More robust methods of low-frequency model building for seismic impedance inversion

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Summary

Seismic impedance inversion is an important tool to estimate rock and reservoir properties from the seismic data. Seismic data is band-limited in nature and lacks the low-frequency component. As the low-frequency component holds the basic information on geological structure, the lack of low-frequency information degrades the quantitative prediction based on seismic inversion. So, it is essential to build an accurate low-frequency model to have confidence in seismic inversion and in turn on the quantitative predictions made therefrom.

In this paper, we develop a new workflow of predicting the low-frequency impedance model that uses a single-well low-frequency model apart from other relevant seismic attributes in the multi-attribute regression analysis. This study was carried out on a dataset from northeastern British Columbia in Canada. Inversion results using this approach have been validated at the blind well locations and an excellent match between well logs and inversion results has been observed. We have also attempted the collocated cokriging technique for building a low-frequency model and used it for seismic impedance inversion. A comparison of both the methods has been discussed.

Introduction

Currently, impedance inversion of seismic data is a standard tool to estimate the elastic properties from seismic data for reservoir characterization projects. Knowledge of absolute impedance is necessary for quantitative as well as qualitative predictions of the reservoir. As the seismic data is band-limited and does not contain the low-frequency band of the spectrum, it is essential to build a proper low-frequency model for better estimates of the reservoir properties. Sams and Saussus (2013) have shown some practical implications of low-frequency model selection on quantitative interpretation results.

Typically such a model is built by using well log data, interpreted horizons and sometimes the seismic velocities provided the velocity data is of good quality. There are a variety of interpolation techniques that could be used to construct the low-frequency model from well log data. These include linear interpolation of single well data, inverse-distance, triangulation, kriging, and cokriging methods. If there is considerable lateral variation in the elastic properties across the 3D area, a single-well model does not work very well. Also, inverse distance and triangulation methods usually generate some kind of bull's eye effect on the low-frequency model that creates artifacts on the inversion results, which are not geological.

A novel approach has been devised that uses the multi-attribute regression technique for building the low-frequency impedance model. Multi-attribute regression is a good interpolation technique that uses both well log and seismic data to establish a relationship between various seismic attributes and the available log curves (Hampson et al., 2001). The application of multi-attribute analysis for building a low-frequency model has been discussed by Zou et. al. (2013). It is important to include suitable attributes to establish a proper regression relationship. In this paper, we adopt a new workflow using multi-attribute regression analysis to predict the low-frequency component for use in seismic impedance inversion.

Furthermore, a collocated cokriging technique has also been used to build low-frequency impedance models for use in impedance inversion. Cokriging is a standard interpolation technique, and it's most common variant in the industry is collocated cokriging that uses seismic data as a secondary variable. It uses the variogram model to distribute the well log properties away from the well location. The variogram model is generally based on some relevant secondary data which can represent the spatial heterogeneity in the study area. Inversion results based on the low-frequency models using both the methods have been compared.

Method and analysis of results

A workflow has been designed to build a low-frequency model for impedance inversion from the dataset of northeastern British Columbia, Canada. As the first step, we generate a low-frequency impedance model using a single well that seems to represent the overall trend within the 3D volume. Then, using this low-frequency model, a model-based inversion is run on the data. Though the inversion result shows a reasonably good match for some of the wells, we notice mismatches for other wells in the 3D area. Therefore, an improved low-frequency model is required for a better estimate of impedance volume from seismic inversion.

For this purpose, we attempted multi-attribute regression analysis (Hampson et al., 2001) to generate the low-frequency impedance model. First, the impedance logs were filtered to extract the low-frequency component of the impedance log data. Seven wells, which were uniformly distributed throughout the 3D volume, were used in the multi-attribute training network. In the first phase of the analysis, seismic amplitude data and relative impedance derived from coloured inversion were used to train the filtered impedance logs. Poor match, with a correlation coefficient of only 0.4, was observed between the actual filtered impedance log and the modelled impedance log, derived from this multi-attribute regression process. Figure 1 shows the match for all the training wells. Due to poor training correlation, it was not advisable to use the predicted impedance as the low-frequency model for the inversion process.

