Novel Approach Based on Topological Simplification Algorithm Optimized with Particle Swarm Optimization

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Abstract. The movement of people can be considered as the flow of liquid, so we can use the methods employed for the flow of liquid to understand the motion of a crowd. Based on this, we present a novel framework for abnormal behavior detection in crowded scenes. We extract a topological structure from the crowd with the topology simplification algorithm. However, a conventional topology simplification algorithm can not work well if we apply it to the crowd directly because there is too much noises produced by the random motion of the people in the original image. To overcome this, we make a step forward by optimizing this model using Particle Swarm Optimization (PSO) [5] to perform the advection of particle population spread randomly over the image frames. Then we propose two new methods for analyzing the boundary point structure and extraction of a critical point from the particle motion field; both methods can be used to describe the global topological structure of the crowd motion. The advantage of our approach is that each kind of abnormal event can be described as a specific change in the topological structure, so we do not need construct a complex classifier, but can classify the crowd anomalies dynamically and directly. Moreover, the approach monitors the crowd motion macroscopically, making it insensitive to the motion of an individual, disregarding the global movement. The result of an experiment conducted on a common dataset shows that our method is both precise and stable.

Key words: topological structure, particle swarm optimization, abnormal behavior, crowd behavior modeling

1. Introduction

Recently, there has been increasing interest in video surveillance of crowded scenes within the computer vision community. This brings many new challenges and problems, like pedestrian detection, tracking in the crowd and crowd behavior modeling. Among these applications, the central task is to automatically analyze and detect abnormal events in a crowd video.

In the field of intelligent monitoring, crowd behavior detection is quite different from individual behavior analysis. In the crowd, the complete trajectory of each individual can not be captured easily by a camera. Besides, handling every state of every person is a tough task for the device. Because of the interactions among a large number of

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people in a crowd, simple analysis of individual behavior will pose more difficulties and lower the accuracy of the task. As further noted, modeling the motion of individual is neither sufficient nor efficient. We need to spend more time analyzing the behavior of the crowd globally. For instance, the trajectory-based method proposed in [14, 15] will be useless if we mainly want to detect global behaviors, such as formation/dispersion and splitting/merging in a crowd.

According to a well-established analysis of the crowd behavior model, we can divide the models into three main approaches. (1) Microscopic approach, defining pedestrians' motivation for the movement and treating the crowd behavior as the result of a self-organization process [4] (2) Macroscopic approach, which focuses mainly on goal-oriented crowds. This method does not pay attention to the motion of each person, and group habits are determined by global goals and destinations. All people in the crowd are partitioned into different groups to follow the predetermined habits. Then a macroscopic model is established [11]. For example, in [18], a dynamic texture model is established to jointly model the crowd's dynamics and appearance. This method explicitly detects both temporal and spatial anomalies in a crowded scene. (3) Hybrid approaches combining microscopic and macroscopic methods to analyze both individual behavior and the overall crowd status simultaneously. This hybrid way corrects every individual's behavior to optimize the features of global behavior. However, none of these three approaches can detect anomalies directly, and a complex classifier is necessary to obtain the final results. Unfortunately, am additional classifier brings extra difficulties to the task.

In various works, different kinds of local motion patterns are captured from the crowd as features. Following this, classifiers are trained by utilizing those features. The global crowd behavior is modeled implicitly by the classifiers. The final performance of anomaly detection is closely related to the choice of the classifier and of the training data. If we want to obtain the results directly, without constructing and training a classifier, we should try analyzing the crowd in another way. The new idea proposed to this end in the present paper is inspired by the method known as topological simplification.

We will extract the topological structure from the particle motion field with topological simplification algorithm, which can represent the global behavior of the crowd motion explicitly. Then we can monitor changes in the topological structure to detect the abnormal crowd behavior directly. Therefore, we do not need to build a classifier to train it and classify the anomalies. We also advance this hypothesis by optimizing the model using Particle Swarm Optimization (PSO) to perform the advection of a particle population spread randomly over the image frames. The population of particles is drifted towards the areas of the main image motion driven by the PSO fitness function aimed at minimizing the interaction force, so as to model the most diffused and normal behavior of the crowd. In this way, particles converge naturally towards the significant moving areas in the scene, and in particular towards the parts that are likely show a high interaction force. So we can find that in a certain area, all of the particles we have extracted have encountered fewer interference factors. There is no need to eliminate the interferential points with velocity close to zero. Therefore, the altered topology simplification algorithm can be used directly in the area where the particles have been updated by PSO. After the PSO optimization, we can use more accurate critical points to form a topology which is closer to the natural conditions in the crowd. Then we can detect anomalies by tracking this topology because the crowd motion varies together with the topology change. The advantage of our method is that we do not need to create a complex classifier; it can detect anomalies directly by monitoring the changes in the topological structure of the crowd. Moreover, the model proposed in this paper has good robustness and it is quite insensitive to the motion of an individual that does not affect the global motion.

