SEISMIC MULTI-ATTRIBUTE FUSION USING FAST INDEPENDENT COMPONENT ANALYSIS AND ITS APPLICATION

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ABSTRACT

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Basic principles of independent component analysis (ICA) and fast independent component analysis (FastICA) algorithm are elaborated, and we propose an automatic fusion method of seismic multi-attribute based on FastICA. This method can calculate the transform kernel matrix rapidly using FastICA algorithm to achieve the feature fusion of several seismic attributes in the ICA domain. After that we map the synthesized attribute to the spatial domain to obtain the fusion result. Our method can remove the correlation hidden in high-order statistical characteristics between features. Finally, the application of 3D seismic data in northeastern Sichuan shows the effectiveness and rationality of the proposed method.

KEY WORDS: ICA/FastICA, transform kernel matrix, feature fusion, seismic attributes.

INTRODUCTION

Seismic multi-attribute fusion technology has developed rapidly in recent years, and has been widely used in sedimentary facies analysis, reservoir description, dynamic monitoring of oil reservoir and other fields. It has become the core issue of reservoir geophysics (Raeesi et al., 2012).

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There are many approaches to achieve seismic multi-attribute fusion, such as, the simplest weighted method, multi-attribute linear regression, principal component analysis (PCA) (Kim et al., 2008), artificial neural networks (Malek et al., 2010; Li et al., 2014), wavelet and multi-resolution analysis (Unser et al., 2009), RGBA color fusion (Stokman et al., 2007) and so on. Although the application of these fusion methods has matured, there are still some deficiencies. For example, some weights selection and parameter settings require human intervention, which can lead to an unstable performance of the algorithm.

As an improved method of independent component analysis (ICA), fast independent component analysis (FastICA) can run much faster than ICA. The ICA theory was first proposed by Jutten and Herault (1988). It was applied to blind source separation (BSS) in early period. After that, it was widely used in face recognition (Yang et al., 2007), blind voice signal separation, extraction of medical signal (Chien et al., 2012), image segmentation (Margadan-Mendez et al., 2010) and many other fields. Nikolaos and Tania (2007) applied it into the fusion of different sensors and multi-focus image for the first time, which realized pixel-based and region-based image fusion.

Based on the previous work, we propose to apply FastICA to seismic multi-attribute fusion. In the framework of feature level fusion, new multi-attribute fusion rules and procedures are designed and implemented to eliminate the shortcomings of existing methods. By using FastICA theory, the transform kernel matrix is rapidly calculated, and then the source attributes are transformed into ICA domain through kernel matrix and merged. Thus, the fusion results can be obtained quickly. Our method can further improve the accuracy of seismic reservoir prediction and fluid identification. Algorithm module “Seismic multi-attribute automatic fusion based on FastICA” developed by us has been integrated by the large-scale seismic interpretation system "GeoMountain" developed by CNPC Sichuan Petroleum Geophysical Prospecting Company, and the processing results of the actual data in northeastern Sichuan show that the proposed method is superior to other methods.

METHODOLOGY

Independent component analysis

ICA is a signal processing technique that can extract the independent components from a group of linear mixed signals. The linear model of ICA (Eriksson et al., 2006) is shown in Fig. 1.

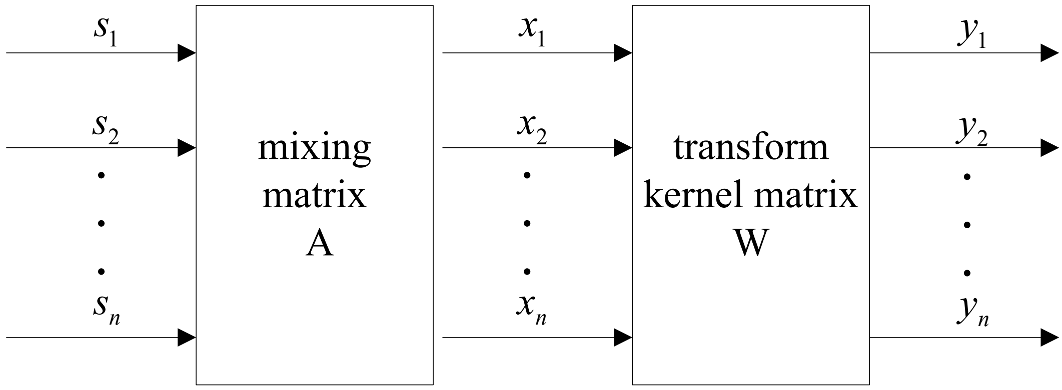


Fig. 1. Linear model of ICA.

