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Weakly Supervised Seismic Structure Labeling via Orthogonal Non-Negative Matrix Factorization

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Outline

• Our Objective: Seismic Structure Labeling
• Our Challenge: Weakly-Supervised Learning
• Our Approach: Orthogonal NMF
• Results
• Conclusion
Weakly Supervised Seismic Structure Labeling via Orthogonal Non-Negative Matrix Factorization
Ultimate goal: End-to-End Automated Seismic Interpretation

- 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.
Labeling of Natural Images vs. Seismic Data

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

1. Seismic data is grayscale
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
Weakly Supervised Seismic Structure Labeling via Orthogonal Non-Negative Matrix Factorization
Recall one of the main challenges is the severe lack of labeled seismic data.
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:

To train any machine learning classifier to classify pixels:
- ideally you would have labeled pixels ➔ supervised learning
- If we only have image-level labels ➔ weakly-supervised learning
Weakly-supervised Labeling of Seismic Structures using Reference Exemplars

salt dome, faults, chaotic

Weakly Supervised Labeling of Seismic Structures

chaotic
faults
other
salt dome

image-level labels
Weakly Supervised Labeling of Seismic Structures

chaotic

faults

other

salt dome

pixel-level labels
Weakly Supervised Labeling of Seismic Structures

This paper is about learning a mapping from image-level to pixel-level labels in a weakly-supervised fashion
Weakly Supervised Seismic Structure Labeling via Orthogonal Non-Negative Matrix Factorization
Non-negative Matrix Factorization (NMF)

- NMF is a “parts-based” representation

\[
X \approx WH \quad \text{s.t.} \ W, H \geq 0
\]

\[
\min_{W,H} \left\| X - WH \right\|^2, \text{s.t.} \ W \geq 0, H \geq 0
\]
Proposed Method:

Proposed Orthogonal NMF problem:

$$\arg\min_{W,H} \|X - WH\|_F^2 + \lambda_1\|W\|_F^2 + \lambda_2\|H\|_F^2 + \gamma_1\|HH^T - I\|_F^2$$

s.t. $W, H \geq 0$ and $\rho(w_i) = \rho_w$

Where:
- $X$: data matrix containing the seismic images
- $W$: a feature matrix initialized using k-means of the sparsified images in $X$
- $H$: a randomly initialized coefficients matrix
- $I$: identity matrix
- $\rho(w_i) = \rho_w$: rho is a sparsity constraint on the features in $W$, insuring that each one is at least sparse.
Proposed Method: Initialization

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\[ X \rightarrow \text{k-Means} \rightarrow \text{impose} \quad \rho(w_i) = \rho_w \]

- **X**: data matrix \( \in \mathbb{R}^{N_p \times N_s} \)
- **H**: coefficients matrix \( \in \mathbb{R}^{N_f \times N_s} \)
- **W**: basis or feature matrix \( \in \mathbb{R}^{N_p \times N_f} \)

- \( N_p \): # of pixels
- \( N_s \): # of samples
- \( N_f \): # of features
- \( N_l \): # of labels
Proposed Method: Solving for $W$ and $H$

**Optimization:**

$$W^t = \frac{(W^{t-1} \odot XH^{t-1T} + \epsilon)_{ij}}{W^{t-1}H^{t-1}H^{t-1T} + \lambda_1 W^{t-1} + \epsilon}_{ij}$$

$$H^t = \frac{(H^{t-1} \odot W^{tT} X + \gamma_1 H^{t-1} + \epsilon)_{ij}}{(W^{tT}W^tH^{t-1} + \gamma_1 H^{t-1}H^{t-1T}H^{t-1} + \lambda_2 H^{t-1} + \epsilon)_{ij}}$$

set column norms of $H$ to one, and adjust $W$ accordingly.

- $X \in \mathbb{R}^{N_p \times N_s}$
- $W \in \mathbb{R}^{N_p \times K}$
- $H \in \mathbb{R}^{K \times N_s}$
- $Q \in \mathbb{R}^{K \times N_i}$
- $Y \in \mathbb{R}^{N_p \times N_s \times N_i}$
Proposed Method: Obtaining the labels

\[ Y_n = W(Q \odot (H_n 1_{1 \times N_l})) \quad \forall n \in [1, N_s] \]

\[ \text{label}_i = \max_j Y_{n,j} \]

Where:
• Y is a 3D matrix containing the labels of all pixels in all the images in X. \( Y_n \) is a slice of Y that contains all the labels for all the pixels in image \( n \).
• Q is a binary cluster membership matrix. It basically encodes our image-level labels.
Results
Results using pure NMF
Results using proposed method

- Chaotic:
- Other:
- Faults:
- Salt Dome:
Results using proposed method

Chaotic:

Other:
Results using proposed method

Faults:

Salt Dome:
Evolution of the labeling results

- Chaotic
- Other
- Fault
- Salt Dome
Evolution of the labeling results

Chaotic  Other  Fault  Salt Dome
Challenges, Future Work and Conclusions
Challenges, Future Work and Conclusions

**Challenges:**
- More data, more data, more data.
- More classes of seismic structures and more hand labeled examples.
- How to quantify the effectiveness of these methods objectively?

**Future work:**
- Test the accuracy of machine learning models trained on such weakly-supervised data
- Extend this weakly supervised approach to facies classification and 3D seismic data
Conclusions

- We have introduced the application of seismic section labeling, and how it can help in end-to-end computational seismic interpretation.
- We presented the challenge of labeling seismic images in a weakly-supervised fashion.
- We proposed an orthogonal-NMF-based approach to solving this problem.
- We have shown some initial results of this approach. For more details, and better results, please see our newly accepted paper in SEG 2017:

Thank You

For more information about the center, please visit:

http://cegp.ece.gatech.edu/