GAS HYDRATE DETECTION IN THE IRANIAN SECTOR OF THE OMAN SEA: APPLICATION OF AVO AND SEISMIC PATTERN RECOGNITION METHODS

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ABSTRACT

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Gas hydrates attracted worldwide attention because of their potential as a new energy reserve in recent years. Therefore their exploration is essential for the strategic future of the world as a new form of energy. In this research we use pre-stack seismic attributes to identify elastic properties of the host sediments in the vicinity of the gas hydrate zone. AVO analysis of pre-stack seismic data is used as a powerful interpretation technique. Moreover, attributes derived in the post-stack seismic domain are used successfully to make a separation between hydrate and non-hydrate sediments by applying pattern recognition and classification methods. It is found that both AVO analysis and seismic pattern recognition techniques are meaningful on a gas hydrate potential zone in the Oman Sea. An integrated scheme is presented for studying similar areas based on joint use of AVO and post-stack attribute analysis.

KEY WORDS: gas hydrate, Oman Sea, AVO, LFDA, seismic attributes, pattern recognition.

INTRODUCTION

Gas Hydrates are known as an unconventional energy source formed in the polar zones and deeper parts of the sea. It is a crystalline material composed of water and light hydrocarbons (mainly methane) in which the gas molecules are entrapped in the cage of water molecules (Kvenvolden, 1993).

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The exploration importance of gas hydrates was discussed by Davy (1811). Observation of gas hydrate in pipelines and their blocking effect attracted the attention of scientists in the oil industry (Hammerschmidt, 1934). Their evidence is reported in marine areas of Mexico (Shipley, 1984) and in the Pacific and Atlantic Oceans (Kvenvolden, 1993).

The normal ratio of stored methane in gas hydrate is 1/164 of its total volume at standard pressure and temperature (Kvenvolden, 1998). Gas hydrates contain more than half of the organic carbon of the earth. Therefore, it is assumed that gas hydrates are considered as an enormous source of natural gas and as one of the main future energy resources. Changes in the thermal-pressure regime result in hydrate instability and may cause the release of large amounts of gas in the atmosphere. It also can cause slope failure in the seabed (Thakur, 2011).

Gas hydrates change the seismic properties of their host sediments. Therefore, seismic methods are useful for their identification. Attributes are one of the appropriate seismic tools in the interpretation phase that can be used to characterize gas hydrates. In a seismic attribute specific information from the whole seismic wave field is extracted based on a physical, geometric or analytical measure.

In this research, two categories of attributes will be used. These attributes relate to pre-stack and post-stack seismic data. Pre-stack seismic data can be obtained from one or more common depth points (CDP) and depends on azimuth and offset. In the stacking process a kind of averaging is applied on offset and azimuth direction while the time relations are preserved.

In pre-stack studies, AVO (amplitude variation with offset) attributes have been used to extract seismic properties of gas hydrate sediments. Post-stack attributes are used for the separation of gas hydrate sediments from non-hydrate ones. For this purpose, some attributes combined with a feature selection algorithm named LFDA (local Fisher discriminant analysis).

PRE-STACK STUDY

The most important seismic marker is the bottom simulating reflector (BSR) that is representative of the gas hydrate underlain by either the brine or free-gas saturated sediments. BSR marks the base of the high-pressure and relatively low-temperature zone in which hydrates are stable (Andreassen et al., 1990; Kvenvolden et al., 1998).

BSR shows specific characteristics that make it detectable on seismic sections. Its morphology obeys approximately the seabed reflector topography.

It shows reversed polarity compared to the seabed reflection. BSR cuts across the dipping strata which are not parallel with the water bottom. Because of high acoustic impedance differences between the hydrated sediment and the free gas saturated sediment, BSR is regarded as a strong reflector with high amplitude (Max et al., 2006). There are more attributes related to gas hydrate such as the flat spot and the bright spot.

