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Intelligent Analysis of Geo-Video by Using Dynamic Graphs

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Abstract

Intelligent analysis is the development direction of the research for Geo-Video. The key is how to extract automatically the implicit spatial-temporal correlation between in the various targets. For this purpose, this paper presents a dynamic graphs framework to simulate the complex moving target's behavior patterns in Geo-Video and uses this model to detect abnormal events. Firstly, compute the moving target's orientation matrix by Optic Flows and use the window clustering algorithm to classify different targets; and then, creating a dynamic graph whose vertex is the cluster center and the weight of edge is the Euclidean distances between two centers; finally, simulate different targets by defining the evolution rule of dynamic graphs in specific geographical scene. Experiments show that the proposed method can directly express the moving target's behavior patterns and detect abnormal events in Geo-Video. In addition, this proposed method provides a new way of thinking about the intelligent analysis for Geo-Video.

Keywords: *Dynamic Graph; Geo-Video; Orientation Matrix; Clustering; Abnormal Detect*

1. Introduction

Geo-Video, as a new method for geographical spatial visualization expression [1], make the video data contains geographic information. The information is obtained by code, transmission and management and operation of the space measurement and three-dimensional solid modeling based on the single frame image analysis [2]. It can provide hypermedia information management and application services by combining videos with spatial position information, and, which have a better value in many fields especially in the field of video surveillance.

Now, analysis of targets in intelligent monitoring are usually using the method of statistical analysis or model estimation and it can't express the natural semantics of moving targets' natural semantic in concrete application scenarios and particular tasks expression scene. However, abundant spatial information in Geo-Video provides the solution channel for video's intelligent processing. But it can only take account of partial knowledge for target motion. Only by a true expression of moving targets' location, shape, size, speed, direction and time-dependent processes can we truly achieve video intelligent analysis in the intricate geographic video. The graph is a common data structure which has a strong expressive force. Its evolution over time can express effectively spatio-temporal correlation between goals. So this paper comes up with a way of graph analysis to simulate the moving target's behavior patterns in Geo-Video.

However, moving targets' state and motion mode changed frequently in video. And there are a lot of relationship between the moving targets, such as interaction and mutual restriction [3], especially in dense areas [4-6]. From what has been discussed above, separately analyze each target not only need a large amount of calculation but also can't take advantage of their interactive relationship to analyze targets' behavior. So this

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article's method is that clustering goals which have larger interaction at first and then use dynamic graph model to simulate moving targets' behavior patterns after clustering. Liu Shang *etc.*, [7] proved that the force between the target is small in the motion with a unified and orderly direction and on the contrary will be larger in the motion with random directions. So the direction is the most direct way to distinguish the size of the force between different moving targets. The innovation in this article is applying this theory to the moving objects' cluster in video.

The major contributions of this paper are as follows: (i) classify the direction system and cluster different moving target by different directions, (ii) using dynamic graph model to simulate moving targets' location, shape, size, speed, direction and their process of change over time after clustering, (iii) using this model to analysis abnormal behaviors in video.

2. Related Works

From the above analysis, we know that the key in intelligent video analysis is first understanding the moving target's behavior patterns and then letting the computer automatically detect anomalies which exist in video. We discuss the following two questions: target behavior analysis and abnormal state detection.

2.1. Target Behavior Analysis

The target behavior analysis include the individual behavior analysis, the interaction between the multiple target behavior analysis, the interaction behavior analysis between moving and the stationary target and the space behavior analysis between the multi-objective [8],etc. The main analysis methods can be divided into supervised leaning and unsupervised leaning methods. Supervised learning method is in advance to determine the behavior model used in the case of predetermined patterns of behavior model behavior and then use training samples train the learned behavior mode, such as PCA (Principal Component Analysis) [9], DTW (Dynamic Time Warping) [10], FSM (Finite State Machine) [11], HMMs (Hidden Markov Models) [12], TDNN (Time Delay Neural Network) [13], Bayesian network behavior analysis [14], etc. While the unsupervised learning method in the absence of any prior knowledge to learn the train samples and automatically get the target movement behavior patterns. Such as [15] to learn the probability density model from the pictures in the sequence obtained by tracking the target trajectory. The model in [15] has been improved in [16], which add a learning prediction framework. The new framework made the original results and the prediction results do a matching and calibration which enhanced expansion adaptability. [17] proposed a way to learn the sport mode by an infrared detector to collect pedestrian data and uses the expectation maximization (EM) algorithm to cluster.

