Attribute combinations for image segmentation

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SEP-138, pp. 81-94

May 20, 2009

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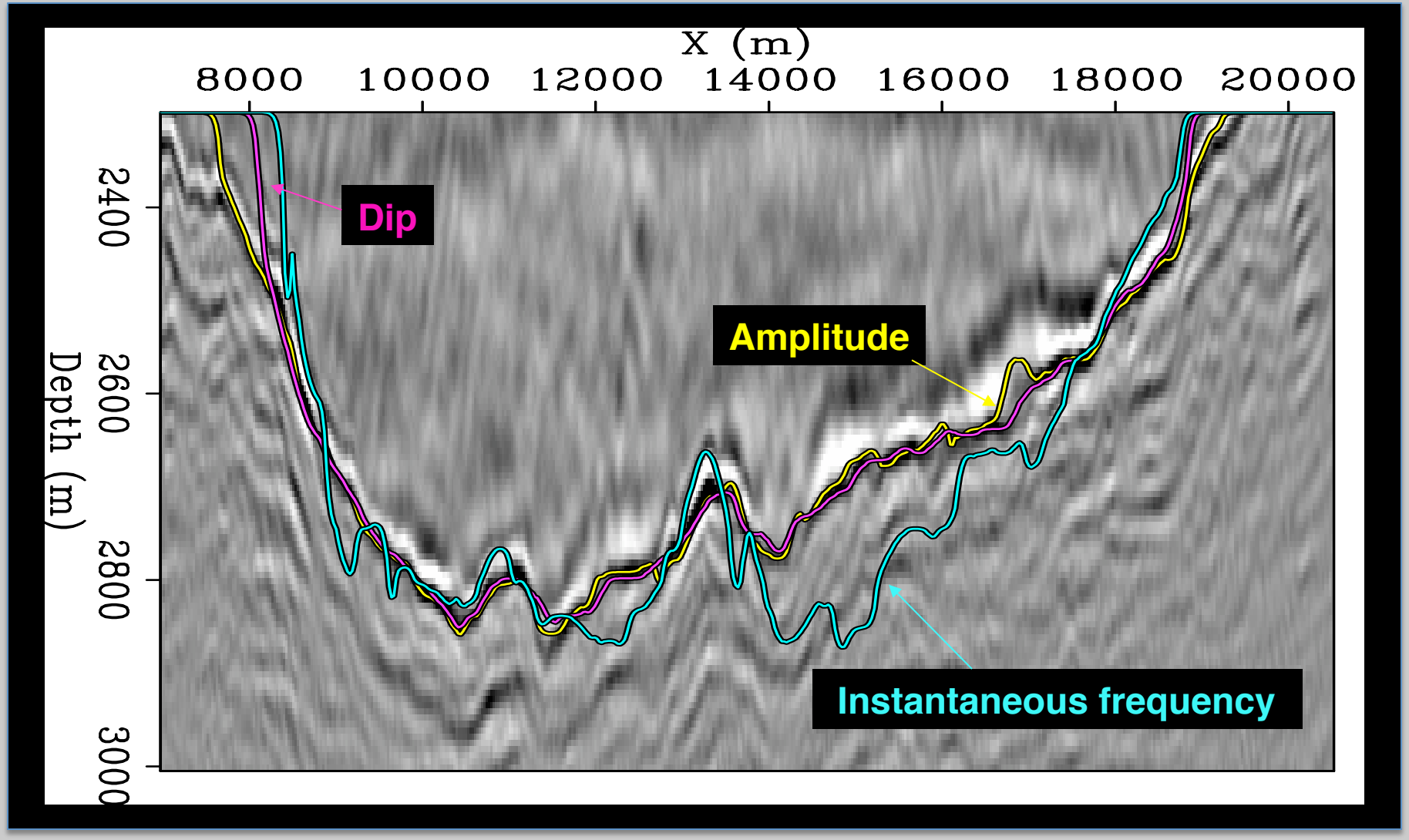
Image segmentation

- **Purpose**
  - Automatically divide an image into two or more regions based on specific characteristics
- **Application**
  - On seismic images, pick interfaces between salt bodies and surrounding sediments
- **Goal**
  - Develop a robust algorithm to automatically pick salt boundaries in 3D, using as much information as possible

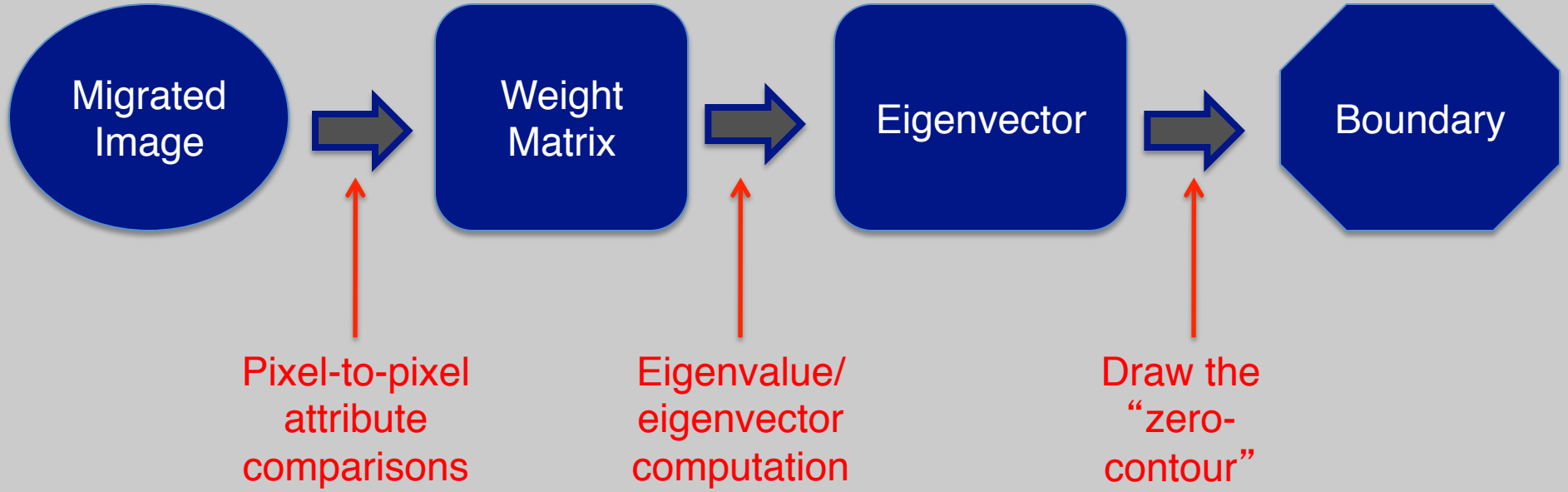
Image segmentation



Topics

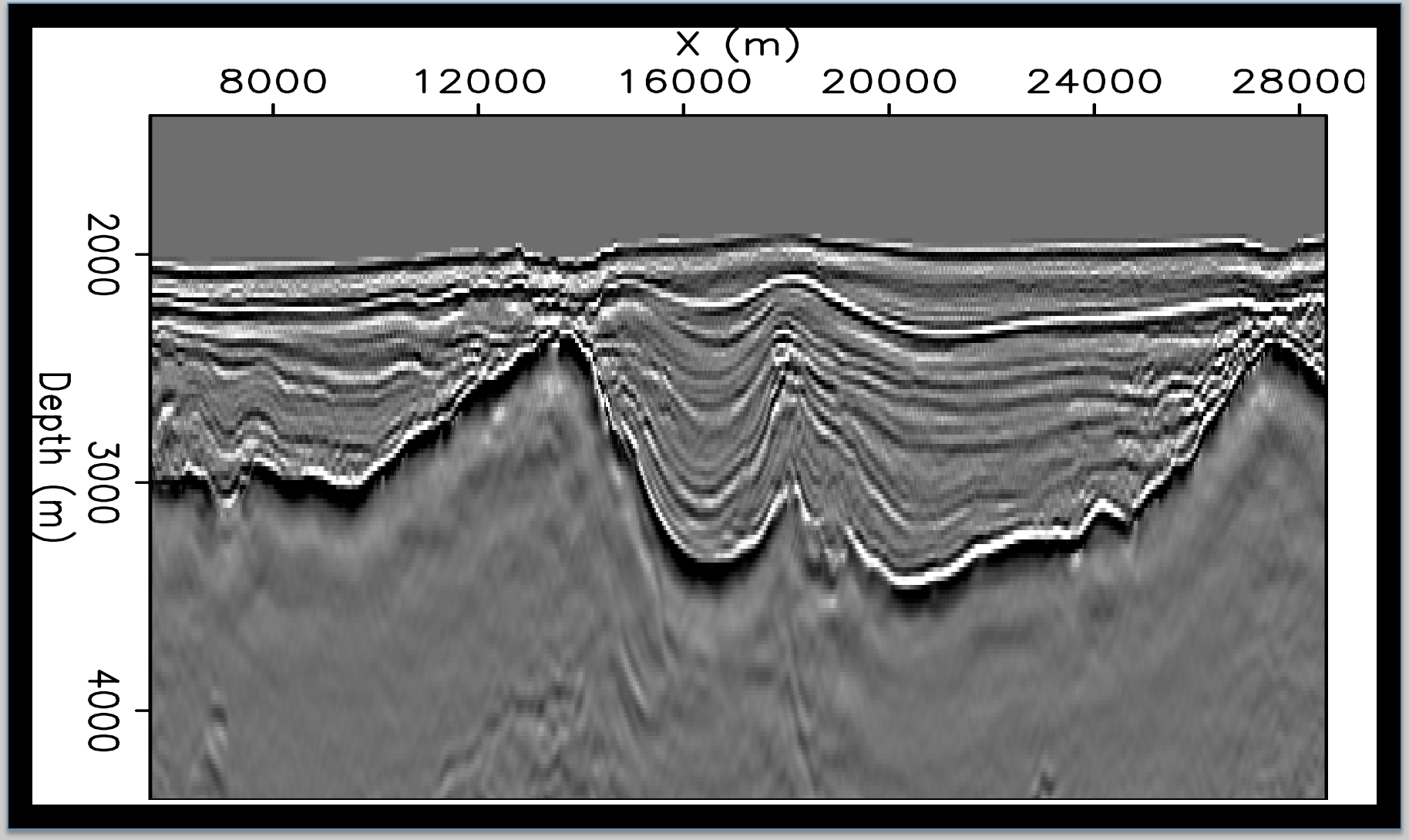
- Segmentation overview
  - Attributes used for segmentation
- Attribute combinations in 2D
  - Strategies and examples
- Extension to 3D
  - Use 2D results to guide 3D segmentation

Segmentation process



For details, see Lomask (2007)

