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Terrain classification based on adaptive weights with airborne LiDAR data for mining area

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Abstract: The fast high-efficiency inspection for mining subsidence of mine area is a reliable way for forecasting accident and evaluating losing expense. In order to monitor mining subsidence of exploitation mine efficiently, LiDAR data were used and a novel strip division method was brought forward based on separating-treatment theory, which divided the mass of discrete three-dimensional point cloud data into a series of parallel strips and reduced the dimension in each strip. Polynomial fitting algorithm based on the adaptive weights, which located in the range of the strip, was used for classification complex terrain data of mine-area. The results show that LiDAR datamation can be greatly reduced. In the mean time, the time spending for calculation is shortened, and computational complexity is simplified. Therefore, high-efficiency terrain classification of LiDAR point cloud method can be great beneficial to monitoring environment of mine area.

Key words: mining subsidence; airborne LiDAR; strip division; adaptive weights

1 Introduction

Development and utilization of mineral resources in large-scale bring social and economic benefits to human, but also cause a range of environmental issues and mine accident. The ground subsidence disasters caused by mining exploitation directly destroy the natural state of the land surface and lead to surface cracks, contamination of groundwater and increase of desertification. Because of the horizontal distortion and uneven subsidence, the industrial and civil construction, in addition to water conservancy facilities, transportation facilities in subsidence area emerge to deform such as cracks and distortion, directly threaten to people's safety [1]. Efficient, rapid and accurate monitoring of subsidence is able to predict ground subsidence hazards, provide a reliable data for damage assessment, give reasonable control measures and reduce the losses [2].

With the development of spatial earth observation technologies, the traditional measurement method has gradually been replaced by GPS monitoring methods which solve the dynamic change monitoring of surface at a point [3]. Although high accuracy can be achieved by employing of GPS, but it still faces some key problems: 1) GPS is not accuracy in spatial resolution; 2) It costs a lot of manpower and resources for setting and maintaining monitoring points in large scale; 3) The stability of the reference point is low. The use of D-InSAR (Differential SAR interferometry, D-InSAR) measurements has the millimeter-level accuracy and is suitable for expressing the trends during long operating time. However, in the active phase of surface subsidence, D-InSAR interferogram will show a series of strong interference fringes, causing a phenomenon of interferometric phase aliasing which makes subsidence measurement ineffective [4].

Airborne LiDAR(Light detection and ranging) technology which has the decimeter-level measurement accuracy is suitable for mine surveying and mapping in large areas. LiDAR has a high resolution (point density can up to 10 point/m^2), high efficiency (airborne platform can cover 100 km^2/h), and is less affected by environmental conditions (terrain, weather conditions, etc.) [5]. Airborne LiDAR is able to detect the surface features and get the high-resolution three-dimensional

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cloud point data directly. One area of 1 km × 1 km LiDAR data may have more than one million laser points [6]. However, how to classify this massive LiDAR data quickly has become a serious problem. Efficient and accurate terrain classification of airborne LiDAR data becomes a pre-conditions and key technology for the mining subsidence monitoring in wide range.

2 Related work

In the literatures, some approaches for classification from laser scanner data have been reported: 1) Hierarchical robust interpolation method [7−8], which classifies footprints by setting elevation threshold. However, after interpolation by linear least square, the elevation fitting residual of footprints does not follow with normal distribution, so the method requires many iterations to achieve reasonable parameters in advance [9]. 2) Progressive TIN encryption method [10]. This obtains an initial sparse TIN from the smallest neighborhood algorithm and puts the points meeting the threshold conditions in the triangulated network, then reconstructs the triangulated irregular network and recalculates the threshold condition, at last filters the remaining points. This method needs to construct complex data structures, so its computational efficiency is low. 3) Improved gradient filter [11−13]. Through calculation the gradient between two terrain points is selected when the height difference exceeded the threshold. Each points should be compared with all other points in this approach, so it costs a large scale of calculation.

In this work, according to the features of mining area a novel strip division method was brought forward based on the separating-treatment theory, which divides the mass of discrete three-dimensional points cloud data into a series of parallel strips and reduces the dimension in every strip. Within the strip, polynomial fitting algorithm based on adaptive weights is used for classification complex terrain data of mine-area. The method can greatly reduce the time of calculation and simplify the computational complexity. In the mean time, the time spending for calculation, is shortened and computational complexity is simplified as well.

