International Journal of Natural Resources and Environmental Studies
ISSN: 3006-2012 (Print), ISSN: 3006-0834 (Online) | Volume 5, Number 1, Year 2025
DOI: https://doi.org/10.62051/ijnres.v5n1.03
Journal homepage: https://wepub.org/index.php/IJNRES/index

Research on Simulation of Mining Subsidence Based on Cellular Automata Model

Xiudong Qi*, Zihao Jiang, Ziheng Zhou

School of Surveying and Mapping and Land Information Engineering, Henan Polytechnic University, Jiaozuo, Henan, China

*Corresponding Author: Xiudong Qi

ABSTRACT

In response to a series of safety and environmental issues caused by displacement and deformation of overlying rock layers during the mining process of mineral resources, the cellular space is constructed by combining three-dimensional laser scanning data and traditional observation station data. Based on the research of subsidence mechanism and prediction methods in subsidence areas, a spatiotemporal model based on extended cellular automata for dynamic simulation of mining subsidence is proposed with DEM and subsidence acceleration parameters as mandatory constraints, and verified with examples. Compared with traditional method based on monitoring point, the fine surface model can better reflect the spatial change characteristics of monitoring surface objects and is more suitable for prediction of mining subsidence.

KEYWORDS

Cellular Automata; Mining Subsidence; 3D Visualization; 3D Laser Scanning.

1. INTRODUCTION

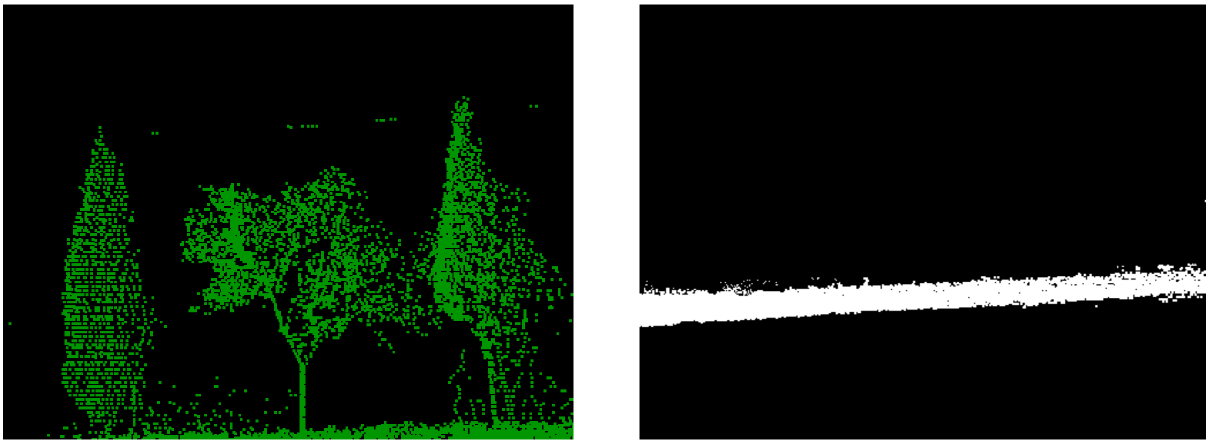
The development and utilization of large-scale mineral resources have brought enormous economic and social benefits to humanity, as well as significant destructive effects on the environment for human survival. In the process of large-scale and continuous development of coal resources, a series of geological environment and disaster problems are caused by displacement and deformation of overlying rock layers, such as collapse of goaf, ground fissures, ground subsidence, building fissures and collapses, road subsidence, mine inundation, etc. At the same time, environmental damage problems such as soil erosion, degradation of land vegetation, and water resource pollution are also induced, leading to the deterioration of the ecological environment in mining areas and surrounding areas[1,2]. Surface movement and deformation are subsidence phenomena caused by the propagation of rock movement to the surface, reflecting the propagation mode and movement status of rock movement. It is a complex three-dimensional, spatiotemporal dynamic process, and data has complexity, multidimensionality, and spatiotemporal characteristics. With the advancement of spatial data acquisition technology, 3D laser scanning and other applications are increasingly being used for monitoring and controlling mining subsidence, providing a new way to solve the problem of mining subsidence prediction and dynamic simulation.

