IOP Conf. Series: Materials Science and Engineering **242** (2017) 012107 doi:10.1088/1757-899X/242/1/012107

Fast manifold spectral clustering algorithm for intelligent traffic remote sensing image fuzzy edge

Cong Deng[1, a)], Zelin Jia[1, b)], Shen'an Li[1, c)] and Pengfei Tang[1, d)]

[1]School of Natural and Applied Sciences, Northwestern Polytechnical University, Xi'an 710072, China

[a)] dengconggood@mail.nwpu.edu.cn

[b)] 2014lishenan@mail.nwpu.edu.cn

[c)] jiazelin@mail.nwpu.edu.cn

[d)]1430342822@ mail.nwpu.edu.cn

Abstract. Intelligent transportation system is the future development of traffic systems. Higher precision map requires a higher absolute coordinate accuracy. However, cluster labels cloud be connected to the wrong pixels near the edges of regions, and edges will be misplaced. This paper proposed a fast Manifold Spectrum Clustering Algorithm for the fuzzy-edge of intelligent traffic remote sensing image. we first construct the fuzzy edge of remote sensing image, then analyze and evaluate the influence degree of the fuzzy edge on detailed image, and proposed a spectrum clustering method based on manifold to improve the accuracy and speed to obtain the fuzzy edge of the road in the high resolution remote sensing image. The simulation environment is built by Matlab 2015a, and it is proved that this paper is superior to the existing method in clustering speed and precision performance.

1. Introduction

Intelligent transportation system is the future development of traffic systems, which is a wide-range, real-time, accurate and efficient integrated transportation management system that plays a role in all-round. Intelligent transportation system relies on the high-precision map, which is much different from the traditional map. Higher precision map requires a higher absolute coordinate accuracy, and more information of details as well as high-precision map contains more rich and detailed road traffic information elements.

This paper aims to improve the accuracy and speed of obtaining the fuzzy edges of the road by using the high-resolution remote sensing image through a new manifold spectral clustering algorithm, which provides more accurate road information for high-precision maps - road shape and width. It provides a feasible method to build high-precision map for the future.

Image clustering is an effective method for image segmentation, but it is usually very sensitive to noise. Some other researchers use texture descriptors or spectral reduction to reduce the difference between pixels in an area. But these methods are usually dependent on some important parameters, resulting in reduced robustness of clustering. To enhance the robustness of clustering, Ahmed et al. proposed bias-corrected fuzzy C-means (BCFCM). Based on the fuzzy C-means clustering algorithm (FCM), BCFCM increases the estimation of offset field and the use of spatial information, which can eliminate the influence of image offset field on segmentation. However, BCFCM has not considered the effect of noise on the estimation of offset field, so the effect of segmentation of high-noise image is poor.

Liew et al. presented an adaptive FCM which local spatial information is applied to impose local spatial continuity, and noise suppression and ambiguity resolution are allowed. Dulyakarn and Rangsanseri added some priori spatial information to FCM, we can see that the segmentation results are improved by the spatial information from the experiments. Krinidis and Chatzis presented a robust method called fuzzy local information C-means (FLICM). FLICM is a noise insensitive method without prior knowledge. FELICM introduce the weights of pixels within local neighbor windows to reduce edge degradation. However, FELICM assumes that the label of one pixel is related to the labels of its spatial neighbors. Therefore, cluster labels cloud be connected to the wrong pixels near the edges of regions, and the edges will be misplaced.

Aiming at the above problems, this paper proposed a fast Manifold Spectrum Clustering Algorithm for the fuzzy-edge of intelligent traffic remote sensing image. By analyzing the hierarchical methods, the partition-based methods, density-based methods and the grid-based methods, which provide the theoretical and methodological basis for building a new clustering algorithm for intelligent traffic remote sensing image. In this paper, we first construct the fuzzy edge of remote sensing image, then analyze and evaluate the influence degree of fuzzy edge on detailed image, and proposed a spectrum clustering method based on manifold to improve the accuracy and speed to obtain the fuzzy edge of the road in the high resolution remote sensing image. The simulation environment is built by Matlab 2015a, and it is proved that this paper is superior to the existing method in clustering speed and precision performance.

