SEISMIC IMAGE PROCESSING FOR FACIES DETECTION USING TEXTURAL ATTRIBUTES AND NEURAL NETS

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Abstract: Seismic stratigraphy is a complex geological processing of seismic data. A seismic facies is a stratigraphic region that has a characteristic reflection pattern that is distinguishable from those of the other areas. The goal of this paper is to describe the method for detection of the facies by texture using the model of probabilistic neural networks. Seismic facies are identified in a volume of seismic data and a set of initial textural attributes representative of the volume of seismic data is calculated.

Keywords: seismic image, facies detection, texture, neural nets.

1. INTRODUCTION

Seismic stratigraphy is a complex geological processing of seismic data and of the particular properties of the seismic reflexions which allow directly application of the concepts usage in the sequential stratigraphy. A seismic facies is a stratigraphic region that has a characteristic reflection pattern that is distinguishable from those of the other areas. Seismic facies analysis is an important step in the interpretation of seismic data for reservoir characterization. Interpretations of seismic facies are the first step in the prospect evaluation, reservoir characterization, and oil field development. Regions of differing seismic facies are usually delineated using descriptive terms that reflect large-scale seismic patterns such as reflection amplitude, continuity, and internal configuration of reflectors bounded by stratigraphic horizons. The parameters of the seismic reflexion are the configuration, the continuity, the amplitude, the frequency, the interval speed, and the intern and extern shape for the unit of the seismic facies. The reflexion configuration is given by the way reflexions are found on the seismic section, and by the information regarding the stratigraphy models and the sedimentation processes. This configuration can be internal which determines the stratigraphy models, and external which determines the general shape of facies units. The internal shape of the reflexion configuration may be missing, and in this case the units are homogenous, un-layered, strongly deformed (massive marls, saltierous structures, big intrusive weights) chaotic, in which case there are strongly tectonic areas that suggest the disorder of layers (sliding structures, submarine channels, reefs), or the units can be layered. Layered reflexions can be simple ones: parallel, sub-parallel, divergent or complex ones: sigmoid, oblique, shingled or hummocky (Fig. 1).

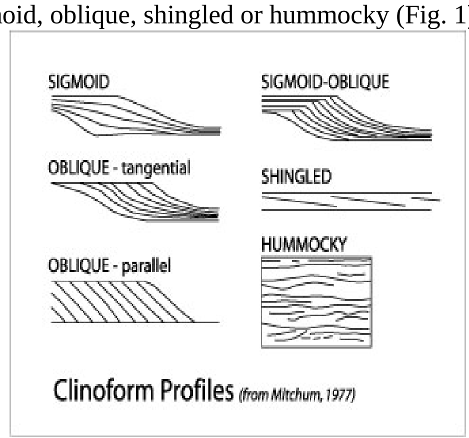

Fig. 1 Samples of the simple stratification reflexion

The external shape of facies units can be: onlap fill, prograded fill, mounded onlap fill, chaotic fill, divergent fill and complex fill (Fig. 2).

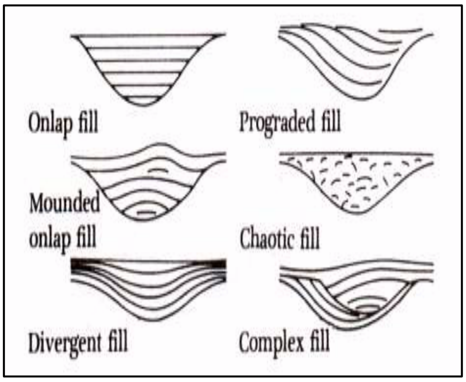

Fig. 2 Samples of the simple stratification reflexion

The stages of interpretation in seismic stratigraphy are:

- Seismic sequence analysis which assumes establishing the limits based on the discordant relations, and correlating the horizons on the entire area;
- Seismic facies analysis through reflexions model recognition, mapping on the entire are using intersections, realizations of facies maps, interpretation (sedimentation conditions, sedimentation source);
- Establishing the interest areas.

2. PROCESSING SEISMIC IMAGE USING TEXTURAL ATTRIBUTES WITH NEURAL NETS

Textural attributes are a powerful characteristic of seismic images, where a facies can be indicated by changes in the color and texture of a tissue. Many methods have been studied to extract texture feature from seismic images. The most used techniques for texture detection in the images are:

- Co-occurrence matrices
- Wavelets
- Gabor Filters
- Based on Fourier transform

Bashar *and al*. (2003) present a method based on wavelet transforms for segmenting a seismic image. In the first step, they transformed the original image into orthogonal wavelet coefficients for non redundant representation of image-information. Then each discrete coefficient undergoes a non-linear transformation to obtain an isophote image, which is convolved with a spatial Gaussian to form a locally orderless image. Designate them as WLOIs, which specify a local histogram at each transform point. These GLOIs or statistical moments computed from them are the new texture features. In the second step, the WLOIs are applied to Kohonen's self organizing map for learning and segmentation.

