Machine learning to enhance the vertical resolution of seismic geostatistical inversion

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Summary

In this paper, I presented a Machine Learning method, Bayesian-based multi-channel Support Vector Machines (SVMs), to incorporate well logs at higher sample rate with seismic attributes for direct, one-step seismic geostatistical inversion to infer the reservoir properties. Using a multi-channel SVMs, we could achieve seismic inversion at 0.25ms sample rate, which has vertical resolution approximately 0.25m to 0.75m. Petrophysical studies found that high-resolution results could accurately interpret the top, base of a thin layer and estimate the true value of reservoir properties, which will be helpful for seismic quantitative interpretation.

Introduction

How higher sample rate is enough for seismic quantitative interpretation based on our current seismic inversion? Petorphysical studies found that seismic inversion results at regular 1ms or 2ms sample rate have serious aliasing, which could mis-interpret the top, base of a thin layer, and inaccurately estimate the real value of reservoir properties, such as porosity and density. According to our study, it is best to achieve as high as 0.25ms sample rate for seismic inversion. Table 1 lists the sample rates of well logs and their vertical resolutions. In order to avoid the petrophysical data aliasing in time domain and achieve very high vertical resolution, it is best to sample the dataset with 0.25ms or even 0.125ms sample rate. Table 2 lists the seismic resolution with different sample rates. It sounds we cannot improve the vertical resolution using the seismic alone because of band-limited seismic data. However, it is possible to enhance the seismic inversion resolution through combining the seismic and petrophysical data. In order to achieve the high vertical resolution, we presented a Machine Learning method, Bayesian-based multi-channel Support Vector Machines (SVMs) (Liu and Sacchi, 2003, Liu, 2017), one of Artificial Intelligent solutions, to enhance the vertical resolution of seismic geostatistical inversion. The methods have the improvements in the following four steps:

Table 1 well logs sample rate vs. vertical resolution

Sample Rate (milliseconds)	Nyquist Frequency (Hz)	Aliasing (sonic frequency 3-5 KHz)	Best Vertical Resolution of Well Logs (meters)				
			Velocity 2000m/s	Velocity 3000m/s	Velocity 4000m/s	Velocity 5000m/s	Velocity 6000m/s
4 (ms)	125 (Hz)	Yes	4 (m)	6 (m)	8 (m)	10 (m)	12 (m)
2 (ms)	250 (Hz)	Yes	2 (m)	3 (m)	4 (m)	5 (m)	6 (m)
1 (ms)	500 (Hz)	Yes	1 (m)	1.5 (m)	2 (m)	2.5 (m)	3 (m)
0.5 (ms)	1K (Hz)	Yes	0.5 (m)	0.75 (m)	1 (m)	1.25 (m)	1.5 (m)
0.25 (ms)	2K (Hz)	Minor	0.25 (m)	0.375(m)	0.5 (m)	0.625 (m)	0.75 (m)
0.125 (ms)	4K (Hz)	No	0.125(m)	0.1875(m)	0.25 (m)	0.3125(m)	0.375(m)

Table 2 seismic sample rate vs. vertical resolution

Sample Rate (milliseconds)	Nyquist Freq. (Hz)	Seismic Major Freq. (Hz)	Vertical Resolution of Seismic (wavelength $\lambda/4$) (meters)				
			Velocity 2000m/s	Velocity 3000m/s	Velocity 4000m/s	Velocity 5000m/s	Velocity 6000m/s
4 (ms)	125 (Hz)	50	10 (m)	15 (m)	20 (m)	25 (m)	30 (m)
2 (ms)	250 (Hz)	50	10 (m)	15 (m)	20 (m)	25 (m)	30 (m)
1 (ms)	500 (Hz)	50	10 (m)	15 (m)	20 (m)	25 (m)	30 (m)
0.5 (ms)	1K (Hz)	50	10 (m)	15 (m)	20 (m)	25 (m)	30 (m)
0.25 (ms)	2K (Hz)	50	10 (m)	15 (m)	20 (m)	25 (m)	30 (m)
0.125 (ms)	4K (Hz)	50	10 (m)	15 (m)	20 (m)	25 (m)	30 (m)