Geochemists and geologists proved that the deep part of the Oman Sea is a favorable region for the presence and the stability of gas hydrate. BSR and other gas-hydrate related attributes are clearly observed in most of the seismic sections of Oman (Hosseini Shoar et al., 2009). BSR as a gas hydrate indicator on seismic sections is shown with its strong and obvious reflection amplitude (Fig. 1).

The AVO method is a kind of analysis which applies to the seismic sections before stacking. This approach can be used to predict the lithological characteristics and the fluid properties based on the relationship between amplitude versus offset (Huaishan et al., 2009).

AVO is a useful technique for detecting the free-gas below the BSR. Various AVO attributes such as intercept (A) and gradient (B) and their various combinations were computed for the BSR and the free gas below it on seismic sections of the Oman Sea.

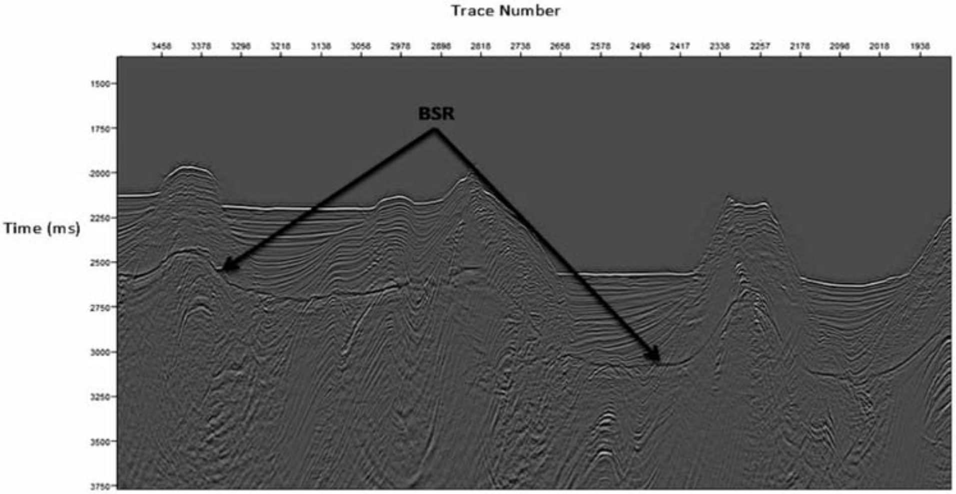

Fig. 1. Signature of gas hydrate on the seismic lines of Oman Sea. High reflection amplitudes following the trend of sea bottom reflection is the BSR.

Theory of AVO

The variation of the P-wave amplitude with offset can be used as a direct hydrocarbon indicator (Ostrander, 1984). The basis of AVO analysis is described by the Zoeppritz equations. The reflection and transmission amplitude changes with the incident angle (offset) is formulated in these equations. As the direct solution of the Zoeppritz equations is not possible, there are many approximations for solving these equations.

The Aki-Richards (1980) approximation linearizes the Zoeppritz AVO equation as below:

$$R(\theta) = A + B\sin^2(\theta) \quad , \tag{1}$$

where $R(\theta)$ is the reflection coefficient, θ is the incident angle, A is the P-wave reflection coefficient at normal incidence, and B is the gradient. AVO inversion is done based on eq. (1).

The input data were the NMO-corrected CDP gathers and the seismic velocity model data. The processing sequence was: geometry assignment, true amplitude recovery, static correction, linear noise attenuation, predictive deconvolution, first step velocity analysis, residual static correction, second pass velocity analysis, radon demultiple attenuation, final velocity analysis, NMO, stacking and pre-stack migration.

