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Seismic Pattern Recognition: Automation of Processing and Interpretation

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ABSTRACT

Is it possible to make every step of seismic processing and interpretation automatic? Is it feasible to have experiences of the best seismic processors of the world in a vital step like velocity analysis? The answer to this question is hidden in definitions of seismic pattern recognition terminology, it is essential to know about many parameters like picking representative objects with all possible spatial variations, minimum size of training set, knowledge on prior probabilities, seismic attribute redundancy reduction, choice of classifiers and posterior probabilities combinations. The issue of categorizing data to different classes has significant and wide ranges of applications in analysis and interpretation of seismic data.

Keywords: Pattern Recognition, Seismic Processing, Seismic Interpretation, Machine Learning, Soft Computing

INTRODUCTION

Specialists are partly involved with the pattern recognition (PR) and machine learning (ML) methods from first stages of seismic processing like automatic first break picking in refraction statics process to final outputs such as AVO classification and seismic object detection. Lees (1996) and van der Bann & Jutten (2000) argued about applicability of neural networks in geophysical studies. Glinsky et al. (2001) used a trained probabilistic neural network for voxel classification using event times, subsurface points, and offsets. Meldahl (2001) showed the gas chimney representation in neural network on a standard set of input directive seismic attributes. Hashemi et al (2008-a) stated a mixture of classifiers output (MLP & SVC) for seismic object detection experiences in North Sea. The detailed algorithm of finding most relevant attributes (among their zoos) is later discussed by Hashemi & Javaherian (2009). Even some efforts have been done to reconstruct the knowledge of fuzzy logic by the author and his team in random noise reduction (Hashemi, 2008-b), seismic facies analysis and Time-Frequency attributes application (Hashemi, 2012), Joint clustering of EM and Seismic data (Shahrabi, et al, 2016), A semi-supervised constrained seismic to well match faces analysis methodology (Hashemi et al, 2017) and SeisART, an ANFIS based seismic facies analysis software (Hadiloo et al., 2017).

Considerations and added values of PR & ML methods in seismic

Different architectures of multilayer perceptron neural networks are described as the good nonlinear classifiers; however, they are not the only powerful ones in pattern recognition discipline. In order to accomplish a seismic classification routine with realistic solutions, one shall consider the fact that the choice of classifier is just one important part of the seismic pattern recognition procedure. The fact is shown in salt dome detection in North Sea (Fakhari & Hashemi, 2017).

There are some serious considerations that must be made in seismic pattern recognition to have reliable answers. The choice of classifier that is mentioned by several researchers is just one of those. It is discussed that each classifier yields a different error trends. Performance of the method is not just defined by statistical term i.e. misclassification error, the geological interpretation of posterior probabilities has equivalent importance. In Figure 1. An example of semi-supervised constrained seismic facies analysis methodology is shown. As it is obvious the way to use well data for seismic facies analysis is so tricky. Also the form of input data (i.e. trace shape or grid base) is highly important based on the purpose of facies application.

