

Abnormal Behavior Detection Based on the Potential Field Forces in Surveillance Scenarios

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Abstract. In a social environment, there is a natural mutual force between people. This paper proposes a method for detecting group abnormal behavior based on the potential field method. The movement of a pedestrian is described as the movement towards the target under the combined action of several forces. Forces on pedestrians include the attractive force for themselves and the repulsive force between pedestrians. By calculating the resultant force between them, the behavior of pedestrians is judged according to a set threshold. It is verified through experiments on public data sets that our method has high accuracy and robustness.

1. Introduction

At present, the behavior analysis of the crowd is a major research hotspot [1–8]. Due to the uncertainty and complexity of the crowd's movement, it is very challenging to study the behavior of the crowd. In [9], a social force model was used to describe the behavior of the crowd. A particle network was set in the video frame, and then the particles were used as individuals. The social force model was used to calculate the interaction force between the particles. The bag of words method is used to distinguish abnormal behaviors from normal behaviors of groups. From this literature, we can know that there is a social power relationship between people. When a pedestrian crosses a road, the entrance and exit are the moving targets of the pedestrian. When other pedestrians are encountered on the road, evasive behaviors will occur between them, and natural repulsion forces will cause them not to contact each other. In this case, we make contact between acquaintances special. The literature [10,11] is a robot path planning based on artificial potential field method, which proposes to construct an artificial potential field in a working environment. This potential field includes attraction points and repulsion points, and defines forbidden areas and obstacles as repulsion points, with target points or desired areas as attraction points. With such an artificial setting, the robot is advanced toward the target in the artificial potential field in accordance with the combined force direction of the attractive force and the repulsive force.

In this paper, inspired by the previous literature, we propose a group behavior detection based on the potential field force. We can define the monitoring scene as a potential field. Considering the domain of pedestrians, there is a repulsive force between pedestrians and pedestrians. And on a road, the import and export is the attractive force with goal-oriented gravity. Therefore, we can proceed to calculate the combined force of repulsive force and attractive force, and determine whether the



pedestrian's behavior is abnormal according to the set threshold. Contributions to this paper (1) propose a pedestrian behavior detection method based on potential field force (2) This method has fast calculation speed, high accuracy, and strong robustness. It can effectively perform pedestrian abnormal behavior detection in monitoring scenarios. (3) The method has good generalization ability and can adapt to abnormal behavior detection in some low-density pedestrian monitoring scenarios.

2. Related work

2.1. Multi-target tracking

There are many research methods in crowd behavior detection. Because of the different population density, it will bring a lot of difficulties to the research. Therefore, there are different research methods based on the video data of different population densities. For example, in the detection and analysis of the behavior of low-density people, some research methods have proposed object-based feature extraction to analyze pedestrian behavior[12]. In [13], the authors cited deep learning methods to analyze behavioral anomaly detection.

In high-density crowd videos, some research analysis is based on the social force model [9] to establish the relationship between particles to determine whether the behavior is abnormal. Some scholars have studied the pedestrian target trajectory as a research object to analyze group behavior [14]. Crowd density estimation is also a judgment method for researchers as a crowd behavior analysis [15].

In this study, it is considered to establish a potential field to analyze the behavior of pedestrians. Therefore, it is necessary to study multi-target tracking for preliminary research analysis. Therefore, we have also carried out a series of studies on multi-target tracking research [16,17]. In this paper, the Kalman filter is used to calculate and predict the position of each trajectory in the next frame. Calculate the predicted trajectory position, and calculate the Euclidean distance between the new detection target and the predicted target trajectory. Take their calculation results as loss function matrix, and then use the matching algorithm to get assigned detection and unassigned detection, assigned tracking and unassigned tracking. Then update tracking and detection to achieve the target tracking effect.

2.2. Definition of potential field



Figure 1. Defining potential field diagrams

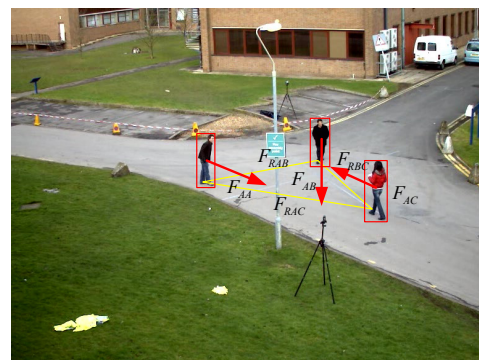


Figure 2. Potential field forces

Figure 1. Defining potential field diagramsshow that there are monitoring scenes where three people are walking normally. The green area represents the entrance and the exit, which belong to the pedestrian's desired destination. The red circles under the pedestrian's feet represent the social sphere of pedestrians. It is generally believed that there is a repulsive force between people. Under no special circumstances, people are mutually exclusive.

