Comparative Analysis of First Break Picking Methods in Noisy and Non-noisy P-wave Signal

Leonardo de Assis Pinto, Marco Antônio Rodrigues de Ceia, Roseane Marchezi Misságia, Irineu Azevedo Lima Neto and Fernando Vizeu Santos.
Laboratório de Engenharia e Exploração de Petróleo (LENEP) – Universidade Estadual do Norte Fluminense Darcy Ribeiro (UENF)

Abstract

The estimative of acoustic velocities is an important data that is extracted from data of exploration seismic, well logging (acoustic logging) and laboratory experiments. To realize this estimative a technique called first break picking is used, which consist in an analysis of time x Amplitude data to identify the wave arrival. The complexity of this analysis is in the fact of the data, generally is contaminated with noise and this one could be either inherent to the measuring equipment or other factors, that could make the simple visual analysis impossible. Considering this problem, the development of techniques which would be capable to identify the wave arrival automatic, accurate and faster, justify the study of advanced methods to accomplish this task.

Introduction

The measurements for estimative of acoustic waves velocities are performed in different scales, which could be, exploration seismic (2D and 3D), well logging and laboratory experiments. Despite the fact of this type of measurement is one of the oldest techniques for exploration of natural resources, the development of advanced methods to process and to interpret the acoustic waves is a constant requirement of the industry. To accomplish this estimative, a commonly performed experiment for these measurements in cores are the first break picking, however this task might not be so trivial considering the data, in generally, contain noise which could be inherent to the measuring equipment or other factors.

Considering a measured data of P-wave which there is not too much noise affecting, a visual estimative is quite fast and easy, whereas in a measured data of S-wave or in P-wave contaminated with noise, the visual estimative will have a huge imprecision or it would be considered impossible to realize. For this problem, different methods to accomplish an automatic estimative and more accurate are being developed and there are in the literature and they can be based on neural networks (McCormack et al, 1983; Dai and MacBeth, 1995) correlation properties (Gelchinsky and Shtivelman, 1983), statistical criteria (Akram, 2011), energy ratio (Wong et al, 2009) and fractal dimensions or/and entropy (Jiao and Moon, 2000; Sabbione and Velis, 2010). The Sabbione and Velis' method, which uses a modification of Coppens' method (Coppen, 1985) as indicated in Sabbione and Velis (2010) will be used for comparison with the implemented method.

The new technique implemented to make the comparison with the method of Sabbione and Velis, is based on the problem presented in David-Pilon (2015), which uses Bayesian Inference to detect a variation in a data set over time. The present work will also present a short computational analysis.

Method

The technique present in this work was developed considering the measured data could be split in two different parts, one consisted basically of noise, which has its end in the wave arrival, and the second one, which start in the wave arrival consisted of the measured wave form and also noise, but for both parts of the data, was considered a normal distribution with zero mean and variance σ_1^2 and σ_2^2.

These considerations were made to apply the Bayesian Inference, which is statistical method used to obtain parameter based on the Bayes' theorem, which could be expressed as in the equation bellow:

$$P(\tau,\sigma_1^2,\sigma_2^2|x) \propto \exp\left(-\sum_{i=1}^{n_1} x_i^2/2\sigma_1^2 - \sum_{i=n_1+1}^{N} x_i^2/2\sigma_2^2\right) \times \sigma_1^{-n_1} \times \sigma_2^{-n_2} \times P(\tau,\sigma_1^2,\sigma_2^2)$$

Where x is the data, x_i are the data samples, n_1 is the number of samples before t=τ, τ is the arrival time, n_2 is the number of samples after t= τ, N is the number of data samples and $P(\tau, \sigma_1^2, \sigma_2^2)$ is the prior distribution of the parameters.

The Figure 1 shows the modeling data, the proposed model in the present work consider all the data samples independent from each other.

