A combined approach based on MAF analysis and AHP method to fault detection mapping: A case study from a gas field, southwest of Iran

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A R T I C L E  I N F O
Article history:
Received 21 January 2016
Received in revised form 16 October 2017
Accepted 9 November 2017
Available online 14 November 2017

Keywords:
Min/Max Auto-correlation Factor (MAF)
Analytical Hierarchy Process (AHP)
Fault Detection Map (FDM)
Gas field
Geostatistics

A B S T RACT
A combined geostatistical methodology based on Min/Max Auto-correlation Factor (MAF) analysis and Analytical Hierarchy Process (AHP) is presented to generate a suitable Fault Detection Map (FDM) through seismic attributes. Five seismic attributes derived from a 2D time slice obtained from data related to a gas field located in southwest of Iran are used including instantaneous amplitude, similarity, energy, frequency, and Fault Enhance Filter (FEF). The MAF analysis is implemented to reduce dimension of input variables, and then AHP method is applied on three obtained de-correlated MAF factors as evidential layer. Three Decision Makers (DMs) are used to construct PCMs for determining weights of selected evidential layer. Finally, weights obtained by AHP were multiplied in normalized valued of each alternative (MAF layers) and the concluded weighted layers were integrated in order to prepare final FDM. Results proved that applying algorithm proposed in this study generate a map more acceptable than the each individual attribute and sharpen the non-surface discontinuities as well as enhancing continuity of detected faults.

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1. Introduction
The subtle faults are among of geological or exploration important targets and usually not obviously detected by conventional seismic sections and time slices displays. Identifying faults and other trace-to-trace discontinuities is essential in successful characterization and mapping of prospect zones both in exploration and production steps. Although the seismically resolvable faults could be interpreted using traditional diagnostic criteria (e.g. abrupt reflector cut off, kinks etc.), the subtle faults can be interpreted more successfully by the use of seismic attributes (Bahorich and Farmer 1995; Chopra and Marfurt, 2007; Greszenkorn and Marfurt, 1999; Marfurt, 2006). Seismic attributes form an important part of qualitative interpretative tools that facilitates structural and stratigraphic interpretation. Due to the importance of identifying fault zones, creating a Fault Detection Map (FDM) seems to be suitable idea for reducing the risk of placing wells within productive zones.

Statistical analysis of seismic attributes is a promising approach to extract useful information from data and improve the accuracy of interpreting studies. Dumay and Fournier (1988) utilized a combined statistical analysis based on the principal component analysis (PCA) and the discriminant factor analysis to identify the seismic facies. MAF analysis de-correlates variables and Desbarats and Dimitrakopoulos (2000) used this property in order to simulate the variables independently to avoid the LMC. Hashemi and Javaherian (2009) used a statistical feature extraction technique for choosing proper seismic attributes in seismic interpretations. Shakiba et al. (2015) have detected fault and non-fault zones based on MAF approach and fuzzy logic method.

Generating a suitable Fault Detection Map (FDM) deals with the evaluation of different criteria as well as various seismic attribute and can be considered as a multiple criteria decision making (MCMD) problem. The Analytical Hierarchy Process (AHP) developed by Saaty (1980) has been widely used in different applications as MCDM approach. The conventional form of AHP has the advantage of simplicity and is based on the judgment and knowledge of expert Decision Makers (DMs) on existing measurements.

In this study an application of AHP method is presented to improve the process of detecting faults from seismic attributes and creating a FDM. Five post-stacked seismic attributes are derived from a selected time slice of 3D seismic data related to a fractured gas field located in southwest of Iran. Using Max/Min Auto-correlation Factor (MAF) analysis, three de-correlated factors are extracted from selected attributes and used as input (evidence layers) for AHP method. Employing AHP method provides the weights belonged to each evidence layer and finally weighted layers are combined to generate a suitable FDM.

2. Methodology
The following sections describe techniques used in this study.
2.1. Min/Max Auto-correlation Factor (MAF) analysis

The MAF analysis is used for spatial de-correlation of attributes. The methodology followed in this study is based on Desbarats and Dimitrakopoulos (2000) which include two main steps: first, applying standard PCA using a particular LMC for input attributes. The second step is defining MAF factors by further rotating the PCA factors using eigenvectors of V by defining:

\[ F_{\text{MAF}}(u) = Q_1Y_{\text{PCA}}(u) = Q_1A^{-1/2}QZ(u) = MZ(u) \]  

For more explanation, assume linear model of coregionalization of attributes is defined as:

\[ \Gamma_x(h) = \sum_{k=1}^{s} B_k \gamma_k(h) \]  

where \( \gamma_k \) is the sill of the variograms and the number of nested structure is shown by K index. B is variance-covariance matrix related to \( \gamma_k \) defined as:

\[ B = Q^T \Lambda Q \]

Matrix Q is orthogonal and describes by contains (the eigenvalues) of Matrix B. Also A is diagonal matrix and describes eigenvalue of matrix B.