Figure 2. Potential field forces shows that there are three pedestrians in the surveillance scene, of which the yellow line represents the repulsive force between the two, and the red arrow indicates the direction of pedestrian action.

2.3. The repulsive force and the attractive force

In this article, the potential function expression of the repulsive force is as follows:

$$U_r(X) = \begin{cases} \frac{1}{2}K_r \left(\frac{1}{|X-X_0|} - \frac{1}{\rho_0} \right)^2, & |X-X_0| \leq \rho_0 \\ 0, & |X-X_0| > \rho_0 \end{cases} \quad (1)$$

Among them, K_r is the position gain coefficient, X is the coordinates of the target pedestrian, X_0 is the coordinates of the target pedestrian X_0 , and ρ_0 is the influence distance set manually. In this paper, because pedestrians and pedestrians affect each other, ρ_0 is twice the impact Distance value.

In the potential field, the negative gradient of $U_r(X)$ is the repulsive force, as shown in Equation 2:

$$F_r = -\nabla U_r(X) = \begin{cases} K_r \left(\frac{1}{|X-X_0|} - \frac{1}{\rho_0} \right) \left(\left(\frac{1}{|X-X_0|} \right)^2 \frac{\partial(X-X_0)}{\partial X} \right), & |X-X_0| \leq \rho_0 \\ 0, & |X-X_0| > \rho_0 \end{cases} \quad (2)$$

Where F_r represents the repulsive force of the target pedestrians X and X_0 . When the distance between the target pedestrians X and X_0 exceeds the influence distance, the repulsive force between them is 0, that is, the repulsive force does not exist.

The attractive force is the self-driving force when the target pedestrian moves. As shown in Equation 3:

$$F_a = m_i \frac{V_{t+\Delta t} - V_t}{\Delta t} \quad (3)$$

In the formula, m_i is the virtual quality of the target pedestrian, $V_{t+\Delta t}$ is the target pedestrian speed at the frame $t + \Delta t$ of the video, and V_t is the speed of the target pedestrian at frame t of the video.

When $X - X_0 \leq \rho_0$, the target pedestrian is the combined force of F_r and F_a . If $X - X_0 > \rho_0$, the target pedestrian is only affected by F_a .

$$F = F_r + F_a \quad (4)$$

In the monitoring scene of multiple target pedestrians, we can take target A and calculate its influence F_A . Other target pedestrians are B, C, D, E, F, \dots , and the repulsive force between them is $F_{AB}, F_{AC}, F_{AD}, F_{AE}, F_{AF}, \dots$.

$$F_A = F_a + (F_{AB} + F_{AC} + F_{AD} + F_{AE} + F_{AF} + \dots) \quad (5)$$

Substituting formula (1) and (2) into formula (5). The value of F_A can be obtained. Similarly, F_B, F_C, F_D can be expressed as the following formula:

$$\begin{aligned} F_B &= F_b + (F_{BA} + F_{BC} + F_{BD} + F_{BE} + F_{BF} + \dots) \\ F_C &= F_c + (F_{CA} + F_{CB} + F_{CD} + F_{CE} + F_{CF} + \dots) \\ F_D &= F_d + (F_{DA} + F_{DB} + F_{DC} + F_{DE} + F_{DF} + \dots) \\ &\vdots \end{aligned} \quad (6)$$

Among them: $F_{AB} = F_{BA}$, $F_{AC} = F_{CA}$, $F_{AD} = F_{DA}$, $F_{AE} = F_{EA}, \dots$.

For the convenience of experiments, when calculating the potential force of the target pedestrian, we normalize the repulsive force in the potential field to $[-1, 0]$, as shown in the following formula:

$$s_r(t) = \frac{F_r(X) - F_r(X)_{\min}}{F_r(X)_{\max}} - 1 \quad (7)$$

3. Experiments

3.1. Datasets

In this article, the public datasets tested are The PETS 2009[18] benchmark data and UCSD Ped[19].

PETS 2009 benchmark data is provided by the University of Reading. There are many video data in the dataset for research use. This article downloads the low-density crowd video frames and the medium-density crowd video frame data. The scenes are all pedestrians walking. The resolution of the video frame is 768×576 .