2. Basic theory of remote sensing image clustering

2.1 Hierarchical Methods

The method has two main paths – agglomerative way (bottom-up) and divisive way (top-down). The beginning of the agglomerative way is to regard every object as a single cluster, then seek the same cluster according to the linkage and finally form clusters. The top-down approach is the opposite process, which regard all objects as one cluster, then exclude object according to the linkage and finally every object belongs to a cluster. These two kinds of path have no difference between the pros and cons. Only in the practical application, we will consider which path is faster according to the feature of the data and the number of clusters. The linkages to decide the cluster are the shortest distance linkage, the longest distance linkage, the median distance linkage and the average linkage, etc. (where the average linkage is usually regarded as the best linkage because its good monotony and its moderate degree of space expansion /concentration). BIRCH (Balanced Iterative Reducing and Clustering Using Hierarchies) is mainly used when the data volume is very large and the data type is numerical; ROCK (A Hierarchical Clustering Algorithm for Categorical Attributes) is mainly used when the data type is categorical; Chameleon (A Hierarchical Clustering Algorithm Using Dynamic Modeling) uses linkage – Knn (k-nearest-neighbor) and its effect of clustering is better than BIRCH but its computational complexity is high (O(n^2)).

2.2 Partition-based Methods

The principle is simple to understand that there is a pile of points need to cluster, the cluster goal is "the points within clusters are close enough, the points between clusters are far enough." We must first determine the number of clusters, then select a few points as the initial center point, then iterative relocate the data points according to the pre-set heuristic algorithm until it reaches the goal. According to the heuristic algorithm, it forms the k-means heuristic algorithm and its variants includes k-medoids, k-modes, k-medians and kernel k-means; k-means++, intelligent k-means, genetic k-means are not sensitive to initial values; k-medoids and k-medians are not sensitive to noise and outliers; k-modes can be used when data type is categorical; kernel k-means can be used to process the non-convex data.

2.3 Density-based Methods

K-means cannot cluster the data with irregular shape. So density-based methods are proposed to systematically solve this problem. These methods handle noise data better. The principle is like drawing circles, in which two parameters need to be defined, one is the maximum radius of the circle, the other is the smallest number of points within a single circle. Finally, the points in a same circle belong to a cluster. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a typical one, but the two parameters of the settings are very sensitive. DBSCAN's extension called OPTICS (Ordering Points To Identify Clustering Structure) The shortcomings of DBSCAN are improved by preferentially searching for high density and then setting parameters according to high density characteristics.

2.4 Grid-based Methods

The principle is to divide the data space into grid cells, map the data object sets into the grid cells, and calculate the density of each cell. According to the pre-set threshold to determine whether each grid cell is a high-density unit and then the adjacent high-density group forms a cluster. The speed of this method is independent of the number of data objects and depends only on the number of cells in each dimension in the data space. Therefore, the advantage is that the execution efficiency is high. But the shortcomings are many, for example, this method is sensitive to the parameters, cannot deal with irregular distribution of data and may cause a dimension of disaster. STING (Statistical Information Grid) and CLIQUE (Clustering In Quest) is the representative algorithm in grid-based methods.

3. Fuzzy edge fast manifold spectral clustering theory

3.1 Fuzzy Edge of Intelligent Traffic Remote Sensing Image

In the late 1970s, scholars have begun to study the extraction of roads in remote sensing images. With the improvement of satellite remote sensing image resolution as well as urban and rural construction, more and more algorithms have been proposed to adapt to the new situation.

The existing algorithm has achieved good results for the road network in the remote sensing image with simple scenes, but few algorithms can extract the complete ones. This is because the presence of trees and buildings, vehicles on the road and a variety of cross-line will cause shadow or occlusion. Similar road feature that might be parking lots, ponds, rivers and roofs, *etc.*, not only makes the road network very messy, also causes the edges of the road in the remote sensing image to be very vague and unclear.

At present, methods to extract road edge from the remote sensing image mainly are the template matching, gradient edge operator detection and others. The template matching algorithm uses the gray scale shape of the image to match the recognition image, but the computation is large and the matching speed is low. The gradient operator edge detection finds the edge by analyzing the gray scale of the image. Commonly used gradient edge detection operators are Roberts, Sobel, Prewitt, Laplacian and Canny et al. However, these traditional operators consider less directional features and often lose some of the edge details. This paper uses the improved 5 * 5 Sobel operator with 8-direction proposed by Yuan Tan *et al*.

3.2 Neighborhood Weighting

Sobel operator is an edge detection operator based on the first-order derivative. The traditional Sobel operator consists of two 2 * 3 matrixes, respectively, the vertical gradient matrix is used to detect the horizontal edge as well as horizontal gradient matrix is used to detect the vertical edges. The advantage of the Sobel operator is the simple principle and the small computation. However, since here are only two directions, the edge detection effect is better for the horizontal and vertical direction, but the effect is not very satisfactory for the image with more complex texture and edges in more directions.