The PCA de-correlated factors are then defined in lag equal to zero (h = 0):

\[ Y_{\text{PCA}}(u) = \Lambda^{-1/2}QZ(u) = AZ(u) \]

Therefore the variogram matrix given by:

\[ \Gamma_{y_{\text{PCA}}}(h) = A\Gamma_x(h)A^T = \sum_{k=1}^{s} AB_k A^T \gamma_k(h) \]

The second rotation implies that the LMC for MAF factor is:

\[ \Gamma_{\text{MAF}}(h) = \Lambda_1 \gamma_1(h) + (I-\Lambda_2) \gamma_2(h) \]

where \( \gamma_1 \) has smaller range than \( \gamma_2 \).

Therefore, the MAF factors can effectively reduce the data dimension by eigenvalue matrix.

2.2. Analytical Hierarchy Process (AHP) method

The Analytical Hierarchy Process (AHP) was firstly introduced by Saaty in (1980). The typical AHP method involves the three main steps including constructing a hierarchy of problem under study, calculating priority weights, and measuring consistency of pairwise comparison matrices (Macharis et al., 2004). The method starts with dividing the problem into a hierarchy of criteria. In each hierarchical level, weights of the elements are computed regarding their pairwise relative importance with respect to the objective of a decision making process. Finally, a decision on the final goal can be made using weights of criteria and alternatives.

2.2.1. Constructing hierarchy

Defining a hierarchical orders help to simplify the illustration of the problem and show the relationships of the goal, criteria, and alternatives. Therefore, a classic hierarchy comprises at least three levels, the goal(s), the criteria, and the alternatives.

2.2.2. Calculating priority weights

In order to determine evidential weights of criteria and alternatives, the pairwise comparison method should be implemented. Using this strategy, all criteria will be compared to each other and their importance defined through employing a system of numbers defined by Saaty (1980) to specify how much one criterion is more important than the other. The above mentioned numerical scale values are shown in Table 1 (Saaty, 1980).

Suppose \( C = \{C_j|j = 1, 2, \ldots, n\} \) be the set of criteria. The pairwise comparisons of n criteria can be shown in an \( n \times n \) evaluation matrix as follow (Dagdeviren, 2008; Boroushaki and Malczewski, 2008):

\[ A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \quad a_{ij} = \frac{1}{a_{ij}} \text{if } a_{ij} \neq 0; \]

where \( a_{ij} \) defined the preference of element \( i \) to element \( j \).

There are several techniques can be used for determining relative weights. The Lambda max technique is a well-known method for determining the weights of criteria in pairwise comparison process. Using this approach, a vector of weights \( w \) is defined as the normalized eigenvector corresponding to the largest eigenvalue \( \lambda_{\text{max}} \):

\[ A w = \lambda_{\text{max}} w \]

where A is the pairwise comparison matrix of the criteria. For the case of consistent pairwise comparisons, the matrix A has rank 1 and \( \lambda_{\text{max}} = n \). Consequently, weights can be obtained by normalizing any of the rows or columns of A matrix.

2.3. Measuring consistency

Consistency of the pairwise comparison judgments determines the confidence of results. The consistency is defined by the relationship between the entries of A as follow:

\[ a_{ij} \times a_{jk} = a_{ik} \]

When the PCMs are completely consistent, the highest eigenvalue \( (\lambda_{\text{max}}) \) is equal to \( n \). In the case of inconsistency, the deviation \( (\lambda_{\text{max}} - n) \) is used as an appropriate measurement of inconsistency. Due to dependency of \( (\lambda_{\text{max}} - n) \) to dimension, the Consistency Index (CI) is defined by:

\[ C \cdot I = \frac{\lambda_{\text{max}} - n}{n-1} \]

To check whether the evaluation are reliable or not, Consistency Ratio (CR) is suggested in Eq. (11):
With R.I is random index and depended to dimension of criteria and defined in Table 2.

The value 0.1 is the accepted upper limit for the systems’ consistency. If the final CR exceeds this value the process of evaluation should be repeated again.

