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School Bullying Identification Based on LSSVM Algorithm

Yanwu Hong[1], Anton Louise De Ocampo[2,*]

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Abstract: This research is about developing a monitoring system that can supervise school bullying. Based on the analysis of characteristics of crowd behaviors, we extract 3 features of crowd behaviors to identify the normal incidents and school bullying, which are crowd density, movement intensity, and degree of movement clutter. The crowd density is estimated with the method-based pixel statistics. According to the optical flow algorithm, we can get the movement vectors of all people in each frame image. Then calculate the mean amplitude of all the vectors as the movement intensity. As for the degree of movement clutter, firstly get all the angles of movement vectors according to the vectors' coordinates of x and y. Then calculate the standard deviation of all the angles as the degree of movement clutter. Finally, We apply the LSSVM algorithm to identify school bullying incidents. Randomly choose 30 groups of images from a video that contains normal incidents and school bullying incidents. Extract the 3 movement features and label all the images as 0 or 1, with 0 representing a normal incident and 1 representing a school bullying incident. Apply the training data to train the LSSVM model and then apply the 20 groups of testing data to test the prediction accuracy. The results show that the classification accuracy is only about 60%. Through the characteristics analysis of school bullying, we only take movement intensity and degree of movement clutter as input parameters to train the SVM model. The results show that the prediction accuracy can be improved to about 90%. So we can use the SVM model to identify school bullying incidents and take the crowd density as an early warning parameter to detect the school bullying ahead.

Keywords: *Intelligent Monitoring System, Crowd Density, Movement Intensity, Degree Of Movement Clutter, Optical Flow Algorithm, LSSVM.*

1. Introduction

Campus bullying is a serious social problem. It not only causes physical and psychological harm to the victims but also harms the entire campus environment and society. To effectively prevent and combat campus bullying, the monitoring system plays a more and more important role in campus life. However, traditional monitoring systems often rely on closed-circuit analog or digital television as the core, transmitting video information from multiple surveillance cameras and storing it. The monitoring system requires security personnel to constantly switch the monitoring display screen at a fixed time to detect abnormal behaviors that can not be realized in real-time detection. So it is necessary to develop an intelligent monitoring system for campus bullying.

There is little research about the intelligent monitoring system for bullying prevention. Most research is about the impact of school bullying on students' physical and mental health or the effectiveness of the school system in preventing school bullying. Ma, Shuoping, et al[1] take high school students in H city as the research object, collect data through the literature research method and questionnaire survey method, and pay attention to the relationship between the middle school system and campus bullying. Hannah Gaffney et al[2] present results from an extensive systematic and meta-analytical review of the effectiveness of school-based bullying prevention programs. Farrington et al[3] indicate the pitfalls of previous reviews and explain in detail how the present systematic review and meta-analysis addresses the gaps in the existing literature on bullying prevention.

In this paper, through analyzing the characteristics of crowd behavior, 3 crowd behavior features which are crowd density, movement intensity, and degree of movement clutter are extracted to identify the normal behaviors and abnormal behaviors. High crowd density is always the first sign of an abnormal incident. High movement intensity is the main characteristic of abnormal incidents. The degree of movement clutter is proposed to identify abnormal incidents and sports activities for the first time. With the record of 3 crowd behavior features of the normal video in a certain monitor area, we can set the appropriate threshold of the 3 features to detect school bullying in real-time.

The intelligent monitoring system should analyze the characteristics of students' behaviors including crowd density, movement intensity, and degree of movement clutter to classify school bullying and normal incidents. Considering that there is not enough research about intelligent monitoring systems of bullying, firstly we search literature about calculating crowd density. Secondly, we search literature about calculating the motion vector of

[1] *College of Engineering, Batangas State University. The National Engineering University, Alangilan Campus. Batangas City 4200, Philippines*
ORCID ID: 0000-0001-8714-5832
[2] *College of Engineering, Batangas State University. The National Engineering University, Alangilan Campus. Batangas City 4200, Philippines*
ORCID ID: 0000-0002-6280-6259
** Corresponding Author Email: antonlouise.deocampo@ieee.org*

people.

Many researchers have realized the calculation of crowd density and applied different methods and improve the recognition and calculation accuracy. Miraclin et al[6] use the advanced MobileNet Single Shot Detection algorithm to detect the human class in the given frame at the given moment. The count of individuals in the frame is dependent on the threshold set by the end-user. This system uses Keras, a high-level deep learning library, and OpenCV, a computer vision library, to perform real-time people counting. Kai Yang et al[8] introduce an end-to-end trainable depth structure, which uses multiple-scale cores to capture image context semantic information and learn the importance of each feature in each image location. In other words, our method adaptively encodes the scale of context information needed to accurately predict population density. Xie Pengcheng[9] applies the estimation method of crowd density in outdoor real-time monitoring. By analyzing the research status and progress of crowd density estimation at home and abroad, the method of combining pixel feature and texture feature is used to estimate the crowd density of low-density crowd and high-density crowd respectively. Wang Daner et al[10] propose a new automatic estimation method for crowd density. The method based on pixel statistics is used for low-density crowd images, and the method based on multi-scale analysis and fractal texture analysis is used for high-density crowd images. A support vector machine was used to classify the population density. Experiments on crowd image sets show that this method is more accurate and effective than previous methods. P. Kishore et al[11] estimate the crowd concentrations using crowd feature tracking with optical flow. Local features are extracted using the Features for Accelerated Segment Test (FAST) algorithm per frame. Optical flow tracks the features between frames of the surveillance video.