The remainder of paper is organized as follows. In section 2, we give a brief introduction to the particle swarm optimization algorithm and the topological representation of a 2D dense vector field. In section 3, our approach to constructing a topological structure optimized by PSO and detecting abnormal behavior using this topology are given. Section 4 provides implementation details and experiment results.

2. Related Work

2.1. Particle Swarm Optimization (PSO)

Over the recent years, the PSO (similar to Evolutionary approach) has been developing very rapidly. In computer science, PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given quality measure. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle position and velocity. Each particle's movement is influenced by its local best known position, and is also guided towards the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions. PSO is applied to monitor abnormal crowd behavior, mainly because the crowd is a biological system as well as a social system. More precisely; there are complex interactions between the communities and the environment, especially interpersonal interactions. Besides, PSO has originated from the simulation of a simple social system, and it can simulate unpredictable group behavior using local information.

PSO is initialized with a population of N-dimensional particles distributed randomly, and then pursues the final optimal solution by iteration. At each iteration, particles track two "Extreme Values" to update themselves. The first one, obtained by the particle itself, is called *pbest*. The other one is obtained by the whole group, and represents the current global best value, denoted by *gbest*. Furthermore, it does not need the whole group; part of the group near the particle is enough to obtain the local extreme value. The *pbest* value represents the position associated with the *best* (i.e., minimum or maximum) fitness value of the particle obtained at each iteration. The *gbest* value represents the best position among all the particles in the swarm, i.e., the position of the particle assuming the minimum or maximum value when evaluated by the fitness function. When the particle velocity changes, the particle will be updated according to the following equations [5]

$$\begin{aligned} v_i^{new} =& w \cdot v_i^{old} + C_1 \cdot rand() \cdot pbest_i - present_i^{old} \\ &+ C_2 \cdot rand() \cdot (gbest_i - present_i^{old}) \end{aligned} \tag{1}$$

$$present_i^{new} = present_i^{old} + present_i^{new} \tag{2}$$

where $v_i^{new}(v_i^{old})$ is the particle velocity after(before) updating, w is the inertia weight used for balancing the local and global search in the PSO, C_1, C_2 are the learning factors or acceleration parameters that drive every particle closer to the *pbest* and *gbest* values, $rand()$ is a random number between 0 and 1, and $present_i^{new}(present_i^{old})$ is the particle's updated(current) position, respectively.

2.2. Topological simplification of a sparse vector field)

Topological simplification is widely used for data simplification and visualization of 2-D and 3-D velocity vector fields in fluid mechanics computations (CFD). The basic idea is to describe the structure of a dense vector field by certain special points, called critical points, and curves connecting these points. These points and curves can be used to determine qualitative behavior of the velocity field. This means that although we cannot reconstruct the original velocity field from this structure, it can be estimated up to topological equivalence, which is good enough for the analysis of the vector field behavior, especially for the particle motion field. Besides, there is a topological classification theory on the classification of these critical points based on the local structure around them. Each category corresponds to one type of anomalies that we want to model in the training phase.

According to theory of calculus, every person in the picture can be represented by a velocity vector field function $v(x, t)$, where, x are the spatial coordinates in the image, and t is the time. However, there are so many pixels in a given image that the velocity vector field will be too complex to calculate. Accordingly, we should simplify the vector field to reduce the number of its dimensions. The method based on topological simplification proposed by Helman and Hesselink [3] can be well applied here. This approach extracts a topological structure by detecting and classifying the critical points. The flow field topology can be used to express the characteristics of the flow field structure. Subsequently, the topological analysis of the flow field is expanded from planar flow field to wide surface flow field, 3D flow field and unsteady flow field [10]. However, the initial topology analysis is not exhaustive. Some important features, such as open boundaries or an extremely isolated limiting ring, may be lost or omitted. This is why, based on the boundaries of the flow detection, Ken Wright proposed another two methods for analyzing the phase plane and the parallel vector [6, 7]. The topological structure can represent the vector field features very well, while also simplifying the vector field very well. The Topological Simplification Algorithm divides the pixels in the image into two parts: normal points, whose velocity exists, and critical points, whose velocity has vanished. The core idea of the method is to extract the topological structure of the vector field, and use this structure to describe the qualitative behavior of the vector field.

