Webinars

Successful Leveraging of Human Visual System Modeling and Machine Learning in Computational Seismic Interpretation

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Prof. Ghassan AlRegib is currently a professor in the School of Electrical and Computer Engineering at the Georgia Institute of Technology.

He is also Director of the **O**mni **L**ab for **I**ntelligent **V**isual **E**ngineering and **S**cience (**OLIVES**) at Georgia Tech.

In 2012, Ghassan was named Director of Georgia Tech's Center for Energy and Geo Processing (CeGP).

Professor AlRegib has authored and co-authored more than 190 articles in international journals and conference proceedings.

He has issued seven U.S. patents and is a Senior Member of IEEE.

Ghassan AlRegib
Professor, School of Electrical & Computer Engineering
Georgia Institute of Technology

Poll Question #1

What is your job title?

Poll Question #2

Who is your employer?

Poll Question #3

What geographic region are you from?

Poll Question #4

How many years of experience do you have?

Poll Question #5

What is your background?

Poll Question #6

What background of you have in Signal Processing, Pattern Recognition, and Machine Learning?

Outline

- Overview of Computational Seismic Interpretation (CSI)
- Human Visual System (HVS) Modeling in CSI
  - Gradient of Texture (GoT) on Salt-dome and Listric Fault Interpretation
  - Motion-based Saliency on Salt-dome Interpretation
- Machine Learning (ML) in CSI
  - Weakly Supervised Learning on Seismic Structure Labeling
  - Tensor-based Subspace Learning on Salt-dome Tracking
  - Generative Adversarial Networks (GAN) for Seismic Data Generation
- Conclusions

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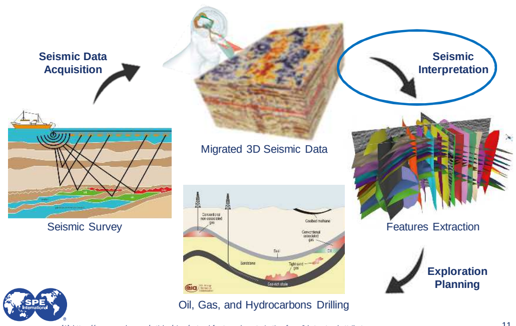
Hydrocarbon Exploration Procedure



[1]. https://csegrecorder.com/articles/view/natural-fracture-characterization-from-3d-structural-attributes
[2]. https://carbturbo.com/features-benefits/

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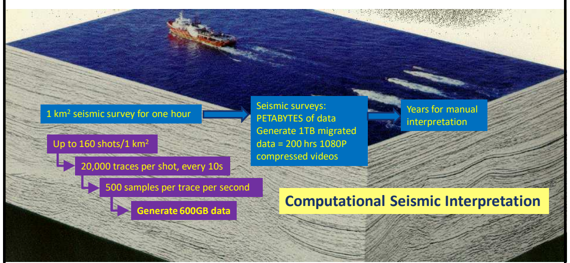
Computational Seismic Interpretation (CSI)



[3]. https://bldl.ii.uib.no/bldl-opening-presentations/Bouzas-BergenV1-Bouzas.pdf

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Computational Seismic Interpretation (CSI)

HVS Attributes

Methods	Attributes				Machine Learning			Others			
	Coherence	GLCM-based Attributes	Gradient of Texture (GoT)	Motion-based Saliency	Weakly Supervised Learning	Multi-Attribute-based Learning	Tensor-based Subspace Learning	Edge Detection	Ant Tracking	2D/3D Hough Transform	Motion-vector-based Interpolation
Horizon Picking	■				■				■		
Fault Detection	■		■	■	■	■		■	■	■	
Fault Tracking											■
Salt-dome Detection	■	■	■	■	■	■		■			
Salt-dome Tracking							■				
Channel Identification	■	■				■					
Gas Chimney Identification			■			■					

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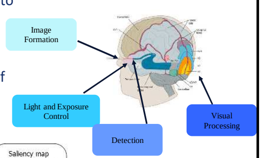
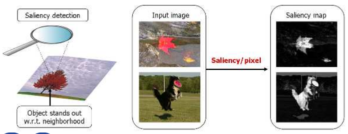
Human Visual System

- Human visual system (HVS) is sensitive to
  - **Texture changes**
  - **Motions**
  - Structures
- Attention models mimic the behavior of human subjects looking at an image or video



Human Visual System [4]



Saliency Detection [5]

[4] https://www.studyblue.com/notes/note/n/visual-process-and-perception/deck/14629318
[5] http://ivrlwww.epfl.ch/supplementary_material/RK_CVPR09/

