Sensors & Transducers, Vol. 167, Issue 3, March 2014, pp. 68-74

www.sensorsportal.com

Sensors & Transducers

© 2014 by IFSA Publishing, S. L.

http://www.sensorsportal.com

Research of the Space Clustering Method for the Airport Noise Data Minings

[1, 2] Jiwen Xie, [1, 2] Tao Xu, [2] Guoqing Yang

[1] College of Computer Science and Technology, Civil Aviation University of China, Tianjin, China
[2] Information Technology Research Base, Civil Aviation Administration of China, Tianjin, China
[1] Tel.: 15922191232, fax: 022-24092286
E-mail: xiejiwenpower@163.com

Received: 20 December 2013 /Accepted: 28 February 2014 /Published: 31 March 2014

Abstract: Mining the distribution pattern and evolution of the airport noise from the airport noise data and the geographic information of the monitoring points is of great significance for the scientific and rational governance of airport noise pollution problem. However, most of the traditional clustering methods are based on the closeness of space location or the similarity of non-spatial features, which split the duality of space elements, resulting in that the clustering result has difficult in satisfying both the closeness of space location and the similarity of non-spatial features. This paper, therefore, proposes a spatial clustering algorithm based on dual-distance. This algorithm uses a distance function as the similarity measure function in which spatial features and non-spatial features are combined. The experimental results show that the proposed algorithm can discover the noise distribution pattern around the airport effectively. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Airport noise, Data mining, Distribution pattern of the airport noise, Dual-distance, Spatial clustering algorithm.

1. Introduction

With the rapid development of civil aviation of China, a large number of airports are being built, rebuilt or expanded across the country in recent years. The throughput and scale of airport are expanding correspondingly [1]. Meanwhile, the airport land and urban land become much closer, and the disputes caused by the airport noise are becoming more and more. It is of great significance to predict airport noise scientifically and reasonably, and to take reasonable and effective measures, at the same time, to deal with the airport noise pollution problem.

The study of distribution patterns of the airport noise is relatively lagging in China, but the related research has developed earlier in the foreign country and has got some theories and methods. However, most of these methods predict the distribution pattern based on the information of flight track rather than the noise data and the geographic information of the monitoring points, so it cannot get the scientific and reasonable distribution pattern.

Data mining refers to extracting a model which is reliable, innovative, and efficient from a large number of historical data, and then finding the implicit, meaningful knowledge [2]. Therefore, it is of great feasibility to use data mining technology to mine noise distribution pattern around the airport from the mass airport noise data and the geographic information of the monitoring points.

Spatial clustering [3] is an important research branch of spatial data mining, which has been widely used in geography, cartography, geology, remote sensing science, biology, economics, and many other areas. According to the agglomeration rules used in the clustering process, spatial clustering algorithm can be divided into hierarchical clustering algorithm, partition clustering algorithm, density clustering algorithm and grid clustering algorithms [4-7]. However, there never exists a kind of clustering algorithm which can be widely applied to a variety of data sets and clustering tasks. Due to the particularity of the airport noise data mining, the traditional clustering algorithms cannot be directly applied to the airport noise data set. Therefore, this paper proposes a spatial clustering algorithm based on dual-distance which can effectively solve the airport noise data mining problem.

2. The Basic Concept and Theory

2.1. Airport Noise

The airport noise refers to a variety of noise produced in the process of taking off, landing and planning of aircraft [8].

The prediction and control of airport noise are closely related to the evaluation of noise. The International Standards Organization (ISO), the International Civil Aviation Organization (ICAO) and other countries all over the world have formulated related airport noise evaluation index. For example, the weighting equivalent continuous perceived noise level (WECPNL) is drawn up by ICAO, and the day and night average noise level (DNL) is drawn up by America [9]. According to the National Standard of China - "surrounding the airport aircraft noise environment standard" (GB9660-1988), WECPNL is adopted in China as the evaluation of airport noise pollution which reflects the average daily airport noise effects on people [10].

The noise values of adjacent monitoring point are high correlation, which means that the values of each point are same or similar to its proximal point. Meanwhile, the areas around the airport can be divided into several bands areas according to the strength of noise influence degree and the closeness of geographical space since the noise around airport possesses a certain distribution pattern. Each of bands areas can be viewed as a cluster.

