded scenes by a feature point tracking algorithm, and are more effective than local motion for analysing the motion pattern and detecting abnormal movement. In addition, our method can reduce the amount of noisy data, which is a major cause of false alarms in abnormal detection. We compare our method to previous approaches, and show that it can improve the results of motion pattern analysis in a crowded traffic scene.

Feature extraction: The partial trajectory is a sequence of observations $PT = \{O_1, O_2, \ldots, O_n\}$. Each observation O_i consists of an occurrence time t, location l, and direction θ. Corner points are used as initial seed points for tracking, and the KLT feature tracker [3] is used to track the points. In a crowded scene, it is less complicated to track corner points than the object of interest. The partial trajectory extracted by this method does not entirely contain the ideal trajectory of the object, but is generally longer than the local motion. This means that the partial trajectory is more useful for analysing the motion pattern.

In addition, we improve the effectiveness of this technique by linking those trajectories that have temporal and spatial continuity. The temporal continuity means that the start time t_i^s of trajectory i and the end time t_j^e of trajectory j are close and do not overlap, $0 < t_i^s - t_j^e < \varepsilon_t$. Spatial continuity means that the start location l_i^s and direction θ_i^s of trajectory i and the end location l_j^e and direction θ_j^e of trajectory j are similar, $\|l_i^s - l_j^e\| < \varepsilon_l$, $|\theta_i^s - \theta_j^e| < \varepsilon_\theta$. Finally, we filter noisy trajectories using a length constraint, and use the remaining trajectories to model the motion pattern and detect abnormal movements.

Motion pattern analysis: We use a latent Dirichlet allocation (LDA) [4] to model the motion pattern using the partial trajectory. LDA is a well-known topic model for document analysis. It clusters co-occurring words into the same topic using word-document analysis. We quantise partial trajectory observations into visual words based on their location and direction using a similar method to that described in [2]. As a result, the partial trajectory is represented by a set of visual words:

$$PT = \{vw_1, vw_2, \ldots, vw_n\} \quad (1)$$

Previous methods generated the visual document using the visual words that occurred over a period of time [2], or using each trajectory [5]. In contrast, we construct the visual document with partial trajectories that terminated during α frames, $t \le t_i^e < t+\alpha$:

$$VD_{[t,t+\alpha]} = \{PT_1,\ PT_2, \ldots, PT_m\} \quad (2)$$

This allows our method to increase the correlation between visual words from the same partial trajectory in the motion pattern analysis.

After the entire video is converted into visual documents, we can obtain the parameters α and β using LDA. The parameter α relates to corresponding latent topics $P(S_k)$, and β is the conditional probability of each visual word given topic $P(vw_i|S_k)$. In the visual domain, this expresses the motion patterns and the distribution of local motion.

Abnormal movement detection: To detect abnormal movement in the test step, we must first generate the visual document for input video VD_{in}. We estimate the motion pattern of the current scene by computing the posterior probability of the input visual document $P(S_k|VD_{in})$ using Bayes' theorem:

$$P(S_k|VD_{\text{in}}) = \frac{1}{m}\sum_{i=1}^{m}\frac{P(PT_i|S_k)P(S_k)}{P(PT_i)} \quad (3)$$

where $P(PT_i)$ is the mean of the marginal probabilities $P(vw)$, and $P(PT_i|S_k)$ is the mean of the conditional probabilities of the visual words that compose PT_i, m is the number of the partial trajectories in VD_{in}. Next, we compute the abnormality of each partial trajectory extracted in the current scene using the following equation:

$$\text{abnormality}(PT_i) = 1 - P(S_k|VD_{\text{in}})P(PT_i|S_k) \quad (4)$$

Experimental results: To evaluate the proposed method, we use real-world traffic scene datasets captured in urban areas. Table 1 shows the composition of the datasets and the number of extracted trajectories per frame (TPF). TPF indicates the degree of crowdedness of the scene. Thus, scene 3 is the most crowded and scene 2 is the least crowded.

