# Innovations in Borehole Microresistivity Image Data Analysis*

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## Abstract

The automation of repetitive tasks in borehole image data analysis increases efficiency and consistency, and delivers time savings that can be invested in more effective integration and interpretation. Such automation has been enabled by the development of multiple innovative technologies, three of which are considered here: the data-driven deterministic reconstruction of missing data to address incomplete coverage from wireline logs (and gaps in LWD images), the calibration and characterization of microresistivity measurements to provide quantitative resistivity values for petrophysical evaluations, and dynamorphic processing for image enhancement, avoiding the artifacts introduced by the ubiquitous dynamic normalization.

Data reconstruction is based on a modified morphological components analysis approach in which features in the image are represented sparsely in an appropriate domain such that inversion of the sparse representation recovers the missing data uniquely and completely to the extent that the information in the measured parts is representative of that in the gaps. Reconstructed images are almost indistinguishable from full-coverage images for coverage loss up to 30%, and the method performs well for coverage loss up to about 50%. Quantitative resistivity moves away from the previous practice of ad-hoc normalization. It imposes a model-derived calibration and correction for borehole effect. We have developed a high-fidelity numerical model of the whole measurement system; this shows that each measurement electrode has its own unique calibration coefficient, and that these vary in a systematic way across the button array. The response to environmental factors such as standoff is similarly unique for each button. Visualization addresses the challenge of rendering high dynamic range resistivity data with a necessarily limited color palette. Among the newly developed visualizations is the dynamorphic image which splits the data into sharp and less-sharp components, scales them independently then re-combines. The innovations have been used with new edge detection algorithms to enable the robust automated detection of planar boundaries. In a test involving 350 m of image data from a fractured shale-sand interval, the new detection algorithm ran 30 times faster than a leading commercial auto-dip program, detected substantially more features, and false picks were reduced by more than an order of magnitude.

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Weatherford

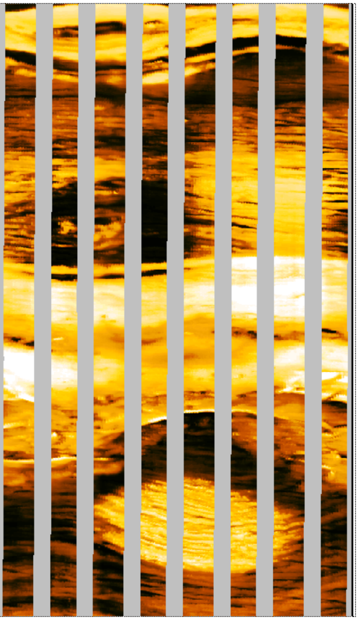
AAPG ICE Istanbul, 14th – 17th September 2014

