Dynamic model of macro crowd merging based on abnormal pedestrian posture

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Abstract. Crowd merging is a complex process, and any sudden external or internal disturbance will destroy the stability of the crowd. The occurrence of abnormal behavior will affect the crowd flow process and inevitably affect the stability of the crowd flow system. The position information of the joint points is obtained through the OpenPose algorithm, and the kinematics characteristics of each node are studied. It is judged whether the number of pedestrians in the crowd and the scale of the building scene are greater than the empirical setting value based on engineering statistical data and expert experience. When the number of pedestrians is more than 2,000 and the total area of the passage is more than 2,000 square meters, the appropriate macro-dynamic model is selected. The Aw-Rascle (AR) fluid dynamics model is selected in this study. The joint point information obtained through the OpenPose is combined with the macroscopic fluid dynamics model to construct a macroscopic crowd flow dynamics model based on the pedestrian's abnormal posture.

Keywords: Aw-Rascle (AR) model, Crowd merging, OpenPose.

1 Introduction

The abnormal behaviour of pedestrians in public places will cause a series of problems such as crowd instability. The abnormal behaviour of pedestrians in public places is mainly manifested as abnormal posture, followed by abnormal expressions and voices. Abnormal postures are the most conductive and harmful, including sudden changes in pedestrian speed, pedestrian U-turns, pedestrians falling, asking for help from illness, gathering fights, and violent terrorist attacks. Unconventional behaviours all have special movement posture characteristics, which directly affect crowd flow. The key node kinematics and dynamics are complex, which often cause local turbulence, disturbance and density-speed fluctuations, and it is easy to lose stability and cause crowds to trample [1].

The occurrence of abnormal behaviour will affect the crowd merging process. It will disturb the crowd's movement direction and forward speed and other factors, causing an instantaneous density surge, which inevitably affects the stability of the crowd flow system. At present, the recognition of abnormal postures is mostly the short-term behaviour of pedestrians. There are few studies on the impact of crowd movement and group behaviour caused by emergencies in group scenarios. Therefore, this study constructs a dynamic model

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of pedestrian abnormal posture and crowd flow, and further obtains the dynamic evolution mechanism of crowd flow. This is of scientific significance and realistic demand for detecting abnormal events in time and avoiding risks.

2 Analysis of human joint points based on OpenPose

Pedestrian individual gesture recognition reflects the behaviour state and trend of pedestrians to a certain extent. Anomaly detection and gesture recognition of people in motion is a hot issue in the field of computer vision. They all belong to the category of human motion recognition. Human motion recognition refers to the use of a certain method to detect and track the motion of the human body, obtain the motion parameters of the human body, and reconstruct the structure and posture of the human body from it, and finally achieve the understanding of human motion and apply it.

Human pose estimation is mainly divided into 2D pose estimation and 3D pose estimation. 2D pose estimation is mostly studied. The 2D pose estimation is divided into single pose estimation and multi-person pose estimation. Multi-person pose estimation is mainly divided into two categories, one is the top-down method, that is, the first detection of each person, and then the pose estimation of each person; The other is the bottom-up method, which first finds out all the parts of all people, then distinguishes the attribution of key points according to the clustering method, and finally performs the humanoid splicing. Representative algorithms include Associative Embedding, Mid-Range offsets, and PAF. In this study, the Open Pose model is used to analyse the abnormal posture of the human body.

In terms of the network model of abnormal posture key nodes, multi-person real-time recognition can divide the human body into 15, 18 or 25 key points of the body/foot. Considering the calculation time and training complexity, 18 joint points are selected for research; OpenPose uses a non-parametric representation called Part Affinity Fields (PAF) to learn how to associate body parts with individuals. The method of predicting Part Affinity Fields (PAF) mainly solves the problem of multi-person gesture recognition. It uses a bottom-up method to first detect the joint points, and then judge which person network structure each joint point belongs to. The position information of the joint points is obtained through the confidence heat map s, and the connection mode of the joint points is determined by the partial affinity domain L. After fusing the global features and the silhouette features of the human body, the abnormal behaviour marking and classification can be realized through the support vector machine. Pedestrian abnormal behaviour is unique in physical manifestation, but it is indeed diverse in visual manifestation. In order to deeply understand the behaviour of the human body, a network matrix of key nodes of abnormal posture is constructed. The kinematic characteristics of a node, such as changes in trajectory, speed, etc., can detect abnormalities in time. The image rendered according to the OpenPose is shown in Figure 1, and the OpenPose human joint point map and the analysis of m and r are shown in Figure 2.

