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Key Point Detection in Images Based on Triangle Distribution of Directed Complex Network

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***Abstract*—Key point detection is still a challenging issue in pattern recognition. With the recent developments on complex network theory, pattern recognition techniques based on graphs have improved considerably. Key point detection can be approached by community identification in directed complex network because image is related with network model. This paper presents a complex network approach for key point detection in video monitoring image, which is both accurate *and fast. We evaluate our method for square and subway* station video monitoring images. Results show that our algorithm can outperform other traditional method both in accuracy and processing times.**

Keywords-Key point detection; Complex network; Community identification

I. INTRODUCTION

Key points are a set of pixels in an image which are characterized by a mathematically well-founded definition, which are rich in terms of information content. They are commonly used as local features in many image applications such as content-based image retrieval or object recognition[1]. The best-known key point detectors include Moravec algorithm, Harris algorithm, genetic-programming algorithms, and so on. The Moravec algorithm defines the corner strength of a point as the smallest sum of squared differences between the point patch and its adjacency patches. The Harris detector computes the locally averaged moment matrix using the image gradients, and then combines the eigenvalues of the moment matrix to compute the strength of each corner. The genetic programming methods automatically synthesize image operators aimed to find the key points in an image using fitness functions which measure the stability of the operators through the repeatability rate, and also promote the uniform dispersion of detected points [1, 2].

With the development of complex networks theory, key point detection based on graph theory is a new research hotspot in the field of image recognition in recent years. This method maps the image to the weighted and directed graph, treats the pixel as the node, and obtains the best key point of the image with the optimal shear criterion. This method essentially transforms the key point detection problem into the optimization problem. It is a kind of point-to-clustering method, and it has a good application prospect for data clustering. At present, the research of key point detection based on graph theory mainly focuses on the following aspects: (1) the design of optimal shear criterion; (2) the spectral method is used for detection; (3) the design of fast algorithm [3, 4, 5, 6, 7].

Communities are defined as subsets of highly inter-connected nodes, relatively and sparsely connected to nodes in other communities[8]. They have intrinsic interest because they may correspond to functional units within a complicated system. In this paper, we introduce a novel approach to computing the key points of an image using complex network community identification. We construct a weighted and directed complex network model to represent each image that gives some valuable information about the location of the key points. The nodes in the network model are the super pixels of the image, which allows a drastic reduction in the number of representative pixels in an image, and the edge is the relationship between the super pixels, according to variations of the intensity, color and other parameters. Then the key points could been identified through the communities identification of the image network model.

II. SPARSE NETWORK MODEL OF IMAGE

The description of the image as a complex network model is based on the complex network theory for image recognition of the premise and foundation. The complex network model is divided into unqualified network, undirected weight network, directed network and directed weight network.

We use the directed and weighted network to describe the image. The super pixels in the image are taken as the nodes of the network, and the luminance difference $|I(p_i)-I(p_j)|$ of the two pixels $[i,j]$ is used as the weight between the two points $w_{i,j}$, when the image is grayscale. When the image is a color map, the edge weight $w_{i,j}$ between node i and j is the RGB European distance of them.

$$W_{i,j}=\frac{\sqrt{\left(R_i\text{-}R_j\right)^2+\left(G_i\text{-}G_j\right)^2+\left(B_i\text{-}B_j\right)^2}}{\sqrt{3}} \tag{1}$$

Where R, G, and B are the RGB values of the pixels, respectively. The direction of the edge in the network is the brightness of the pixels point to the brightness of small pixels.

In order to make the uniform network into a complex network, we calculate the Euclidean distance between any two pixels. Then set the radius threshold r and delete the links between the nodes in the network where the distance are greater than r. The final weight of the complex network links w_{ij} is given by the formula (2) [9, 10, 11, 12]. The complex network model of the image is constructed as shown in Fig. 1. The characteristics of the complex network model of image are shown in the Table 1.

$$w_{ij}=\begin{cases}\left|I(p_i)-I(p_j)\right|, & \left(dist(p_i,p_j)\le r\right)\\ 0, & \left(dist(p_i,p_j)>r\right)\end{cases} \tag{2}$$

TABLE I. THE CHARACTERISTICS OF THE COMPLEX NETWORK MODEL

Characteristic	**Value**
Node	3775
Link	610561
Average in-out-degree	4132.2
Average in-closeness	0.0463
Average out-closeness	0.0928
Average betweenness	4635.7
r	35

Degree measure the number of edges connected to it in a network. Although degree is a simple centrality measure, it can be very illuminating. Closeness measures the mean distance from a node to other vertices. This quantity takes low values for vertices that are separated from others by only a short geodesic distance on average. Such vertices might have better access to information at other vertices or more direct influence on other vertices. Betweenness measures the extent to which a node lies on paths between other vertices. Vertices with high betweenness centrality may have considerable influence within a network by virtue of their control over information passing between others[14].

III. NETWORK COMMUNITY IDENTIFICATION

Before you begin to format your paper, first write and save the content as a separate text file. Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

Finally, complete content and organizational editing before formatting. Please take note of the following items when proofreading spelling and grammar:

A. Triangle Vertexes Weightiness

In general, the simple building blocks of complex networks are a small structure of several nodes called motif[15]. Network motifs are small subgraphs that can be found in a network statistically significantly more often than in randomized networks. Among the possible motifs, the simplest one is the triangle which represents the basic unit of transitivity and redundancy in a graph, see Fig. 2.

