Multimed Tools Appl (2019) 78:28703–28713
https://doi.org/10.1007/s11042-018-6379-5

A methodology for 3D geological mapping and implementation

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Received: 17 April 2018 / Revised: 3 June 2018 / Accepted: 3 July 2018 /
Published online: 10 July 2018

Abstract Using 3D visualization models to exhibit geological structure has become a trend in geological studies. Compared to 2D geological mapping, 3D geological mapping is dependent on more geological sampling information. Geophysical methods (e.g., gravity, seismic, and electric) thus become the major tools in 3D geological mapping. In traditional works, people must extract the geological information from various data grids acquired through different geophysical methods and subsequently integrate the information to manually construct a 3D geological model. This approach usually causes inconvenience and inefficiencies in practice. Therefore, we propose a methodology of 3D geological mapping. It first constructs visualization models from different geophysical data grids and subsequently integrates these models for interpretation and finally converts to a 3D geological model. Based on this methodology, we implement the corresponding system which can accomplish the above process automatically. As an example, we gave a detail description for constructing the 3D lithological model by the methodology mentioned above with the geological survey data acquired in the western Jungger, Xinjiang of China. The demonstration show us that the methodology can effectively solve the matter of 3D geological modeling in case of enriched in geophysical data but in lack of sufficient geological sampling information.

Keywords 3D geological mapping · Geophysical data interpretation · Data visualization · Knowledge extraction

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1 Introduction

With the rapid development of geophysical techniques, geophysicists have been able to perform geological exploration studies using tomography [6]. As a result, we can acquire the relevant geophysical parameters of rocks (such as density, resistivity, and seismic velocity) and further construct the 3D geophysical visualization model. On the other hand, the traditional 2D geological mapping can't fully meet needs of geologists [13]. People are eager to apply 3D geological mapping in the practical work with more advanced computer graphics technologies [1]. For these reasons, 3D geological mapping based on geophysical data has become a very important and meaningful line of study [11]. Especially when the geological sampling information is scarce, the question is, how can we directly transform the geophysical visualization model into a 3D geological model?

But there exists an essential difference between the geophysical visualization model and the 3D geological model. The geophysical visualization model is defined by the geophysical parameters of each point in the grid space with the expression $g = f\,(x, y, z)$. And the 3D geological model is concerned with the geometrical relationship among geomaterials classified by some geological feature (such as lithology, stratum, etc.), which is often recorded in GIS [4]. In current studies and applications, researchers usually find mapping rules between the geophysical data and the geological feature from the rock samples' measurement first, then carry out the manual interpretation in images of different geophysical visualization models, and finally construct the 3D geological model artificially [10]. Because the above process is essentially fragmented, it causes great inconvenience in practice [14]. Furthermore, traditional methods might be inefficient when be coupled with massive 3D geophysical data sets [7].

Here, we present a 3D geological mapping methodology in following steps shown in Fig. 1: firstly reconciling 3D visualization models constructed with multi-source geophysical data grids, then interpreting their geological meaning, and after several repeated feedback operations and amendments finally transforming the interpreted result into the 3D geological model. Unlike other 3D geological modeling and mapping methods, the methodology which mainly generates the boundary of the geological feature according to the geophysical data characteristics has a high degree of automation. Additionally, it can support functions as dynamic 3D model update and reconstruction when geophysical data update. Based on the methodology, the system GGMS (Geophysical data to Geological information Mapping System) was developed and applied to the actual 3D geological mapping work in the western Junggar, Xinjiang, China.

This paper elaborates the methodology mentioned above. It is organized as follows: after a brief introduction, we first give a description of how to build and reconcile the geophysical

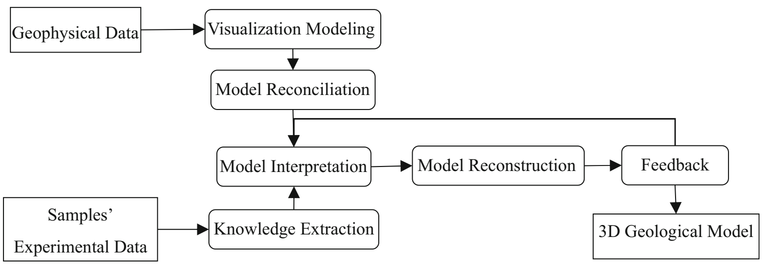

Fig. 1 The process of the method

visualization model with various data grids. Next, we discuss the implementation of the geophysical data interpretation. Then techniques of visualization model reconstruction and feedback are elaborated. Finally, the system implementation of the methodology is described and conclusions are presented.

