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Seismic Waveform Classification for Direct Hydrocarbon Indicators (DHIs) using Siamese Networks

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Summary

Due to the presence of hydrocarbons, the rock physical properties, such as density and velocity, will dramatically change and then the seismic amplitude anomalies around the hydrocarbon-filled areas are possible to be identified using the Direct Hydrocarbon Indicators (DHIs). For example, the geophysical experts can identify a geological event, such as bright spots or dim spot, based on seismic anomalies using DHIs, but the accurate interpretation of seismic anomalies using DHIs to improve the success drilling rates is still a challenge. In this study we proposed Siamese Networks (Koch et al, 2015), normally used on human face recognition, to classify and identify the problems of seismic amplitude anomalies.

Usually the seismic recordings can be demonstrated and interpreted based on the original seismic digital data, seismic wiggle trace, seismic variable-area fill wiggle display, color density display, density variable and super-imposed display. Different display types of seismic data can be used for different geological goals. For example, the seismic inversion needs the original seismic data to calculate the rock physical properties, but seismic horizon pick and fault interpretation can be classified using the visual knowledge such as color, shape and texture, in which the seismic density variable display and other displays contain these characteristics for human visual perception to interpret these events. However, how to extract the characteristics, such as shape, from these seismic waveform display images is crucial for the seismic waveform classification and identification.

We proposed the Siamese Networks to extract the visual knowledge, such as the seismic shape and characteristics for the seismic waveform classification. The network is supervised and is trained using only one or few model-waveform images with some labels, such as bright spots. The two same Convolutional Neural Networks (CNNs) can be used for the Siamese training and prediction. Basically, the two CNNs share the same parameters. Assuming the CNNs model is trained properly using one or few model images, the target input images are fed onto the CNNs to extract the same length feature vector as the model image. if the target image and model image belong to the same waveform class, then their feature vectors must also be similar, while if the two images belong to the different waveform class, then their feature vectors will also be different. The Cosine similarity is used to measure the similarity between two feature vectors, in which two vectors with the same orientation have a cosine similarity of 1, otherwise two vectors have a similarity of 0.

Unlike Deep Learning, in which big samples are necessary for training (Liu, 2019), and Bayesian-based Support Vector Machine (Liu and Sacchi, 2003; Liu, 2018; Liu, 2019), in which hundreds of samples are better for the classification and regression, the Siamese Network has the capability of handling one or few samples for training. Fortunately, usually there are only very limited seismic anomaly events in a seismic study area. For example, there are only few bright spots with hydrocarbon accumulation in a seismic study area and the Siamese Network (Koch et al, 2015) is perfect to fit the study using one or few shot learning.

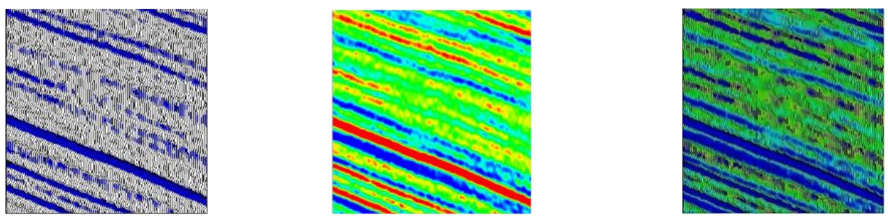
A case example using different seismic waveform images was tested in the study. It sounds the Siamese Network can be helpful to classify the seismic anomalies for DHIs and other geological events.

Seismic waveform image

The color, shape and texture of the seismic waveform are associated with the facies and hydrocarbon accumulations because of the seismic anomalies. In traditional seismic waveform analysis, a result is based on how well a target trace compares to the model trace. However, a trace within a small time-window length is not unique for the analysis. Usually, one often identifies the geological events, such as bright spots, using a waveform image, in which includes several traces and several time samples and the waveform image makes it possible to better identify the geological events.

The seismic waveform image can be generated using original seismic data and seismic wiggle/density display. Seismic data can be shown in different displays and then the seismic waveform image can be generated using the displays. Figure 1 (a) is the original seismic data within several traces and time samples, (b) is wiggle trace display, (c) is color density display, (d) is the color density and superimposed display. According to the study goal, one can select different waveform image to analyze the seismic signature. For example, one is happy to use the seismic original data for seismic inversion to estimate the density and velocity. But for other geological event classification, such as horizon pick, fault interpretation and even the bright spots identification for DHIs, the human visual perception of color display or wiggle trace display make geologist to better classify the events.

158.3493	-2495.99	-2190.74	-5427.53	257.7883
278.6351	-2531.94	-1723.18	-4121.73	10.89141
231.0161	-2521.85	-1006.53	-2401.98	-531.501
183.3972	-2511.76	-289.877	-682.231	-1073.89
-90.2665	-2400.69	393.7563	142.5075	-1602.43
-363.93	-2289.63	1077.39	967.2459	-2130.97
-442.583	-1873.59	1512.507	877.0316	-2437.48
-521.235	-1457.56	1947.624	786.8173	-2743.99
-5.40921	-760.635	2217.169	593.4628	-2914.79
510.4167	-63.7118	2486.714	400.1083	-3085.6
1205.269	514.7228	2704.645	546.325	-3303.9
1900.122	1093.157	2922.576	692.5417	-3522.21
1732.72	1168.461	2944.417	957.2845	-3684.62



(a) (b) (c) (d)

Figure 1 seismic waveform image display: (a) seismic original data, (b) wiggle traces, (c) color densiity, (d) color density + superimposed variable area wiggle trace

In order to mimic the geologists to classify the events using the visual information of the seismic waveform images, we proposed the Siamese Network using two CNNs to compare the target image with model image to identify and classify the target geological events.