Segmentation process

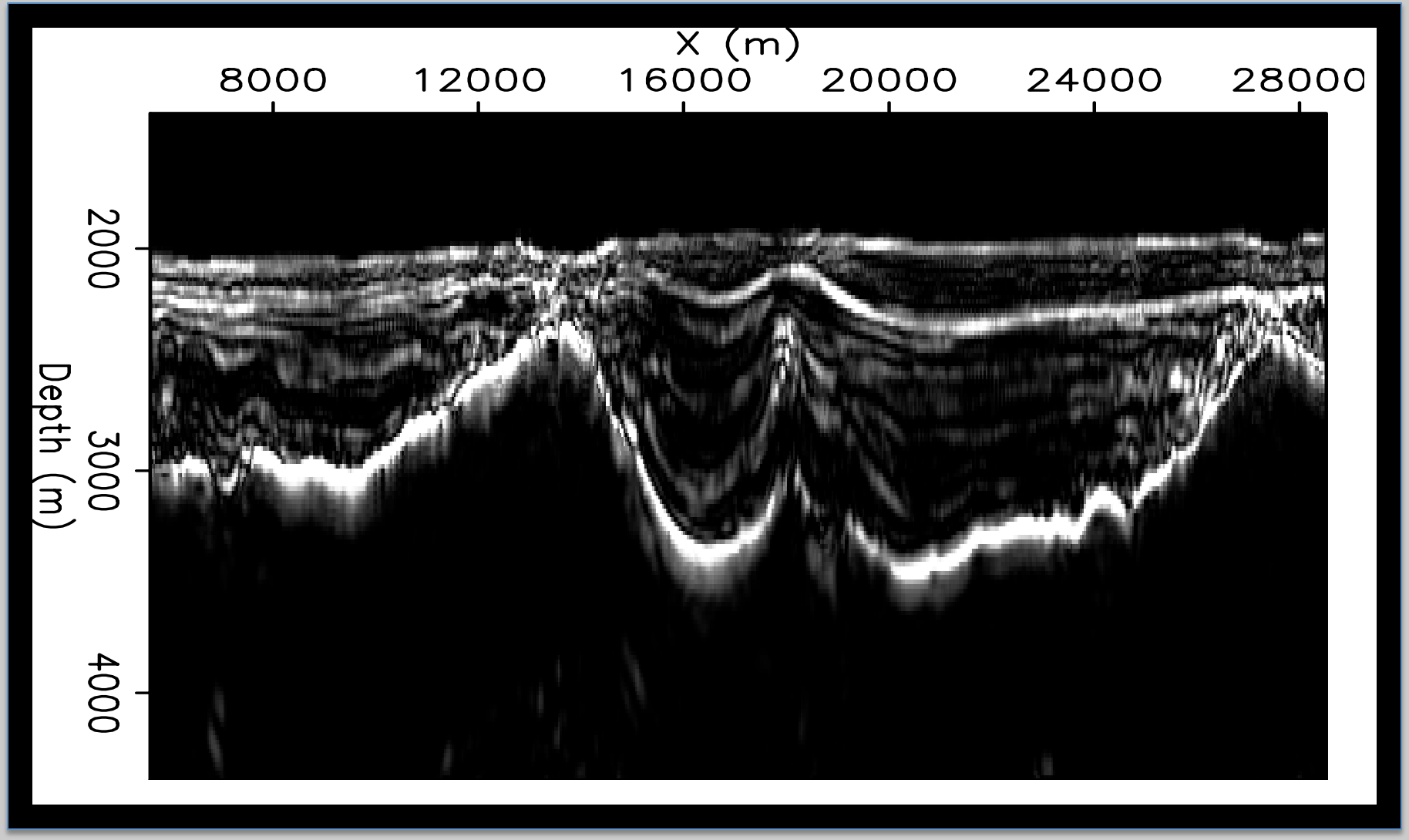


Segmentation attributes

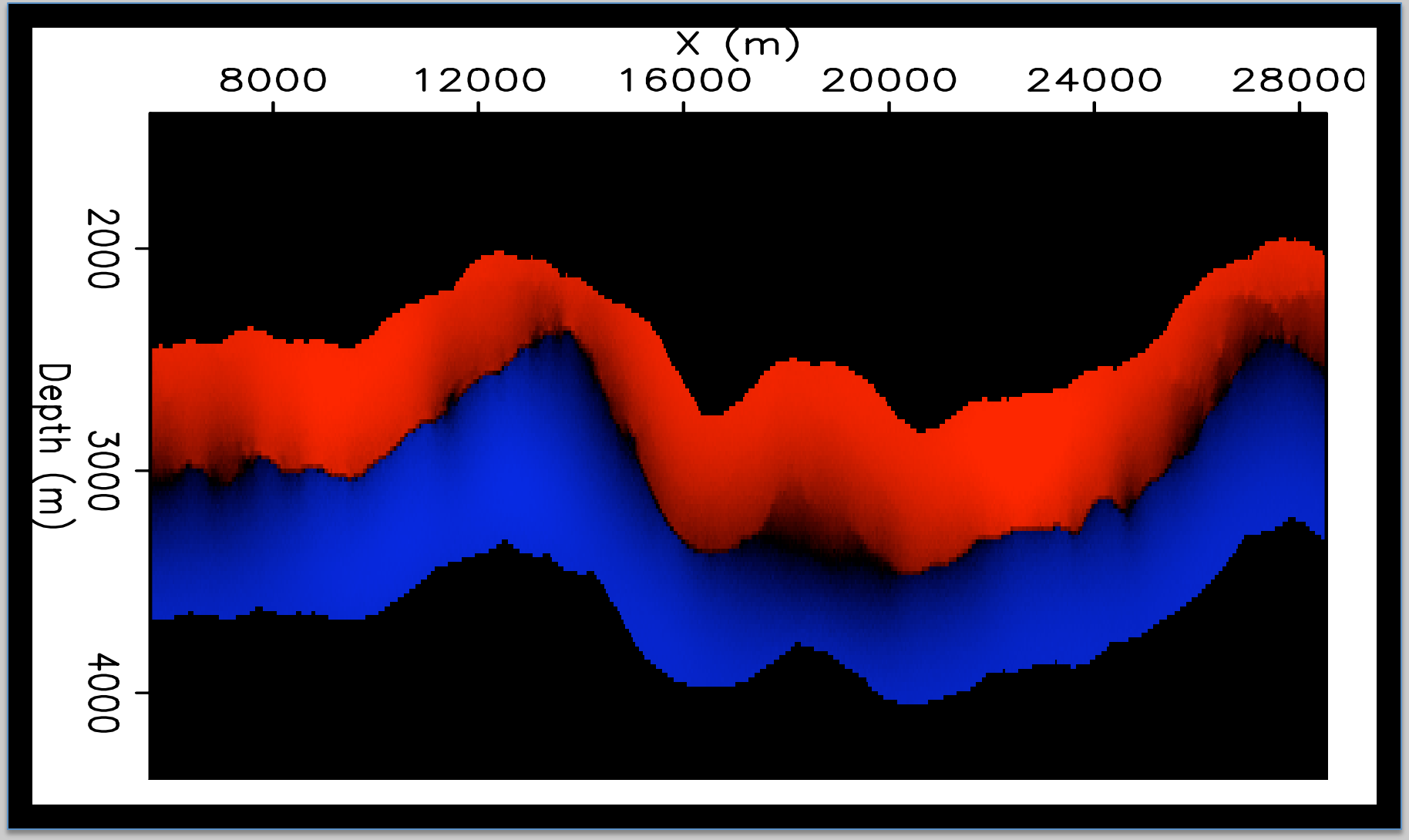
- Most intuitive attribute: amplitude of the envelope
  - A large amplitude in between two pixels is indicative of a salt boundary

- Sometimes, amplitude information alone is not sufficient
  - Discontinuous boundary, poor illumination, etc