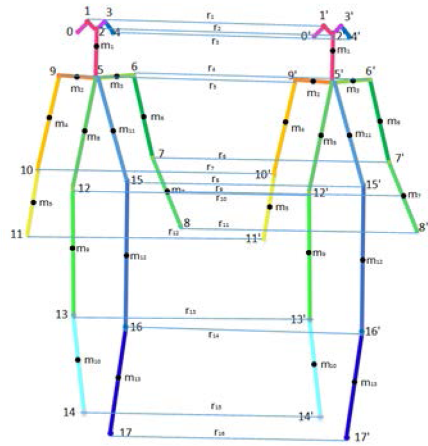

Fig. 1. OpenPose rendered image. **Fig. 2.** Pedestrian's OpenPose human joint point map.

The method of calculating the speed and direction of the centre of mass is not suitable for the analysis of abnormal postures regarding pedestrians as mass points. In this study, equations (1) and (2) are used to analyse the speed of the human body's abnormal posture combined with the human body joint point information obtained by the OpenPose algorithm.

$$\overrightarrow{r_c} = \frac{\sum m_i \overrightarrow{r_i}}{\sum m_i} \tag{1}$$

$$\overrightarrow{v_c} = \frac{d\overrightarrow{r_c}}{dt} \tag{2}$$

3 Dynamic model of abnormal posture and crowd merging

Crowd dynamics began in 1950 and is still a research hotspot in the field of crowd evacuation and protection. According to the different research granularity, it can be divided into macro model and micro model. At the macro level, the typical model is the crowd fluid dynamics model [2]. In the limited space of public places, the flow of people conforms to the laws of conservation of mass, conservation of momentum and conservation of energy. Based on the LWR traffic flow model, a large-scale crowd dynamics model can be established to assess the risk of crowd gathering [3-5]. Based on the PW model, an anisotropic two-dimensional crowd evacuation model (AR model) can be established [6]. By solving and simulating partial differential equations, the AR model can more accurately simulate crowd movement behaviour [7]; in terms of microscopic models, individual pedestrians are the research objects, including social force models [8,9] and centrifugal force models [10,11], velocity model[12]; lattice gas model and cellular automata model[13].

Crowd merging is a complex process, and any sudden external or internal disturbance will destroy the stability of the crowd. The occurrence of abnormal behaviour will affect the crowd flow process, disturb the crowd's movement direction and forward speed and other factors, cause an instantaneous density surge phenomenon, and inevitably affect the stability of the crowd flow system. Some typical merging scenes are shown in Figure 3, and the pictures are referenced from some references[14].

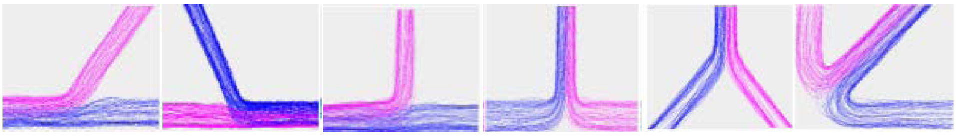

Fig. 3. Typical merging scenes(1) Asy- 45° (2) Asy- 60° (3) Asy- 90°(4) Sym- 180° (5) Sym- 90° (6) Sym- 270°.

