Identification of Gas Chimney in the Krishna-Godavari basin, eastern Indian margin

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Keywords

Gas Chimney, Artificial Neural Network, Seismic attributes, KG Basin, Interpretation, Dip Steered Median Filter.

Summary

The chimney analysis tool is very useful for identifying fluid migration paths from source through the reservoir to the surface. We apply this tool to the multi-channel seismic data in the Krishna-Godavari (KG) offshore basin with a view to imaging the chimneys. After having conditioned the seismic data, multiple attributes such as the frequency washout, energy, dip variance, similarity have been computed and then merged using a non-linear Multi-Layer Perceptron (MLP) to derive a meta attribute, defined as the chimney attribute. This study helps in better interpretation of seismic data in terms of understanding the petroleum system of KG basin, and risk assessment in future drilling.

Introduction

The main aim of studying chimneys is to identify the hydrocarbon migration pathways. Chimneys are the vertical chaotic disordered features having low reflection strength. These are the spatial link between source, reservoir and cap rocks, spill-point and shallow fuel anomalies. Chimneys are interpreted on a seismic section as upward migrating gas seepages, which show a clear signature of migration from the bottom up to near the seabed. Seismic attributes based on directionality principle help in improving the perceptibility and mapping effectiveness of certain geological features like faults, chimneys, folds, reflections etc. Selection of attributes in the best possible way plays an important role in enhancing a particular geological feature (Meldahl et al., 2001). The similarity, strength, dip variance, frequency attributes are very sensitive in enlightening the chaotic activities from the environment (Brouwer et al., 2008), and can be used to create a new attribute through a supervised Neural Network in which multi-trace attributes are steered in a user determined or data determined manner. Mapping of gas chimneys from the seismic section helps in understanding the hydrocarbon seepage history from the source rock to the shallower prospects (Heggland, 1998). These geological features also provide an appraisal of pre-drilling shallow gas vulnerability or geo-hazard. Here we employ this concept to the multi-channel seismic data in Krishna-Godavari (KG) basin (Fig.1) in the eastern margin of India where disordered vertical zones have been observed on seismic section. To conform these features as seismic chimneys, we implement the neural network training to the directionality attributes at every chimney and non-chimney locations chosen on the seismic data.

Data

The present study is carried out on 2D post stack time migrated seismic data (Fig.2) in the KG basin. The data was acquired using a streamer of 4500 meter (360 channels) at a nominal towing depth of 8 meters by CSIR-NGRI (Sain et al., 2012) for the exploration of gas hydrates at water depths varying between 500 m to 2500 m (Fig.1).

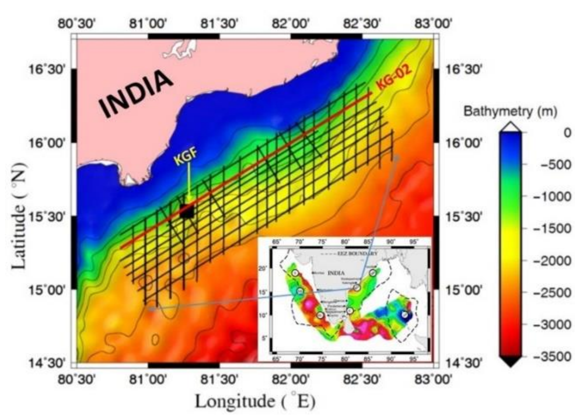

Fig.1. Location of seismic lines covering an area of 3369.249 km^2 in the southeast part of KG basin. The seismic line (KG-02), marked by red, is studied here.