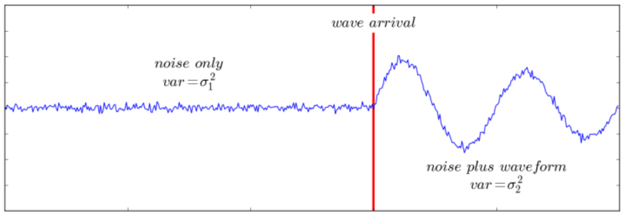

Figure 1 Scheme of the probabilistic model used

To determine the prior distributions, a uniform distribution across all measured times was made for the arrival time τ, since τ is the main parameter of interest and there is not information about the real value. For the variances, was selected an inverse-gamma distribution, because it is the conjugate prior for the variance of a normal distribution with known mean.

For the gamma distribution is necessary determine the parameters α and β which could be done with few data's samples. Was used the first 1% of the data, where we know there is only noise for the σ_1^2 and was used the last 1% of the data, where we know there is data for the σ_2^2 and from these samples, α was set as half the number of samples used and β as half of the sum of the square of the data values.

To obtain these three parameters was made the Markov chain Monte Carlo (MCMC) simulation, using the Metropolis-Hastings algorithm. The implementation of this algorithm was in a Python library, called PyMC (Patil et al, 2010). The posterior distribution was sampled 50000 times discarding the first 10000 for the Markov chain converge to the stationary state and the posterior mean of τ was used to estimate the arrival time of the wave.

Results

To perform the simulation was used two measurements. The first one, was used a measurement of a direct shot from the source to the receiver transducer (face – to –face). The second one using a sample of 50 mm Titanium, with 1 ton of axial pressure and the measurement was performed in the System Triaxial Deformation Physics of Rocks LENEP/UENF. The first break picking in both situation were estimate with the proposed method and with the Sabbione and Velis' method (Sabbione and Velis, 2010).

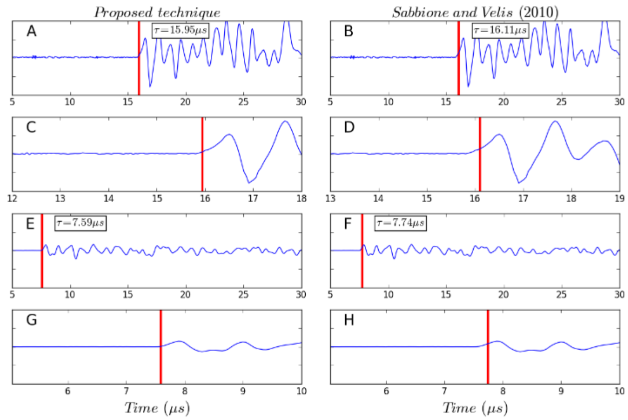

Figure 2 Authomatic first break picking using the proposed and Sabbione and Velis' (2011) methods. Vertical red line marks the first break obtained. Left column (A, C, E and G) shows the results for our method, and the right column (B, D, F and H) for Sabbione and Velis' method. A, B, C and D refers to the 50 mm titanium plug experiment. E, F, G and H refer to the face-to-face experiment. C, D, G and H are zoomed versions of the figures shown above them.

It is possible to observe the both methods perform similar, but the proposed method could be considered more accurate, what could be better observed in the figures 1C, 1D, 1G and 1H (zoomed figures). However, the calculation of the estimate velocity using each time are 3,134.79 m/s for the proposed method and 3,094.06 m/s for the Sabbione and Velis' method, a difference of only 1.2%.

The biggest difference between the two methods is in the computational cost. The proposed method took to estimate the first break picking an average of 7.76 seconds, while the Sabbione and Velis' method took 0.21 seconds, a considerate difference if it is necessary process a huge number of data.

In both data, the presence of noise was not considerable, so, to test the sensitivity of the methods for noise, all the titanium data was contaminated with different levels of gaussian noise, using the function random. Both methods process again the data and the results are shown on Figure 3.