The topological structure consists of certain critical points and certain curves. A critical point is a domain in the image where the magnitude of the corresponding vector field vanishes. It is also known as a singular point, or singularity. The curves join a critical point to the next one, and divide the field domain into regions. In each region, the vector field has a different behavior. Qualitative behaviors of the velocity field can be completely determined by these points and curves. The use of such techniques significantly reduces the amount of data we need to process. In a 2-D dense field, there are six kinds of critical points (Fig. 1): repelling node, attracting node, repelling focus, attracting focus, saddle point and center point. Among them, the most special point is the saddle point, which has been proposed by Scheuermann [8]. Since the crowd cannot perform as well as the saddle, we will not discuss the saddle point any more. For each point x in the whole domain of an image $I \subset R^2$, the velocity field in the neighborhood of the critical points can be linearly approximated by the linear flow equation

$$v(x,t) = \frac{d_x}{d_t} \approx A(t)x + b(t) \tag{3}$$

where, x is the position of the critical point we are interested in, and t is the time. For each explicit vector field, we can define a flow $\phi_t : I \to I$ that can make the flow as smooth as possible, where $\phi_t(x) := \phi(x,t)$. In the above Equation, $b(t)$ is a 2D vector representing the position of the critical point in the velocity field, and $A(t)$ is the $2 * 2$ Jacobian matrix [3] proposed by Helman and Hesselink, defined as

$$A \begin{pmatrix} u_x & u_y \\ v_x & v_y \end{pmatrix} \tag{4}$$

Here u and v represent the projections of the velocity vector V on the x-axis and the y-axis, respectively. If A is invertible, then in the neighborhood of the critical point the local shape of $v(x,t)$ can be determined by the two eigenvalues of the matrix A. In

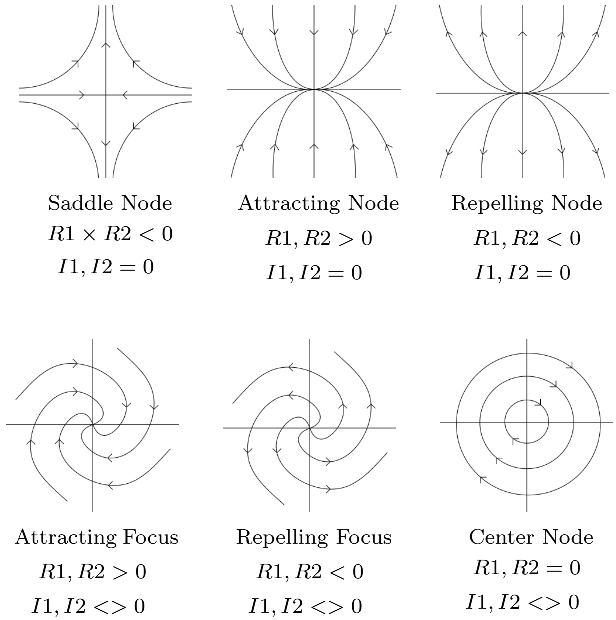


Fig. 1. Classification of critical points. $R1$ and $R2$ denote the real parts of the eigenvalues of the Jacobian, while $I1$ and $I2$ denote their imaginary parts.

Fig. 1, if both eigenvalues are real-valued and have opposite signs, this is a saddle point; if the two eigenvalues are both positive real numbers, the point is an attracting node; if the two eigenvalues are both negative real numbers, the point is a repelling node; if the two eigenvalues are conjugate complex numbers and their real parts are positive, the point is an attracting focus; if the two eigenvalues are conjugate complex numbers and their real parts are negative, the point is a repelling focus; and finally if the two eigenvalues are conjugate imaginary numbers, then the critical point is a center point.

According to the invariance of the topological structure, if a vector field is transformed by applying a continuous map to the original vector field in the neighborhood of critical points, then the type of the corresponding critical points does not change. In other words, although the velocity fields may seem to be quite different in different scenarios, the behavior of the velocity field can be characterized by the same type of critical points. The situation is like in Fig. 2, where the three critical points are of the same kind.

Thus, we can track a critical point to analyze the topology of the crowd using the method of extracting the crowd velocity field. For example, we can consider a repelling

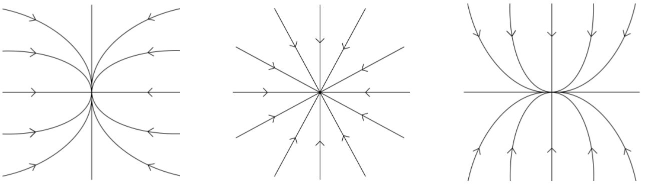


Fig. 2. Three different motion fields belonging to the same type of critical node: an attracting node.

point, which represents the situation where all the persons near the critical point are moving away from that point to all directions.