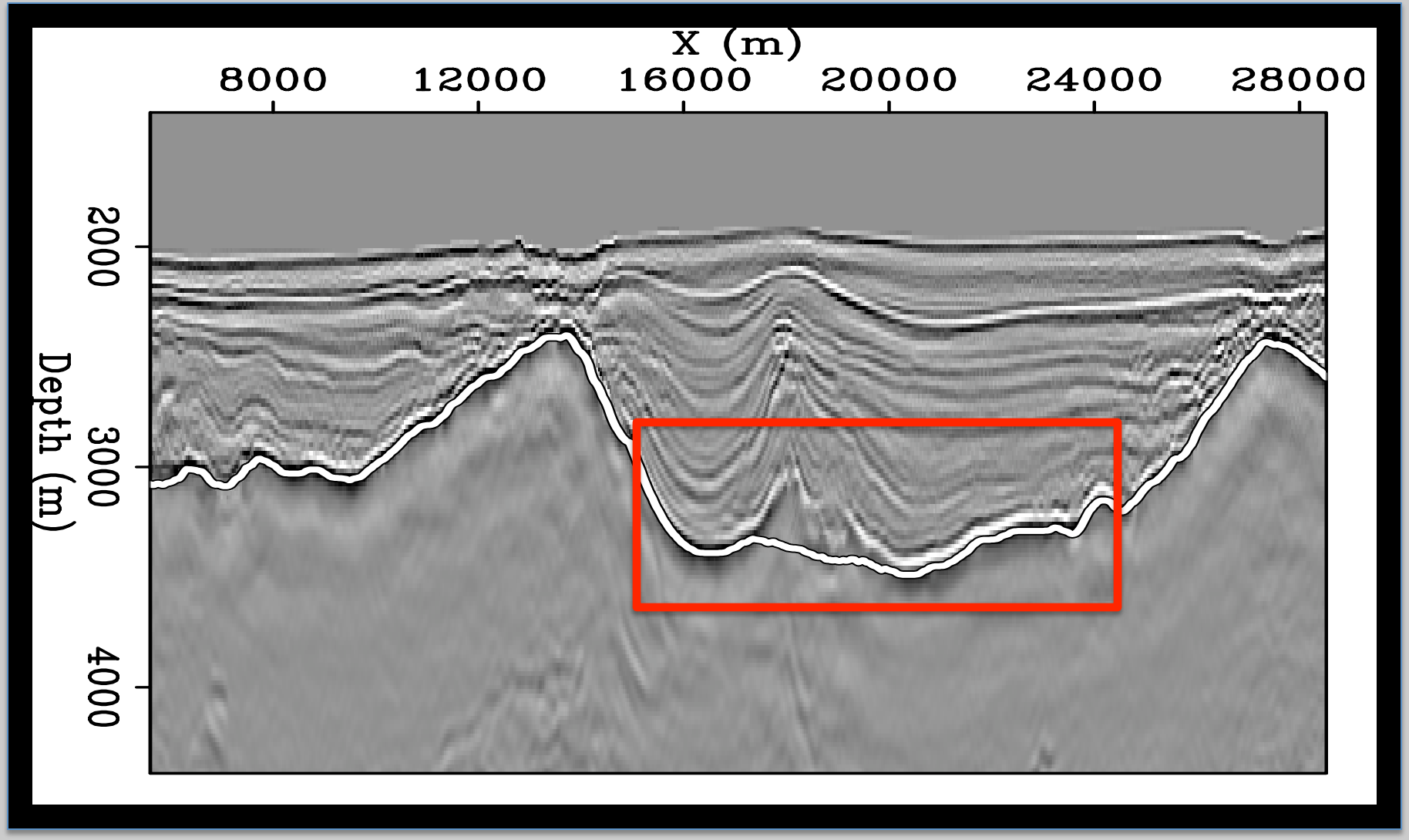
Amplitude attribute



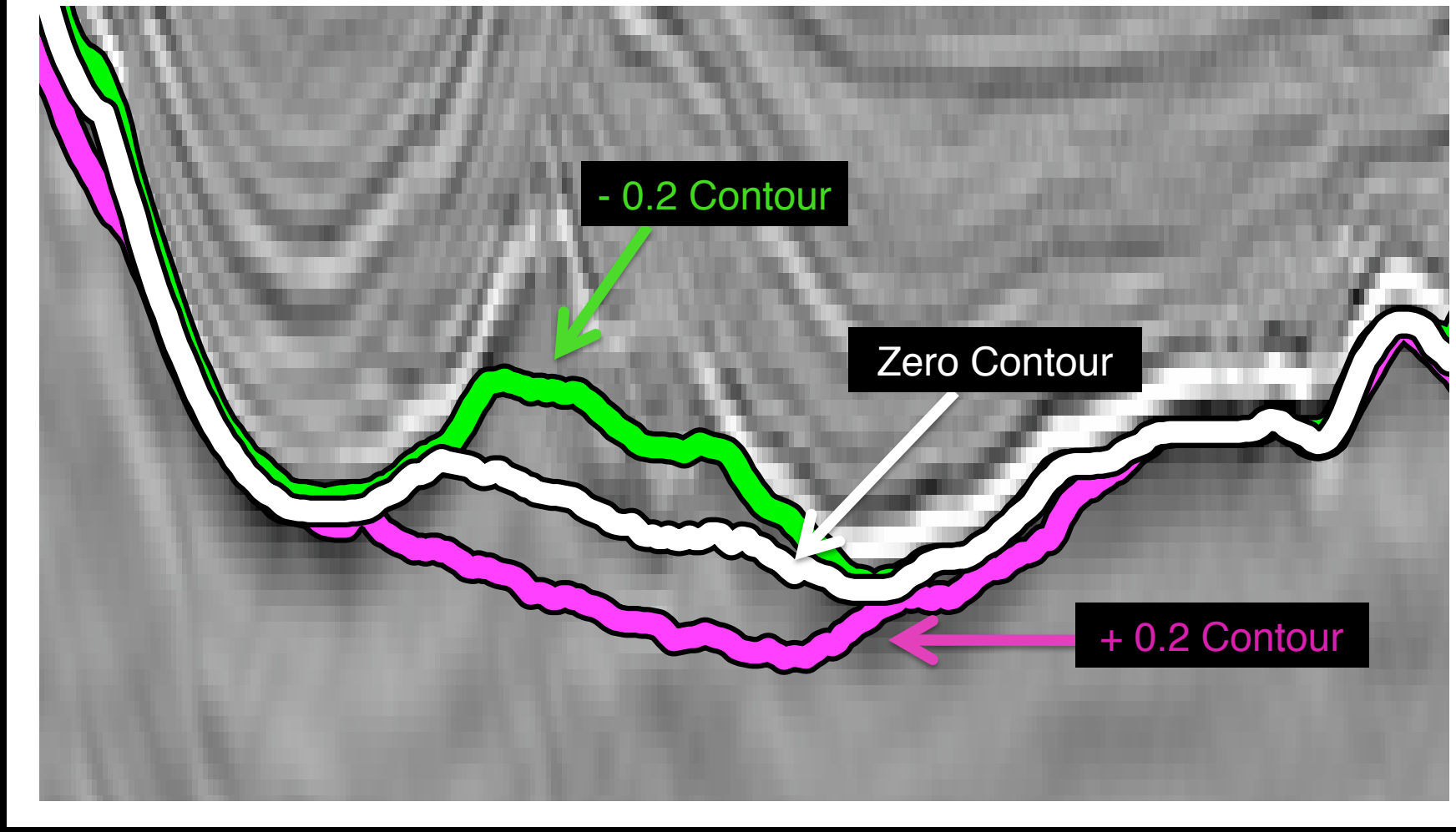
Amplitude eigenvector



Amplitude boundary



Boundary uncertainty



Using other attributes

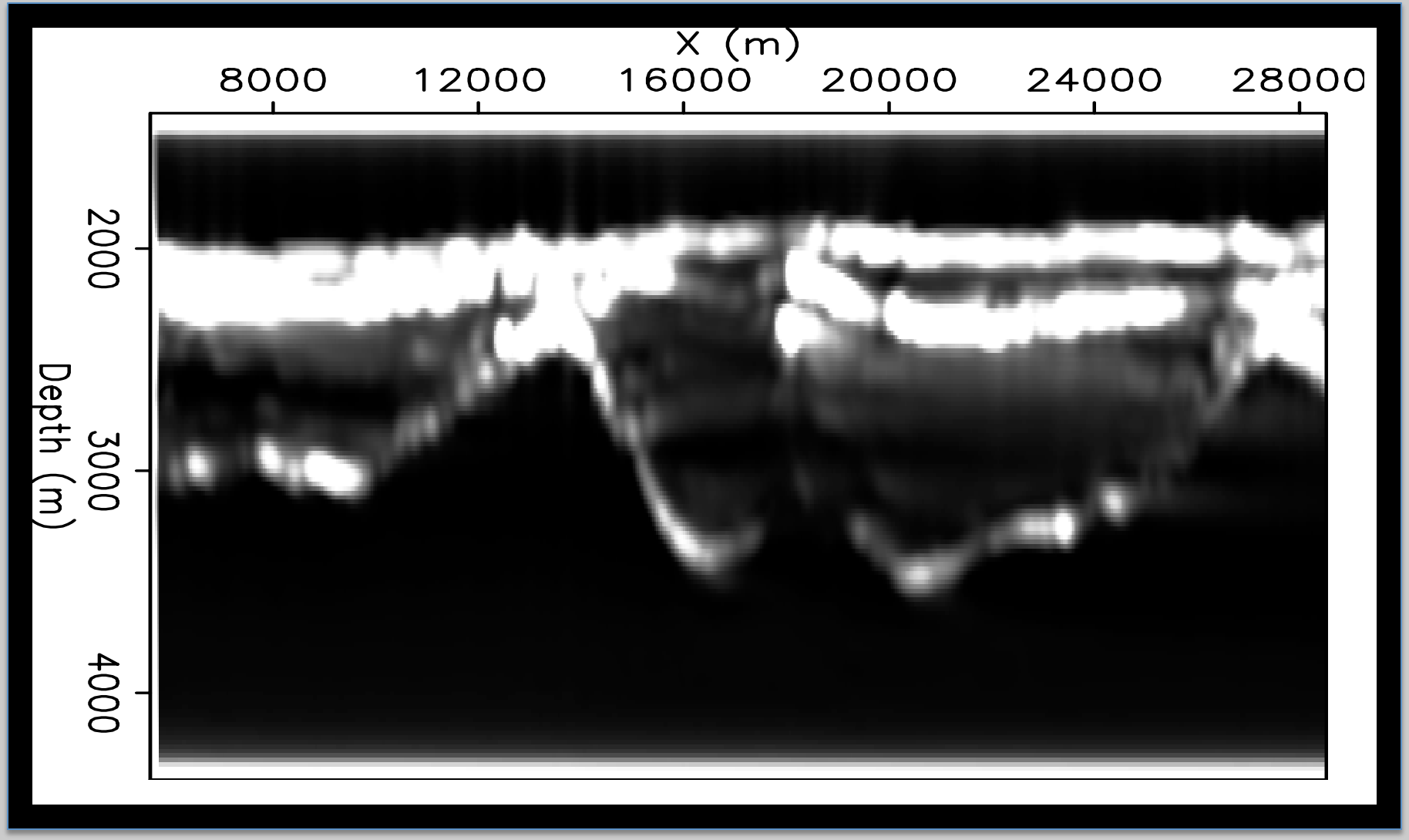
- *Any* quantifiable seismic attribute may be used for segmentation

- One very useful additional attribute is dip variability
  - Salt interfaces often have drastically different dips than surrounding sediments

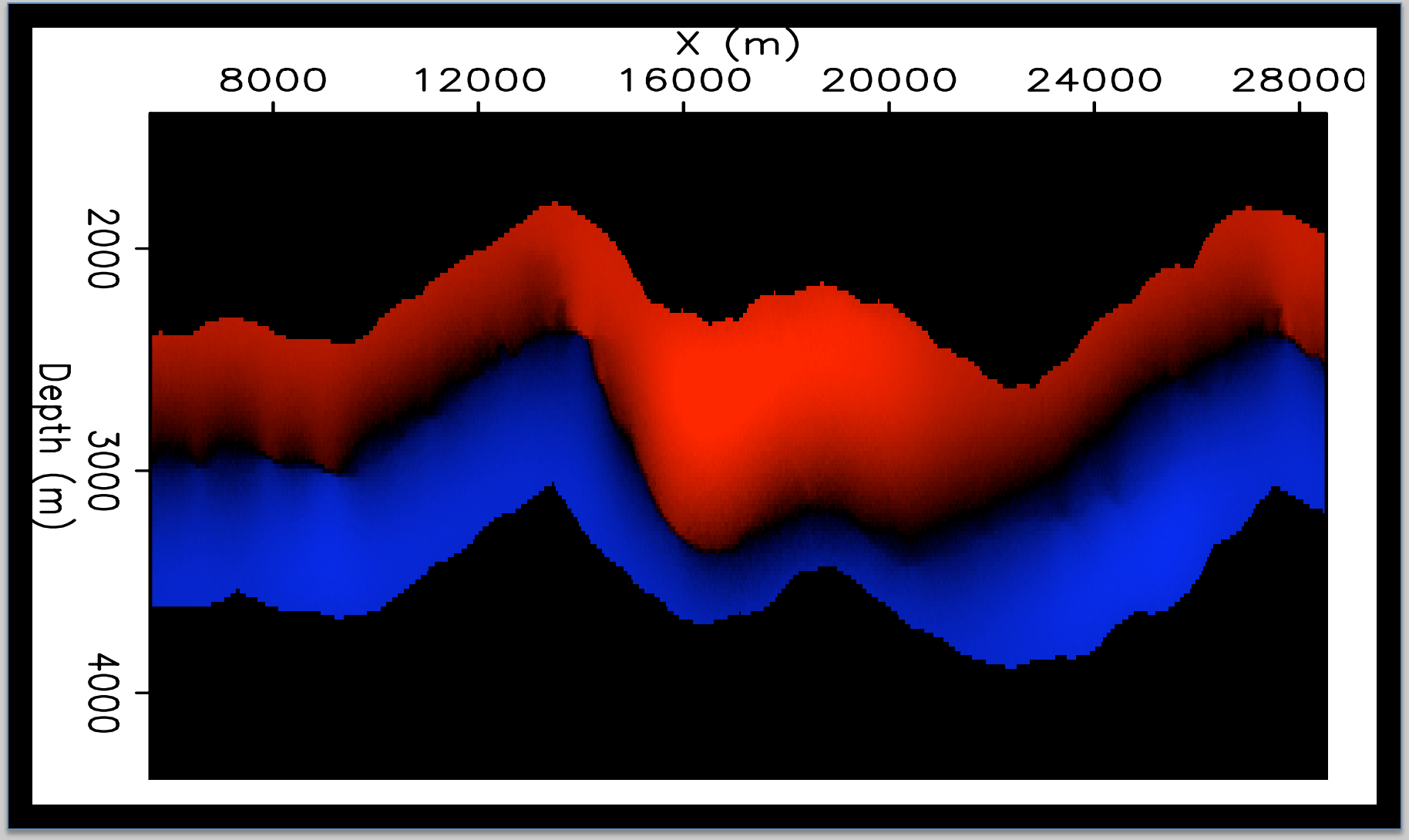
Dip variability calculation

- Estimate dips from the seismic image
  - Here, using Hale's (2007) dip filters
- Apply the helical derivative (Claerbout, 1998) to highlight changes in the dip field
- The envelope of this volume is used for segmentation
  - For further details, see SEP-136

