International Conference on Problems of Logistics, Management and Operation in the East-West Transport Corridor (PLMO), October 27-29, 2021
http://conf.cyber.az

AI-Based Processing of Seismic Signals During Oil Exploration

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***Abstract*—Preprosessing of seismic data is one of the most widely used methods in oil and gas exploration which is providing comprehensive information about various layers and rock properties underneath the Earth without any expensive drilling operations. The accuracy and efficiency of the seismic data analysis mainly depend on the quality and the quantity the seismic receivers - geophones or hydrophones located on the Earth or marine surface. Furthermore, the choice of the seismic source energy is also important factor in the reliability of the acquired seismic data. Unfortunately, such seismic data analysis usually appears with an excessive amount of noise generated by various sources and erratically missing information due to inaccessible points in the field. The attenuation or suppression of random noise is of great importance for geologists to achieve high quality and precise seismic data in oil and gas exploration. According to this data, the potential oil or gas resources can be found out, even an approximate capacity of the reservoir can be estimated by expert geoscientists and engineers. Many methods have been investigated for random noise attenuation and each of them has certain advantages and disadvantages. The selection of the appropriate method depends upon the preferred criteria on the acquired results in the seismic data analysis. In this paper is considered the application of Artificial Neural Network in seismic data analysis using MATLAB. As result Artificial Neural Network (ANN) filter is designed. While comparing with other classical filters this method has showed his efficiency.**

Keywords—seismic data, preprocessing, Artificial Neural Network, root-mean-square error, seismic signals, filter, signal-to-noise ratio

I. INTRODUCTION

In recent years, major improvements and innovations have been developed in energy exploration. Oil and gas exploration is one of the most expensive processes in fuel energy acquisition. Millions of dollars are being spent to find out if there is a potential petroleum reservoir to continue drilling and complete the well. Seismic surveys have become one of the most efficient methods applied in energy exploration providing huge return on investment. Seismic technique is a remarkable option to analyze the subsurface structure in advance of drilling and to determine the design of the well trajectories in order to achieve the reservoir in the safest and most effective way. Obtaining a detailed record of the geological formations, which is known as well logging, allows the geologists to gather comprehensive information about different layers of rock formations. This contributes greater certainty about whether or not the hydrocarbons exist beneath Earth's surface. If there is not any latent petroleum reservoir, the drilling process needs to be stopped and the well should be abandoned to prevent incurring higher costs of completing a well. In consequence, seismic data analysis leads to a more profitable hydrocarbon extraction with fewer wells drilling.

Seismic data with high quality is very crucial in seismic exploration to accurately analyze the subsurface structure. However, in real industrial experiments, the seismic signals are usually obtained with high frequency noise which could cause losing useful information about the rock formations underneath the Earth. So that, noise attenuation is one of the important stages in seismic signal analysis. Although a number of methods have been suggested to attenuate the seismic noise signal, the efficiency of these methods is evaluated with the preservation of the original signal amplitude. Traditional attenuation algorithms, such as transform domain algorithms [1], [2], [3], spatial domain algorithms [4], curvelet transform [5], comprehensive types denoising algorithms [6], [7] can manage to eliminate the noise to some extent, they usually appear with some drawbacks such as inaccurate design assumptions and problems in estimating parameter values ([8]-[11]). Furthermore, a comprehensive experience and knowledge about the noise are required before the traditional methods applied in seismic noise attenuation. As the random noise is obscure in the real exploration process, it needs to be tested at different variances which contributes to time-consuming and inefficient process. Considering the drawbacks of the traditional methods. contemporary science and industry demand more effective and intelligent denoising methods. In recent years, deep learning or ANN has rapidly and extensively developed, consequently it has also applied in seismic exploration field.

II. DESIGN OF NEURAL NETWORK FOR RPOCESSING OF SEISMIC DATA

The suggested method for preprocessing of raw seismic signal learns the difference between noisy and clean data. The data representation and noise cancellation will be performed using Matlab software. Matlab has a range of features for filtering the noisy signal and its Neural Network Toolbox – "$nntool$" enables to design an Artificial Neural Network structure with desired number of layers and flexible parameters. There are mainly five steps in the method described in this paper:

1. Generate a clean - ideal output signal using traditional filtering methods.
2. Design a neural network framework.
3. Train the network and test the network performance.
4. Compare the denoising results of neural network and traditional methods.
5. Calculate the signal-to-noise ratio to check the efficiency of the result.

