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Anomalous Situations Detection Based on Confluence

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Abstract: Recently, surveillance cameras have been set up everywhere such as streets and public places in order to detect anomalous situations. In the existing surveillance systems, since only a handful of surveillance agents watch a lot of images from surveillance cameras, there may be some possibilities that they miss the important scenes such as accidents or abnormal incidents. So, we propose a method of the sequential learning and recognition of comprehensive behavioral patterns in the crowded places. Firstly, we extract the comprehensive confluence from an input image using optical flows. Secondly, we extract the behavioral patterns based on change-point detection of the confluence. Finally, we recognize the behavioral pattern by comparing the previous behavioral pattern in the database with a newly observed one. We carried out experiments to verify the effectiveness of our approach by placing a surveillance camera on our campus.

***K*eywords**: Behavioral pattern recognition, Optical flow, Dynamic programming.

1 Introduction

Recently, surveillance cameras have been set up everywhere such as streets and public places in order to detect anomalous situations. In the existing surveillance systems, since only a handful of surveillance agents watch a lot of images from surveillance cameras, there may be some possibilities that they miss the important scenes such as accidents or abnormal incidents. In order to solve this problem, there have been the considerable researches on the system which automatically recognizes human behavior in a surveillance footage. It warns security guards when it detects anomalous situations.
Several methods[1, 2, 3] for recognizing human behavior focus on a few people in a room, and it is difficult to apply the methods to more people in crowded places.
The methods for recognizing crowd behavior using a range scanner or a 3D point measurement device[4, 5] have been proposed. These researches, they can make confluence analysis of dense crowd possible. However, it is not easy to apply these methods because most of the existing surveillance systems use only a monocular surveillance camera.
So, we propose a method for detecting an anomalous situation in crowded places using a monocular surveillance camera.

2 Learning and Recognition of Comprehensive Behavioral Patterns

In this section, we describe a method for recognizing the behavioral patterns of people in such places as multiple people keep moving. In the public places, occlusion occurs frequently, hence it is difficult to keep track of people individually. Because there is an enormous types of motions of people, it is not easy to recognize every behavioral pattern. So, in order to learn the comprehensive behavioral patterns of multiple people and to recognize them, we regard the motions of people as one comprehensive confluence based on the moving direction of people.

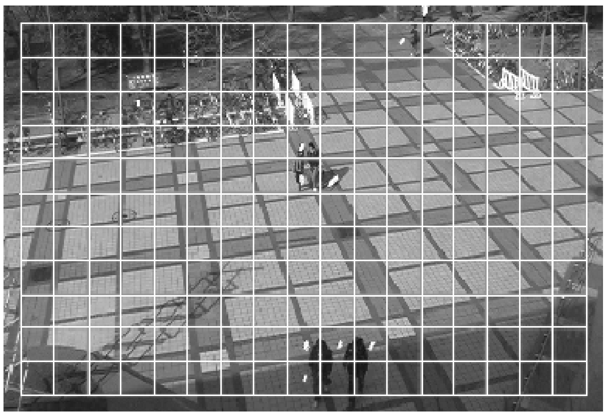

Figure 1: A mode values of optical flows and a divided image into 20 20[pixels] segments. A mode value was drawn on center of each segment.

2.1 Extraction of Feature Vector of Confluence

In this subsection, we explain a technique for extracting a feature vector of motions.
Firstly, to extract a feature vector of the motions, we compute an optical flow of each pixel in an input image. Secondly, a mode value $\boldsymbol{v}_n = \{du, dv\}(n = 1, 2, ..., N)$ are computed by dividing an input image into 20 20 [pixels] segments and in each segment,