Du Yuzhu, Gao Kuiying, and others have conducted research on subsidence monitoring in mining areas based on multi-source data fusion technologies such as unmanned aerial vehicle LiDAR[3,4], but the accuracy of the model is relatively low, only reaching 0.25m. Xu Liangji, Wang Li, Zhang Zhongjie, and others have conducted dynamic prediction research on surface subsidence areas based on time functions[5-7], and the above models can either only achieve single point prediction or integrate traditional probability integration methods. Chen Qiuji used a cellular automaton model and probability integration method to construct a transition probability function to achieve the prediction of surface subsidence damage[8]. In response to the shortcomings of traditional probability integration method models and time function models, this paper proposes a spatiotemporal model for dynamic simulation of mining subsidence based on extended cellular automata, with DEM and subsidence acceleration parameters as mandatory constraints. The model is driven by three-dimensional laser scanning deformation measurement data to dynamically simulate the entire process of instability and failure of mining subsidence.

2. PREPROCESSING OF 3D LASER SCANNING DATA

2.1. Separation of ground points

In order to obtain surface reflection information, it is necessary to separate ground points from building and vegetation laser points. Using the Micro Station platform, a surface triangulation model is established through a loop to achieve surface point separation.



(a) Original point cloud data before separation (b) Ground point cloud data after separation

Figure 1. Ground point cloud data isolation from raw dataset

Start selecting some low points as initial surface points and control the selection of initial points through the "Maxbuilding size" parameter. If the maximum side length of a building is 60 meters, it can be assumed that there is at least one point located at the surface every 60 meters. The initial model is established by selecting the low point first, and the model is expanded by repeatedly adding new laser point which makes the model closer to the subsidence surface, and finally an approximate subsidence area surface is obtained, as shown in Figure 1.

2.2. Noise Removal

In order to obtain more accurate information about objects within the subsidence range of the mining area, it is necessary to remove the noise contained in them. For obvious outliers and scattered points, they can be visually identified and directly deleted, while other commonly used smoothing filters are used for denoising. The three-dimensional laser scanning system contains geometric information stored in the form of distance images and signal intensity information stored in the form of intensity images. The median filter has a good effect on eliminating data glitches, while the Gaussian filter can effectively maintain the shape of the original data. According to the characteristics of the expression requirements in the subsidence area, a median filter is used to remove noise using intensity information, and a Gaussian filter is used to eliminate noise using geometric information.

2.3. Data Simplification

Directly utilizing massive raw point cloud data for 3D reconstruction not only requires high computer resources for data storage and processing, but also consumes a lot of time to generate 3D models. Therefore, point clouds can be simplified while ensuring a certain level of accuracy. Data reduction mainly uses the uniform grid method, which distributes point cloud data into an established equidistant grid and selects a point to represent all points belonging to that cell. To avoid losing the edge information of the scanned object, mesh encryption is performed in areas where the curvature of the point cloud data changes significantly.

3. DYNAMIC SIMULATION OF SUBSIDENCE MINING BASED ON CELLULAR AUTOMATA

3.1. Cellular Automata

Cellular automata are not determined by strictly defined physical equations or functions, but by rules constructed from a series of models[9-11]. Discrete time, space and state are its characteristics, each variable only takes a finite number of states, and the rules for its state changes are local in both time and space. Cellular automata mainly consist of four parts: cells, cell spaces, cell neighbors, and evolutionary rules, as well as time variables. The surface movement and deformation caused by mining is a complex spatiotemporal dynamic system, and cellular automata are a spatiotemporal discrete dynamic model with distinct spatiotemporal coupling characteristics[12-15]. From the high-dimensional perspective of cellular automata models, the evolution of the surface in mining subsidence is actually a four-dimensional spatiotemporal system.

3.2. Construction of cellular automata evolutionary model

Using mathematical symbols to represent cellular automata, the general evolutionary model is

$$S^{t+1} = f(S^t, N) \tag{1}$$

In the formula, S represents the cellular state; N represents the nearby range; f is the conversion function; t is the time parameter.

Cellular space: The actual research area is divided into discrete grid cellular spaces at a certain resolution. The grid cells are square cells that are consistent with the GIS grid data structure and match the resolution of digital elevation model data, 3D laser scanning simplified point cloud data, etc.