Many other researchers have realized the calculation of motion vectors with different algorithms. Pallavi D Chakole et al[12] propose a mechanism based on the optical flow that must be implemented to compensate for all of these factors. The amount of motion present in two successive frames is estimated using optical flow. It includes information on velocity in the x & y plane, along with magnitude and line of action. Amna Sajid et al[13] present an algorithm that observes crowd optical flow in real time and detects any abnormal events in crowds automatically. The system takes the frames at regular intervals through a video camera and processes these frames using image processing techniques. The proposed system further uses certain rules to classify the normal or abnormal activities of the crowd. Yunyoung Nam[14] presents a real-time abnormal situation detection method in crowded scenes based on the crowd motion characteristics including the particle energy and the motion directions. The particle energy is determined by the computation of optical flow derived from two adjacent frames. The particle energy is modified by multiplying the foreground-to-background ratio. The motion directions are measured by mutual information of the direction histograms of two neighboring motion vector fields. H. Zhi[15] introduces block-based motion directions to model those events and uses a support vector machine (SVM) to detect abnormal actions from real-time monitoring video sequences. To increase the robustness against noise and to capture the slight movement of the object, we select the foreground frames (the frames having human objects) with a background edge model before the action feature extraction. Then, action features are extracted using normalized histogram analysis from the motion directions of all the foreground frames.

However, few researchers apply the motion vectors to calculate the motion intensity and degree of motion clutter for the reason of large amounts of vector data. So we combine the crowd density and motion vector to detect school bullying as the core of the intelligent monitoring system. Applying the optical flow algorithm to gain the motion vectors in huge numbers, we composite the vectors of a certain person to several vectors and then calculate the values of vectors as the motion intensity. Finally, divide the space into 12 directional spaces, and count the number of vectors falling into the corresponding direction space. Then calculate the variance as the degree of motion clutter. By applying the LS-SVM classification model, the intelligent monitoring system can effectively detect school bullying.

2. Research Methodology

2.1. Characteristics Analysis of Crowd Behaviors

Through the observation of some surveillance videos, we study the evolution process of abnormal behaviors. We select some frames of surveillance videos to show the process of abnormal behaviors.

Fig.1. The Evolution Process Of Abnormal Behaviors

As we can see, the first sign of abnormal behaviors is crowd gathering and then it gradually turns into fighting and conflict incidents, so we need to detect the crowd density first. Once there is an abnormal crowd gathering, the security should be informed.

The biggest difference between normal crowd gathering and abnormal behaviors is movement intensity. As we can see in the pictures above, it is obvious that the abnormal behaviors have high movement intensity. However, when it comes to sports activities, it is difficult to classify the normal activities and abnormal behaviors with the only feature parameters movement intensity.

Fig.2. Sport Activities Pictures

As we can see in the pictures shown in Figure 2, the yellow arrows stand for the motion vectors of the players. The length of the arrow stands for the motion intensity, and the direction of the arrow stands for the moving direction at the moment. The players are competing fiercely with high movement intensity, but they are either under offense or defense. So the moving direction is under some degree of consistency. However, as for the abnormal behaviors shown in Figure 1, whether people are escaping or fighting, all the activities are under the individual autonomous sense. So there is little consistency which means a high degree of movement clutter.

The results of the analysis of crowd behaviors show that if the crowd density increases, it may turn into abnormal behavior. if the movement intensity and degree of movement clutter are both high, there is a high possibility of the occurrence of abnormal behaviors. On the other hand, there is a lot of uncertainty in group movement, so there must be a certain normal movement with high movement intensity and a high degree of movement clutter at a certain time. However, abnormal behaviors usually last for some time, so in conclusion, high crowd density, high movement intensity, high degree of movement clutter, and sustainability are the four main characteristics of abnormal behaviors.

According to the results of the analysis of crowd behaviors, we design the principle of the intelligent monitoring system to detect campus bullying behaviors.

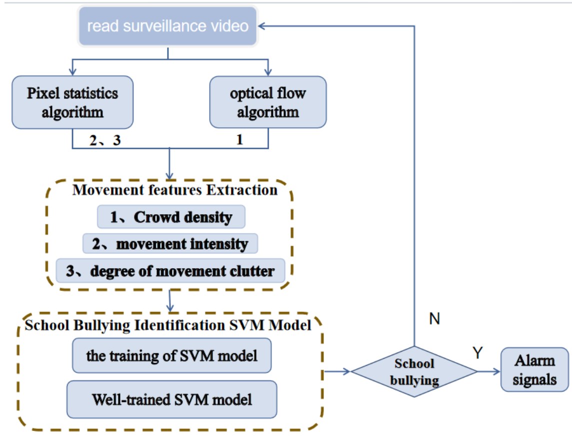


Fig.3. The Principle Of Intelligent Monitoring System

2.2. Specific Solution To Calculate The 3 Features Of Crowd Behaviors

2.2.1. Crowd density estimation algorithm based on pixel statistics

The density estimation method based on pixel statistics generally estimates the density of the crowd by statistical foreground clumps or internal edge proportions. Generally speaking, there is a direct relationship between the crowd density and the moving foreground or inner edge. The more people in the area, the higher the proportion of foreground image and edge. The method has high real-time performance and a good extraction effect.

To gain the crowd density, Firstly the input video is smoothened and de-noised, and the background is updated using the smoothened image. Then the foreground edge is obtained by the Xor operation between the background image and foreground image. Finally, by turning the foreground edge image into a binary image and some morphological process, we can get the foreground clumps which will be used to estimate the crowd density with the formula below. The framework to estimate the crowd density is shown in Figure 4.