1) Higher sample rate conversion of petrophysical data from depth domain to time domain. According to table 1, it needs 0.25 or 0.125ms sample rate to avoid the aliasing. Sometimes in order to avoid aliasing, the low-pass filter or block average can apply for the petrophysical data to remove the higher frequency components. However it sounds the higher frequency components are crucial to interpret the thin layer and accurately estimate the real values. Thus higher sample rate inversion could be one of best solutions to avoid aliasing for seismic quantitative interpretation.
2) An advanced inversion technology has the capability of incorporating the higher sample rate's petrophysical data with regular 1ms or 2ms seismic data. Because the seismic is band-limited, any higher sample rate (table 2) cannot improve its resolution. In fact, it is not necessary to interpolate the seismic data to match well logs with higher sample rate, but we need to develop advanced technology to handle the issues. In our study, we developed a multi-channel Bayesian-based Support Vector Machine method to incorporate the different sample rate's data and other prior knowledge.
3) An advanced technology achieves good performance on validation and testing data. Validation is crucial step to evaluate the performance. Using our multi-channel Bayesian-based Support Vector Machine method, usually we can achieve almost 100% accuracy for classification and very small mean absolute errors for the regression data.
4) An advanced technology propagates the higher sample rate's petrophysical properties from well location onto seismic space. Although we can achieve good performance on validation data, it is important to make best prediction of reservoir properties based on the machine learning model and good representation of seismic data. Our real data examples have demonstrated the multi-channel Bayesian-based Support Vector Machine method has the capability of making best prediction based on a small training dataset.

Higher sample rate conversion

Usually the newer sonic tools have the frequency between 3 and 5k Hz. In order to avoid the aliasing, it is best to sample the data at 0.125ms sample rate (table 1). Sometimes, the low-pass filter or block average can apply to avoid the aliasing to remove the higher frequency components. However, according to our study and from practical application point of view, a 0.25ms sample rate could be one of best sample rates for seismic inversion to achieve the vertical resolutions approximately 0.25 to 0.75m, which is enough to interpret 1-meter thin layer to meet seismic quantitative interpretation requirements.

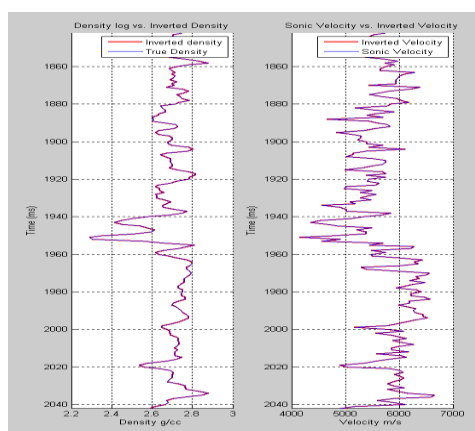

Figure 1: well log velocity (left, blue) and inverted velocity (left, red); well log density (right, blue) and inverted density (right, red)

An advanced technology for training phase

In this study, we presented a Machine Learning method, Bayesian-based Support Vector Machine, for the geostatistical inversion. Firstly, the method is direct, one-step inversion, which can incorporate of a wider range of well logs, geological data and experience to infer the reservoir properties from seismic data instead of two-step process of estimating impedance and then converting impedance to reservoir properties. Secondly, the method has the capability of incorporating the higher sample rate's petrophysical data with regular 1ms or 2ms seismic data. Thirdly, the method can better handle small dataset and achieve good performance for the training and validation data. Usually we can achieve very small mean absolute errors for the geostatistical inversion. For example, the mean absolute error of P-velocity is less than 10 m/s, density's is less than 0.005 gm/cc and porosity's is less than 0.1%. Figure 1 is one example of inverted velocity and true velocity (time domain) from well logs (left), and inverted density and true density from well logs (right).

An advanced technology for prediction phase

Although our methods can achieve good performance with training and validation data, most importantly, we need high performance for seismic vertical and lateral prediction. Usually the goodness of the data representation has a large impact on the performance of machine learners on the data. Thus, seismic attribute extraction and petrophyscal property evaluation are crucial steps to build a good data representation for our machine learning application, which will be used in our direct, one-step inversion process. Then our machine learning methods, Bayesian-based multi-channel Support Vector Machines, has the capability of projecting the small dataset onto a very high dimension space in order that one can easily classify the data or generate physical training model to make the predictions. The real data examples have demonstrated the multi-channel Bayesian-based Support Vector Machine method has the capability of making best prediction using a small training dataset.

Comparisons between well logs with different sample rates

In order to accurately estimate the reservoir properties, we investigated which rate is best enough for the seismic quantitative interpretation. Figure 2 shows one example of the gamma ray (left), density (middle) and velocity (right) logs with different rates. The two horizontal magenta lines are the top and base of one 29-meter layer. The red curve is log curve in depth domain at 0.125cm sample rate, blue is log curve in time domain at 0.25ms sample rate, green is log curve at 0.5ms sample rate, black is log curve at 1ms sample rate and cran is log curve at 2ms. It sounds the log value at 0.25ms in time domain has similar value to 0.125cm in depth domain, but at 1ms sample rate there are differences because of the aliasing effects and bigger differences at the 2ms. Within the thick limestone layer, there are several thin beds, which cannot interpret based on 1ms or 2ms' results, but it is possible to interpret using 0.25ms or 0.5ms data. According to the results, we can interpret the top and base of the thick layer using the well logs at 0.125cm and 0.25ms, but there are big errors if we use the well logs at 1ms or 2ms sample rate. In addition, we found the density and velocity at the 1ms or 2ms rate have errors compared with the real well logs, especially around the boundary.