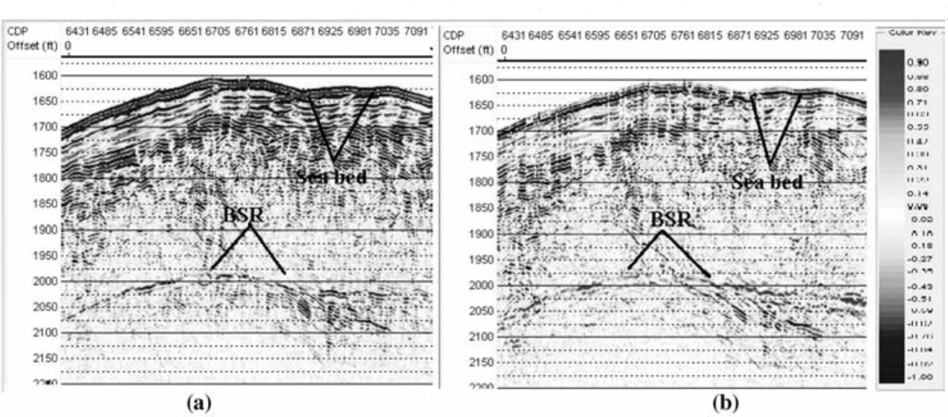

Fig. 2. AVO attributes for a part of a seismic line in Oman. (a) Intercept section. (b) Gradient section.

In Fig. 2, the A-attribute section is shown. "A" implies the P-wave zero-offset reflection coefficient, which indicates the variation of P-wave impedance. The BSR shows negative values in the A profile [Fig. 2(a)] which reveals that the impedance is smaller below the BSR than above the BSR. Acoustic impedance increases in hydrated sediment and decreases in the gaseous zone.

The B-attribute reveals the P-wave reflection coefficient variations with incident angle. In Fig. 2(b), the "B" section shows positive values along the BSR. It indicates that the absolute value of the BSR amplitude decreases with the incident angle. Pre-stack analysis was carried out by the Hampson-Russel software and A, B, A+B, A*B and the fluid factor attribute sections are obtained.

The A+B section [Fig. 3(a)] is an identifier of the Poisson's ratio reflectivity. It shows negative values for the BSR implying that the values of the Poisson's ratio below the BSR are far smaller than theirs above. This coincides with the nature of the BSR and suggests the concentration of the shallower hydrated sediment overlaying the free-gas. Gas hydrate increases the Poisson's ratio by cementing the sediments and hence show a high amplitude reflection. On the other hand in the free gas zone the Poisson's ratio decreases as a result of P-wave velocity reduction. As is seen in Fig. 3(b), the fluid factor also shows negative values for the BSR. According to Fatti (1994), nonzero values of ΔF at the top and the base of the gas zone is expected.

(a) (b)

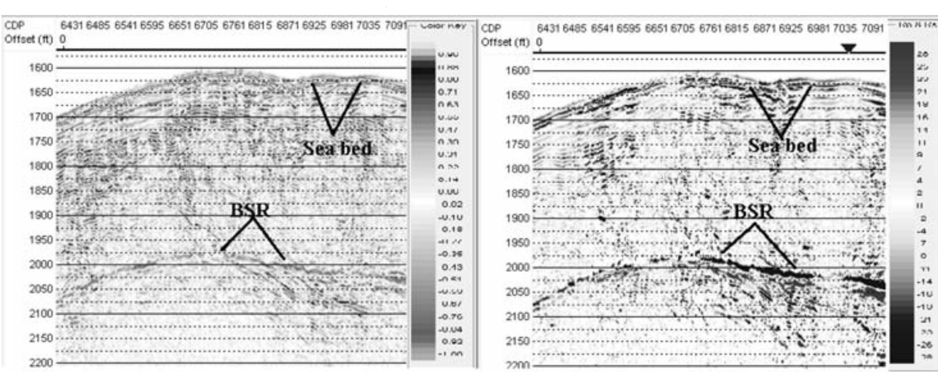

Fig. 3. AVO attributes for a part of a seismic line in Oman. (a) Poisson ratio reflectivity. (b) Fluid factor section.