2 3D geophysical modeling and reconciliation

As we known, the geophysical 3D visualization model with geophysical methods are built from a data grid. The regular grid (in which each cell has the same size) or irregular grid (in which cell sizes are unequal) can be represented as a set of the quad *(x, y, z, data),* where *x, y, z* represent a position in space and *data* represents a geophysical parameter [2]. In the process of constructing the visualization model, the continuous parameter value is usually obtained by interpolating the data value corresponding to the grid points' positions in space [3]. Using visualization techniques in scientific computing to create the mapping relationship between color level and the geophysical parameter value, the 3D geophysical model is easily to be constructed.

But in practice, 3D geophysical models obtained from different geophysical methods (for example resistivity and seismic velocity) usually have different specifications for the data grid; that is to say quads as $(x_1, y_1, z_1, ERData)$ and $(x_2, y_2, z_2, SVData)$ usually have inconsistent positions in space [12]. So we must reconcile different data grids to form a geophysical parameter set with the same spatial position, with sets formed as *(x, y, z, ERData, SVData ...)*.

A process of models reconciliation we designed is consisted of three parts: 1) extract the position information *(x, y, z)* in the data grid of reconciling models and map the position to the unified geodetic coordinate system; 2) compare the coordinates of models' data grids and select a space region which is covered by all reconciling models; 3) use an uniform grid cell to resample (interpolate) reconciling models in the selected space region. The most important step above is to find the region in space which is covered by all data grids (we call it the resample reference grid). In the ideal case, the resample reference grid itself is one of the reconciling model's data grids. Meanwhile the resample grid cell is also identified. As an instance of model reconciliation implemented in our system, Fig. 2 shows a visualization

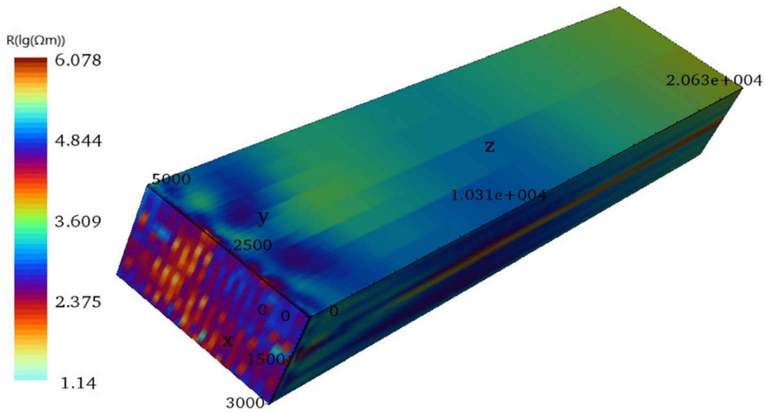

Fig. 2 The visualization model of resistivity

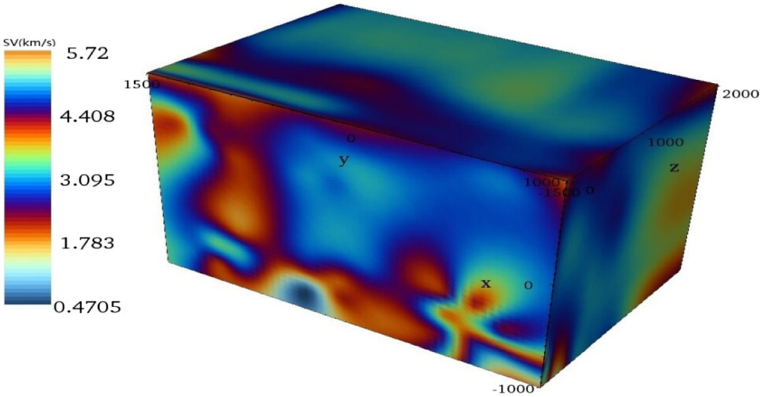

Fig. 3 The visualization model of S-wave velocity

model of resistivity and Fig. 3 shows a visualization model of S-wave velocity; then after the operation of data grids reconciling by using the resample reference grid of Fig. 3, the original model shown in Fig. 2 is turned into the reconciled result as Fig. 4. In addition, the coordinate in the Fig. 2 is mapped to the standard geodetic coordinate in Fig. 4.