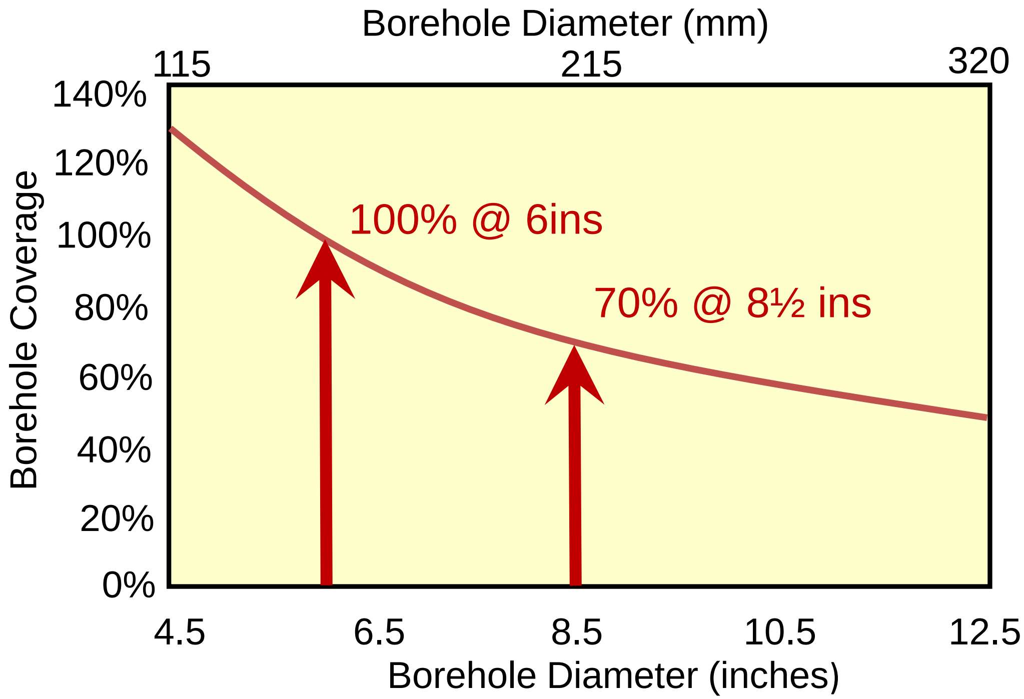
# Motivation & Outline

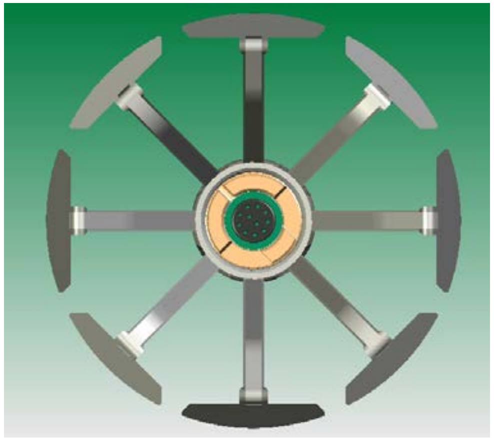
- Introductory Comments
- Image Reconstruction
- Quantitative Image Resistivity Values
- Appropriate Visualization
- Automation Example – Feature Picking
- Wrap-up

# Image Reconstruction - Inpainting

- CMI circumferential overage is 100% in 6-inch wells, reducing to 50% in 12 ¼ inch wells
- MCA Inpainting  reconstructs the ***whole*** image – including missing parts