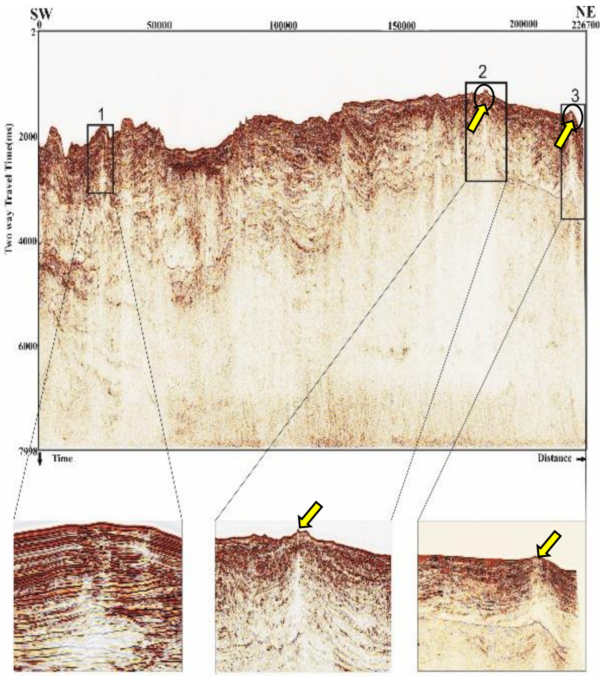

Fig.2. Seismic section (top) showing a number of chimneys, denoted by 1, 2, 3, which are zoomed below.

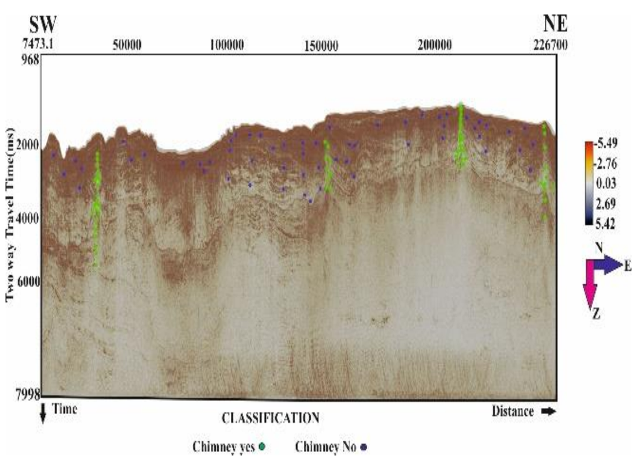

Fig.3. Pattern location of pick sets on the seismic section, categorized into chimney-yes (green dots) and chimney-no (blue dots) groups. The multi-layer perceptron (MLP) network learns through these examples.

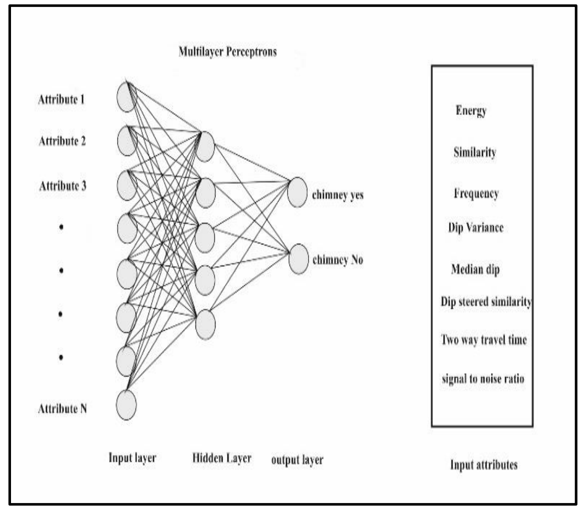

Fig.4. General Multi-Layer Perceptron (MLP) network. Input attributes are shown in the right side box and consists of three different layers: input layer, hidden layer and output layer (after Singh et al. 2016).

Methodology

The methodology used for the delineation of fluid migration paths, observed on seismic data (Fig.2), starts with the conditioning that produces trace to trace information of the dip and azimuth. The steering gives detailed information for interpretation. After that, the dip steered median filter outlet (8, 8) (sample, trace) is applied to eliminate the random and coherent noises. The dip steered median filtered data is then used as an input to extract several seismic attributes. We iteratively select the chimney and non-chimney locations by manually picking the pick sets (green picks, Fig.3) at locations that are indicated by fluid migration paths such as the gas seepage and spill points. The locations that do not represent the fluid migration (blue picks, Fig.3) are also picked. Numerous seismic attributes are extracted, and trained using supervised neural networks through a nonlinear multi-layer perceptron (MLP) (Fig.4). The computational workflow is shown in Figure 5. The training and testing phases are iteratively performed until the RMS error between the observed and predicted data is minimized.