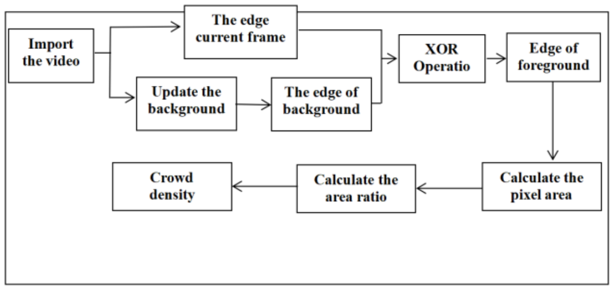


Fig.4. The Framework Of Getting The Edge Of Foreground

After the foreground edge is obtained, the area ratio of the foreground edge in the region can be calculated according to the formula as follows.

$$R = \sum_{i=1}^{N} \frac{s_{(i)}}{m \times n} \quad (1)$$

In the formula, *m* and *n* are the width and length of the image of monitoring area. $s_{(i)}$ is the pixel area of i[th] foreground edge. We can take the R as the crowd density of a certain frame image.

2.2.2. Estimation of crowd movement intensity and degree of movement clutter based on optical flow algorithm

2.2.2.1.The principle of optical flow algorithm

Based on the principles of human visual perception, generally speaking, objective objects in space are relatively continuous in motion, and the images projected on the retinal plane are also continuously changing. So we can regard the moving image function $I(x, y, t)$ as a continuous function about variables x , y , t . Assuming the intensity value $I(x, y, t)$ of the imaging point of the object at a time t and position (x, y) . Represent the horizontal and vertical velocity components of the image at that point as $v_x(x, y)$ and $v_y(x, y)$, respectively. At time $t + dt$, the image point will move from (x, y) to the position point $(x + dx, y + dy)$, with an intensity value of $I(x + dx, y + dy, t + dt)$, where $dx = v_x dt$, $dy = v_y dt$, represent the displacement in the horizontal and vertical directions. For the same target point, we believe that the intensity $I(x + dx, y + dy, t + dt)$ of the image point at time $t + dt$ and $(x + dx, y + dy)$ should be the same as the intensity $I(x, y, t)$ of the image at time t and (x, y) , that is:

$$I(x, y, t) = I(x + dx, y + dy, t + dt) \quad (2)$$

Using Taylor's formula to expand and ignore higher-order terms, when d_x , d_y , d_z is very small, there is

$$I(x + dx, y + dy, t + dt) \approx I(x, y, t) + \frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt \quad (3)$$

By combining (2) with (3), we can approximately obtain:

$$\frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt = 0 \quad (4)$$

Formulas (3) are represented by the displacement vector (dx, dy) . Now, dividing both sides by dt simultaneously equals :

$$\frac{\partial I}{\partial x} v_x + \frac{\partial I}{\partial y} v_y + \frac{\partial I}{\partial t} = 0 \quad \text{or} \quad \nabla I^T v + \frac{\partial I}{\partial t} = 0 \quad (5)$$

Among them, $v = (v_x, v_y)$ represents the velocity vector, also known as the optical flow vector, and $\nabla I = [\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}]^T$ refers to the spatial gradient vector of $I(x, y, t)$. We often refer to formulas (5) as the basic optical flow equation. We assume that dt is very small, so that $v_x = dx / dt$ and $v_y = dy / dt$. This formula can only be established based on the assumption of constant optical flow.

There is an aperture problem, which states that for the sum of two unknowns v_x and v_y. If there is only one equation, the velocity vector cannot be determined from the sum. It's only possible to solve for two unknowns if you give them new constraints, so what kind of constraints are reasonable for video images? Generally speaking, constraint refers to the smooth change of the flow vector in space, so that a small neighborhood around it can use its brightness change to estimate the motion of the place. One way to do this is in terms of the gradient sum of squares of the two velocities:

$$\varepsilon_c^{\ 2} = (\frac{\partial v_x}{\partial x})^2 + (\frac{\partial v_x}{\partial y})^2 + (\frac{\partial v_y}{\partial x})^2 + (\frac{\partial v_y}{\partial y})^2 = \| \nabla v_x \|^2 + \| \nabla v_y \|^2 \quad (6)$$

Another way to express this is using the Laplacian operator:

$$\varepsilon_c^{\ 2} = \frac{\partial^2 v_x}{\partial x^2} + \frac{\partial^2 v_x}{\partial y^2} + \frac{\partial^2 v_y}{\partial x^2} + \frac{\partial^2 v_y}{\partial y^2} = \nabla^2 v_x + \nabla^2 v_y \quad (7)$$

Let's do it the second way. The following procedure is similar to the approximation of the Laplacian operator:

$$\nabla^2 u \approx \kappa(\bar{u}_{i,j,k} - u_{i,j,k}) \quad \nabla^2 w \approx \kappa(\bar{w}_{i,j,k} - w_{i,j,k}) \quad (8)$$

2.2.2.2 Calculate The Intensity Of Motion Vector

Since the research object of this paper is fighting, brawling, stampeding and other abnormal crowd events, only when the intensity of crowd movement reaches a relatively large degree can the above crowd anomalies occur. According to the motion vectors calculated by the optical flow method, we can calculate the motion intensity with the coordinates of x and y of all the motion vectors. The calculation formula is shown below.

$$\delta = \sum_{i=1}^{N} \sqrt{(x_i)^2 + (y_i)^2} / N \quad (9)$$

Where N stands for the number of all the motion vectors, and (x_i, y_i) is the pixel coordinates of motion vector i. δ is the average value of motion intensity of a certain image.