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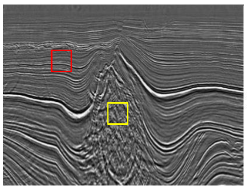
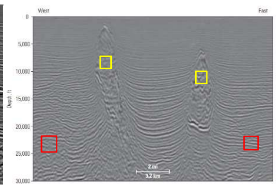
Texture Changes

- Texture changes between the inside and the outside of salt domes provide quantitative visual clues that assist geophysicists' interpretation tasks



Texture Difference Inside and Outside the Salt dome [6]



Two Salt Diapirs Beneath the Continental Shelf, Offshore Louisiana [7]

[6] https://math.berkeley.edu/~sethian/2006/Applications/Seismic/seismic_analysis.html
[7] Dribus, John R., et al. "The prize beneaththe salt." *Oilfield Review* 15 (2008): 4-17.

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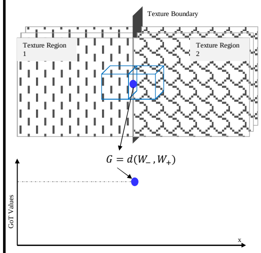
Gradient of Texture (GoT)



[8] M. A. Shafiq, Z. Wang, G. AlRegib, A. Amin, and M. Deriche, "A texture-based interpretation workflow with application to delineating salt domes," Interpretation, 5(3), SJ1-SJ19, 2017.

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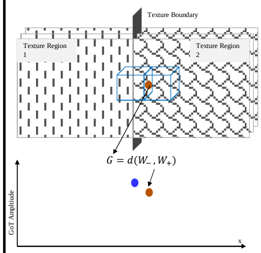
Gradient of Texture (GoT)



[8] M. A. Shafiq, Z. Wang, G. AlRegib, A. Amin, and M. Deriche, "A texture-based interpretation workflow with application to delineating salt domes," Interpretation, 5(3), SJ1-SJ19, 2017.

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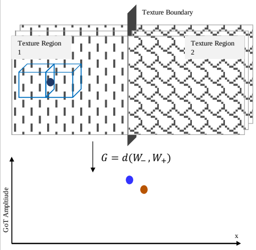
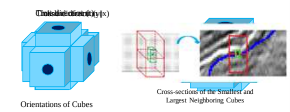
Gradient of Texture (GoT)





$$\mathbf{G}_i[t,x,y] = d\left(\mathbf{W}_{i-},\mathbf{W}_{i+}\right), \quad i \in \{t,x,y\}, \tag{1}$$

$$\mathbf{G}[t,x,y] = \sqrt{G_t^2 + G_x^2 + G_y^2}, \tag{2}$$

$$\mathbf{G}[t,x,y] = \left(\sum_{i \in \{t,x,y\}} \left(\sum_{n=1}^{N} \omega_n \cdot d\left(\mathbf{W}_{i-}^{n}, \mathbf{W}_{i+}^{n}\right)\right)^2\right)^{\frac{1}{2}}, \tag{3}$$

where $\mathbf{W}_{i-}^{n}$ and $\mathbf{W}_{i+}^{n}$ denote the neighboring cubes with edge length $(2n+1)$, N represents the number of cubes, and ω_n represents the corresponding weights.

Perceptual Dissimilarity Measures

[8] M. A. Shafiq, Z. Wang, G. AlRegib, A. Amin, and M. Deriche, "A texture-based interpretation workflow with application to delineating salt domes," Interpretation, 5(3), SJ1-SJ19, 2017.

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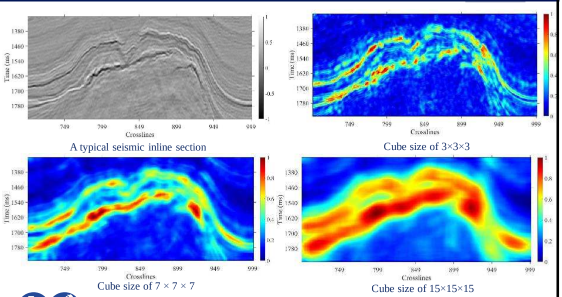
Multi-Scale GoT of 2D Seismic Section