In Fig. 1, mixing matrix A represents the mixed mode of independent source signals $\mathrm{s}=(s_1,s_2,\cdots,s_n)^T$, and matrix A is the transform kernel calculated by the FastICA algorithm. Each observed signal x_i is a linear combination of $\mathrm{s}=(s_1,s_2,\cdots,s_n)^T$, and $\mathrm{y}=(y_1,y_2,\cdots,y_n)^T$ are the independent signals extracted from the observed signals $\mathrm{x}=(x_1,x_2,\cdots,x_n)^T$ by the FastICA technology. In the model, the key of FastICA technology is to find the transform kernel matrix A so that the output signals $y_1,y_2,\cdots,y_n$ can approximate the source independent signals $s_1,s_2,\cdots,s_n$ to the utmost extent (Blanco et al., 2005).

We regard each seismic source attribute as a linear combination of several independent attributes. The seismic source attribute can be represented by the observed signal x_i in Fig.1. In order to extract the independent attributes from the seismic source attributes one by one, we use the FastICA algorithm to find out the transform kernel matrix W quickly. From Fig. 1, we know that $\mathrm{x}=\mathrm{As}$. Assuming $y_i=\mathrm{w}^T\mathrm{x}$ and $Q=\mathrm{A}^T\mathrm{w}=\left(q_1,q_2,\cdots,q_n\right)^T$, we can obtain

$$y_i=\mathrm{w}^T\mathrm{x}=\mathrm{w}^T\mathrm{As}=Q^T\mathrm{s}=\sum_{i=1}^{n}q_i s_i, \tag{1}$$

where y_i is a linear combination of s_i, and $q_i \in Q$ represents the weight. When the independence of y_i is the strongest, y_i will be a proper independent attribute feature of seismic source attributes. According to this method, we can find all the proper column vectors and finally obtain the transform kernel matrix W.

In the process of calculating matrix W, we use the negative entropy function to measure the independence so that we can distinguish whether it is the proper column vector (Shen et al., 2008). Negative entropy of random variable y can be defined as

$$J(y) = \int p(y) \log \frac{p(y)}{p_G(y)} dy, \tag{2}$$

where $p_G(y)$ is the probability density function of a Gauss random variable with the same mean value and variance as random variable y, and $p(y)$ is the probability density function of y. To simplify, we use the maximum entropy principle to calculate the negative entropy estimation and can obtain the negative entropy approximate equation

$$J_G(y) \approx [\mathrm{E}\{G(y)\} - \mathrm{E}\{G(v)\}]^2, \tag{3}$$

where v is a standard Gauss random variable, and $G(y) = \log(\cosh(by))/b$, $1 \le b \le 2$ is a non-quadratic function, and $\mathrm{E}[\cdot]$ is a mean operator.

Seismic attributes fusion principles based on FastICA

In this paper, we apply the FastICA algorithm to the multi-attribute fusion. This is because that the correlation between multiple attributes is usually hidden in the high-order statistic characteristics, and FastICA can effectively reduce the high-order correlation and maintain the high-order mutual independence between features. It is better than the classical PCA and singular value decomposition (SVD) (Jha et al., 2011), which can only eliminate second-order correlation.

The FastICA algorithm first preprocesses the seismic source attributes, including removing mean value and whitening, to simplify the following process. The preprocessed attribute data x satisfies the conditions $\mathrm{E}[x] = 0$ and $\mathrm{E}[xx^T] = I$. Then we can select a proper vector w to make the negative entropy function reach the maximum value and thereby the transform kernel matrix W is obtained. Combining $y_i = \mathrm{w}^T x$ with eq. (3), there is

$$J_G(y) = [\mathrm{E}\{G(\mathrm{w}^T x)\} - \mathrm{E}\{G(v)\}]^2 . \tag{4}$$

Because v is a Gauss variable that has the same mean and covariance matrix as v_i, the maximization problem of eq. (4) can be converted into an optimization problem of $\mathrm{E}\{G(\mathrm{w}^T x)\}$. According to the Kuhn-Tucker condition (Primlos et al., 2001), we can solve $\mathrm{E}\{G(\mathrm{w}^T x)\}$ under the condition $\mathrm{E}\{(\mathrm{w}^T x)^2\} = 1$, that is

$$\mathrm{E}\{xg(\mathrm{w}^T x)\} - \beta \mathrm{w} = 0, \tag{5}$$

where $\beta = \mathrm{E}\{\mathrm{w}_0{}^T x g(\mathrm{w}_0{}^T x)\}$ is a constant obtained through the intial value w_0 of w, and Function $g(\cdot)$ is the derivative of $G(\cdot)$. FastICA uses the Newton's method (Dontchev et al., 2010) to solve eq. (5) to get

$$\mathrm{w}(k+1) = \mathrm{w}(k) - \frac{\mathrm{E}\{xg[\mathrm{w}^T(k)x]\} - \beta \mathrm{w}(k)}{\mathrm{E}\{xx^T g'[\mathrm{w}^T(k)x]\} - \beta}, \tag{6}$$

where k represents the iteration number. Eq. (6) is complicated because it involves matrix inversion. Since the preprocessed attribute data satisfies the condition $\mathrm{E}[xx^T] = I$, there is

$$\mathrm{E}\{xx^T g'[\mathrm{w}^T(k)x]\} \approx \mathrm{E}[xx^T]\mathrm{E}\{g'[\mathrm{w}^T(k)x]\} = \mathrm{E}\{g'[\mathrm{w}^T(k)x]\}. \tag{7}$$