2.2.2.3 Calculate The Degree Of Motion Clutter

After reading a lot of literature, two-dimensional space is generally divided into 12 equal regions. Since the total angle of two-dimensional space 360 degrees can be divided by 12, there will be no missing angle in the direction classification of the space after classification. Therefore, the scene is divided into several equal regions to calculate the number of motion vector distributions in each region. That is, 360 degrees of two-dimensional space are divided into nine regions, where$(0,\frac{\pi}{6})$ is the space in the first direction. $(0,\frac{\pi}{3})$ is the space in the second direction, and $(0,\frac{\pi}{2})$ is the space in the third direction. $(0,\frac{2\pi}{3})$is the fourth directional space; $(0,\frac{5\pi}{6})$is the fifth directional space; $(0,\pi)$ is the sixth directional space; $(0,\frac{7\pi}{6})$ is the seventh directional space; $(0,\frac{4\pi}{3})$is the eighth directional space; and $(0,\frac{3\pi}{2})$ is the ninth directional space, $(0,\frac{5\pi}{3})$ is the tenth directional space; $(0,\frac{11\pi}{6})$ is the eleventh directional space; $(0,2\pi)$ is the 12th directional space, as shown in figure 5. Then count the number of vectors in each directional space where the motion vector of each frame falls.

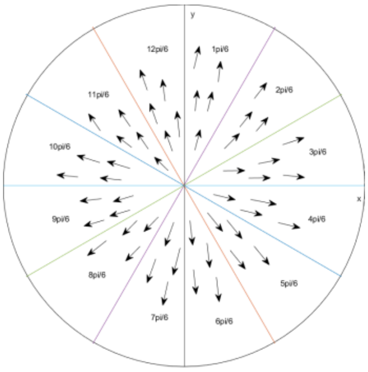


Fig.5. Schematic diagram of 12 directional spaces

Through the distribution statistics of optical flow vectors in each directional space, we can calculate the variance of the histogram to be the degree of motion clutter.

$$\alpha_i = tan^{-1}({}^{y_i}/_{x_i}) \tag{10}$$

$$\mu = \sum_{i=1}^{n} \frac{\alpha_i}{n} \tag{11}$$

$$\varepsilon = \sum_{i=1}^{n} \sqrt{(\alpha_i - \mu)^2}/n \tag{12}$$

Where (x_i, y_i) is the pixel coordinate of motion vector i. n is the number of motion vectors . μ is the average number. ε is the variance of angel of movement vectors which is taken as the degree of motion clutter.

2.2.3. The LS-SVM Model Of Identifying School Bullying

Support vector machine is mainly used to solve the problem of data classification in the field of pattern recognition, which belongs to a kind of supervised learning algorithm. The problem that SVM solves can be described as a classic binary classification problem. As shown in Figure 6, the red and blue two-dimensional data points can be separated by a straight line.

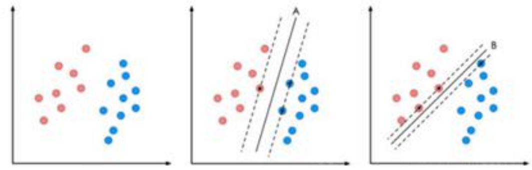


Fig.6. Schematic diagram of the classification principle of SVM

Least Squares Support Vector Machines (LS-SVM) starts from the machine learning loss function, uses the two-norm in the objective function of its optimization problem, and uses equality constraints instead of inequality constraints in the standard SVM algorithm. The solution of the optimization problem of LS-SVM method is changed into the solution of a set of linear equations obtained by Kuhn-Tucker conditions.

For the SVM problem, the constraints are inequality constraints:

$$\min_{w,b,\xi} J(w,\xi) = \frac{1}{2} w^T w + c\sum_{k=1} \xi k \tag{13}$$

$$\text{S. t. } y_k \left[w^T \varphi(x_k + b) \right] \geq 1 - \xi_k, k = 1,\dots,N \tag{14}$$

$$\xi_k \geq 0, k = 1,\dots,N \tag{15}$$

For LS-SVM, the original problem becomes an equality constraint:

$$\min_{w,b,c} J(w,e) = \frac{1}{2} w^T w + \gamma \sum_{k=1} e_k{}^2 \tag{16}$$

$$\text{S.t } y_k \left[w^T \varphi(x_k + b) \right] \geq 1 - e_k, k = 1,\dots,N \tag{17}$$

ξ in the original SVM problem is a relaxation variable whose significance is to introduce outliers into the support vector. For the equality constraint of LS-SVM, the meaning of e on the right side of the equation is similar to that of the SVM ξ, and the final optimization objective also contains e.

3. Experimental Validation

Firstly we choose a frame image as the background image and then choose 1 frame images. Through the above process, we calculate the crowd density, movement intensity and degree of movement clutter of both images to have a comparison. The background image and current frame images are shown below.

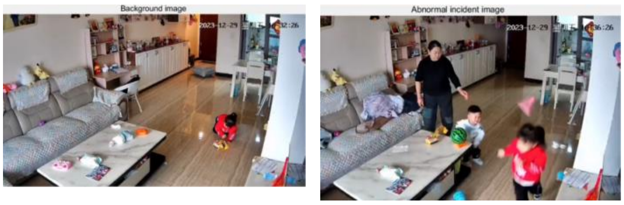


Fig.7. The Background Image, The Normal Incident Image and The Abnormal Incident Image.

3.1. The Process Of Estimating Crowd Density

3.1.1The Process To Get The Clumps Of Foreground Edge

3.1.1.1 Get the clump image of the foreground edge

Firstly through the Xor operation of background image and normal incident image, we can get the foreground edge. Then through the erosion operation with a sphere area 3, removing pixel area under 100, and dilation operation with a sphere area 7, we can get the final clumps of the normal incident image shown below.