However, the key in the target behavior analysis is to extract the implicit spatial-temporal correlation between in all kinds of targets. Such as the target's location, shape, size, speed, direction and their process of change over time, etc and reflected in the way that the computer can understand. Therefore, this article puts forward the dynamic graph model to deal with the problem. And which through dynamic graph's vertices, edges, and the evolution of each parameter change to express the mode of each target's state and behavior in a scene.

2.2. Abnormal Detection

At present there are two main video abnormality detection methods. One is the use of images by low-level content features, such as corners, contours, textures and colors, and use statistical analysis methods for detecting anomalies. For example, Albiol *et al.*, [18] to extract image corner features to calculate the velocity field and made the speed

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expectations as the standard to detect high-speed motion events. Srivastava *et al.*, [19] has proved by experiments that the number of goals in a specified region is associated with the cumulative number of foreground pixels. They utilize texture features to describe the scene crowding scale factor and determine whether the scene is dangerous according to the size of the scaling factor. Chan *et al.*, [20] regard videos as a result of different texture sampling. They put the development of the texture method to the similarly Gaussian mixture method of hybrid dynamic texture systems, used the expectation maximization algorithm to obtain linear system parameters which first of all cluster a video segment separately in time and space to achieve the purpose of the motion segmentation and then detect abnormal. The second is to create a scene model and utilize the learning method to estimate the parameters of the model then use the model to detect abnormal. Wu *et al.*, [21] compute the optical flow and particle advection transfer and they obtain target trajectory by clustering the particle trajectory and then take advantage of the chaotic trajectory invariance extract the track's chaotic dynamic feature and build a probabilistic model. By studying samples to obtain the model parameter and using maximum likelihood estimation to identify normal and abnormal video. Mehran *et al.*, [22-23] extended the social force model which applied it to a relatively sparse on target behavior modeling and then use the word bag method for mode analysis to detect the target event. Wang *et al.*, [24] use high frequencies and temporal-spatial characteristics to detect target abnormal in the global and local two scales.

All above methods are lacking adaptation and generalization ability on the actual the ability to adapt and generalize to the real environment. A feature or a set of parameters can't effectively detect all abnormal events in video. Therefore, it is crucial to research a kind of anomaly detection methods which have good adaptable and generalization ability from a global perspective to analyze the moving target in video overall situation. In this paper, we detect anomalous on the basis of dynamic graph model which has good generalization ability and can be a useful method to analyze anomalous events in video.

3. Preprocessing

Geo-Video is a special video which combining both images and positions. Due to the different height and posture in the process of shooting a video, which makes targets have different performance characteristics in video [25]. So the "near greater far smaller" characteristics showed in targets of video can't do unify analysis and it is not conducive to video analysis. So first of all, we need to make perspective correction on video images and thus make the target of the image space be projected onto a real geographical space, for using dynamic graph model to represent moving objects in video. In this paper, we use the method of one-point perspective two times and then respectively rectify images in x and y directions[26].