As is evident in Fig. 4, the absolute value of the amplitude decreases with offset for a selected CDP gather. From a cross plot of intercept versus gradient and amplitude versus offset curves for different CDP gathers type IV of Williams's classification is identified for the BSR. For hydrate saturation above 50%, "A" is highly negative and "B" is positive, which can be classified as an indicator of type IV gas sands (Castagna et al., 1998).

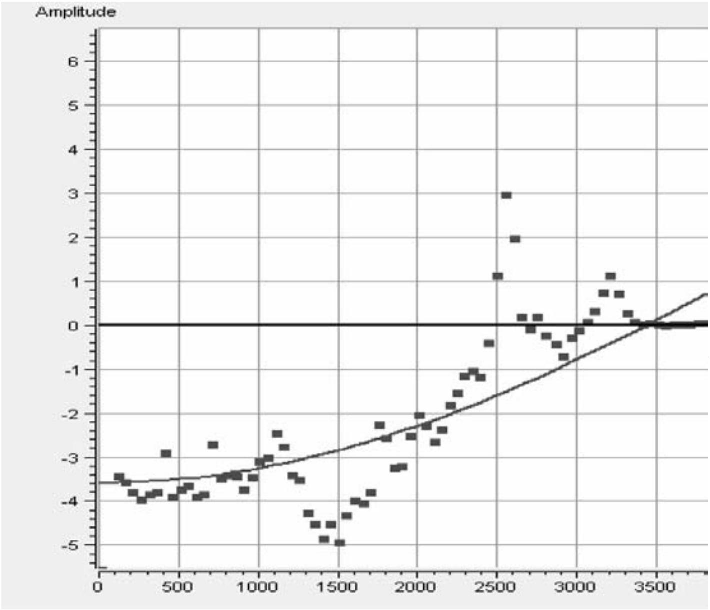

Fig. 4. Cross plot of Amplitude values versus offsets for a selected CDP location. A nonlinear trend fitted to observed data point shows AVO type IV.

Other attribute sections such as P-wave impedance reflectivity, S-wave impedance reflectivity, pseudo Poisson reflectivity, P-wave and S-wave velocity and Lame's constant are obtained as well. Based on these various attribute sections and AVO analysis derived from the angle gathers, the presence of gas hydrate and the free-gas sediment in this area is proven.

POST-STACK STUDY

Identification of BSR in a seismic section together with logical conditions for its formation and stability ensures reporting the presence of gas hydrate with higher confidence. However, in some areas such as the Gulf of Mexico, gas hydrates were explored while there is not any observed BSR (Zhang, 2010). In these cases, it is necessary to investigate other integrated methods to identify gas hydrates precisely.

In this study, seismic attributes have been selected as complementary information for separating hydrate sediments from non-hydrate ones. The process of seismic attributes selection is based on their original classification concept, e.g., physical versus geometric ones. BSR as a continuous reflector is well represented by attributes like instantaneous phase, event and low pass filters. Moreover, the frequency distortion caused by the hydrate sediments is another evidence that frequency-dependent attributes are also relevant in this study. For this purpose, a multi attribute analysis method has been utilized and pattern recognition algorithms - PCA and LFDA - are used in combination with initial attributes. Meta-attributes are then produced with higher efficiency together with accumulated knowledge of the focused seismic pattern (BSR).

Seismic pattern recognition in practice

In multi attribute analysis, two data sets are needed, i.e., test and training (Fig. 5). Training data is used to find an appropriate pattern for the classification. Test data is appropriate to investigate the performance of the obtained pattern. To provide these two sets, a set of labeled data is chosen. In the labeled set the class of each object is determined by the user. A basic assumption in the process of picking is that BSR acts as the boundary of the gas hydrate and non-hydrate sediments.

The training data must be labelled. So, 45 points above the BSR and 45 ones below the BSR are selected. The selection is pretty subjective, i.e., highly dependent on the initial guess of the seismic interpreter. Then bins with dimensions of 11 traces and 12 ms are chosen around each point that form the training dataset.

