Seismic Well-Tying via Deep Learning

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Summary

When a seismic project contains lots of wells, well-ties become tedious work. But good well-ties on as many wells as possible is still very critical for the whole project to be successful. As an industry, we have now seeing the prediction of missing logs via deep learning routinely. In this work, we present a method to apply deep learning to predict time-depth curves for well-tying. We will show an earlier approach that does not work and our new approach that works.

Method and Results

Let's first review the workflow to predict missing log (target log) which will be adapted to do well-ties in our study. Carefully chosen logs in wells in which the target log is not missing are selected as the training data set. These logs must have good quality, be meaningful for the predicting log if possible and present in most wells. Then, a neural network (NN) is created and trained to use the chosen logs to predict the target log. If a successful training is obtained, the predictions on wells in which the target log is missing are carried out.

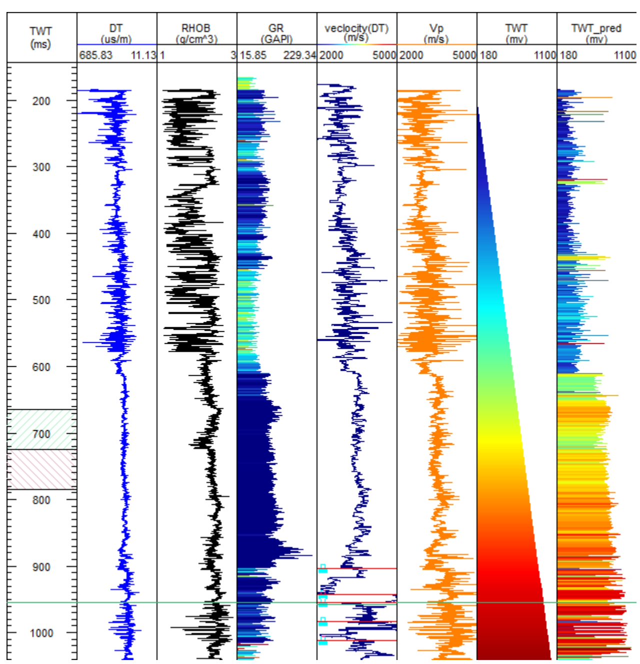


Figure 1 Using three logs to predict T-D curve directly

The essential work in well-tying is to look for a time-depth (T-D) curve that can convert a seismic trace in time domain to depth to match the well. Based on this idea we use the workflow for predicting missing logs described above to predict a T-D curve for some of the wells. Five wells are used in this example. From them, logs from three wells are used for training. Figure 1 shows the results at a well that is not used for training.

The first three tracks are the chosen logs in one well used as training input. They are sonic, density and gamma ray logs. The fourth track shows the interval velocity generated from the T-D curve that comes from manual well-ties, and the fifth track shows the interval velocity estimated from sonic and density logs. The six track shows the two-way time from the afore mentioned T-D curve. We run a deep learning workflow described before to predict a T-D curve shown in the last track. As can be seen that predicted curve is way off the true curve (shown in the second last track). This shows the T-D curve cannot be predicted directly.

We propose an approach in which the interval velocity is predicted first, then converted to average velocity, then converted to T-D curve. The workflow is similar to the one used in Figure 1, where logs from three wells are used for training. Figure 2 shows the predicted results at a well not used for training. This is the same well shown in Figure 1.