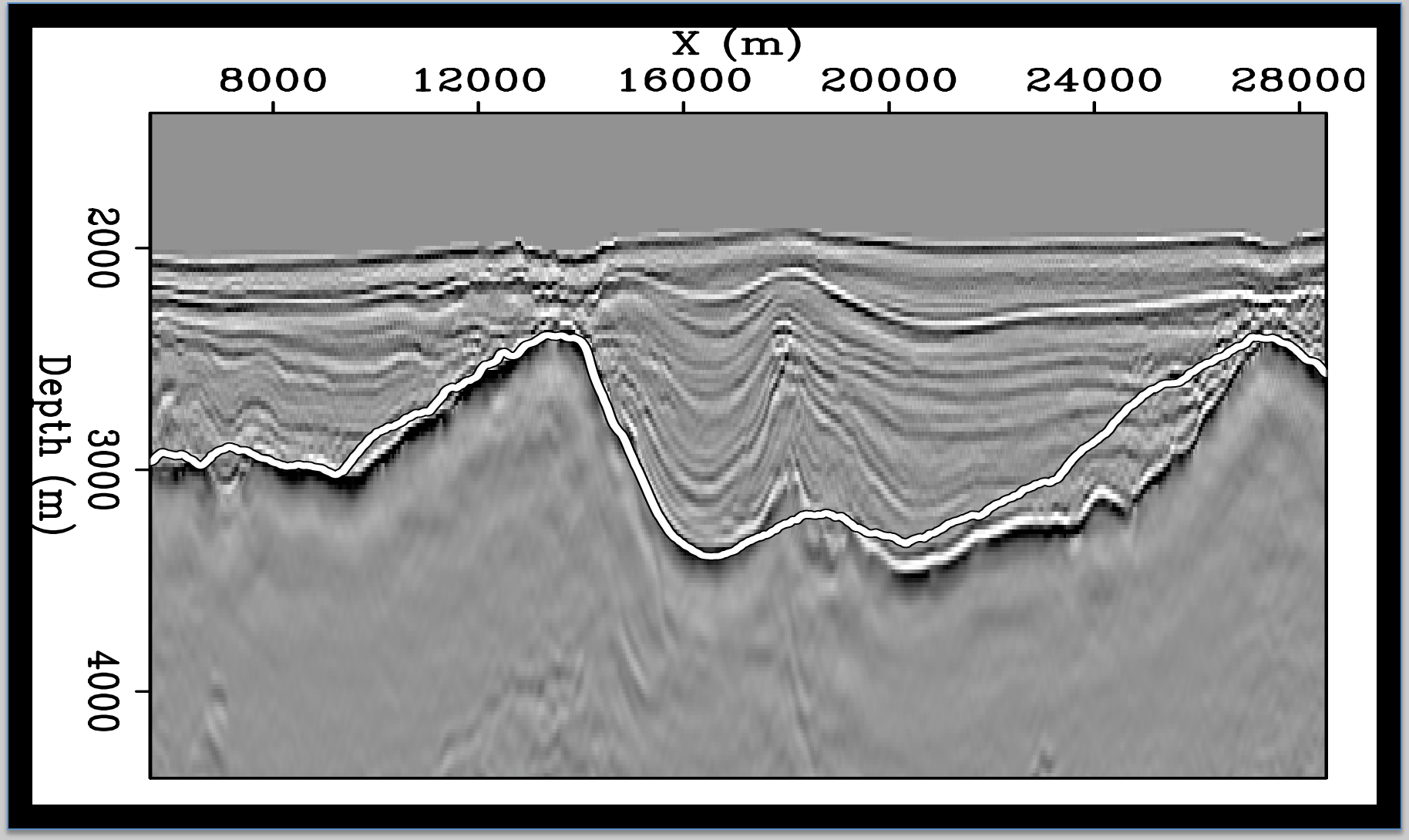
Dip variability attribute



Dip variability eigenvector



Dip variability boundary

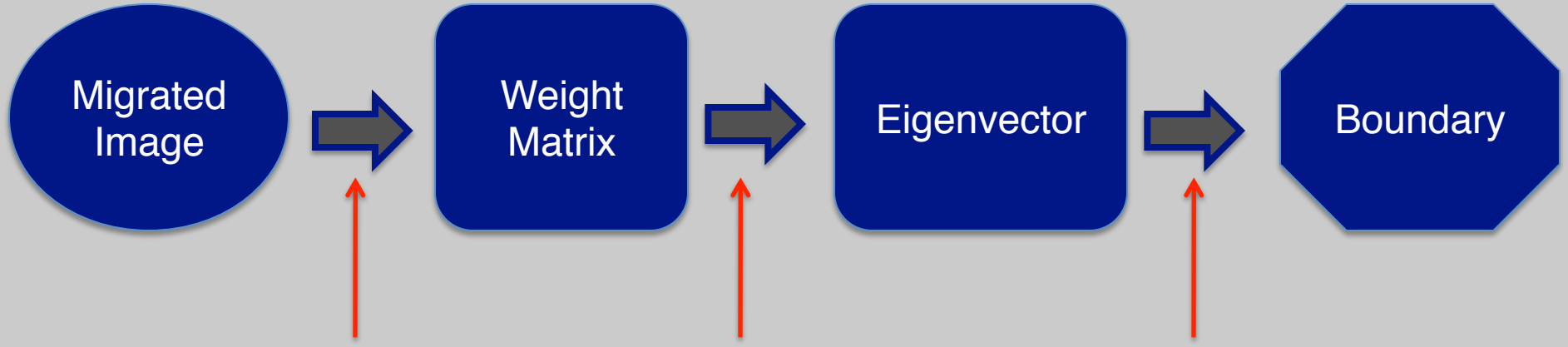


Combining attributes

- Having several different segmentation results (one for each attribute) is not ideal

- Our goal is to produce a single result, incorporating the most reliable information from each attribute

Combination strategies



1) Create a single attribute volume

3) Produce multiple eigenvectors, then combine them

2) Produce multiple boundaries, then combine them

Attribute domain

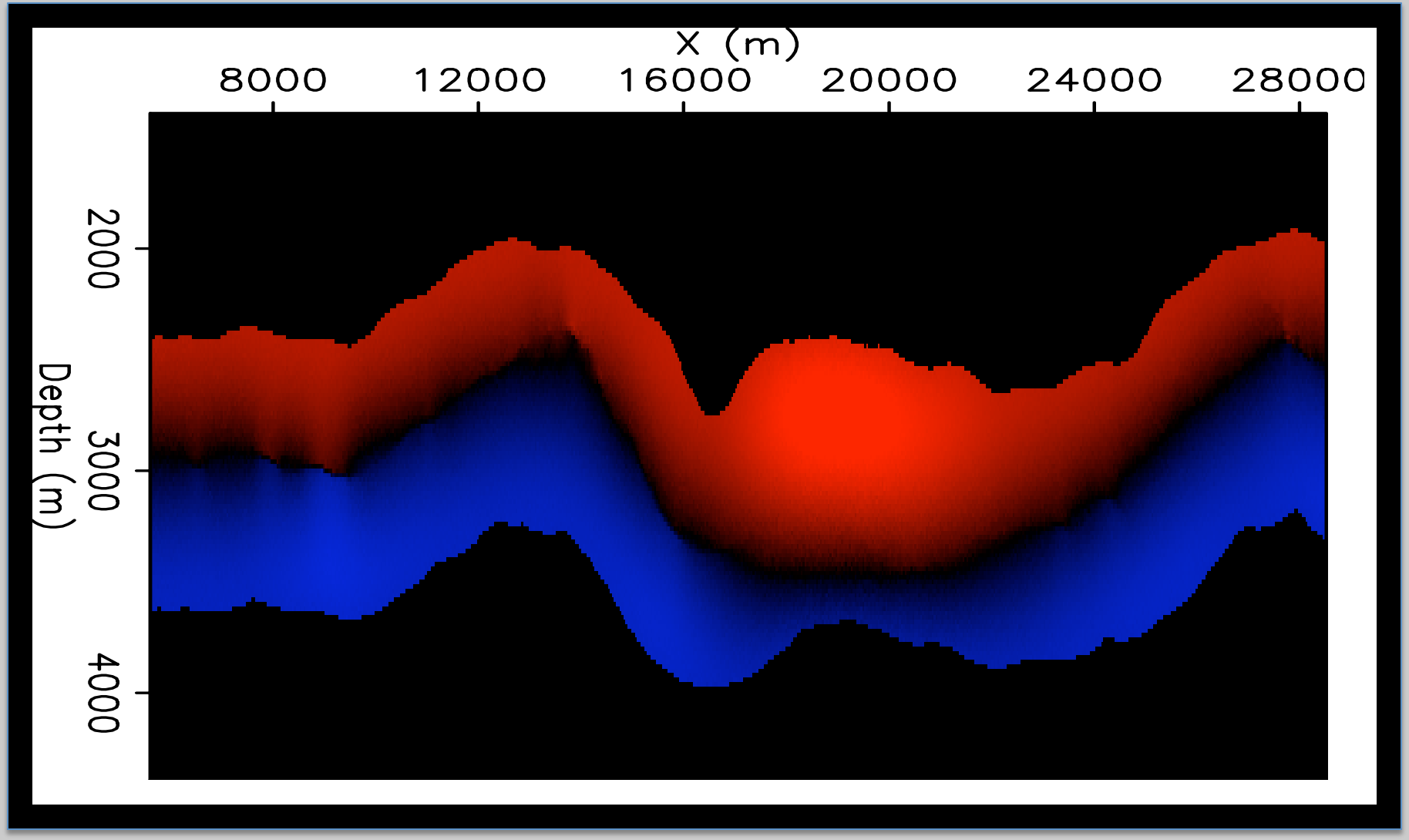
- Multiply attribute envelope volumes together:

$$\prod_{i=\text{dip, amp}} \lambda_i \text{vol}_i$$

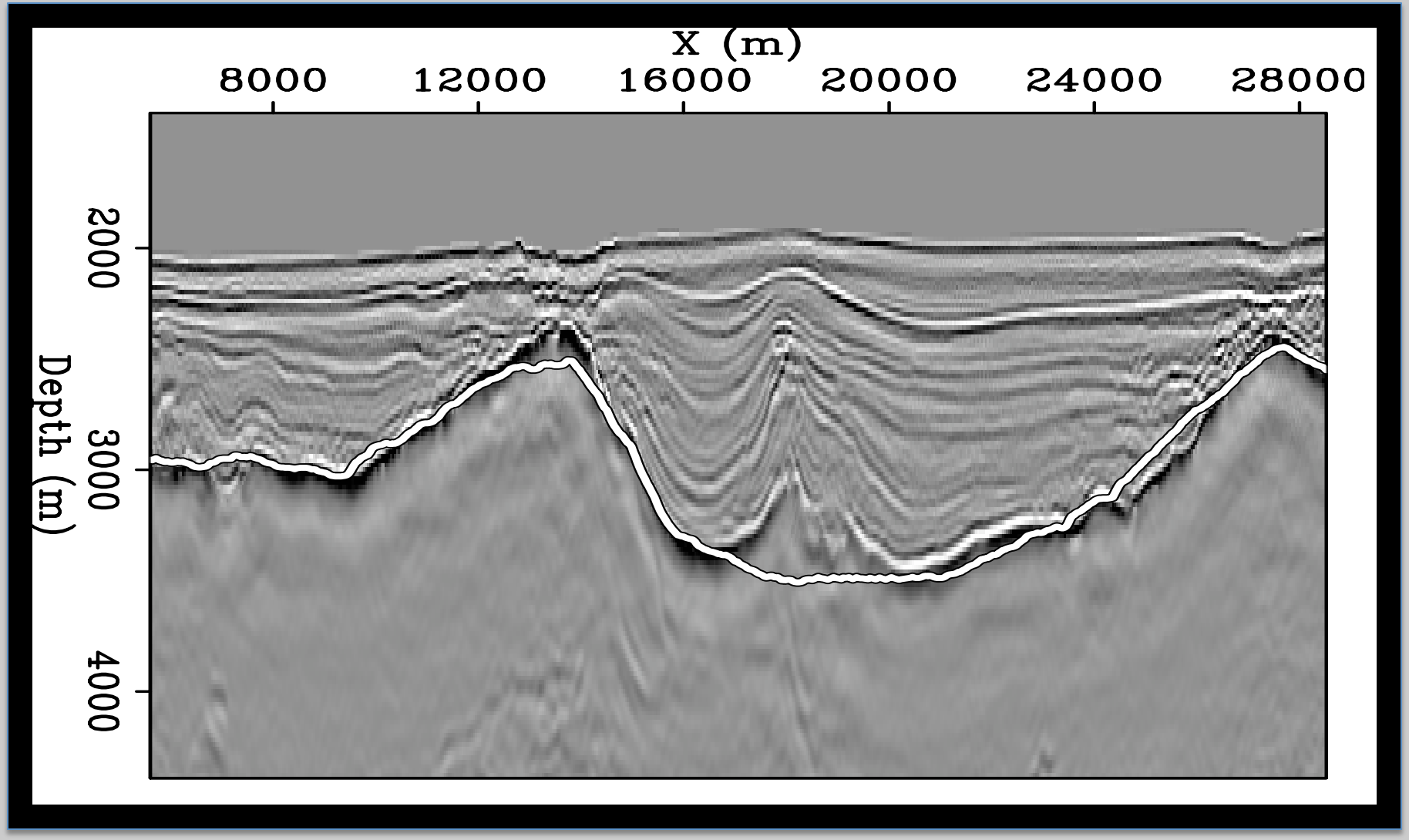
- Idea: Multiplication will reinforce areas where the attribute measures agree

- Drawback: If one attribute succeeds where another fails completely, it will still be penalized

Eigenvector: attribute multiplication



Boundary: attribute multiplication



Boundary domain

- We can combine multiple boundaries if we can measure their relative "uncertainties"
  - A combined boundary would incorporate the most certain elements of each individual boundary

- Analysis of the eigenvectors offers a relatively simple way to measure uncertainties