3.1. Correction in the x Direction

In Figure 1, first of all, we rotate the image so that ab is parallel to the x axis ($ab//cd$) and then obtain a vanishing point coordinates (m_x, m_y) according to the coordinates points (a, b, c, d). For the correction on x direction, we can choose any horizontal width as a standard width within the image height. This paper selects the top edge of the image (width W) as the standard width. Making the ac correction to the $a'c'$, which perpendicular to the x axis. According to Similar Principle of Triangle, we can find the ac (on i highly) by the offset in the x direction (Δx_i). Then (j, i), the original point in the image becomes ($j + \Delta x_i, i$), among that the coordinate of the y direction remains unchanged in the calibration of the x direction. Correction formula is as follows:

$$\begin{cases} i_0 = i \\ j_0 = j + ((H - i) \times (m_x - j)) / (m_y - i) \end{cases} \quad (1)$$

(j, i) is a coordinate points of the perspective image, j_0, i_0 is the coordinate points after corrected, H is the height of the image, m_x, m_y is a vanishing point coordinates.

3.2. Correction in the y Direction

According to the principle of pinhole imaging, scaling is the same both on y and x direction. So we can obtain the correction formula of y direction according to the correction formula on x direction. Correction formula is as follows:

$$\begin{cases} j_0 = j \\ i_0 = (i / m_x) / (m_x - ((H - 1) \times m_x / (m_y - 1))) \end{cases} \quad (2)$$

After the two converts (both on x and y directions), we can reconstruct the corrected image by calculating transform relationships between corresponding points of a two-dimensional image. Gray values of each point can be obtained by bilinear interpolation method.

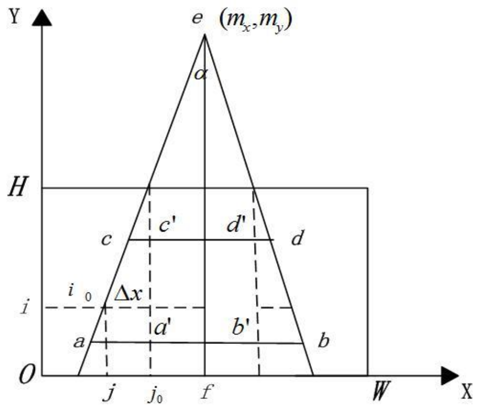

Figure 1. Single Vanishing Point Perspective Correction

4. Targets Clustering based on Directions

There are two steps. First of all, we can use optical flow method to calculate the target speed and direction matrices for a given Geo-Video, and then do direction cluster based on the windows.

4.1. Calculate Speed Matrix

Assuming a video sequence is $\{S\}^{\tau}$ and τ is the number of video images. We superimpose sequential frame images (S_t, S_{t+1}) to form a new image sequence ($\{S'\}^{\tau'}$) to reduce noise ($\tau' = \lceil \tau / 2 \rceil$, $t < \tau$ and t=1, 3, 5…). Calculating continuous frames of optical flow in the new sequence $\{S'\}^{\tau'}$ by using pyramid optical flow method. According to the principle of optical flow, the movement speed of the object is determined by calculating the feature points' Euclidean Distance in adjacent frames. That is $v_x \approx \Delta x, v_y \approx \Delta_y$. Therefore, the speed of a pixel P is $v_i = \sqrt{v_x^2 + v_y^2} = \sqrt{\Delta x^2 + \Delta y^2}$. By this calculation, we will be able to get velocities for all characteristic points in an

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image and then form a speed matrix V on the new sequence $\{S\}^{r}$. But there are often contain a lot of noises in V. Generally speaking, P is a noise point if the speed at P is too big or too small and needs to be set an appropriate threshold depending on a specific situation to reduce the noise.

4.2. Calculate Orientation Matrix

Suppose that the direction of a moving target is represented by ∂ ($\partial \in (-180^{0}, 180^{0})$), which is an angle and formed from the current pixel's velocity vector and the horizontal coordinate axis. If the velocity of a point is V, component in the horizontal direction is Δ x and in the vertical direction is Δy. So when |v|>0, $\partial = \arctan(\Delta y / \Delta x)$. If v=0, indicate that the pixel corresponding to the position without movement and provision the corresponding direction is $\partial = -\infty$. Though the above methods, we can calculate the orientation matrix, $D = \{\partial\}$ on the video sequences $\{S^{'}\}^{r^{'}}$. Among them, every value in the matrix is a direction of a pixel and represented by angle system. Suppose P_i is a feature point and ∂_i is the direction of P_i at the time t and similarly ∂_j is the direction of P_j in the same time. So $|\partial_i - \partial_j|$, represents the two pixels' difference of direction. When $|\partial_i - \partial_j|$ =0, we say the two pixel are moving in the same direction and when $|\partial_i - \partial_j|$ =180, we say the two pixel are moving in an opposite direction. If $|\partial_i - \partial_j| \leq$ 30, we say that the two moving pixels' direction is similar.