1) The Sobel Operator Used in This Paper

As the traditional Sobel operator has a limitation on the edge direction, we used the improved 5*5 Sobel operator with 8-direction to reduce the deviation and increase the detection directions of edges. Eight directions are 0 º, 22.5 º, 45 º, 67.5 º, 90 º, 112.5 º, 135 º and 157.5 º as the Fig.1 shows,

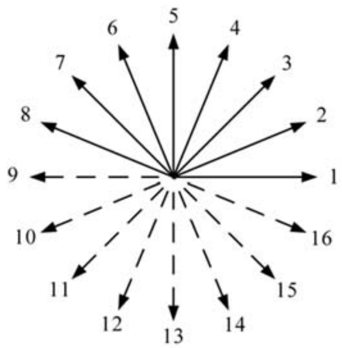

Figure 1. The improved Sobel operator

2) The Direction Templates

Traditional Sobel operator and conventional Sobel expansion operator are typically 3*3 matrix templates, we use the 5*5 matrix templates to describe the edge of the image more accurately and reduce the impact of noise on the detection results. The templates of each directions are as Fig.2 shown.

$$\begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 2 & 8 & 12 & 8 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ -2 & -8 & -12 & -8 & -2 \\ -1 & -4 & -6 & -4 & -1 \end{pmatrix}$$

(a) 0°

$$\begin{pmatrix} 4 & 6 & 4 & 1 & 2 \\ 1 & 12 & 12 & 8 & 0 \\ 2 & 8 & 0 & -8 & -2 \\ 0 & -8 & -12 & -12 & -1 \\ -2 & -1 & -4 & -6 & -4 \end{pmatrix}$$

(b) 22.5°

$$\begin{pmatrix} 6 & 4 & 1 & 2 & 0 \\ 4 & 12 & 8 & 0 & -2 \\ 1 & 8 & 0 & -8 & -1 \\ 2 & 0 & -8 & -12 & -4 \\ 0 & -2 & -1 & -4 & -6 \end{pmatrix}$$

(c) 45°

$$\begin{pmatrix} 4 & 1 & 2 & 0 & -2 \\ 6 & 12 & 8 & -8 & -1 \\ 4 & 12 & 0 & -12 & -4 \\ 1 & 8 & -8 & -12 & -6 \\ 2 & 0 & -2 & -1 & -4 \end{pmatrix}$$

(d) 67.5°

$$\begin{pmatrix} 1 & 2 & 0 & -2 & -1 \\ 4 & 8 & 0 & -8 & -4 \\ 6 & 12 & 0 & -12 & -6 \\ 4 & 8 & 0 & -8 & -4 \\ 1 & 2 & 0 & -2 & -1 \end{pmatrix}$$

(e) 90°

$$\begin{pmatrix} 2 & 0 & -2 & -1 & -4 \\ 1 & 8 & -8 & -12 & -6 \\ 4 & 12 & 0 & -12 & -4 \\ 6 & 12 & 8 & -8 & -1 \\ 4 & 1 & 2 & 0 & -2 \end{pmatrix}$$

(f) 112.5°

$$\begin{pmatrix} 0 & -2 & -1 & -4 & -6 \\ 2 & 0 & -8 & -12 & -4 \\ 1 & 8 & 0 & -8 & -1 \\ 4 & 12 & 8 & 0 & -2 \\ 6 & 4 & 1 & 2 & 0 \end{pmatrix}$$

(g) 135°

$$\begin{pmatrix} -2 & -1 & -4 & -6 & -4 \\ 0 & -8 & -12 & -12 & -1 \\ 2 & 8 & 0 & -8 & -2 \\ 1 & 12 & 12 & 8 & 0 \\ 4 & 6 & 4 & 1 & 2 \end{pmatrix}$$

(h) 157.5°

Figure 2. Templates of each directions

3.3 Fuzzy Edge Spectrum Clustering Based on Manifold

In order to meet the overall importance of clustering, ensure high similarity of data in the same manifold structure, and low similarity of data in the different manifold structure, manifold distance kernel measure is adopted in this paper, which is described as follows.

Firstly, we define the line length, manifold distance and manifold distance kernel.

1) Line Length on Manifold

$$L(x,y) = e^{\rho d(x,y)} - 1 \tag{1}$$

where, $d(x,y)$ presents the Euclidean distance between x and y; ρ presents the extension factor to control the line length between two data points.