In the video scene of UCSD Ped2, the road is parallel to the video frame, and the pedestrian walking direction on the road is parallel to the video surface. Furthermore, Ped2 contains 16 training video samples and 12 test video samples. The abnormal events include carts, wheelchairs, skaters and biker shuttles among pedestrians. The resolution of the video frames is 238×158 .

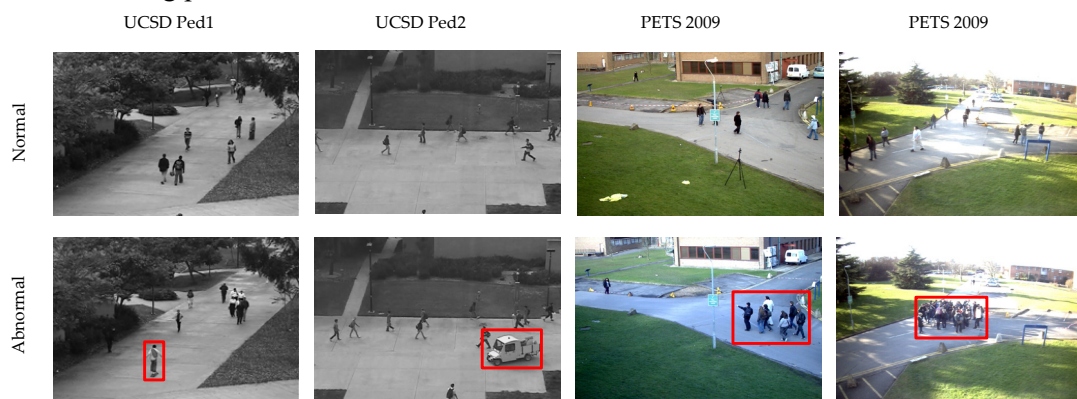


Figure 3. Normal and abnormal behavior in public datasets

As shown in Figure 3. Normal and abnormal behavior in public datasets, several public data sets are exemplified. It is divided into two parts, one is normal behavior and the other is abnormal behavior. In all normal events, pedestrians walk on the road normally, and the road is a sidewalk that only allows pedestrians to pass. The abnormal event includes several different abnormal events. The anomalous event under UCSD Ped1 was a person quickly crossing the road on a skateboard. The anomalous event under UCSD Ped2 was a car passing the road. The abnormal event under the PETS 2009 benchmark data is group aggregation behavior, because the research needs in this article, the group aggregation behavior is judged as abnormal behavior.

3.2. Anomaly detection

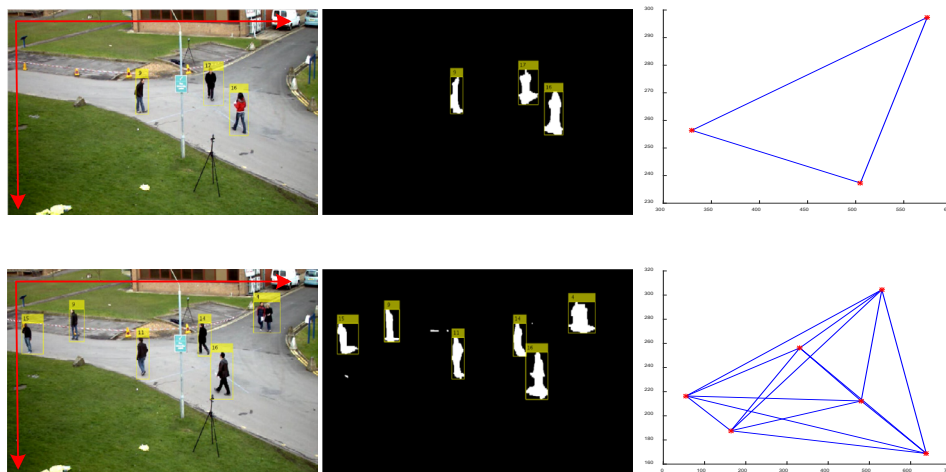


Figure 4. Schematic diagram of multi-target tracking and pedestrian coordinates

The whole experiment is to define the video frame as a potential field, each target pedestrian has a domain scope, and the entrance and exit of the road is the subjective active target of the target pedestrian. Combine the repulsive force and the attractive force of the target pedestrian to calculate their combined force. Determine whether they have behaved abnormally by a given threshold.