A typical seismic inline section

Cube size of 3×3×3

Cube size of 7 × 7 × 7

Cube size of 15×15×15

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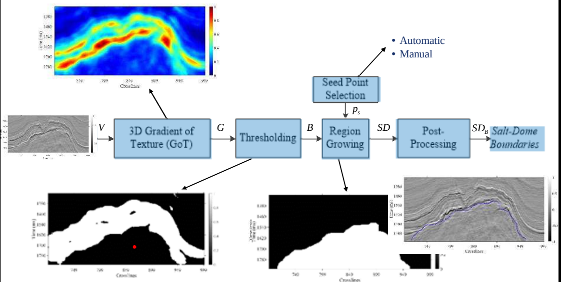
Structural Interpretation of Salt Domes



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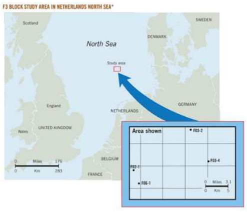
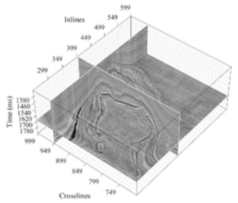
Dataset: F3 Block in the North Sea



F3 Block Location in the North Sea



Migrated Seismic Volume

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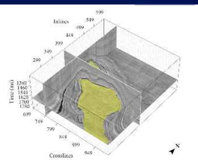
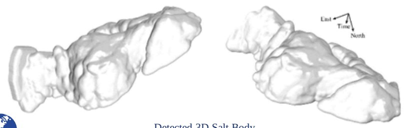
Detected Salt Dome

01_3DGoT_Delineation.avi

Detected Salt Dome in 2D Seismic Sections



3D slice of Detected Salt Dome



Detected 3D Salt Body

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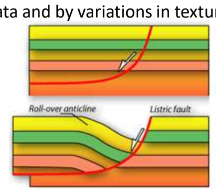
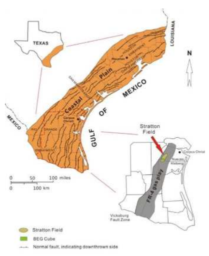
Listric Faults

- Listric faults are concave upwards and are identified by either decreasing dip with depth, which flattens out at the bottom of the fault or changes in strata and by variations in texture.



Listric Faults [9]



Stratton Field in Texas [10]

[9] http://www.geosci.usyd.edu.au/users/prey/ACSGT/EReports/eR.2003/GroupD/Report2/web%20pages/Listric_Faults.html
[10] Zheng, Zhihong, and Dengliang Gao. "Along-strike variation in extension and cross-strike fractures in Stratton Field, south Texas: Implications for fractured reservoir description and characterization." *SEG Technical Program Expanded Abstracts 2013.*, 2013. 1534-1539.

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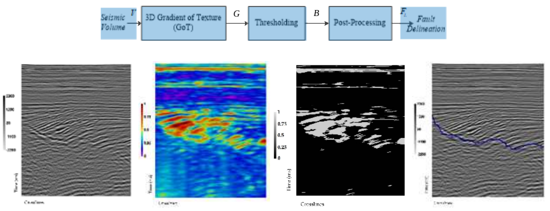
Listric Fault Detection



Seismic Inline Section 70 | GoT Map | Thresholding | Delineation Post-Processing

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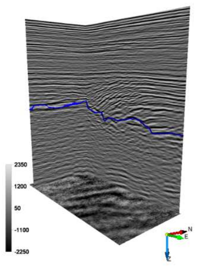
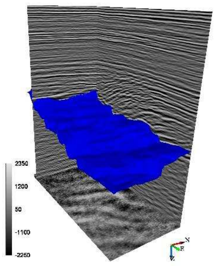
Listric Fault Surface



3D View Depicting Inlines and Crosslines



Detected Fault Surface

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Motions of Structures Across Seismic Sections

02_SeismicVolume.avi

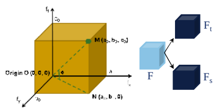
Seismic Volume

03_SeismicSaliency.avi

Saliency Map

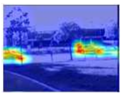
Motion-based Saliency Detection

- Advantages of a FFT-based saliency detection method compared to other detection algorithms
  - Effectively captures temporal and spatial saliency
  - Better computational efficiency
  - Few parameters selection

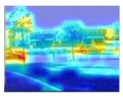


Geometric Decomposition

A Video Frame



Temporal Energy Distribution

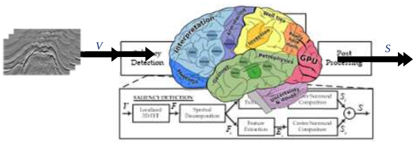


Spatial Energy Distribution

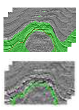
[11] Zhiling Long and Ghassan AlRegib, "Saliency detection for videos using 3D FFT local spectra," *Proc. SPIE*, vol. 9394, pp. 93941G–93941G-6, 2015.