In the second phase of the analysis, we added the single-well impedance model as one of the inputs along with the other attributes used in the earlier training network. This approach helped in improving the training process considerably. Figure 2 shows the match between

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the actual filtered impedance log and the modelled impedance log derived with this new approach. It is now observed that there is an excellent match between the actual filtered impedance log and the modelled impedance log and the correlation coefficient improves to 0.96. Moreover, the validation correlation is also considerably high and gives a correlation coefficient of 0.92. In the process of validation, one well at a time is excluded from the training data set and prediction error is calculated at the blind well location. The analysis is repeated as many times as there are wells, each time leaving out a different well. The validation match is shown in Figure 3. While a low-frequency model based on inverse distance method shows bull's eye artifacts on the horizon slice (Figure 4), the low-frequency model generated based on the new approach does not show those kind of artifacts on the horizon slice (Figure 5).

Next, we run model-based post-stack inversion using the low-frequency model generated with the new approach. We get an excellent match between the actual impedance log and the inverted impedance log for all the wells on the 3D volume. Figure 6 shows the match in a blind well between the actual impedance log (blue curve), inverted impedance using single well low-frequency (black curve) and the inverted impedance using the low-frequency based on the new approach (red curve). It is noticed that the low-frequency based on the new approach gives an excellent and improved match with the actual impedance log when the blind well is considered. This lends more confidence in the new approach for generating low-frequency model.

Additionally, we have used a collocated cokriging technique to build a low-frequency impedance model. Collocated cokriging is a variogram-based geostatistical technique that uses a relevant secondary attribute to guide populating the well log properties of interest away from the well. Variogram modeling is the critical part of the whole process to obtain the property of interest that not only matches at the blind wells but also conforms to the geology.
The variogram is estimated by

$$2\gamma(\boldsymbol{h}) = \frac{1}{N(\boldsymbol{h})}\sum_{\alpha=1}^{N(\boldsymbol{h})}[Z(u_\alpha) - Z(u_\alpha + \boldsymbol{h})]^2$$

where $Z(u_\alpha)$ is a variable under consideration at a location u_α $N(\boldsymbol{h})$ denotes the number of pairs of data locations approximately a distance vector **h** apart.

Identification of proper variogram ranges is important to capture the lateral variations as well as geologically congruent results. In order to produce a valid variogram model for use in collocated cokriging, it is reasonable to use one of the predefined functional forms such as linear, logarithmic, quadratic, Gaussian, spherical, exponential etc. for fitting the experimental data (Cressie, 1985). Relative impedance derived from coloured inversion were used as a secondary attribute in the variogram modelling. We used spherical function to fit the experimental data points for the horizontal as well as vertical directions**.**

Gringarten and Deutsch (2001) have discussed the methodology for variogram interpretation and modelling in detail. The major horizontal direction of continuity has been determined from the 2D variogram map shown in Figure 7(a). Figures 7(b), 7(c), and 7(d) show the variogram plots for major, minor and vertical directions respectively. Correlation ranges thus obtained from variogram modelling for all three directions were used in the collocated cokriging to estimate the P-impedance property. The same seven wells that were used previously in the multi-attribute regression analysis were taken as input in the collocated cokriging analysis. The P-impedance so generated was filtered to generate a low-frequency impedance model and used to invert the seismic data. Figure 8 shows a horizon slice of the low-frequency impedance model in the zone of interest. We don't see any kind of bull's eye effect on the horizon slice and so the model is devoid of any artifact which is geologically inconsistent. Figure 9 shows a comparison of the inverted impedance based on the low-frequency model at a blind well using collocated cokriging and the new approach we adopted using multi-attribute regression. We get a fairly good match between the well log impedance and the inverted impedance derived based on both the low-frequency models. Moreover we see a very close match between the inverted impedances based on the low-frequency models using collocated cokriging and the new approach of multi-attribute regression. This confirms that the new approach we adopted for building the low-frequency model is equally good and can be implemented with confidence for building the low-frequency model.

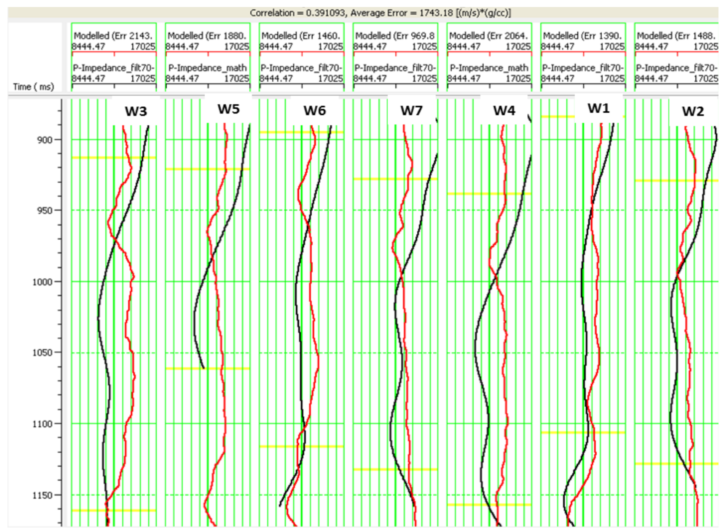

Figure 1: Match between the modeled impedance log and actual filtered impedance log using multi-attribute regression. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. Poor correlation coefficient of 0.4 is observed.

