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Lithofacies prediction from well log data using a multilayer perceptron (MLP) and Kohonen's self-organizing map (SOM) – a case study from the Algerian Sahara

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Abstract. In this paper, a combination of supervised and unsupervised leanings is used for lithofacies classification from well log data. The main idea consists of enhancing the multilayer perceptron (MLP) learning by the output of the self-organizing map (SOM) neural network. Application to real data of two wells located the Algerian Sahara clearly shows that the lithofacies model built by the neural combination is able to give better results than a self-organizing map.

1 Introduction

The artificial neural network (ANN) has been largely used for reservoir characterization from well log data (Ouadfeul et al., 2012). One of the main applications of the artificial neural network is the lithofacies prediction from raw well log data. Ouadfeul and Aliouane (2012) have showed that the so-called multilayer perceptron (MLP) neural network machine requires a good number of coupled input–output for MLP training. The input used for the training of the multilayer perceptron is the raw well log data; however, the desired output is the measured core rock data. Core rock data are very expensive and do not continue over depth. For that reason, the multilayer perceptron suffers from insufficient training data, which push the MLP machine to give erroneous results. Ouadfeul and Aliouane (2012) have suggested resolving this ambiguity by enhancing the output of the MLP machine by the generalized output of the self-organizing map (SOM) in the full depth interval where the MLP and the SOM are trained and core rock information is not available. Obtained results show that the combined ANN machines are able to give more precise lithology. In this article, we show a case study of SOM and the MLP combination in the Algerian Sahara. The whole process is applied to data of a well located in the Algerian Sahara; another borehole is used for neural network generalization and for checking the performance of the neural machines.

2 The self-organizing map

The self-organizing map (SOM) is a kind of a neural network invented by professor Teuvo Kohonen (1998). It is constituted of two layers (Fig. 1). The SOM is based on unsupervised learning based on the Euclidean distance and a neighborhood function. This function is generally given as a Gaussian. For better information about the training algorithm of the SOM machines, we invite readers to the paper of Kohonen (1998) or the paper of Ouadfeul et al. (2012).

3 The multilayer perceptron

The multilayer perceptron (MLP) is a kind of network based on supervised learning. In this case, we need a desired output for each input vector. The MLP is constituted of input and output layers and N hidden layers. It has been shown that one hidden layer is sufficient to resolve many scientific problems (Mejia, 1992). Figure 2 gives an example of an MLP machine

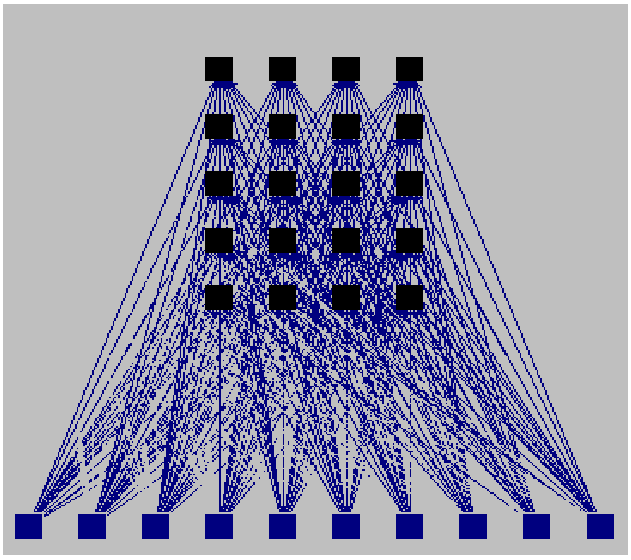

Figure 1. Graphic schematization of the self-organizing map.

with five neurones in the input layer, three neurons in the hidden layer and one neuron in the output layer.

4 The processing algorithm

The proposed idea is based on the training of the MLP using the output of the SOM. The first step consists of training Kohonen's map using the raw well log data as input. Well log data to be used are as follows: the natural gamma ray (G_r), slowness of the P wave (DT), neutron porosity (NPHI), bulk density (RHOB) and the photoelectric absorption coefficient (P_e). The SOM is trained in an unsupervised learning mode where the desired output is not required. The obtained weights of connection by the training of the SOM will be used for propagation of the input and generalization of the lithology for the full depth interval. At this step, the core rock data are required for map indexation and to attribute to each class (output of the SOM) a kind of lithology. The coupled raw well log data, generalized lithology will be used for the training of the MLP. Figure 3 shows a detailed flowchart of the processing algorithm.

5 Application to real data

The proposed combination is applied to the raw well log data of two wells A1 and A2 located in Hassi Messaoud field (Algerian Sahara). Figure 4 shows the raw well log data versus the depth. Gamma ray and slowness logs clearly show that the main interval target is constituted of shale and sandstone intercalations. Four classes will be used for the SOM indexation: (1) sandstone, (2) shaly sandstone, (3) sandy shale, and (4) shale.