Cellular state: Each cell has four states, 0 represents an unaffected ground point, 1 represents an unmoved ground point, 2 represents a moving ground point, and 3 represents a stable ground point. The boundary composed of points that are not affected by the ground and whose elevation remains unchanged is determined based on the DEM established from the first and last point cloud data.

State 2 is further divided into three sub states, where 21 represents the ground point that has just started moving, 22 represents the ground point that is moving violently, and 23 represents the ground point that is transitioning from violent movement to slow movement (gradually stopping). Due to different geological and mining conditions, the duration of each point on the ground varies, and the coal mining process and working face advancement speed also have an impact on the duration of the ground point movement stage. Therefore, the model needs to determine the time YT1, YT2, and YT3 corresponding to the three sub stages of movement. The time of the three sub stages can be calculated based on traditional subsidence monitoring data to obtain the subsidence acceleration α, which can be calculated using equation (3).

$$v_n = \frac{w_{m+1} - w_m}{t} = \frac{H_{m+1} - H_m}{t} \tag{2}$$

$$a_n = \frac{v_{m+1} - v_m}{t} = \frac{H_{m+2} - 2H_{m+1} + H_m}{t^2} \tag{3}$$

In the formula, v represents the sinking speed; a represents the sinking acceleration; w is the sinking value; H is the elevation value; t is the monitoring time interval.

The sinking acceleration α develops from 0 to its maximum during the YT1 time period, which is the stage when the ground point begins to move; The development of the sinking acceleration α from the maximum (positive maximum) to the minimum (negative maximum) occurs during the YT2 time period, which is the stage of severe ground point movement; The sinking acceleration α develops from the minimum (negative maximum) to 0 during the YT3 time period, that is, the ground point turns slowly and moves to the final stopping stage.

Neighborhood definition: Each cell has 8 adjacent cells as its neighborhood cells.

Conversion rule: The ground point sinking movement rule has been extended. Assuming that only cells with a state of 22 can undergo changes in the state of their neighboring cells due to the violent movement of ground points; The cell with a state of 21 is a ground point that has not moved violently at the beginning, and the degree of sinking movement is low enough to cause changes in the surrounding cells; The cell with a state of 23 cannot cause the surrounding cells (ground points) to move due to the slower sinking movement.

The specific conversion rules take the following form:

If $n_{ij}(t) = 0$ or $n_{ij}(t) = 3$, then $n_{ij}(t+1) = n_{ij}(t)$;

If $n_{ij}(t) = 21$,

If $YT_{ij} > YT1$, then $n_{ij}(t+1) = 22$;

Otherwise $n_{ij}(t+1) = 21$, $YT_{ij} = YT + 1$;

If $n_{ij}(t) = 22$,

If $YT_{ij} > YT1 + YT2$, then $n_{ij}(t+1) = 23$;

Otherwise $n_{ij}(t+1) = 22$, $YT_{ij} = YT + 1$;

If $n_{ij}(t) = 23$,

If $YT_{ij} \geq YT1 + YT2 + YT3$, then $n_{ij}(t+1) = 3$;

Otherwise $n_{ij}(t+1) = 23$, $YT_{ij} = YT + 1$;

If $n_{ij}(t) = 1$ and $n'_{ij}(t) = 22$ (n is an element in the set of neighboring cells);

If the possibility of instability in the current cell exceeds the set probability level, then $n_{ij}(t+1) = 21$, $YT_{ij} = 0$;

Otherwise, $n_{ij}(t+1) = 1$.

The possibility of ground point cells being moved by neighboring cells is calculated as follows:

Firstly, obtain the probability vector Pkij of the movement of surrounding ground points caused by each cell with a cell state of 22, as shown in Figure 2.

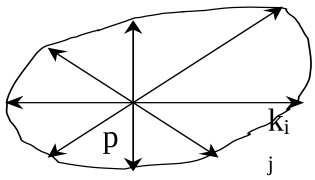


Figure 2. Vector diagram of the possibility of instability of surrounding ground points caused by a cell

Secondly, calculate the probability of instability caused by the current ground cell as the sum of the probabilities of all adjacent cells causing a change in its state. If the set probability level is exceeded, the method of generating random numbers can be used to determine whether the current cell has sunk.