The same wavelet transformation was used and presented by Deighton and Petrou (2003) to carry out the supervised segmentation. Texture features are calculated on the expansion wavelet coefficients of the images.

Fernandez *and al*. (2000) analyze and evaluate the image properties with the help of multi-channel Gabor filters. Certain features are computed on the wavelet expansion and on the Gabor-filtered signal, and used by a Mahalanobis classifier to recognize and subsequently segment the seismic section. The Gabor filters of the multi-channel scheme are designed by considering the minimal classification error in the recognition of geologically well understood zones, taken as patterns. As a result of the segmentation, zones of different internal stratification are identified in the seismic section. This recognition is based on the comparison of the 3D seismic data with the reference patterns extracted from the representative areas, characterized by different textures. A sandy channel is detected in both cases to a given depth. Applied to these data, the methods distinguish clearly between different layers and efficiently separate zones of different internal stratification.

An experimental study on a set of seismic images with different facies is presented by West *et al.* (2002). The study takes into consideration the following texture description: gradient, entropy, homogeneity, variance, inverse variance and energy, based on the used statistical measures to classify textures using gray-level co-occurrence matrices (CMs). It is presented a statistical approach of the texture description. Specifically, it introduces the use of first- and second-order statistics on texture color spaces. The statistical measures used are energy (denoting textural homogeneity), entropy (measuring predictability from one texel or voxel to another), contrast (emphasizing the difference in amplitude of neighboring voxels) and homogeneity (highlighting the overall smoothness of the amplitude). Energy, entropy and homogeneity have been found to be the most effective in characterizing seismic data.

While one given attribute is sensitive to a specific geologic feature of interest, a second attribute may be sensitive to a different kind of feature. We can therefore combine multiple attributes to enhance the contrast between features of interest and their surroundings. Different methodologies have been developed to recognize such features. Meldahl *et al.* (2001) used neural networks trained on combinations of attributes to recognize features that were first identified in a seed interpretation. The network transforms the chosen attributes into a new ‘meta-attribute’, which indicates the probability of co-occurrence of the identified features at different seismic positions. Such highlighted features definitely benefit from the knowledge of shapes and orientations of the features that can be added to the process. Haralick introduced co-occurrence matrices for grey-scale textures. They are defined as a histogram, in which the probability of the simultaneous occurrence of two grey-scale values according to a predefined neighborhood is stored.

3. FACIES DETECTION USING PROBABILISTIC NEURAL NETWORKS

Analyzing the seismic facies (Fig. 3) plays an essential role in the process of oil reservoir detection. Texture is the most important characteristic of image processing applications. The goal of this paper is to described the method for detection and analyze of the facies by texture using the model of probabilistic neural networks, and, also, to verify the performance of this method with multi-texture images. Seismic facies are identified in a volume of seismic data, wherein, first, a plurality of initial textural attributes representative of the volume of seismic data is calculated. After, a probabilistic neural network is determined from the calculated initial textural attributes. Then, final textural attributes are calculated throughout the volume of seismic data. Finally, the calculated final textural attributes are classified using the constructed probabilistic neural network.