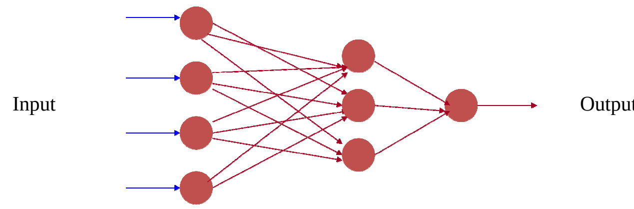

Figure 2. An example of MLP with one hidden layer.

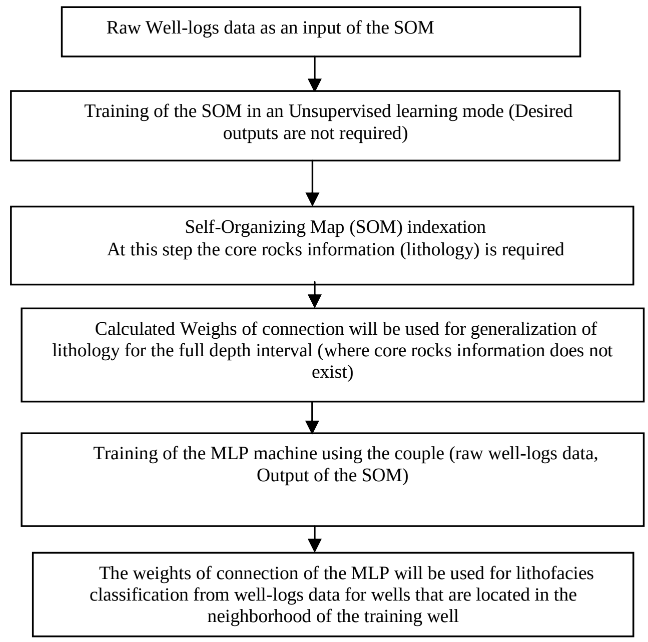

Figure 3. Flowchart of the proposed processing algorithm of well log data.

6 Results, interpretation and conclusion

Application to wells A1 and A2 is down. Well A1 is used as a pilot. At this step, the weights of connection for the SOM and the combination of SOM and MLP are calculated. Figure 5 show four tracks: the first one is the depth, the second the classification based only on the gamma ray log (core rock information), the third track the classification after the propagation of the input (raw well log data) in the SOM machine, while the last one is the lithofacies model after propagation in the MLP based on the output of the SOM as a desired output. To check the efficiency of each neural model, we have generalized each of them for the second well A2. At this stage, we use the weights of connection calculated for each machine in the training step in A1 well to propagate the raw well log data of the second well. Obtained results clearly show that the MLP based on the SOM output as a desired output is able to give better results and a lithofacies model, which is not very far from the lithofacies model based on the natural gamma ray log (core rock lithology information). The