2.2. Spatial Clustering

Spatial clustering is an important technology of space pattern recognition and spatial data mining. It can reveal the object space distribution, draw spatial object structure features, and predict the trend of the development of spatial entities [11, 12].

2.2.1. The Basic Features of Space Objects

Space object has the following main features:

1) Space features.

Spatial features [13] are used to describe space object position, geometric features and the relation with other space object. Usually, it uses different coordinate system to describe the location of the object space.

2) Non-space features.

The non-spatial features [13] are used to describe the other features of spatial entities.

Usually, by using the spatial clustering algorithm, the relationship of space features based on non-space features can be discovered.

2.2.2. The Main Method of Spatial Clustering

Space object has spatial features and non-spatial features, therefore, spatial clustering results which need to meet the proximity adjacent of space position and the similarity of the non-spatial features [14]. That is to say, only considering both the features of space object, there is possible to mine the better spatial distribution patterns of objects. At present, the spatial clustering method considered both of the features mainly includes the partition method and integration method [15].

1) Partition method.

The spatial features and non-spatial features of space object are considered respectively in the partition method, that is to say, this method is divided into two steps. In the first step, it will get two clustering results based on the spatial features and non-spatial features respectively. In the second step, both of the clustering results will be combined into one clustering result based on a certain measurement.

2) Integration method.

The spatial features and non-spatial features are seen as the whole in the integration method, in other words, this method is constituted by two steps. In the first step, the spatial features and non-spatial features are unified into a similarity metric based on a certain regulation. In the second step, it will get a reasonable clustering result based on the similarity metric.

2.3. Partition Clustering Algorithm

Partition clustering algorithm usually refers to a given data set of n data objects, which is divided into k groups. Each group represents a cluster, and $k < n$. At the same time, these clusters need to meet the following conditions [16].

1) Each cluster must contain a data object at least.

2) Each data object can only belong to one cluster.

At the beginning of the partition clustering algorithm, the number of cluster and the initial center of clusters must be given, and then according to the evaluation function grouping, the division becomes more scientific and reasonable after the iteration. The advantage of this algorithm is simple and suitable for medium and small scale data sets, but the existing partition clustering algorithm cannot deal with hybrid, symbol type data effectively.

2.4. Singular Value Decomposition Method

Singular value decomposition is an effective method of feature extraction, which is widely used to achieve matrix reduction in many fields [17]. By using the singular value decomposition method, any real matrix can be transformed into diagonal matrix.

Lemma (SVD). Assume that the matrix $A_{n\times m}$ is a real matrix and rank (A)=k, then there will be two orthogonal matrix ($U_{n\times n}$, $V_{m\times m}$) and one diagonal matrix ($D_{n\times m}$) make the formula (1) set up.

$$A = UDV^T \tag{1}$$

Here:

$$D_{n\times m} = \begin{pmatrix} Z_{k\times k} & 0 \\ 0 & 0 \end{pmatrix}, Z_{k\times k} = diag(\lambda_1, \lambda_2, \ldots \lambda_k)$$

$$U_{n\times n} = (u_1, u_2, \ldots, u_k, u_{k+1}, \ldots, u_n)$$

$$V_{m\times m} = (v_1, v_2, \ldots, v_k, v_{k+1}, \ldots, v_m)$$

The singular value of the matrix A is represented in the symbol σ_i ($i=1,2,\ldots k,\ldots m$), which is equal to $\sqrt{\lambda_i}$. Here the symbol λ_i represents the i^{th} eigenvalue of A^TA, and $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_k > 0$, $\lambda_{k+1} = \lambda_{k+2} = \ldots = \lambda_m = 0$.