Combining eqs. (6) and (7), through simplification we can obtain the following form

$$\mathrm{w}(k+1) = \mathrm{E}\{xg[\mathrm{w}^T(k)x]\} - \mathrm{E}\{g'[\mathrm{w}^T(k)x]\}\mathrm{w}(k). \tag{8}$$

In order to improve the stability of the algorithm, we normalize w(k) after each iteration and judge the iteration termination at last.

The algorithm in (8) just estimates one independent component. We need to run the algorithm (8) using several vectors $\mathrm{w}_1, \mathrm{w}_2, \cdots, \mathrm{w}_n$ to get the whole transform kernel matrix W. Through the above discussion we can summarize the basic procedure of FastICA algorithm (Hyvarinen, 1997, 1999) as follows with Fig. 2:

(1) Get the preprocessed attribute data x, including removing mean value and whitening;

(2) Select initial vector w_0 randomly and let $k = 0$;

(3) Calculate $\mathrm{w}_i(k+1)$ according to eq. (8);

(4) Normalize $\mathrm{w}_i(k+1) = \mathrm{w}_i(k+1) / \|\mathrm{w}_i(k+1)\|$;

(5) Judge the iteration termination. If $|\mathrm{w}_i(k+1) - \mathrm{w}_i(k)| < \varepsilon$ is not valid, k pluses one and return to step (3). Otherwise iteration ends, and output $\mathrm{w}_i(k+1)$ ($i = 1, 2, \cdots, n$) gives one of the rows of the matrix W.