3. Our Approach

In a word, traditional topological simplification methods cannot be directly applied to monitor a video; we must find a new way to solve the problems given by the original image. In the original image, there are many points whose velocity fields are zero, such as background points. The points we obtain from the image are affected by a lot of noise caused by human arm and leg swings, and the velocity fields obtained from image pixels are noncontiguous or piecewise continuous. On the other hand, a drawback of using traditional topological simplification is only that it assumes that the crowd follows a fluid-dynamical model, which is too restrictive when modeling masses of people. Elements of the crowd may also move along unpredictable trajectories, which will result in an unstructured flow. To overcome these drawbacks, we propose a novel particle advection using PSO that can update the position of each particle to get rid of the noise directly, and form a better topological structure to be monitored. Then we can obtain the parameters of a linear stream model in strong interference with the RANSAC algorithm to determine the crowd type.

3.1. Fitness functions and particle position updates

According to previous studies, because of the fact that a pedestrian in a video will be sheltered from other people, or due to random variation in the population density or differences in the image resolution, we cannot track the trajectory of each single person in a dense crowd. On the opposite, we use the same method as proposed in [13, 16] and apply particle convection to analyze the crowd behavior in the video. We need to calculate the optical flow (OF) information to obtain the particle motion field. The OF represents the velocity distribution of the brightness mode in the image. It can represent not only the spatial arrangement of a moving object, but also the change rate of its distribution.

Every particle extracted from every frame of the video can be considered as the clue of the driving force. Then the particle will be revalued by the fitness function just because of the driving force. This important factor was neglected by most of the previous studies. Even if the driving force was calculated just like in [13, 16], particle convection was calculated on a coarse level. The researchers imposed a grid on the original image, and used every node on the grid to represent a particle. To solve the problem, we propose a novel approach. It amounts to using PSO to improve the particle position, which can make the particle come closer to its real position. Then we can locate the anomalies based on the new result we have obtained. First of all, we define random initialization of the particles in the first frame of the video as the first input of the PSO algorithm. In order to simplify our simulation, we always choose about 1/3 evenly distributed pixels in the first frame as the first original particles. The same way of choosing a random input is applied in the subsequent experiments in this paper. From such an initial stage, we obtain the first estimate of *pbest*, and the global *gbest* for each particle. The particles are defined by their 2D value corresponding to the pixel coordinates in the frames. At each iteration, the *pbest* value is updated only if the present position of the particle is better than the previous position according to the fitness function. We consider the result obtained as the input for the next frame, then apply the same procedure until the video ends. Actually, the fitness function can capture the most wanted interactions among the crowd which drive the pedestrians' movement. For each particle, the fitness function is the factor which can revalue every particle using the OF. We first define the intensity of the optical flow at a given position in the image for a particle i as

$$W_i = O_{avg}(x_i^{new}) \tag{5}$$

where O_{avg} represents the average optical flow at the particle coordinates x_i^{new}. Thus, the average on can be obtained by all of the previous frames. Then we define the velocity field W_i^p for the most wanted particle

$$W_i^p = O(x_i^{new}) \tag{6}$$

where $O(x_i^{new})$ is the current OF of particle i updated by PSO. In fact, this OF value is the average value computed in a small spatial neighborhood to avoid numerical instabilities in the optical flow. Like in [16], we consider the velocity derivative $\frac{dW_i}{dt}$ as the force driving the particle, where t is the time between the current video frame f and the previous frame $f-1$. This process is in some way mimicked by the particles which are driven by the optical flow towards the areas with larger motion in the image. In this way, the more regular the pedestrians' motion, the smaller the interaction force, since the flow of people movement varies in a smooth way. Accordingly, we define the fitness function as

$$FitPos = \min_{i=1,2...K}\{\frac{1}{\tau}W_i^p - W_i - \frac{dW_i}{d_t}\} \tag{7}$$

where K is the number of particles we have initialized in the image. Particle position can be updated every time to bring it closer to reality.

3.2. Analysis of crowd behavior based on topological structure

The approach proposed in Section 2.2 cannot be applied to detecting anomalies in the crowd, because the motion field of the particle is sparse. In order to capture the crowd topology, we propose an improved method for determining the type of a critical point.

3.2.1. Virtual critical points

In the conventional method, the boundary points do not change over time. However, when analyzing the crowd, the situation is opposite; the boundary points might work as virtual critical points. Boundary points are the points whose velocity tends to zero, and their behavior can be described by the sets $\alpha - limit$ and $\beta - limit$, where $\alpha - limit$ ($\beta - limit$) are defined through subsets $\alpha(x)$ ($\beta(x)$) of the image domain I consisting of points $y \subset I$ such that $\phi(x) \to y$ when the time $t \to \infty(-\infty)$. In other words, the particle at position x will reach $\alpha(x)(\beta(x))$ after an infinitely long time. In a sparse velocity field, the limit set can be determined by numerical integration. In order to extract virtual critical points, we need to integrate the boundary points. For this purpose, Tricoche's cluster algorithm [9] can be used. Since points in the same cluster will exhibit the same action, a virtual point can be defined at the center of each cluster. The type of each virtual point can be determined by the type of the limit set: $\alpha - limit$ and $\beta - limit$.