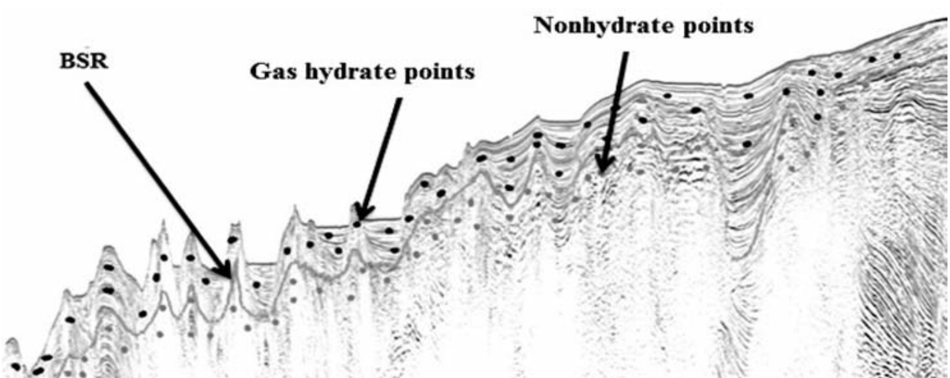

Fig. 5. Process of labeling input data. Dataset in two classes of hydrate and non-hydrate that are picked above and below the BSR respectively.

To study the gas hydrates of the Oman Sea, 27 different seismic attributes related to basic seismic characters - like frequency, phase, amplitude and attenuation - are selected (Table 1). All of these attributes are generated in the OpendTect software.

The value of the initial attributes in each point of the training and test data has been extracted. These values formed a data space with 27 dimensions. More attributes ensure more information about the recorded wave field and thus result in higher accuracy. On the other hand, there are some constraints in the pattern

Table 1. Initial attributes set with their parametrization.

Symbol	Initial attributes with their characters
o_1	**lowpass-20 :** FreqFilter type=LowPass maxfreq=20 isfftfilter=yes window=Hamming fwindow=CosTaper
o_2	**energy-48** : Energy gate=[-48,48]
o_3	**energy-28** : Energy gate=[-28,28]
o_4	**Event** : Event issingleevent=yes tonext=yes output=2`6'
o_5	**average frq** : Frequency gate=[-20,20] normalize=yes window=Hamming
o_6	**Q** : Frequency gate=[-10,10] normalize=yes window=Hamming
o_7	**Max spectral amplitude** : Frequency gate=[-20,20] normalize=yes window=Hamming
o_8	**Average frequency squared** : Frequency gate=[-20,20] normalize=yes window=Hamming
o_9	**spectral decomposition Mexican Hat 30** : SpecDecomp transformtype=CWT cwtwavelet="Mexican Hat"
o_{10}	**spectral decomposition Mexican Hat 40** : SpecDecomp transformtype=CWT cwtwavelet="Mexican Hat"
o_{11}	**spectral decomposition Mexican Hat 50** : SpecDecomp transformtype=CWT cwtwavelet="Mexican Hat"
o_{12}	**spectral decomposition Mexican Hat 60** : SpecDecomp transformtype=CWT cwtwavelet="Mexican Hat"
o_{13}	**spectral decomposition Gaussian 30** : SpecDecomp transformtype=CWT cwtwavelet=Gaussian
o_{14}	**spectral decomposition Gaussian 40** : SpecDecomp transformtype=CWT cwtwavelet=Gaussian
o_{15}	**Variance** : VolumeStatistics stepout=0,2 shape=Ellipse gate=[-20,20] nrtrcs=1
o_{16}	**spectral decomposition Gaussian 50** : SpecDecomp transformtype=CWT cwtwavelet=Gaussian
o_{17}	**spectral decomposition Gaussian 60** : SpecDecomp transformtype=CWT cwtwavelet=Gaussian
o_{18}	**lowpass-30** : FreqFilter type=LowPass maxfreq=30 isfftfilter=yes window=Hamming fwindow=CosTaper
o_{19}	**instantaneous amplitude** : Instantaneous
o_{20}	**instantaneous frequency** : Instantaneous
o_{21}	**instantaneous cos phase** : Instantaneous
o_{22}	**spectral decomposition Morlet 30** : SpecDecomp transformtype=CWT cwtwavelet=Morlet
o_{23}	**spectral decomposition Morlet 40** : SpecDecomp transformtype=CWT cwtwavelet=Morlet
o_{24}	**spectral decomposition Morlet 50** : SpecDecomp transformtype=CWT cwtwavelet=Morlet
o_{25}	**spectral decomposition Morlet 60** : SpecDecomp transformtype=CWT cwtwavelet=Morlet
o_{26}	**Norm Variance** : VolumeStatistics stepout=0,2 shape=Ellipse gate=[-20,20] nrtrcs=1
o_{27}	**Seismic**