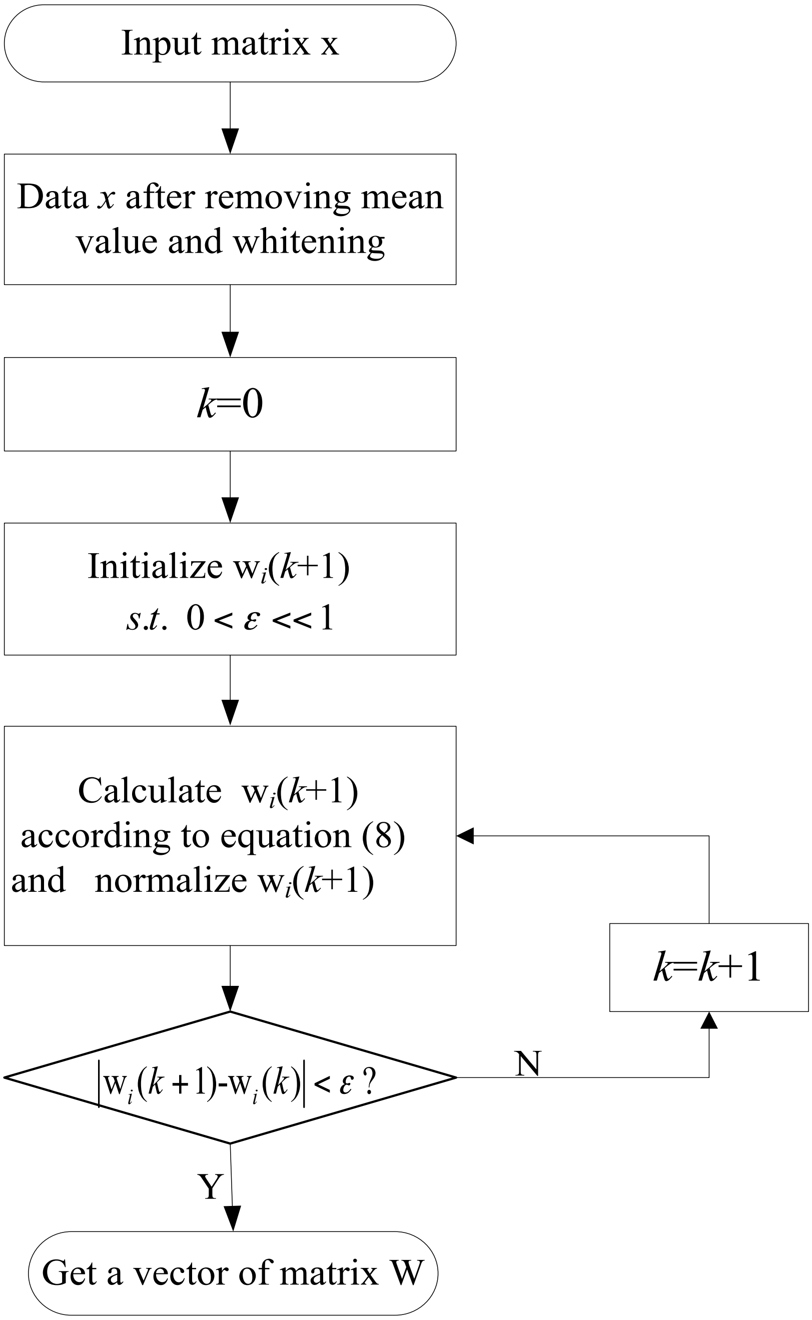


Fig. 2. Flowchart of using FastICA to calculate transform kernel matrix W.

MULTI-ATTRIBUTE FUSION

Using FastICA algorithm to realize seismic multi-attribute fusion, we assume that $f(\cdot)$ represents the fusion rule and $I_1, I_2, \cdots, I_n$ are seismic attributes to be good fused. Fusion in the ICA domain can be presented by

$$I_{\mathrm{f}}(\cdot) = f(I_1, I_2, \cdots I_n) \ . \tag{9}$$

The entire process can be summarized as

$$I_{\text{fusion}}(\cdot) = \mathrm{T}^{-1}\left\{f(\mathrm{T}\{I_1\},\mathrm{T}\{I_2\},\mathrm{L}\ \mathrm{T}\{I_n\})\right\}. \tag{10}$$

The fusion process will be described in detail below. Fig. 3 is the flowchart of seismic multi-attribute fusion based on FastICA.

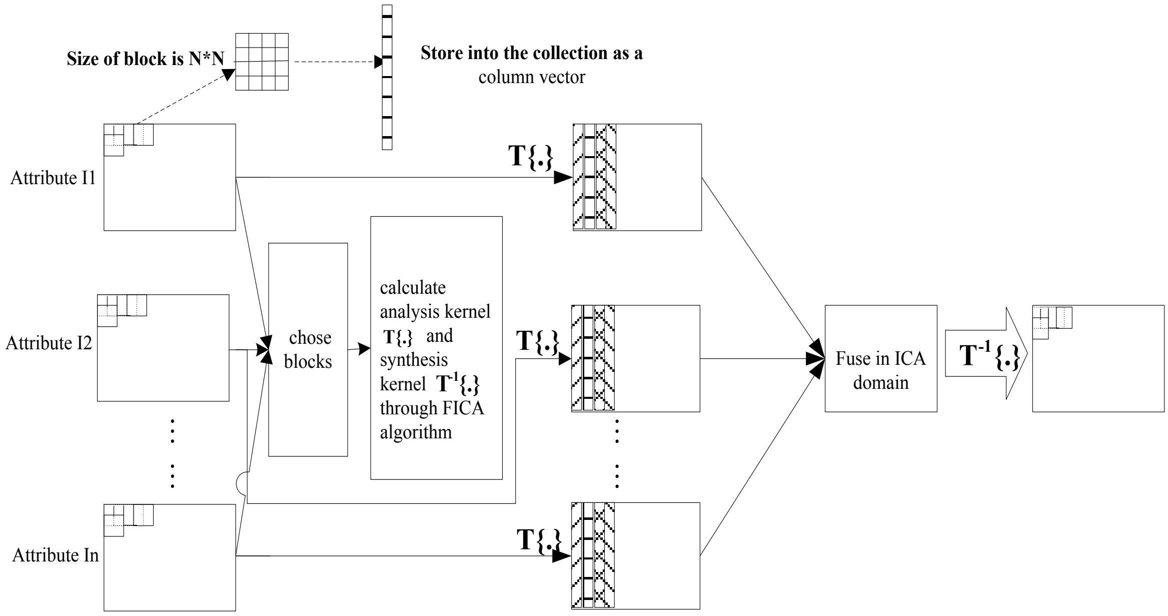


Fig. 3. Flowchart of seismic multi-attribute fusion using FastICA.

(1) Divide source attributes data into patches.
Assume that *n* source attributes will be fused and each attribute data is a matrix with a size of $M1\times M2$. Select a rectangular sliding window *W* with a size of $N\times N$ to divide each source attribute into *m* patches. The patches of each source attribute are stored as a N^2-dimensional column vector in collection $C=\left\{I_{11},I_{12},\cdots,I_{1m},I_{21},I_{22},\cdots,I_{2m},\cdots,I_{n1},I_{n2},\cdots,I_{nm}\right\}$, where $I_{ij}(i=1,2,\cdots,n,j=1,2,\cdots,m)$ represents the column vector obtained from the *j*-th patch of *i*-th source attribute. The size of collection *C* is $N^2\times(n\times m)$.

