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Seismic Attribute Reduction Method and its Application

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Abstract: In oil-gas prediction, the effects wouldn't get better if more seismic attributes were used. Due to calculation errors, the redundant seismic attributes get lower forecast accuracy instead. In this study, we studied the rough polarization matrix seismic attribute reduction, the principal component seismic attributes reduction and covering rough set seismic attributes reduction. By comparing these methods, the study further illustrated their different applicable conditions, results, advantages and defects. Simulation tests and actual applications proved that seismic attributions reduction can not only reduce multiple solutions but also improve the accuracy of oil-gas prediction and the speed of processing, its effect is remarkable in oil-gas prediction. Being faster speed of the principal component seismic attributes reduction and higher precision of the covering rough set seismic attribute reduction, both of them have been widely applied to oil-gas prediction.

Key words: Seismic attribute, attribute reduction, principal component analysis, rough set, covering rough set

INTRODUCTION

Seismic attribute (Eastwood, 2002) is a comprehensive reflection of subsurface strata and is used to depict and describe the seismic characteristics of geological information ranging from stratum structure, lithology and physical property, etc. Based on seismic attributes, interpreters obtain more information of seismic data to achieve the main purpose of reservoir prediction. With on going advances of various new mathematical methods, signal processing technology, computer technology in oil and gas exploration domain, it gradually becomes a hot topic (Hart, 2008; Chopra and Marfurt, 2005; Yin and Zhou, 2005; Meng *et al*., 2006) for researchers to predict the subsurface hydrocarbons with seismic attributes. In practical applications, especially oil-gas prediction, a variety of attributes associated with hydrocarbons should be introduced. However, it is not that the more seismic attributes introduced the better, a large increase of attributes will bring adverse effects for oil-gas prediction. Therefore, effective reduction attributes, namely, attribute optimization, can minimize multiple solutions and enhance the accuracy of oil-gas prediction. Currently, existing methods of seismic attribute reduction include comparison method, Sequential Forward Selection (SFS), Sequential Backward Selection (SBS), searching algorithm and clustering analysis method (Wang *et al*., 2007; Schultz *et al*., 1994), etc. Although got considerable effects on some issues to date, no one has ever been recognized as an effective method. The Principal Component Analysis (PCA) (Abdi and Williams, 2010; Yan, 1998) is a multivariate statistical analysis method which can select less number important variables through linear transformation, so as more easy to seize the essence of things and improve the analysis efficiency. Rough set theory (Pawlak, 1982) is a kind of new mathematical theory in studying uncertain and incomplete data and attribute reduction is one of its key issues. Many scholars have discussed a lot of algorithms, such as Jelonek algorithm and fuzzyrough set (Jelonek *et al*., 1995; Zhao and Tsang, 2008), etc. Zakowski proposed the covering rough set model and discussed the relevant properties (Zakowski, 1983). Chen, in 2007, proposed a reduction method by means of covering rough set respectively on the consistent and inconsistent covering decision systems (Degang *et al*., 2007). The covering rough set is more general which can solve the data continuity problems that the conventional rough set cannot cope with. Therefore, this thesis studied and compared the rough polarization matrix seismic attribute

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reduction, PCA based seismic attributes reduction and covering rough set on seismic attribute reduction and further illustrated their different applicable conditions, results, advantages and limits.

THEORIES AND METHODS

Rough polarization matrix seismic attribute reduction method: Attributes reduction of rough set (Zhang *et al*., 2001; Liu *et al*., 2007a) is mainly used to get the minimum set of attributes and its theory is described as follows (Liu *et al*., 2008):

Set the polarization matrix:

$$M(a_k) = \begin{bmatrix} c_{11}^k & c_{12}^k & \cdots & c_{1s}^k \\ c_{21}^k & c_{22}^k & \cdots & c_{2s}^k \\ \vdots & \vdots & \ddots & \vdots \\ c_{s1}^k & c_{s2}^k & \cdots & c_{ss}^k \end{bmatrix}$$

where, $i = j$, $c_{ij}^k = 0$, $i < j$, $c_{ij}^k = 0$, $i \neq j$, $j \le s$ and:

$$c_{ij}^k = \begin{cases} 1, f_i^k(x_p) = f_j^k(x_q)\ p \le n_i, q \le n_j \\ 0, \text{others} \end{cases}$$

where, $f_i^k(x_j)(i \le s, j \le s, k \le m)$ represents k attribute values of the jth object in the ith decision class.