Motion-based Saliency on Salt-dome Interpretation

Attention Models based on HVS



Detection and delineation of salt domes



[12] M. Shafiq, T. Alshawi, Z. Long, and G. AlRegib, "SalSi: A New Seismic Attribute For Salt Dome Detection," IEEE Intl. Conf. on Acoustics, Speech and Signal Processing (ICASSP), Shanghai, China, Mar. 20-25, 2016.
[13] M. Shafiq, T. Alshawi, Z. Long, and G. AlRegib, "The role of visual saliency in the automation of seismic interpretation," Geophysical Prospecting, 2017.

Detected Salt Dome

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04_SeismicVolume.avi

Original Seismic Volume

05_SalSi.avi

Highlighted Salt-dome Boundaries

06_Seismic.avi

A subset of Original Seismic Volume

07_SaliencyDelineation.avi

Detected Salt Dome in 2D Seismic Sections

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Attention Models and Saliency

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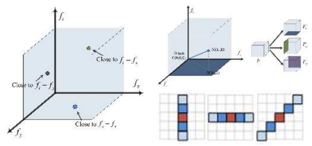
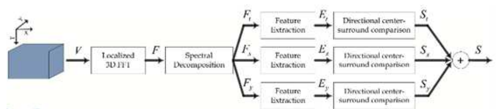
- Temporal domain for seismic
- A priori information
  - Top-down
  - Directionality
- Resolution





[14] M. A. Shafiq, Z. Long, T. Alshawi, and G. AlRegib, "Saliency detection for seismic applications using multi-dimensional spectral projections and directional comparisons," IEEE International Conference on Image Processing (ICIP), Beijing, China, Sep. 17-20, 2017.

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Seismic Saliency

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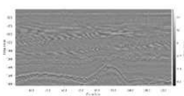
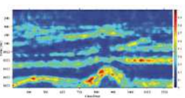
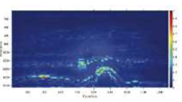


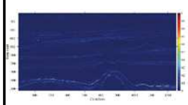
A typical seismic inline



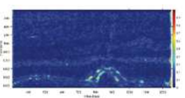
Zhang et al. (2008)



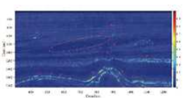
Fang et al. (2014)



Achanta et al. (2008)



Long and AlRegib (2015)



Shafiq et al. (2017)

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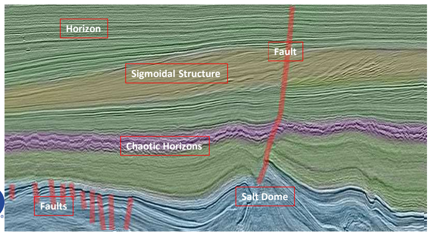
Seismic Structure Labeling

- Ultimately, machine learning would automate the most laborious interpretation tasks.
- The role of the interpreter will then transform from manually doing the interpretation, to *verifying* and *modifying*, if necessary, the automated interpretation result.



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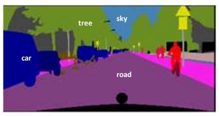
Labeling of Natural Images vs. Seismic Data

car, tree, road, sky



- This is an well known (and difficult) problem in computer vision.
- However, applying this to seismic data brings new challenges.

1. Seismic data is textural in nature and does not have color information.
2. Subsurface structures are characterized by texture, and lack the *clearly defined boundaries* between objects in the natural world
3. Severe lack of labeled seismic data

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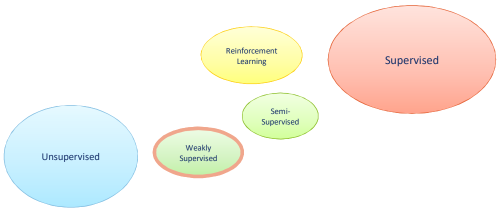
Machine Learning Paradigms



Recall one of the main challenges is the severe lack of labeled seismic data

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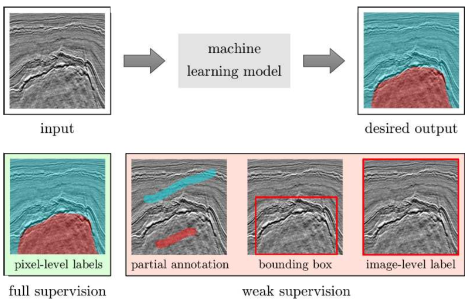
Weakly-Supervised Learning