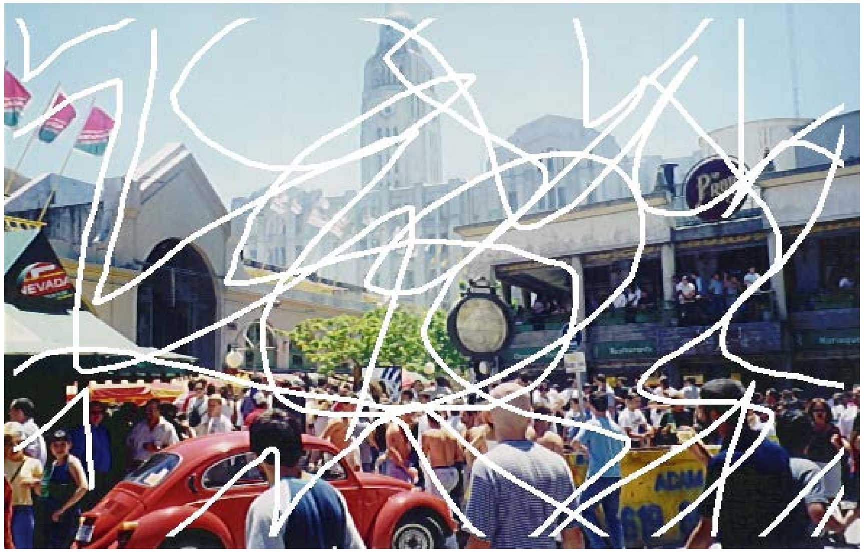


8-inch (203mm) hole

# Humans Are Skilled Inpainters…..

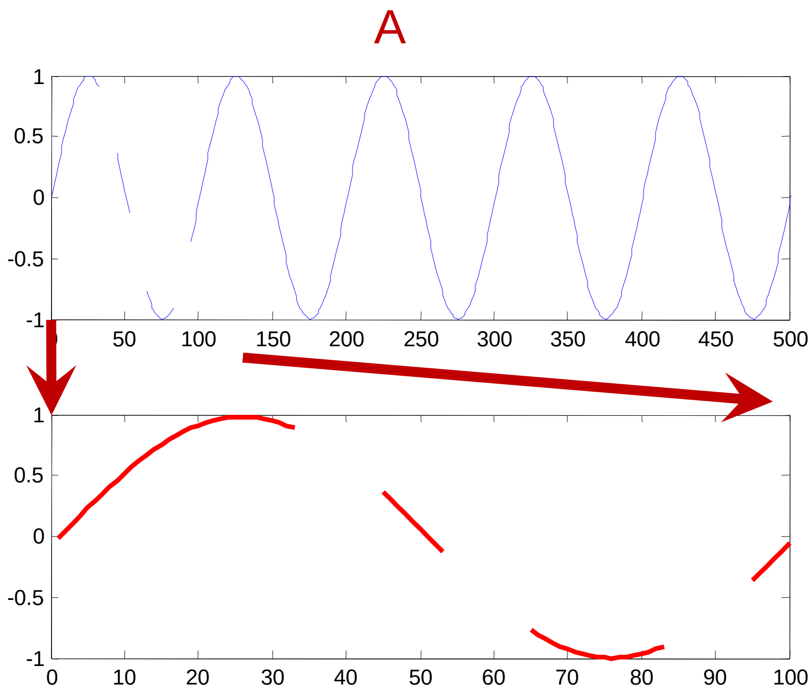
……..Can Machines be do the same?

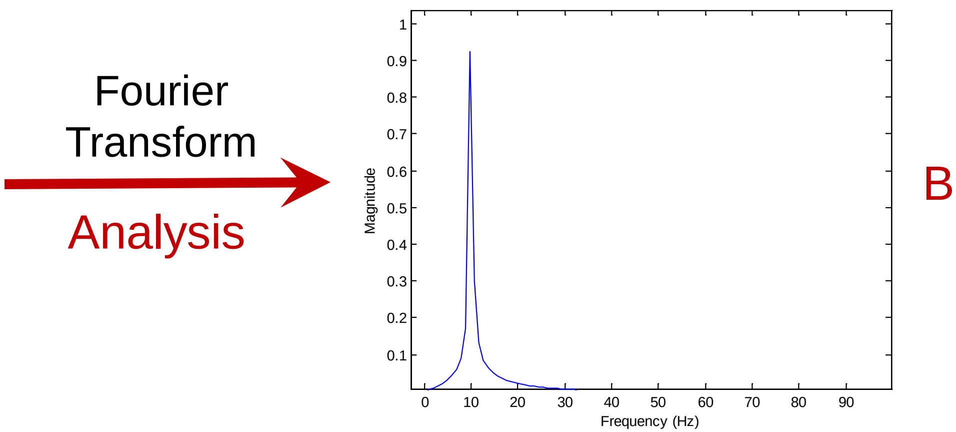


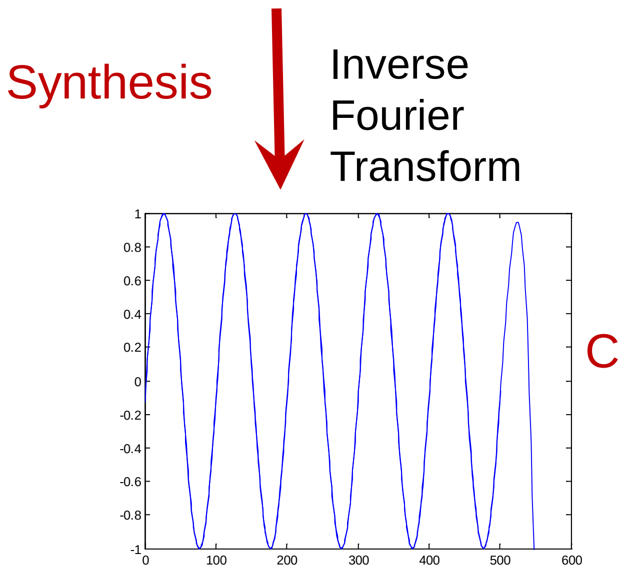
Bertalmio et al (2000)