The input data is represented as a tabular data which shows the measurements of seismic sensors on 513 traces of the Earth. When the seismic sources – air guns are fired and send acoustic waves to the lower layers of the Earth surface, seismic receivers or hydrophones towed behind the seismic ship collect the depth values of the rocks according to the time duration between sent and received signals. As a result of multitude bombing actions from air guns, a table of data in the size of 886 x 513 is obtained. Each column in the table depicts one trace or layer in the Earth subsurface and each raw shows a time at which the sample is acquired from the sensors. Considering the acoustic signal speed (v_s) in the water and two sequential depth samples (s_1, s_2) the data parameters are initialized in Table 1 below:

Table 1. Acoustic Signal Parameters

v_s	$1500\ m/s$
$s1$	$-2.385\ m$
$s2$	$-1.803\ m$

Using the known signal parameters represented above, the sampling time ($T_{samplig}$) and sampling frequency ($F_{sampling}$) parameters can also be easily calculated as shown below:

$$T_{sampling} = \frac{|s2 - s1|}{v_S} = 0.388\ ms \quad (1)$$

$$F_{sampling} = \frac{1}{T_{sampling}} = 2.577\ kHz \quad (2)$$

Each trace – column consists of error measurements due to sensor accuracy or environmental noises. Therefore, the experimental raw data obtained directly from hydrophones or geophones is not helpful for geologists and geoscientists to predict the potential of hydrocarbon resource.

The noise interference on the pure signal is apparently observed in the 2D representation of the original experimental data in time and frequency domains (Figure 1):

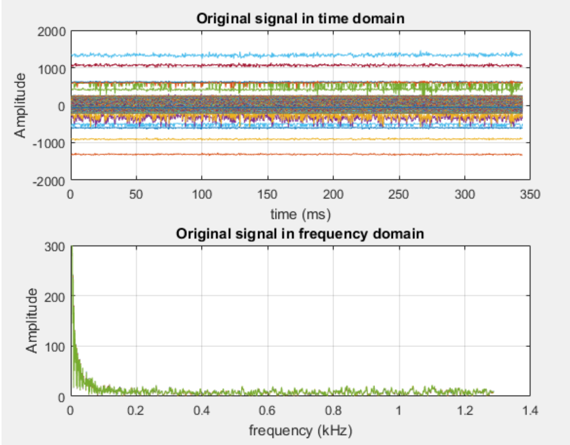

Fig.1. 2D representation of raw seismic data

Due to neural network design, we need a target data to train the network. This target data can be obtained by applying traditional filters on the input data. As the random noise signals are generally high frequency signals, we need a lowpass filter to vanish the noise from the signal.

While designing the low-pass filter, the choice of cutoff frequency at which the signal is sufficiently cleaned is very important. Based on the noisy signal frequency response, the cutoff frequency has been chosen 0.02 kHz approximately in order to minimize the amplitude of the noise on the seismic signal. Furthermore, the passband and stopband frequencies should be less than Nyquist frequency, which is half of sampling frequency. The low-pass Butterworth filter with minimum order was designed using Matlab FFtool (Figure 2):

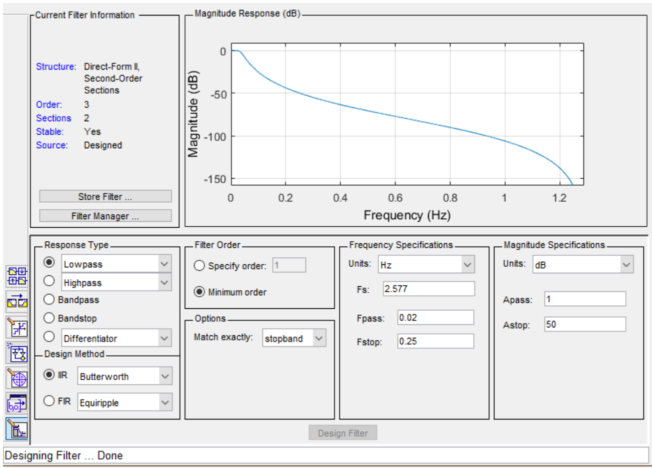

Fig.2.Lowpass Filter Design

After applying the designed low-pass Butterworth filter on the original noisy seismic signal, the noise was attenuated and an ideal – noise-free signal was obtained (Figure 3 & Figure 4):

