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An Approach to Calculating Rainfall for Each Transmission Tower in Geographic Information System

Teng-Shih Tsai [1 +] and Leehter Yao [2]

[1,2]Department of Electrical Engineering, National Taipei University of Technology

Abstract. In transmission systems, an important goal is how to decrease the disaster occurrence and increase the supply quality. Since the towers are long located outdoors which are easily affected by natural disaster. Specially, the landslides triggered by rainfall are important reasons for becoming tower collapses. Therefore, this paper proposes an inverse-distance weighting (IDW) method to calculate rainfall on tower location. Moreover, in this paper, a fast indexing method also has been developed for detection whether the tower is located in a landslide area or close to a landslide. The results suggest that the proposed method is an effective tool for the tower environmental monitoring and would be easily transferred to other similar applications.

Keywords: Transmission Systems, Supply Quality, Landslides, Inverse-Distance Weighting, Environmental Monitoring

1. Introduction

The transmission lines of Taiwan Power Company (TPC) run all over the entire island of Taiwan. The inspection and maintenance of transmission facilities is always a big challenge for the TPC's engineers. Since the location and environment of Taiwan, the frequency of nature disaster occurring is high. Moreover, the landslides triggered by rainfall are severe damage to security for tower bases. Therefore, the disaster prevention and disaster management are more important goal for the maintenance of transmission systems[1].

The rainfall is the mainly reason of landslides triggered[2]. However, many transmission towers are scattered in the mountain areas of Taiwan, thus the rainfall monitoring is very important for the security of tower basis. In applying rainfall estimation, the observed points are often scattered in space due to limited number of rainfall stations. Therefore, the rainfall of many tower locations can not directly refer to near rainfall station since the distance excessively far between towers and rainfall stations. Recently, the Spatial interpolation techniques have been applied in fields such as subsurface hydrology, oil reservoir engineering, environmental pollutant mapping and risk assessment, mining exploration and reserves estimation, and environmental health studies[3]. Various interpolation methods have been formulated over the years, and different standards exist in different research fields. A general distinction of interpolation methods is between deterministic and stochastic. The former are often easier to implement such as nearest-neighbor method, inverse-distance weighting (IDW) method, etc., and the latter provide estimates of prediction uncertainty, such as Kriging method and minimum curvature method[4]-[5]. The IDW method, a deterministic spatial interpolation model, is one of the more popular methods adopted by geoscientists and geographers because it has been implemented in many geographic information system (GIS) packages. This method is that the attribute values of any given pair of points are related to each other, but their similarity is inversely related to the distance between the two locations [6]. However, many studies, especially in the spatial interaction literature, have revealed that the decline in spatial relationship between any two locations

+ Corresponding author.
E-mail address: tst05106@gmail.com

is not simply proportional to distance[7]. As a result, a power or exponential function modifying the distance weight is often used to model spatial interaction between places.

Despite its popularity, the IDW method still suffers from several limitations, including the weighting parameters are chosen a priori, but not empirically determined. In addition, IDW cannot estimate the variances of predicted values in unsampled locations as compared to what geostatistical methods such as kriging can provide[8]. Another limitation is that the distance-decay parameter is applied uniformly throughout the entire study area without considering the data distribution. In other words, the IDW method assumes that the distance-decay relationship is constant over space. Nevertheless, a constant distance-decay value could be part of the reason that IDW provides less accurate predictions as compared to other interpolation methods[9]-[10]. Since the existence of uncertainty factors in spatial properties such as terrain, wind direction, etc., thus the advantages of other interpolation methods are inconspicuous compared to the IDW method. Furthermore, many towers are scattered extensively in each space. Hence, the computational complexity of calculating rainfall is much higher because the terrain is diverse.

In GIS systems, buffer analysis is one of important functions of spatial analysis[11]. Its basic idea is to create a zonal area of a certain distance around its boundary, namely buffer zones and to identify the impact range and service range to surrounding environment[12]. The problems of buffer analysis are how to improve the computing performance and exactly detecting the situation of target. Especially, in disaster potential analysis, the computing velocity must be fast enough for applying to real-time disaster analysis. This paper proposes a real-time buffer analysis method for detection of tower environments around in transmission systems. Since this method can effectively reduce the calculating time, thus which may be easily applied to other disaster analysis.