3 Terrain classification method based on adaptive weights

The flow chart of our method is shown in Fig. 1. There are three steps in this algorithm: 1) strip division for huge points cloud data; 2) curve fitting with adaptive weights; 3) automatic classification of laser footprint.

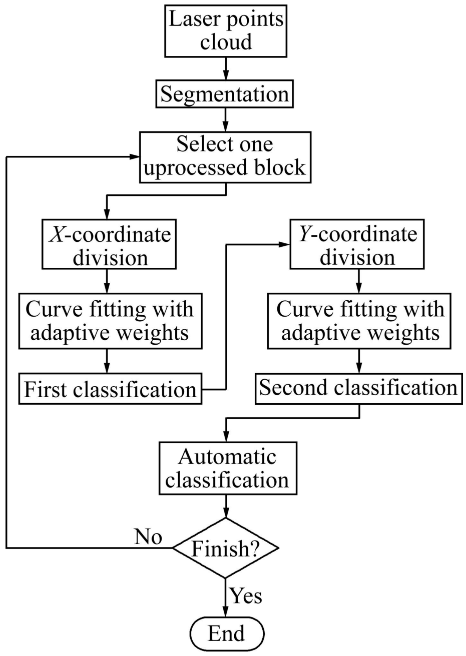

Fig. 1 Flow chart of terrain classification based on adaptive weights for LiDAR data in mining area

3.1 Huge points cloud strip division

As shown in Fig. 2, the whole LiDAR data are divided into many independent strips according to coordinate. There is appropriate number of points in each strip, and the coordinate change in the X-coordinate is slight but obvious in the Y-coordinate. The terrain features are represented by the Z-coordinate.

Several advantages of this partition processing are listed as follows.

1) The LiDAR cloud point data of mining area are very huge. Therefore, computer cannot deal with it in once time because of the hardware limitation. So separating-treatment must be used, and then all the results are integrated to setup LiDAR data model of mining area.

2) All cloud points are divided into parallel strips in X- and Y-direction at a small distance. The heights of the points of one strip are considered to depend only on the X-coordinate or the Y-coordinate, respectively. This method reduces the three-dimensional data processing to two-dimensional polynomial curve fitting.

In order to decrease the error caused by strip division, we divided data twice, first in X-coordinate and second in Y-coordinate. For example, a X-coordinate division has strip width which is supposed to be d, so the number N of strips can be calculated.

$$N=\frac{y_{\max}-y_{\min}}{d} \tag{1}$$

The range of y value of i strip is from $y_{\min}+(i-1)\times d$ to $y_{\min}+i\times d$, a point is classified into i strips if its y value is in this field.