3 Models interpretation

As the core of this methodology, the purpose of geophysical models interpretation is to map all integrated vectors *(x, y, z, ERData, SVData,* etc.*)* on the reconciled data grid to a geological feature. This procedure consists of two parts: the sampling data inversion from geophysical measurement experiment and the geophysical survey data forward calculation. Because the forward calculation just uses the inversion result for a simple computation, we focus on the process of experimental data inversion in this section.

The essence of the data inversion is to use the experimental data of rock samples for knowledge extraction between the geophysical parameters and the geological feature. Because the experimental data usually record all properties (geographical, geophysical and geological)

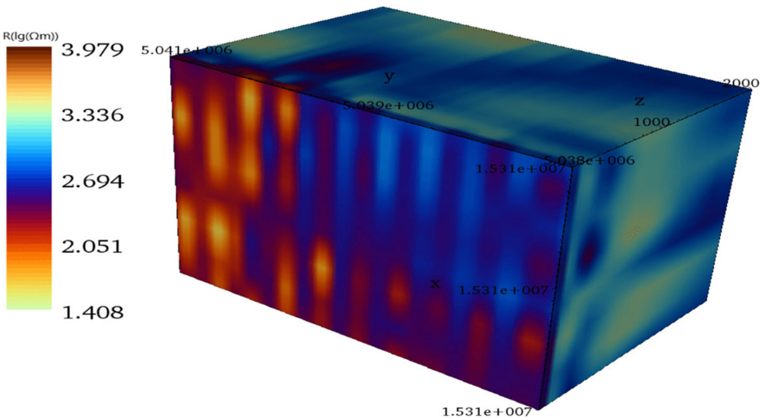

Fig. 4 The visualization model of resistivity after reconciliation

together, we need to separate all records into the input vector, which is represented as a combination of geographic information and geophysical parameters *(for example, x, y, z, ERData, and SVData),* and the output result, which is represented as a geological feature (for example, *lithology)*. To facilitate the numerical calculation, we use a quantized value instead of the real geological feature.

As we all know, it is difficult to use some mathematical functions to express the mapping knowledge between the input vector and the output result. For this reason, machine learning methods are often applied to extract the mapping knowledge from the input vector to the output result [19]. According to this approach, typically we first must choose a machine learning model, and then continuously optimize its structure and parameters to obtain a minimum deviation between the output result calculated by the model and the actual output result [15]. However, with so many existing machine learning models, how does one choose a model which best meets the specific experimental data interpretation? Here, we use three indicators to evaluate alternative models: 1) accuracy, which measures the conformance between the output value calculated by the machine learning model and the actual determined result of the sample data; 2) convergence capability, which represents whether the model can easily obtain a stable output from the data training process; and 3) generalizability, which measures the credibility of results using the machine learning model for calculating data outside the sample set. Table 1 compares these indicators of some commonly used machine learning models extracted from the same sample data in the survey project of 3D geological mapping in the western Junggar, Xinjiang, China (the sample's size is 3060). After a contrast, we find that there are two main factors affecting the index calculation result besides the structure of learning model itself: 1) the size of sample data. Some learning models need a large collection of training data to achieve a satisfied result (for example SVM), but in most 3D geological mapping applications the size of sample data are often limited for the cost of sampling; 2) the distribution of sampling position. As the geographic information is an important part of the input vector for model learning, the sampling position has an evenly distribution can cause a good knowledge extraction result. But in many geological applications the sampling position is often restricted by natural conditions. Above two points have demonstrated that the machine learning model we chosen need to achieve a relatively good effect with the no-ideal training data.