- The answer is “Yes” – if we can make them mimic the brain
- The brain uses cues from the visible parts to fill the gaps
- The **data** is missing, but the **information** may not be
- Formalized in **Morphological Component Analysis (MCA)**

# MCA – Conceptual Overview (1 of 2)



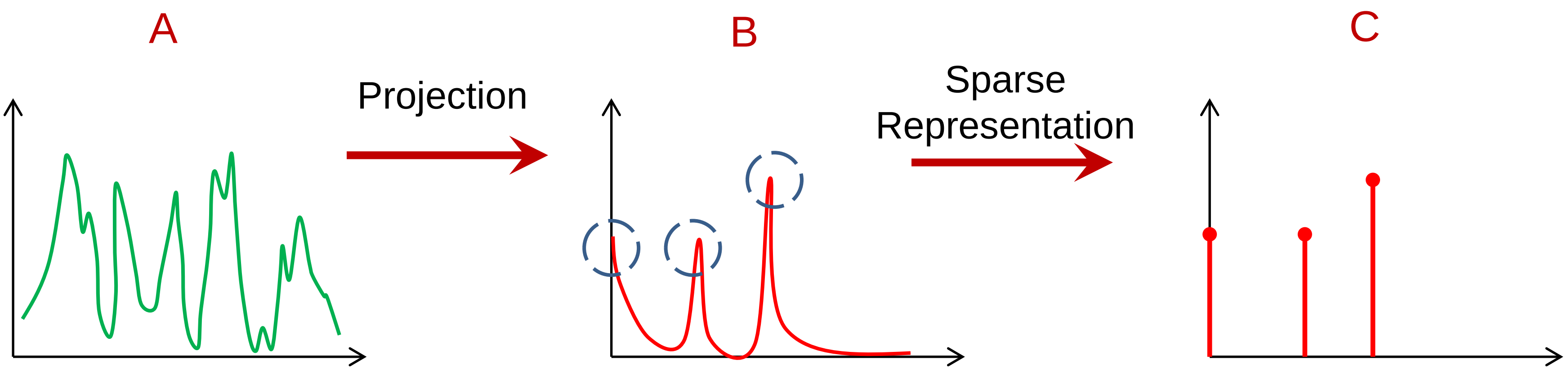




A. Pure sine wave with gaps

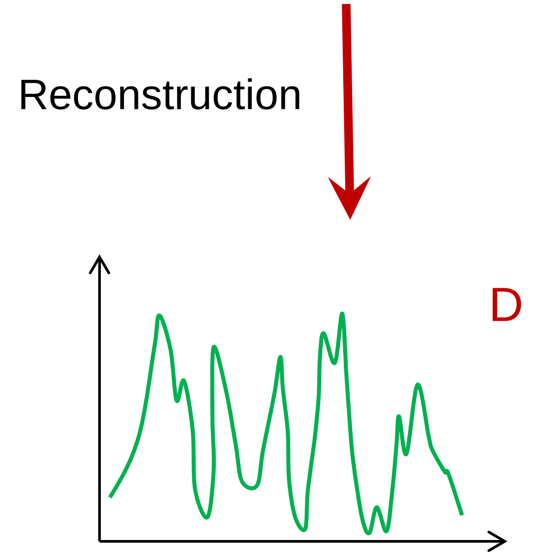
B. Transform domain (in this case Fourier)