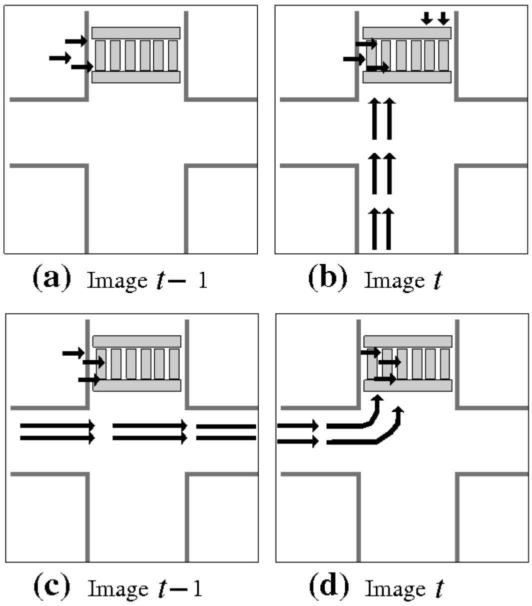

Figure 2: Example of change-point detection by degree of congestion and confluence.

we compute a mode value of optical flows. Where N is the number of segments. Fig.1 shows an example of the mode values. Finally, a feature vector of confluence $\boldsymbol{V}_t = \{\boldsymbol{v}_1, \boldsymbol{v}_2, ..., \boldsymbol{v}_N\}$ is created by raster-scanning the mode value of the optical flows $\boldsymbol{v}_n$ in each segment.

2.2 Extraction of Behavioral Patterns

Generally, the following behavioral patterns are observed in crowded places.

I. People appear in sight of a camera → people go out of sight of a camera

II. As shown Fig.2 (a) people walk on a pedestrian crossing → (b) when they are walking, vehicles go toward the people

III. As shown Fig.2 (c) people and vehicles go straight → (d) they turn to the left

We regard the time when people appear in sight of surveillance camera, the time when degree of congestion changes (Fig. 2(b)) and the time when confluence changes (Fig. 2(d)) as new behavioral pattern starts and we called it division point. We set the division points to the sequence of feature vectors $\{..., \boldsymbol{V}_{16}, \boldsymbol{V}_{17}, ..., \boldsymbol{V}_{21}, \boldsymbol{V}_{22}, ...\}$ to extract the behavioral patterns. We define the feature vectors of confluence between division point as a behavioral pattern. We describe it the extracted p-th behavioral pattern $\mathbf{I}_p = \{\boldsymbol{V}_1^p, \boldsymbol{V}_2^p, ..., \boldsymbol{V}_{T_p}^p\}$. Where T_p is length of the sequence $\mathbf{I}_p$. Fig.3 shows, an example of $\mathbf{I}_p$ and $\mathbf{I}_{p+1}$ extracted from a sequence of feature vectors.

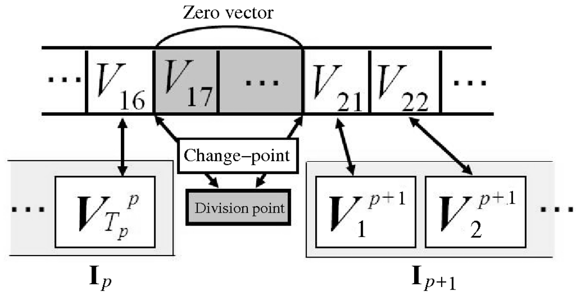

Figure 3: The behavioral pattern extraction by checking the existence of motion.

2.2.1 Division Point Setting Method by Checking Motion Existence

We regard the time when $\boldsymbol{V}_t = \mathbf{0}$ were observed for the fourth time in a row afterward $\boldsymbol{V}_t$ returned to non 0 as division point for the start of the behavioral pattern.

2.2.2 Division Point Setting Method by Detecting Congestion Changes

Firstly, we calculate the number of the non $\mathbf{0}$ mode values $\boldsymbol{v}_n (n = 1, 2, ..., N)$ in the $\boldsymbol{V}_t$. We defined it as h_t. h_t express a degree of congestion. Secondly, when h_t meets the following requirement, we consider the time t to be a division point on a sequence of the feature vectors, where is a threshold value.

$$|h_t \quad \frac{1}{5}\sum_{m=1}^{5} h_{t \quad m}| > \qquad (1)$$

2.2.3 Division Point Setting Method by Detecting Confluence Changes

In this method, in order to survey the similarity between the confluence at time t ($\boldsymbol{V}_t$) and the confluence at time $t \quad 1$ ($\boldsymbol{V}_{t \quad 1}$), we use Wilk's Λ and M-BOX. Significant level is 5%. The null hypothesis is "distribution of $\boldsymbol{V}_t$ and $\boldsymbol{V}_{t \quad 1}$ is identical", and the alternate hypothesis is "distribution of $\boldsymbol{V}_t$ and $\boldsymbol{V}_{t \quad 1}$ is different". When the null hypothesis is rejected, the alternate hypothesis is adopted. We set division point when the alternate hypothesis is adopted.

