Ground crack extraction in mining subsidence areas based on point cloud data

Ao Jianfeng[1, 2*]

[1] *School of Environment and Spatial Information, China University of Mining and Technology, Xuzhou 221116, China*

[2] *Jiangsu Provincial Key Lab of Resources and Environmental Information Engineering, Xuzhou 221116, China*

Received 1 January 2014, www.tsi.lv

Abstract

During the underground mining of mineral resources, some ground points within a certain range above the working face will migrate correspondingly. The inconsistent horizontal migration of various ground points, due to different impacting time and degree, will lead to deformation of the ground surface, and when it reaches a certain degree, discontinuous damages to the continuous ground surface will occur, which are shown as cracks on the ground surface. In this paper, to extract planar cracks contained in the point cloud data, the point cloud data was firstly projected in the elevation direction for 2D processing and then a thickening algorithm for scattered point clouds was proposed. The point cloud data at different distances from the instrument was thickened block by block by choosing different thickening windows in order to highlight the crack data in the 2D image and to obtain the point cloud image applicable to the regular edge detection algorithm. Finally, the Canny operator was used to extract the edge information of cracks. In the end, the algorithm was tested in engineering projects and proved to be highly effective in extracting crack data.

Keywords: Crack Extraction, Point Cloud, Mining, Subsidence

1 Introduction

The underground mining activities in mine areas have tremendously impact upon the ground surface. Under serious circumstances, the impact upon rock stratum and surface will lead to unwatering of the underground water, landslide, debris flow and other geological disasters. In mining subsidence study, in addition to ground surface subsidence [1], cracks are also a common consequence induced by underground mining. Their development degree is an important criterion for identifying the damage degree of mine exploitation activities. In order to timely identify cracks and monitor their development, as well as to take an effective ground protection and underground mining control measures, the affected areas must be monitored in an effective manner.

In traditional mining subsidence monitoring, the crack data is collected by the total station based on several feature points at two terminals and the middle points of a crack to fit the whole shape of the crack. This method involves huge work and the practice of identifying feature points through human eyes easily gives rise to omission in massive data collection work and collected data is very limited. With the development of the surveying and mapping technology, the photogrammetry and remote sensing technologies have been successively applied to extract crack data. Atsushi et al. Ref [2] used a high-resolution camera to capture images and applied the integrated image processing technology to automatically extract micro cracks on the concrete block surface; Yang et al. Ref [3] designed the clustering target criterion function based on inter-data manifold distance and optimized the function using the iterative method to monitor and extract data concerning road surface cracks; and Wei et al. Ref [4] combined the UAV image and TM image and used the ERDAS software to establish the knowledge model to extract crack data.

The introduction of 3D laser scanning technology provides a new means to acquire crack data. By using this method, the data may be collected quickly and sufficiently, thus enabling the crack data to be reflected in the point cloud in its completeness, and providing a reliable data bank for crack fitting. Moreover, the obtained true 3D coordinates are very helpful in crack positioning and measurement. Li et al. Ref [5] generated a profile based on the 3D laser scanning data to extract a crack on all profile lines. However, as the points on strip-shaped data clouds were selected as points to be interpolated, the elevation value at the interpolating points was smoothed to mitigate the abruptness on the profile lines, which would impact the effect of wavelet detection. Liu et al. Ref [6, 7] firstly projected the point cloud data onto the mean normal plane of the rock mass structural surface, and then, extracted the crack data on the structural surface by adopting the automatic fuzzy clustering algorithm [8].As the ground cracks have various shapes, different approaches shall be adopted to guarantee a better extraction effect. In Ref [9], the author proposed a crack detection algorithm for stepped cracks in mine areas based on scanning line wavelet detection and carried out corresponding experiments, which produced good results. In consideration of different

*Corresponding author - E-mail: jfao008@163.com

development shapes, this paper mainly deals with the extraction method for another crack shape (i.e. planar cracks) in mine areas.

