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Semi-Supervised DeepMachine Learning Assisted Seismic Image Segmentation and Stratigraphic Sequence Interpretation

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Summary

Geological / geophysical interpretation of seismic survey commonly requires segmenting a seismic image into different layers/sequences, highlighting certain geobodies, or picking different horizon surfaces, for multiple purposes including, but not limited to, earth model building, velocity model building, stratigraphic analysis, etc. The traditional approach requires the interpreter significant amount of effort to interact with computer and label the data.

We demonstrated an innovative workflow for seismic image/sequence/geobody segmentation and horizon picking, where a key aspect is that, it requires much less labels and hence significantly reduce interpreter's workload.

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Geological / geophysical interpretation of seismic survey commonly requires segmenting a seismic image into different layers/sequences, highlighting certain geobodies, or picking different horizon surfaces, for multiple purposes including, but not limited to, earth model building, velocity model building, stratigraphic analysis, etc. The traditional approach requires the interpreter significant amount of effort to interact with computer and label the data.

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Introduction

Seismic image segmentation, geobody segmentation, stratigraphic sequence interpretation and horizon picking from seismic data is fundamentally important for subsurface interpretation and reservoir characterization with the objective to generate the most geologically sound annotation and earth model. Several types of human-computer interactions are involved in the workflow, such as highlighting object, picking surfaces, seed point selections, etc. It requires interpreter's special knowhow and significant turnaround time to perform the tasks.

A typical example is automatic horizon tracking: interpreter picks a pixel/voxel as seed point and the program will automatically track the horizon that is connected to the seed point based on the lateral continuity of seismic signals such as amplitude, gradient, etc (e.g., Leggett *et al.* 1996; Yu *et al.* 2008). When the seismic survey contains relatively complex geological structures or when the signature of the horizon is weak (Di *et al.* 2018), which is not uncommon, manual pixel/voxel-wise labelling of horizon is required. Overall, this approach is time consuming and requires a skilled interpreter to finish the task. Moreover, the output of such an approach are horizon surfaces instead of sequence/geobody which can be directly used by interpreter to build earth model. Post processing is required to further segment the seismic cube into sequence/geobody from the horizon surfaces.

We presented a machine learning based method for seismic segmentation and horizon picking, which could simplify the human-computer interaction, and reduce the interpreter's effort to build earth models.

Methodology

Modern machine learning methods, especially neural networks (NN), having amply demonstrated their potential by addressing challenging problems in fields such as computer vision (Long 2015, Ronneberger 2015, Badrinarayanan 2017), could potentially be applied to automate various arduous steps for earth model building. However, since it is costly to obtain sufficient well-balanced and accurately labelled seismic data, development of NN based applications for robust horizon interpretation have been curtailed. Unsupervised learning, such as clustering and autoencoders, doesn't require input labels as training data. However, special regularizations and prior information has to be incorporated in the training in order to achieve satisfactory results (Zeiler 2011, Kallenberg 2016). By combining unsupervised learning and supervised learning, we demonstrated a novel machine learning based methodology for seismic image/sequence/geobody segmentation and horizon picking, where a key aspect is that, it requires a very small amount of labels to train the NN model and thereby allow the interpreter to build seismic earth models with significantly less effort.

The presented methodology requires input labels (training data for supervised learning) to be pixel-wise categorical labels selectively marked on seismic inline and/or crossline slices. It requires a very small percent of seismic slices to be labelled. Interpreter can provide such input labels in the format of bounding boxes, scribble lines or paint-brush swaths. Labels could have different sizes and shapes: they could be in the shape of straight lines, curved lines, cross lines, triangle, rectangle, polygons, circles, or any convenient shape which the interpreter can easily draw to cover the target sequence/geobody. Interpreter's input label can also be trace-wise labels where, on single or multiple seismic traces, pixels are picked to separate two stratigraphic sequences above and below. The interval between such labelled seismic traces, as well as the density of the lines/paint-brush labels could vary depending on the complexity of the underlying geology. Finally, complete pixel-wise labelling of the entire inline or crossline image can be another option for interpreter as a complement of the above methods. Deep neural networks, with special training procedures, can utilize this small labelled dataset to perform seismic image/sequence segmentation and horizon picking across the entire seismic survey. Furthermore, the interpreter can iteratively finetune the result by providing addition input based on the NN model performance and/or geological complexities discovered. As an example, Figure 1 illustrates different types of labels which interpreter can mark on a seismic inline/crossline slice using a mouse.