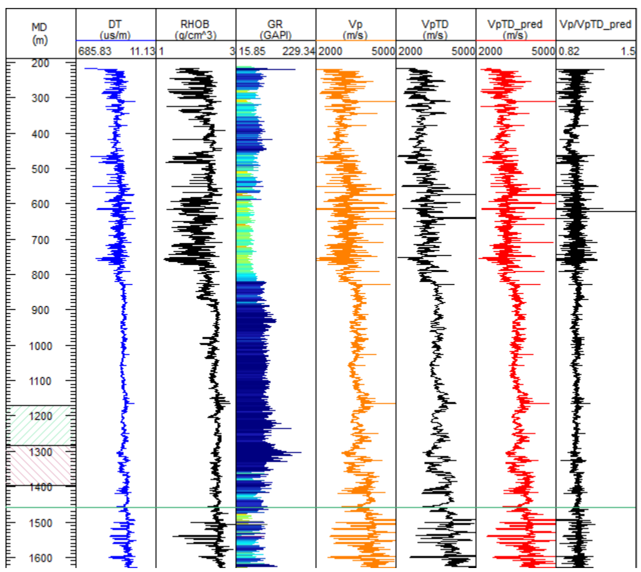
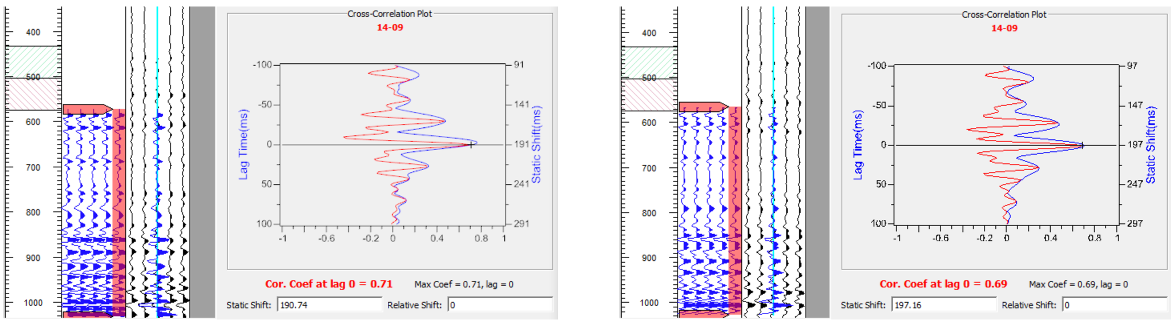


Figure 2 New approach to predict interval velocity

The first three tracks show the same inputs as in Figure 1. The fourth track (Vp) shows the interval velocity calculated directly from sonic and density logs. The fifth track (VpTD) shows the interval velocity calculated from T-D curve of the well. The sixth track (VpTD_pred) shows the predicted interval velocity. Note, this well does not participate in the training which means T-D curve and its derived velocities are not used in the training. Only the three input logs are used for prediction. From the figure, it can be seen that the predicted interval velocity (red) matches quite well with that from T-D curve (black). Well, it also resembles the calculated interval velocity directly calculated from sonic and density logs, but they are still different. The last track shows the ratio of the two which proves that they are indeed different. The predicted interval velocity (red) has extra information coming from the stretch and squeeze done in other wells that are used for training!

From the predicted interval velocity, we can calculate average velocity, and so the T-D curve can thus be generated and used for well-tie.

Figure 3 shows a comparison of well-ties done manually and from this latter NN method. It is the same well shown in Figure 2, that is not used in the training. The two synthetics are generated using the exact same parameters, such as logs, wavelet and correlation window (pink) with the exception of the T-D curve. Figure 3(a) shows the results from the manual tie and Figure 3(b) shows the results from the NN. Look at the cross-correlation plots, they are very similar. The cross-correlation coefficients are very close, 0.71 vs. 0.69. In some other tests we did, we have seen results that the coefficient using the NN is even better than the coefficient for the manual tie.



(a) Manual well-tie (b) Well-tie via deep learning

Figure 3 Synthetics and well-tie comparison

Conclusions and Discussion

We have introduced a novel approval to do well tie via deep learning. It works well in this small data set, but we have not tried it on a large data set yet. If it works on a large data set, it will be very helpful for practitioners in the field.

However, we must point it out that even though the predicted results do contain the correct stretch and squeeze information, they do not have the correct static shift. So, if the logs do not start from seismic datum, which happens only rarely, or the replacement velocity is not accurate, we still need to know the average velocity above the first point of the logs. In this study, we have manually static shifted the synthetics. In practice, this can be achieved by using one consistent seismic horizon - well top pair.

Acknowledgements

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References

Neural network inversion of λρ and μρ from post-stack seismic attributes, Rongfeng Zhang, et al. Geoconvention 2020