The topological structure consists of points and relationships between points represented by curves. We define those relationships as below. If there is a trajectory linking points in the limit sets corresponding to a sink N and a source S, we connect the sink and the source by a curve. The process can be described as follows: For every moving point x, we first find the $\alpha - limit$ set and the $\beta - limit$ set, and then the corresponding critical points $Sink_i$ and $Source_j$; following this, we add the connection relationship count C_{ij}. When we obtain the complete count set, we search for an element c which is bigger than the threshold $C_{threshold}$ in the count set; then this c is added to the topological structure. As a result, the procedure of extracting the topological structure can be defined as in Fig. 3.

3.2.2. Critical points

The boundary points have been treated above, so we will not consider them again in this section. The points that could possibly be critical are determined by the PSO at first. In the area under consideration, the particles are clustered, and definitely have non-zero-velocity. So we do not need to define a threshold to remove the points whose

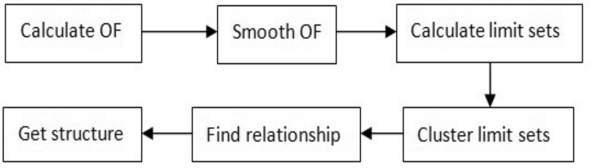


Fig. 3. Overall procedure of topological structure extraction.

velocity tends to zero. Like in [10], the original image is cut into a few grids, and the revised RANSAC [13] algorithm is applied to each area where the particles have been updated by the PSO. Then the linear stream parameters A and b can be determined. After the estimation of critical points, the critical point type can be determined by calculating the eigenvalue of the Jacobian matrix A. If a critical type which looks like the anomaly type we are interested in has just occurred, we will calculate the probability of the anomaly to reduce error accumulation. Here, we just simply define the probability as the percentage of points moving abnormally, i.e. $P(abnormal) = N_{total}/N_{abnormal}$. Whether a point is an abnormal point or not can be determined based on the differences between the calculated results and the estimated results for the point's velocity vector. If the difference is bigger than the threshold, the point can be considered an abnormal one. The overall estimation procedure is listed in Fig. 4.

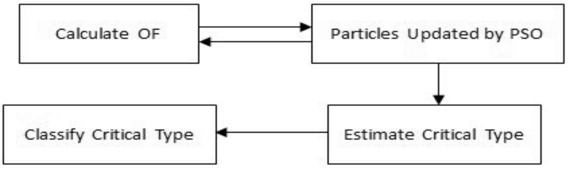


Fig. 4. Overall procedure of critical points estimation.

3.2.3. Detection of anomalies

Based on the theory above, the topological structure of the crowd can be described by particle motion field. Accordingly, to monitor the crowd status, it suffices to track the topology. If the topology changes, there must be something happening in the crowd. For the holistic behavior case, the gathering of the crowd can be approximated by a sink in the particle motion field, and the dispersion — by a source. If these structures are detected frequently during some time interval, the corresponding event occurs. For example, as shown in Fig. 5, when the crowd moves as a single entity at first, and then splits into two flows at some moment, then the sink set of the extracted structure will split into two sinks. Finally, the original source-sink will become two separate sources-sinks.

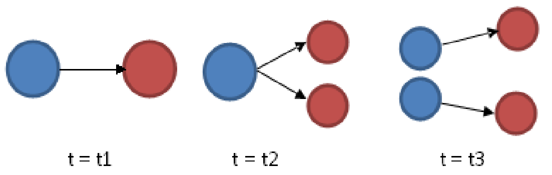


Fig. 5. Example of a crowd as one entity splitting in two. The blue nodes represent sources, the red ones — sinks. The structure will change when the crowd splits.

If the proposed approach is used here, topological invariance can be inherited, and it is not sensitive to noise, while it is loosely related to the individual's motion status. Macroscopical monitoring of the crowd motion appears to be both precise and stable.

4. Experimental Results and Comparisons

The purpose of the approach proposed in this paper is that anomalies in the crowd can be extracted and classified in a precise way. In order to evaluate the method we have proposed, we will consider a few existing methods and compare their results on standard common datasets used for detection of abnormal behavior.