2 Theoretical foundation

2.1 GENERATION OF CRACKS

The ground surface subsidence induced by mining of underground coal resources is a spatial development process evolving with time [10, 11]. The impact of mining activities will lead to the migration of all ground points after being transmitted to the ground. The imbalance migration between all ground points will result in internal deformation of soil mass and after the tensile deformation goes beyond the deforming resistance of the ground, cracks occur [12]. The planar cracks generally occur outside the corresponding boundaries within the mining area and in front of the working face, as shown in Curve 3 in Figure 1 [13]. This area is the maximum tensile range of the underground subsidence basin. In the rear area of the working face advancement, as shown in Curve 4 in Figure 1, impacted by the mining activities, the surface soil within the region is compressed and deformed. With the progress of the mining program, the planar cracks start to close. However, as the earth surface cannot be restored to the original state and the cracks are closed to different extent, i.e. some planar cracks are not fully closed, with the final width smaller than that during the mining process, as shown in Figure 2(a); while some are over-closed, and form steps at the closing points, as shown in Figure 2(b).

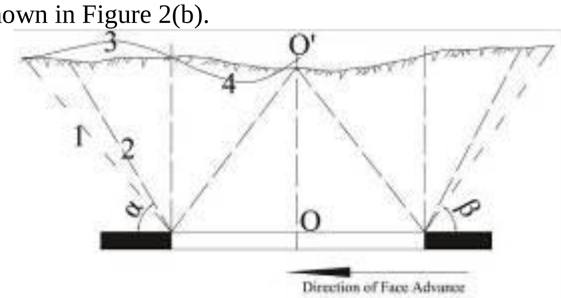


FIGURE 1 Model of surface migration. (1) Boundary of surface migration; (2) Crack surface; (3) Tensile deformation curve; (4) Compressive deformation curve; (α) Crack angle; (β) Boundary angle

(a) (b)

FIGURE 2 Shape of cracks. (a) Shape of planar crack; (b) Shape of stepped crack

2.2 CANNY OPERATOR

In this paper, the edge detection based on Canny operator [14] was used to extract crack edges. The Canny operator used the first-order differential of the Gaussian function and the non-maximum suppression and the "hysteresis" threshold value method to identify the maximum derivative for balancing the relationship between the anti-noise and detection and has showed good results.

The three optimization criteria for the first-order differential filter $h'(x)$ are as follows:

(1) ***Criteria of signal to noise ratio***

$$SNR = \frac{\left|\int_{-w}^{w} G(-x)h(x)dx\right|}{\sigma\sqrt{\int_{-w}^{w} h^2(x)dx}}, \tag{1}$$

where, G(x) is the Marginal function; h(x) is the impulse response of the low-pass filter with bandwidth of W; σ is the mean-squared error of Gaussian noise.

(2) ***Criteria of positioning precision***

$$L = \frac{\left|\int_{-w}^{w} G'(-x)h'(x)dx\right|}{\sigma\sqrt{\int_{-w}^{w} h'^2(x)dx}}, \tag{2}$$

where, G'(x) and h'(x) are the first-order derivatives of G(x) and h(x) separately; L is the positioning precision of the margin.

(3) Criteria of single edge response

To ensuring the uniqueness of edge response, the mean distance of zero-cross point of the impulse response derivative of the detecting operator should be:

$$D_{zca}(f') = \pi\sqrt{\frac{\int_{-\infty}^{\infty} h'^2(x)dx}{\int_{-w}^{w} h''(x)dx}}, \tag{3}$$

where, h'(x) is the second-order derivative of h(x); f' is the image after detection.

Three criteria above depicted the criteria of edge detection. However, since the ability of anti-noise conflicts against the precision of edge detection, e.g. it will lower the precision of edge positioning after proper anti-noise procession; or to higher the precision of positioning, the ability of anti-noise will be influence, and some procession of compromising should be taken. The first-order of Gaussian function is the best compromising operator, which firstly take convolution on the original image for de-noising and then detect edge with derivation, the optimal detector Canny proposed is similar to the first-order derivative of Gaussian function.

The Gaussian is circular symmetry, so it is symmetrical along the marginal direction of Canny operator and antisymmetrical perpendicular to the marginal direction, so, aiming at the edge along the direction of most sudden change, the operator is very sensitive, but along the marginal direction is not sensitive.

Set 2-dimensional Gaussian function to be:

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}), \quad (4)$$

where σ is the distributional parameter of Gaussian function to control the smooth degree of image.

The optimal step edge detection operator based on the convolution $\nabla G^* f(x,y)$, the intensity of the edge is $|\nabla G^* f(x,y)|$, the direction is:

$$\rho=\frac{\nabla G * f(x,y)}{|\nabla G * f(x,y)|}. \quad (5)$$

Since the Gaussian function is unlimited, original templates are used to cut it off and get limited size N. Experiments show that when $N=b\sqrt{2}\sigma+1$, the effect of detection is proper.