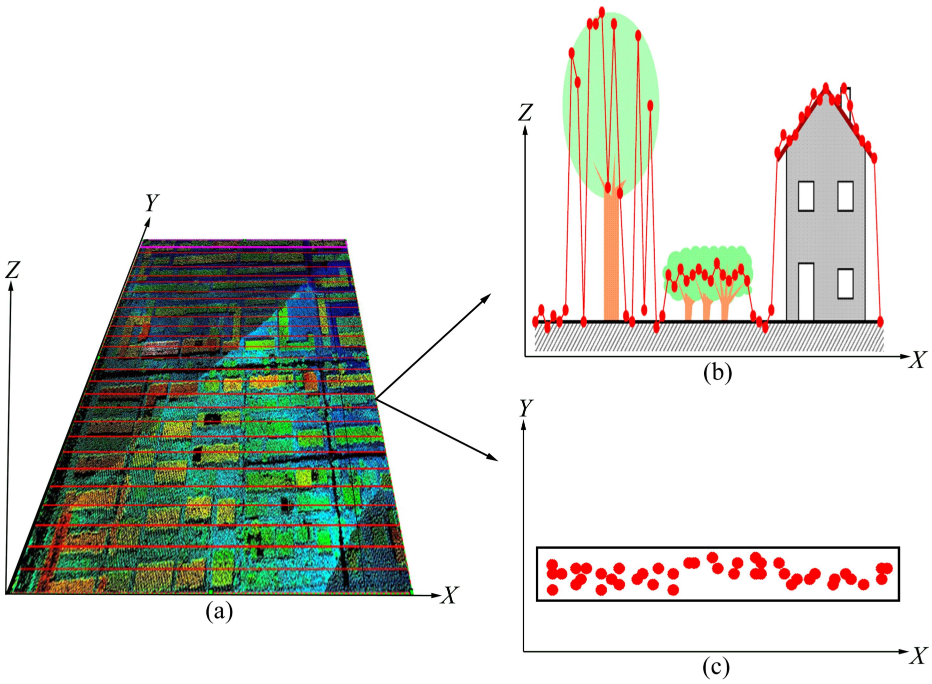

Fig. 2 Divided laser points cloud (a) into *Y*-coordinate strips (b) and *X*-coordinate strips (c)

3.2 Adaptive weights based curve fitting

The elevation of laser point *Z* is determined by the *X*-coordinate and *Y*-coordinate of itself, so function ϕ is defined as

$$Z=\phi(x,\ y) \tag{2}$$

After dividing the point clouds through strips, the value of *Z* is determined only by the coordinates in the strip direction. If a strip is in *X*-coordinate, the *Z*-coordinate of the strip are considered a function of the variable *X*-coordinate. Similarly, the function of variable y can be expressed as

$$Z=\begin{cases}\varphi(x),\ \text{when considering } x\text{-coordinate}\\ \varphi(y),\ \text{when considering } y\text{-coordinate}\end{cases} \tag{3}$$

Then the residuals of every point are calculated through curve fitting. In order to improve the data accuracy, it usually takes several iterations. Algebraic polynomial with the weights was used in the curve fitting [14]:

$$\phi'_m(x)=w(x)\cdot(c_1+c_2x+c_3x^2+\cdots+c_mx^{m-1}) \tag{4}$$

where *m* represents the number of polynomials plus 1; $w(x)$ is the weight function which is used to adjust the point contribution to the curve fitting. The contribution is depended on the residual adaptively. The bigger the contribution is, the further the distance to the curve is, so the contribution to the curve fitting should be reduced in the next recursive computation by decreasing the weights of this point. For those points with small residuals, the weight should be maintained. After several iterations, the curve will be able to match a majority of points adaptively, and will not be influenced by individual coarse points.

Suppose that there are *n* footprints in one strip, using $m-1$ polynomial to calculate curve fitting. Substitute the coordinate of points into the curve fitting polynomial, and then an over-determined equation is achieved as

$$\begin{cases}w(x_1)\cdot(c_1+c_2x_1+c_3x_1^2+\cdots+c_mx_1^{m-1})=z_1\\ w(x_2)\cdot(c_1+c_2x_2+c_3x_2^2+\cdots+c_mx_2^{m-1})=z_2\\ w(x_3)\cdot(c_1+c_2x_3+c_3x_3^2+\cdots+c_mx_3^{m-1})=z_3\\ \qquad\vdots\\ w(x_n)\cdot(c_1+c_2x_n+c_3x_n^2+\cdots+c_mx_n^{m-1})=z_n\end{cases} \tag{5}$$

This over-determined equations had the least squares solution which was the solution to the equation: $\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A}\boldsymbol{c}=\boldsymbol{A}^{\mathrm{T}}\boldsymbol{z}$. So the polynomial coefficients can be calculated.

$$\boldsymbol{c}=(\boldsymbol{A}^{\mathrm{T}}\boldsymbol{A})^{-1}\boldsymbol{A}^{\mathrm{T}}\boldsymbol{z} \tag{6}$$

where the polynomial coefficient $\boldsymbol{A}$ is

$$\boldsymbol{A}=\boldsymbol{P}\cdot\boldsymbol{W}=\begin{bmatrix}1 & x_1 & x_1^2 & \cdots & x_1^{m-1}\\ 1 & x_2 & x_2^2 & \cdots & x_2^{m-1}\\ 1 & x_3 & x_3^2 & \cdots & x_3^{m-1}\\ & & & \vdots & \\ 1 & x_n & x_n^2 & \cdots & x_n^{m-1}\end{bmatrix}\cdot$$

$$\begin{bmatrix} w(x_1) & w(x_2) & w(x_3) & \cdots & w(x_n) \\ w(x_1) & w(x_2) & w(x_3) & \cdots & w(x_n) \\ w(x_1) & w(x_2) & w(x_3) & \cdots & w(x_n) \\ & & \vdots & & \\ w(x_1) & w(x_2) & w(x_3) & \cdots & w(x_n) \end{bmatrix} \quad (7)$$

The observations matrix of z is $z=[z_1 \ z_2 \ z_3 \ \cdots \ z_n]^{\mathrm{T}}$. Put the matrix $\boldsymbol{A}$ and z in the formula 6 to get the polynomial coefficients matrix $\boldsymbol{c}$.