4.3. Direction classification

Firstly, we divided the direction system ($\partial \in (-180^{0}, 180^{0})$) into 12 categories as showed in fig.2 and each category are marked with a different color. Secondly, project all angles which in the matrix respectively into the 12 categories, that is, to compute the value of the ratio on the 12 categories. We calculate this ratio using the histogram method. The orientation histogram of an image is as follows:

$$h = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}, p_{11}, p_{12}\} \quad (3)$$

Due to the presence of noise and errors, there may be only existing very small angles in some direction of the computed direction histogram. Assuming a video has been corrected, there is a total of m pixels on one frame of a video image and the average number of a target are about have the size of n pixels. Then n/m is the minimum percentage of a target on one video image. If $P_i < n / m$, then that value is assumed to be generated by the noise and should be ignored (in this paper the value of P_i will be replaced by $-\infty$).

Final provision, if $P_i > n / m$ then P_i is the main direction. All main directions are reserved and non-primary directions are replaced by $-\infty$. As is shown below that each category can be represented by a specified color.

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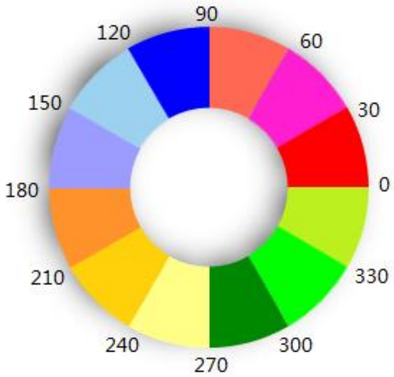

Figure 2. Direction Classification

4.4. Window-based Clustering

In 4.3, the value in the direction matrix has been made a preliminary classification. However, due to the light, wind speed, target velocity and many other effects, there always contain obvious noises and errors in the classified matrix. So we need to find some way to remove these noises and obvious errors. In this paper we use the method of clustering. The steps are as follows:

(1) $A = \{A_i, CA_i, SA_i\}$ save the clustering resultes ($A_i\,(i = 1 \dots n)$ represents a total of i-th class, CA_i is a cluster center of A_i , SA_i is the density of A_i).

(2) Assuming the shape of a target is a rectangular in Geo-Video and represented by R= (l, b) (l is length, b is width).

(3) The window W has a half size of R. Using W to go through every area of matrix D until find all regions $A_i\,(i = 1 \dots n)$ which satisfied $A_i \in W$ $\& -\infty \notin A_i\,(i = 1 \dots n)$.

(4) For every $A_i\,(i = 1 \dots n)$, increase the length and width of W to get W' (W' =2W) until could not find the area which can connectivity with $A_i\,(i = 1 \dots n)$.

(5) All $A_i\,(i = 1 \dots n)$'s center is their cluster center.

(6) Setting all the isolated regions in $A_i\,(i = 1 \dots n)$ to $-\infty$.

(7) Fill angles in all cavities whose value is $-\infty$ in $A_i\,(i = 1 \dots n)$, the size of which is the average value of adjacent eight angles. And set all areas which do not belong to $A_i\,(i = 1 \dots n)$ to $-\infty$ in matrix D.