Uncertainty calculations

- The uncertainty at every point along each boundary is calculated as follows:

$$d = |p_1 - n_1|,$$

where p_1 and n_1 are the two eigenvector values adjacent to the boundary, along a line perpendicular to the boundary

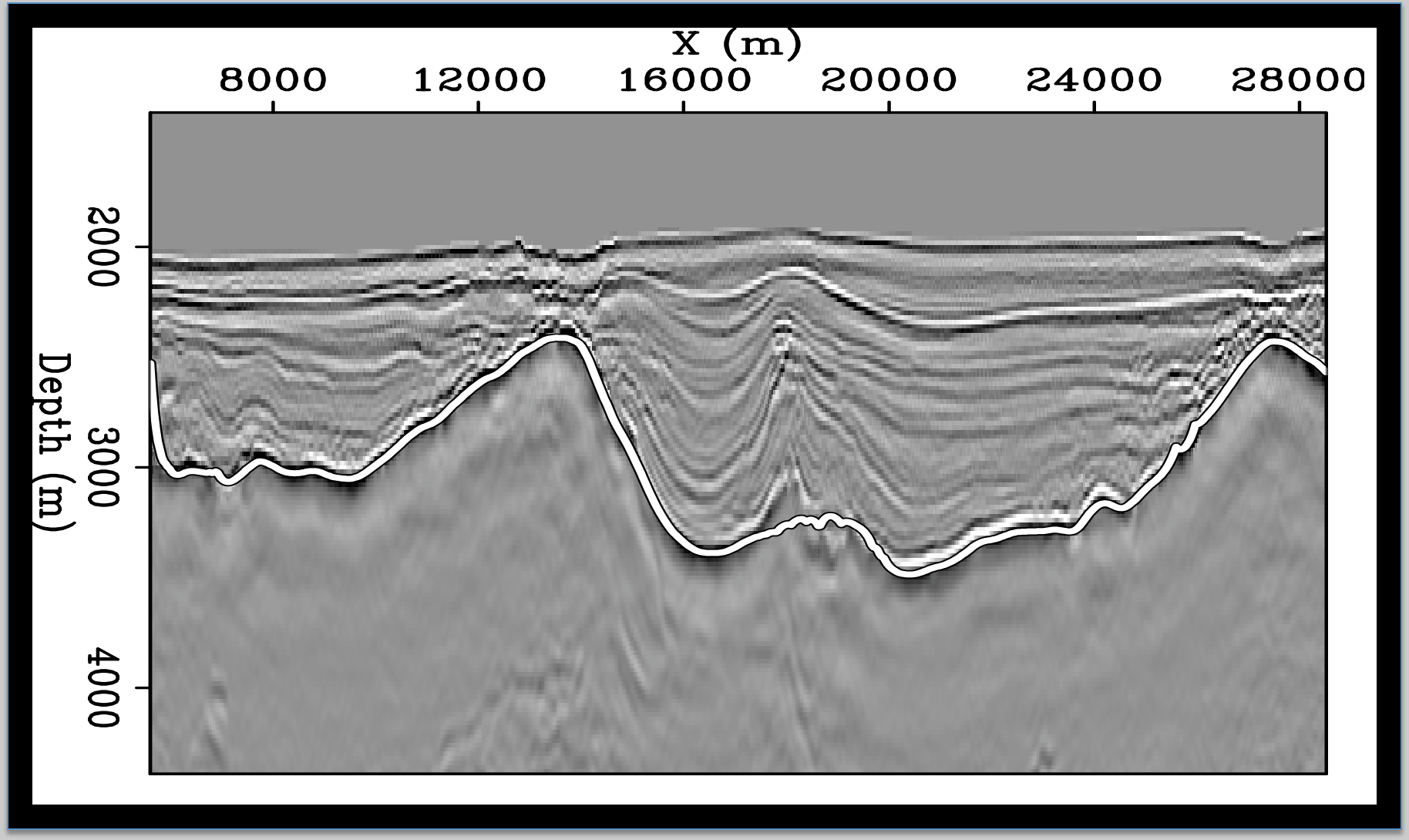
- Large *d* values (a sharp positive/negative transition) indicate relative certainty
  - Small *d* values indicate uncertainty

Boundary combinations

- At each point across an image, take the boundary (depth) value corresponding to the single-attribute boundary with the larger *d*-value

- Problem: Could lead to erratic, “either/or” behavior
  - Exacerbated in 3D

Boundary combination



Eigenvector domain

- After calculating individual eigenvectors, create a single eigenvector via linear combination:

$$\sum_{i=\text{dip, amp}} \lambda_i \Psi_i \qquad \Psi \equiv \text{Eigenvector}$$

- Problem: how to determine weight values (λ's)?

Eigenvector combinations

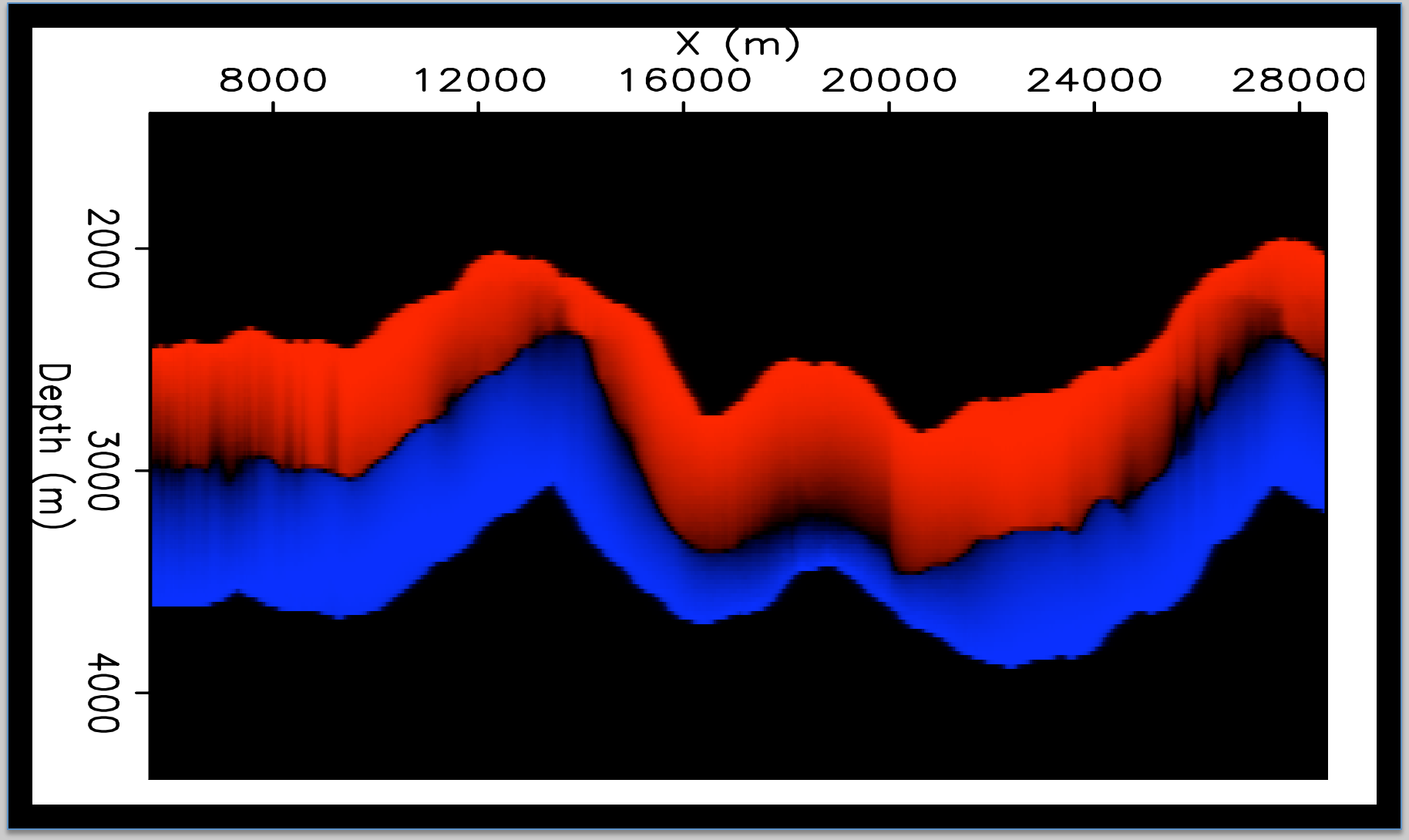
- We can take advantage of the same uncertainty measure we used for the boundary combination method, and determine weights as follows:

$$\alpha = \frac{1}{2}(1 + d_{amp} - d_{dip})$$

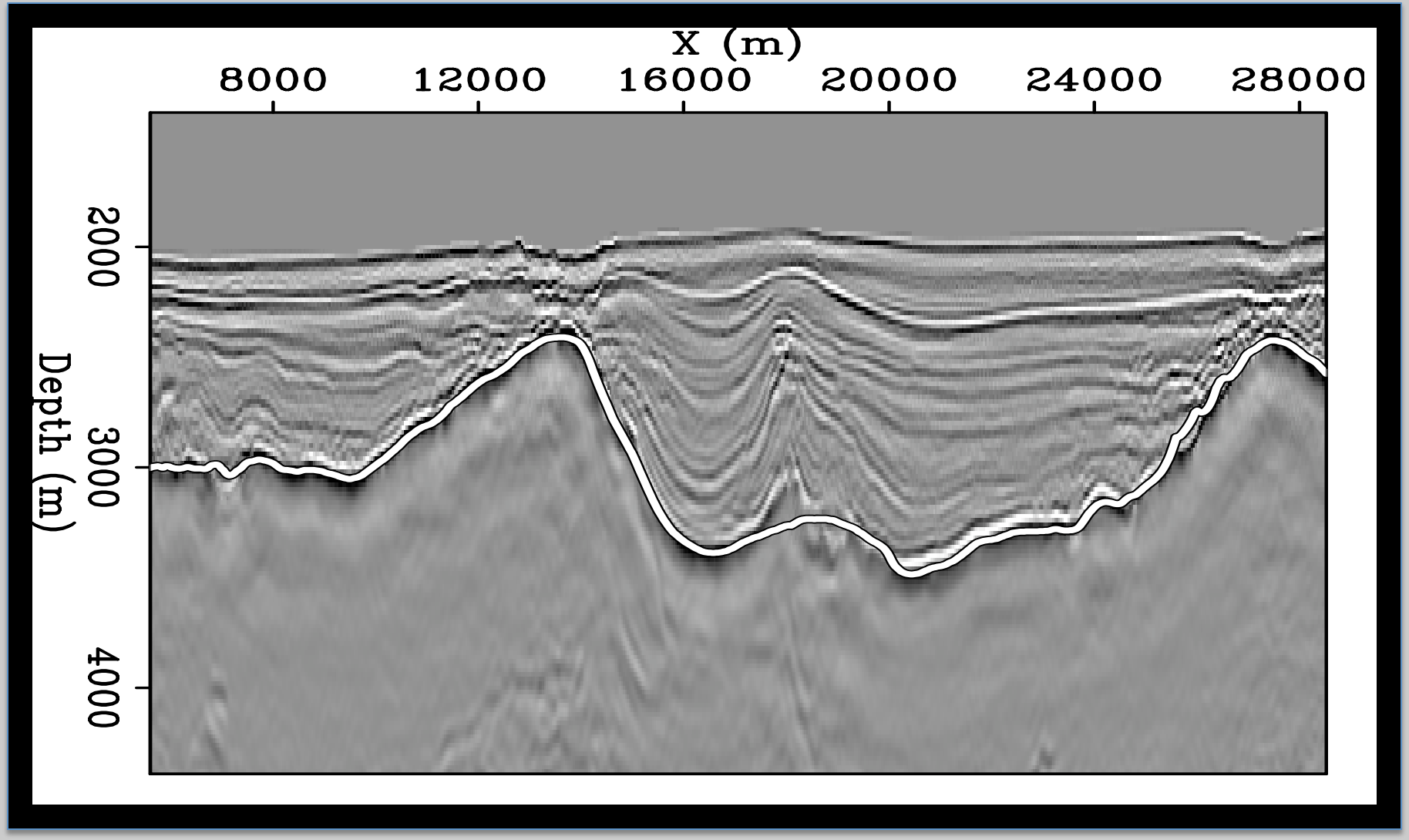
$$\lambda_{amp} = \begin{cases} \alpha^2 & \text{if } \alpha \le 0.5 \\ \sqrt{\alpha} & \text{if } \alpha > 0.5 \end{cases}$$

$$\lambda_{dip} = 1 - \lambda_{amp}$$

Eigenvector combination



Eigenvector combination boundary



Extension to 3D

- Humans excel at 2D pattern recognition, but face limitations in 3D
  - Significant opportunity for 3D image segmentation
- We can generate 3D eigenvectors for each attribute
  - Computer hardware advances making larger problems much more tractable