(2) Randomly select *p* column vectors from the collection *C*.

(3) Calculate the transform kernel matrix in ICA domain.
The selected column vectors make up a matrix x as the input of FastICA algorithm and to obtain the transform kernel $\mathrm{T}\{\cdot\}$, i.e., matrix W shown in Fig. 2.

(4) Map the source attributes from the spatial domain to the ICA domain by multiplying the transform kernel $\mathrm{T}\{\}$ and the attributes data.
Remove the mean value of each column of collection C and we can obtain $C' = \{I'_{ij}\}$. Mean value of each column makes up a vector $M = \{m_{ij}\}$. Map the attribute patches from the spatial domain to ICA domain through $s_{ij} = \mathrm{T}\{\} \times I'_{ij}$.

(5) Fusion in the ICA domain.
When source attributes is mapped to the ICA domain, the fusion results can be obtained using

$$F_j = \sum_{i=1}^{n} \frac{|s_{ij}| \cdot s_{ij}}{\sum_{j=1}^{n} |s_{ij}|} . \tag{11}$$

Eq. (11) is the fusion rule used in the ICA domain. s_{ij} is the j-th column of the i-th attribute slice in the ICA domain. According to eq. (9), we can get the fusion result of all the attribute patches.

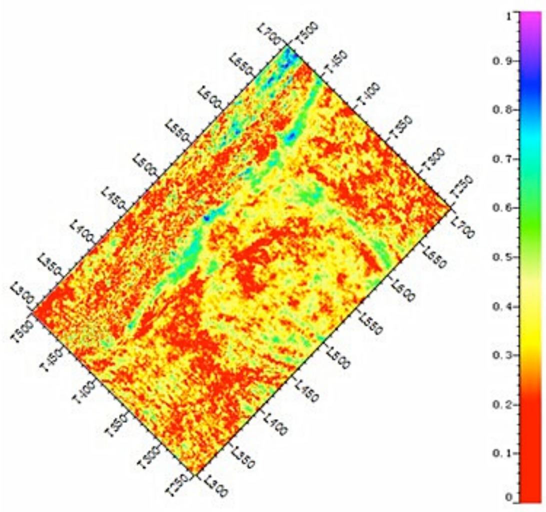
(6) Map the fusion result from the ICA domain to the spatial domain by multiplying the fusion result F in the ICA domain and the inverse transform kernel $\mathrm{T}^{-1}\{\cdot\}$.
The fusion result of the j-th attribute patch in the spatial domain can be obtained through

$$MF_j = \mathrm{T}^{-1}\{\cdot\} \times F_j + \frac{1}{n} \sum_{i=1}^{n} m_{ij} . \tag{12}$$

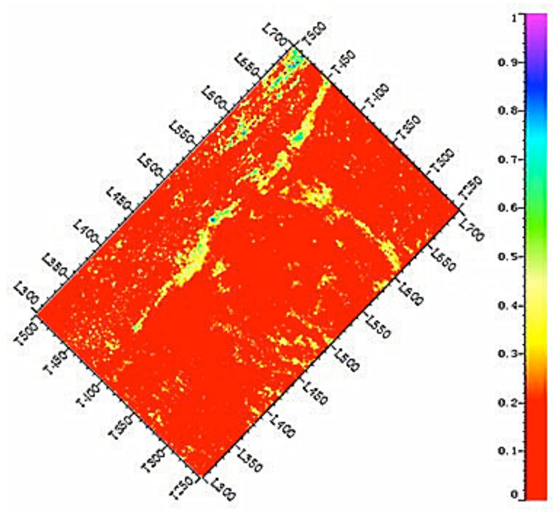
According to eq. (12), we can get all the patches in the spatial domain. Use the averaging method to process the overlapped area and get the final fusion result.