C. Inverse domain fills the gaps perfectly.

# MCA – Conceptual Overview (2 of 2)




Several transforms may need to be considered to find maximum sparsity



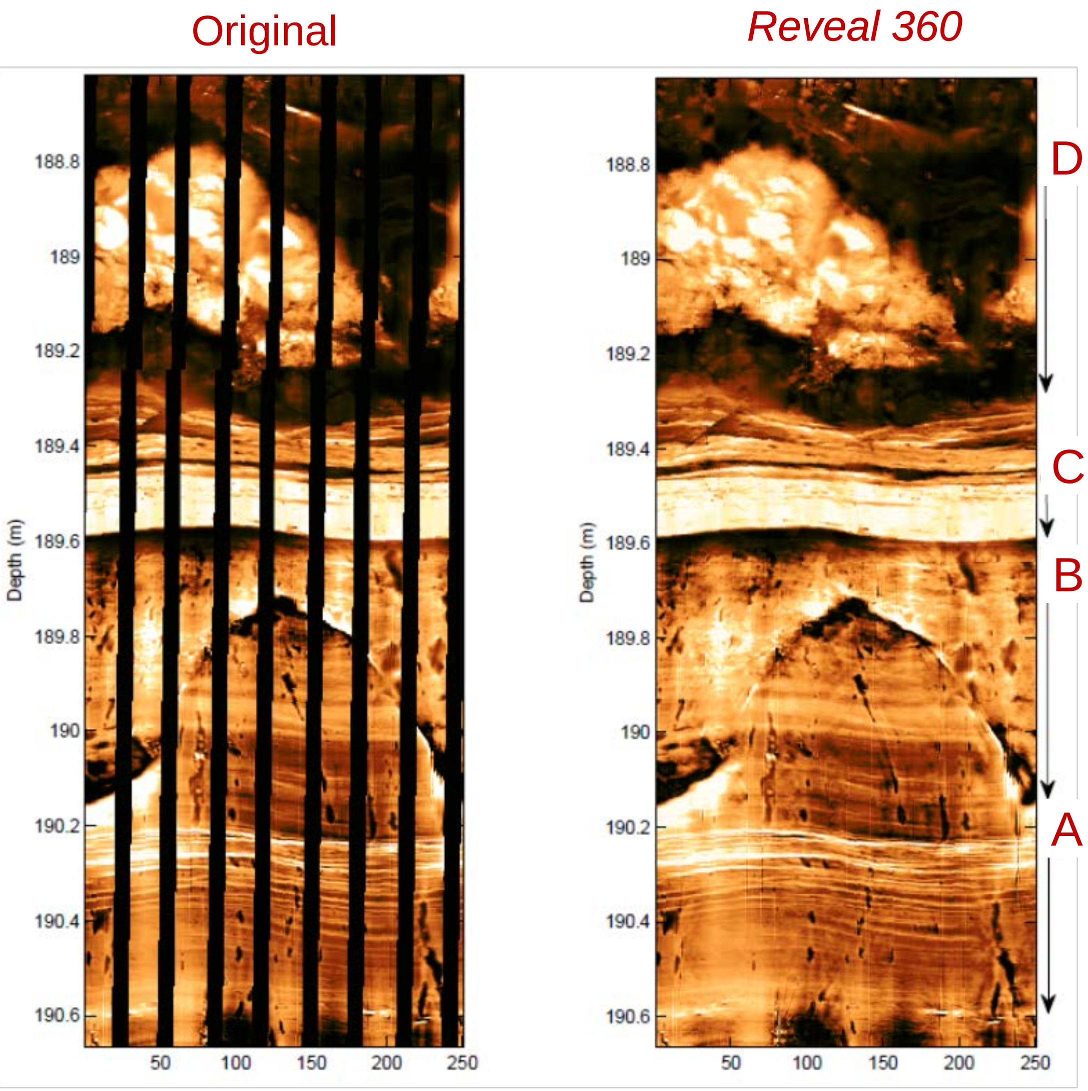

A. Original signal

B. Projection (using FT, DCT, wavelet, curvelet.....)

C. Sparse representation of projection

D. Reconstruction

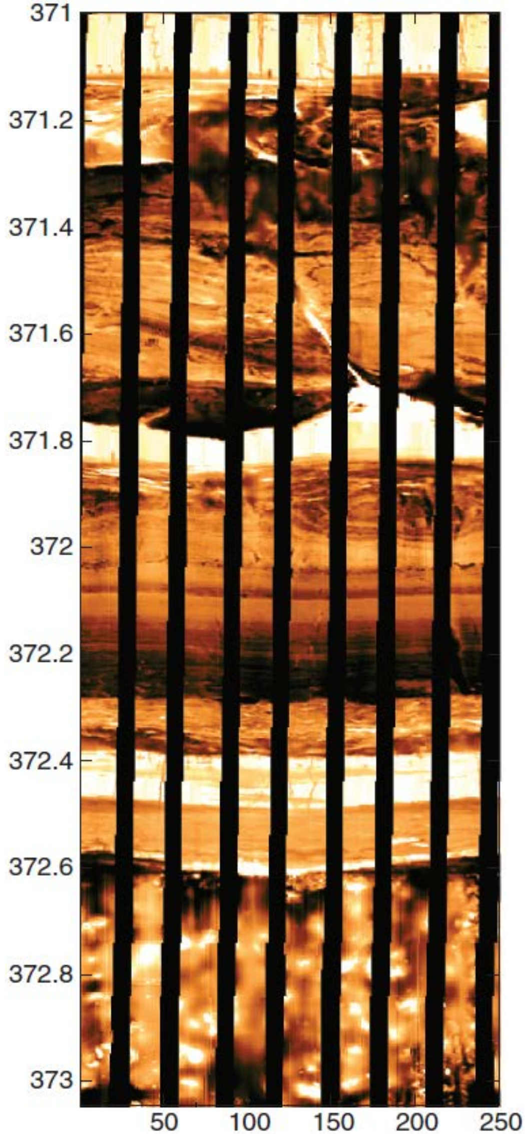