Finally, the model is integrated into the GIS system. With the support of spatial databases, subsidence area data obtained from mining areas, digital elevation models, and other data, model parameters are extracted to dynamically simulate and predict the subsidence process under different geological mining conditions.

4. APPLICATION EXAMPLE SIMULATION RESEARCH

This simulation experiment selected point cloud data obtained from a three-dimensional laser in a mining subsidence area and observation data obtained from a ground observation station. The point cloud data was processed and separated to obtain point set data of the ground during different periods of mining subsidence, as shown in Figure 3. The data from ground observation stations is mainly used for comparison and to calculate the boundary and acceleration of the sinking basin at a certain point in the construction of the model, that is, to participate in the simulation of the shape of the sinking basin as constraint conditions. The main steps are:

(1) Export the pre organized point cloud data in the software in ". xyz" format and save it as TXT text format;

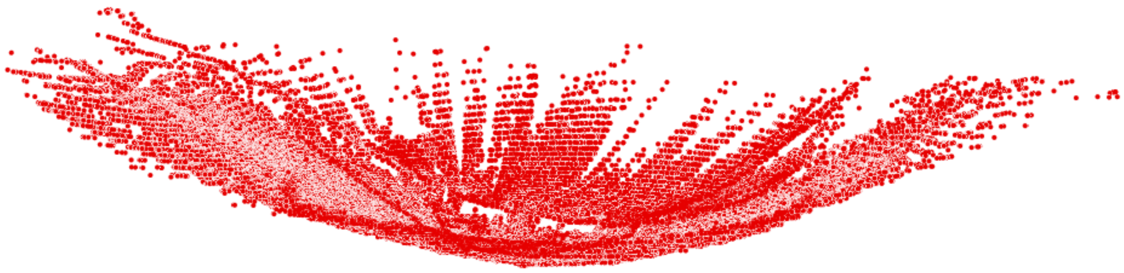


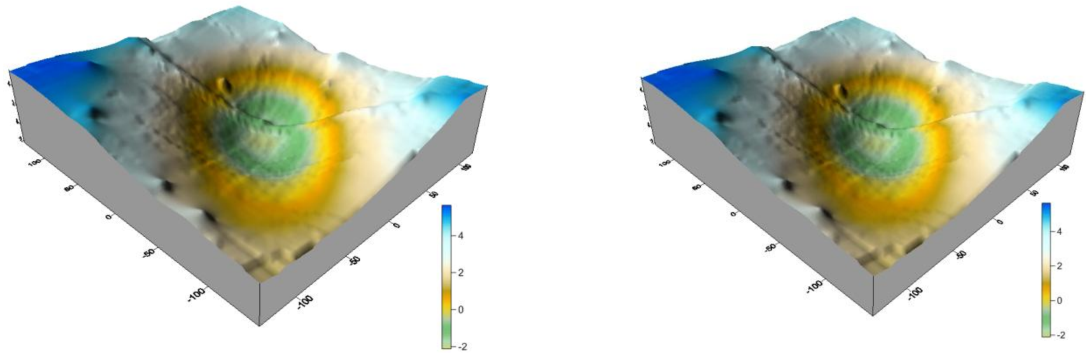
Figure 3. Scan and process final data

(2) Open Arcgis10.0- ArcMap, import the TXT format file, open ArctoolBox, use the thinning point extraction tool to selectively process the data, and then output the ". shp" format file, open its attribute list, and output the ". dbf" format file;

(3) Open the exported '. dbf' file in Excel, delete any unnecessary columns, leaving only the X, Y, and Z columns, and then save it as a 'text file (tab separated)';

(4) Use the extended mining subsidence cellular automaton to expand the model and set corresponding transformation rules.

Set the threshold parameters for simulating subsidence based on the subsidence acceleration, simulate and generate point data files at different time intervals, corresponding to the mining of subsidence basins in different periods.



(a) Simulate the final mining basin model (b) and scan the final mining basin model

Figure 4. Comparison between simulated last stage mining basin model and scanned late stage mining basin model

Through simulation experiments, the extended cellular automaton model and the scan end model results are shown in Figure 4. The extended cellular automaton model has achieved satisfactory results in simulating the impact range of subsidence areas. However, in terms of simulating subsidence values across the entire basin, extended models with two-dimensional or higher dimensions involve a large number of parameters, and there is still a certain gap compared to the real situation. There is still much work that needs to be further studied in future work.