Table 1 shows that the Fuzzy Neural Network (FNN) model produces a relatively best result. The structure of FNN, which we used, is shown in Fig. 5. In fact, it is a combination of Fuzzy Clustering and the Radial Basis Function (RBF) Neural Network [5]. The complete model consists of four layers: Input Layer, Clustering Layer, Function Layer and Output Layer. At the Clustering Layer, the input vector is classified by the FCM (Fuzzy C-Means) algorithm to generate fuzzy rules. At the Function Layer, the data in the classification is calculated by the interpretation function, which corresponds to each fuzzy rule. The final result is the weighted

Table 1 Comparison of results of several models

Model name	Accuracy (%)	Convergence capability	Generalizability
Fuzzy Neural Network(FNN)	85.4	Good	Very good
Fuzzy Clustering (FCM)	76.6	Very good	Good
Hard Clustering (HCM)	68.8	Very good	Bad
Back-Propagation Neural Network (BPNN)	81.6	Bad	Bad
Support Vector Machine (SVM)	79.5	Bad	Very good

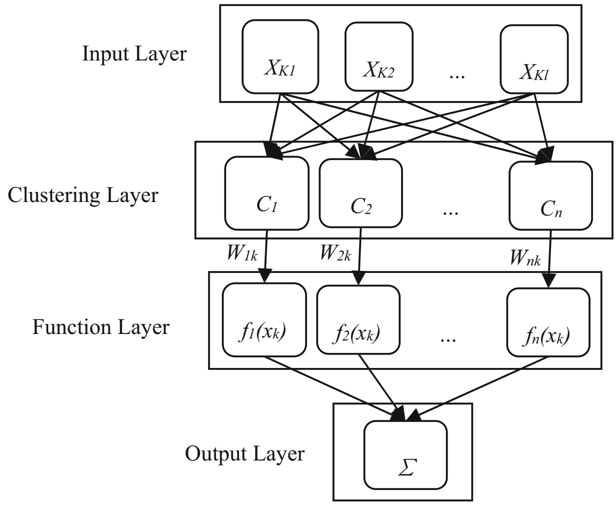

Fig. 5 The architecture of the FNN model

composite of these function values [8]. The interpretation function at the Function Layer has some alternative types, as shown in Table 2. About some mentioned expressions in the table, $x_k = \{x_{k1}, x_{k2}, \ldots, x_{kl}\}$ is the input vector; $v_i = \{v_{i1}, v_{i2}, \ldots, v_{il}\}$ represents the *ith* center value, which is obtained by the FCM algorithm; and $w_k = \{w_{1k}, w_{2k}, \ldots, w_{nk}\}$ is the fuzzy membership between the input vector x_k and the cluster v_i. The final output geological feature is calculated using the expression (1).

$$y_k = \sum_{i=1}^{n} w_{ik} f_i(x_k) \tag{1}$$

In addition, we can find in Table 2 that the number of parameters in the function type of Linear Inference is moderate. In fact, it is the best choice for building the FNN model from our test results. With this function type, we need to solve the corresponding parameters in the function to make the objective function as expression (2) obtains the minimum value. Let w_i and x_i take expression as (3), (4) respectively, then using the Weighted Least Squares method, the values of parameters $a_i = [a_{i0}\ a_{i1}\ \ldots\ a_{il}]$ can be determined by the expression (5) [16]. Here, y represents the quantized value of the geological feature. Of course, we can also use

