METHODS FOR MULTI-HORIZON DRIVEN WAVEFORM CLASSIFICATION

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Summary

In this paper, new approaches involving waveform classification on a stack of horizons are presented. The first method consists in gathering classic classification maps in a new stack in order to quickly analyze horizons heterogeneities. Yet, the detection and extraction of geological features visible on several horizons is challenging because each classification map results from its specific templates. To tackle this issue, a second approach based on dependent templates shared by all classification maps is proposed. Applied to a real dataset, a multi-horizon volume has been classified from envelope waveforms leading to the extraction of a turbidite system geobody.

Methods for multi-horizon driven waveform classification

Introduction

Automatic pattern recognition applied to seismic waveforms enables the creation of facies by gathering portion of seismic traces with similar amplitude, frequency and phase. Assuming waveform changes are not caused by source signature nor processing, classification maps can highlight variations of lithology, stratigraphy, fluid contents or bed thickness (Singh et al., 2004). Waveforms are usually extracted from a seismic volume along an interpreted horizon in a defined vertical window in order to be compared from the same chronostratigraphic event. Hence, the classification is very sensitive to the horizon picking quality and the window size (Barnes, 2016). An unsupervised machine learning algorithm such as k-means or Self-Organizing Map (SOM) is subsequently used to create representative templates of extracted waveforms (Zhao et al., 2015). The classification map is finally generated by associating each waveform to a template and its assigned color.

This paper presents new approaches involving waveform classification on a stack of horizons. This stack behaves as a volume, but each frame represents a surface by opposition to a time or depth slice. The multi-horizon volumes are obtained from a comprehensive signal-driven seismic interpretation method (Pauget et al., 2009).

Independent classification: A classic workflow

The first approach corresponds to an independent classification of horizons. This consists in classifying each horizon from the classical workflow (Roy et al., 2010) and then gathering all classification maps into a new multi-horizon volume (Figure 1). By applying this method, all horizons are independently classified using the same vertical window size for the extraction and the same number of output classes. The 2D SOM clustering algorithm, an unsupervised machine learning algorithm based on a non-linear projection onto a lower dimensional latent space, is then applied and appreciated for its natural sort of waveform templates by similarity (Barnes, 2016).

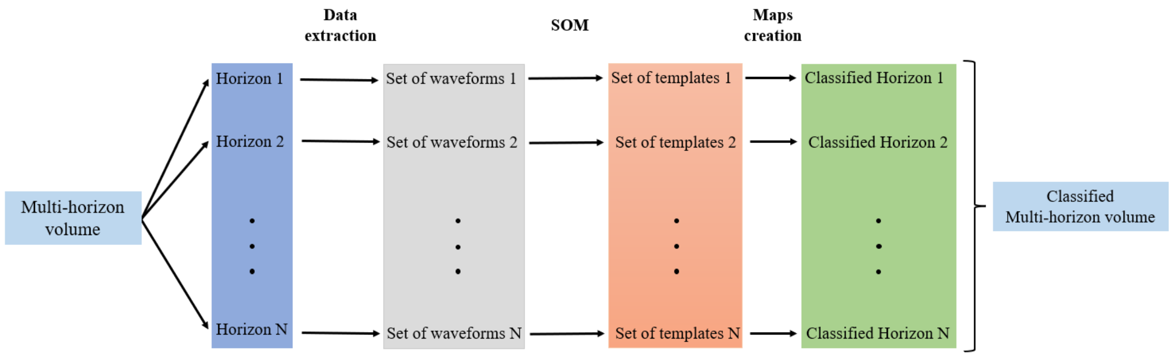

Figure 1 *Independent waveform classification workflow equivalent to the classical workflow applied on a multi-horizon volume.*

To illustrate this method, multi-horizon volumes have been generated from the interpretation of the Maui field, located in the Taranaki basin, offshore New Zealand (Durot et al., 2017). Independent classification gives an insight on the horizons heterogeneity and their stratigraphic features. This approach emphasises seismic facies distribution even though correlating the classification maps remain challenging. Indeed, the changing templates between the classification maps make the interpretation difficult, especially for the detection and extraction of a common geological feature as a unique geobody (Figure 2).