Set relative reduction degree be ρ, hence:

$$\rho = \frac{C^T}{C}$$

where, denominator C is the number of the lower triangles' position of the differentiation polarization matrix and does not include diagonal matrix, namely:

$$C = \{\sum |S_{ij}| : i \neq j, i > j\}$$

numerator C^T is the number of the lower triangles' position of the differentiation polarization matrix that are equal to 0 and does not include diagonal matrix, namely:

$$C = \{\sum |a_{ij}| : a_{ij} = 0, i \neq j, i > j\}$$

Rough polarization matrix seismic attribute reduction algorithm steps are as follows:

- Calculate polarization matrix $M(a_i)$, $(1 \le i \le m)$, $E=\{\}$
- Calculate relative reduction degree ρ_{ai} which is correspondent to $M(a_i)$
- Check all of the ρ_{ai} in turn, if there is $\rho_{ai}=1$, then let $E=E \cup \{\{a_i\}\}$. Hence, E is the minimal reduction set, then, turn 8 End. If not, keep on
- Let k = 2
- Calculate k relative reduction degrees of the polarization matrix $\rho_{a_{s_1},\ldots,a_{s_k}}$ $(1 \le s_1 \ldots < s_k \le m)$ which are shaped like $M(a_{s1})^* \ldots {}^*M(a_{sk})$ and $1 \le s_1 \ldots < s_k \le m$
- In all relative reduction degrees calculated in step 5, if $\rho_{a_{s_1},\ldots,a_{s_k}} = 1$, let $E=E \cup \{\{a_{s1},\ldots, a_{sk}\}\}$ and turn to 8, else, go on
- k=k+1, go to 5
- End, output the minimal reduction set E

Principal component analysis based seismic attribute reduction method: Principal component analysis (Abdi and Williams, 2010; Yan, 1998) is mainly used in seismic attribute reduction method to reduce dimensions of seismic attributes. A number of seismic attributes can be transformed into several principal component seismic attributes at the premise of less loss of information. Each main component is a linear combination of the original attributes and unrelated with other main components, the principal component contains more than 80% of the original variable information. The purpose is that: Compress the number of seismic attributes then, use the least number of attributes to explain most of the seismic attributes of the original data and eliminate the redundant ones, eliminate co-linearity in seismic attributes and overcome problems caused by it such as operation instability and pathological matrix.

Set correlation matrix be:

$$R = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1p} \\ r_{21} & r_{22} & \ldots & r_{2p} \\ . & . & \ldots & . \\ r_{p1} & r_{p2} & \ldots & r_{pp} \end{bmatrix}$$

Where r_{ij} (i, j = 1, 2, 3, ..., p) is correlation coefficient of original seismic attributes x_1 and x_j and $r_{ij} = r_{ji}$:

$$r_{ij} = \frac{\sum_{k=1}^{n}(x_{ki} - \overline{x}_i)(x_{kj} - \overline{x}_j)}{\sqrt{\sum_{k=1}^{n}(x_{ki} - \overline{x}_i)^2}\sqrt{\sum_{k=1}^{n}(x_{kj} - \overline{x}_j)^2}}$$

Calculate eigen values and eigen vectors:

- Solve the eigen value equation:

$$|\lambda I - R| = 0$$

Jacobian method is usually used to find out eigen values then, rank them in descending order:

$$\lambda_1 \ge \lambda_2 \ge \ldots \ge \lambda_p \ge 0$$

- Calculate eigen vector e_i (i = 1, 2, 3, ..., p) corresponding to eigen value λ_i and required $\|e_i\| = 1$, namely:

$$\sum_{j=1}^{p} e_{ij}^2 = 1$$

where, e_{ij} represents the jth component of vector e_i

PCA based seismic attribute reduction method steps are as follows:

- Standardize the seismic data
- Calculate the correlation matrix
- Calculate eigen values and eigen vectors
- Calculate contribution

  Contribution:

$$\lambda_i / \sum_{k=1}^{p} \lambda_k$$

  total contribution:

$$\sum_{k=1}^{i} \lambda_k / \sum_{k=1}^{p} \lambda_k, \ (i = 1, 2, 3, ..., p)$$

- Output data
- Compute principal component load

$$l_{ij} = \sqrt{\lambda_i} e_{ij}, \ (i, j = 1, 2, ..., p)$$

- Calculate each principal component's score:

$$\begin{cases} z_1 = l_{11}x_1 + l_{12}x_1 + ... + l_{1p}x_p \\ z_2 = l_{21}x_1 + l_{21}x_1 + ... + l_{2p}x_p \\ ...... \\ z_m = l_{m1}x_1 + l_{m2}x_1 + ... + l_{mp}x_p \end{cases}$$

Covering rough set seismic attribute reduction method: The basic concept of covering rough set is as follows (Degang *et al*., 2007; Zhang *et al*., 2001; Liu *et al*., 2007a; Liu *et al*., 2008; Liu *et al*., 2012).