Table 2 Interpretation functions for fuzzy rules

Function type	Function form
Simplified inference	$f_i(x_k, v_i) = a_{i0}$
Linear inference	$f_i(x_k, v_i) = a_{i0} + a_{i1}(x_{k1} - v_{i1}) + a_{i2}(x_{k2} - v_{i2}) + \ldots + a_{il}(x_{kl} - v_{il})$
Quadratic inference	$f_i(x_k, v_i) = a_{i0} + a_{i1}(x_{k1} - v_{i1}) + a_{i2}(x_{k2} - v_{i2}) + \ldots + a_{il}(x_{kl} - v_{il}) + a_{i(l+1)}(x_{k1} - v_{i1})^2 + a_{i(l+2)}(x_{k2} - v_{i2})^2 + \ldots + a_{i(l+2)}(x_{k2} - v_{i2})^2 + a_{i(2l+1)}(x_{k1} - v_{i1})(x_{k2} - v_{i2}) + \ldots + a_{i((l+1)(l+2)/2)}\left(x_{k(l-1)} - v_{i(l-1)}\right)(x_{kl} - v_{il})$
Modified quadratic inference	$f_i(x_k, v_i) = a_{i0} + a_{i1}(x_{k1} - v_{i1}) + a_{i2}(x_{k2} - v_{i2}) + \ldots + a_{il}(x_{kl} - v_{il}) + a_{i(l+1)}(x_{k1} - v_{i1})(x_{k2} - v_{i2}) + \ldots + a_{i(l(l+1)/2)}\left(x_{k(l-1)} - v_{i(l-1)}\right)(x_{kl} - v_{il})$

optimization algorithms as genetics evolution (GE) or particle swarm optimization (PSO) to determine the appropriate cluster number and optimize the calculation process.

$$J_L = \sum_{i=1}^{n} \sum_{k=1}^{l} w_{ik}\left(y_k - f_i(x_k - v_i)\right)^2 \tag{2}$$

$$w_i = \begin{bmatrix} w_{i1} & 0 & \dots & 0 \\ 0 & w_{i2} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & w_{in} \end{bmatrix} \tag{3}$$

$$x_i = \begin{bmatrix} 1 & (x_{i1} - v_{11}) & \dots & (x_{il} - v_{1l}) \\ 1 & (x_{i1} - v_{21}) & \dots & (x_{il} - v_{2l}) \\ \dots & \dots & \dots & \dots \\ 1 & (x_{i1} - v_{n1}) & \dots & (x_{il} - v_{nl}) \end{bmatrix} \tag{4}$$

$$a_i^T = \left(x_i^T w_i x_i\right)^{-1} x_i^T w_i y \tag{5}$$

4 Model reconstruction and feedback

Using the machine learning model extracted in the previous section, the geological feature of each point in the data grid can be determined through a forward calculation process [18]. The next task is to construct the 3D geological model with this calculation result.

Geologists often use the basic voxel (wedge, tetrahedron, hexahedron, etc.) construction method for the 3D geological modeling. Each voxel represents a unique geological feature [9]. Taking the cell (cuboid) of the geophysical data grid as the basic voxel, we design the following decomposition-merge strategy to construct the 3D geological model. To easily describe, we use the 2D grid as an example (the 3D grid can make an analogy). Suppose that in the left part of Fig. 6, the geological feature in the four vertices have been calculated (shown as the quantized values 1-4 in Fig. 6). We divide the cell (the rectangle on the left part of Fig. 6) into four parts as shown in the right part of Fig. 6. Each part is assigned a geological feature the same as the vertex (for example, the geological feature of vertex 1 on the left of Fig. 6 determines the geological feature of rectangle 1 on the right of Fig. 6). Certainly, if the geological feature in four vertices is identical, the cell need not be divided (shown as Fig. 7).