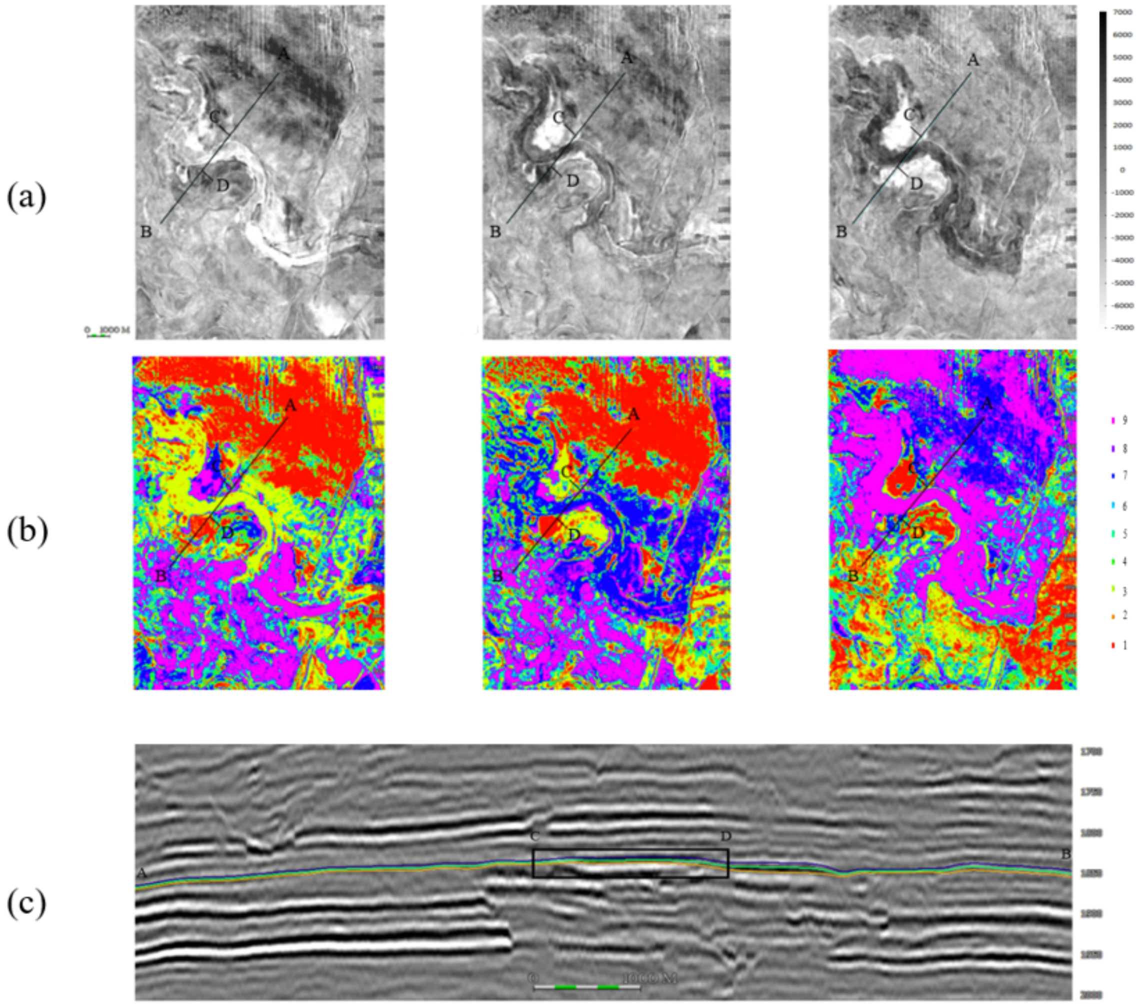

Figure 2 *(a) Three horizons mapped with seismic derived from the multi-horizon volume, (b) their corresponding independent classifications with 9 classes and (c) the seismic intersection panel. A turbidite expression system is highlighted within the three horizons. Each classification map has been created with its specific templates making their comparison challenging.*

Dependent classification

The objective of the dependent classification (Figure 3) is is to have a single set of waveform templates shared by all classification maps in order to facilitate the interpretation. At first, each horizon is classified such as in the independent method previously described. The set of initial templates associated to each horizon is then stored and used as input for a subsequent SOM algorithm. The resulting dependent templates are representative of every initial template and embed the waveform variability of each horizon. The merge of independent classes could also be applied, but reduces the accuracy and variability in classification maps, whereas a clustering algorithm preserves most of templates heterogeneity and recreates a distribution of extracted waveforms in new suitable classes. In addition, a same geological feature (i.e. channel, magmatic intrusions, etc...) at different depths is described by different seismic waveforms, mostly due to a phase variation, making its extraction as a 3D geobody harder. A trade-off between precision and comparability is proposed by using envelope waveforms. This amplitude attribute has the advantage of being invariant under phase rotation (Barnes, 2016).