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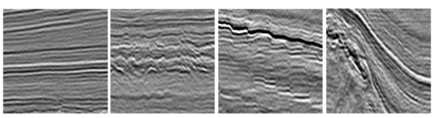
Weakly-Supervised Labeling

- LANDMASS dataset (http://cegp.ece.gatech.edu/codedata/landmass/)
- Thousands of automatically retrieved, and manually verified seismic images classified into four classes:



Horizons Chaotic Faults Salt Dome

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Weakly Supervised Labeling of Seismic Structures

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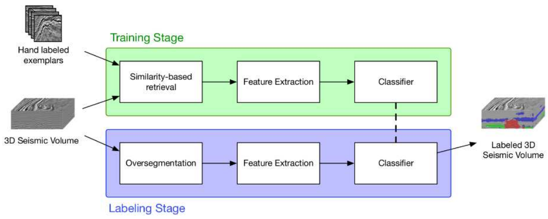

[15] Y. Alaudah and G. AlRegib, "Weakly-Supervised Labeling of Seismic Volumes Using Reference Exemplars," *IEEE Intl. Conference on Image Processing (ICIP)*, Phoenix, Arizona, USA, Sep. 25-28, 2016.

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Weakly Supervised Labeling of Seismic Structures

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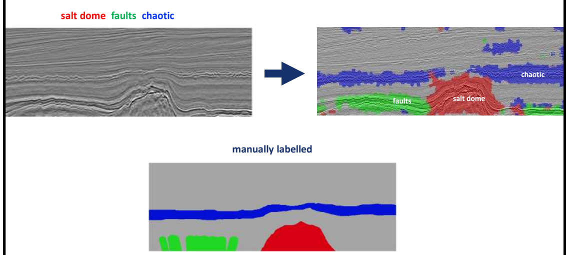

[15] Y. Alaudah and G. AlRegib, "Weakly-Supervised Labeling of Seismic Volumes Using Reference Exemplars," *IEEE Intl. Conference on Image Processing (ICIP)*, Phoenix, Arizona, USA, Sep. 25-28, 2016.

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Weakly Supervised Labeling: Results Using Spatial Texture Attributes

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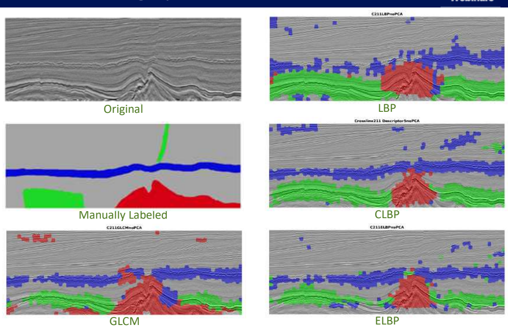

[16] Z. Long, Y. Alaudah, M. A. Qureshi, Y. Hu, Z. Wang, M. Alfarraj, G. AlRegib, A. Amin, M. Deriche, and S. Al-Dharrab, "A comparative study of texture attributes for characterizing subsurface structures in migrated seismic volumes," Submitted to Interpretation.

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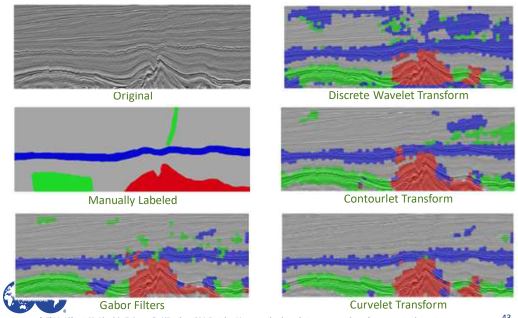
Weakly Supervised Labeling: Results Using Spectral Texture Attributes



[17] M. Alfarraj, Y. Alaudah, Z. Long, G. AlRegib, and M. Deriche, "A survey of multiresolution texture attributes for computational seismic interpretation," Submitted to Signal Processing: Image Communication.