Extension to 3D

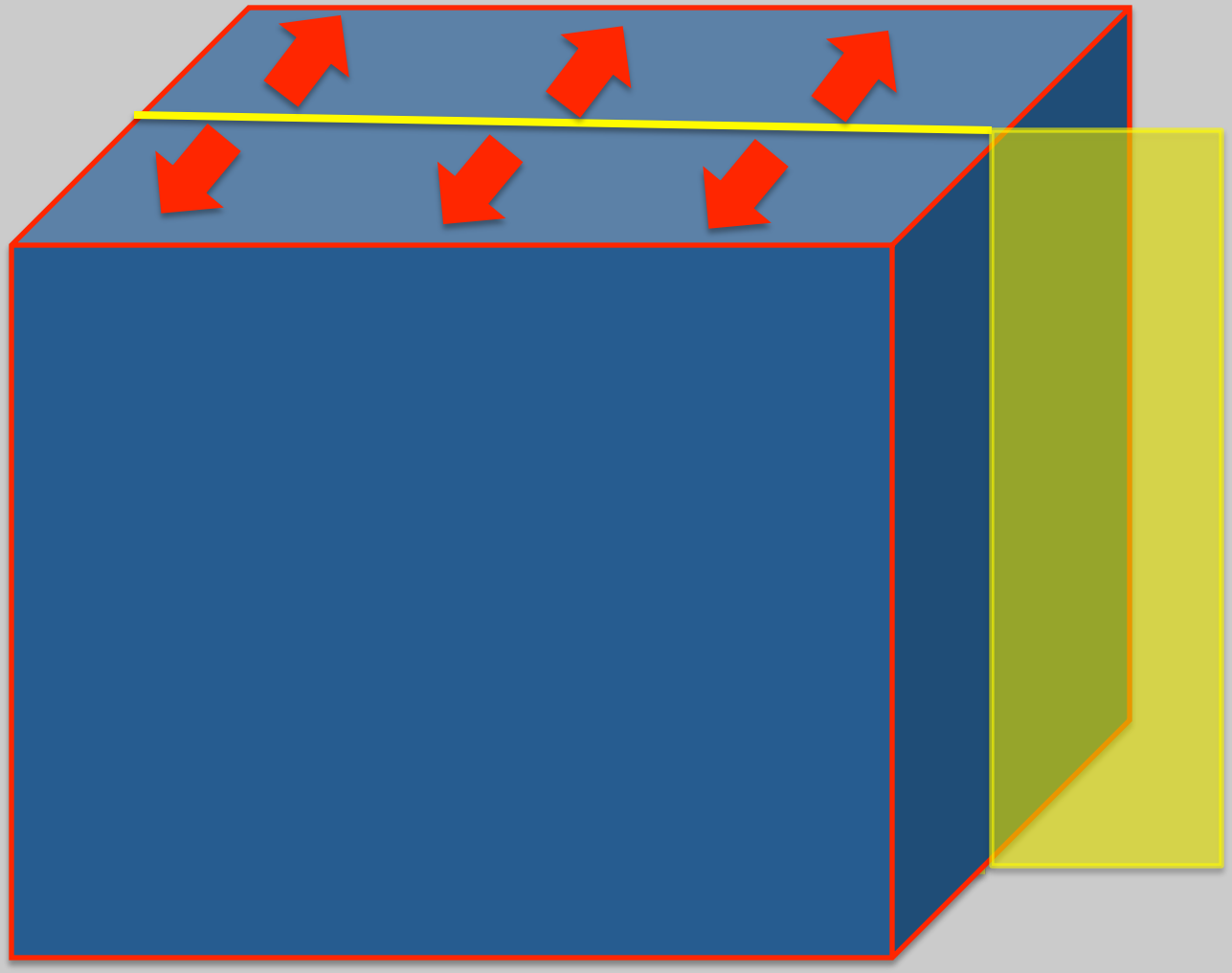
- Can we start from a 2D interpretation, and use it to guide segmentation of a 3D cube?

- Ultimate goal: determine relative importance of attributes using small number of 2D interpretations, and use this information for 3D segmentation

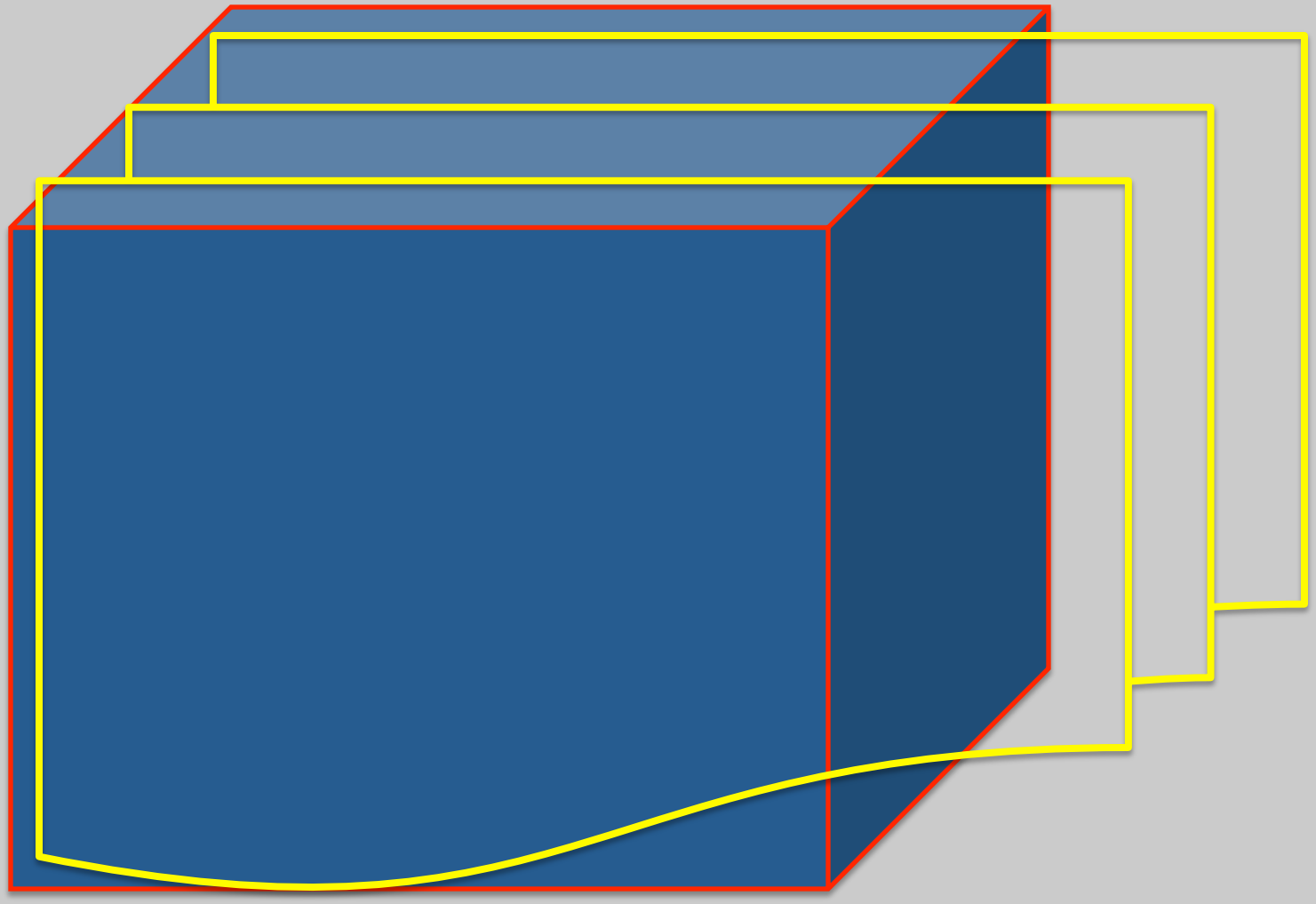
Extension to 3D

- Here, test whether 2D weights calculated for a single inline section are valid for the entire cube
- Apply the attribute weight values we determined previously on the 2D section to all of the other inline sections