recognition discipline. A higher number of input attributes create a more complex space whereas some attributes are redundant and not informative. So it is needed to identify these significant similarities before classification and reduce the dimension of data (Hashemi, 2010). Principal Component Analysis (Jolliffe, 2002) and Local Fisher Discriminant Analysis (Sugiyama, 2007) algorithms are used to achieve this goal. Based on the chosen training set, these algorithms highlight the importance of each attribute in classification with their coefficients. The higher the coefficient the more dominant direction in data spread. With this method a linear combination is made from the initial attributes, called new attributes, which are more efficient for classification. After making new attributes, a neural network is designed and applied to classify the data.

The role of the dimensional reduction method

There are many factors that affect the results of the gas hydrates classification. The choice of the dimensionality reduction method is essential. A proper method can produce some appropriate attributes and results in a reasonable pattern identifying gas hydrate sediments.

In this research, two methods have been applied. The first one is PCA which is an unsupervised method hence no labeling of input data is needed. In PCA the number of new attributes is the same of the initial ones. The new attributes are sorted according to the scattering of the data. The first new attribute is in the direction of lower variance of the scatter plot and so on for the second and the third.

The other method is the LFDA. LFDA is a supervised method (unlike PCA) and hence the training data should have labels. In this method, the user can choose the number of the new attributes. LFDA is the combination of FDA (Fukunagaand, 1990) and LPP(He et al., 2004) methods. It is a proper way for classification of a multi-modal data - that has some clusters - (Sugiyama, 2007).

To compare these methods, training data has been extracted and imported into MATLAB and two different dimensional reduction algorithms (PCA and LFDA) were applied. The plots of the second new attribute in terms of the first new attribute of each method are represented in Fig. 6. LFDA attributes can separate the gas hydrate points from non-hydrate points much better than PCA that shows an overlapping class problem. The first five attributes of PCA, LFDA and all of the 27 initial attributes entered into a neural network architecture separately in three experiments. The neural network had 5 neurons repeated 15 times in the cross validation procedure to achieve better results (Fig. 7).