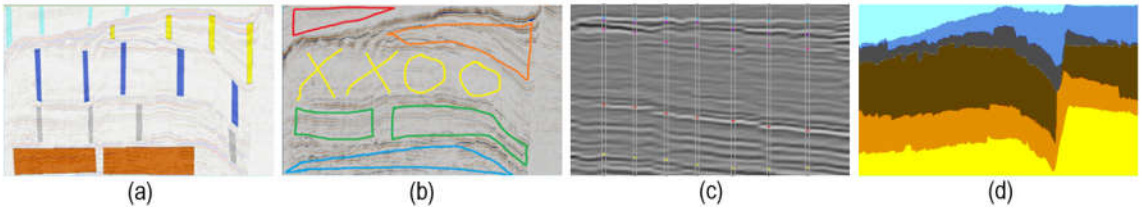

Figure 1 *Possible format of input labels.* ***a)*** *paint-brush labels;* ***b)*** *scribble-lines labels with variety of shapes;* ***c)*** *trace-wise labels on seismic traces at sequence boundaries;* ***d)*** *fully-labelled slices.*

There are two stages involved in this workflow: unsupervised feature learning/extraction stage and supervised learning stage. The output of unsupervised feature learning/extraction, combined with interpreter's input labels, will become the input of supervised learning stage. During unsupervised feature learning the deep network identifies a comprehensive feature set from seismic data in unsupervised manner (without interpreter's input). The supervised learning stage involves training the deep network with the output features obtained from the first stage and interpreter's input labels. The unsupervised learning stage is typically formulated for simple tasks which can be computationally automated and does not require any special effort on part of the interpreter.

Various machine learning method may be applied in the unsupervised learning stage to extract features from seismic data. Some examples are: autoencoder, self-learning, dynamic filtering, Bayesian based methods, etc.

During the supervised learning stage, one or more slices from inline or crossline direction may be picked by the interpreter to create input labels in an above-noted format. The slices used to generate labels may be selected in a manner so as to provide samples of patterns occurring in the seismic cube. The deep NN will be trained on all the input labels from selected slices.

The trained CNN model will be applied to predict the pixel-wise categorical classes for the remaining unlabelled seismic cube. If input labels provided in supervised learning stage include slices from both inline and crossline direction, predictions will be generated on both direction and final output will be calculated based on merging predictions from both direction. Figure 2 illustrates the proposed training and prediction workflow.

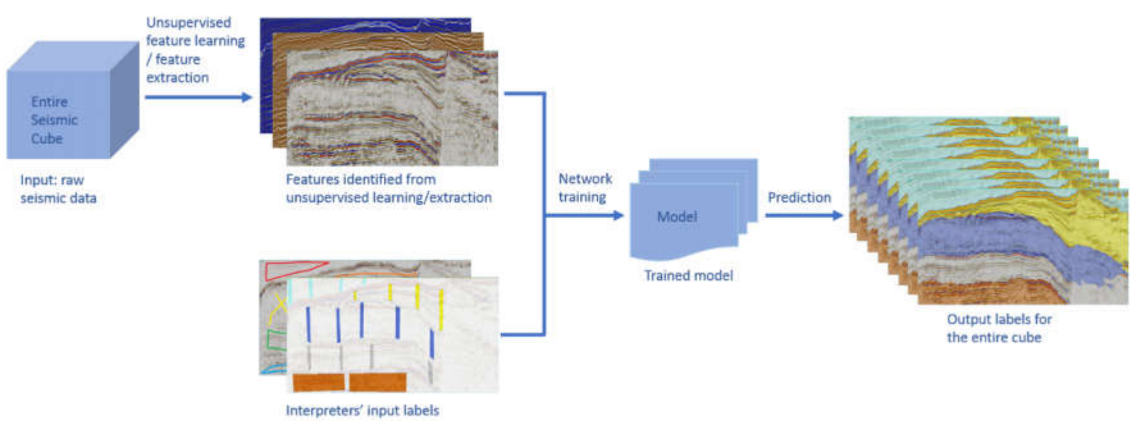

Figure 2 *Training and prediction workflow that combined unsupervised and supervised learning.*