We partition the image into 88 grids and use Black's optical flow algorithm to calculate the velocity of the crowd motion, keeping 25% pixels of the original image to serve as the random input to the PSO. Our experiment is conducted on the abnormal behavior dataset, UMN or PETS. There are two different University of Minnesota scenarios in the UMN dataset, and the total of eleven videos for testing. Pedestrians wander all over the scene for a while, then escape. Abnormal activity can be defined as the escaping motion. As Fig. 6 shows, the left frame is normal, and the right one — abnormal. In order to test the validity of our approach, based on extracting the topological structure, we conduct an experiment based on PETS. Fig. 7 below shows the structure we extract first, and the structure after PSO reconstructed smoothly using RANSAC, which is similar to the original one. When the people in the crowd escape, we can easily find there is high probability of change in the extracted structure.

Fig. 8 is the result we obtain when detecting anomalies in the crowd based on Fig. 6. In Fig. 6, people first wander, and then escape to every direction at an uncertain time. Here, we use the way we have proposed above to detect the time when the abnormal motion began. In Fig. 8, the horizontal coordinate denotes the time, the vertical coordinate represents the probability of anomalies, and the dotted line denotes the threshold determined by experience. To obtain a better result, we build a filter whose average

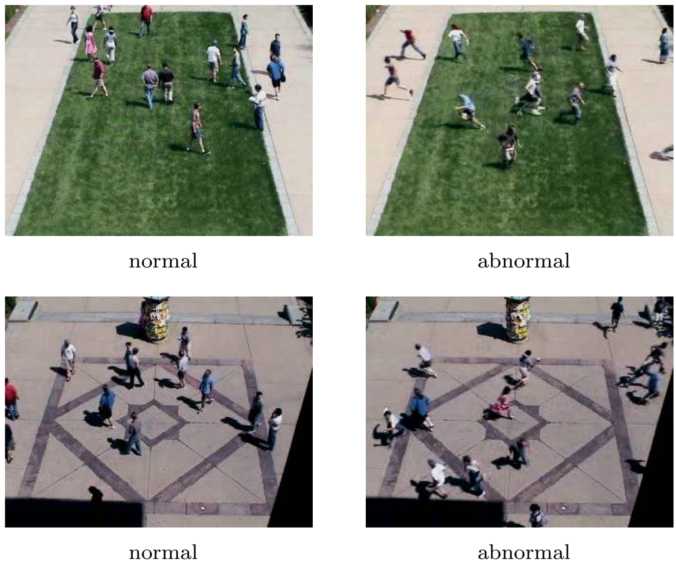


Fig. 6. Sample frames in two different scenes from the UMN dataset: Normal (left) and abnormal (right).

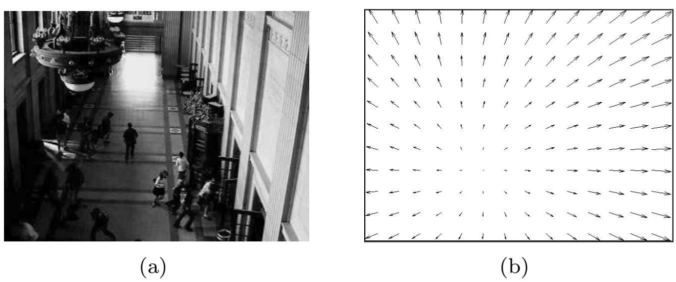
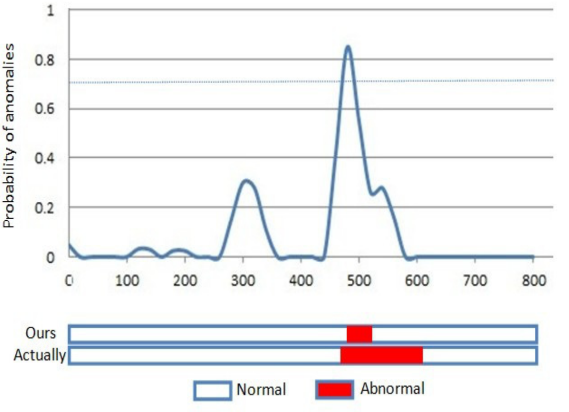
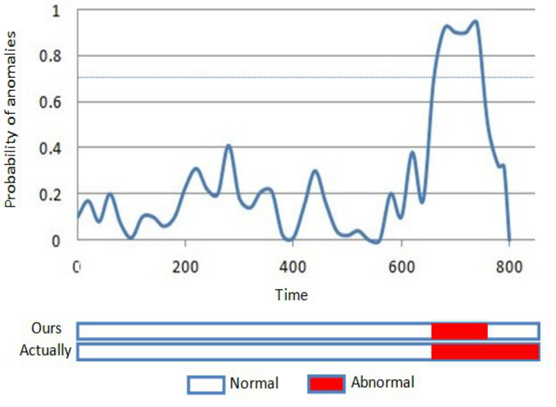