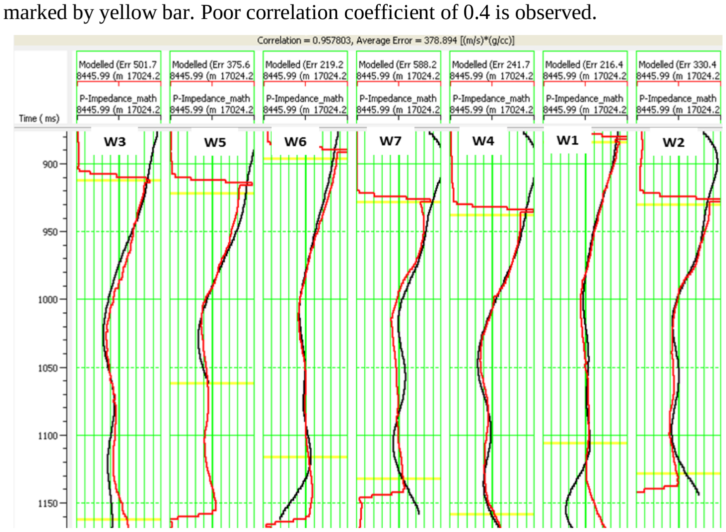

Figure 2: Match between the modeled impedance log and actual filtered impedance log using multi-attribute training network after including single well low-frequency model as one of the input. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. Correlation coefficient improves significantly to 0.96.

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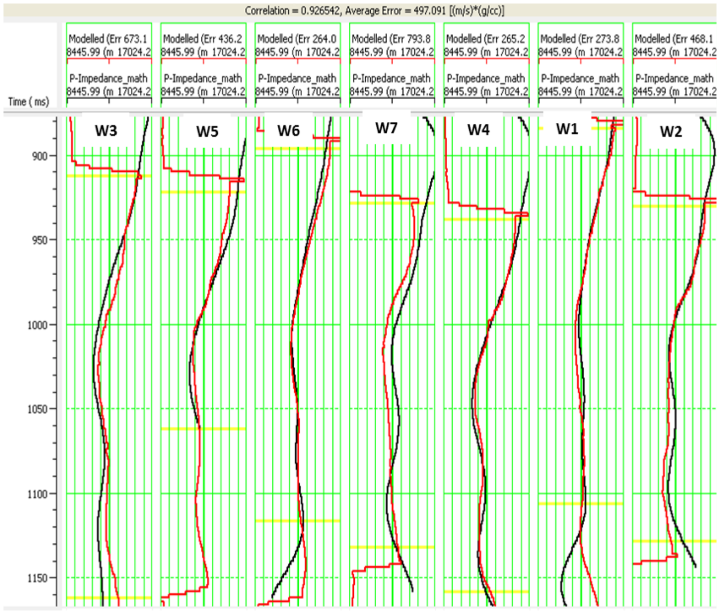

Figure 3: Validation match between the modeled impedance log and actual filtered impedance log using multi-attribute network after including single well low-frequency model as one of the input. Black curve represents the filtered impedance log and red curve represents the modelled impedance curve. Analysis window is marked by yellow bar. A high correlation coefficient of 0.92 is observed.