2) Manifold Distance between Data Points

$$D_{i,j}^{\rho} = \frac{1}{\rho} ln(1 + d_{sp}(x_i, x_j))^2 \tag{2}$$

$$d_{sp}(x_i, x_j) = \min_{p \subset P_{ij}} \sum_{k=1}^{|\rho|-1} \left(e^{\rho d(p_k, p_{k+1})} - 1\right) \tag{3}$$

where, $d_{sp}(x_i, x_j)$ presents the shortest path distance between node x_i and node x_j on graph G. $d_{sp}(x_i, x_j)$ presents the shortest path Euclidean distance between x_i and node x_j on graph G. $d_{sp}(x_i, x_j)$.

3) Manifold Distance Kernel

$$K_{ij} = exp\left(-\frac{D_{i,j}^{\rho}}{2\sigma^2}\right) \tag{4}$$

Then we give the algorithmic process of fuzzy edge spectrum clustering based on manifold:

a) Input the data points $\{x_l\}_{l=1}^n$, the number of classes k, and the extension factor ρ.
b) Construct similarity matrix $K \in \mathrm{R}^{n\times n}$ based on similarity measurement of manifold distance kernel where $K_{ij} = \exp\left(-\frac{D_{i,j}^{\rho}}{2\sigma^2}\right)$ presents the matrix elements (the kernel width σ is obtained by repeated experiments) ; $K_{ii} = 0, 1 \le i, j < n$ matrix main diagonal elements.
c) Construct the Laplacian matrix $\boldsymbol{L} = \boldsymbol{D}^{-1/2}\boldsymbol{K}\boldsymbol{D}^{-1/2}$ where $\boldsymbol{D}$ presents the diagonal degree matrix $D_{ii} = \sum_{j=1}^{n} k_{ij}$.
d) Solve the eigenvectors $v_1, v_2 \cdots, v_k$ corresponding to the k maximum eigenvalues of Laplacian matrix $\boldsymbol{L}$. And construct the eigenvector matrix $\boldsymbol{V} = [v_1, v_2 \cdots, v_k] \in \mathrm{R}^{n\times k}$ where v_k is column vector.
e) Unitize the row vectors of matrix $\boldsymbol{V}$ and get matrix $\boldsymbol{Y}$ where $Y_{ij} = V_{ij}/\left(\sum_j {V_{ij}}^2\right)^{1/2}$.
f) Regard each row of matrix $\boldsymbol{V}$ as a point in the cluster space, then cluster them into k class.
g) Divide the data points of each line of the eigenvector matrix.
h) Output the result of classes $c_1, c_2, \cdots, c_k$.

4. Experiment and simulation

4.1 Simulation Environment

The experiment was carried out under the Matlab 2015a. The satellite remote sensing images were from the Quick Bird satellite and the original images were pretreated with ENVI. The purpose of pretreating the original image is to obtain the part that needs to be clustered while eliminating the influence of the vehicle on the road by cutting the remote sensing image. Secondly, the edge detection experiment is carried out on the pretreated image, and the test result is labeled on the original image and compared with the actual road edge, and the accuracy performance of the algorithm is analyzed statistically.

The result of edge detection experiment is shown in Figure 3.

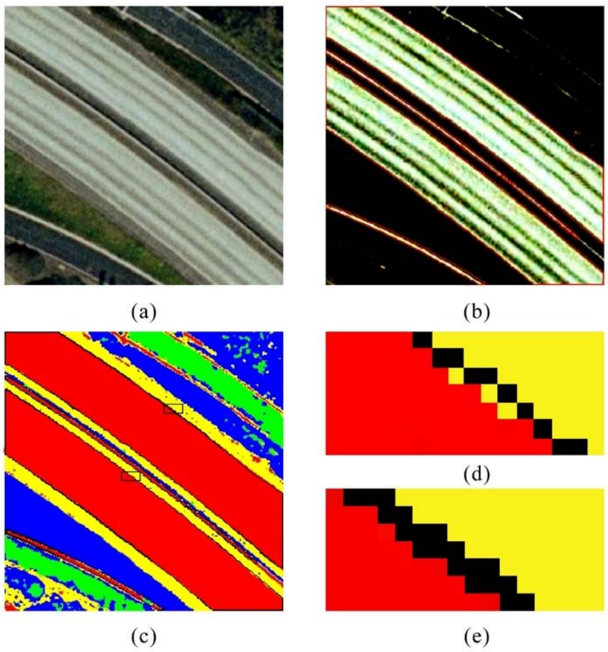

Figure 3. Edge detection experiment

4.2 Accuracy Analysis and Comparison of Simulation Results

For the complex image, many different objects have similar features, and the objects cannot be distinguished well by only increasing the number of clusters. We compare the results of edge detection and clustering to evaluate the different clustering methods.