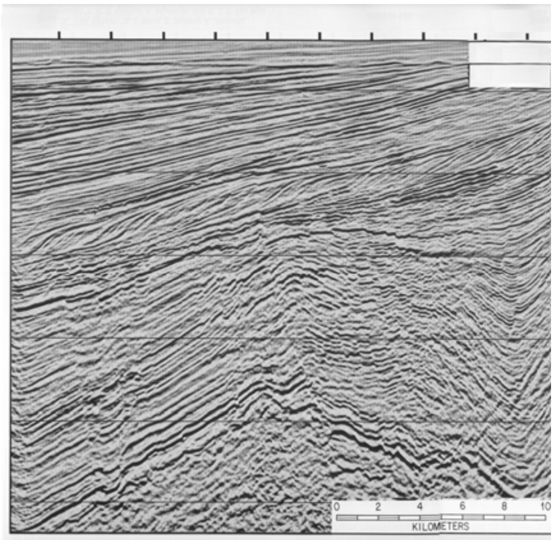

Fig. 3 Sample of the seismic image with facies

The proposed detection algorithm is the supervised learning. The input image of this algorithm is made of different texture classes. Initially it takes place a pre processing phase in which the image id made binary, and are eliminated the eventual noises. The next step is putting a label to each pixel of the image with one of the texture classes. For each class of texture it is built a neural network and is trained each network with sample images that contain the corresponding class of texture. Once the neural networks are trained, the current pixel of the tested image together with its neighbor can be used for training any network, and the label of the current pixel is given by the neural network with the minimum error. In the training phase, first the network formed of N = n x n neurons, is built for each class. Then using each n x n window from the working image, the network is trained with secure learning algorithm. When the training is over, the texture parameters, represented by the weights of the network, are determined.

Texture classifying algorithm:

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Step 1:
  for each class c of the input image do
     • build the neural network
     • initialize the weights of the neural network using
       Hebb’s rule
     • for each n x n window do
        * determine data(c)
        * train the network using as input data(c)
Step 2:
   for each class c of the input image do
      • for j=0 to N
         * distance(j)<-MAXDOUBLE
         * for each n x n window do
             *output_image<-nn_output(input_image)
              *dist<-Euclidian_distance(input_image,
                output_image)
              * distance(j)<-min(dist, distance(j))
Step 3:
   for each pixel p of the input image do
      • classify(p)<-arg_min(dist, distance(p))
```

The classifying phase is divided into two phases. In the first one there are determined the distances for each pixel, for every class. For this, each n x n window from the processed image is given as input for the network. The matrix of distances is created for the same dimension of the input image and the computed value is assigned to the pixels. If another distance was already assigned to a pixel, which may happen when the pixel belongs to another window, then it is assigned the minimum of the distances. After all the distances were found it can be done the assignation to a certain class. For training the neural network it is used the back propagation algorithm, which involves the following steps:

Step 1: Initialize the weights at random values.
Step 2: Initialize the vector of inputs of the network and determine average sum of each neuron by using the sigmoid function.
Step 3: Set all the outputs to zero, except the one corresponding to the current class.
Step 4: Compute the error for each output.
Step 5: Compute the error for each hidden neuron.
Step 6: Sum the delta weight determined for each processing unit (neuron).

Repeat steps 2 to 6 until the error is in reasonable limits and, after that, the adjusted weights will be memorized inside detection process.

The main parameter of facies detection using the texture characteristic is the number N of neurons (the size of the window n). N must be big enough to construct the zone which is homogenous as the texture. On the other side a big N affects the time of computing.

The textures used for training are also an important factor, so that the algorithm may recognize the facies in a correct way.

The main modules of the application will be represented by:

- the pre-processing of the current image;
- the building and training neural networks;
- the belonging decision of an facies to a certain class of primitives facies;
- the validation of facies detection.

Initially, inside the first module are taking place pre processing operations that are done both on the wanted facies for detection and on the set of facies containing the textures for training the neural networks. The role of these operations is to reduce the noise or the not useful information, from the image, or they may represent recovery operations. Such kind of processing is useful for improving both the execution time and the results of the detection algorithms. It is done a filtering operation for noise reduction, using a pass down filter that will standardize the image spectrum. At the output of the image acquisition block the result may be a distorted image; these distortions are due to known physical phenomena. A possible source of distortion is the optical system. The acquired images may present distortion of the following types: pillow or barrel. These errors can be corrected using the operation of re-sampling: for this kind of geometrical distortion it is determined the mathematical relation needed for the correction and, using this relation, it is computed the value of each sample (pixel) from the new image, based on a number of samples from the distorted image. Also, because of the optical system, the image may present on portions different illuminations.

The model for building and training neural networks starts initially from a set of primitives' facies; each facies has only one texture corresponding to a class of facies. For this set of facies there are computed the co-occurrence matrix, given thus the input of the neural network. The next step is analyzing the current image, that is to be processed, and building, the neural network based on this analyze. Such a texture detection algorithm was described earlier, the same as the training algorithm (the back propagation algorithm).

The module that establishes if a facies belongs to a class, takes into account the supervised learning, made a priori by the neural network, using a set of test facies. If during this decision operation it results that the facies doesn't belong to any of the existing classes it is created a new class, and the current facies is added to the set of test facies.

4. CONCLUSIONS AND FUTURE WORK

Application of 3-D seismic technology to the study of detection facies provides important results into the processes and products of petroleum industry, and gives an important tool that may be used in hydrocarbons reservoir analysis. A future direction of development is the detection of the facies from 4-D seismic image. Another direction is the usage of others types of neural networks.

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