Fig. 7. (a) is the original, and (b) is the structure we extracted from (a) after PSO and RANSAC revised.

window size is 25. Then the result we obtain is handled by a filter. If the value of the result is beyond the threshold, the given frame is most likely an abnormal one. The white part of the strip-chart at the bottom of Fig. 8 denotes the normal frames of the test sequence, and the red part represents the abnormal frames. Hence we can see that the approach we have proposed works well in classifying the abnormal frames in the whole video sequence. Also, the time when attack/repelling anomalies happened can be easily found in this way.



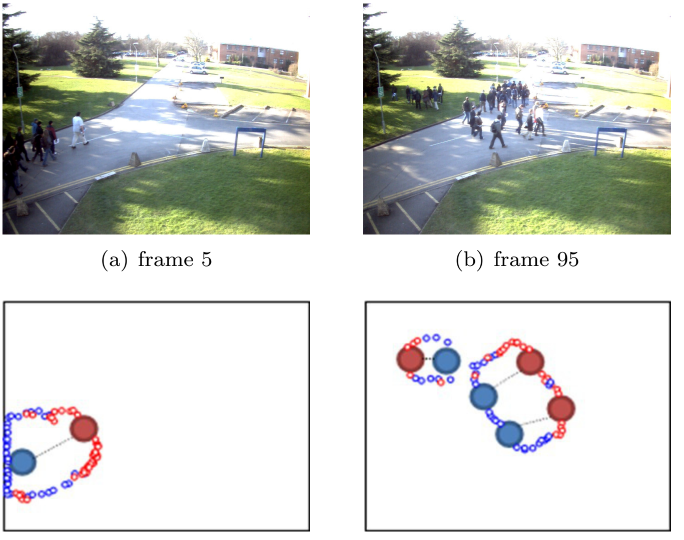
(a) UMN sample 1



(b) UMN sample 2

Fig. 8. Two examples of detecting dispersing motion of the crowd based on the common dataset UMN. The dotted line determined by experience denotes the threshold.

We extract the topological structure from the sample frames just as shown in Fig. 9. If the pedestrians split into two independent smaller groups, topological structure (a) changes to (b). Actually, we can find that the 95th frame is just as (d) shows, and there are only two groups in this frame. This proves that topological structure can represent the real situation in the crowd very well. To verify our approach effectively, we reemploy the classical methods: optical flow [2], social force and MDT(mixture of



(a) frame 5 (b) frame 95

(c) Topology of frame 5 (d) Topology of frame 95

Fig. 9. The structure extracted from an image in the PETS dataset. The blue nodes in (c),(d)are sources, and the red ones — sinks. The smaller blue and red circles denote the $\alpha - limit$ and $\beta - limit$ sets. The dashed lines denote the relationship between the source and the sink.

dynamic texture) [18] on the PETS dataset. Each of the other three methods has been proved effective in detecting the splitting/emerging anomalies of the crowd. Moreover, they analyze the crowd's behavior at the macroscopic level, just as our approach.

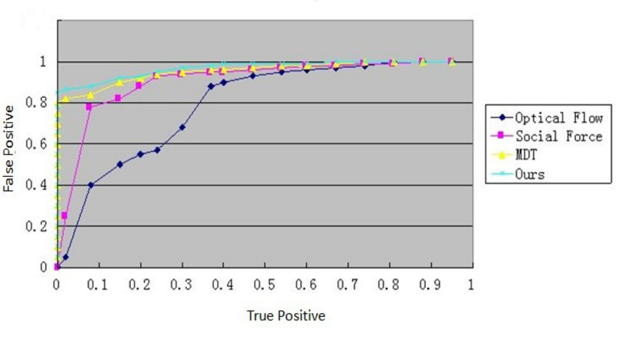


Fig. 10. ROC curves of the three existing methods and of our method.

Tab. 1. The area under ROC of the four approaches.

Approach	Optical Flow	Social Force	MDT	Ours
AUC	0.832	0.955	0.983	0.992

Fig. 10 shows the ROC curve of our method for the frame level anomaly detection on the PETS dataset, while Table.1 shows the quantitative results of the method compared to all three other methods.

Experimental results show that our approach outperforms the optical flow method, the social force method and the MDT method. Moreover, we discover that we do not need to analyze every frame of image data from the video like in the other approaches - for only half of the frames are enough for detecting an anomaly. If we do not use the PSO algorithm, using 2 frames we can also determine the crowd type with some loss of accuracy. On the other hand, there is no need to construct a complex classifier to classify the anomalies in our method, so our approach to finding the time when splitting/emerging anomalies (or other anomalies) occurred is much faster and simpler.