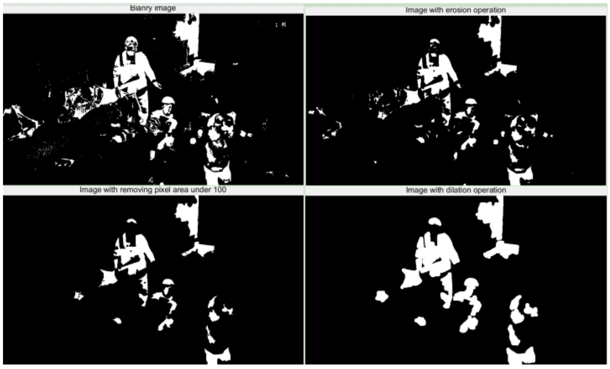


Fig.8. The Process Of Image Process To Get The Clumps Of Foreground Edge

According to the image with dilation operation, we can see that there are about 12 connected regions. We should get the pixel area of each region to calculate the crowd density.

3.1.2、Calculate the crowd density

To show the clumps of foreground edge image more clearly, we tag each clump with a number from 1 to 12 and detect the area of each region shown in table 1.

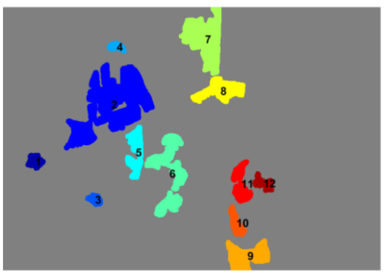


Fig.9. The Clumps Of Foreground Edge Tagged With 1 To 12

Table 1 The Area Of Each Region

Serial number	1	2	3	4	5	6
Area	1072	16165	759	747	2911	6380
Serial number	7	8	9	10	11	12
Area	7254	3684	3941	1376	2431	1186

Sum up all the area to get the pixel area of detected crowd $A = \sum_{i=1}^{5} A_i = 47913$. The size of image is 540×960, so the area of the whole image is 522240. We can calculate the crowd density $R = A/m/n$=47913/518400=0.0917.

3.2. The process of calculating the movement intensity and degree of movement clutter

We select 2 images to show the evolution of 2 kids from playing with toys to fighting shown as follows. The 2 images are about to be used to calculate the movement intensity and degree of movement clutter.

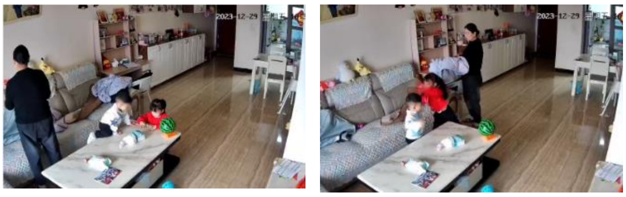


Fig.10. Normal behavior, fighting behavior

3.2.1 Get the movement vectors of the crowd

We will apply the optical flow method to gain the movement vectors of a certain frame image. The Lucas-Kanade method is applied to estimate the movement vectors in this paper. First, we need to select 2 successive frame images, and then search the corner points of each image. According to the corner points, apply the Lucas optical plow algorithm to calculate the partial derivatives of the image in the x direction I_x and y directions I_y of the point (x,y). Finally, get the movement vector in the horizontal direction and vertical direction.

To choose 2 successive frame images appropriately, we choose the T_{i+2},T_{i+5} and T_{i+10} frame image. We can find that violent behaviors may have a big displacement in short time intervals, which may cause big errors in the calculation of movement vectors. So we choose 2 successive frame image as T_i and T_{i+2} to calculate the movement vectors.

3.2.1.1 The movement vectors of the normal incident image

According to the normal incident image chosen previously, we get its second frame to gain the movement vectors. The 2 successive frame images are shown below.

Fig.11. The 2 successive frame images of normal incident

Searching the corner points of (T+2)th frame image, and removing the interference points at the edge of the image shown in the figure as follows. The number of left points is about 187 which will be used in the optical flow algorithm of Lucas to calculate the corresponding data.

Fig.12. The Corner Points Of Image

According to the formula (1) to (9), we can get the movement vectors' coordinates (u, v). Draw the movement vectors at the corner points shown as follow.

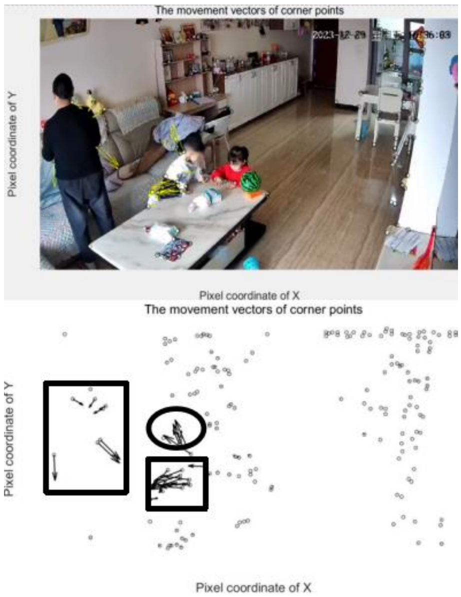


Fig.13. Movement Vectors At The Corner Points

The movement vectors in the black circle represent the movement of the boy's head and those in the black square represent the movement of the boy's leg. According to the successive images, the movement vectors calculated are consistent with the movement trend of the persons in the picture.

3.2.1.2 The movement vectors of abnormal incident image

Regarding the abnormal behaviors, we chose 2 images the first one is 2 kids fighting and the other is the boy chasing the girl after being hit. Get the second frames of the abnormal images shown as follows.

Fig.14. The 2 Successive Frame Images Of Abnormal Incident

Searching the corner points of (T+2)th frame image, and removing the interference points at the edge of the image shown in the figure as follows. The number of left points is about 187 which will be used in the optical flow algorithm of Lucas to calculate the corresponding data.