APPLICATION AND ANALYSIS

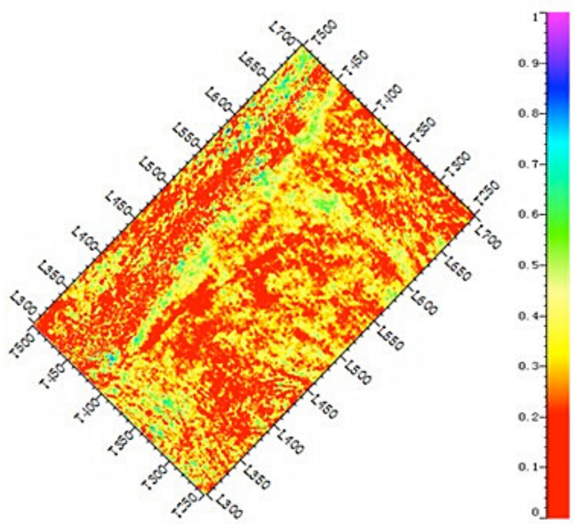
In order to verify the effectiveness of our method, we use a 3D seismic attribute data in northeastern Sichuan region for testing. Since different attributes have different magnitude, a data standardization is required first. We select Root Mean Square amplitude, Frequency Attenuation Gradient and Average Energy as the three source attributes to be fused, which are regarded suitable by geological experts. The Root Mean Square amplitude can show the stratification of lithology and lithological changes. Besides, it can identify amplitude anomalies and describe sequence. It can also be used to track seismic anomaly, such as amplitude anomalies caused by delta, watercourse or gas sand, and differentiate integrated sediment, hummocky sediment and messy sediments and the oil and gas reservoir prediction (Xie et al., 2014). As a low frequency band shadow, Frequency Attenuation Gradient has been proven to be an effective fluid factor. It is sensitive to hydrocarbons and is a derived attribute based on the spectral decomposition, which can do hydrocarbon detection directly. It is an ideal attribute for gas detection and mainly applied to detect low-frequency gas sand and chasm especially suitable for thin reservoir. Average Energy can identify amplitude anomalies or sequence characteristics and identify lithology and gas sand changes effectively. It is a common attribute to predict hydrocarbon potential (Rezvandehy et al., 2011). Fig. 4 shows the time-slicing slices of the selected three attributes, belonging to the reservoir in the second section of Feixianguan group called Ertan. The size of data matrix is 401×251. It can be seen from Figs. 4(a)-(c) that any single attribute cannot describe the reservoir plane characteristics completely, and it cannot satisfy the accuracy requirements of reservoir prediction and fluid detection. Therefore, we use our method to fuse the three attributes to realize the complementation of advantages between attributes.



(a) RMS amplitude



(b) Average energy



(c) Frequency attenuation gradient

Fig. 4. Source seismic attributes.

In order to verify the validity of the method, we do the contrast test and analysis through the conventional PCA method and our method in this paper. Fig. 5 shows the fusion result of the above three attributes fused by PCA method. Fig. 6 shows the fusion result of the above three attributes fused by our method.

It is not hard to see that the fusion results of both PCA and FastICA method are superior to any single attribute in Fig. 4 in describing the characteristics of the riverway. But the color distribution of the PCA result (Fig. 5) is relatively simple, and some details of the information are lost. By contrast, the fusion result of our method (Fig. 6) is rich in detail components. It is easier for interpreters to delineate favorable areas. Since entropy reflects the amount of information, a larger information entropy means more information in image fusion. So entropy is introduced (Zheng et al., 2008) to evaluate the results quantitatively, defined as

$$H(x) = -\sum p(x)\log_2 p(x), \tag{13}$$

where x is the fusion result, and $p(x)$ is the probability density function of x.

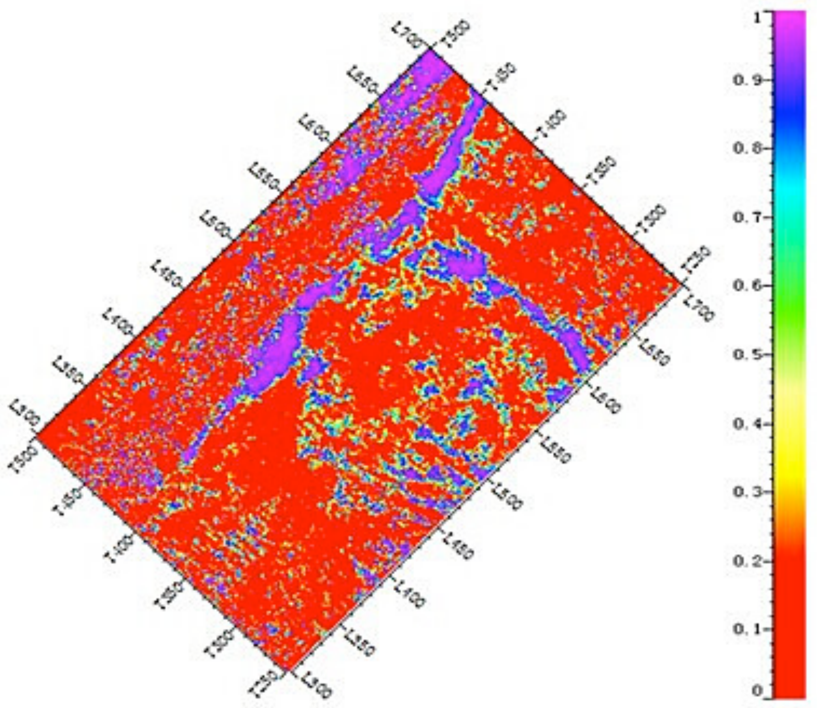


Fig. 5. Fusion result by PCA.