The specific realization is as follows:

First, since the Gaussian function is 2-dimension separable, two convolution templates of ∇G are divided into two 1-dimension filters:

$$\frac{\partial G(x,y)}{\partial x}=kx\exp(-\frac{x^2}{2\sigma^2})\exp(-\frac{y^2}{2\sigma^2})=h_1(x)h_2(y), \quad (6)$$

$$\frac{\partial G(x,y)}{\partial y}=ky\exp(-\frac{y^2}{2\sigma^2})\exp(-\frac{x^2}{2\sigma^2})=h_1(y)h_2(x), \quad (7)$$

where,

$$h_1(x)=\sqrt{k}x\exp(-\frac{x^2}{2\sigma^2}), h_1(y)=\sqrt{k}y\exp(-\frac{y^2}{2\sigma^2}),$$

$$h_2(x)=\sqrt{k}\exp(-\frac{x^2}{2\sigma^2}), h_2(y)=\sqrt{k}\exp(-\frac{y^2}{2\sigma^2}),$$

$h_1(x)=xh_2(x)$, $h_1(y)=yh_2(y)$, k is a constant.

Take convolution on the two templates with f(x,y) separately:

$$E_x=\frac{\partial G(x,y)}{\partial x}*f; E_y=\frac{\partial G(x,y)}{\partial y}*f. \quad (8)$$

Set $A(i,j)=\sqrt{E_x^2+E_y^2}, a(i,j)=\arctan\frac{E_y(i,j)}{E_x(i,j)}$.

Then A(i,j) reflects the marginal intensity and a(i,j) is the direction perpendicular to the edge.

According to *Canny's* definition, the central edge point is where the convolution of operator G_n and the image *f(x,y)* hits its maximum in the direction of edge gradient. This law may be applied to determine whether a point is the edge point. A pixel is an edge point if meeting the following conditions:

1) Its boundary strength is greater than other pixels;
2) The directional difference between the point and its two neighbouring points in the gradient direction is smaller than 45°;
3) The maximum boundary strength of the 3x3 neighbouring field cantered on this point is smaller than a certain threshold value.

In addition, if the first two requirements are met simultaneously, the neighbouring pixels in the gradient direction shall be deleted. The point 3 is used to match the threshold value image composed by the edge points and the maximum gradient value within the range. The false edge points shall be deleted.

3 Flow of crack extraction

As there are huge amounts of noise data contained in the raw point cloud data, it is imperative to conduct corresponding de-noise processing before extracting ground cracks in order to eliminate non-ground points and obtain relatively smoothed point cloud data to facilitate the detection and extraction of crack data. The flow of crack detection is shown in Figure 3.

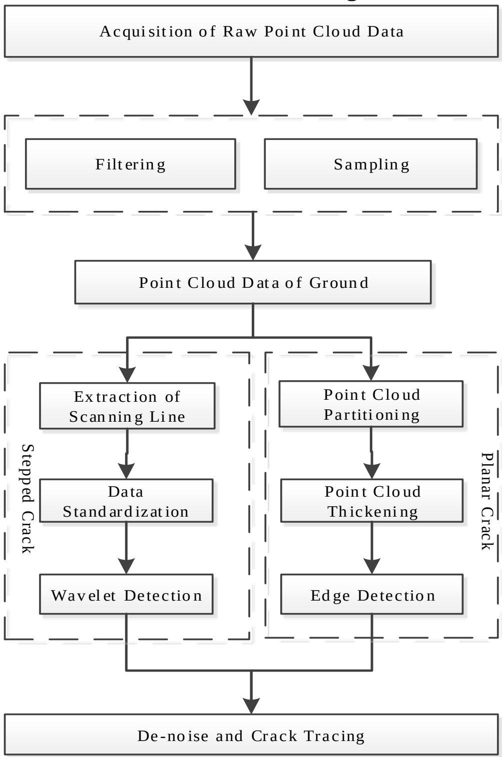
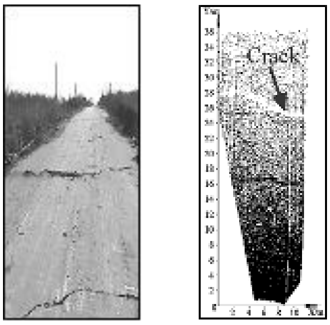


FIGURE 3 Flow of crack detection

For a planar crack, its data will be significantly missing in the point cloud data. The missing points are concentrated on one edge of the crack directly against the instrument. After the point cloud data is projected in the elevation direction, it may be observed clearly that there is a relatively large blank area in the crack area, as shown in Figure 4(b). If this point cloud data is processed graphically, i.e. the coordinates, after integer processing, serve as rows and columns of image pixels, and the elevation values of all points are converted into attribute values of pixels at the corresponding rows and columns (binarization processing is adopted in this paper, set values to 1 and blank to 0), the dimension reduction of point cloud data may be achieved. Then the edge detection technique for 2D images may be used to extract cracks from the data.