Example I

In this example we demonstrate the application of using paint-brush labels to train the NN model and predict the sequence segmentation on the slices that the NN model has never seen. The data set include 160 inline, 1856 crossline and 448 time slices. Paint-brush labels were applied on inline slice 0, 80 and 160 and these three slices were input to NN models for training. After the training was completed, the

NN model was applied to predict on these slices as well as the slices that the network has never seen. Figure 3 shows training and prediction process, input labels and prediction results on inline 0, 40, 80, 120 and 160.

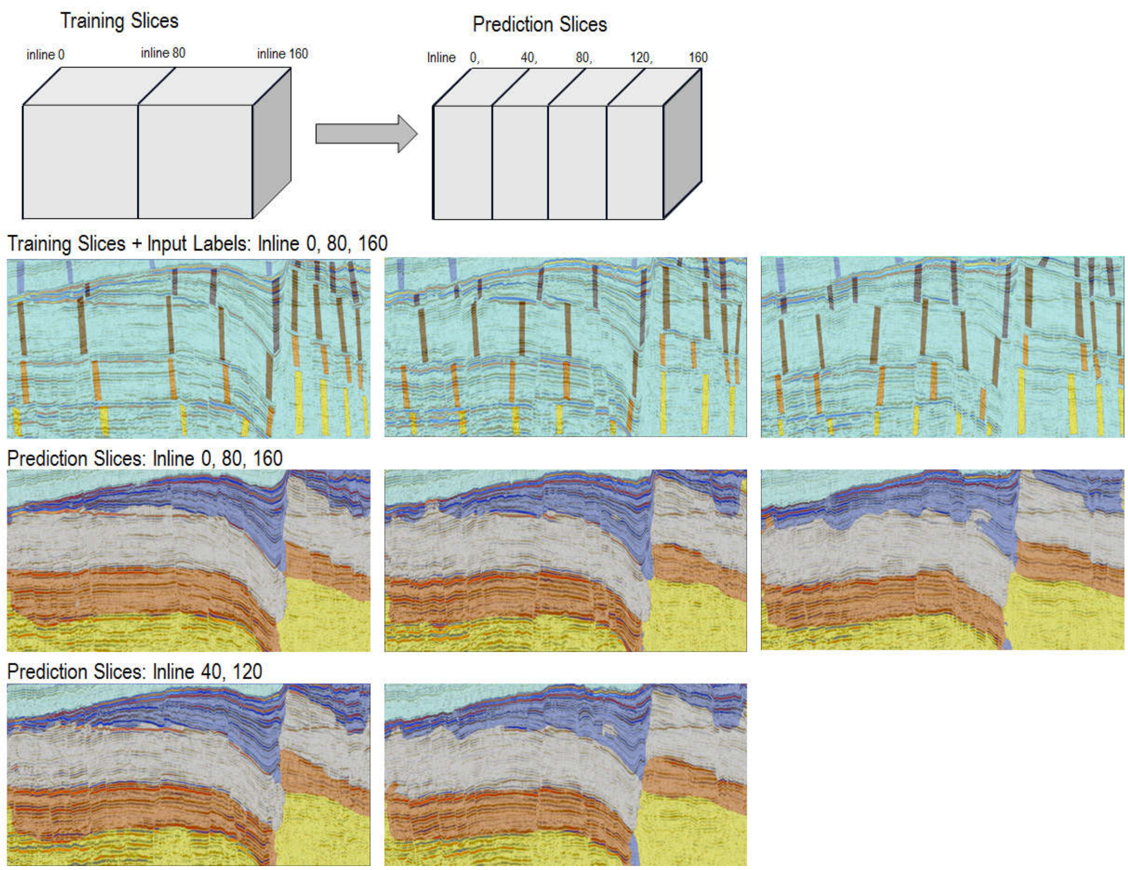

Figure 3 *Example I results.* ***First row****: schematics of how training and prediction were performed. Paint-brush labels were input on three inline slices (inline 0, 80 and 160) and the neural network was trained on these slices. Prediction was made on inline 0, 40, 80, 120, and 160;* ***Second row****: Input labels on inline 0, 80 and 160;* ***Third row****: Predictions on inline 0, 80 and 160;* ***Forth row****: Predictions on inline 40 and 120.*

Example II

Then we provide one example for seismic sequence interpretation using trace-wise labels. The testing seismic cube include 1665 inlines, 2751 crosslines, and 1400 time slices. 