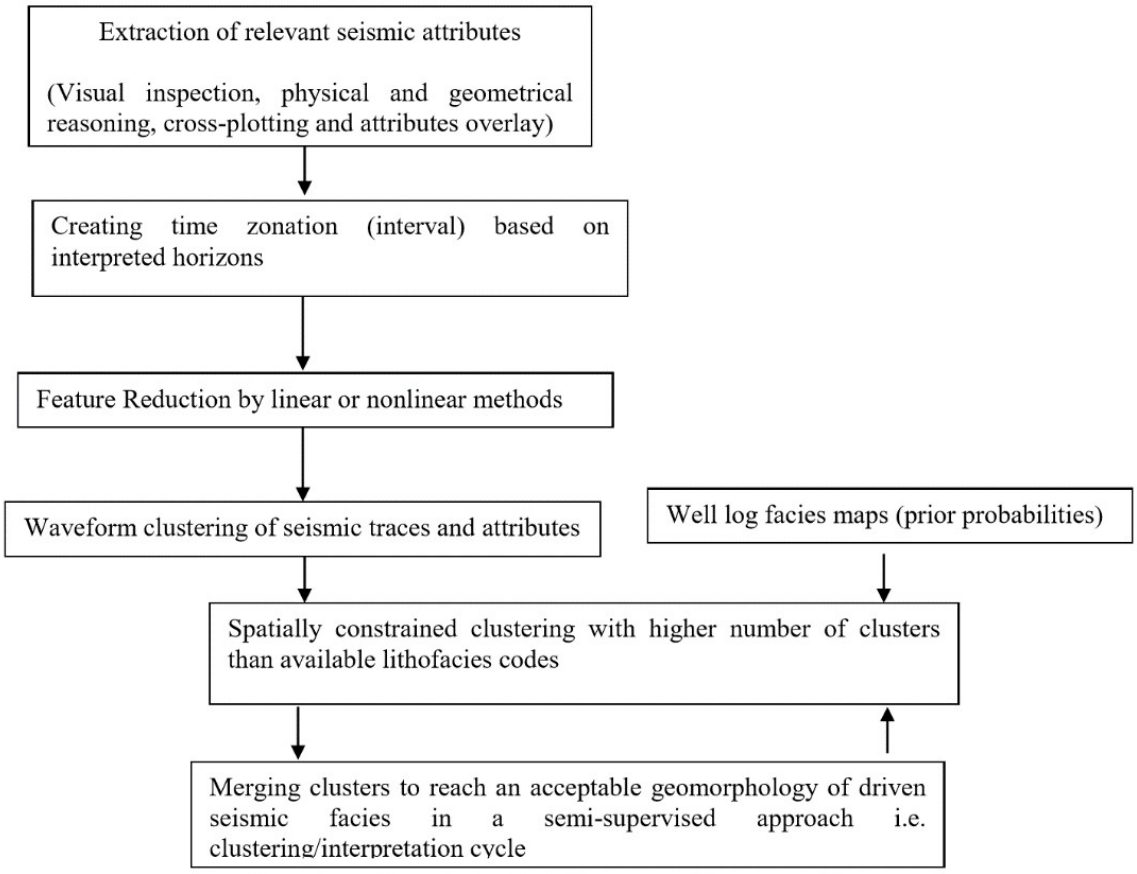


Figure 1. Workflow of semi-supervised constrained seismic facies analysis methodology (Hashemi et al. 2017)

Automation of seismic processing is the next target for the future pattern recognition studies where it is targeted to provide a brute stack out of the field data without user intervention. The scheme below shows the proposed methodology. The added value will be online usage in VRC centers of oil companies to interactively find and locate the targets while acquisition. The feasibility of finding appropriate parameter testing in an optimized range within few minutes for 2D lines and few hours for 3D cubes is another advantage! Figure 2 illustrates the implementation of the method in diagrams.
The final Brute stack is compared with the traditional on site processing in Figure 3.

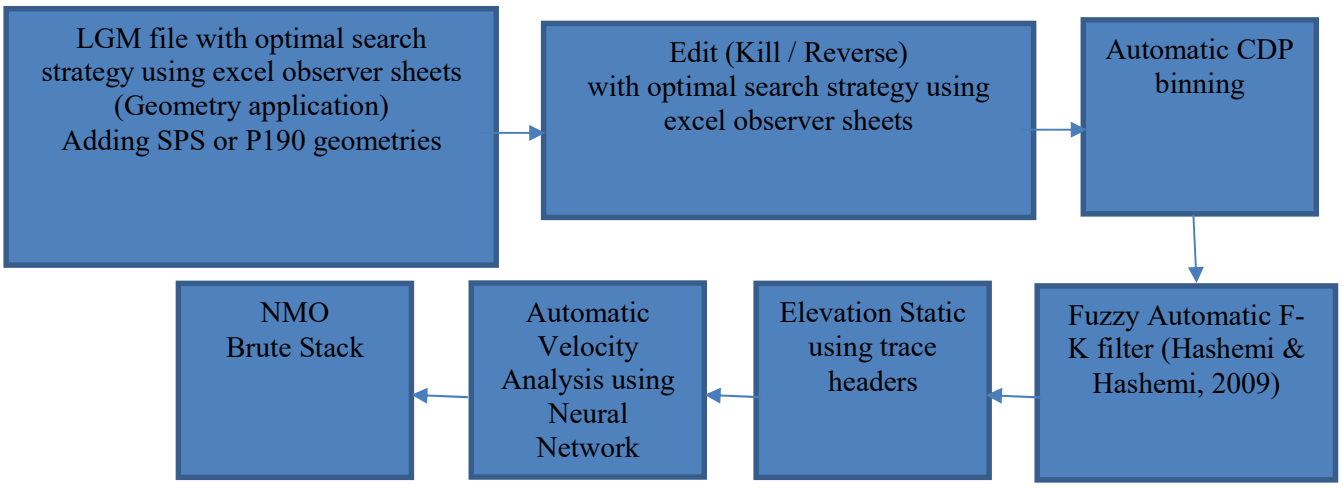
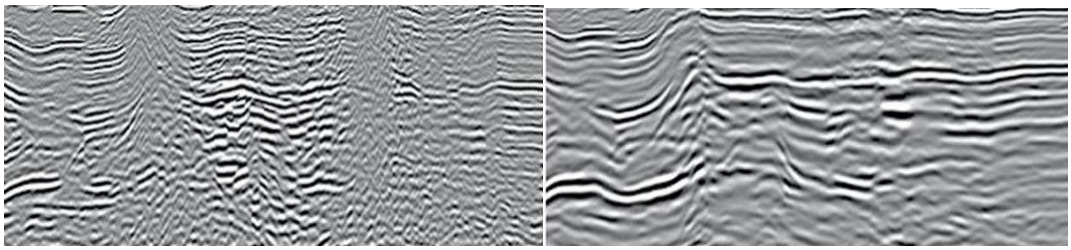


Figure 2. Workflow of Automatic Seismic Processing using PR and ML methods



(a) (b)

Figure 3. Comparison of two brute stack, (a) The result of automatic workflow stated in figure 2, (b) The result of traditional workflows for processing in field. The higher resolution is because of higher accuracy in adaptive filter picking, better elevation calculation for static compensation and better velocity analysis

CONCLUSION

The world of seismic and petroleum engineering is jointing to each other due to increasing need for the prompt seismic responses for static and dynamic modeling in virtual reality centers (VRCs). Pattern recognition machine learning and computational intelligence are three concepts with same main functionalities in classification, state estimation and automation of processes. The later functionality is quite important for seismic exploration specialists to have faster results for petroleum engineers and office managers and specialists. The presented workflows for processing and interpretation shall be used in conjunction with traditional human based seismic processing and interpretation. However, it is a dream now, but it is maybe feasible to rely solely on computers with AI knowledge for entire processing and interpretation in future!

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