2.3 Learning and Recognition Method

The procedure of sequential learning and recognition of behavioral patterns and detection of anomalous situations was composed the three general phases. Firstly, when behavioral pattern $\mathbf{I}_p$ is observed, we perform the comparison process (Fig. 4 Comparison) to confirm the existence of the same patterns in the database. Secondly, we carry out the recognition (Fig. 4 Recognition) of $\mathbf{I}_p$. When $\mathbf{I}_p$ is

Table 1: Experimental results of sequential learning, recognizing and anomalous situation detection.

Date	Number of patterns	Behahioral		anomalous		Number of Cumulative patterns
		recognition	misclassification	recognition	misclassification	
2 – 8	12,993	11,920 (94.9%)	635 (5.1%)	420 (95.9%)	18 (4.1%)	793
9 – 15	11,749	-	18	415	-	950
Total	24,742	-	658	835	-	-

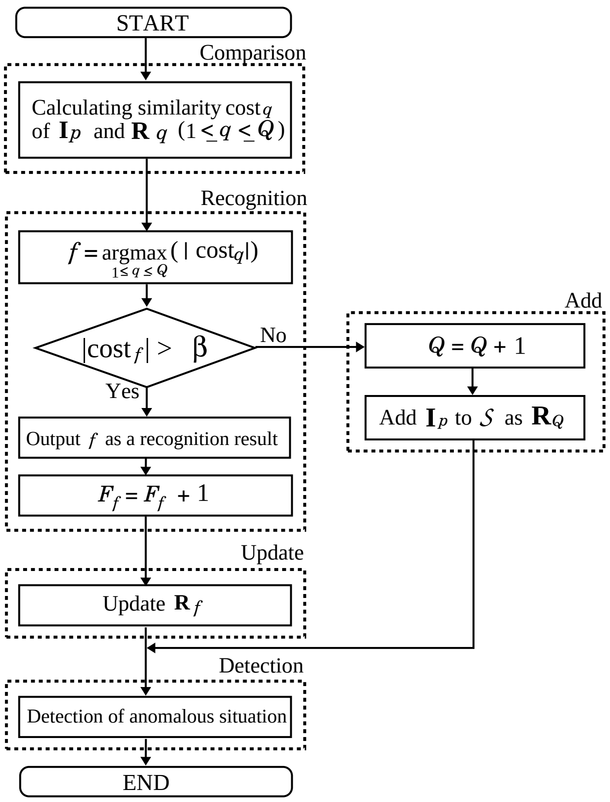

Figure 4: The procedure of sequential learning and recognition behavioral patterns and constructing reference patterns and detecting anomalous situations.

extracted, we compare $\mathbf{I}_p$ with the fore-past behavioral patterns $\mathbf{R}_q$ in the database by computing the similarities $|\mathrm{cost}_q|(q = 1, 2, .., Q)$ using the dynamic programming. After that, $\mathbf{R}_f$ that has the highest similarity is chosen from the database. If the $|\mathrm{cost}_f|$ is higher than , we recognize $\mathbf{I}_p$ as $\mathbf{R}_f$, and we perform updating process (Fig. 4 Update). Where is a threshold value for recognition. If the $|\mathrm{cost}_q|$ is lower than , we add (Fig. 4 Add) $\mathbf{I}_p$ to the database as a new behavioral pattern $\mathbf{I}_{Q+1}$. Finally, we perform detection process (Fig. 4 Detection) of anomalous situations.