After the polynomial coefficients are determined, every point of the strip is substituted into the polynomial and the calculated value z_{calcu} of z_{observ} is gotten, then residual ρ of every point can be gained.

$$\rho=z_{\mathrm{observ}}-z_{\mathrm{calcu}} \quad (8)$$

Weight function $w(x)$ plays a very important role in the calculation of polynomial coefficients; well-designed adaptive weight function not only makes the curve fitting more accurately, but also reduces the time of iterations. The weight function used in this work is as follows:

$$w(x)=\begin{cases} 1, z_{\mathrm{observ}} \le z_{\mathrm{calcu}} \\ \dfrac{1}{1+[a(z_{\mathrm{observ}}-z_{\mathrm{calcu}})^b]}, \\ \qquad z_{\mathrm{calcu}} \le z_{\mathrm{observ}} \le z_{\mathrm{calcu}}+\omega \\ 0, z_{\mathrm{calcu}}+\omega < z_{\mathrm{observ}} \end{cases} \quad (9)$$

Figure 3 shows the weight function.

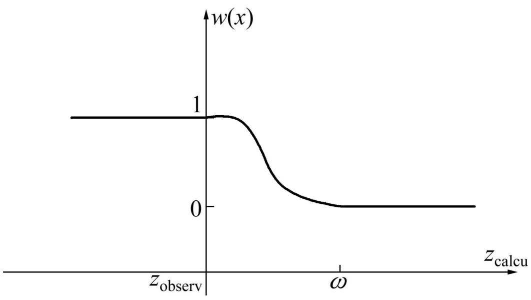

Fig. 3 Weight function

We use polynomials of orders 15−20. In the first calculation the weights of all points are the same. When the polynomial is determined, new weights for the points are set. The weights of points beneath the polynomial function stay 1. The weights of the points above the polynomial function decrease with increasing height difference. The new weights generate a new polynomial. The calculation of the polynomial and the new weights is repeated until the change of the polynomial is below a given threshold. As shown in Fig.4, usually after five iterations, the relative error will be smaller than the threshold and curve fitting will be finished.

3.3 Automatic classification of laser points

Afterwards, the height of the points is compared with the polynomial. Only points above a certain threshold, the polynomials are classified as off-terrain. As there are polynomials in x- and y-direction, each point is classified twice. Only the points, which are classified as off-terrain twice, are considered to be off-terrain. Points that are classified different in x- and y-direction can be found at steep slopes [15].

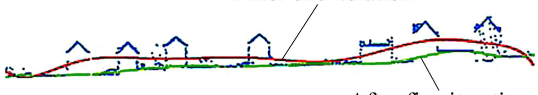

Fig. 4 Iteration result of polynomial fitting and adjusted polynomial after one iteration and five iterations

4 Result

The curve fitting is not accurate if the strip width is too broad, thus affects the final classification accuracy, also leads to mismatch between adjacent strips. On the contrary, the too narrow strips will greatly increase the number of strips and computation of curve matching. The experiment shows that the accuracy of the results will not be improved by narrowing strip division. The characteristics of mine area data were analyzed and the strip width was set to be 3 m. Table 1 shows the parameters of LiDAR data used in the experiments and Table 2 shows the classification result.

Figure 5 shows the classification result of mining area.