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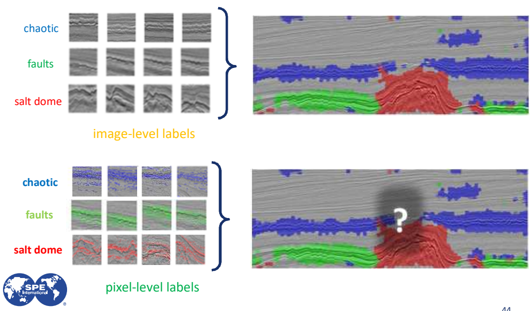
Weakly Supervised Labeling of Seismic Structures



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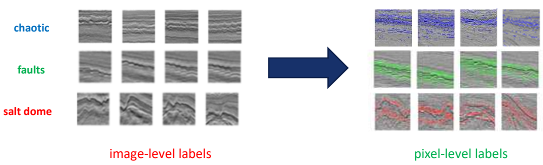
Weakly Supervised Labeling of Seismic Structures



$$\underset{\mathbf{W},\mathbf{H}}{\arg\min}||\mathbf{X}-\mathbf{W}\mathbf{H}||_F^2+\lambda_1||\mathbf{W}||_F^2+\lambda_2||\mathbf{H}||_F^2+\gamma_1||\mathbf{H}\mathbf{H}^T-\mathbf{B}||_F^2$$

$$\text{s.t.}\mathbf{W},\mathbf{H}\geq 0 \quad \text{and} \quad \rho(\mathbf{w}_i)=\rho_w$$

[18] Y. Alaudah, H. Di, and G. AlRegib, "Weakly Supervised Seismic Structure Labeling via Orthogonal Non-Negative Matrix Factorization", 79th EAGE Annual Conference & Exhibition, Paris, France, June 12-15, 2017.

[19] Y. Alaudah and G. AlRegib, "A weakly-supervised approach to seismic structure labeling," 87th Annual SEG Meeting Extended Abstracts, Houston, Texas, 2017.

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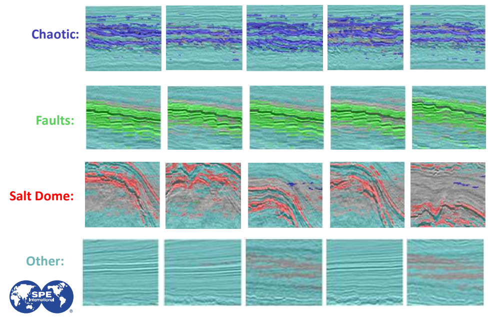
Results



[20] Y. Alaudah, H. Di, and G. AlRegib, "Weakly Supervised Seismic Structure Labeling via Orthogonal Non-Negative Matrix Factorization", *79th EAGE Annual Conference & Exhibition*, Paris, France, June 12-15, 2017.

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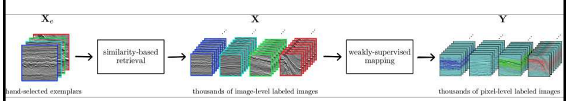
Weakly Supervised Labeling of Seismic Structures



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Outline

- Overview of Computational Seismic Interpretation (CSI)
- Human Visual System (HVS) Modeling in CSI
  - Gradient of Texture (GoT) on Salt-dome and Listric Fault Interpretation
  - Motion-based Saliency on Salt-dome Interpretation
- Machine Learning (ML) in CSI
  - Weakly Supervised Learning on Seismic Structure Labeling
  - Tensor-based Subspace Learning on Salt-dome Tracking
  - Generative Adversarial Networks (GAN) for Seismic Data Generation
- Conclusions