First, apply singular value decomposition to decompose the matrix. Second, select the first t items of λ_i $(i=1,2,\ldots k,\ldots m)$ to make the formula of $\sum_{i=1}^{t} \lambda_i \Big/ \sum_{j=1}^{m} \lambda_j \geq \delta$ set up, the symbol δ is a threshold value. Third, select the first t^{th} column of $U_{n\times n}$ to constitute the matrix $U_{n\times t}$, select the first tth row and the first t^{th} column of $D_{m\times m}$ to constitute the matrix $D_{t\times t}$, select the first t^{th} row and the first tth column of $V_{m\times m}$ to constitute the matrix $V_{t\times t}$, then use the formula (2) to calculate the matrix A^* which is the matrix be reduced.

$$A^* = U_{n\times t} D_{t\times t} V_{t\times t} \tag{2}$$

By the method of singular value decomposition, the dimension of target matrix is reduced to t.

3. The Airport Noise Data Mining

The purpose of mining airport noise data is to search the clusters which possess the following features:

1) The geographical space is near.

2) In any flight event, the noise value is close to each other.

According to the features of these clusters, the noise control measures are formulated, so that the airport noise pollution problem would be solved scientifically. Fig. 1 shows the process of airport noise data mining.

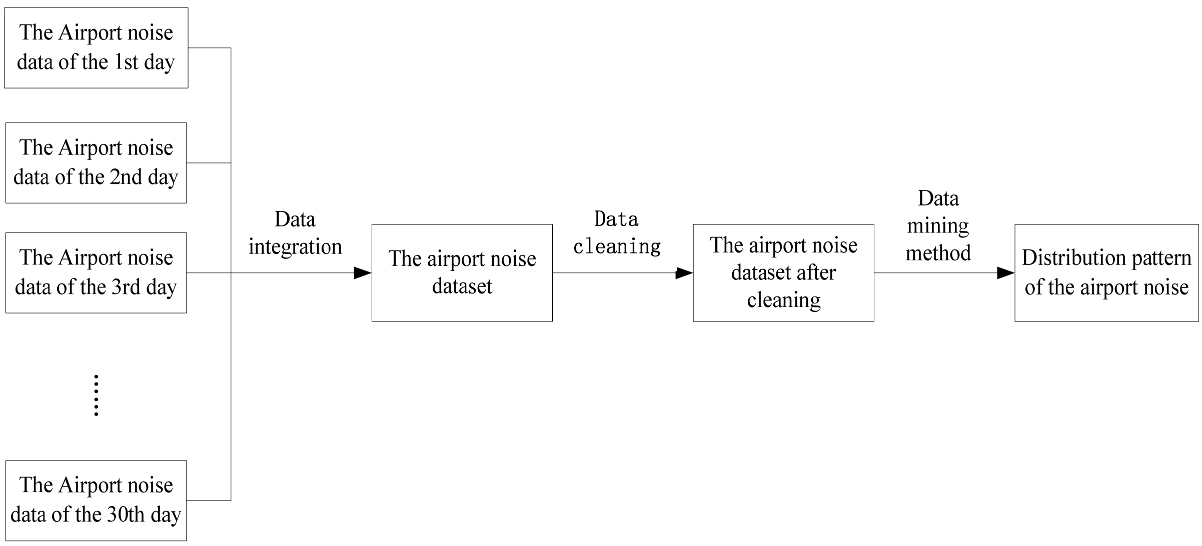

Fig. 1. The process of airport noise data mining.

3.1. The Description of the Problem

Clustering is a process that groups the physical or abstract objects into couples of different clusters formed by similar objects, and the entities in the same cluster are similar, otherwise, they are dissimilar [18].

For the problem of airport noise data mining, some basic concepts are explained as follows:

Clustering object refers to each noise monitoring point around the airport. Object property includes monitoring point space features and non-spatial features.

The ith noise monitoring point is expressed in the set $Pos_i(x_i, y_i, h_i, nl_{i1}, nl_{i2}, ...nl_{im})$ which can be abbreviated to Pos_i. The $A(x_i, y_i, h_i)$ triples represents the space features of Pos_i, that is, the geographical space coordinates of monitoring point. The symbol x_i and y_i is the longitude and latitude of Pos_i respectively, and the symbol h_i is the altitude of Pos_i. The set $B_i(nl_{i1}, nl_{i2}, ..., nl_{im})$ represents the non-spatial features of Pos_i, where the $nl_{it}(t = 1, 2, ...m)$ represents the noise value of Pos_i in the tth flight event, and the symbol m is the number of flight event.

