Seismic Fault Detection From Post-stack Amplitude by Convolutional Neural Networks

Haibin Di, Zhen Wang, and Ghassan AlRegib
Center for Energy and Geo Processing (CeGP)
Georgia Institute of Technology, USA
• Motivation
• Workflow description
• Result analysis
• Why CNN performs better?
• Conclusions
Outline

• Motivation
• Workflow description
• Result analysis
• Why CNN performs better?
• Conclusions
Fault interpretation is important for subsurface structure mapping and reservoir characterization in 3D seismic data.

Manual interpretation is labor intensive and time consuming.

The size of seismic data is significantly increasing, which requires more efforts for interpreting a 3D seismic volume.

---

Existing solutions to Fault Interpretation

1. Post-stack amplitude + manual interpretation

2. Attribute analysis + manual interpretation, such as
   - Coherence (1995)
   - Similarity (2005)
   - Semblance (1998)
   - Fault likelihood (2013)

3. Attribute analysis + post processing, such as
   - Hough transform (2014)
   - Lineament thinning (2013)
Machine learning is successful in big data analysis and pattern recognition.

How is its performance on seismic fault detection?

Neural network (1999) and support vector machine (SVM) (2017) have been involved in attribute analysis to implement fault interpretation.
ML-based Fault Interpretation Workflow Using Multiple Attributes

- Dependent on attribute selection by interpreters
- Repeated attribute selection from one dataset to another

Is attribute analysis always necessary?
Object Interpretation from Image

**Natural**

**Image**: Image of a person riding a motorcycle on a road.

**Object**: 1. Person
2. Vehicle
3. Others

**Interpretation**

**Seismic**

**Image**: Seismic pattern showing wave patterns.

**Object**: 1. Fault
2. Non-fault
Outline

• Motivation
• Workflow description
• Result analysis
• Why CNN performs better?
• Conclusions
CNN-based Workflow

- Features of CNN-based workflow:
  - Amplitude volume as the only input
  - Volume in, volume out
  - Single dataset interpretation
  - A seismic section cut into multiple small patches
  - Applied to every sample throughout the entire volume
Seismic Dataset

- A subset of Great South Basin (GSB) dataset
- Polynomial faulting
- 480 inline x 497 crossline x 76 samples

Training Dataset Preparation

- 3 crossline labelled (#2790, #2800, #2810)
- ~0.6% of the entire volume
- ~20,000 fault samples
- Patch size: 15 x 15

25 fault patches
CNN Architecture

- 1 convolutional layer with 16 filters
- 1 fully-connected layer with 1024 neurons
- 2 output labels: binary classification
- Activation function: ReLU
- Softmax function for probability

- Filter mask size: 9x9
- Maximum pooling: 2x2
- Dropout: 0.5
CNN Training Details

• Batch size: 50

• Epoch: 1000

• Learning rate: 1e-4

• Validation dataset:
  • 20% of training dataset
  • Randomly shuffled per epoch

Confusion matrix

<table>
<thead>
<tr>
<th>Actual</th>
<th>Non-fault</th>
<th>Fault</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prediction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-fault</td>
<td>262248</td>
<td>37744</td>
</tr>
<tr>
<td>Fault</td>
<td>94</td>
<td>18154</td>
</tr>
</tbody>
</table>

Total precision: 0.88
True positive rate: 0.99

Accuracy over epochs graph
Outline

• Motivation
• Workflow description
• Result analysis
• Why CNN performs better?
• Conclusions
3D View of the Seismic Volume with Labeled Faults
Various Interpretation Applications

- Fault volume imaging
- Seeded fault picking
- Automatic fault extraction

THE EAGE ANNUAL 2018
Comparisons on Training Sections

- Manual interpretation (Crossline #2800)
- CNN (Crossline #2800)
- SVM (Crossline #2800)
- MLP (Crossline #2800)
Detection Results on Non-training Sections

Four randomly-selected vertical sections not seen in the training process

Inline #1791
Inline #2011
Crossline #2600
Crossline #3000
Outline

• Motivation
• Workflow description
• Result analysis
• Why CNN performs better?
• Conclusions
CNN vs. MLP on Non-training Sections

CNN

MLP

Time 1132 ms

Crossline #2600

Crossline #3000
Architecture Comparison between CNN & MLP

- Automatic attribute generation
- Patch instead of sample
Outline

• Motivation
• Workflow description
• Result analysis
• Why CNN performs better?
• Conclusions
Conclusions

• Supervised CNN classification is applied to seismic domain for fault detection;
  • capable of generating attributes automatically to complete fault classification, which requires less from an interpreter;
  • Local pattern incorporated into learning to avoid artifacts and noises.

• More work is in need for deep exploring the advanced neural networks, e.g.,
  • Transfer learning
  • Real-time detection and segmentation

• Collaboration is suggested for building open training datasets and/or pre-trained networks for further R&D
Thank you.

Codes, resources, and tools are available on

www.ghassanalregib.com
https://haibindi.wixsite.com/haibin-di