4 inlines (#333, 750, 1246, and 1624) and 3 crosslines (#740, 1300, and 2224) are manually labelled for training NN models. Finally, the sequence volume is generated by applying the trained NN model to the entire seismic survey. Figure 4 demonstrates the prediction of 10 sequences on two vertical slices (Inline #1300and Crossline #1400). The important seismic features are clearly delineated from the prediction slices, particularly the pinch-out in the top area and the faulting in the bottom area, both of which are consistent with the manual interpretation from experienced interpreters.

Conclusion

Modern machine learning method, especially deep neural network, with its capability to address complex computer vision problem, could potentially find its application in seismic interpretation. By combining the advantage of unsupervised and supervised learning, we demonstrated that a deep neural network based approach can significantly reduce interpreters' effort on seismic image segmentation and stratigraphic interpretation.

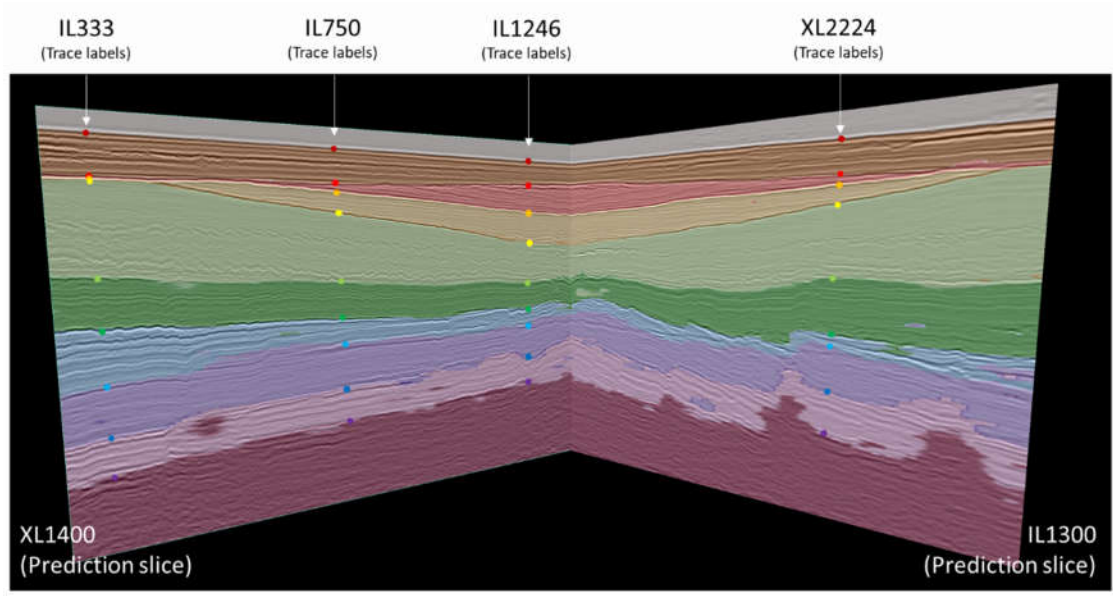

Figure 4 *Example II results of predicting 10 sequences in two vertical slices, with the trace-wise labels marked as dots. Note the good delineation of the pinch-out in the top area and the faulting in the bottom area. Colours are randomly assigned for the sole purpose of visualization.*

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