Siamese Networks

The Convolutional Neural Networks have been widely studied for seismic inversion (Liu, 2018; Liu, 2019; Jin, 2018; Das et al, 2019) and seismic fault detection (Zhang et al, 2014). But the CNNs needs a large amount of data for the training and the more training samples we have, the better the results get. However, it is still a challenge to generate or collect these massive samples from seismic data and geological data and in fact it is more convenient for us to learn from few samples. For example, for seismic DHIs there are only one or few seismic hydrocarbon-related anomaly samples in a seismic study area. One has to make a decision based on the limited information.

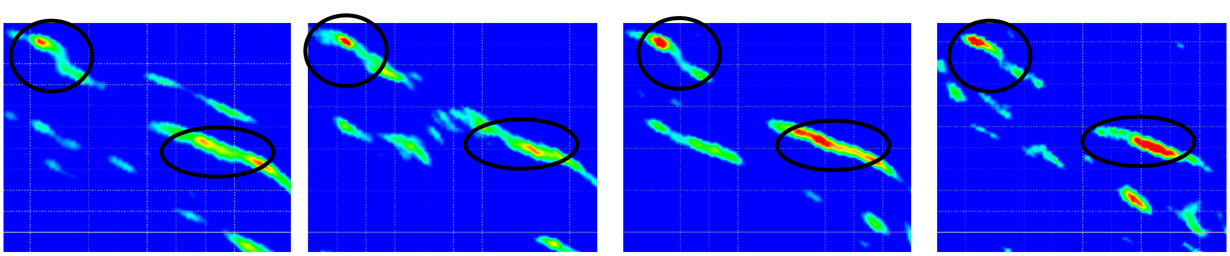
Fortunately, the Siamese Networks (Koch et al, 2015), normally used character classification and human face recognition, only need few samples for training. The term Siamese means twins. The Siamese Networks use two Convolutional Neural Networks for the training and prediction. In the prediction phase, the network will share the same weights and parameters as the training phase. The training and prediction samples, such as model and target seismic waveform images, are fed onto Siamese Networks to extract the same length feature vectors respectively. if the target image and model image belong to the same waveform class, then their feature vectors must also be similar, while if the two images belong to the different waveform class, then their feature vectors will also be different.

The Cosine similarity is used to measure the similarity between two vectors, in which two vectors with the same orientation have a cosine similarity of 1, otherwise two vectors have a similarity of 0. If one has a good understanding of the model seismic waveform signature, such as bright spots, one can classify the DHIs for the target seismic waveform image using a high similarity between the vectors of both model and target waveform images.

Example

In traditional seismic waveform classification, a result is based on how well a seismic trace compares with the model trace. However, the new Siamese Networks work well for a small image, in which includes several seismic traces and a few time window lengths. The geologists can identify a geological event, such as bright spots, based on the seismic waveform signature. In our case study, we define a model seismic waveform image associated with a bright spot based on the petrophysical study. The model seismic waveform image consists of 20 traces and 20 samples of each trace. In order to mimic the vision of geologist to interpret the bright spots, different types of seismic displays can be used to show the seismic recordings. In our study, we compared the results using the original seismic data with 20 traces and 20 samples of each trace, the waveform images from wiggle trace, color density display and color density with superimposed wiggle variable display. The wiggle and color displays were interpolated to generate an image with 121x121 pixels from 20 traces and 20-time samples of each trace.

Figure 2 is Siamese prediction results. The red color represents high similarity with possible bright spots and blue color represents low similarity. (a) is the prediction result using original data, (b) results using the wiggle trace, (c) results using color display, (d) result using color density and superimposed wiggle display. It sounds we got similar results (black circular) with high similarity from four different displays, but also, we got some differences based on different waveform images. The different seismic waveform images can demonstrate different seismic signatures with the color, shape and texture because seismic display has to be normalized for computer display to match the RGB or HSI model, which means that very high amplitude data will be overlap or masked in the seismic display. The fake DHIs could be classified and identified because of the waveform displays. In order to improve the success drilling rates using DHIs, it is best to combine the results from different displays and geological knowledge to de-risk the interpretation.



(a) (b) (c) (d)

Figure 2 Siamese prediction results: (a) results from seismic digital data, (b) result from wiggle trace display, (c) result from color density display, (d) result from color density + superimposed varible wiggle trace display

Conclusion

The shape, color and texture of seismic waveform are associated with seismic anomalies due to facies and reservoir accumulation. Unlike traditional seismic waveform analysis, a seismic waveform image consists of several waveform traces and it can be generated using different seismic displays, in which it has better human visual perception compared with original seismic data and a single seismic trace classification.

In order to mimic the geologist to interpret the waveform image, Siamese Networks were proposed to extract the seismic feature vectors from the model and target waveform images. If one has a good understanding of the model waveform signature with bright spots, for example, one can identify the DHIs for the target seismic waveform image using a high similarity between the model and target waveform images. An example demonstrated the possibility of the new classification technique using Siamese Network.

Usually any interpretation of seismic geological events is associated with geological facies and stratigraphy. In future we will study how to combine the geological knowledge and seismic waveform image to make better and unique classification using the Siamese Networks for DHIs.

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