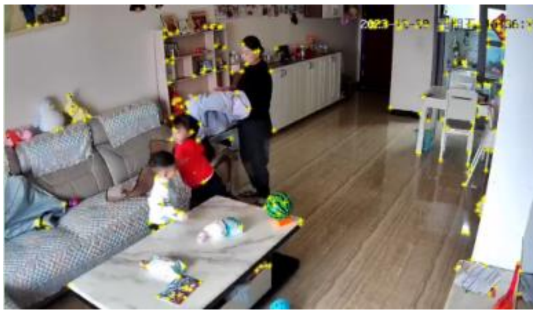


Fig.15. The Corner Points Of Image

According to the formula (1) to (9), we can get the movement vectors' coordinates (u, v). Draw the movement vectors at the corner points shown as follow.

Fig.16. Movement Vectors of Fighting

The motion vectors in the black circle represent the motion of the boy and those in the black square represent the motion of the girl. The motion vectors of the boy and girl go in different directions in the fighting incident image.

3.2.2 Estimate the movement intensity

After getting the movement vectors, we can calculate the crowd density with the formula (10). since there are many negligible vectors of which the norms are under 0.3, we remove these kinds of vectors and show the norms of motion vectors in a bar graph.

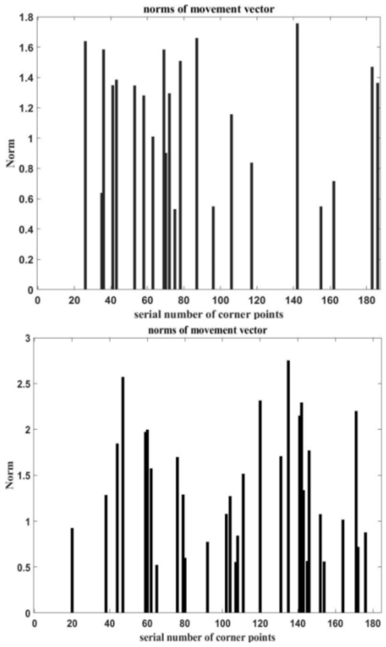


Fig.17. Norms Of Movement Vectors Of Normal Behavior, Fighting Behavior

According to the diagrams above, it shows the movement intensity of abnormal incidents is larger than that of normal incidents. Calculate the mean value of norms of all the vectors to get the final movement intensity of each frame shown in Table 3.

Table 2 Calculating Results Of Movement Intensity

	Normal Behavior	Fighting Behavior
Movement intensity	1.18	1.41
Max movement intensity	1.75	2.76

The result shows that the movement intensity of fighting behavior is much larger than that of the normal behavior..

3.2.3 Calculate the degree of movement clutter

To gain the degree of movement clutter, we need to calculate the angles of all the movement vectors. Divide the space into 36 directional every 10 degree and then count the number of vectors falling into each directional space. Finally, calculate the variance of all the angles as the degree of movement clutter according to the formulas from 10 to 12.

3.2.3.1 The degree of movement clutter of normal incident image

With the formula 11, we calculate the angels of all motion vectors, and remove the vectors of which the norms are under 0.3. According to the angles, we can get the distribution situation of the motion vectors of normal behavior shown below.

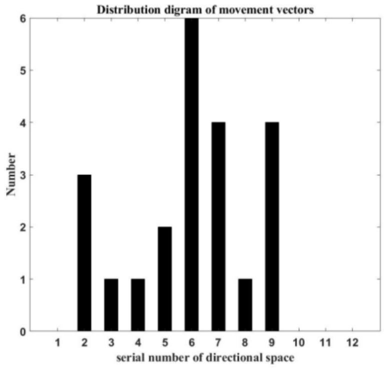


Fig.18. Distribution Diagram Of Motion Vectors of Normal behavior

According to the distribution result, we can calculate the μ and ε through the formula 11 and 12 shown in table 3.

Table 3 The Result Of μ And ε of Normal Incident Image

The mean value/μ	The variance/ε
2.78	1.14

The degree of movement clutter of normal behavior image is can be taken as 1.14.

3.2.3.2 The degree of movement clutter of abnormal incident image

With the formula 11, we calculate the angel of all motion vectors of fighting behavior and remove the vectors of which the norms are under 0.3. According to the angles, we can get the distribution situation of the motion vectors of normal behavior shown below.

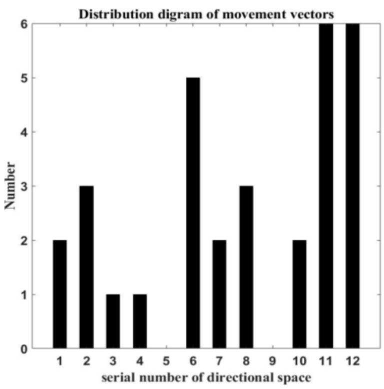


Fig.19. Distribution Diagram Of Motion Vectors of Fighting Behavior

According to the distribution result, we can calculate the μ and ε with the formula 11 and 12 shown in table 4.

Table 4 The Result Of μ And ε of Abnormal Incident Image

The mean value/μ	The variance/ε
3.8	2.01

The degree of movement clutter of fighting behavior can be taken as 2.01.

3.2.4 The Comparison Of Results

The results of movement intensity of normal behavior, fighting behavior, and chasing behavior are respectively 1.18,1.41 and 1.81. The result shows the chasing behavior image has the largest movement intensity. As the boy was hit, the girl tried to run away and the boy tried to hit the girl, which caused the strenuous movement. The normal behavior image has the least movement intensity for the reason that everyone's motion is slight.

The results of the degree of movement clutter of normal behavior, fighting behavior, and chasing behavior are respectively 1.14, 2.01, and 1.64. The results show the fighting behavior image has the largest degree of movement clutter. As the 2 kids are fighting, the motion trends of their heads, hands, and bodies go in different directions. When chasing behavior happens, the motion vectors may go in the same direction which is why the chasing behavior image has a much less degree of movement clutter than the fighting behavior. Undoubtedly normal behavior has the least degree of movement clutter.