Algorithm 1 Direction matrix clustering based on sliding window.

```
begin
A={ A_i , CA_i , SA_i }, CA_i = ∅ , SA_i = ∅ , R=(l,b), W=R, D={e,e ∈ ((-180°,180°)&-∞ )}, count=1.
for i=1,W=(l/2,b/2)
  Find(Ai)={e∈ W and e!=-∞ };
  add correspond Ai to A and i+1;
  count=i;
end for
   for each Ai∈ A and i∈ count
       for j=1 and j∈ N
           Wi=(l+l/2j,b+b/2j);
           if(every e∈ Wi at least have one laber)
             j=j+1;
```

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```
            else
              Ai=Wi;
             i=i+1;
        end for
         CA_i = sqrt((l + l/2j)^2 + (b + b/2j)^2 / 2);
         SA_i =sum(e∈ A_i);
         add CA_i to A and add SA_i to A;
    end for
End
```

5. Generate Dynamic Graph

In this paper, we create a dynamic graph on the basis of the result of clustering in 4.4. By defining the graphs' vertices, edges, and evolution rules to simulate the moving targets' position, shape, size, speed, direction, the spatial-temporal correlation between them and so on, which can provide a model reference for the intelligent video analysis especially abnormal state detection. We put each of the clustering result called a node. The dynamic graph is described as a triplet, $G = \{V, E, R\}$ (V is vertex, E is the edge, R is evolution rule).

5.1. Vertex

The vertex is defined as a 4-tuple, $V = \{P, O, V, C\}$. P is the position of the i-th node at time t and be determined by the clustering center which represented by P ((x_i, y_i, t_i)). O is the average direction of the node which determined by the main direction. V is the average velocity of the i-th node and represented by V= $(v_{value}, v_{vector}, t_i)$, v_{value} is the velocity value, v_{vector} is the velocity vector. C is the density of the node and its unit is pixels.

5.2. Edge

In this paper, edges of dynamic graph represent interactions between two nodes and the interaction are expressed by Euclidean distance. Because we have already did a perspective correction for image pre-processing, so the moving target has a same distance ratio between in the Geo-Video and in a real geographic space. So you can directly use of Euclidean distance between the two targets on the image to reflect their true distance. Suppose $p_i(x_i, y_i)$ and $p_j(x_j, y_j)$ is the center coordinates of the two vertices, then their distance is calculated as follows:

$$d(p_i, p_j) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{4}$$

We stipulate that a "new" node will form an edge with all other nodes. The "new" node has two meanings in this paper. One is the point just entering the scene and another is the point just mutation (refers to the direction of mutation).

5.3. Evolution Rules

Evolution rules are defined as follows:

(1) Suppose there are pi（i>=0）nodes in the current scene(frame j). The "new" node p into the frame j (there are two cases, one is the point just entering the scene, another is the point's direction mutation).