2.3.1 Method of Anomalous Situations Detection

If $\mathbf{I}_p$ which was observed is daily behavior, the frequency of observation F_f of $\mathbf{R}_f$ is greater than that of other reference pattern $\mathbf{R}_q(q = 1, 2, ..., Q)$ in the database. If $\mathbf{I}_p$ is anomalous behavior, F_f is lower than that of other $\mathbf{R}_q(q = 1, 2, ..., Q)$. So, we calculate the observation probability $Pr(f)$ to detect anomalous situation. If the value is lower than the threshold γ, we detect $\mathbf{I}_p$ as an anomalous situation.

$$\mathrm{Pr}(f) = \frac{F_f \quad 1}{\sum_{q=1}^{Q} F_q} \tag{2}$$

3 Experiments and Discussions

In order to verify the effectiveness of the proposed method, we performed an experiment. We evaluated the recognition success rate and the misclassification rate of the behavioral patterns and the recognition success rate and the misclassification rate of the the anomalous situations. Data set were observed between Dec.2, 2008 and Dec.15, 2008 using a surveillance camera placed on Osaka-Prefecture University. The image size is 360 240 [pixels]. The thresholds are $= 2.0$, $= 0.05$ and $\gamma = 0.01$.

3.1 Experimental Results

The second column of Table 1 shows the number of observed patterns in several days. The third and fourth columns show the number of recognition success and misclassification of the behavioral patterns. The recognition success of the behavioral patterns is that the classifier correctly recognizes behavioral pattern as behavioral pattern. The misclassification of behavioral patterns is that the classifier falsely recognizes behavioral pattern as anomalous situation. The fifth and six columns show the number of recognition success and misclassification of the anomalous situations. The recognition success of anomalous situations is that the classifier correctly recognizes anomalous situation as anomalous situation. The misclassification of the anomalous situations is that the classifier falsely recognizes anomalous situation as behavioral pattern. The last column shows

the number of patterns that were registered in the database.
In terms of experiments during Dec.2–Dec.8, in order to verify recognition accuracy of our method, we survey observed all patterns. In Table 1, 12,993 observed patterns during Dec.2–Dec.8 were recognized by 793 different reference patterns. We had 94.9% recognition success rate of the behavioral patterns and 95.9% recognition success rate of anomalous situations. In Dec.5, misclassification of the behavioral patterns occurs because it is rainy. In the case that we omit the data of Dec.5 from the data sets, we had 99.8% recognition success rate of behavioral patterns and 95.6% recognition success rate of anomalous situations, during Dec.2–Dec.8.
In terms of during Dec.9–Dec.11, in order to verify detection accuracy of anomalous situations of our method, we survey the objects which the classifier recognizes as anomalous situations. During Dec.9–Dec.11, 749 different reference patterns were registered in the database, and 11,749 observed patterns were recognized by 950 different reference patterns. Therefore, we confirmed a satisfaction of our method.

3.2 Discussions

In this paper, we have proposed a novel method for detecting the anomalous situations in crowded places using a monocular surveillance camera. We describe bellow outline of the proposed method.

Extraction of feature vector of confluence
In this method, we divided an input image and we compute the mode values of optical flows to extract comprehensive confluence. We could extract confluence in crowded places by this approach.
However, we could not extract the feature of quiescent people using optical flows. To tackle the problem, we will use optical flows and background-subtraction.

Extraction of behavioral patterns
We extract of behavioral patterns by using the three rules combination. These are people motion existence, congestion changing points and confluence changing points. We could extract the behavioral patterns correctly using the rules. If we use only the first rule, we do not extract behavioral patterns under the situation that constant flow of confluence is observed always. However, we could extract behavioral pattern under such a situation by using second and third rules.

Learning, recognition and detection
From the results, The increase in the number of patterns in the database is reductive as day goes on. From this reason, we could see that the classifier learns many behavioral patterns on earlier stage, and the classifier learns the behavioral patterns which are not existent in the database.
In order to detect anomalous situation, we use the observation probability. Detected anomalous situations are throwing the ball back and forth, lingering around. These behaviors were too observed. Therefore, we confirmed that the proposed method can recognize behavioral patterns and can detect anomalous situations.

4 Conclusion

We presented a novel method for detecting the anomalous situation in crowded places using a monocular surveillance camera. To learn and to recognize behavior of the multiple people and to recognize them, we regard the motions of people as one comprehensive confluence with a focus on the moving direction of people. Besides, in order to detect anomalous situations, we calculated the observation probability based on the frequency of observation.
In the results, we confirm the effectiveness of the proposed method in crowded places.

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