# Inpainting Results (1)



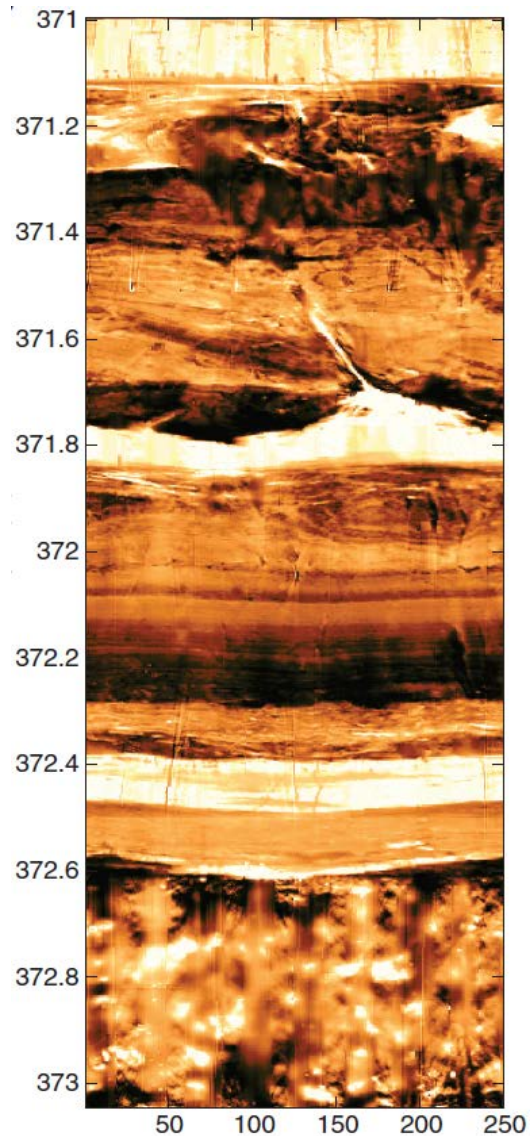

- 30% coverage loss example
- A. Continuity of the fine laminations maintained.
- B. Continuity of fine laminations and irregular high-angle fracture maintained. Halo effect preserved.
- C. High contrast boundaries inpainted successfully
- D. Irregular boundaries and complex textures inpainted successfully