As shown in Fig. 2, there are 13 triangle cases at most, including 39 vertexes, in an arbitrary directed network. We compare all three vertexes one another for each triangle T_i and merge the code of vertexes had the same place. Then, there are 30 special vertexes for triangles, encoded from 1 to 30 in Fig. 2. We assign different weights w_i to different vertexes i, because some complex triangles contain the simple triangles, such as triangle 11 contain 1. We assign higher weights to the vertexes whose are not affected by other vertexes, and lower weights to depend on other vertexes. The w_i is calculated using a function as follows:

$$w_i=\frac{TC_i}{\max(TC_i)} \tag{3}$$

where TC_i means the number of vertexes affected by vertex i. We consider that each vertex affects itself. For instance, for vertexes 1, TC_1=2, since it affects vertexes 25 and itself; similarly, TC_6 = 3, since vertex 6 affected vertexes 17, 20 and itself.

B. Triangle Degree

The number of triangles that the node touches is the triangle degree of it. The eigenvalue of nodes is used to measure the structure characteristic of nodes in network. The eigenvalue of node i is defined as follow：

$$\xi\left(n_i\right)=\sum_{t\in\phi}n_t^i w_t \tag{4}$$

where n_i is a node in the network n_t^i is the number of triangle vertexes connected node i in the position t.

C. Process of Network Community Identification

- Construct the complex network model of image.
- Calculate the triangle degree of each node in a complex network model.
- Hierarchical clustering according to node degree.
- Calculate the best value of each segmentation.

- Extract key points from the image according to the division of the communities in the complex network model.

IV. Results and Discussion

In order to verify the effectiveness of the proposed algorithm, we use this method for square and subway station video monitoring image. In two experiments we compare our method with Harris algorithm, which is a well know key point detection approaches.

A. *Experiment 1-Square*

This first experiment, we employed a square image. The characteristics of the complex network model of square image are shown in the Table 2. Fig. 3 shows the key point detection results of square image produced by our algorithm (a) and Harris algorithm (b). The clustering results of square image by our algorithm obtained a total of 6 communities. Our algorithm based on community identification producing 55 key points, which 41 nodes are valid nodes. Harris algorithm producing 138 key points, which 24 nodes are valid nodes.

TABLE II. The Characteristics of the Square Image Complex Network Model

Characteristic	**Value**
Node	885
Link	3344
Average in-out-degree	128.21
Average in-closeness	0.0566
Average out-closeness	0.0658
Average betweenness	148.22
r	35
Maximum Q_{od}-value	0.1736

B. *Experiment 2-Subway Station*

In this experiment, we employed a subway station image. The characteristics of the complex network model of square image are shown in the Table 3. Fig. 4 shows the key point detection results of subway station image produced by our algorithm (a) and Harris algorithm (b). The clustering results of subway station image by our algorithm obtained a total of 7 communities. Our algorithm based on community identification producing 51 key points, which 30 nodes are valid nodes. Harris algorithm producing 6 key points, which 3 nodes are valid nodes.

TABLE III. The Characteristics of the Subway Station Image Complex Network Model

Characteristic	**Value**
Node	732
Link	24146
Average in-out-degree	1280.9
Average in-closeness	0.0489
Average out-closeness	0.0513
Average betweenness	640.66
r	50
Maximum Q_{od}-value	0.1040

V. Conclusion

Is this paper we presented a feasible algorithm based on complex networks and pixels for the key point detection in video monitoring images. This algorithm construct the complex network model of image based on the characteristics of image super pixels, firstly. Then identify the key nodes according to triangle distribution features of image directed complex network model by community identification. We showed that it provides accurate key point of video monitoring images within very low processing times.

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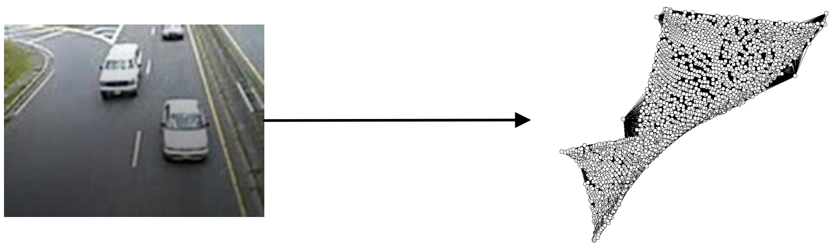


Figure 1. Complex network model of image. The picture has been done using the software Pajek[13]

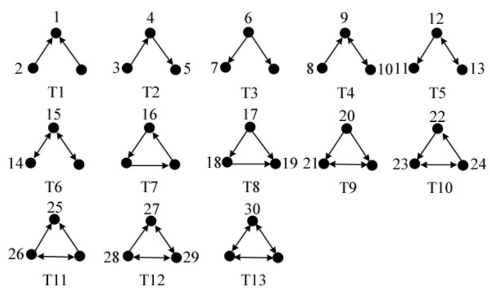
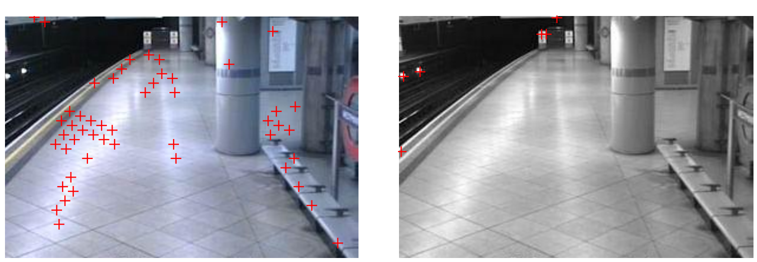


Figure 2. List of all 13 types of triangles

(a) Our algorithm (b) Harris algorithm

Figure 3. Key point detection in square image



(a) Our algorithm (b) Harris algorithm

Figure 4. Key point detection in subway station image