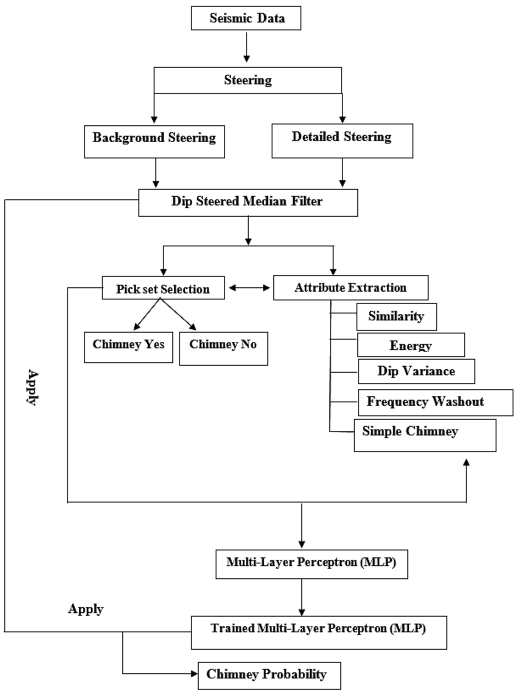

Fig.5.Workflow for computing chimneys

Interpretation

The output (Fig.6) obtained from the artificial neural network shows that the chimneys have deeper origin. The high chimney probability is observed on the seismic section, and it shows a link between the chimneys (Fig.3) observed on seismic section and predicted chimneys after the artificial neural networks are applied (Fig.6). They also represent a high correlation with the attributes like similarity, Energy, Frequency washout and Dip variance. The low similarity chaotic values are observed on the seismic section after applying the similarity attribute analysis. The low similarity represents the chimney as chaotic nature (Fig.7(A)). Likewise, we employ the energy attribute to the seismic data, and we observe energy absorption on the seismic section, which gives confidence on mapping the chimneys on the seismic section (Fig.7(B)). These are also validated with the high frequency washout, which is the best indicator for gas chimneys (7(C)). This has more weight (~ 99.85%), comparing to all other attributes, in indicating the chimneys. We use the dip variance attribute to identify the chimney that is chaotic in nature. The low dip variance implies the chimney (Fig.7(D)). The low similarity, high frequency washout, low energy, low dip variance are the best indicators for identifying chimneys, which reveal gas outflow or possibly the shallow gas reservoirs.

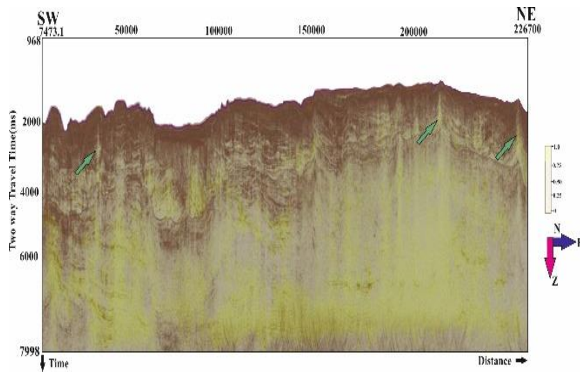

Fig.6. Output after applying the Artificial Neural Network. Arrows represent the chimneys.

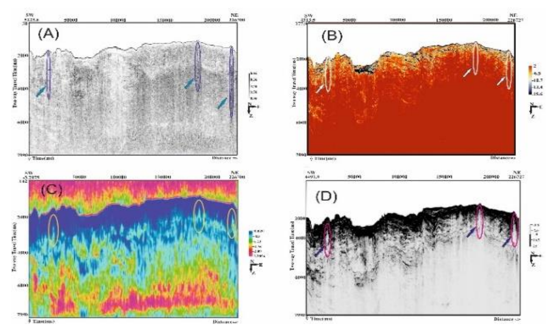

Fig.7. Low similarity attributes (A), low energy attributes (B), high frequency washouts (C), and low dip variances(D), represented by circles followed by arrows, imply the chimneys as chaotic in nature.

Conclusions

The present study provides vital information about the flow pattern of gas seepage. Study of multiple attributes confirm the presence of gas chimneys, and helps in understanding the petroleum system in the KG basin. The low disordered features (Fig.2 and Fig.6) represent gas migration paths, associated with the chaotic, low amplitude, low reflection strength seismic characters. The study also illustrates the reservoir seepage (indicator of deeper prospective) and spill points etc., which are important in understanding the drilling risks.

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