Let U be a universe of discourse, C={C_1, C_2, ..., C_n} a family of subsets of U. The C is called a cover of U if no subset in C is empty and:

$$\bigcup_{i=1}^{n} C_i = U$$

Definition 1: Let $C = \{C_1, C_2, ..., C_n\}$ be a cover of U. For every x∈U, let $C_x = \cap\{C_k : C_k \in C, x \in C_k\}$, $Cov(C) = \{C_x, x \in U\}$ be then also a cover of U. We call it the induced cover of C.

Definition 2: In covering decision system (U, Δ, D), let (U, Δ, D) be a consistent covering decision system. Suppose U={x_1, x_2, x_3, ..., x_n} by M (U, Δ, D) we denote a n×n matrix c_{ik}, called the discernibility matrix of (U, Δ, D), defined as:

$$c_{ik} = \begin{cases} \{C \in \Delta : (C_{xi} \not\subset C_{xk}) \cap (C_{xk} \not\subset C_{xi})\} \cup \{C_s \cap C_t : (C_{sx_i} \subset C_{sx_k}) \cap (C_{tx_k} \subset C_{tx_i})\}, & d(\Delta_{x_i}) \neq d(\Delta_{x_k}) \\ \Delta, & d(\Delta_{x_i}) = d(\Delta_{x_k}) \end{cases} \quad (1)$$

for $x_i, x_k \in U$. If $c_{ik} = \{C_s : s = 1, ..., l\}$ the relations between elements in c_{ik} is a disjunction. If $c_{ik} = \{C, C_s \cap C_t : s, t \leq n\}$, we mean it is conjunction between C_s and C_t.

Covering rough set seismic attribute reduction (namely, CRSSAR) algorithm steps are as follows:

- Convert seismic attribute decision table into covering decision system
- Universe of discourse is U={x_1,x_2,..., x_n}. Δ={C_i: i = 1, 2, ..., m} is a family of covers of U. Calculate COV(c_i) of each seismic attribute
- Calculate COV(Δ)={Δ_x: x∈U} based on:

$$\Delta_x = \cap\{C_{ix}, C_{ix} \in COV(C), x \in C_{ix}\}$$

- Calculate discernibility matrix (c_{ik}). For any x_i, x_k∈U, calculate c_{ik} $(1 \leq k < i \leq n)$ according to formula (1)
- Delete redundant normal forms from ranked disjunction table. If disjunctive normal forms A and B have a relation of A⊂B then, delete B
- Standardize the above results by disjunctive normal form into conjunctive normal form. Each conjunctive normal form is a reduction

SIMULATION TEST AND PRACTICAL APPLICATION

Example analysis and comparison: To testify the effects of above method, select Table 1 as decision table of seismic attributes. The extracted attributes are: Arc length (c_1), instantaneous frequency (c_2), instantaneous phase (c_3), instantaneous amplitude (c_4), energy half time (c_5), mean amplitude (c_6), RMS amplitude (c_7), slope at energy half-time (c_8), slope of instantaneous frequency (c_9), total amplitude (c_{10}) and total energy (c_{11}). No. 1-20 are oil or dry training samples. D denotes decision attribute set. Where 1 stands for training oil well or untested oil sample and 2 for training dry well or dry sample before test. No. 21-100 are untested samples.