Table 1 LIDAR data

Parameter	Value
Range of X-coordinate	496 400.060 000−497 850.310 000
Range of Y-coordinate	5 418 705.660 000−5 419 211.810 000
Range of Z-coordinate	231.010 000−525.110 000
Number of footprint	3 665 873
Return number	4
Collection style	Strip scanner

Table 2 Result analysis

Experiment item	Value
Segmentation time/s	10
Strips division time/s	32
Classification time (including polynomial fitting)/s	54
Total time for running the method/s	96
Total number of points	3 665 873
Number of terrain points	743 174
Number of off-terrain points	2 922 699

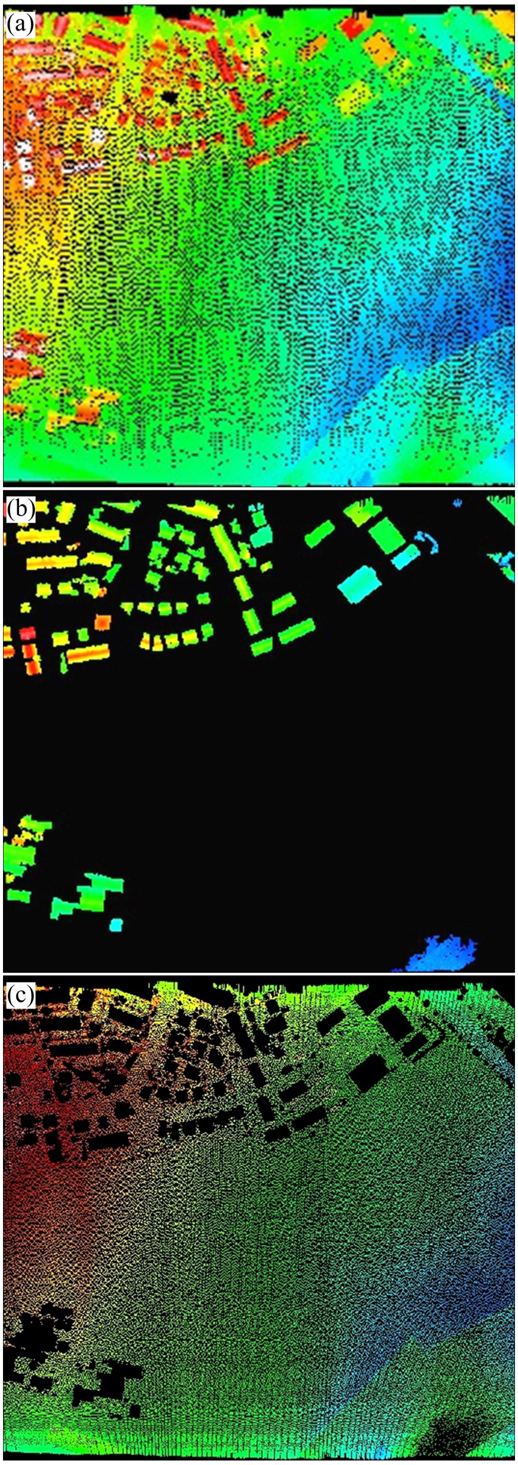

Fig. 5 Classification result of mining area: (a) Original LiDAR data of mining area; (b) Surface buildings of mining area; (c) Terrain data of mining area

Through analyzing the experimental result, the accuracy of our classification method could achieve 92%−97%. By comparing with progressive TIN encryption method and gradient filter classification method, the algorithm in this work increases the speed of classification by 10 times at least. About 100 km^2 of mining area was classified by this method within the time of less than 1 h. Such high efficient measurement is difficulty to be exceeded by traditional methods, such as progressive TIN encryption method and gradient filter classification method.

5 Conclusions and future work

A method of terrain classification based on adaptive weights with airborne LiDAR data is proposed for mining area. In this approach, the whole area is divided into parallel strips in *x*- and *y*-direction. A set of one-dimensional polynomials are fitted into the strips based on adaptive weights. Then, the polynomial tentatively goes through the terrain points. It spends 96 s in processing 1 km^2 LiDAR data and costs less than 1 h to classify 100 km^2 of mining area. The test shows that the method can delete noisy points and achieve more than 90% classification accuracy. The method directly processes huge three-dimensional points without secondary sampling. While maintaining the accuracy of the original cloud, the time spending can be greatly reduced for calculation and the computational complexity is simplified.

In the next work, we plan to identify vegetation in off-terrain points which will provide technical support for the use of LiDAR technology in mining environment monitoring. With development of accurate measurement of airborne LiDAR, we believe that airborne LiDAR will play more and more important role in mining environmental monitoring in the near future.

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