2. Analytical Methods

2.1. Inverse-distance weighting method

The IDW method is a straightforward and noncomputationally intensive method. It has been regarded as one of the standard spatial interpolation procedures in geographic information science and has been implemented in many GIS software packages. In fact, many GIS users without much background in spatial statistics and geostatistics will use IDW as a default method to generate a surface when attribute values are available only at sampled locations. The IDW method is used to estimate the unknown value in location S_o, given the observed values at sampled locations, which can be expressed as

$$\hat{y}(\mathrm{S}_o) = \sum_{i=1}^{n} \lambda_i y(\mathrm{S}_i) \tag{1}$$

where $\hat{y}(\mathrm{S}_o)$ is estimated value in location S_o which is a linear combination of the weighting value λ_i and observed values $y(\mathrm{S}_i)$ in location S_i, where λ_i is defined as following:

$$\lambda_i = \frac{d_{oi}^{-\alpha}}{\sum_i^n d_{oi}^{-\alpha}} \tag{2}$$

with $\sum_i^n \lambda_i = 1$, here $d_{oi}^{-\alpha}$ is the distance between S_o and S_i with a power α. The α parameter is expressed as a geometric form which is a positive real number. The specification implies that if $\alpha > 1$, the distance-decay effect will be more than proportional to an increase in distance, and vice versa. Thus, small α tends to yield estimated values as averages of S_i, while large α tends to give larger weights to the nearest points and increasingly down-weights points farther away. Therefore, when $\alpha = 0$ with $\lambda_i = 1/n$, then

$$\hat{y}(\mathrm{S}_o) = \sum_{i=1}^{n} \frac{1}{n} y(\mathrm{S}_i) \tag{3}$$

From above equation, estimated value is average of all sampled values. When $\alpha = \infty$, the weighting value λ_i will be expressed as

$$\lambda_i = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \tag{4}$$

and $\hat{y}(\mathrm{S}_o) = y(\mathrm{S}_i)$. In this case, the estimated value $\hat{y}(\mathrm{S}_o)$ will be the same as the observed value in the nearest sampled location S_i and $\alpha = 1$ for all simulations in this paper.

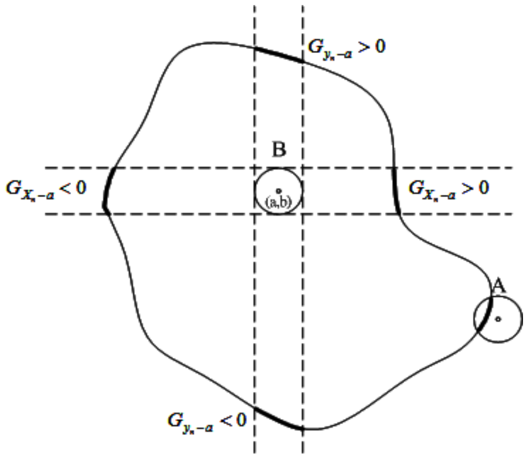

Fig. 1: The buffer analysis of different situations.

The IDW is a deterministic method, that the weighting parameters are chosen a priori, but not empirically determined. In addition, IDW cannot estimate the variances of predicted values in unsampled locations as compared to the geostatistical methods such as kriging can provide. Due to the kriging method requires the extra steps to derive the empirical variogram, thus that the estimated error of kriging method is lower than IDW method. Despite this, the computational complexity of IDW method is lower compared to the kriging method.

2.2. Fast indexing method

To detect whether the tower and the disaster area are located in same space, when the tower coordinates are matched successfully, the tower would be detected whether it is located in a disaster area or near a disaster area. Fig. 1 shows above two cases, in this figure, where A point and B point are denoted respectively: the tower location is close a disaster area and the tower is located in a disaster area. Furthermore, a detection method is proposed for buffer analysis, and its detecting condition is given by

$$\left(x_n-a\right)^2+\left(y_n-b\right)^2\le r^2 \tag{5}$$

where (a,b) are tower coordinates, (x_n,y_n) are coordinates of number n disaster area with $n=1,2,\cdots,N$ and r is the detection distance based on tower-centered, here we choose $r=30m$. To detect whether the tower is located in disaster area, the detection method as follows:

$$G_{x_n-a>0}=\left\{(x_n,y_n)\,|\,(b-\alpha)\le G(y_n)\le(b+\alpha),\ \forall(x_n,y_n)\in n\right\} \tag{6}$$

$$G_{x_n-a<0}=\left\{(x_n,y_n)\,|\,(b-\alpha)\le G(y_n)\le(b+\alpha),\ \forall(x_n,y_n)\in n\right\} \tag{7}$$

$$G_{y_n-b>0}=\left\{(x_n,y_n)\,|\,(\mathrm{a}-\alpha)\le G(\mathrm{x}_n)\le(\mathrm{a}+\alpha),\ \forall(x_n,y_n)\in n\right\} \tag{8}$$

$$G_{y_n-b<0}=\left\{(x_n,y_n)\,|\,(\mathrm{a}-\alpha)\le G(\mathrm{x}_n)\le(\mathrm{a}+\alpha),\ \forall(x_n,y_n)\in n\right\} \tag{9}$$

where $G_{conditions}$ are coordinates group of number n disaster area with horizontal and vertical limitation range based on tower-centered, respectively, which denote deciding conditions of relations between the tower and the disaster area. Here we define

$$D_r=\begin{cases}1\,, & \text{if } G_{conditions} \text{ is established}\\ 0\,, & \text{otherwise}\end{cases} \tag{10}$$

and $C=\sum_{r=1}^{4}D_r$ where C denotes the number of detection, and the tower is located in disaster area when $C=4$. In other words, if $G_{conditions}$ all become valid, which denotes the coordinates of disaster area are distributed the tower around. On the contrary, when any $G_{conditions}$ become invalid, which represents the tower is located the outside of disaster area.