Table 2 shows the result of predictions before and after seismic attributes reduction. When take no reduction

Table 1: Decision table of seismic attributes

U/A	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	D
1	6.56	20.66	58.67	106.89	64.74	-89.86	85.28	10725.47	295.16	-629	60227	1
2	11.30	29.11	-54.87	133.82	37.76	-94.00	95.26	14152.90	370.62	-658	73812	1
.	.	.	.	.	.	.	.	.	.	.	.	.
20	8.01	37.48	33.02	60.16	34.81	31.86	36.87	2788.35	-293.26	223	12563	2
21	6.50	19.13	58.70	95.00	67.05	-81.29	82.65	10137.82	707.84	-569	49967	1
22	6.34	20.42	14.53	93.30	60.76	-80.71	81.96	9950.28	256.27	-565	47577	1
.	.	.	.	.	.	.	.	.	.	.	.	.
100	8.00	37.27	38.44	56.69	31.49	28.86	37.15	2739.98	-99.09	202	11524	2

Table 2: Comparison of before and after seismic attributes reduction

Methods	No. of attributes before reduction	No. of attributes after reduction	No. of correct prediction	Accuracy rate (%)
Rough polarization matrix seismic attribute reduction	11	11	69	86.25
	11	1	63	78.75
PCA based seismic attribute reduction	11	3	68	85.00
	11	4	71	88.75
	11	5	73	91.25
Covering rough set seismic attribute reduction	11	3	72	90.00
	11	4	74	92.50
	11	5	76	95.00

in Table 1, through the discriminant analysis system (Liu *et al*., 2007b) for oil and gas reservoir prediction, the number of correct prediction is 69 and accuracy is 86.25%.

Rough polarization matrix seismic attribute reduction method: The results of this method (as shown in Table 2), are $\{c_6\}$, $\{c_7\}$ and $\{c_{10}\}$, respectively. The number of reduction is 1. Through the discriminant analysis system (19) for oil and gas reservoir prediction, the number of correct prediction is 63 and accuracy is 78.75%. Replacing 11 original seismic attributes $\{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{11}\}$ with only one to describe seismic attribute decision system makes the problem simple and clear.

Compared with the traditional stepwise discriminant analysis (Liu *et al*., 2007b), the rough polarization matrix seismic attribute reduction is featured with more objective and does not need prior knowledge of property distribution which solves the problem of large storage capacity possession in the process of selecting variables and the problem that the overall test variables must obey the normal distribution. In polarization matrix seismic attribute reduction, the knowledge is represented by polarization matrix. Starting with the polarization matrix, obtain the reduction attributes by computing the relative reduction degree. It is easy to achieve the rough polarization matrix seismic attribute reduction as well as it is effective to deal with small sample decision tables.

PCA based seismic attribute reduction method: The results of the experiment show that, as shown in Table 2, composing 3 principal components, the accumulated contribution rate had reached 88.76% (>85%). It made 68 correct predictions while the correct recognition rate was 85% by oil and gas reservoir prediction discriminant analysis system (Liu *et al*., 2007b). When using 4 principal components, the accumulated contribution rate was as high as 95.28% and it made 71 correct predictions whose correct recognition rate got 88.75%. When using 5 principal components, the accumulated contribution rate rose to 97.69% and it made 73 correct predictions making the correct recognition rate 91.25%. The results indicate that the correct recognition rate increased with the amount of principal components. However, the correct recognition rate decreased when the principal components added to 6.

In the PCA based seismic attribute reduction, the original multiple seismic attributes that concentrate most information of original variables are replaced by few composite seismic attributes using the dimensional reduction techniques. At the same time, the seismic attribute decision table is scientifically evaluated by calculating the comprehensive functional principal component scores.

Covering rough set seismic attribute reduction method: The results of experiment show that, as shown in Table 2, when results are combination of seismic attributes $\{c_1, c_8, c_{11}\}$, $\{c_5, c_6, c_9\}$ and $\{c_5, c_9, c_{10}\}$, it made 72 correct predictions while, the correct recognition rate was 90.00% by oil and gas reservoir prediction discriminant analysis system (Liu *et al*., 2007b). When results are combination of $\{c_5, c_6, c_7, c_9\}$, $\{c_5, c_6, c_8, c_9\}$ and $\{c_5, c_7, c_9, c_{10}\}$, it

Table 3: Comparison of computing time

Methods	No. of attributes after reduction	Computing time (s)	No. of correct prediction	Accuracy rate (%)
Rough polarization matrix seismic attribute reduction	1	0.000000	63	78.75
PCA based seismic attribute reduction	5	0.000852	73	91.25
Covering rough set seismic attribute reduction	5	10.918795	76	95.00

made 74 correct predictions while the correct recognition rate was 92.50%. When results are combination of $\{c_1, c_5, c_6, c_7, c_8\}$, $\{c_1, c_5, c_7, c_8, c_{10}\}$ and $\{c_1, c_8, c_9, c_{10}, c_{11}\}$, it made 76 correct predictions while the correct recognition rate was 95.00%. The experiment results indicate that the correct recognition rate is increased with the increase of seismic attributes combination. However, when the combination increased to a certain number, the correct recognition rate does not increase any more.