The noise monitoring point possesses features of space and non-space and the clustering results should not only meet the need of closeness of geographical space, but also satisfy the maximum similarity of non-space features. That is, only taking account of these both features, the distribution pattern of space object could be mined better. Therefore, it is necessary to propose a similarity measure function based on dual-distance. Assuming that the function $d(i, j)$ denotes the similarity based on dual-distance between Pos_i and Pos_j, and then the $d(i, j)$ is defined as following.

$$d(i,j)=\begin{cases}\alpha d(A_i,A_j)+\beta d(B_i,B_j) & \mathrm{i}\neq \mathrm{j}\\ 0 & \mathrm{i}=\mathrm{j}\end{cases} \tag{1}$$

In the Equation (1), the function $d(A_i, A_j)$ and $d(B_i, B_j)$ represents the space distance and the non-space distance between Pos_i and Pos_j respectively. The symbol α and β denotes the proportion of $d(A_i, A_j)$ and $d(B_i, B_j)$ respectively.

The calculating of $d(A_i, A_j)$ is shown as following.

$$d(A_i,A_j)=\sqrt{\frac{\left(\left(\frac{x_i-x_j}{x_{\max}-x_{\min}}\right)^2+\left(\frac{y_i-y_j}{y_{\max}-y_{\min}}\right)^2+\left(\frac{h_i-h_j}{h_{\max}-h_{\min}}\right)^2\right)}{3}} \tag{2}$$

In the Equation (2), the symbol $x_{\max}$ and $x_{\min}$ is the maximum and minimum longitude value of monitoring points respectively. The symbol $y_{\max}$ and $y_{\min}$ is the maximum and minimum latitude value of monitoring points respectively. The symbol $h_{\max}$ and $h_{\min}$ is the maximum and minimum altitude value of monitoring points respectively.

Furthermore, the $d(B_i, B_j)$ can be obtained as following.

$$\mathrm{d(B_i,B_j)}=\frac{1}{\sqrt{\frac{\sum_{k=1}^{m}(\mathrm{nl_{ik}}-\mathrm{nl_{jk}})^2}{\mathrm{m}}}} \tag{3}$$

The center of the ith cluster is expressed in the set $V_i(v_{i1}, v_{i2}, v_{i3}, v_{i(3+1)}, v_{i(3+2)}, ..., v_{i(3+m)})$, and the symbol v_{ij} represents the j^{th} dimension of V_i, and the v_{ij} is defined as following.

$$v_{ij}=\begin{cases}\dfrac{\sum_{t=1}^{n}x_t\times IS(t,i)}{number(i)} & \mathrm{j=1}\\[2ex] \dfrac{\sum_{t=1}^{n}y_t\times IS(t,i)}{number(i)} & \mathrm{j=2}\\[2ex] \dfrac{\sum_{t=1}^{n}h_t\times IS(t,i)}{number(i)} & \mathrm{j=3}\\[2ex] \dfrac{\sum_{t=1}^{n}nl_{tj}\times IS(t,i)}{number(i)} & \mathrm{j>3}\end{cases} \tag{4}$$

The n is the number of monitoring point around the airport, and the number of monitoring point belongs to the i^{th} cluster is presented in the symbol $number(i)$. The function $IS(t,i)$ is a membership function. If the t^{th} monitoring point belong to the i^{th} cluster, which is expressed in the symbol C_i, then the value of $IS(t,i)$ is 1, otherwise, the value of $IS(t,i)$ is 0.

$$IS(t,i)=\begin{cases}1, & Pos_t\in C_i\\ 0, & Pos_t\notin C_i\end{cases} \tag{5}$$

If the geographical space of some monitoring points is adjacent, and the noise value of these points is close to each other in any event flight, then these monitoring points form a cluster.

The clustering evaluation index is expressed in the symbol E which could be calculated as following.

$$E=\sum_{i=1}^{k}\sum_{j=1}^{number(i)}d(C_{ij},V_i) \tag{6}$$

The i is the serial number of cluster and the k is the number of cluster. The symbol C_{ij} represents the j^{th} object of C_i. The function $d(C_{ij},V_i)$ denotes the distance between C_{ij} and V_i which can be calculated according to the Equation (1).