3.3. LSSVM Model Of School Bullying Identification

To get the training data for the SVM, we chose a video that contains the school bullying incident. Randomly we choose 39 frames images as the training data samples and 20 frames images as the test data samples. The information from the video is shown in Table 5.

Table 5 Detailed Information Of The Video

Duration of video	The number of frames	Size of frame	Contain School Bullying incident ?
128s	1922	856×480	Yes

3.3.1 Extract the movement features of training data samples

Import the 39 training data images into the system above to calculate the 3 movement features crowd density, movement intensity, and degree of movement clutter. The results of the crowd movement feature calculated are shown in table 6.

Table 6 The Results Of Extraction Of Movement Feature Of Training Data Images

Frame number	11	31	51	71	91	111	131	151	171	191	301	321	341
Crowd density	0.025	0.025	0.024	0.015	0.012	0.009	0.013	0.014	0.014	0.014	0.012	0.012	0.011
Movement intensity	0.847	0.706	0.995	1.782	1.449	1.688	1.670	1.729	1.399	1.842	2.309	1.278	1.548
Degree of movement clutter	1.437	1.435	1.396	1.420	1.642	1.111	1.091	0.892	0.984	0.251	0.269	1.500	1.432
Frame number	361	381	401	421	441	461	481	1001	1021	1041	1061	1081	1101
Crowd density	0.011	0.011	0.012	0.450	0.011	0.011	0.012	0.014	0.015	0.014	0.012	0.015	0.013
Movement intensity	1.266	1.260	1.208	31.691	1.255	1.184	1.828	1.898	1.549	1.930	1.345	1.657	1.221
Degree of movement clutter	1.639	1.702	0.166	1.607	1.413	0.155	0.593	0.614	1.644	1.317	1.292	1.089	1.898
Frame number	1121	1141	1161	1181	1201	1221	1241	1261	1281	1301	1321	1341	1361

Crowd density	0.015	0.015	0.013	0.013	0.015	0.017	0.023	0.023	0.021	0.022	0.019	0.019	0.018
Movement intensity	1.675	1.613	2.693	2.463	2.229	6.182	1.963	1.180	1.450	1.597	1.885	1.758	0.532
Degree of movement clutter	1.345	1.538	1.717	0.972	1.203	0.763	1.820	1.659	1.765	1.023	1.379	1.119	0.000

3.3.2 Label the training data sample images

According to the training data images randomly chosen, we need to label the images with 1 and 0. 1 means the image contains a school bullying incident and 0 means the opposite. Since there are 39 training data images, only 4 images are chosen to show the label results shown as follows.

Table 7 Illustration of School bullying Incident Label Results for Training

Training image	**Label**	**Training image**	**Label**
	1		1
	0		0

3.3.3 The training result of SVM model of school bullying identification

3.3.3.1 Apply the 3 movement features to train the SVM model of school bullying identification

Import the 39 groups of training data into the SVM to train the model of school bullying identification, firstly we apply all the 3 movement features as the input parameters and the label result as the output parameter. The classification result is shown as follows. Figure A is the result image of classification and Figure B is the ROC curve.

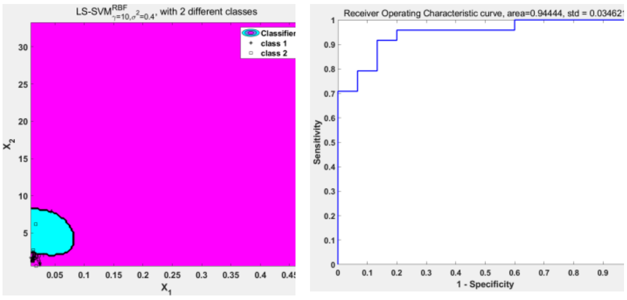


Fig.20. The training result of LS-SVM model with 3 features

From the above figures, it is obvious that the classification result is not satisfactory. We apply the test data samples to this well-trained SVM model to test the school bullying identification accuracy.

Import the 20 testing images into the feature-extracting system to get all the movement feature data. Apply the testing data to the LS-SVM model to get the prediction classification results and compare the prediction results with the results of label to calculate the prediction accuracy. The results of comparison are shown as follows.