Rough set theory is based on the indiscernible relation namely, equivalence relation. However, in some cases, it is hard to get the equivalence relation or division in the universe of discourse. This method is more effective in dealing with discrete data but is easily influenced by discrete result when dealing with continuous seismic attribute and the traditional rough set has some limitations. Covering rough set is a generalization of the traditional rough set theory. Covering rough set seismic attribute reduction not only can solve the problems of continuous data that the traditional rough set method cannot solve, but also overcomes the limitation of rough set theory.

All experiments are run on PC with Intel (R) Xeon (R) CPU, 16G memory, Windows 7 operation system. The algorithm is programmed and compiled in MATLAB R2010B.

Table 3 shows a comparison of 3 reduction methods in computation time. When using the rough polarization matrix seismic attributes reduction, the number of the reduction is 1, the computation time of the reduction is 0.00000 sec, the number of correct prediction is 63 and the rate of correct recognition is 78.75%. When using the PCA based seismic attributes reduction, taking a combination of 5 principal components as an example, the computation time of the reduction is 0.000852 sec, the number of correct prediction is 73 and the rate of correct recognition is 91.25%. When using the covering rough set seismic attributes reduction, taking a combination of 5 principal components as an example, the computation time of the reduction is 10.918795 sec, the number of correct prediction is 76 and the rate of correct recognition is 95.00%.

The experiment results showed that the method of the rough polarization matrix seismic attribute reduction can obtain the minimal number of the reduced attributes and have the fast computing speed but lowest accuracy. For the PCA based seismic attributes reduction, its computing speed is slower than former method but the accuracy is much higher. When the number of reduced attributes is same, the computing speed of the PCA based method is much higher than that of the covering rough set based method but the accuracy is lower. The result of the covering rough set seismic attributes reduction is accuracy and effective. It has highest accuracy compared with other two methods but lowest computing speed.

Table 4: Identity results of oil and dry samples

Sample No.	Results	Fitness of PCA based reduction	Fitness of covering rough set reduction
S1	Oil	√	√
S2	Oil	√	√
.	.	.	.
S29	Oil	√	√
S30	Oil	×	×
S31	Oil	×	√
S32	Oil	×	√
S33	Oil	√	√
.	.	.	.
S36	Oil	√	√
S37	Oil	×	×
S38	Oil	×	√
S39	Oil	×	×
S40	Oil	×	×
S41	Dry	√	√
S42	Dry	√	√
.	.	.	.
S80	Dry	√	√

√: Correct, ×: False

Practical application: In order to further illustrate this problem, take the PCA based seismic attributes reduction and the covering rough set attributes reduction as examples, respectively. Table 1, a seismic attribute decision table, is derived from X region in Junggar Basin. This region is located in the delta front in the middle Jurassic which help to form the lithologic trap so, it is a favorable area to deepen exploration of lithologic stratigraphic reservoirs. Compared with the surrounding areas, X region is characterized by weaker tectogenesis, smaller fold amplitude, fault dimension and relatively simple structure. A series of lithologic stratigraphic reservoirs has been discovered in this region which fully shows the potential of exploration in this area. In this experiment, strata C in this area is regarded as the target strata. Table 4 shows the identity results of oil and dry samples.

From Table 4, it is clear that the whole number of test samples is 80. The result of PCA based seismic attributes reduction is that the number of correct is 73 and false is 7.