The pure crowd flow model provides the dynamic basis of crowd movement. In terms of crowd flow dynamics models, most of them simplify pedestrians to mass points or crowds to continuous fluids. The pedestrian node is converted into a pedestrian mass point, the individual pedestrian's centre of mass position is calculated, and the individual's movement speed is calculated. When the instantaneous speed changes drastically, it means that the pedestrian's centre of mass has a sudden change, and events such as falls and fast running may occur. In the dynamic model, acceleration is an important internal factor index for system changes, which can be obtained by integrating speed over time, but the speed changes of some abnormal behaviours are not obvious, such as crowding, pushing, fighting and other events. The pure crowd flow model has not yet described more fine-grained pedestrian posture characteristics and comprehensive analysis of the acceleration change characteristics of each node. It is difficult to detect signs of abnormal behaviour in advance, and it needs to be combined with new posture recognition methods. Gesture recognition can effectively detect the precursors of abnormal crowd disturbances, but it cannot fully support the analysis of crowd flow stability. This study combines the advantages of the two, analyses the characteristics of the abnormal posture of pedestrians in crowds of public places, and selects micro- or macro-dynamic models according to the number of crowds and the scale of the scene, and further obtains the dynamic evolution mechanism of crowd flow.

The study judges whether the number of pedestrians in the crowd and the scale of the building scene are greater than the empirical setting value (given according to engineering statistics and expert experience, if the number of pedestrians is greater than 2000, the total area of the passage is greater than 2000 square meters) to select the appropriate dynamic model under different merging scenarios. According to different merging scenarios, a macro fluid dynamics model or a micro social force model is selected to construct a dynamic model of pedestrian abnormal posture and crowd merging.

In the scenario where the number of pedestrians is greater than 2,000 and the total area of the passage is greater than 2,000 square meters, the macro-fluid dynamics model is selected to analyse the dynamic evolution mechanism of crowd flow. This study uses the macro-Aw-Rascle (AR) model combined with the OpenPose model to analyse the dynamic model of pedestrian abnormal posture and crowd merging.

The Aw-Rascle model is a model composed of two nonlinear hyperbolic partial differential equations. The equation (3) is determined by the partial differential equation of conservation of mass,

$$\rho_t + (\rho v)_x + (\rho u)_y = 0 \tag{3}$$

where v and u are obtained by decomposing $\overrightarrow{v_c}$ based on the OpenPose model to get the horizontal and vertical velocities, the flux flow ρ_{t} is the partial derivative of time t and $(\rho v)_x$ is the partial derivative of distance.

$$(v + P_h)_t + v(v + P_h)_x + u(u + P_h)_y = s_1 \tag{4}$$

$$(v+P_v)_t + v(v+P_v)_x + u(u+P_v)_y = s_2 \tag{5}$$

where τ is the relaxation time, s_1 and s_2 represent the relaxation terms when the speed is in equilibrium, P_h is the pressure term in the horizontal direction, and P_v is the pressure term in the vertical direction. The initial conditions are $\rho(x,y,0) \geq 0, v(x,0) \leq |v_{f1}|$ and $u(y,0) \leq |v_{f2}|, v_{f1}$ and v_{f2} are the maximum speeds of evacuated individuals in two directions based on the analysis of the open pose model. $P_h(\rho,v)$ and $P_v(\rho,v)$ functions are given by equations (6) and (7).

$$P_h(\rho,v) = \frac{v\rho^{\gamma+1}}{\beta-\rho^{\gamma+1}} \tag{6}$$

$$P_v(\rho,v) = \frac{u\rho^{\gamma+1}}{\beta-\rho^{\gamma+1}} \tag{7}$$

Equations (1)-(7) together form a macroscopic crowd flow dynamics model based on pedestrian abnormal postures.

4 Summary

After the analysis of the joint points of the pedestrian's abnormal posture, is obtained based on the OpenPose model in this study. This study judges whether the number of pedestrians in the crowd and the scale of the building scene are greater than the empirical setting value, selects the Aw-Rascle (AR) macro-fluid dynamics model, and obtains the macro-crowd merging dynamics model based on the abnormal posture of pedestrians. However, this study lacks the analysis of micro-fluid dynamics models that are smaller than the number of pedestrians in the crowd and the scale of the architectural scene, and lacks a macroscopic crowd flow dynamics model based on the abnormal posture of pedestrians.

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