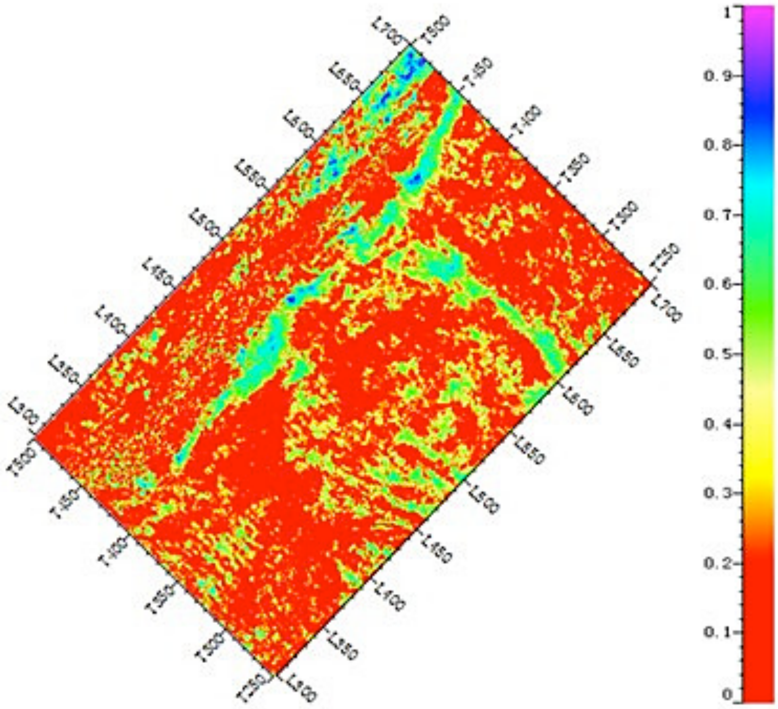


Fig. 6. Fusion result by our method.

Table 1. Quantitative evaluation of fusion results.

fusion method	PCA	FastICA
entropy	6.5690	7.0764

As we can see from Table 1, the entropy value of the fusion result by our method is larger than that of PCA method, which shows that the FastICA result has more information than the PCA result. Purple area represents the main part of the riverway and red area represents background in Fig. 5. Since the PCA fusion process does not include the attribute features corresponding to smaller eigenvalues, only the main components are extracted to participate in fusion, which destroyed the integrity of source information, resulting in loss of background details in the fusion result. And from the comparison of Fig. 5 and Fig. 6, we can see that Fig. 6 not only clearly shows the backbone of the riverway, but also shows the clear background without the influence of clutter. It is obvious that FastICA better maintains the integrity of source information because the fusion process does not remove the features corresponding to smaller eigenvalues and highlights the high frequency components and details of each source attribute. Fusion result is rich in detail and is closer to the real reservoir information. Fig. 4(b) shows the distribution of "average energy". Although it shows the outline of the riverway clearly, the width of the riverway is cut and background information is lost. Fig. 4(a) and 4(c) can fully display the backbone of the riverway, but there are too much clutter in the background, blurring the main reservoir characteristics. Fig. 6 not only depicts the backbone of the riverway clearly but also eliminated the clutter in the background, making the background information clear. So the fusion result by FastICA is closer to the real reservoir information. Tests show that our method can effectively integrate multiple attribute characteristics and remove the redundancy between attributes. The fusion results can better highlight the reservoir sand information and emphasize energy distribution, which can provide interpreters or computers with scientific basis to analyze reservoir characteristics automatically and solve the multi-solution problem of single attribute reservoir prediction.

CONCLUSIONS

We introduced the FastICA algorithm into seismic multi-attribute fusion in this paper. The transform kernel matrix and the synthesis matrix are calculated by FastICA algorithm so that the ICA decomposition of seismic attributes can be realized quickly. According to certain rules, a variety of attributes are fused into an integrated attribute in the ICA domain. Algorithm module "Seismic multi-attribute automatic fusion based on FastICA" developed by us has been integrated to a large seismic interpretation system called GeoMountain of CNPC Sichuan Petroleum Geophysical Prospecting Company. The processing results are verified by the actual data in the northeast of Sichuan and are superior to other methods. The major advantage of our method is that it can automatically eliminate redundancy between the seismic multiple attributes and highlight the fine features. The fused attribute can highlight the abnormal characteristics of reservoir hydrocarbon to improve the accuracy of reservoir prediction. In addition, our method is simple, fast and effective. Theoretically, it can realize the fusion of any number of attributes. And the fusion rules and parameters selection are flexible, which can avoid factitious interference factors of the conventional methods. Therefore, it has certain application value in lithology section analysis, description and prediction of reservoir space.