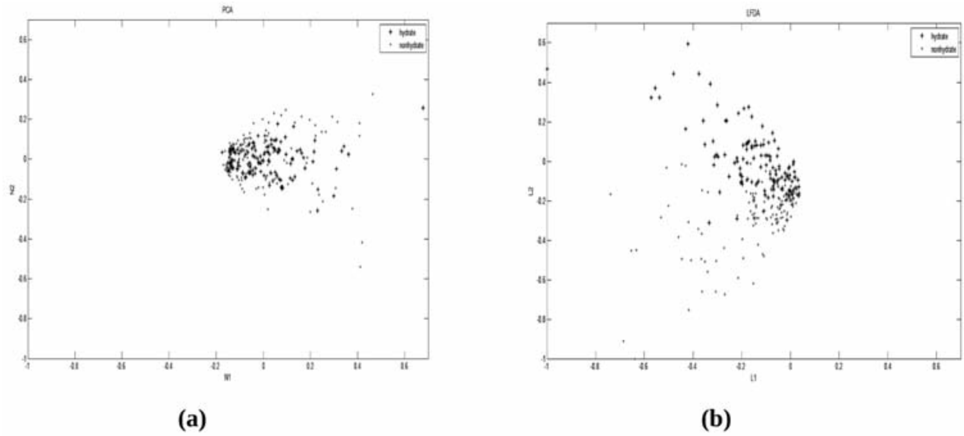

Fig. 6. The cross plot of the first new attribute vs. the second new one for the blue points (hydrates) and the green ones (non-hydrate), (a) LFDA method. L1 and L2 represent the first and the second output attributes of the LFDA (b) PCA method. N1 and N2 represent the first and the second output attributes of the PCA.

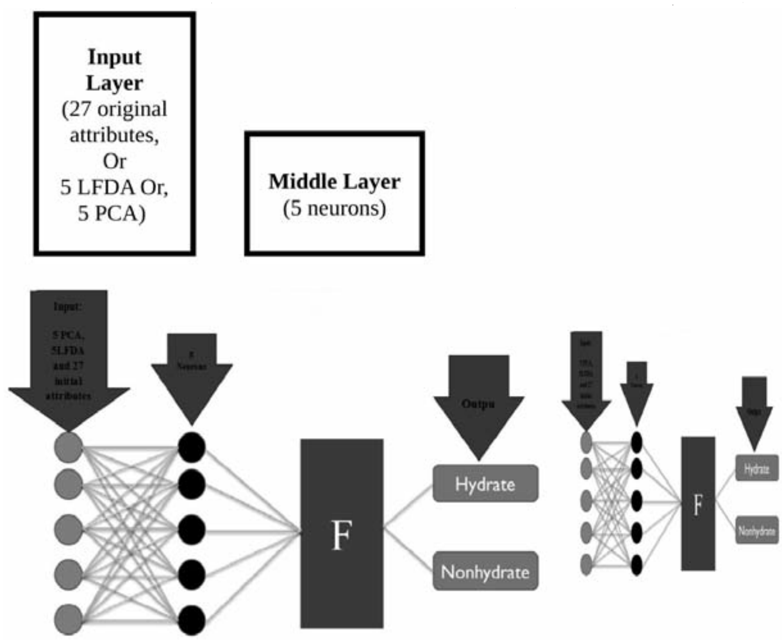

Fig. 7. Scheme of the neural network designed for the pattern recognition. Inputs nodes (left) are either the output attributes of LFDA or PCA. The nodes also can be original 27 attributes. Outputs nodes (right) are the classified patterns of the hydrate and non-hydrate points. This neural network has 5 neurons and repeated 15 times to find more exact results.

The mean network errors in the produced pattern of LFDA, PCA and initial attributes are 19.73, 27.93 and 28.11%, respectively. As can be seen, the error of LFDA attributes pattern is less than the others while the errors of the PCA and initial attribute pattern are close. The next step is the derivation of the value of the new attributes in every point of the unlabeled data. The map of the neural network that is calculated on the training set, now applies to the whole seismic section. The result is a labeled section with the hydrate and the non-hydrate probability map (Fig. 8). It is clear that the LFDA attributes separate the gas hydrate zones from the non-hydrate ones better and the ability of this method in the identification of gas hydrates of the Oman Sea is proven.