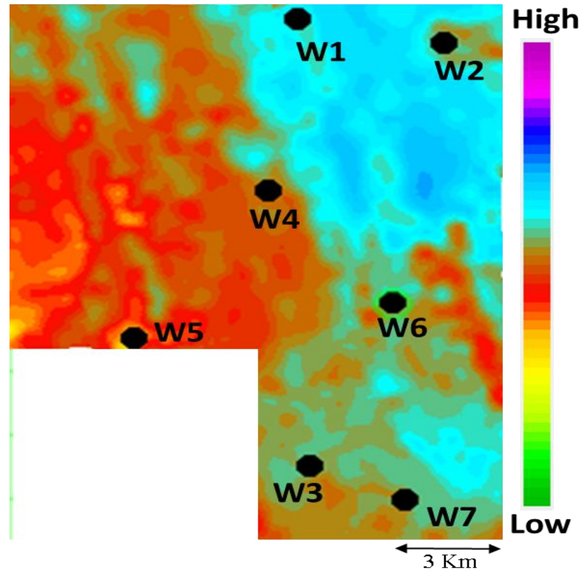

Figure 5: Horizon slice in the ZOI for the low-frequency model generated using inverse distance interpolation method

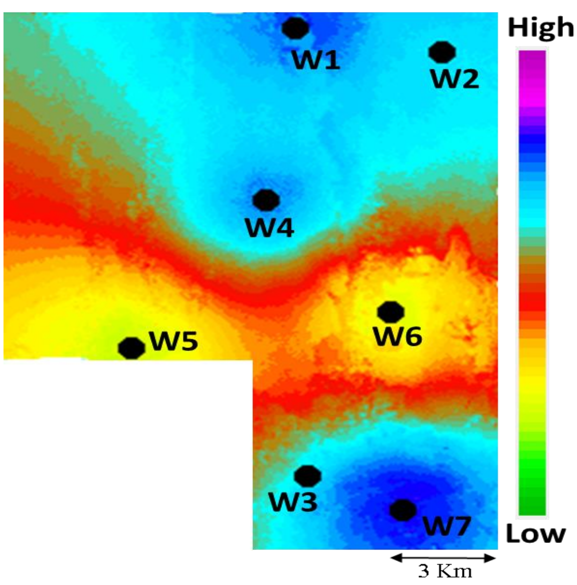

Figure 4: Horizon slice in the ZOI for the low-frequency model generated using inverse distance interpolation method

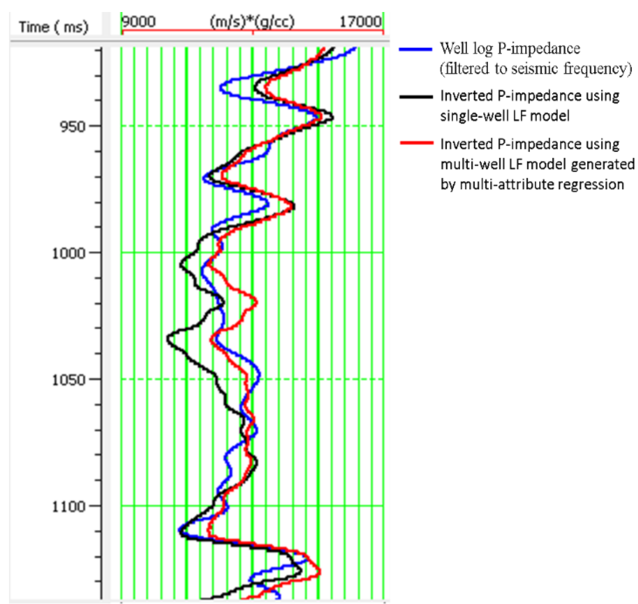

Figure 6: Match at the blind well between the actual impedance logs (blue curve), inverted impedance using single well low-frequency model (black curve) and the inverted impedance using the low-frequency model based on the new approach (red curve).

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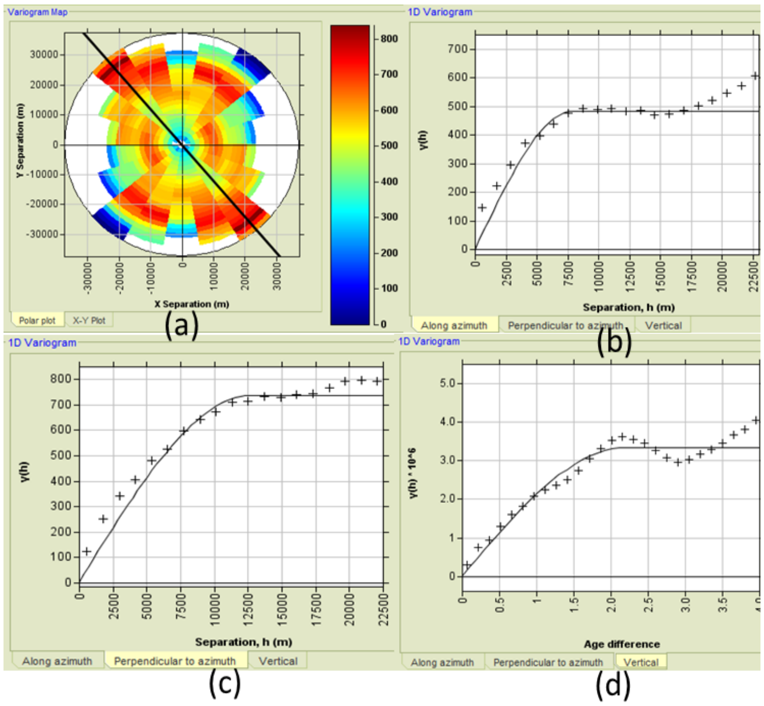