We use two different accuracies to quantitatively evaluate the image clustering methods: regional accuracy and edge accuracy.

First, the regional accuracy is defined as:

$$RA = \frac{\sum_{i=1}^{n} max\{A_{ik}\}}{N} \tag{5}$$

where N presents the total number of pixels in the remote sensing image, n is the number of objects in the result of edge detection, A_{ik} is the number of pixels of cluster k in object i, and $max\{\cdot\}$ is used to get the maximum number of pixels in an object.

The regional accuracy of different algorithms including FCM, MeanShift, FLICM and Ours are shown in Table 1.

Table 1. Regional accuracy

	FCM	*MeanShift*	*FLICM*	*Ours*
Accuracy	65.2%	75.3%	78.2%	83.1%

Then we use the accuracy of pixels around edges to represent the accuracies of edges. The edge accuracy can be described as:

$$EA = \frac{\sum_{i=1}^{n} A'_{ik}}{N'}, K = arg \max_{k\in\{1,c\}} A_{ik} \tag{6}$$

where N' is the number of pixels which are get by edge detection with a window, A'_{iK} is the number of pixels of cluster K in object i within the range of detection area, and K is the cluster which has the maximum number of pixels in the object.

The edge accuracy of different algorithms including FCM, MeanShift, FLICM and Ours are shown in Figure 4.

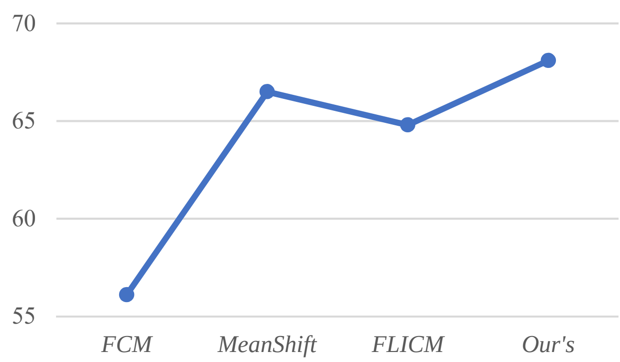

Figure 4. Performance of edge accuracy

5. Conclusion

It is an innovative practice to introduce spectral clustering method into the fuzzy edge of the road. However, the resolution of remote sensing image is limited (1 pixel equals 60 cm), and the precision of clustering cannot fully meet the requirement of high precision map. At present, our work shows that the manifold spectral clustering method is available for the map to make the road blurred edges become more accurate.

In the future, with the increase of satellite remote sensing resolution, manifold spectral clustering method can also provide more accurate road edge information.

Acknowledgments

First and foremost, I would like to show my deepest gratitude to my advisor, Dr. Lin Wei, a pleasingly affectionate rigorous and reliable scholar, have put forward many valuable opinions in the process of the thesis writing. She doesn't mind taking the trouble to give me timely help, so I can finally finish writing work. Her accurate and forward-looking academic observation benefits me in my future study.

I want to thank all the teachers in the Department of mathematics in Northwestern Polytechnical University, their selfless devotion and dedication of the attitude of academic benefits me a lot.

I would also thank Ms. Guo for all her help in the process of my research. She made valuable comments on the revision of the paper, which made my paper more perfect.

This work is supported by the National Training Programs of Innovation and Entrepreneurship for Undergraduates (No.201610699328).

Finally, I' d like to thank all my friends and my family members, especially my parents.

Reference

[1] Prabhu, S., & Tensing, D. (2015). Adapted normalized graph cut segmentation with boundary fuzzy classifier object indexing on road satellite images. International Arab Journal of Information Technology, 12(6), 597-603.

[2] Tan Y, Huang H X, Xu J M, et al. Road edge detection from remote sensing image based on improved Sobel operator[J]. Remote Sensing for Land and Resources, 2016, 28(3):7-11.

[3] Zang, Yu, et al. "Joint Enhancing Filtering for Road Network Extraction." PP.99 (2016):1-15.

[4] Shi, J, and J. Malik. "Normalized cuts and image segmentation." IEEE Transactions on Pattern Analysis & Machine Intelligence 22.8(2000):888-905.

[5] Luxburg, Ulrike. "A tutorial on spectral clustering." Statistics and Computing 17.4(2007):395-416.

[6] Ozertem, Umut, D. Erdogmus, and R. Jenssen. "Mean shift spectral clustering." Pattern Recognition 41.6(2008):1924-1938.

[7] Jung, Cheolkon, et al. "Image segmentation via manifold spectral clustering." Journal of Allergy & Clinical Immunology 127.2(2011):1-6.