Actually, the method described in this article can be easily extended to detecting some other anomalies of the crowd, such as abnormal speed. Since the average velocity of the crowd is proportional to the Euclidean norm of the matrix A of the linear flow function, we have $v_{crowd} \propto ||A||_2 = \sqrt{\lambda_{max}(A^T A)}$, where $\lambda_m ax$ is the biggest eigenvalue of matrix A. Here we have used another common dataset, PETS, to testify the effectiveness of the algorithm. In this video sequence, the pedestrians walked into the screen from the right hand side, and then began to run away at a certain frame-time. And then they walked in from the left hand side, and began to run away again at another certain frame-time. What can we define about the abnormal activity is that the crowd is moving at a faster rate. Fig. 11 is a shortcut of this experiment. In order to show the performance of our approach, a comparison test with HOG algorithm [17] will be carried on.

Fig. 12 is the result of abnormal speed detection, where the solid line is the Euclidean norm of the matrix A of the linear flow function. The dotted line is a preset threshold, which is configured according to the experience and convenience. If the norm is beyond the threshold, we believe that the crowd may be moving at a faster rate. The strip-chart in Fig. 12 represents the comparison of results obtained with our method and hand-labeled ones. We can see that the Euclidean norm can basically reflect the average speed of the crowd. Our method can be a reliable way of monitoring anomalies in the crowd movement speed.

Table 2 shows the comparison of the performance of the HOG algorithm and our method in velocity anomaly detection, where: TP is the true positive, which represents the number of correctly detected frames among the abnormal frames obtained in the experiment; FP is the false positive, denoting the number of wrongly detected frames

Fig. 11. The structure extracted from an image in the PETS dataset; the blue nodes in (c,(d) represent sources and the red ones — sinks. The smaller blue and red circles represent the $\alpha - limit$ and $\beta - limit$ sets. The dashed lines denote the relationship between source and sink.

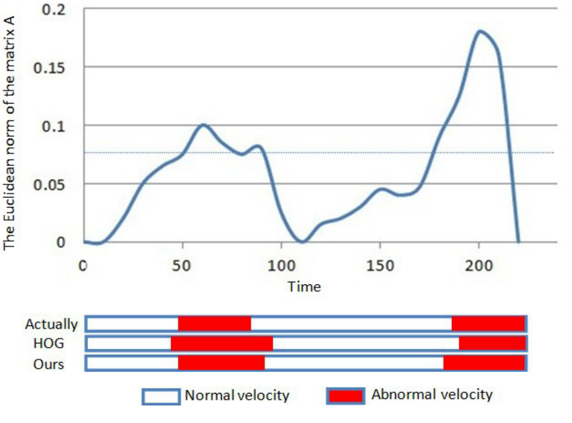


Fig. 12. Result of abnormal velocity detection.

among the abnormal frames obtained in the experiment. The sensitivity is defined as $TP/(TP + FP)$. Compared to HOG, our approach is more accurate. Accordingly, we can employ this improved method to detect the velocity anomalies in a crowd very conveniently and easily.

However, it inevitably also has some drawbacks. In order to avoid building a complex

Tab. 2. Comparison of the two methods with regard to detecting abnormal crowd velocity.

Methods	TP	FP	Sensitivity
HOG	198	22	0.90
Ours	202	18	0.92

classifier, we often use a threshold defined by experience to determine directly whether the crowd is abnormal. Moreover, the saddle point type is not considered in this paper which is a blind spot. This is a very arbitrary behavior. However, the goal of this paper is not to assign blame but to identify important areas for further projects. The experiments have shown that the results are often very close to the real situation, so this method is feasible.

5. Conclusion

In this paper, we have proposed a new approach, based on a topological simplification algorithm, to detecting anomalies in a crowd. To make the conventional topology simplification algorithm applicable directly, we use the PSO algorithm to improve the position of the particle at the next frame. Moreover, use of the PSO can make the particles cluster in a certain calculation area, where the particles meet in a dense state. After process adjustment with the PSO, we obtain a typical topological structure, which consists of critical points and a relationship described by curves linking them. In consequence, each type of crowd anomaly can be represented by a special change in the structure. We can monitor the crowd motion macroscopically instead of analyzing each person. Unlike other known methods, this method does not require constructing a complex classifier, which means that we can skip the learning phase and classify the anomalies of the crowd dynamically and directly. The results are demonstrated for four cases of the crowd motion: formation/dispersion and splitting/merging, and we believe that this approach can be applied to other types of variations, including more general motion.

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