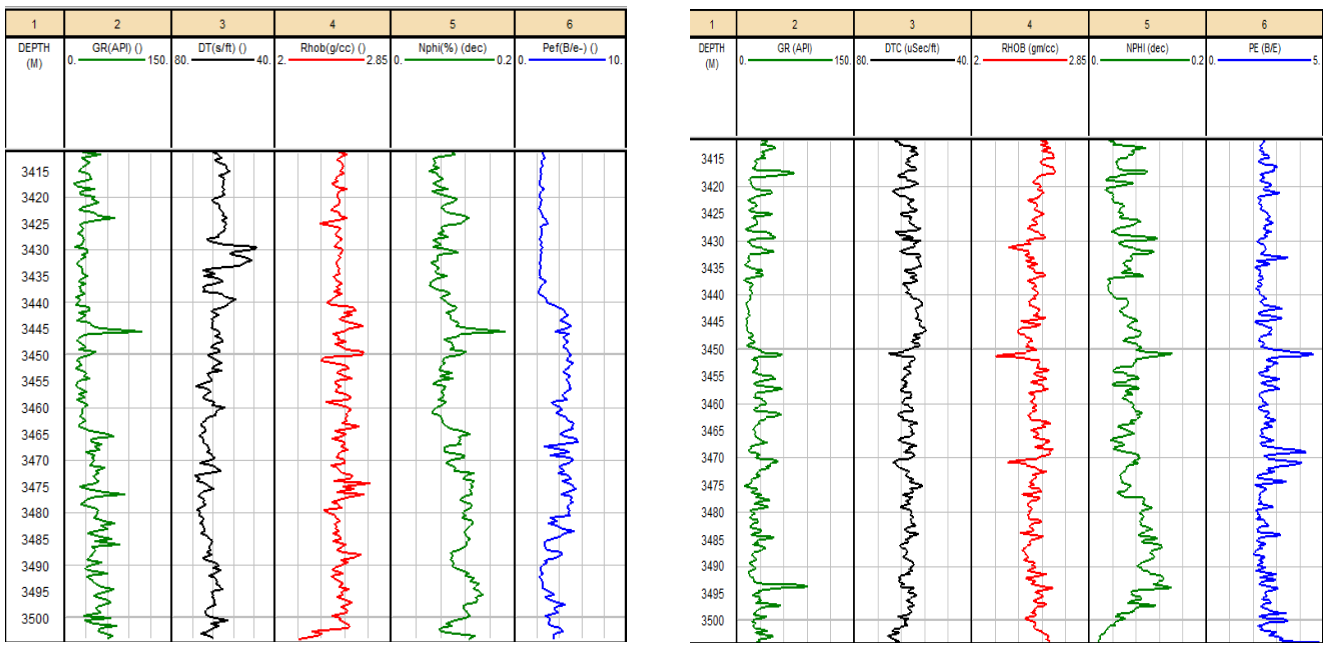

Figure 4. Raw well log data of A1 and A2 wells: (2) gamma ray (G_r), (3) slowness of the P wave (DT), (4) bulk density (RHOB), (5) neutron porosity (Nphi), and (6) photoelectric absorption coefficient (P_e).

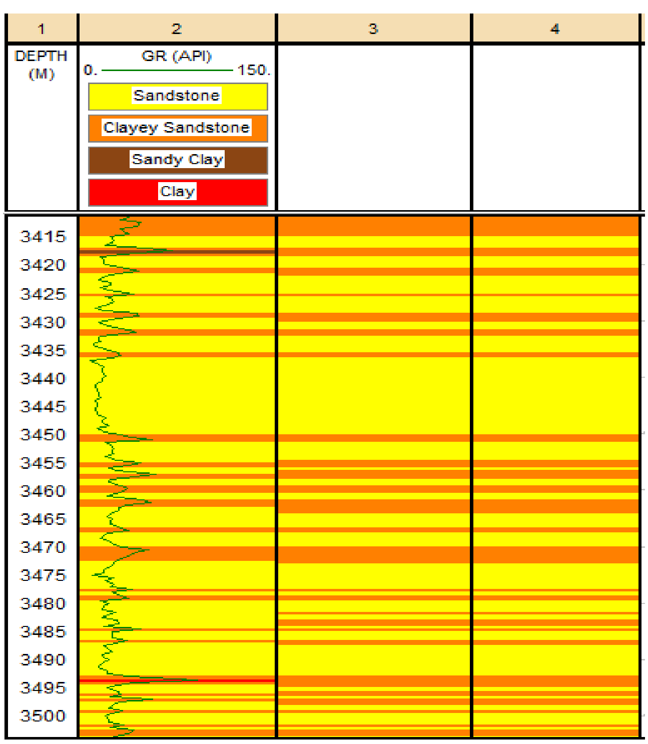

Figure 5. Lithofacies classification in well A1 using (2) gamma ray, (3) SOM, (3) SOM and MLP

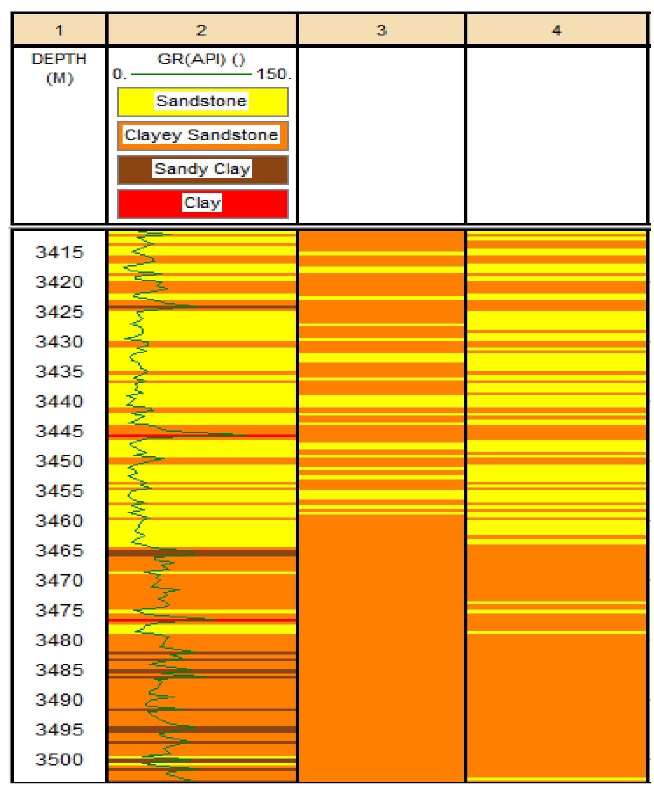

Figure 6. Lithofacies classification in well A2 using (2) gamma ray, (3) SOM, (4) SOM and MLP.

provided lithologic information can be used for petroleum exploration where core rock information is not available. By consequence, the proposed ANN model can greatly enhance reservoir characterization and improve oil recovery.

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