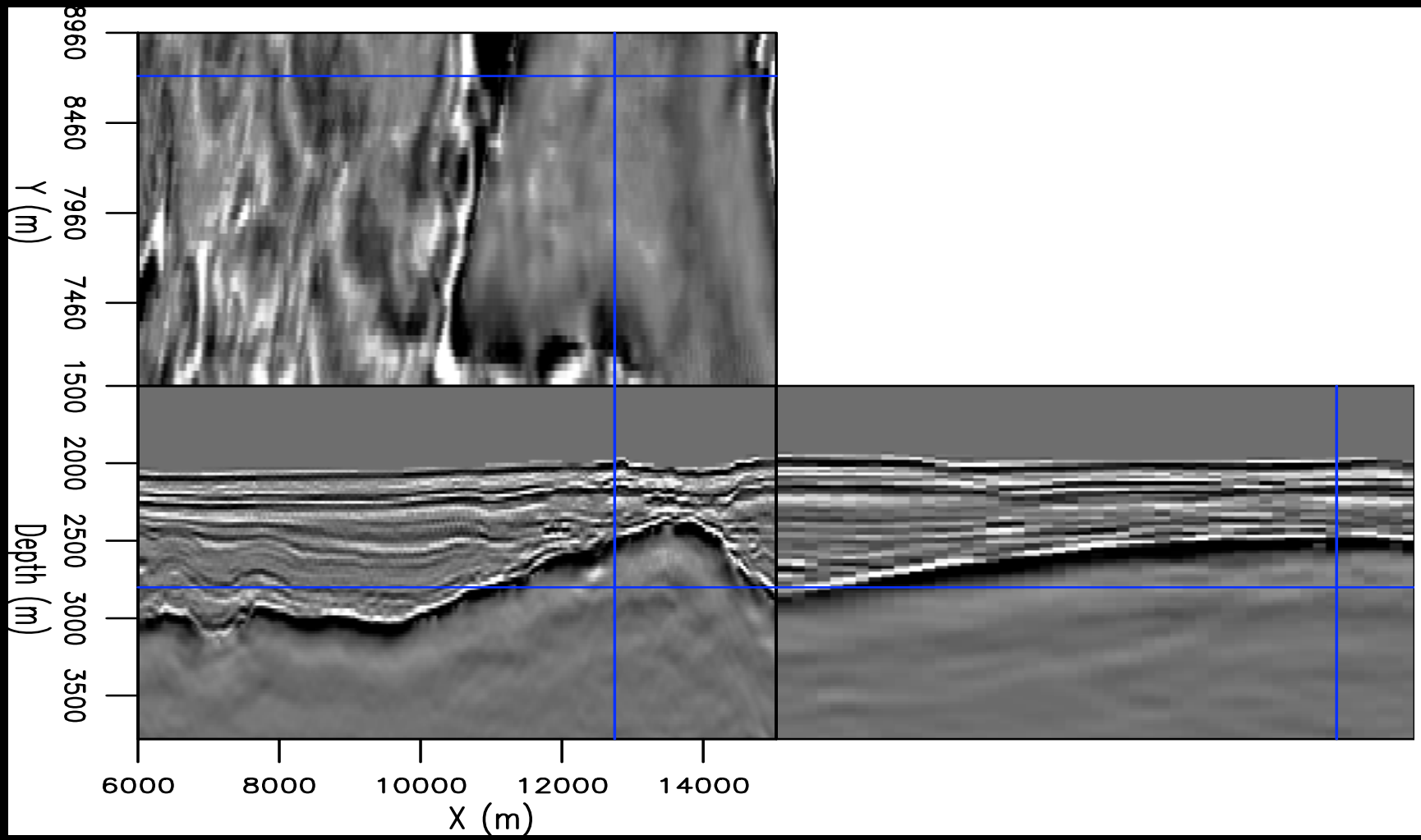
Extension to 3D



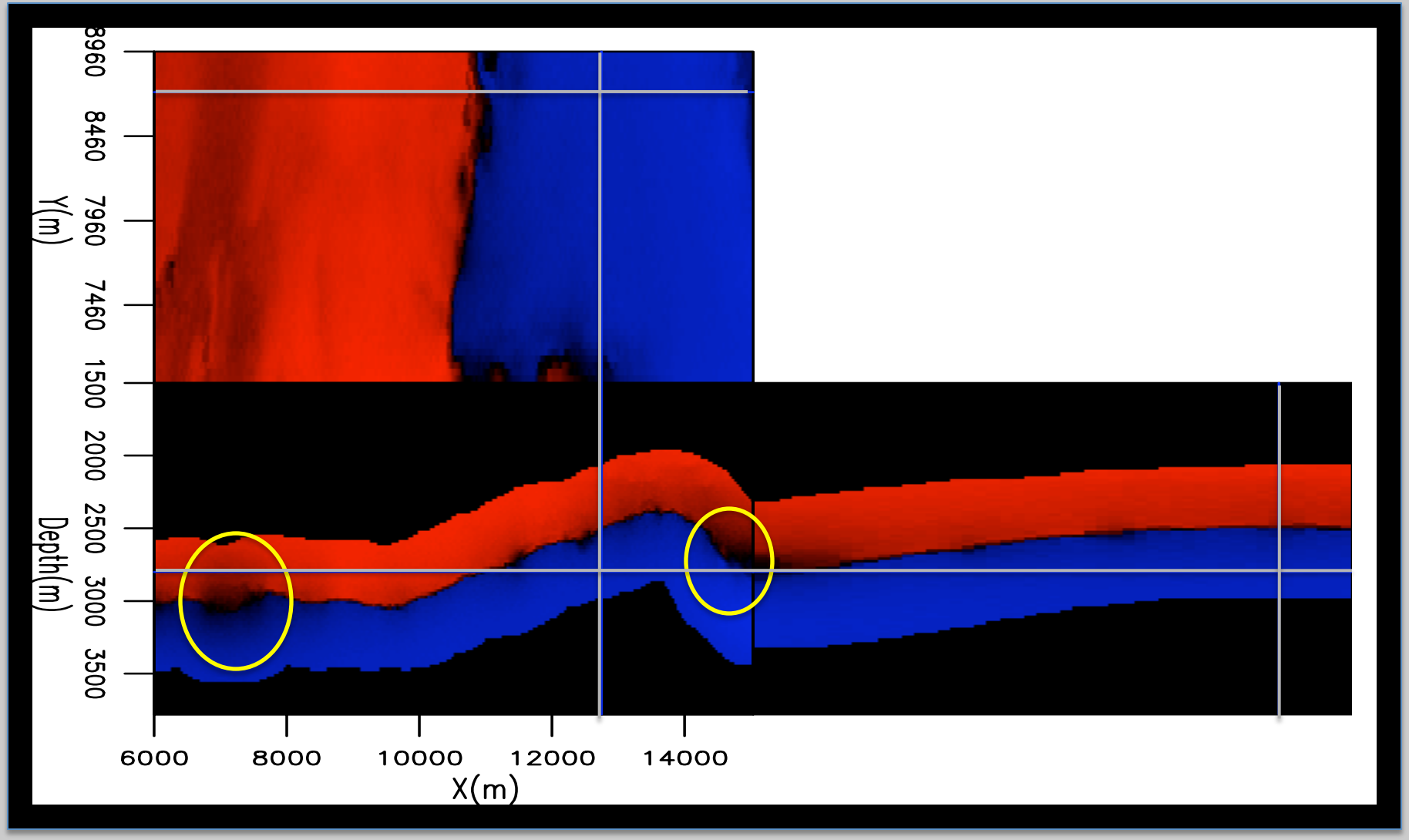
Extension to 3D



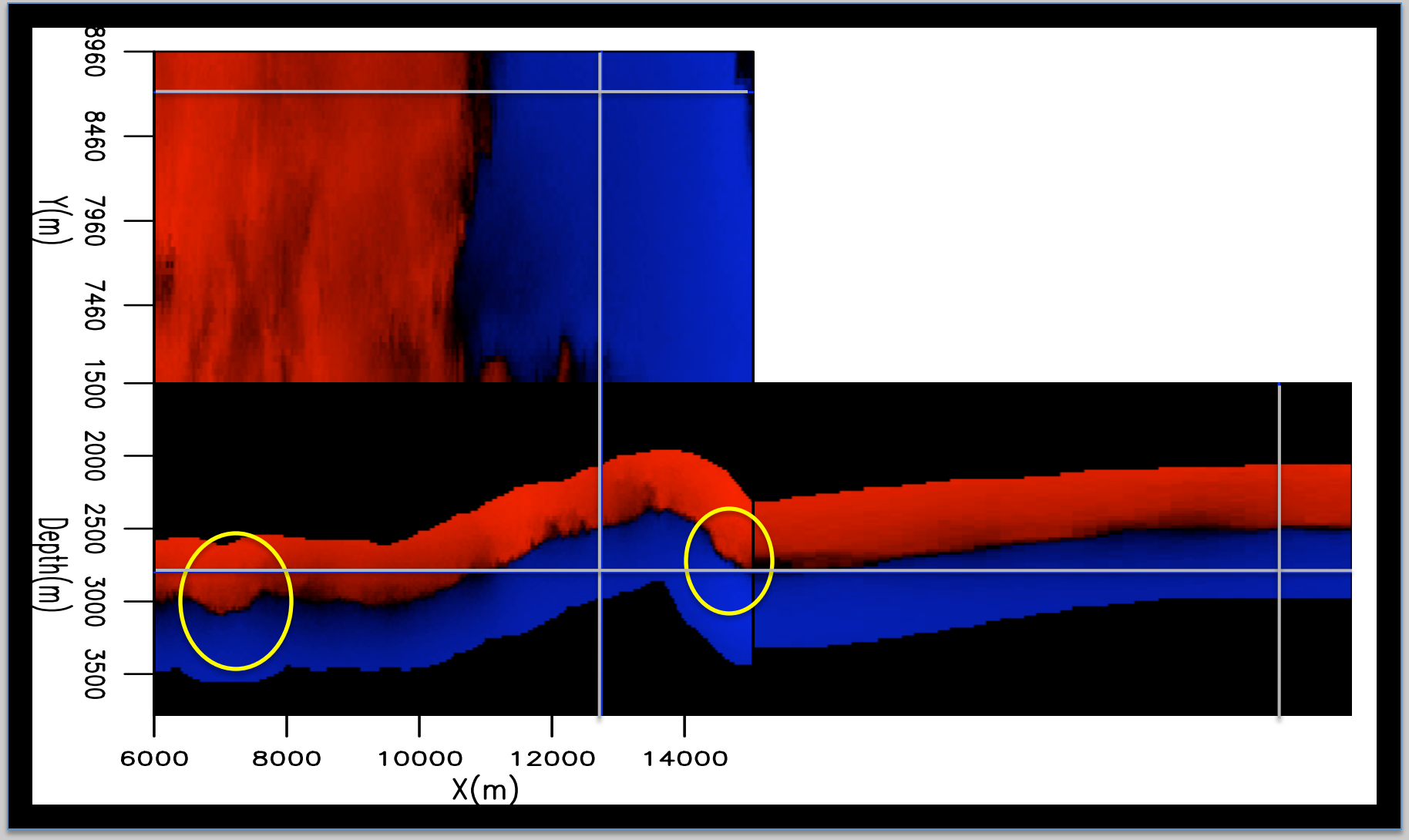
3D example


8960
8460
7960
7460
Y (m)
1500
2000
2500
3000
3500
Depth (m)
6000
8000
10000
12000
14000
X (m)