As shown in Figure 4. Schematic diagram of multi-target tracking and pedestrian coordinates, the left color image is multi-target tracking in the video scene, and each pedestrian is identified. The middle gray value image is a background extraction algorithm commonly used in motion detection, and then uses the inter-frame difference method to identify moving pedestrians. The coordinates on the right refer to the coordinates of pedestrians in the video frame. In this experiment, the origin of the coordinates is in the upper left corner of the video. Besides, the image frame resolution of each dataset is different, and the resolution of Figure 4. The schematic diagram of multi-target tracking and pedestrian coordinates is 768×576 .

Calculate their repulsive force and the attractive force based on the coordinates of the research target. The total force value is obtained according to the formula, and a threshold is manually set to determine whether their behavior is abnormal.

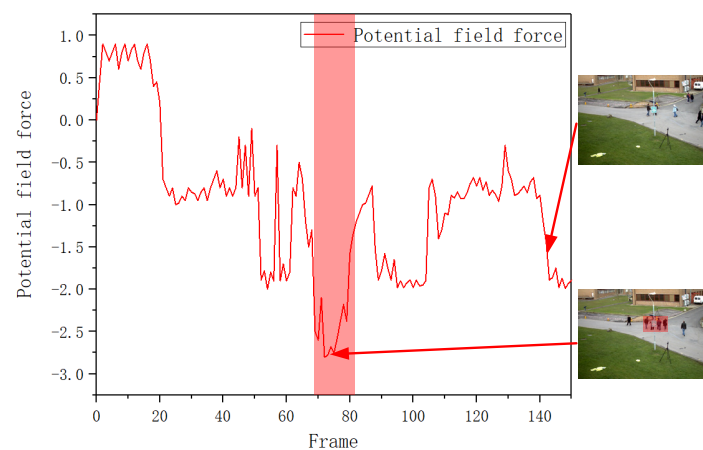


Figure 5. Graph of the potential field force

As shown in Figure 5. Graph of the potential field force, select video frames in the dataset pets2009 S2 L1 for the experiment. After setting a threshold and performing anomaly detection, we calibrate a pedestrian to calculate his potential field force. The red area in the picture is for detecting abnormal behavior in the video, and the rest is normal behavior. The red curve is the potential field force, and the coordinate axis frame represents the number of video frames. According to different monitoring scenarios, different aggregation numbers are defined as abnormal behaviors. In this experiment, we manually set the aggregation behavior of more than four pedestrians and defined it as abnormal behavior.

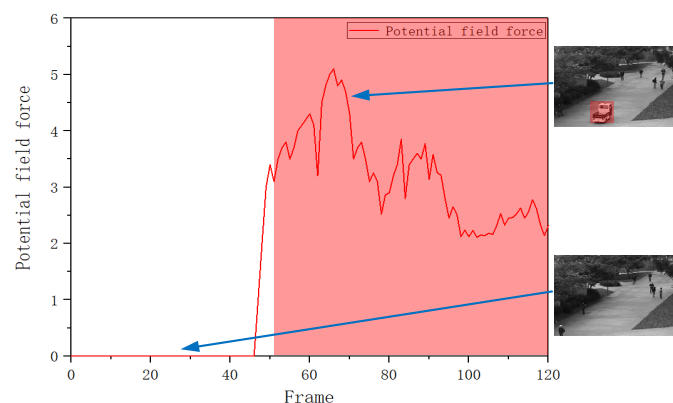


Figure 6. Graph of the potential field force

As shown in Figure 6. Graph of the potential field force, the video frames in the data set UCSD Ped1 are selected for experiments. Set the attractive force threshold and perform anomaly detection. The red area in the figure is for detecting abnormal behavior in the video, and the rest is normal behavior. The red curve is the potential field force, and the coordinate axis frame represents the number of video frames. According to different monitoring scenarios, different thresholds of the attractive force are defined. When the threshold is larger than this threshold, the behavior is abnormal.

4. Conclusions

We define the video surveillance scenario. Each target pedestrian has a potential field, and each person has his field of scope. Under the consideration of general social force, each pedestrian will not approach other pedestrians. Besides, everyone has his subjective initiative, actively walking towards the entrance of the road. Under such a scenario, a potential field force is proposed to detect the abnormal behavior of pedestrians. When multiple pedestrians gather together, a potential field force exceeding a given threshold is thus obtained, and thus abnormal behavior is detected. When the attractive force of a detection target exceeds a certain range, its abnormal behavior is also defined. According to experiments in public data sets, we know that our method is highly accurate and robust. Taking into account the light changes in the monitoring scene, the target is blocked and so on. This adds much challenge to the experiment. Therefore, in future research work, we will study how to improve the method to improve the accuracy of these special cases.

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