(a) (b)

FIGURE 4. Photo of the ground and raw points of the ground. (a) Photo of the ground; (b) Raw points of the ground

However, when the 3D laser scanner is used to scan the surface of the mine areas, the space between the point cloud data will increase with the rising of distance, as shown in Figure 5(a). In addition, the instrument is short, and the angle of incident is small. These will gravely compromise the effective reflectivity of laser. The density of point clouds also reduces significantly with the increase of distance. Therefore, the point cloud data is sparsely distributed after the distance to the instrument reaches a certain limit, as shown in Figure 5(b). Therefore, the dispersion degree of non-zero pixels (i.e. pixels with attribute value $\neq 0$) in the point cloud image, which is gained through a graphical processing of point cloud data, is high and the space between non-zero pixels is large. The edge detection algorithm [17] based on image processing will fail if it is applied directly to point cloud data in this area. Therefore, it is necessary to thicken the 2D point cloud image first to narrow down the space between non-zero pixels in the non-crack area, and thus enabling the application of edge detection algorithm. Although this method will compromise the precision, with the increase of density of point clouds, the thickening windows may be narrowed appropriately to enhance the precision of crack extraction.

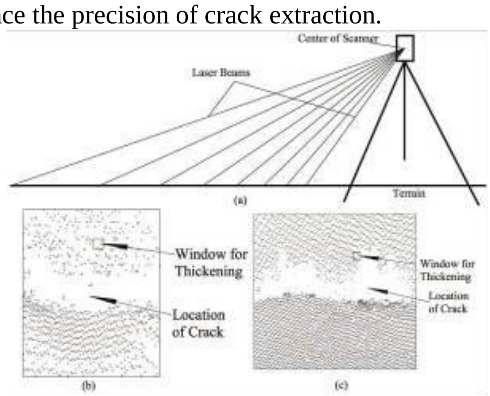


FIGURE 5. Thickening windows for point clouds with different density. (a) Style of scanning; (b) Points from long distance; (c) Points from short distance

In this paper, the moving window algorithm was adopted to thicken the point cloud image. The size of windows is dependent upon the scanning resolution at corresponding location of the point clouds, namely, the preset maximum point spacing at this location. The window size is normally 4 times the spacing, to ensure there are certain points within the window when it is in the non-crack areas, as shown in Figure 5(b) and 5(c). With respect to every zero pixel in the point cloud image, first, move the window centre to the pixel, and then analyse the pixels in the window. As shown in Figure 6 that if there are scanning points within 4 quadrants of the window taking the zero pixel as centre, this zero pixel is within the non-crack area (see Figure 6 (a)); if at least one of 4 quadrants of the window has no scanning points, this zero pixel is within the crack area (see Figure 6 (b)). Therefore, during the analysis of the shifting window, if 4 quadrants of the window include non-zero pixels, set the pixels to 1, otherwise, keep the original value. After the pixels in the point cloud image have been thickened one by one, the edge detection algorithm based on Canny operator may be applied to the image. Through selecting different threshold values, the ground planar crack with different effects may be extracted. By combining the coordinates of all crack points and applying the algorithm in Literature [15, 16], the cracks may be traced.

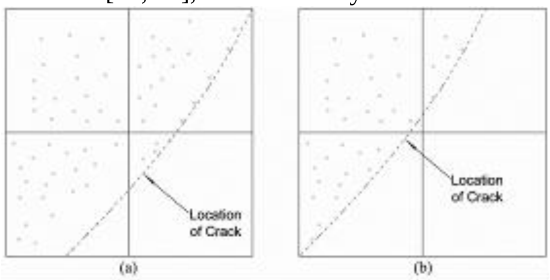


FIGURE 6 Point cloud thickening principle. (a) Points within non-crack area; (b) Points within crack area

4 Experimental verification

For a planar crack, first process the point cloud data graphically; then thicken the point cloud image obtained to highlight the crack area and smooth the non-crack areas; finally, detect and extract the crack edge with Canny operator. The detection results using the Canny operator with different threshold values are shown in Figure 7. It can be seen from the detection results that with the increase of the threshold value, the anti-noise ability of the crack detection effect based on the Canny operator is increasing till the noise data is completely deleted and the crack is extracted in its entirety.