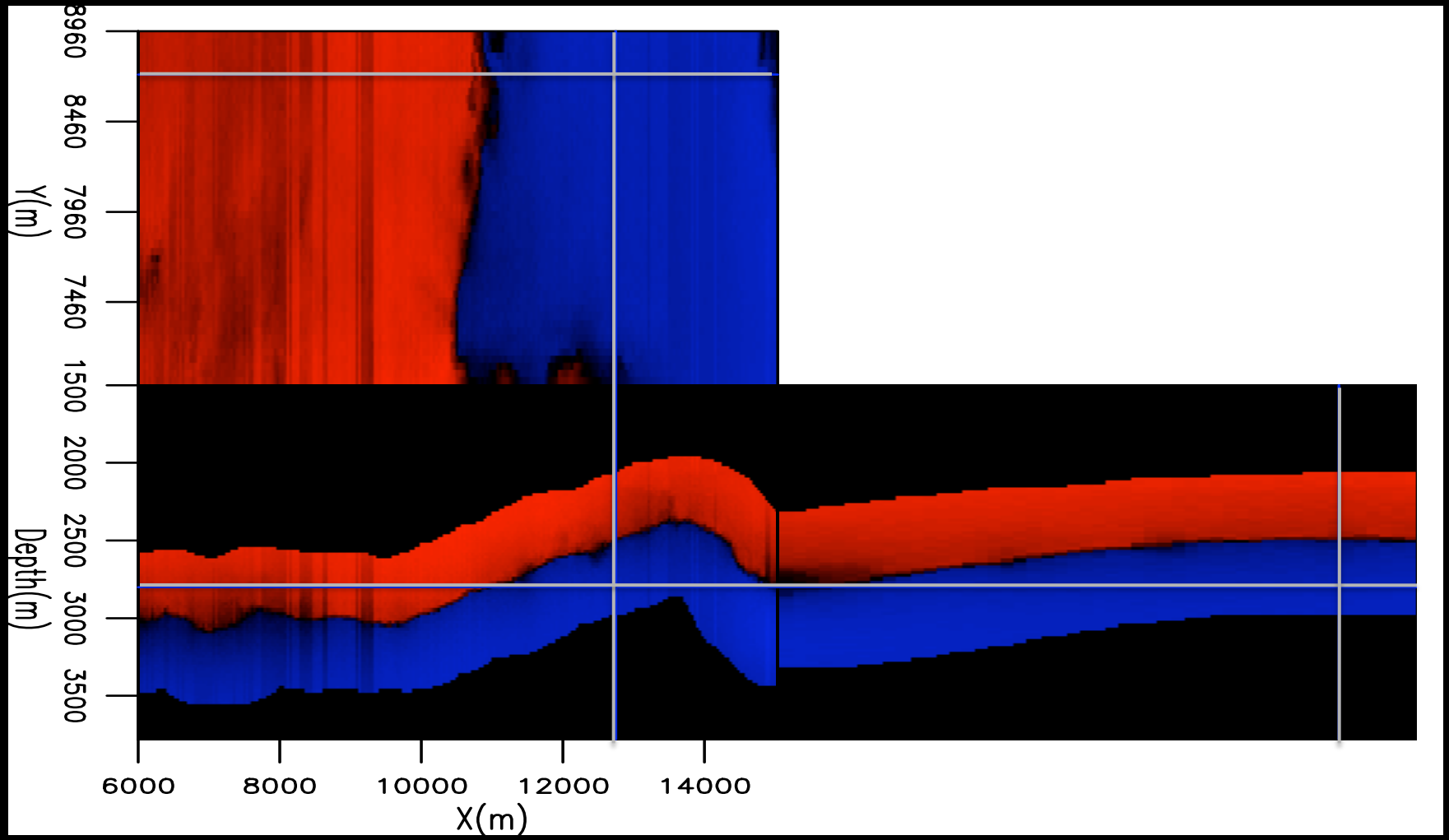
3D eigenvector: amplitude



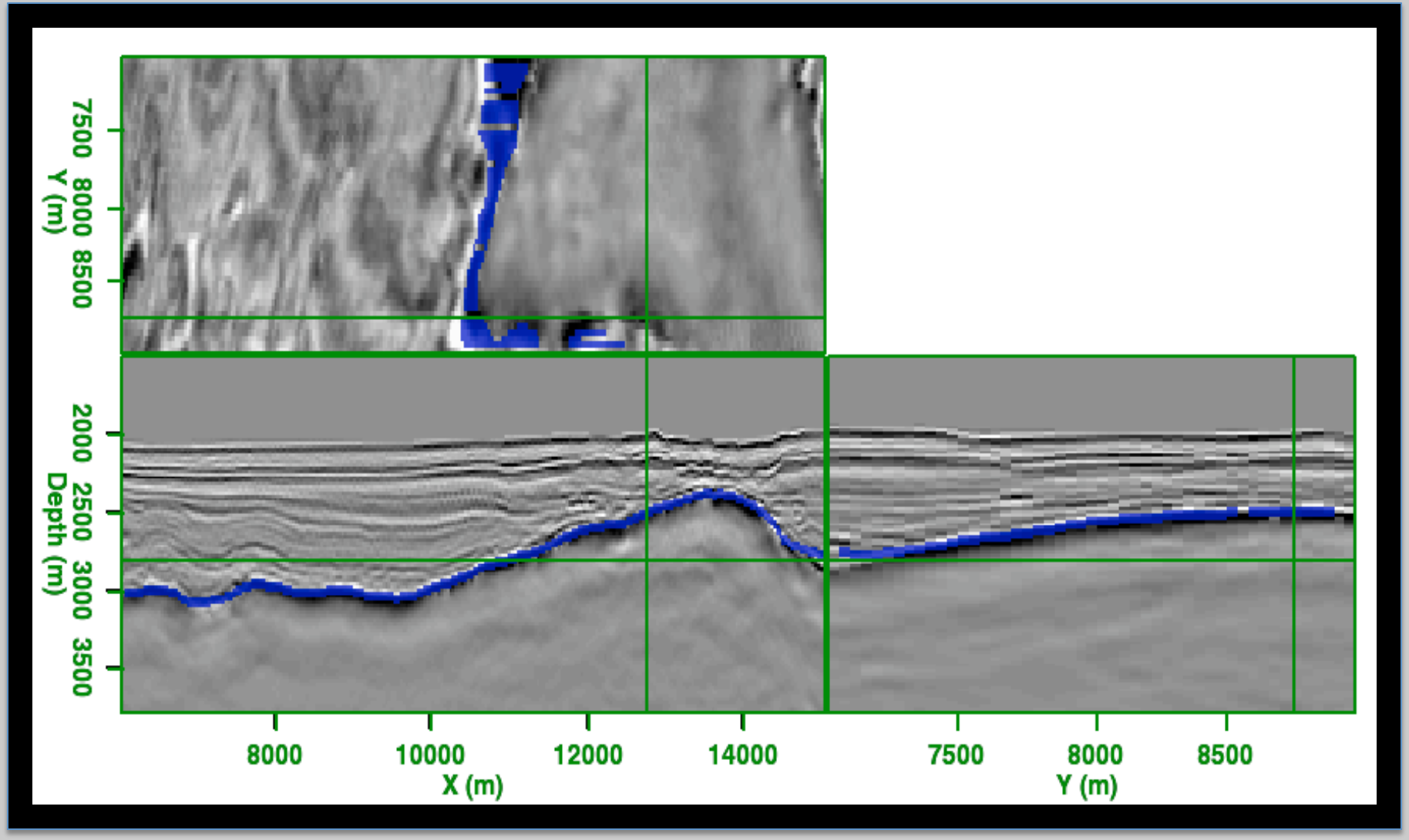
3D eigenvector: dip



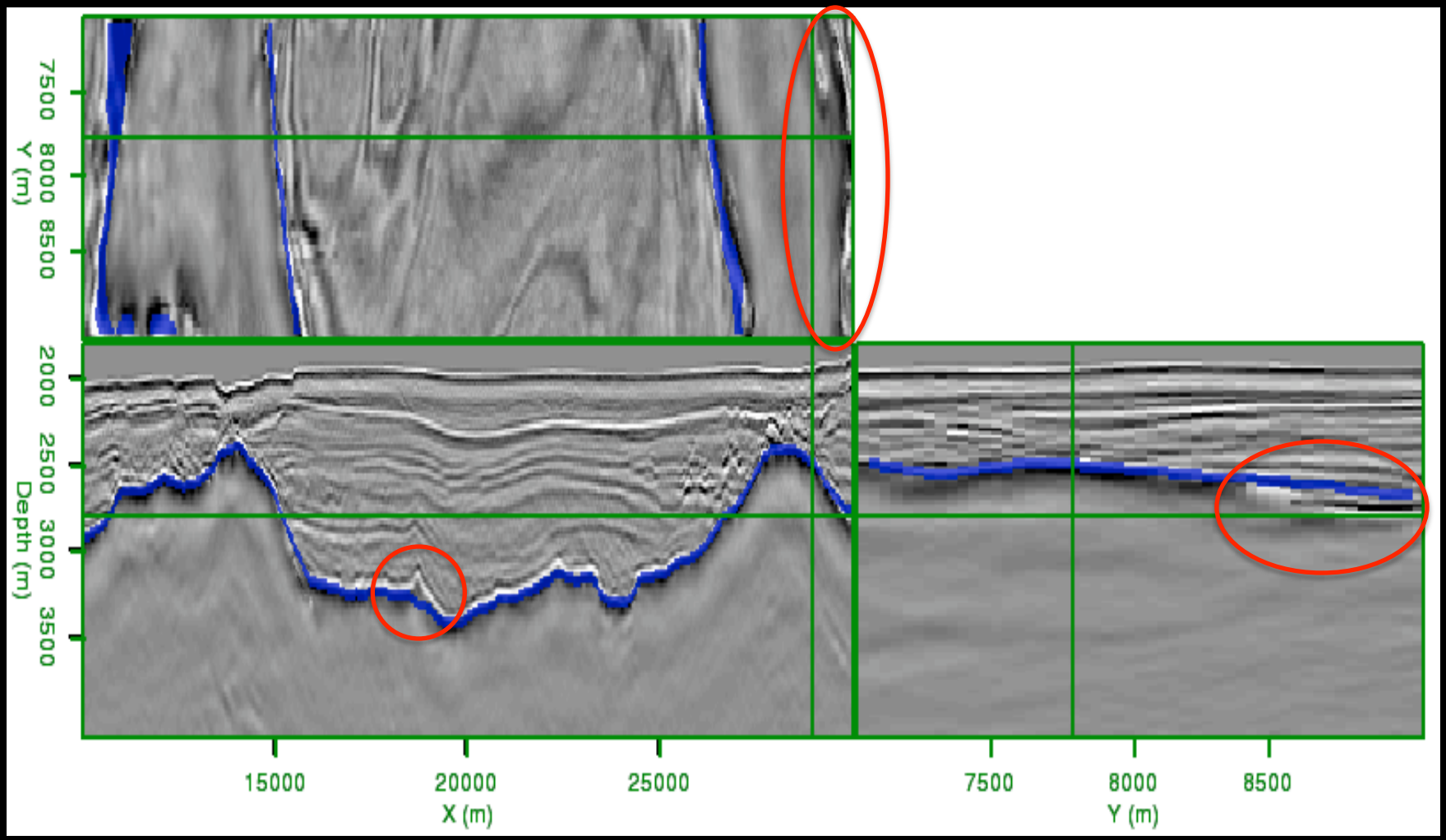
3D eigenvector: combined



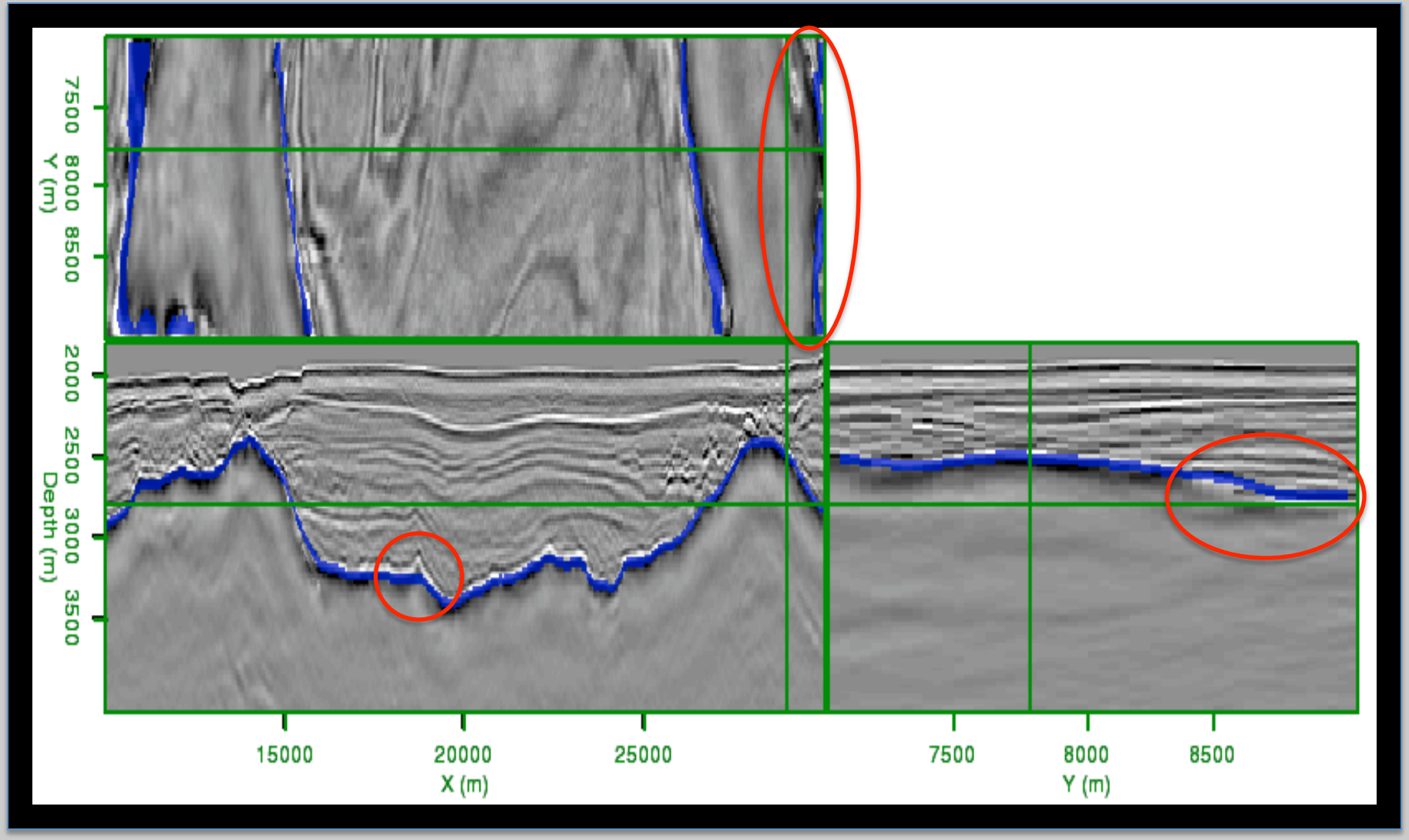
3D boundary


7500
8000
8500
Y (m)
2000
2500
3000
3500
Depth (m)
8000
10000
12000
14000
X (m)
7500
8000
8500
Y (m)

3D example: amplitude only



3D example: combined attributes



Conclusions

- Any quantifiable seismic attribute can be used as a basis for automatic image segmentation
- Uncertainty-weighted eigenvector combinations produce robust, relatively accurate results
- Results obtained from 2D sections can be successfully applied to guide 3D segmentations

Acknowledgments

We thank Unocal/Chevron for providing the data used in these examples, and all SEP sponsors for their support