3. The study area and selected seismic attributes

The study area is a gas field located in southwest of Iran. The focus of this study is on Gotnia Formation which consists of Jurassic siliciclastic rocks. A 3D seismic survey was performed in the studied area which covers the area of 500 km². Data were sampled at an interval of 4 ms and stored in SEG-Y format. Fig. 1 shows a time slice at $t = 2900$ ms. As can be seen in this figure, two groups of faults could be identified at angles of about 10° and 90° with respect to the horizon.

Five attributes including Fault Enhancement Filter (FEF), similarity, energy, and instantaneous amplitude were derived from this slice to conduct this study (Fig. 2).

4. AHP prospectivity model

4.1. Applying MAF analysis

Considering several attributes for detecting faults could make the process of generating FDM more complicated and time consuming; therefore, MAF method was applied on selected attributes to reduce the number of variables for creating a suitable FDM. The result is a new set of de-correlated attributes. Since MAF, similar to many

<table>
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<th>2</th>
<th>3</th>
<th>4</th>
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<td>1.12</td>
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Table 2
Random index (RI).

<table>
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<tr>
<th>Energy</th>
<th>FEF</th>
<th>Similarity</th>
<th>Ins. amplitude</th>
<th>Frequency</th>
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<td>0.66</td>
<td>0.88</td>
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<tr>
<td>FEF</td>
<td>0.75</td>
<td>1</td>
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</tr>
<tr>
<td>Similarity</td>
<td>0.76</td>
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<td>1</td>
<td>0.68</td>
</tr>
<tr>
<td>Instantaneous</td>
<td>0.89</td>
<td>0.81</td>
<td>0.71</td>
<td>1</td>
</tr>
<tr>
<td>Amplitude</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
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<td>0.17</td>
<td>0.26</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Table 3
Correlation between attributes before (upper diagonal) and after (lower diagonal) normal score transformation.

Fig. 1. A time slice of used seismic data at $t = 2900$ ms.

Fig. 2. Attributes used in this study a. Energy, b. FEF, c. Instantaneous Amplitude, d. Frequency, e. Similarity.
statistical methods, is based on the assumption of normality; to apply this technique, the normal transform was carried out on values of five selected seismic attributes.

Table 3 shows the correlation between derived attributes before and after applying transformation. Upper diagonal is the original data and lower diagonal shows the correlation coefficients after applying normal score transformation.

The linear model of co-regionalization was then obtained considering two structures, spherical and Gaussian models. Fig. 3 shows the variograms of the other directions. As can be seen, it is show an isotropic system in other directions. It is noteworthy that the variograms in other direction reach to their sill in smaller range (about 2000 m) than fault direction (near to 4000 m).
First structure corresponds to a non-isotropic spherical variogram model with a range of 4 km, with co-regionalization matrix given by

\[
B = Q^T \Lambda Q
\]

where \( \Lambda \) is the eigenvalue matrix. The matrices in the spectral decomposition of \( V = Q_1 \Lambda_1 Q_1 \) are shown as:

\[
\Lambda_1 = \begin{pmatrix}
6.0574 & 0 & 0 & 0 & 0 \\
0 & 1.6310 & 0 & 0 & 0 \\
0 & 0 & 0.0264 & 0 & 0 \\
0 & 0 & 0 & 0.1827 & 0 \\
0 & 0 & 0 & 0 & 0.8835
\end{pmatrix}
\]

Finally, by multiplying \( M \) matrix by attributes, MAF factors were obtained. Fig. 5 displays CDF of the MAF factors that is approximately in normal score form. The factors with the least amount of correlation are selected for employing AHP method. As seen in Fig. 6, MAF1, MAF2 and MAF5 could express almost all of the variation in the data matrix and are approximately de-correlated. This means that the dimension of the variables has been reduced from 5 to 3.

The maps of three selected MAF are shown in Fig. 7. As seen, MAF2 can effectively enhance the location of faults compared to the other factors and ranked first.
Fig. 8 shows the correlation between three selected MAF factors: MAF1, MAF2 and MAF5. According to this figure, the correlations between MAF1, MAF2 and MAF5 are $-0.15$ and $-0.22$.

Table 4

<table>
<thead>
<tr>
<th>CR</th>
<th>Criteria</th>
<th>MAF1</th>
<th>MAF2</th>
<th>MAF5</th>
</tr>
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<tbody>
<tr>
<td>DM1</td>
<td></td>
<td>0.0416</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DM2</td>
<td></td>
<td>0.0583</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DM3</td>
<td></td>
<td>0.0631</td>
<td></td>
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</tbody>
</table>

Fig. 9. Final FDM generated by AHP method and considered section in it.
respectively, which means the de-correlation is achieved. As it was expected, the correlation between the MAFs has to be very small. In other means the MAFs should be de-correlated.