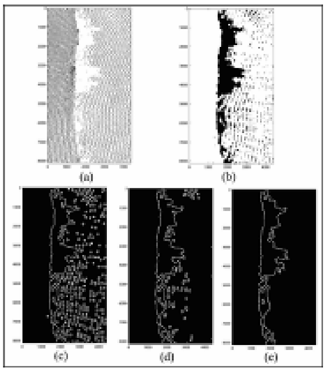


FIGURE 7 Detection of planar crack. (a) Raw points; (b) Image after t hickening; (c) Threshold=0.15; (d) Threshold=0.55; (e) Threshold=0.95.

As the distribution of point cloud data obtained by the ground laser scanner is uneven and their density varies at different locations relative to the instrument, the thickening of ground point clouds shall be carried out block by block, and the thickening window shall be selected according to the local density of point clouds. The images of extracted cracks with different density are shown in Figure 8.

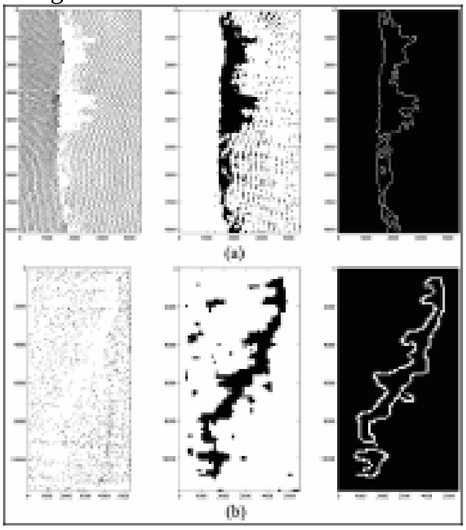


FIGURE 8 Extraction of cracks with different density. (a) Detection result of dense point clouds; (b) Detection results of sparse point clouds

5 Engineering practice

To verify the detection results obtained with the crack detection algorithm proposed in this paper, the ground point cloud, which was obtained by Trimble GX 3D from 5305(2) working face of Baodian Coal Mine Yanzhou mine area, was used to extract cracks, and the detection results were compared with the crack location surveyed with the total station. The undulation of ground surface is gentle within the area. See Table 1 for details of the 5305(2) working face.

TABLE 1 Basic information of 5302(2) working face

Working face length	Working face width	Average mining depth	Average ground elevation	Average coal seam thickness	Average mining rate	Coal seam dip angle
2400m	108m	305m	45m	8.7m	5.23m/d	8°

Figure 9 is the impression drawing based on crack detection results and an algorithm described in Literature [9].

It can be seen from Figure 9 that the crack data contained in the point cloud may be effectively extracted by combining two crack detection methods and the crack location thus extracted is consistent with that obtained with the total station. However, impacted by the point cloud density, the cracks with smaller width cannot be reflected in the point cloud, and therefore, cannot be extracted with the method described in this paper. To solve this problem, the point cloud density needs to be enhanced when data is collected to enable the smaller cracks to be better reflected in the point cloud data; moreover, some point cloud data is probably missing due to oversized spacing between stations or shielding. The blank area is easy to be mistakenly extracted as a crack data when the detection algorithm is used to extract crack edges, and thus leading to problems shown in Figure 9. To solve this, the spacing between stations shall be reasonable and supplementary survey shall be conducted for shielded data.