3.2. Data Preprocessing

Data processing mainly includes the following three parts: the cleaning of noise data generated by the single flight event, data preparation and data dimension reduction.

3.2.1. The Cleaning of Noise Data Generated by the Single Flight Event

The data collected from the real world is generally incomplete or inconsistent, so is the airport noise data. Inclement weather (high winds, high temperatures, rain) makes that noise monitoring equipments cannot work in normal and stable state and so that the noise data collected is not complete and accurate. Therefore, it is necessary to clean the noise data using some suitable data mining method.

Cleaning methods for noise data produced by single flight event include filling the missing data and correction dirty data. Considering that the airport noise data has neighborhood features, neighborhood averaging method [19] can be used to do both the tasks mentioned above. For the example, assume that the nl_{ik} is missed, and the average of its neighborhood is θ, then the nl_{ik} can be set θ.

3.2.2. Data Preparation

Each noise monitoring points around the airport exists as a data unit and its geographical space coordinates and the noise values of different flight events are chosen as properties to create noise data storage matrix $Noise_{n\times(m+3)}$, in which n is the number of noise monitoring points and m is the number of flight events. This matrix is used to store the large amounts of airport history noise data and the geographic information of the noise monitoring points.

3.2.3. Clustering Algorithm

The monitoring point around the airport has spatial features and non-spatial features, and the aim of airport noise data mining is to find the clusters which contain some monitoring points of similar space position and noise values. However, most of the existing clustering algorithms cannot solve the problem of airport noise data mining, since these algorithms only take the distance between the spatial features or non-spatial features as index of similarity measurement. Therefore, this paper proposes a spatial clustering algorithm based on dual-distance. This algorithm uses a distance function as the similarity measure function in which spatial features and non-spatial features are combined. The similarity measure function is shown as the Equation (1).

The steps of mining the airport noise data by using the spatial clustering algorithm based on dual distance are shown in the Fig. 2.

Step 1: To input the number of clusters and select K monitoring points randomly as the initial cluster centers;

Step 2: To calculate the distance between the monitoring point and each cluster center based on the Equation (1), and then assign the monitoring point to its nearest cluster;

Step 3: To recount the center of each cluster based on the Equation (4), and then to calculate the clustering evaluation index E based on the Equation (6);

Step 4: To judge whether the clustering evaluation index E can converge towards a certain value. Turning to step 2 if it cannot; otherwise, the algorithm stop.

Fig. 2. The steps of the spatial clustering algorithm.

4. The Experiments and Analysis

The experimental data comes from the history noise data of a large domestic airport in some month. The airport has 21 noise monitoring points, and each monitoring point has 33-dimension features, which includes 3-dimension space features and 30-dimension non-space features. The experimental data is shown in Table 1.

The contribution of space and non-spatial features in the similarity function is changed by adjusting the coefficient α and β in the similar metric function, which is showed as the Equation (1), in different experiments. In order to prove the effectiveness of the clustering algorithm proposed by this paper, all experiments are performed in the same environment: the value for parameter K is set as 5, the monitoring points (1, 5, 9, 13, 17) are chosen as the initial center of the clusters, the processor is Intel (R) Core (TM) Duo CPU with 2.94 GHz frequency and 2.00 GB memory, and the operating system is Windows XP. Five experiments are done in this paper, the results of which are shown as Table 2, Table 3, Table 4, Table 5 and Table 6. (Note: the first row (Cluster number) represents the ID of the cluster, the second row (the monitoring points within a cluster) represents the objects belong to the cluster, and the third row (*E*) represents the clustering evaluation index).

Table 1. The information of the monitoring points and noise data.

Serial number of monitoring point	Longitude	Latitude	Altitude	The 1st day	The 2nd day	The 3rd day	The 4th day	…	The 30th day
1	116.58	40.42	39.6	78	83	79	80	**…**	81
2	116.55	40.41	38.9	67	65	68	66	**…**	69
3	116.67	40.56	42.5	75	82	80	77	**…**	79
4	116.56	40.44	40.3	76	80	82	79	**…**	81
5	116.44	40.27	36.8	92	87	95	91	**…**	88
…	…	…	…	…	…	…	…	**…**	…
21	116.57	40.43	37.7	65	68	66	69	**…**	67

Table 2. The clustering results where $\alpha = 1, \beta = 0$.