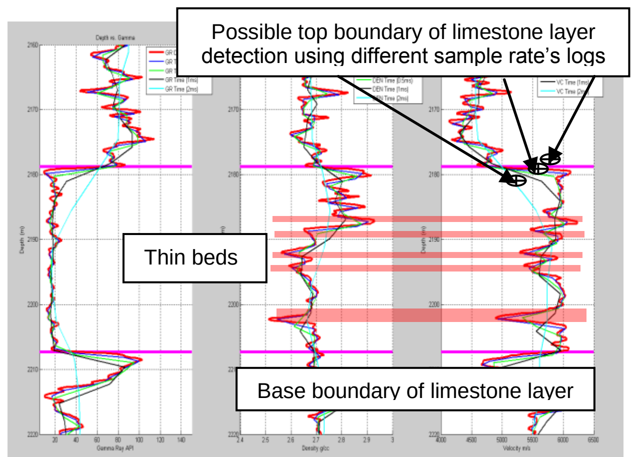

Figure 2: well logs and their responses with different sample rates.

In our traditional inversion workflow, we can only achieve 1ms (black curve) or 2ms (cran curve) inversion results. However, according to petrophysical studies, the inverted results are uncertainties and limitations for quantitative interpretation. Firstly, it is difficult to accurately interpret the top and base of a layer whether it is thick or thin bed. Secondly, there are differences between the inverted values and the real logs. Although it is still possible to detect the hydrocarbon anomalies using these inverted results at the 1ms or 2ms sample rate, it is difficult to accurately interpret the top and base of the hydrocarbon layer and estimate the real reservoir properties for quantitative interpretation.

Comparisons between seismic geostatsitical inversions among different sample rates

According to petrophysical studies, a higher sample rate's seismic inversion could avoid the aliasing to enhance the vertical resolution. In the study, we presented the multi-channel SVMs method to handle the data representation with different sample rates from both petrophysical and seismic data to achieve the resolution to interpret as 1-meter as thin layer. The inversion rate could reach as high as 0.25ms sample rate. Figure 3 is one example of velocity inversion results. The top is the inverted velocity at 1ms rate, and middle is 0.5ms rate and bottom is 0.25ms rate. We found the 0.25ms inversion results have best vertical resolution, which could help us accurately interpret the top and base of a thin or thick bed.

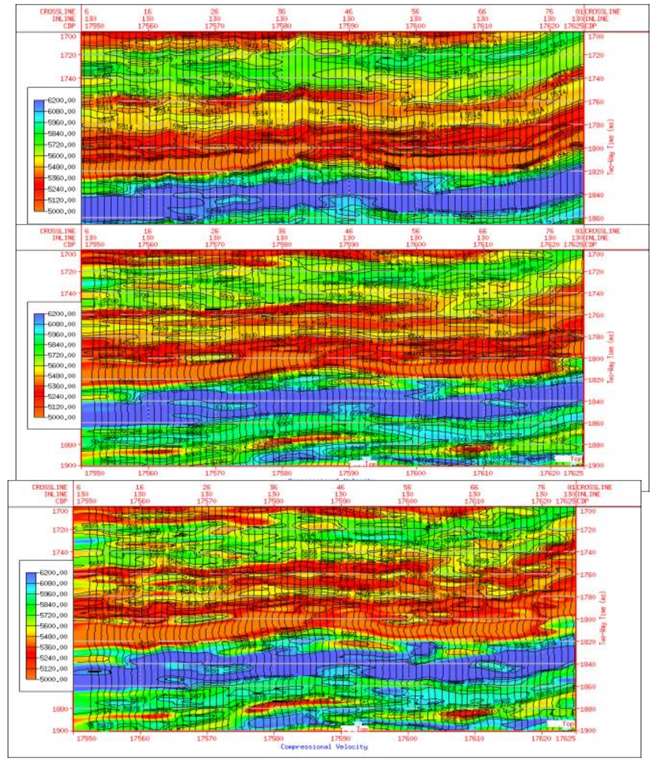

Figure3: The velocity inversion using different sample rates (top 1ms, middle 0.5ms and bottom 0.25ms) based on our Bayesian-based Support Vector Machine geostatistical inversion.

Conclusions

We studied the well log responses with different sample rates in time domain and found how a sample rate is best rate for seismic quantitative interpretation. The study shows that the 0.25ms is one of best rates for seismic inversion to accurately interpret the top and base of a layer. Then we presented a Machine Learning method, Bayesian-based multi-channel Support Vector Machines (SVMs), one of Artificial Intelligent solutions, to incorporate well logs at higher sample rates with seismic attributes for direct, one-step seismic geostatistical inversion. The primary results have demonstrated that we can achieve the results with higher vertical resolution approximately 0.25 to 0.75m.

References

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