5. CONCLUSION

The paper focuses on the visualization and dynamic simulation of mining subsidence in mining areas, mainly studying the following contents:

(1) This study focuses on the data acquisition scheme and mode of 3D laser scanning technology in mining subsidence monitoring, and discusses the point cloud data processing method in mining subsidence, proposing a method of using point cloud data to construct an effective surface subsidence basin.

(2) In the study of subsidence mechanism and prediction methods in subsidence areas, a spatiotemporal model based on extended cellular automata for dynamic simulation of mining subsidence is proposed with DEM and subsidence acceleration parameters as mandatory constraints, and verified with examples. Compared with traditional monitoring point based methods, using a fine surface model to monitor spatial changes can more accurately reflect the spatial characteristics of the monitored surface objects and is more suitable for predicting mining subsidence.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

ACKNOWLEDGEMENTS

This research was supported by several grants:The Science and Technology Project of the HenanProvince (Grant No. 232102320244), University BasalResearch Fund of Henan Province (Grant No. NSFRF 230623) National Natural Science Foundation of China, Research on the Triaxial Effect of Geodetic Reference Earth (42074002).The authors express their gratitude to the editors and the anonymous reviewers for their valuable comments and suggestions.

REFERENCE

[1] Yue Fubin. Report on the Development of China's Coal Industry (2019) [M]. Social Sciences Literature Press, 2019.

[2] He Youguo. 2019 China Coal Development Report [M]. Emergency Management Press, 2019.

[3] Du Yuzhu, Liang Tao. Multi source data fusion method and application for monitoring surface subsidence in mining areas [J]. Surveying and Mapping Bulletin, 2024 (11): 120-125.

[4] Gao Kuiying, Du Weibing, Chen Jianhua, et al. Application research of OT technology combined with unmanned aerial vehicle LiDAR in monitoring surface subsidence in mining areas [J]. Journal of Henan University of Technology (Natural Science Edition), DOI:10.16186/j.cnki.1673-9787.2023110010.

[5] Xu Liangji, Sun Zhihao, Liu Xiaopeng, et al. Dynamic prediction of surface subsidence at any point based on Boltzmann time function [J/OL]. Coal Journal, DOI：10.13225/j.cnki.jccs.2024.0613.

[6] Wang Li, Wang Karen, Yan Hongbo. Dynamic subsidence prediction model for coal mining subsidence areas based on Weibull time function [J]. China Mining, 2024, 33 (S2): 158-162.

[7] Zhang Zhongjie, Chen Zhennan, Liu Jiangbin, et al. Research on the Prediction Model of Surface Dynamic Movement and Deformation Based on Improved Knothe Time Function [J]. Journal of Henan University of Technology (Natural Science Edition), 2024, 43 (6): 82-89.

[8] Chen Qiuji. Mining subsidence simulation based on cellular automata model [J]. Science and Technology Review, 2013, 31 (11): 65-67.

[9] A.K. Dewdney.Cellular Automata.Encyclopedia of Ecology, 2008, Pages 541-550.

[10] Zhou Chenghu, Sun Zhanli, Xie Yichun Research on Geographic Cellular Automata [M]. Beijing: Science Press, 1999.

[11] Li Xia, Ye Jia'an, etc Geographic Simulation System: Cellular Automata and Multi agents [M]. Beijing: Science Press, 2007.

[12] S. Bandini, G. Mauri, R. Serra. Cellular automata: From a theoretical parallel computational model to its application to complex systems.Parallel Computing, Volume 27, Issue 5, April 2001, Pages 539-553.

[13] Wu Lun, Liu Yu, etc Principles, Methods, and Applications of Geographic Information Systems [M]. Beijing: Science Press, 2004.

[14] Yuan Yaoming. Analysis and Simulation Study of Traffic Flow Cellular Automata Model [D]. University of Science and Technology of China; 2009.

[15] Yang Qingsheng. Transformation Rules of Geographic Cellular Automata and Simulation of Urban Spatial Form [D]. Sun Yat sen University, 2007.