Cluster number	The monitoring points within a cluster	*E*
1	1, 2, 4, 9, 15, 21	3.21
2	3, 6, 13, 17	
3	5, 10, 12, 18	
4	8, 11, 19, 20	
5	7, 14, 16	

Table 3. The clustering results where $\alpha = 0, \beta = 1$.

Cluster number	The monitoring points within a cluster	*E*
1	1, 3, 4, 11, 17	3.16
2	2, 8, 13, 18, 21	
3	5, 7, 16, 19	
4	6, 12, 20	
5	9, 10, 14, 15	

Table 4. The clustering results where $\alpha = 0.2, \beta = 0.8$.

Cluster number	The monitoring points within a cluster	*E*
1	1, 4, 12, 17	2.54
2	2, 8, 11, 18, 21	
3	3, 7, 10, 19	
4	5, 6, 16, 20	
5	9, 13, 14, 15	

It can be seen from the Table 1 that the spatial features of monitoring points (1, 2, 4, 21) are close to each other; The non-spatial features of points (2, 21) are similar to each other, so are points (1, 3, 4); Comparing with the spatial and non-spatial features of points (1, 2, 3, 4, 21), the point (5) is of great difference.

It can be seen from the Table 2 that if just the spatial features of monitoring points are taken into consideration in the similarity function, then points (1, 2, 4, 21) would be partitioned into the same cluster. However, considering the difference of non-spatial features between points (1, 4) and points (2, 21), the result of clustering is unreasonable. But the Table 5 shows that if both features be taken into consideration, just the spatial features exist as the more important role, then points (1, 4) would be partitioned into the same cluster, and points (2, 21) would be partitioned into another cluster, so the clustering result is obviously improved. As the clustering evaluation index *E* shown, the result of Table 5 is better than the result of Table 2.

Table 5. The clustering results where $\alpha = 0.8, \beta = 0.2$.

Cluster number	The monitoring points within a cluster	*E*
1	1, 4, 9, 16	2.68
2	2, 7, 14, 19, 20, 21	
3	3, 6, 10, 17	
4	5, 12, 15, 18	
5	8, 11, 13	

Table 6. The clustering results where $\alpha = 0.5, \beta = 0.5$.

Cluster number	The monitoring points within a cluster	*E*
1	1, 4, 17, 21	2.97
2	2, 7, 14, 18	
3	3, 5, 12, 20	
4	6, 9, 13, 19	
5	8, 10, 11, 15, 16	

The Table 3 shows that if only the non-spatial features of monitoring points are taken into account, then points (2, 21) would be partitioned into the same cluster, and points (1, 4) would be partitioned into another cluster, but the point (3) also would be partitioned into the cluster where points (1, 4) are partitioned. Considering the difference of the spatial features between point (3) and points (1, 4), the result is unsatisfactory. From the Table 4, it can be seen that if both features would be taken into consideration, just the non-spatial features play a more important role, then points (1, 4) would be partitioned into the same cluster, points (2, 21) would be partitioned into another cluster, and the point (3) would be partitioned into a cluster, which is different from the former. The clustering result, therefore, is more reasonable. Judging by the clustering evaluation index E, it can be seen that the result of Table 4 is better than the result of Table 3. And it can be seen from the Table 6 that if the spatial features and the non-spatial features each contribute about 50 %, the clustering result is not better than the result of Table 4 or Table 5.

As it is seen from the Table 2, Table 3, Table 4, Table 5 and Table 6, the spatial clustering algorithm based on dual-distance presented in this paper can gain reasonable clustering result by setting the proportion of distance between spatial and non-spatial features of clustering objects according to the clustering tasks and goals.

5. Conclusions

In order to govern the issue of airport noise pollution scientifically and reasonably, it is necessary to mine the distribution patterns and evolution of the airport noise from the mass airport noise data set. However, the traditional clustering algorithm cannot take into account both the spatial features and non-spatial features of the monitoring points. Therefore, this paper proposes a spatial clustering algorithm based on dual-distance. The experimental results show that this algorithm can effectively discover the noise distribution pattern around the airport.