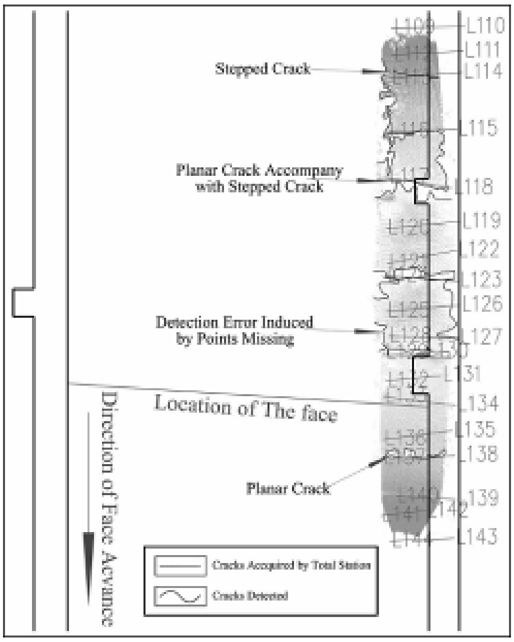


FIGURE 9 Impression drawing of crack detection

6 Conclusions

The 3D laser scanning technology may be applied in mining subsidence monitoring to gain abundant point cloud data, including subsidence information, crack information and features of characteristic constructions as well as other information conducive to the monitoring and study of mining subsidence. How to extract this kind of information is the key to the application of this technology. In this paper, the ground crack data in mine areas was successfully extracted, further pushing up the utilization efficiency of point cloud data.

First, the point cloud data was processed graphically to produce a 2D point cloud image; then the image was thickened and optimized to highlight the crack area, making the edge detection technology, which has been commonly applied in image processing, applicable to the detection and extraction of crack data.

Second, in this paper, the crack detection algorithm was also applied to field engineering projects to test its practicability. The good results further confirmed the reliability of this algorithm.

Acknowledgments

The research has been supported by a project funded by the Priority Academic Program Development of the Jiangsu Higher Education Institutions (PAPD, approval number: SA1202).

References

[1] Dawei Z, Kan W, Ranli C, Liang L 2014 *Nat Hazards* **70**(2) 1197-208
[2] Ito A, Aoki Y, Hashimoto S 2002 Accurate extraction and measurement of fine cracks from concrete block surface image *IECON 02*, 2202-07
[3] Ruiui Y, Jianqiang N, Hongfei M 2011 *Computer Engineering* **37**(12) 212-4. (*in Chinese*)
[4] Changjing W, Yunjia W, Jian W, Hui Z 2012 *Metal Mine* **436**(10) 90-2 (*in Chinese*)
[5] Liang L, Kan W, Ranli C, Shu Z 2010 *Science of Surveying and Mapping* **35**(1) 165-6 (*in Chinese*)
[6] Changjun L, Liuqian D, Dongya S 2011 *Chinese Journal of Rock Mechanics and Engineering* **30**(2) 358-64 (*in Chinese*)
[7] Changjun L, Liuqian D, Baohui N, Shunfu Z 2011 *Chinese Journal of Rock Mechanics and Engineering* **30**(11) 2330-6 (*in Chinese*)
[8] R E H, J H C 1998 *Int J Rock Mech Min* **35**(7) 889-905
[9] Jianfeng A, Ming Z, Yanan X, Haixia Y 2013 *Metal Mine* **444**(6) 158-60 (*in Chinese*)
[10] Guoqing H, Lun Y, Gengdi L, Fengcai J, Du H 1991 Mining subsidence science *China University of Mining and Technology Press* (*in Chinese*)
[11] Youfeng Z, Kazhong D, Weiming M 2003 Mining subsidence engineering *China University of Mining and Technology Press* (*in Chinese*)
[12] Jianrong K 2008 *Chinese Journal of Rock Mechanics and Engineering* **27**(1) 59-64 (*in Chinese*)
[13] Xueyi Z 1996 *Journal of Xi'an University of Science & Technology* **16**(4) 295-9 (*in Chinese*)
[14] Zhimeng X, Xiangdong G 2006 *Transactions of The China Welding Institution* **27**(1) 29-32 (*in Chinese*)
[15] Yunpeng Z, Kan W, Yanan X 2012 *Coal Mining Technology* **17**(6) 10-3 (*in Chinese*)
[16] Yunpeng Z, Kan W 2012 *Coal Science and Technology* **40**(8) 28-31 (*in Chinese*)
[17] Ruijun G, Shenglei C, Jiacai W 2013 *Journal of Engineering Science and Technology Review* **6** (3) 10-5

Author

Jianfeng Ao , 06 1985, Xuzhou County, Jiangsu Province, P.R. China

Current position, grades: Ph.D studies in School of Environment and Spatial Information, China University of Mining and Technology, China.
University studies: BSc in Surveying and Mapping Engineering from China University of Mining and Technology in China. MSc from China University of Mining and Technology in China
Scientific interest: Mining Subsidence Monitoring, LiDAR Points Processing
Publications: more than 10 papers
Experience: participation in three scientific research projects