Table 1: Number of extracted initial trajectories

	Scene 1	Scene 2 [2]	Scene 3	Scene 4
Frames	26750	165880	19588	92157
TPF	22.65	8.25	33.45	33.20

First, to evaluate the effectiveness of our feature extraction method, we compared the average length of the linked partial trajectory (LT) and the ratio of the valid partial trajectory (number of observations >3) with the initial trajectory (IT) and local motion (LM). As shown in Fig. 1, the average length increases by 7.82 pixels (46.38%) and the valid partial trajectories increase by 28.43% compared to IT. In particular, LT is about six times longer than LM.

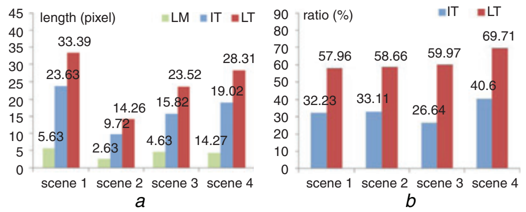

Fig. 1 *Performance of our feature extraction method*

a Average length of feature
b Ratio of valid partial trajectory

To evaluate the performance of the motion pattern analysis, we also compared the results from the proposed method with those using a local motion approach. Fig. 2 shows the comparison for the scene 3 dataset, which is the most crowded. The proposed method detected the dominant motion patterns more accurately than the local motion approach. In particular, local motion could not properly separate motions in motion pattern 1. However, the proposed method separates motions into motion pattern 1 and 2 according to the changing traffic signals. The result with the proposed method is less noisy and more stable.

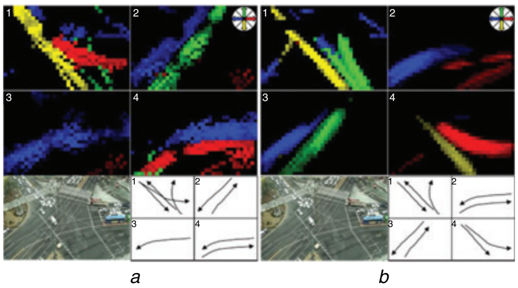

Fig. 2 *Comparison of motion pattern analysis result for scene 3*
a Using local motion
b Using proposed method

Furthermore, to evaluate the accuracy of the proposed method quantitatively, we compared our results with the ground truth (real traffic signal patterns). The transition and period of the motion pattern are almost identical to the ground truth, as shown in Fig. 3. This shows an accuracy level of 88.79% (scene 3) and 94.06% (scene 4). Movement during the yellow light is the major cause of false estimations. Motion pattern 0 means that there was no movement.

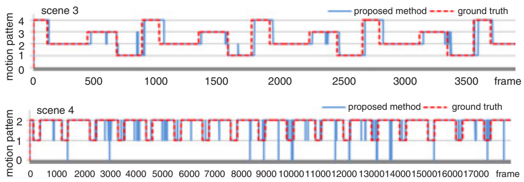

Fig. 3 *Comparison of motion patterns and ground truth*

Finally, we evaluated the performance of the proposed abnormal movement detection method. Fig. 4 shows the detection results for each dataset, with the red line indicating abnormal movement. The inset boxes indicate the estimated dominant flow at the time. As shown in Fig. 4, our method detects abnormal movement well. Furthermore, it shows the path of the detected abnormal movement.

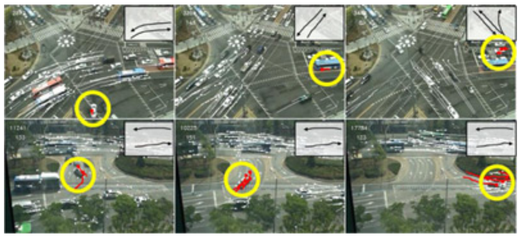

Fig. 4 *Results of abnormal movement detection in scenes 3, 4*

Conclusion: In this Letter, we have proposed a motion pattern analysis method using partial trajectories for abnormal movement detection. Our method enables motion patterns and abnormal movements to be detected in crowded scenes more accurately than a local motion approach. We have demonstrated that our method improves the results using real-world traffic scene datasets.

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One or more of the Figures in this Letter are available in colour online.

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