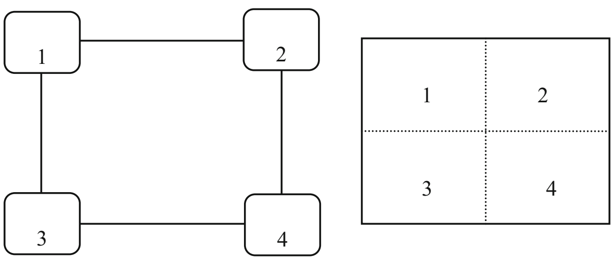

Fig. 6 An example of cell decomposition

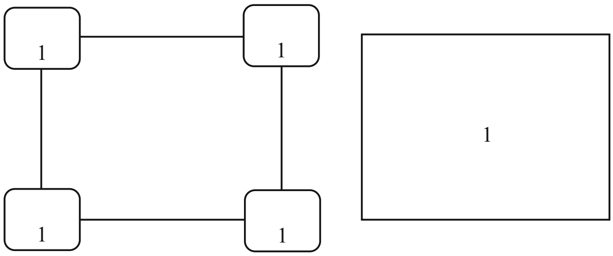

Fig. 7 Another example of cell decomposition

After the decomposition process, the interpreted model is restructured. However, the construction model is too fragmented, so a merging operation must be performed. For each geological feature in the calculation result, repeat the following procedure: search in the x, y, and z directions, checking whether the next cell (cuboid) has the same geological feature as the current and can be merged into a new cuboid. If so, merge the two cuboids. Using this strategy (including the octree decomposition for the 3D grid, a cuboid cell is divided into eight cells), the spatial morphology of each geological feature can automatically be formed respectively. These discrete 3D models of geological feature are combined to construct the final 3D geological model. Figure 8 shows the final 3D lithological model, which is interpreted by the geophysical visualization model shown in Figs. 3 and 4. And it is produced by combining 3D models which represent one geological feature, as in Fig. 9. The whole process is as follows: 1) extract the interpreted model from rock samples measured in a laboratory which focusing properties of S-wave velocity and resistivity; 2) use the interpreted model to compute the geological feature value; 3) reconstruct the compute results to the 3D geological model.

For the final 3D geological model constructed by the method described in the paper, a question is how to evaluate the result and make some corrections? Therefore, we must increase a feedback mechanism to allow the user to evaluate and correct the interpretation results with their own geological knowledge or hypothesis. In most similar applications, people usually adapt two evaluate methods: 1) evaluation based on geological assertion from other data sources (for example drilling data). It means taking the interpretation result and the geological knowledge from other data sources to compare and get the coincidence