Acknowledgement

This paper is supported by the key project of the National Nature Science Foundation of China (61139002) and the High Technology Research and Development Program of China (2012AA063301) and Technology Fund of Civil Aviation Administration of China (MHRD201006, MHRD201101).

References

[1]. Xia Z., Huang X., A Study on the Legislation Issues of Airport Noise Abatement in China, *Journal of Beijing University of Aeronautics and Astronautics (Social Sciences Edition)*, 4, 24, 2011, pp. 38-45.

[2]. Koperski K., Han J., Adhikary J., Mining Knowledge in Geographical Data, *Transaction on Knowledge and Data Engineering*, 10, 23, 1993, pp. 903-913.

[3]. Liu Q., Li G., Deng M., A Local Distribution Based Spatial Clustering Algorithm, *Geomatics and Information Science of Wuhan University*, 3, 35, 2010, pp. 373-377.

[4]. Niu X., She K., Study of Fast Parallel Clustering Partition Algorithm for Large Data Sets, *Computer Science*, 1, 39, 2012, pp. 134-151.

[5]. Ni W., Huang Y., Li F., Liu S., An Agglomerative Hierarchical Clustering Algorithm Based on Weighted Representative Points, *Computer Science*, 5, 32, 2005, pp. 150-154.

[6]. Jiang M., Pi D., Sun L., Research on Density Clustering Algorithm with a Multiple Constraints, *Computer Science*, 10, 38, 2011, pp. 143-146.

[7]. Sun J., Liu J., Zhao L., Clustering Algorithms Research, *Journal of Software*, 1, 19, 2008, pp. 48-61.

[8]. Jandl B., Rokitansky C., Prediction of Noise Exposure Levels Using Simulated Flight Trajectories, in *Proceedings of Digital Avionics Systems Conference*, 2011, pp. 1-16.

[9]. Shen Y., Chen R., Wu X., Study of Evaluation Indexes of Aircraft Noise around Airport, *Journal of Southeast University*, 5, 29, 1999, pp. 126-130.

[10]. Ding W., Xu T., Yang G., Locating of Airport Noise Monitoring Points Based on Minimum Vertex Cover Model of Single Aircraft Noise Event, *Noise and Vibration Control*, 6, 3, 2012, pp. 166-170.

[11]. Hu C., Qin X., A Survey of Spatial Data Mining Research, *Computer Science*, 34, 5, 2007, pp. 14-19.

[12]. Li G., Deng M., Cheng G., Zhu J., A Dual Distance Based Spatial Clustering Method, *Acta Geodaetica et Cartographica Sinica*, 37, 4, 2008, pp. 482-487.

[13]. Chen L., Guo G., Jiang Q., Adaptive Algorithm for Soft Subspace Clustering, *Journal of Software*, 21, 10, 2010, pp. 2513-2523.

[14]. Deng M., Liu Q., Li G., Cheng T., Field-theory Based Spatial Clustering Method, *Journal of Remote Sensing*, 14, 4, 2010, pp. 694-709.

[15]. Zeng S., Li G., Liao Z., A New Category of Spatial Clustering Methods, *Science of Surveying and Mapping*, 5, 37, 2012, pp. 103-106.

[16]. Huang Z., Extensions to the K-means Algorithm for Clustering Large Data Sets with Categorical Values, *Data Mining and Knowledge Discover*, 2, 5, 1998, pp. 283-304.

[17]. Yu H., Ma X., Tan S., Tang S., Yang D., Exceptional Slices Mining Based on Singular Value Decomposition, *Journal of Software*, 7, 16, 2005, pp. 1282-1288.

[18]. Kumar P., Krishna P., Bapi R., De S., Rough Clustering of Sequential Data, *Data and Knowledge Engineering*, 3, 2, 2007, pp. 183-199.

[19]. Han J., Data Mining Concepts and Techniques, *Machinery Industry Press*, Beijing, 2001.

2014 Copyright ©, International Frequency Sensor Association (IFSA) Publishing, S. L. All rights reserved. (http://www.sensorsportal.com)