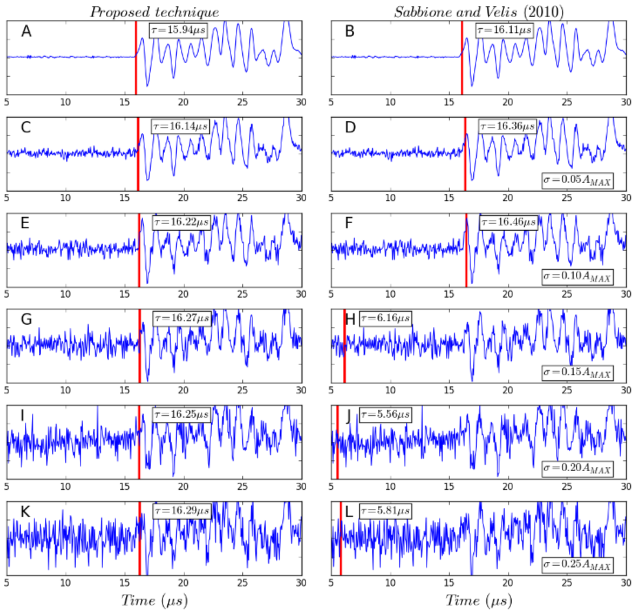

Figure 3 Automatic first break picking under different noise conditions. Vertical red line marks the first break obtained. Left column (A, C, E, G, I, K) refers to the proposed method, and right column (B, D, F, H, I, L) to Sabbione and Velis' method (Sabbione and Velis, 2010). The noise level increases from top to bottom of the figure. The noise standard deviation was set to 5% of maximum signal amplitude on C and D, 10% on E and F, 15% on G and H, 20% on I and J and 25% on K and L and A and B do not have increase of noise, both are the same of Figure 1A and 1B.

It is possible to observe, when the signal is considerable affect with noise, the Sabbione and Velis' model could not be used to estimate the first break picking, while the proposed method is affect by the noise, but still keep an accuracy of the original measurement.

The better computational result for the Sabbione and Velis' method could be lost with the result present in the Figure 3, because create a necessity of filter the data, while the proposed result do not have this necessity. More than the computational cost, a filtering process always affects the data, and consequently, the final result of the experiment.

Conclusions

The necessity of new techniques to analyze the data of acoustic measurements can be observed when we principally see the plot in the Figures 2I, 2J, 2K and 2L. It could be considered almost impossible to give an accurate answer with a visual analysis, confirming this necessity.

Even the acoustic measurements are considerate an old technique in comparison with the most modern ones, it is possible to consider an technique in development whereas a technique developed in 2010 (Sabbione and Velis, 2010) shown results which could be considerate unsatisfactory for noisy data.

Considering all these factors, the present work proposed a new technique to accomplish this task using Bayesian Inference to do the first break picking. The main advantage of this technique is robustness to different noise levels, the problem presented in Sabbione and Velis' method.

However, the computational cost is the biggest disadvantage, the presented example had a file of 500 amplitude measurements in 500 different times and it took 35 times longer than the Sabbione and Velis' method, 7.76 versus 0.21 seconds to process. Considering a possibility to process 500 files, with the same number of measurements, it will take almost 1 hour and 5 minutes, a long time considering the necessity of fast answers nowadays. Another disadvantage it is necessary to mention is the stochastic nature of the used method, which may lead to slightly different results at each run.

Acknowledgments

The authors would like to thank UENF/CCT/LENEP for the available structure and the PRH-226/PETROBRAS for the financial support of this study.

References

Akram, J., 2011. Automatic P-wave Arrival Time Picking Method for Seismic and Microseismic Data. CSPG CSEG CWLS Convention.

Coppens, F., 1985, First arrivals picking on common-offset trace collections for automatic estimation of static corrections: Geophysical Prospecting, 33, 1212–1231.

Davidson-Pilon, C., 2015. Bayesian Methods for Hackers. Addilson-Wesley Professional; 1 edition.

Gelchinsky B. and Shtivelman V., 1983. Automatic picking of first arrivals and parameterization of traveltime curves. Geophysical Prospecting, 31, 915-928.

Jiao, L. and Moon, W.M., 2000. Detection of seismic refraction signals using a variance fractal dimension technique. Geophysics, 65, 286-292.

McCormack, M., Zaucha, D. and Dushek, D., 1993. First-break refraction event picking and seismic data trace editing using neural networks. Geophysics, 58, 67-78.

Patil, A., Huard, D., Fonnesbeck, C. J., 2010. PyMC: Bayesian Stochastic Modelling in Python. J Stat Softw, 35(4), 1-81.

Sabbione, J. I. and Velis, D., 2010. Automatic first-breaks picking: New strategies and algorithms. Geophysics, 75, V67 – V76.