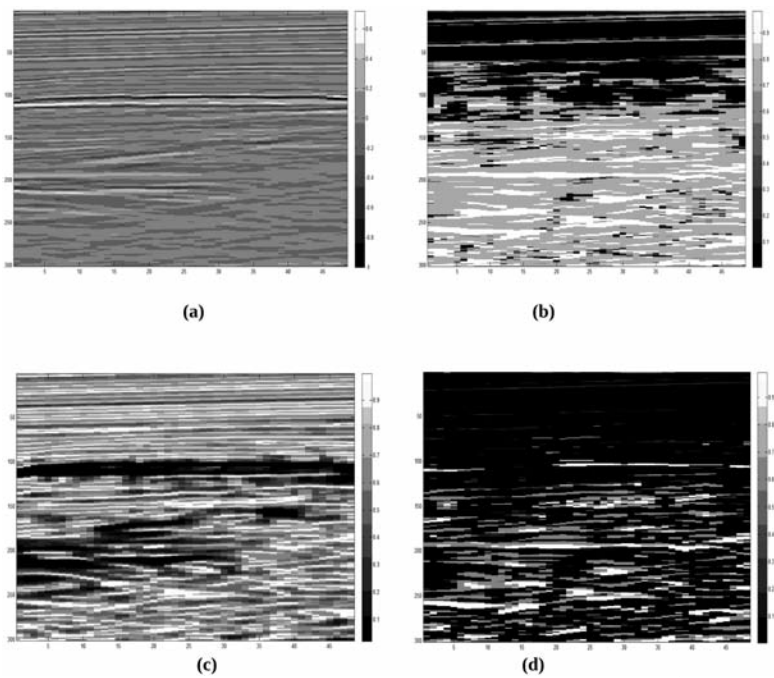

Fig. 8. The results of classification with neural network of Fig. 7 on different input attributes. (a) Seismic section of the input line. (b) Classification on 5 good attributes of LFDA. (c) Classification on 5 good attributes of PCA. (d) Classification on initial attributes without any feature extraction. LFDA attributes have separated the gas hydrates and non-hydrates zones better than the other methods.

DISCUSSION

Lithology and fluid content changes dramatically in the deep water area. AVO crossplotting as a standard quantitative interpretation technique is used to find the type of anomaly. Change of amplitudes with offset on BSR of Oman shows type IV of AVO. On the other hand, the mentioned changes affect the data in post-stack domain. Seismic data is not homogeneous and has many clusters which give rise to the concept of multi-modality. For a classification of multimodal data, it is important to have a method that recognizes the desired property in different parts of data. Using the initial set of attributes in classification, all the attributes are considered as relevant ones with the same coefficient in calculations, although they do not have the same role in the classification eventually. Also, seismic data are influenced by many factors whereby some attributes may have similar values in gas hydrate and non-hydrate sediments. Two feature reduction methods (PCA and LFDA) are used to select the relevant seismic attributes for classification.

The PCA attributes are found based on the scattering of data in each direction. This implies that the more important PCA attribute is made in the direction of the greater eigenvalue. Most often relying on scattering, which underlies PCA, is not an appropriate way to recognize the gas hydrate sediments as it can not treat class overlap.

Using the LFDA method instead training data with a label is entered in the calculation. The algorithm derives the characteristics of desired classification from this data and can find the main attributes that are effective. Furthermore, LFDA is a specific method for the sorting of multimodal data by decreasing within-class scattering while increasing the between-class one. This guarantees the closer samples in each class and more apart classes in feature space. It is found that LFDA is successful in proper identification of the relevant attributes for this classification experiment.

Application of a standard 5 neurons neural network structure on three sets (initial 27 attributes, 5 PCA good attribute, 5 LFDA good attributes) results in the lower classification error and the higher confidence for the five LFDA input attributes (Fig. 8).

CONCLUSIONS

AVO analysis is helpful to identify the hydrate, and the free gas above and below the BSR. Using this method, the hydrate above the BSR zone is proven the in the Iranian sector of the Oman Sea. On the other hand, post-stack attributes are proper tools to identify gas hydrates. The linear combinations of these attributes are more useful for this purpose. To make these combinations, application of LFDA criterion dimensionality reduction methods is successful. Because of the multimodal characteristics of the seismic data, unsupervised methods like PCA are not appropriate for the identification of gas hydrate sediments. On the other hand, LFDA is an effective tool for dimensionality reduction in terms of the classification error and interpretability of meta-attribute section. Results of feature reduction are then used as input to a neural network to classify seismic data as hydrate or non-hydrate bearing.

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