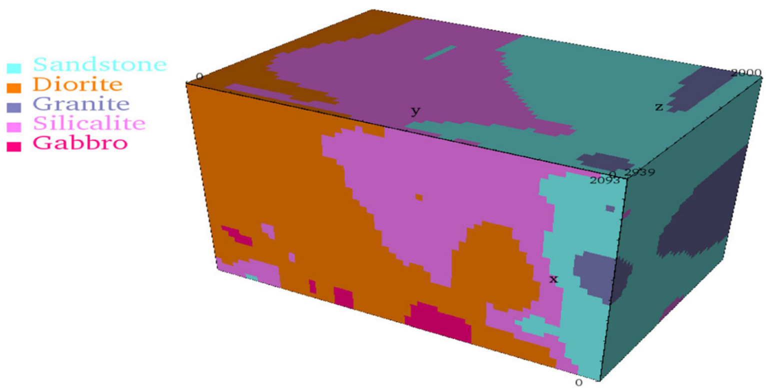

Fig. 8 The 3D geological model of lithology

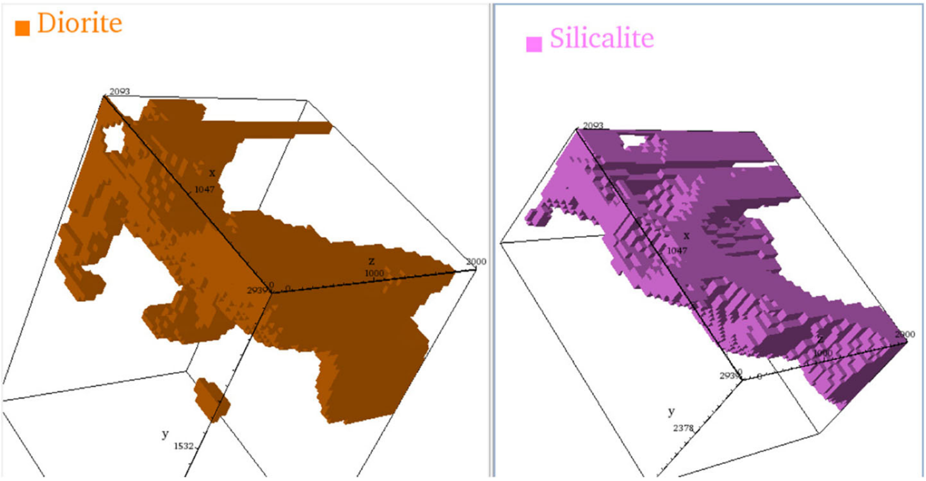

Fig. 9 The 3D model of specific lithology

degree; 2) evaluation based on users' own knowledge. It means the user subject determines whether the model is consistent with his experience or knowledge. In the system implementation, we design a feedback mechanism to continually correct the interpreted model by users' evaluation results. The concrete implementation procedure of the feedback function are as follows: 1) cut the interpreted 3D model for the section output according to the need of users; 2) let the user find out the area which assigned a wrong geological feature in the section based on his experience or other acquisition information, then reassign the area a correct geological feature; 3) get the grid points in the reassigned area and add them to the training data set with the new geological feature value; 4) use the new training data set for knowledge extraction and get the new machine learning model. Then the corrected 3D model can be constructed by the model interpreted and reconstructed operation.

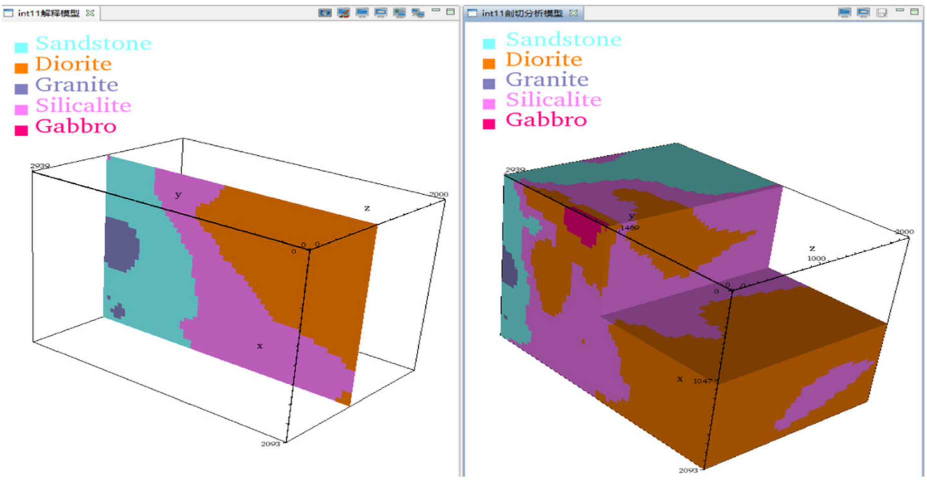

Fig. 10 The analysis model of a cut effect in software

5 System implementation and conclusions

Based on VTK (the Visualization Toolkit, http://www.vtk.org), Eclipse RCP (http://www.eclipse.org) and other open source projects, we developed the software GGMS, which implements the proposed methodology on the Windows platform [17]. A video demonstration about its Chinese version can be found at http://v.youku.com/v_show/id_XODk0NjI0NTg4.html.

In addition to providing geophysical visualization modeling and interpretation, GGMS has powerful model analysis capabilities. Figure 10 shows a cut effect produced in GGMS for the lithological model of Fig. 8. GGMS has played an important role in the case study (the geological survey work in the area of Karamay, Xinjiang, China). It not only helps users quickly obtain the distribution of geological features from the geophysical data but also effectively obtains the 3D geological model from the geophysical data without a complicated software processing.

From GGMS we can see the methodology of 3D geological mapping described in this paper is more dependent on the variation in geophysical data. So the methodology can solve such 3D geological mapping problems which have inadequate geological sampling or for which the existing geological sample is insufficient to construct a 3D geological model (for example, the survey area is too large). Although GGMS has a high level of automation and can save a lot of manual work, there are still some shortcomings, which are mainly reflected in two aspects:

a) Any geophysical data has its own accuracy and resolution. When interpolating in the data grid, the results of different geophysical data sets may differ in credibility. In fact, the geological feature calculated by this methodology contains a certain range of marginal error.
b) In many 3D geological mapping works, we still need to generate some 2D sectional views for print. As we construct the 3D model by cuboids, the polygon edge of geological features in the sectional view is difficult to avoid jagged. In order to achieve a better mapping effect, we need to repair the feature polygon in other software as ArcGIS. And in our future work, we will improve the system to automatically repair or polish the feature polygon for 2D mapping.

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