This dependent method is applied with envelope waveforms (Figure 4), centered at the horizon depths, on the same multi-horizon volume as in the independent classification. The comparison between different

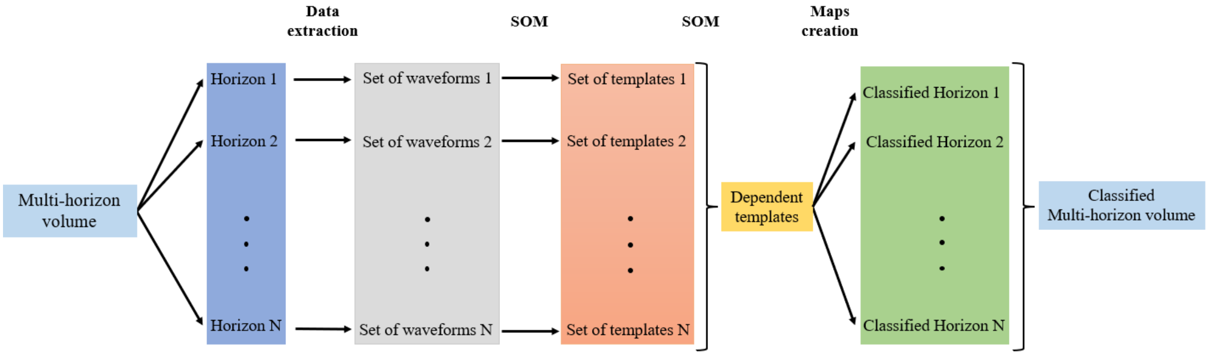

Figure 3 *Dependent waveform classification workflow applied on a multi-horizon volume. The dependent representative templates are created based on each horizon variability.*

classification maps is more relevant thanks to the dependent templates, making the interpretation easier. It facilitates the extraction of dipping geological features and the analysis of their heterogeneity at a multi-horizon scale.

Discussions

With the dependent classification, waveforms around all horizons are compared and classed with the same set of templates. Even if the envelope attribute suppresses phase variations, comparing waveforms from several horizons that might be in different geological settings (variation of lithology) and physical environments (temperature or pressure) can lead to erroneous correlations. Ideally, all horizons have to be seismic consistent and in the same stratigraphic setting. Moreover, the vertical spacing between horizons has a real impact. For a low density multi-horizon volume, the gap between consecutive horizons will be too important for an accurate waveform comparison. On the contrary, a high vertical density will permit precise comparison and consistent geobody extractions. Therefore, dependent classification is more relevant in a comprehensive sedimentary system modelling approach whereas the independent classification should be more suitable for single key surfaces analysis.

Conclusion

Waveform classification is an important tool for the creation of meaningful facies in seismic data. A classic workflow consists in classifying a single horizon with seismic waveforms but it makes the interaction between different classification maps impossible, hence limiting the interpretation to the scale of a horizon. Thus, this abstract presents approaches based on stacks of several horizons to help the interpreter. At first, by independently gathering horizon classification maps in a single volume. This method is useful to quickly analyze horizons heterogeneity and stratigraphic features but the independent templates make their comparison difficult. To tackle this challenge, a second approach has been implemented with a unique set of templates allowing the creation of all classification maps. The method classifies each horizon independently with the same parameters to gather all initial templates as input for a SOM algorithm. The output is a set of dependent templates representative of the input templates. By removing the phase variation, envelope waveforms facilitate the extraction of 3D geobodies. Applied to a real dataset, a multi-horizon volume has been classified with the dependent method leading to the modelling of a turbidite system geobody depicted by a single class. To increase the geological meaning of templates, it will be interesting to include supervised techniques in the dependent classification workflow (Singh et al., 2004).