3. Application Results

In this section, we proceed several experiments employing IDW method and fast indexing method, respectively. In calculating rainfall experiments, the locations of 566 rainfall station and QPESUMS points are regarded as estimated points and observed points, respectively. On the other hand, the real landslide coordinates are applied to analyzing the potential situation for each tower environment.

3.1. QPESUMS data

Quantitative Precipitation Estimation and Segregation Using Multiple Sensors (QPESUMS) is a total system integration incorporating data from multiple radars, numerical models, satellite, lighting and surface sensors. All data are mosaiced to a common grid providing a one-stop radar analysis tool. The QPESUMS systems produce quantitative precipitation estimates mainly including three parts: 1) Determining Z-R relation where Z and R are reflectivity factor and rainfall intensity, respectively; 2) The rainfall obtained by radar observing; 3) Compute precipitation rates and distributions using appropriate Z-R relations. Here Z-R relation is computed from the raindrop density function, which can be expressed as $Z = 32.5R^{1.65}$, where the units of Z and R are mm^6/m^3 and mm/h, respectively. Presently, the grid ranges of QPESUMS system in Taiwan are latitude 20 °N ~ 27 °N and longitude 118 °E ~ 123.5 °E, that the overall grid is 561 $\times$ 441 and resolution is 1.25km $\times$ 1.25km.

While so far the QPESUMS system still need to improve the exactitude of rainfall prediction, but the spatial rainfall analysis based on high resolution is of great value for reference.

3.2. Rainfall estimated results

Table 1 lists, respectively, the cumulative rainfall of 2013/01/10, 2013/01/11 and 2013/01/12. Particularly, since the front staying on Taiwan at 2013/01/12, the total rainfall of 2013/01/12 is much more than other days. To calculate exactly the estimated error, a cross validation method is used to evaluate the IDW prediction results. The cross validation method is based on percent error, which is defined as

$$PE = \frac{RMSE}{\frac{1}{N}\sum_{i=1}^{N} P_i^*} \times 100\% \tag{11}$$

where

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(P_i - P_i^*\right)^2} \tag{12}$$

and the root mean square error (RMSE) is the mean of the squared difference between observed value P_i^* and predicted value P_i, and N is the number of observations.

Table 1: The RMSE comparison between three days.

Date	2013/01/11	2013/01/10	2013/01/12
Total cumulative rainfall (mm)	1022.81	3231.88	6345.32
RMSE (mm)	0.07	0.18	0.24
PE (%)	4.04%	3.29%	2.18%

The RMSE comparison between the calculating results of IDW method and the actual precipitation of 566 rainfall stations are shown in table 1. In spite of the estimated errors have slight difference at these three days, the calculating results of IDW method are applied to rainfall estimation still of great value for reference. At 2013/01/11, the estimated error is increased slightly due to less rainfall. On the contrary, when rainfall is plentiful, the estimated error is decreased gradually. Thus, it can be seen that the IDW method would be more exactly to calculate rainfall when precipitation is increased. By the way, most landslide disasters usually occurred on larger rainfall events.

3.3. Buffer analysis results

In order to demonstrate that the buffer analytical method is effective proposed in this paper. 6372 tower coordinates and 1113339 landslide coordinates are together analyzed in this experiment, and then the analyzed results are shown in GIS systems. Table 2 lists five towers in north of Taiwan have higher disaster potential, respectively. In this analysis, first we spent some operation time to build indexing table for coordinates of the disaster area, and then to execute the buffer analysis. Specifically, we get 1 second the computing time in this experiment. Thus, confirming the fast indexing method can decrease effectively the operation time of the buffer analysis.

Table 2: The results of buffer analysis for towers in north of Taiwan.

Number	The names of lines	Tower number	Situations of buffer analysis
1	Jinshan~Qianhua	#008	outside
2	Jinshan~Maolin	#008	outside
3	Yangming~Xingren	#030	inside
4	Wulai~Ankang	#039	outside
5	Cukeng~Tutan	#012	outside

4. Conclusions

In this paper, a IDW method is used for calculating rainfall over the tower locations. The results have shown that the IDW method can provides considerable value for reference. Moreover, the IDW method has slightly more estimated error than other spatial interpolation method. However, since the existence of uncertainty factors in spatial properties, thus the results of each spatial interpolation method are very unstable. Despite this, them still can provide high reliability and applicability in applications of calculating rainfall. This paper provides a IDW method apply to calculating rainfall in real-time mode. In addition, its lower computational complexity is a remarkable advantage.

Furthermore, a fast indexing method also has been developed for detection of tower environments, that the method can effectively detect the tower environment around. In preprocess step, despite spent slightly more time to build the indexing table, in preprocess step later, which still has better calculating performance. Therefore, this method can be easily transferred to other similar applications and improve effectively the work performance. Finally, this paper proposes a fast and effective method which can easily applies to environmental detection of other important building thus decrease the disaster occurring.

5. References

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