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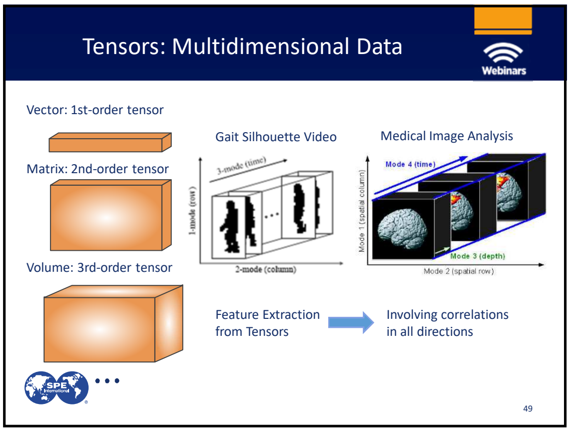
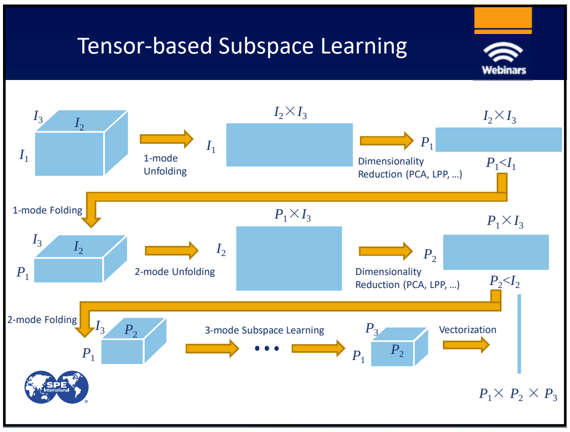
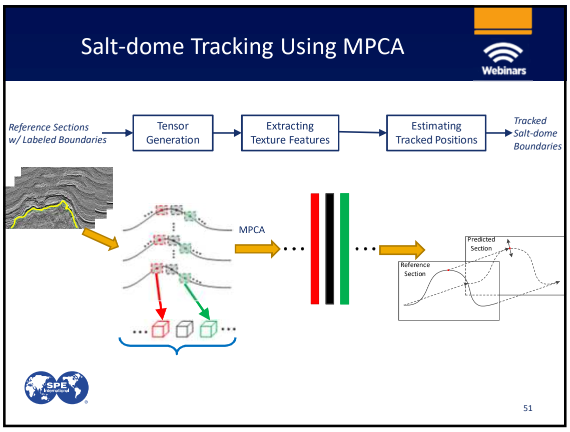
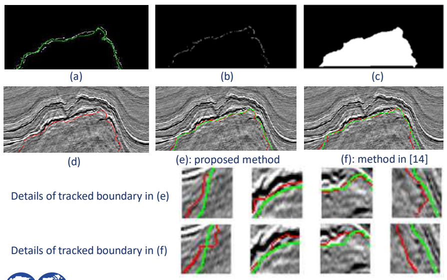

Tensors: Multidimensional Data
Webinars
Vector: 1st-order tensor
Matrix: 2nd-order tensor
Volume: 3rd-order tensor
Gait Silhouette Video
Medical Image Analysis
Mode 4 (time)
Mode 3 (depth)
Mode 2 (spatial row)
Mode 1 (spatial column)
3-mode (time)
2-mode (column)
1-mode (row)
Feature Extraction from Tensors
Involving correlations in all directions
49


Tensor-based Subspace Learning
Webinars
I_1 I_2 I_3
1-mode Unfolding
$I_2 \times I_3$
Dimensionality Reduction (PCA, LPP, …)
$P_1 < I_1$
1-mode Folding
$P_1 \times I_3$
2-mode Unfolding
$P_2 < I_2$
2-mode Folding
3-mode Subspace Learning
Vectorization
$P_1 \times P_2 \times P_3$


Salt-dome Tracking Using MPCA
Webinars
Reference Sections w/ Labeled Boundaries
Tensor Generation
Extracting Texture Features
Estimating Tracked Positions
Tracked Salt-dome Boundaries
MPCA
Predicted Section
Reference Section
51

Experimental Results



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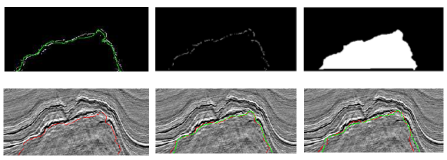
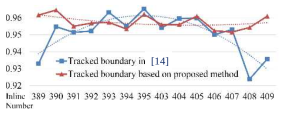
[21] Z. Wang, T. Hegazy, Z. Long, and G. AlRegib, "Noise-robust Detection and Tracking of Salt Domes in Post-migrated Volumes Using Texture, Tensors, and Subspace Learning," *Geophysics*, November 2015, v. 80, p. WD101-WD116.

Experimental Results





Tracking Method	Mean	Standard Deviation	AMD (pixel)	Elapsed CPU Time(s)
Proposed Method	0.9587	0.0039	7.86	44.84
Method in [14]	0.9517	0.0115	9.32	70.82

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[22] Z. Wang, T. Hegazy, Z. Long, and G. AlRegib, "Noise-robust Detection and Tracking of Salt Domes in Post-migrated Volumes Using Texture, Tensors, and Subspace Learning," *Geophysics*, November 2015, v. 80, p. WD101-WD116.

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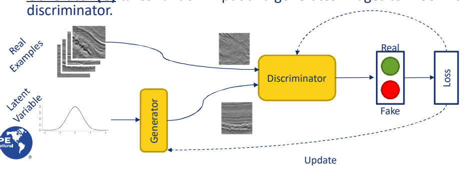
Adversarial Networks

Webinars

- ***Adversarial networks*** "adopt machine learning techniques in adversarial settings"
- For example, Generative Adversarial Networks (GANs) focus primarily on sample generation from the distribution of the real data instead of estimating the model directly.
  - Two networks competing to achieve a common goal "model estimation"
  - **Discriminator (D)** distinguishes real and fake data.
  - **Generator (G)** takes random input and generates images to ``fool'' the discriminator.