(2) P with all nodes in the current scene to form an edge, the edge's value is the Euclidean distance between each two nodes. That will form the initial state of dynamic graphs: $G^{j} = \{V, E, R\}^{j} = \{V, < p, p_i >, R\}^{j}$ $(i \geq 0)$ (V is vertex, E is the edge, r is evolution rule, j is the number of frames and i is the number of nodes).

(3) Comparing the weights of each side in the current frame and the size of the previous frame. If $< p, p_i >^{j} > < p, p_i >^{j-1}$ then delete the $< p, p_i >$ in current graph G; if $< p, p_i >^{j} < < p, p_i >^{j-1}$ then retain $< p, p_i >$ and edge weight updated to $< p, p_i >$; if $< p, p_i >^{j} = < p, p_i >^{j-1}$ then G will unchange.

(4) If one of the point mutation (refers to the direction of mutation) in the current scene, then delete all edges which associated with the current node and regard the node as a "new" node, that is, go to step 2.

(5) If the value of an edge becomes 0 for some times and has the same color with its associated nodes then merge these nodes with a new node. If the associate nodes' color is different, then remains unchanged.

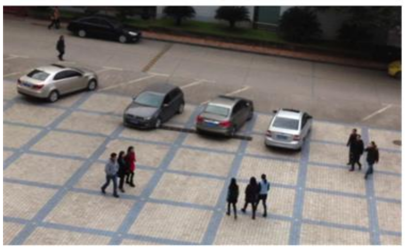
(6) If a node leaves the scene, and then deletes all the edges associated with the node. Here's departure has three meanings: the node really leave the scene, the node be blocked, the node stop motion.

6. Experiment and Analysis

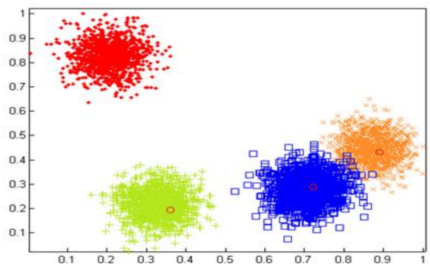
We use the CAMPUS-surveillance video dataset that is shot on campus to verify the validity of the method. The video surveillance dataset has provided the appropriate position reference information. As the scene has some regular plane areas, in Figure 3 (a), and the perspective correction has been done in advance. The measurement of plane spatial distance on the CAMPUS-surveillance video dataset can have a high precision. All the videos are filmed by a same fixed camera and the resolution of the video is 640×360, and the frame rate is 15fps. Experiment contents include: 1) use dynamic graph method to detect anomalies; 2) experimental comparison.

6.1. Use Dynamic Graph Method to Detect Anomalies

The goal of this paper is to simulate the moving target in Geo-Video and detect anomalies by dynamic graph model. The vertexes on the dynamic graph describe the information about each node, including location, speed, direction, density and so on, and the edges describe the distance between each cluster. Our idea is that, firstly, clustering moving targets which have different directions according to the method in 4.1-4.4, as showed in Figure 3 (b). Secondly, obtain the relationship between each node according to the rule in 5.3 (Figure 3 (c)), and finally get the dynamic evolution of the time series diagram (Figure 3 (d)). We use these nodes parameters' change to determine whether an exception occurred and we position each exception by recording location information in vertex. The below figures show the experimental data:



(a) Video Data



(b) Cluster Result

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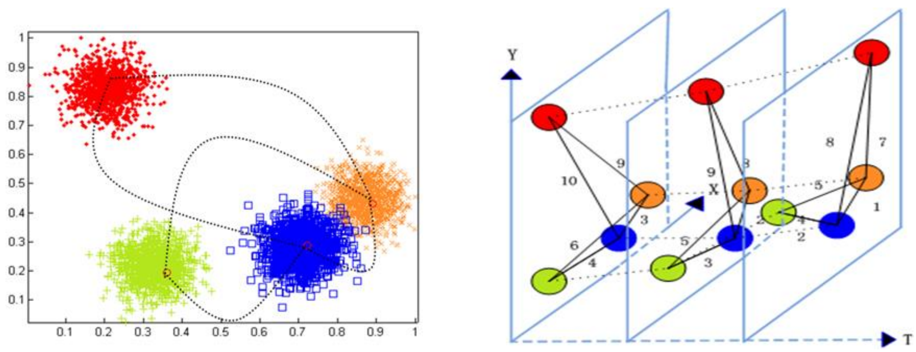

(c) node relationships (d) evolution

Figure 3. Dynamic Graph's Generation