4.2. Weighting to individual evidential layers

Three DMs who are expert in seismic interpretation were employed to determine the weights of each of the three evidential layers (i.e. MAF1, MAF2 and MAF5) by asking proposing questions. They were asked to form individual pairwise comparison matrices (PMCs) by the aim of Saaty’s 1–9 scales. The consistency ratios were then computed and reliable answers were used for the next steps. The consistency ratios resulted from the PCM for applying AHP are presented in Table 4. As it could be seen in Table 4, all consistency ratios are less than 0.1. So, the results are considered to compute weights of each evidence layer.

Fig. 10. Variogram plotting to quantify fault: a) Energy, b) FEF, c) Similarity, d) Instantaneous Amplitude, e) Spectral decomposition, f) MAF1, g) MAF2, h) MAF5 and i) AHP.
To generate final FDM, weights obtained by AHP were multiplied in normalized valued of each alternative (MAF layers). Then, the concluded weighted layers were integrated in order to prepare final FDM. Since the final map should represent the degree of possibility for the presence of the fault, three cut-offs were applied on values in final FDM using its standard deviation ($\sigma$) and mean ($\overline{x}$) and four different classes were defined. The values less than ($\overline{x} - \sigma$) were considered non-fault and values more than ($\overline{x} + 3\sigma$) were considered fault zones. The values of $\overline{x} + 2\sigma$ and $\overline{x} + 3\sigma$ were used to define possible and probable fault zones.

Fig. 9 shows the FDM resulted from applying AHP method on three de-correlated MAF factors.

4.3. Evaluation of generated FDM

To investigate the accuracy of the proposed algorithm in detecting fault zones, variography in fault direction is performed; since there is high correlation between discontinued seismic traces, consequently the sill of variogram would have less value in fault direction. To follow this strategy, a section was applied on final FDM (Fig. 9), and variogram of all attributes was computed in this direction.

The main purpose of showing the variograms (Fig. 10) is to emphasize the fact that the adopted integrated approach in this paper strengthens the fault direction. Compared to the case of using single seismic attribute for fault detection, we suggest an algorithm which combines different attributes in order to enhance the process of fault identification.

Each single attribute can only show a part of the fault and is not able to clearly show the fault path individually. If we draw a variogram for a specific attribute, the concluded variogram reach to its sill faster than the case of employing the combined attributes. That’s why the variogram of MAF factors (which is a combination of different attributes by a mathematical transformation) is different from each single attribute.

Moreover, when we apply the AHP on selected MAF, the similar effect would be seen in the concluded variogram. This means that the method can improve the process of fault detection and it can be examined through the variograms and comparing the sill of each variable. Here, the variogram of considered section on FDM map, gradually reach to the sill.

Furthermore, the variogram of the considered section on FDM map has lesser value compare to the others (about 0.002 in 4000 m), so the fault direction is distinguished very well (Fig. 10 i).

5. Conclusion

Fault detection is one of the key steps in hydrocarbon reservoir characterization. Subtle faults are usually not visibly imaged by the conventional seismic sections and time slices displays. In this paper a new combined approach based on Min/Max Auto-Correlation Factors (MAF) analysis and AHP method was presented to create a fault detection map (FDM).

To this end, five different seismic attributes which are useful for fault detecting and stratigraphy interpretations were derived from a time slice at $t = 2900$ ms. MAF analysis was applied on selected attributes to find important de-correlated factors and reduce the dimension of the data. The factors that show low correlation were selected for applying AHP method. Consequently, three de-correlated MAF, i.e. MAF1, MAF2, MAF5 were chosen as evidential layer for AHP methods. Three expert DMs were given the task of forming pairwise comparison matrices (PCMs) for determining weights of evidence layers and generating final FDM.

Through applying three cut-offs on final FDM, the studied area were divided into four classes representing the likely region for exploring fault.

The concluded map effectively increases the continuity of the fault direction. The results were validated by plotting variograms in identified fault directions.

Moreover, the generated map indicates that applying the proposed algorithm and combining useful attributes provide more acceptable map than single attribute. The obtained results reveal that the proposed technique is a hopeful tool for integrating multiple seismic attributes for fault detection mapping and may be employed in other area for similar cases.

References