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REFERENCES

Blanco, D. and Mulgrew, B., 2005. ICA in signals with multiplicative noise. IEEE Transact. Sign. Process., 53: 2648-2657.

Chien, J.T. and Hsieh, H.L., 2012. Convex divergence ICA for blind source separation. IEEE Transact. Audio Speech Lang. Process., 20: 302-313.

Dontchev, A.L. and Rockefeller, R.T., 2010. Newton's Method for Generalized Equations: a Sequential Implicit Function Theorem. Mathematical Programming, 123: 139-159.

Eriksson, J. and Koivunen, V., 2006. Complex random vectors and ICA models: Identifiability, uniqueness, and eparability. IEEE Transact. Inform. Theory, 52: 1017-1029.

Hyvarinen, A., 1997. A family of fixed-point algorithms for independent component analysis. IEEE Internat. Conf. Acoust. Speech Signal Process., 5: 3917-3920.

Hyvarinen, A., 1999. Fast and robust fixed-point algorithms for independent component analysis. IEEE Transact. Neural Netw., 10: 626-634.

Jutten, C. and Hérault, J., 1988. Une solution neuromimétique au problème de séparation de sources. Traitem. Signal, 5: 389-403.

Jha, S.K. and Yadava, R.D.S., 2011. Denoising by singular value decomposition and its application to electronic noise data processing. IEEE Sensors J., 11: 35-43.

Kim, Y.G., Song, Y.J., Chang, U.D. and Kim, D.W., 2008.. Face recognition using a fusion method based on bidirectional 2DPCA. Appl. Mathemat. Computat., 205: 601-607.

Li, Q.Z., Peng, Z.M., Zhou, J.J. and Zhang, P., 2014. Seismic multi-attribute fusion based on pulse coupled neural networks. Oil Geophys. Prosp., 49: 316-321.

Malek, A. and Yashtini, M., 2010. Image fusion algorithms for color and gray level images based on LCLS method and novel artificial neural network: Neurocomput., 73: 937-943.

Margadan-Mendez, M., Juslin, A., Nesterov, S.V. and Kalliokoski, K., 2010. ICA based automatic segmentation of dynamic $H_2{}^{15}O$ cardiac PET images. IEEE Transact. Inform. Technol. Biomed., 14: 795-802.

Mitianoudis, N. and Stathaki, T., 2007. Pixel-based and region-based image fusion schemes using ICA bases. Informat. Fusion, 8: 131-142.

Primlos, J.A. and Giannelli, M., 2001. Kuhn-Tucker-based stability conditions for systems with saturation. IEEE Transact. Automat. Contr., 46: 1643-1647.

Raeesi, M., Moradzadeh, A., Doulati Ardejani, F. and Rahimi, M., 2012. Classification and identification of hydrocarbon reservoir lithofacies and their heterogeneity using seismic attributes, logs data and artificial neural networks. J. Petrol. Sci. Engineer., 82: 151-165.

Rezvandehy, M., Aghababaei, H. and Raissi, S. H., 2011. Integrating seismic attributes in the accurate modeling of geological structures and determining the storage of the gas reservoir in Gorgan Plain (North of Iran). J. Appl. Geophys., 73: 187-195.

Stokman, H. and Gevers,T., 2007. Selection and fusion of color models for image feature detection. IEEE Transact. Patt. Analys. Mach. Intellig., 29: 371-381.

Shen, H., Kleinsteuber, M. and Huper, K., 2008. Local convergence analysis of FastICA and related algorithms. IEEE Transact. Neural Netw., 19: 1022-1032.

Unser, M., Sage, D. and Van De Ville, D., 2009. Multiresolution monogenic signal analysis using the Riesz-Laplace wavelet transform. IEEE Transact. Image Process., 18: 2402-2417.

Xie, C.F., Peng, Z.M., Zhou, J.J., Zhang, P. and Zhang, W., 2014. Seismic multi-attribute fusion based on contourlet transform. Oil Geophys. Prosp., 49: 739-744.

Yang, J., Zhang, D. and Yang, J., 2007. Constructing PCA baseline algorithms to reevaluate ICA-based face-recognition performance. IEEE Transact., Man, Cybernet., Part B (Cybernetics), 37: 1015-1020.

Zheng, Y., Qin, Z., Shao, L. and Hou, X., 2008. A novel objective image quality metric for image fusion based on Renyi entropy. Informat. Technol., 7: 930-935.