As shown above, (a) is the captured video data on CAMPUS; (b) is the cluster result calculated by the method in 4.4 and the vertices' spatial distribution; (c) is the node relationship of dynamic graph according to the rules in 5.3; (d) is the evolution of video data between frame 34th and 244th.

An abnormal event means the anomalous situation that people can cognition with common sense and it is a random event which has a very small probability to occur. In this paper, several abnormalities on CAMPUS-surveillance video dataset are analyzed with the use of the model: the suddenly gathered or scattered off the crowd's, foreign matter intrusion, reverse driving, collision and so on. Figures 3 to 5 are the motion parameters changes of each node on dynamic graph. N1, N2, N3, N4 representative 4 target sets after clustering. As is shown in the figures below:

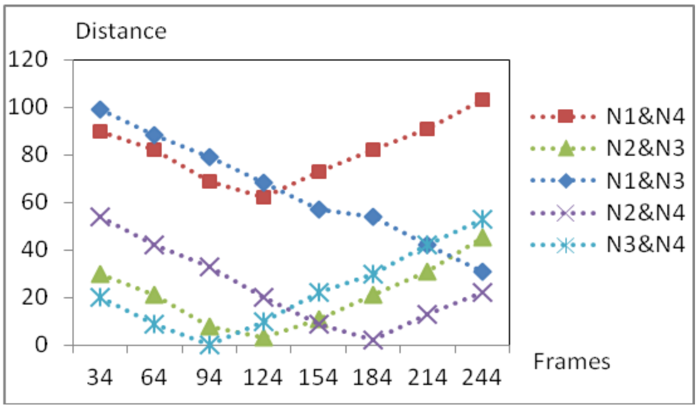

Figure 4. The Distance between each Cluster Nodes

Figure 4 shows the changes of distance between each cluster node. We can see that nodes' distance between N1 and N3 is continued to decline between frame 34th and 244th.

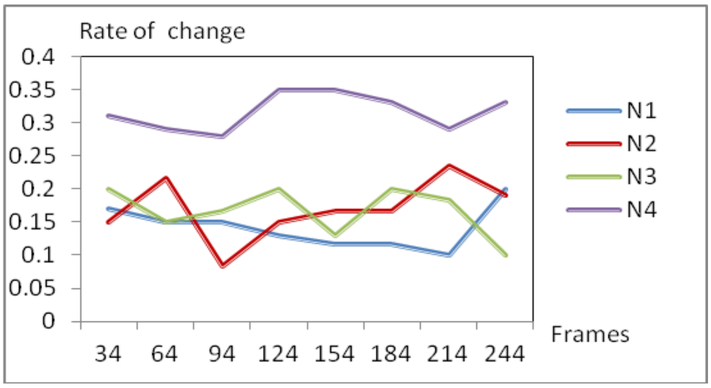

Figure 5. Average Speed of each Cluster Nodes

Figure 5 is the changes of average speed for each cluster node. We can see the speed of N4 is slightly faster than the other three nodes. There is not any node's speed is significantly higher than others.

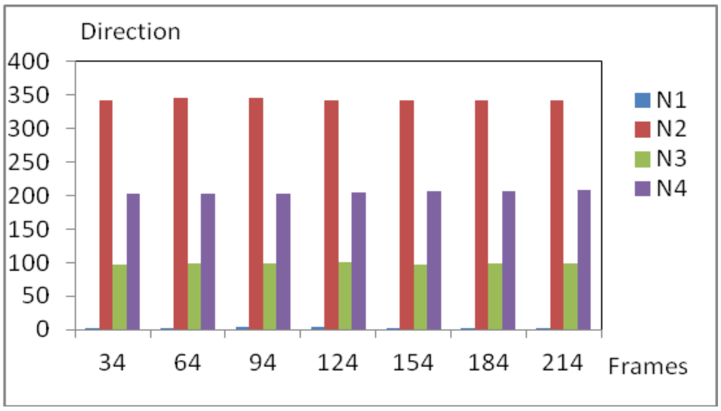

Figure 6. The Direction of each Cluster Node

Figure 6 is the changes of direction for each moving target. We can see that the moving direction has not changed for each node between frame 34th and 244th.

There are analyses of the anomalies that may exist in this scenario:

6.1.1. Suddenly Gathered or Scattered: This exception generally occurs in the crowd emergency evacuation or emergence. According to rule 3 in 5.3, if the distance between two nodes becomes narrow they will form an edge on the dynamic graph, or there is no edge if the distance is too great. So if a dynamic graph in a certain period was an undirected complete graph or very close to an undirected complete graph, the targets in this scene have a great chance of suddenly gather. Similarly, if there are many isolated nodes on a dynamic graph, there will be a great chance of suddenly scattered. According to this rule, we can conclude that this kind of anomaly will not occur on the CAMPUS between frame 34th and 244th.

6.1.2. Foreign Matter Intrusion: This kind of anomaly occurs mainly on the pavement breaking into motor vehicles. In this case, the speed of the foreign matter is usually higher than other targets. So we only need to analyze the speed parameters in Figure 5. If within a certain period of time, one node's rate is significantly higher than the remaining nodes, then there is a great chance that a foreign matter has invaded. Similarly, we can conclude that this kind of anomaly will not occur on CAMPUS between frame 34th and 244th according to this rule.