Figure 7: (a) 2D variogram map showing the major direction of continuity. Plots showing different analytical variograms fitted to the experimental data for (a) major, (b) minor and (c) vertical direction.

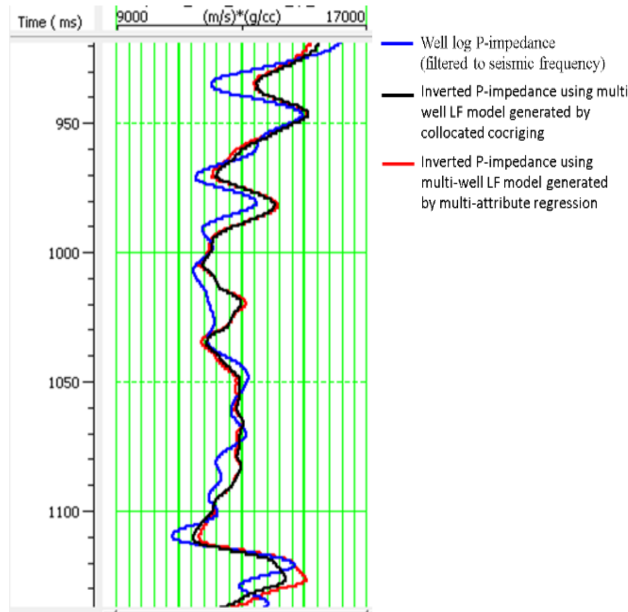

Figure 9: Match at the blind well between the actual impedance logs (blue curve), inverted impedance using the low-frequency model based on collocated cokriging (black curve) and the inverted impedance using the low-frequency model based on the new approach (red curve). Note a very close match between the inverted impedances based on two different low-frequency models.

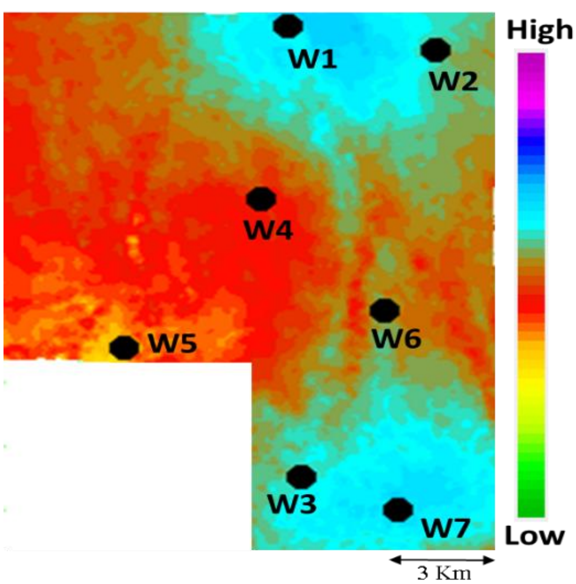

Figure 8: Horizon slice in the ZOI for the low-frequency model generated using collocated cokriging.

Conclusions

The low-frequency model is an important aspect for model-based inversion to generate absolute elastic properties from seismic data. A single-well low-frequency model does not always work well and other interpolation methods such as the one following an inverse-distance approach, create bull's-eye artifacts on the low-frequency model. Our new approach for generating a low-frequency model gives a very good estimate of the low-frequency component for use in the model-based impedance inversion. The very good match at the blind well, between the actual impedance log and the inverted impedance using the low-frequency based on the new approach, gives confidence in the new approach of generating low-frequency model.

Moreover, we see a very close match between the inverted impedances based on the low-frequency models using collocated cokriging and the new approach of multi-attribute regression. This confirms that the two methods that we adopted for building the low-frequency models are equally good and can be implemented with confidence.

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EDITED REFERENCES

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