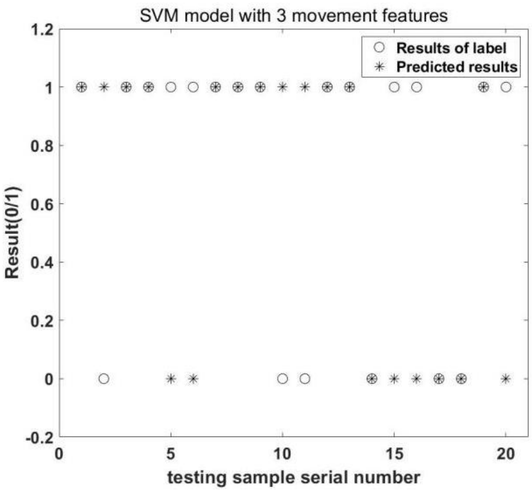


Fig.21. The comparison between prediction results and results of label

Table 8 The results of extraction of movement feature of testing data images

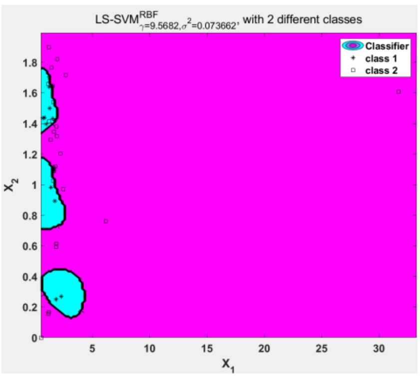
Frame number	697	265	1187	567	433	831	793	745	957	153
Crowd density	0.026	0.012	0.015	0.014	0.011	0.012	0.012	0.018	0.017	0.014
Movement intensity	30.283	1.371	2.010	2.260	0.948	1.366	1.430	2.182	2.023	2.327
Degree of movement clutter	1.472	0.161	1.441	1.059	1.368	0.894	1.914	1.748	1.557	1.189
Result of label	1	0	1	1	1	0	1	1	1	1
Prediction result	1	1	1	1	0	1	0	0	1	1
Frame number	107	839	1289	241	433	445	151	117	781	551
Crowd density	0.010	0.012	0.022	0.014	0.011	0.011	0.014	0.010	0.013	0.015
Movement intensity	1.418	1.585	1.547	1.631	0.948	0.795	1.729	1.407	2.130	1.475
Degree of movement clutter	1.312	1.823	1.477	1.048	1.368	1.433	0.892	1.141	1.009	1.542
Result of label	1	0	1	0	1	1	0	0	1	1
Prediction result	1	0	0	1	1	1	0	0	1	0

The results show that the predicted results were inconsistent with the actual results in 8 of the 20 test groups, so the prediction accuracy is only about 60%.

A higher crowd density may have a higher possibility of occurrence of school bullying, but there is no direct correlation between crowd density and school bullying incidents. Based on that, we only apply movement intensity and degree of movement clutter as the input parameters to train the SVM model.

3.3.3.2 Apply the 2 movement features to train the SVM model of school bullying identification

Choose the same 39 groups of training data samples shown in Table 7, and just apply the movement intensity and degree of movement clutter as the input parameters and the results label as output parameters to train the SVM model. The training results of the SVM model are shown as follows. Figure a is the result image of classification and Figure B is the ROC curve.



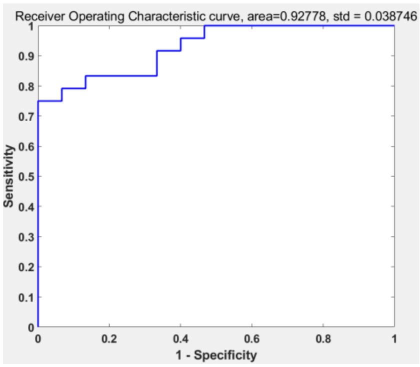


Fig.22. The training result of LS-SVM model with 2 features

From Figure above, we can figure out that the trained SVM model can well classify the training data into 2 classes. Then apply the 20 groups of testing data to calculate the classification accuracy.

We just choose the movement intensity and degree of movement clutter as the testing input data shown in Table 10. Import the testing data into the well-trained SVM model to get the predicted classification results. Compare the predicted results with the results of the label shown in the figure below.

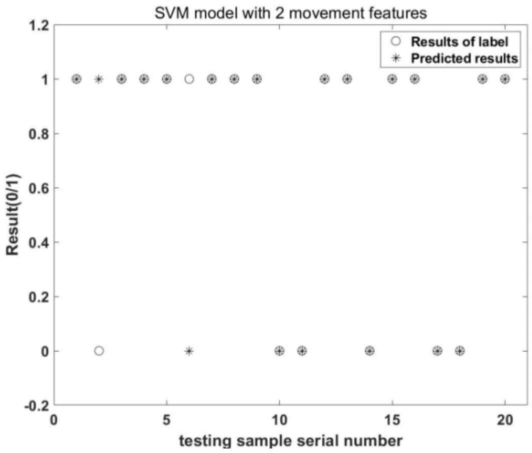


Fig.23. The comparison between prediction results and results of label

The figure shows that the predicted results were inconsistent with the actual results in 2 of the 20 test groups, so the prediction accuracy is about 90%. The prediction accuracy is highly improved, so we can apply this SVM model to identify school bullying incidents. Meanwhile, we can take the crowd density as an early warning parameter, so we can identify the school bullying incident ahead of when there is an unusual increase in crowd density.

4. Conclusion

This study proposes a method for school bullying recognition with the following innovations:

The paper proposed a new method to identify abnormal behavior according to the 3 features of crowd behavior. Crowd density can detect crowd gathering, which is always a sign of the occurrence of violent incidents. The method proposed to calculate the crowd density may be affected by the layout of items, however, we can update the background image to reduce the impact. On the other hand, the increasing number of crowds may cause the disorder of scene which will make the crowd density increase.

Through the optical flow method applied in this paper, we can get the motion vectors of corner points of each frame, of which the average norm and variance of degree are taken as movement intensity and degree of movement clutter of crowd respectively. The comparison results show that crowd intensity and degree of movement clutter can be effectively used to identify abnormal violent incidents.

When applying crowd density, movement intensity, and degree of movement clutter as input parameters to train the SVM model of school bullying identification, we found that the classification accuracy is only about 60%. Through the analysis of characteristics of school bullying, we only apply movement intensity and degree of movement clutter as the input parameters to train the model. It turns out that the prediction accuracy can be improved to about 90%.

In conclusion, the intelligent monitoring system proposed in this paper can effectively detect violent behavior by calculating the values of 3 features of crowd behavior. With normal surveillance videos in a certain area imported into the monitoring system to get the appropriate threshold values, this system can be used to detect school bullying..

Author contributions

Hong Yanwu initiated the research topic and provided guidance throughout the project. **Anton Louise De Ocampo** strictly reviewed the whole article and offered helpful insights and suggestions on various aspects of writing the paper.

Conflicts of interest

The authors declare no conflicts of interest.

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