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6.1.3. Reverse Driving: This situation mainly occurs in the situation when a motor vehicle retrogrades on the highway or city's one-way street. On the dynamic graph, figure 3 (d), if within a certain period of time, only a node or very small number of nodes' color is different from other nodes, and even the direction of movement is a straight line, there is a great chance that the target is reverses driving. According to this rule, we can conclude that this kind of anomaly will not occur on the CAMPUS between frame 34^{th} and 244^{th}.

6.1.4. Collision: Collision generally occurs in an urgent situation. In fig.4, nodes' distance between N1 and N3 is continued to decline. So they have a trend of collision. But whether they would eventually collide need to analyze the change from fig.4-6. From figure 6, the absolute value of the difference of the movement direction between N1 and N3 is about 100^0. We need to consider changes in speed between N1 and N3 from Figure 5 and the nodes' positions on dynamic graph simultaneously. Whether N1 and N3 may collide or not can be predicted by a simple linear operation. Through the above analysis, we can conclude that this kind of anomaly has a great possibility to occur on the CAMPUS between frame 34^{th} and 244^{th}.

6.2. Experimental Comparison

We compared this method with the social force model [21] and the optical flow method [22]. Figure 7 is the ROC curve of these three methods for the test results about collision in CAMPUS. Judging from the results, the optical flow method is sensitive to illumination and camera shake, so when the light changed rapidly or the light is too dark it will be unstable. Social force model has a relatively large error when the advection particles' precision is lacking. The method proposed in this paper combines the spatial distribution of the target, speed, direction, and density information to judge the scene, so in this scenario the performance of detect abnormal is stable and adaptable.

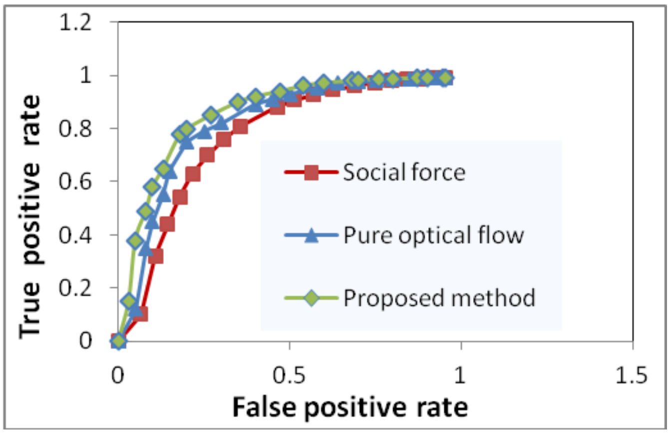

Figure 7. Effect Contrast

7. Conclusions

This paper proposes an intelligent analysis method for video based on dynamic graph model. First, we cluster goals which have the same direction and constitute a dynamic graph by this cluster results. And then, we describe the moving targets' position, shape, size, speed, direction and the spatial-temporal correlation between them by defining the graphs' vertices, edges, and evolution rules and so on to reach the complete semantic description requirements of the target. Last, we analyze the changes process of these spatial characteristics at a certain time dimension to find possible anomalies. Experiments show that, this model can clearly describe the target's movement cues and spatial relationship over time from a global perspective and can be used as a model reference for intelligent video analysis especially abnormal event detection. In addition, further studies include how to combine specific scenarios to analyze probable anomalous events in advance (such as the crowd's sudden gather or scattered, foreign matter intrusion and so on), embodied in the each parameters on the dynamic graph, and set the alarm threshold to achieve the purpose of automatic warning.

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