Acknowledgements

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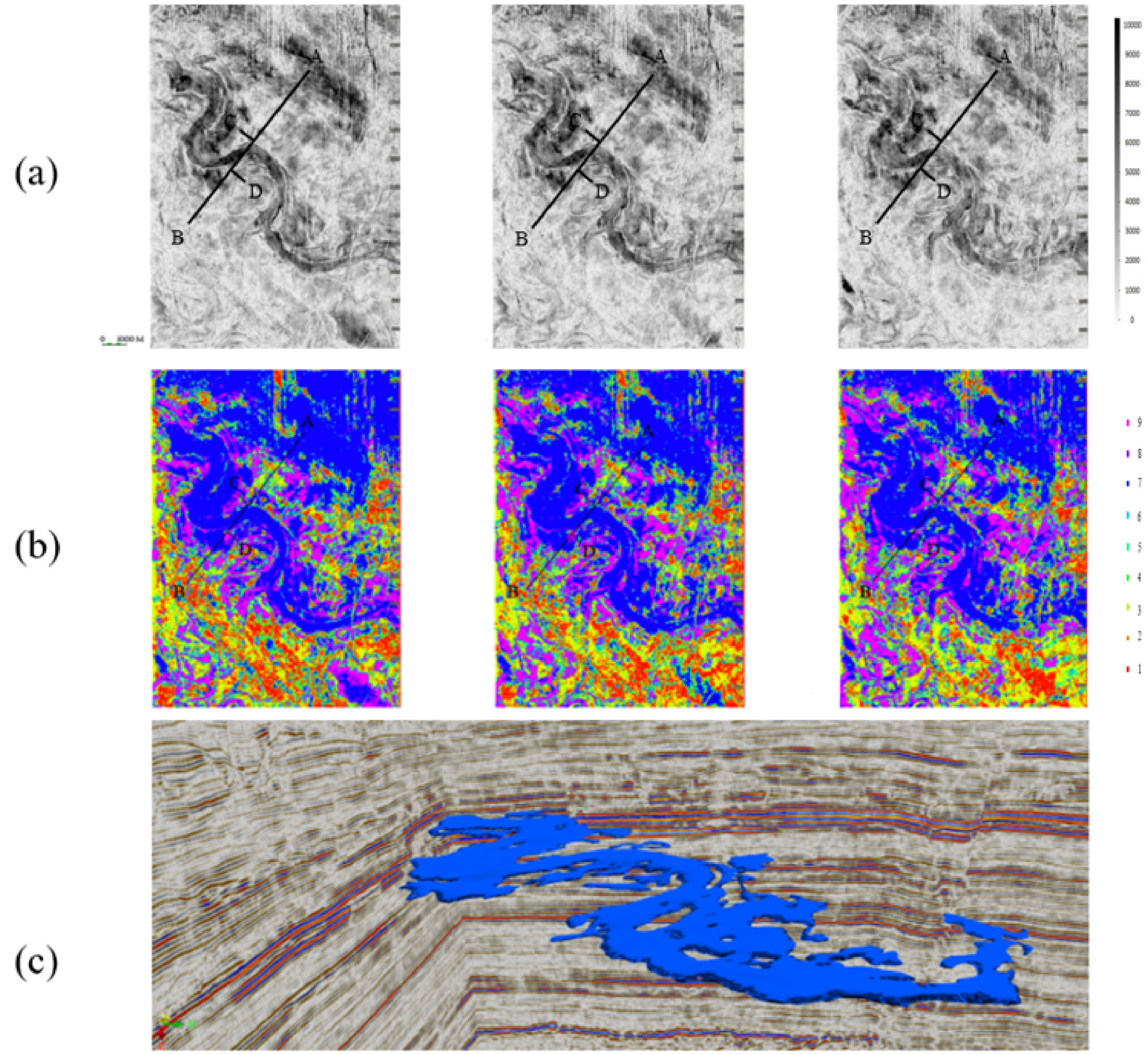

Figure 4 *(a) Three horizons mapped with the envelope attribute derived from the multi-horizon volume and (b) their corresponding dependent classification with 9 classes. The class depicted by the blue color well highlights the turbidite system in the three horizons enabling (c) an automated 3D geobody extraction.*

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