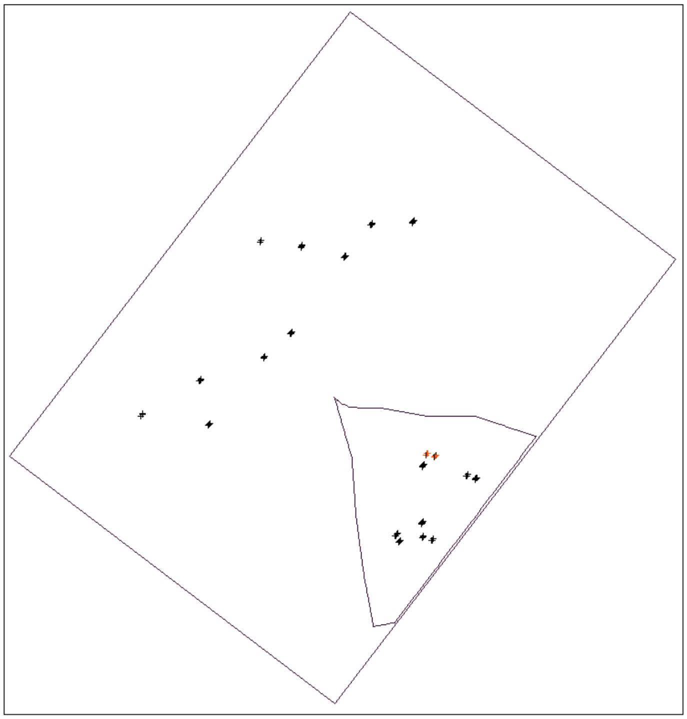

Fig. 1: Result of prediction

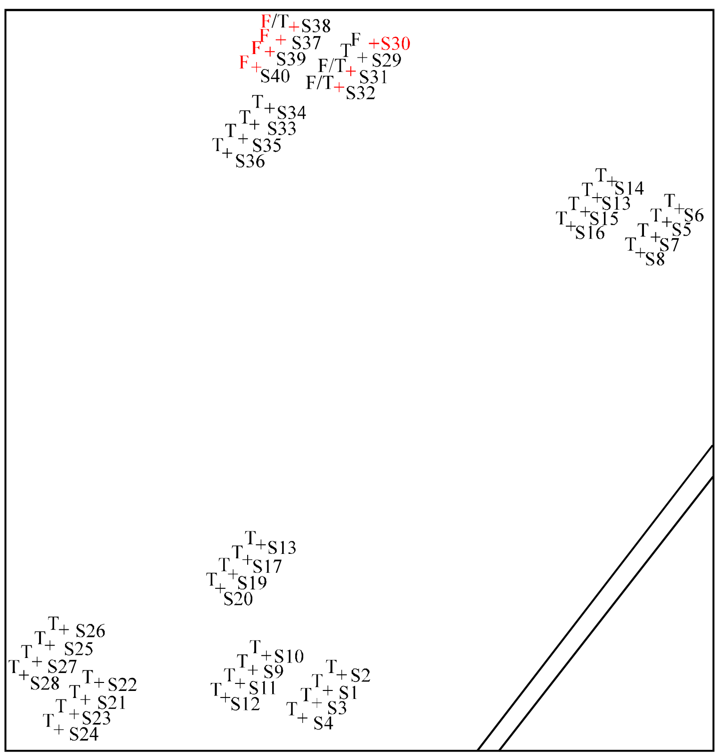

Fig. 2: Partial enlargement of the result of prediction

The result of covering rough set seismic attributes reduction is that the number of correct is 76 and false is 4. Fig. 1 is the result of actual prediction. In this figure, the square denotes 3D work area and the triangles in the square are the proven reservoir area. Figure 2 is a drawing of partial enlargement of the prediction result where, T is the correct sample and F is the false. F/T denotes respectively false samples using the PCA based method and correct one using the covering rough set based method. "+" represents actual sample and S is the sample number. Both results are wrong when using the two methods in S30, S37, S39 and S40. In S31, S32 and S38, the results obtained by the PCA based method is wrong and correct using the covering rough set based method.

CONCLUSION AND PROSPECT

For the results of these three reduction methods above, experts of exploration and interpretation think that is reasonable through their experience and the situation of this area they mastered. At the same time, from seismic attribute meaning perspective, there are no repetitive or similar attributes in seismic attribute sequence after reduction. The results of prediction further show that seismic attribute can not only reduce the multiple solutions but also improve the prediction precision.

The PCA based seismic attributes reduction is a linear approach so, the excellent results can not be obtained when dealing with nonlinear problems. At present, particular for researches of the Support Vector Machine (SVM) were launched, the study of feature extraction method based on kernel function gets increasingly attention. The kernel principal component analysis, a combination of PCA and kernel function, is not only suitable for non-linear problems but also for obtaining more information. To improve prediction accuracy, we will extend PCA based seismic attributes reduction to KPCA based seismic attributes reduction and extend linear approach to non-linear field. Meanwhile, we will take different kernel functions into consideration and introduce high-dimensional wavelet into kernel principal component analysis to enhance the accuracy of seismic attributes reduction.

In addition, in the covering rough set seismic attributes reduction method, the method of discernable matrix is used to deal with seismic attributes reduction. Although it can obtain all kernels and reductions, the time complexity of the method is increased. The maneuverability of method might be weakened when processing large data.

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