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Why Generative Adversarial models[15]?

Webinars

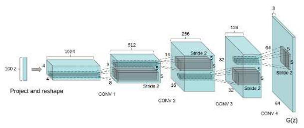
- They can **represent and manipulate high-dimensional** probability distributions.
- They can be **trained with missing data** and can provide **predictions on inputs that are missing data.** (semi-supervised learning)
- Generative models enable machine learning to work with **multi-modal outputs**.
- Many tasks intrinsically require realistic **generation of samples** from some distribution.
- Adversary models **entirely learn from the data**

[23] Goodfellow, Ian. "NIPS 2016 Tutorial: Generative Adversarial Networks." *arXiv preprint arXiv:1701.00160* (2016). 56

Example: DCGAN[16]

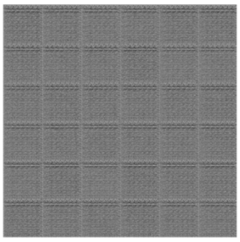
Webinars

- Deep Convolutional Generative Adversarial Network
  - The goal is to create a model to synthesize seismic images of different structures, i.e. salt domes, faults, .. , etc.
  - We trained the model using 1000 images for each of 4 classes: Salt, Fault, Chaotic, and Horizons.



[24] Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv preprint arXiv:1511.06434 (2015). 57

Seismic Patches Generated by GANs



Initial generated images

Results after 50 iterations for all structures

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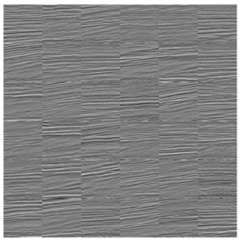
Sample Patches Generated by Fine-tuning

Results after 20 iterations for Faults



Results after 20 iterations for Horizons

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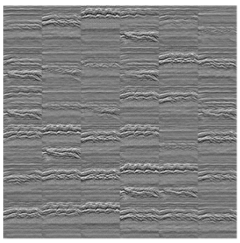
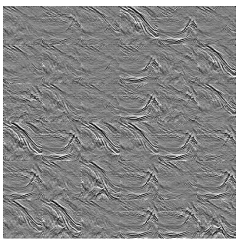
Sample Patches Generated by Fine-tuning



Results after 20 iterations for Chaotic



Results after 20 iterations for Salt

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Conclusions

- Leveraging the HVS modeling into interpretation is an effective component of CSI
  - using existing HVS models
  - a framework to model a senior interpreter's process
  - useful to design ML algorithms
- Machine learning resurrection is promising for CSI
  - new framework and work flow for the problem using labeling
  - hybrid handcrafted- and data-based models
- Community
  - share codes and results freely
  - share data freely
  - more competitions
  - more visible presence outside the community

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Products

Publications: https://ghassanalregib.com/publications/

Software:

- Seismic Simulation, Survey, and Imaging (S3I)

The S3I provides an easy MATLAB-based library to simulate seismic imaging and produces synthesized data for any given velocity model to facilitate seismic interpretation and reservoir modeling. More details can be found at http://cegp.ece.gatech.edu/codedata/s3i/

- CSI Toolbox

The Graphical User Interface (GUI) is developed for visualizing, testing, and benchmarking various algorithms for salt dome delineation. It also compares different salt dome delineation algorithms, which have been processed offline. More details can be found at http://cegp.ece.gatech.edu/codedata/salt

- Cloud Visual Explorer (CLeVER)

The CLeVER is a cloud-based visual explorer developed in Django for Microsoft Azure. It allows efficient storage and computing resources to probe large datasets even from devices that do not have necessary minimum system requirements to run similar software. More details can be at http://cegp.ece.gatech.edu/codedata/

Datasets:

- Large North-Sea Dataset of Migrated Aggregated Seismic Structures (LANDMASS)

The LANDMASS dataset is created for development, testing, and benchmarking of various techniques aimed towards seismic applications such as retrieval, classification, machine learning, etc. It contains 20K+ grayscale images extracted from the public F3 Block dataset, which are auto-labeled with manual verification into four major seismic structures: faults, salt dome, horizon, and chaotic horizon.
More details can be found at http://cegp.ece.gatech.edu/codedata/landmass/

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Ph.D. student in Texture analysis and Machine learning for seismic interpretation
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