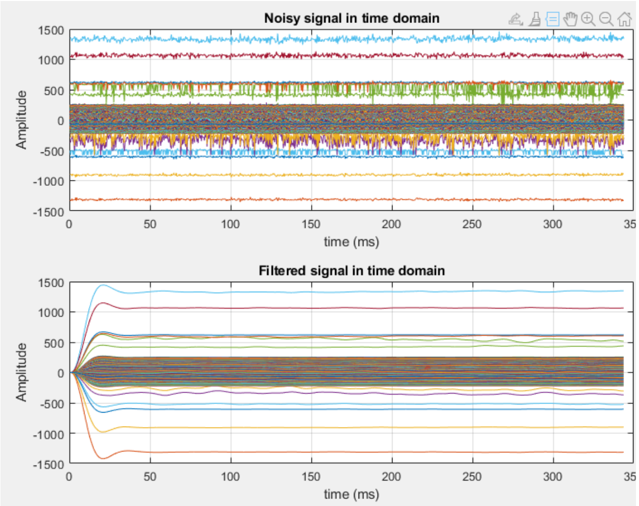

Fig.3.Raw and filtered data in time domain

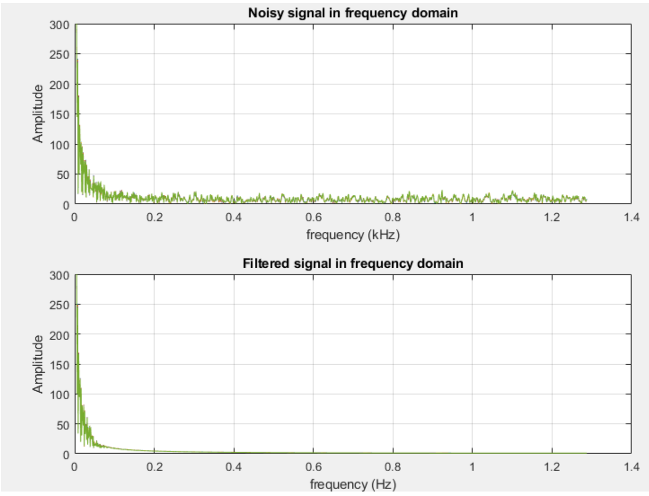

Fig.4.Raw and filtered data in frequency domain

Comparing with original noisy signals, the acquired results are much smoother and ideal both in time and frequency domain representation. There are some ripples in time domain as demonstrated in Figure 3, this is because of the allowable passband attenuation indicated in magnitude specifications of the filter. The obtained signal will be the target data for the neural network to learn the system and will be used to validate the acquired results.

ANN learns how ideally the system performs and implements it on the other samples in the same manner, afterwards. As discussed in the previous subsection, the input data was filtered using traditional low-pass filter firstly. The input signal together with the ideal filtered signal are two main inputs of the neural network to be able to calculate the respective weights of the hidden layers. Since the provided seismic signal data is quite big, only some portion of the data is used to train the system. In this instance, 200 samples of traces obtained in 100 ms time were used for learning purpose of the neural network and the next 200 samples were used to test and validate the results. Matlab has NNTool function which opens Neural Network/Data Manager window in order to import the input data, create a neural network with desired parameters and to export the neural network results.

After input and target data were imported, a neural network structure is designed. The neural network design used in this work is a 7 layers (6 hidden, 1 output) network with 10 neurons at each hidden layer. The hidden layers have a hyperbolic tangent activation function which is more successful than sigmoid function and is applied in many neural network problems. As it is regression type prediction problem, Linear activation function has been selected for the output layer. After creating the neural network, it needs to be trained with the imported input and target data. Training parameters are specified as represented in Figure 5:

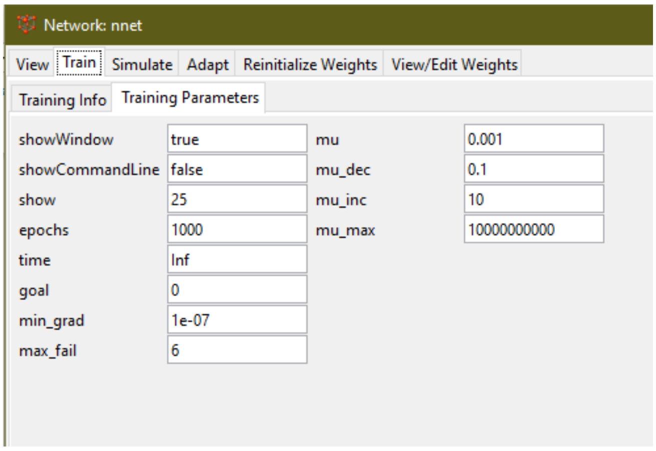

Fig.5.Trainning parameters of neural network

The training process lasted for 13 minutes approximately, and after 57 iterations the goal was achieved (Figure 6):

Fig.6.Neural network structure and obtained parameters

The performance of the training and error histogram as represented in Figure 7, also validates the neural network successful results:

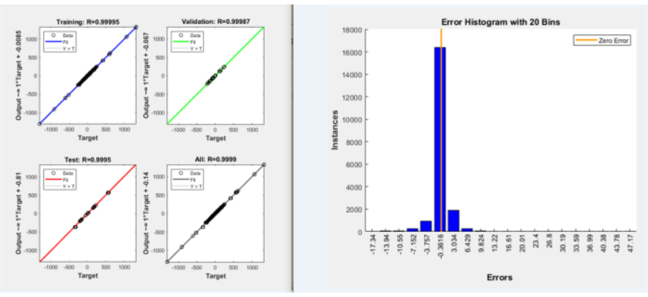

Fig.7. Regression performance and Error histogram of the neural network

As mentioned above, 200 samples different from the trained data were used to check and validate the neural network performance. When the testing data was initiated as an input to the trained network model the obtained result was compared with the desired output in time (Figure 8) and frequency domain (Figure 9):

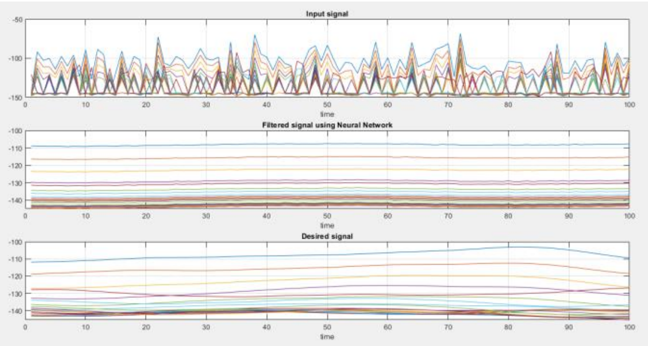

Fig.8.Neural network's output and target signals in time domain

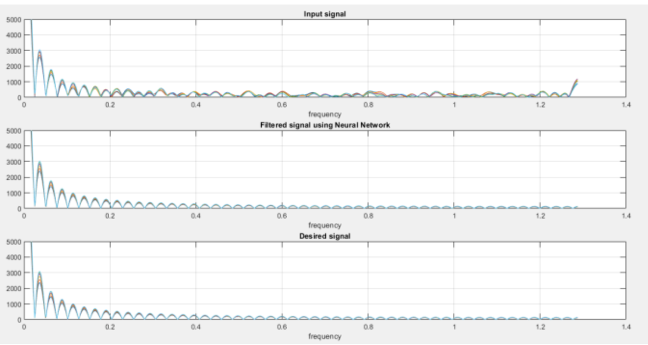

Fig.9.Neural network's output and target signals in frequency domain

As can be seen from the figures above, the results are very close to the desired ones and the noise on the signal has considerably been attenuated. Different sets of data were tested with the designed network and all results were the satisfying as represented in Figure 8 and Figure 9.

Furthermore, the statistical properties of the input and output signals were also calculated to verify the model efficiency (Table 2):

Table 2.Statistical properties of Neural network

$mean\ (input)$	-81.1607
$mean\ (output)$	-82.3470
$variance\ (input)$	275.7967
$variance\ (output)$	0.1800
$RMSE\ (training)$	0.2050
$RMSE\ (testing)$	0.4444
$SNR\ (input)$	0.9054
$SNR\ (output)$	8.8955

The derived values show that the signal has been cleaned from the noise successfully as its $mean$ and $variance$ have decreased as expected. Another important parameter, root-mean-square-error ($RMSE$) is almost the same for the training and testing data. Finally, the most essential parameter to confirm the noise attenuation in the signal is the Signal-to-noise ratio (SNR). A significant increase in the signal-to-noise ratio value also implies the noise reduction in the output signal.

III. Conclusion

As implemented in many areas of industry, a neural network can successfully be applied in oil and gas exploration to achieve a desired result in a more efficient and eco-friendly way. A detailed and systematic analysis of seismic data can guide the geologists to decide the potential capability of the reservoir and can save millions of dollars for oil and gas companies if the well does not worth to drill. Moreover, a careful preprocessing and interpretation of seismic signals can result in an accurate drilling direction and depth due to precise assumptions about rock formations. Although the preprocessing of seismic signals using ANN model is time consuming, it can deal with the seismic signal without requiring any prior knowledge or comprehensive analysis of the signal. Despite the fact that the traditional methods are more accurate and reliable, Artificial Intelligence (AI) or Machine Learning has become main focus of industry due to its convenience and flexibility.

This paper mainly discusses the AI application in noise cancellation in seismic signals which is known as preprocessing of seismic signals. A future work could be to apply a CNN in seismic signal processing and improve the processing of seismic signals in order to make a judgement about reservoir capability and to identify the rock properties. Certainly, it requires a deep knowledge about various rock formations and their characteristics, afterwards, a neural network can be trained to be implemented in seismic signal processing.

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