# Inpainting Results (2)

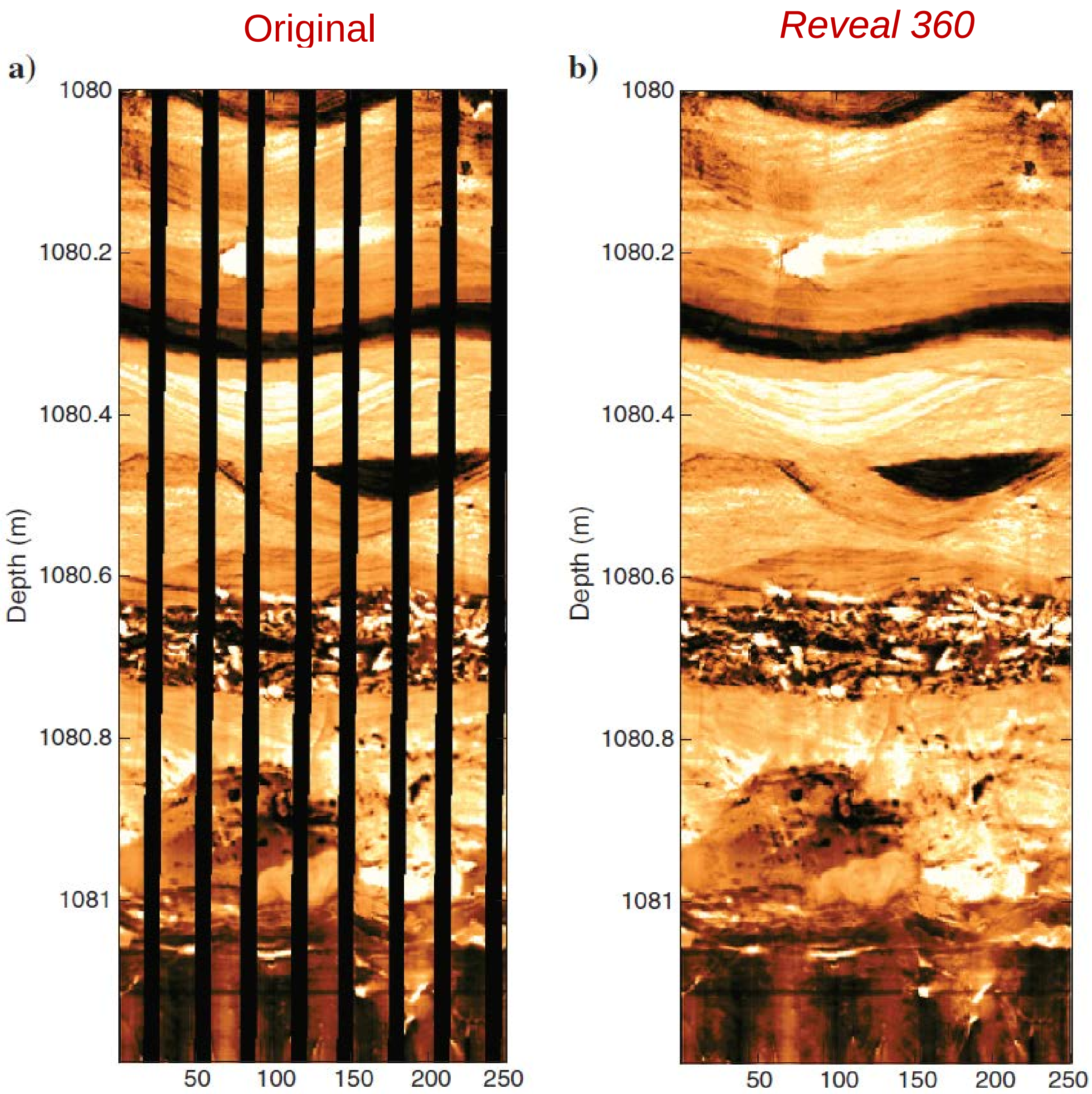
Original




*Reveal 360*

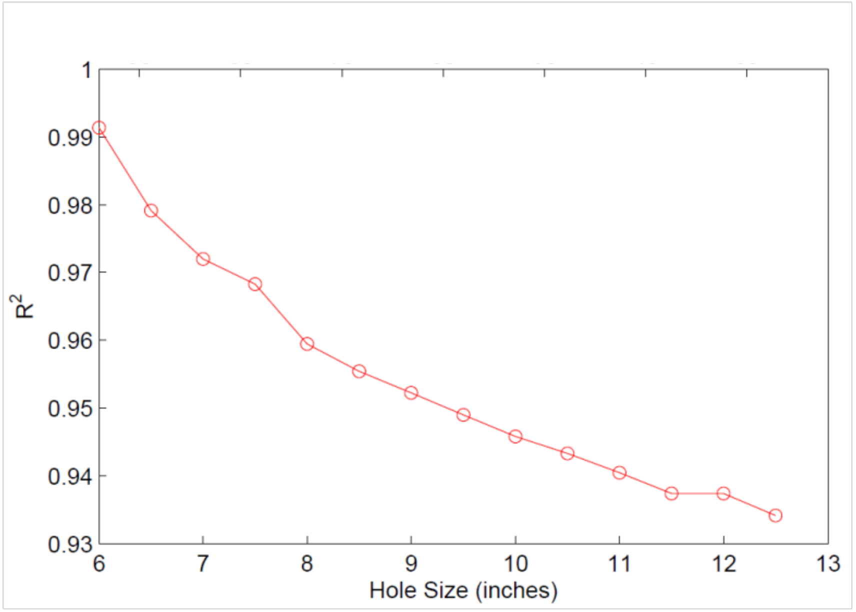


# Inpainting Results (3)

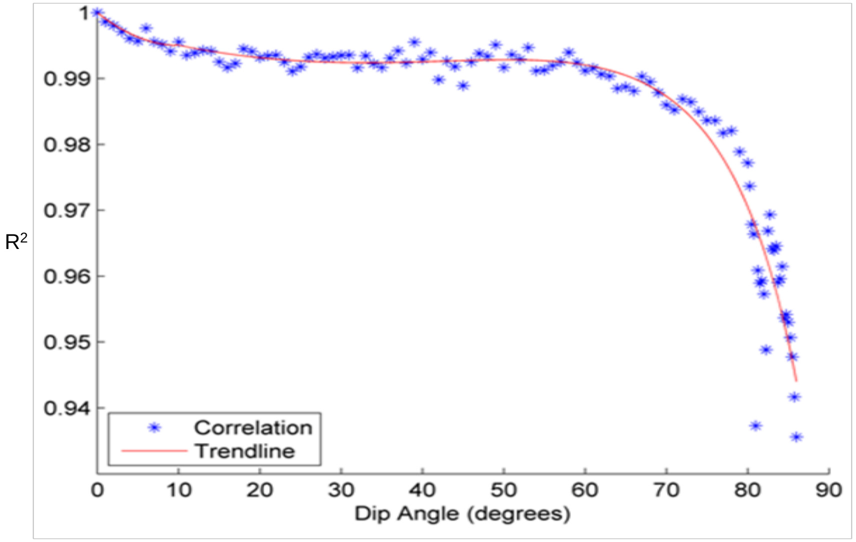


# Inpainting Operating Envelope

- Method evaluated on field data (clastic formations) and synthetic images
- Full-coverage field data artificially obscured to simulate partial-coverage data
- Better than 95% reconstruction accuracy for coverage loss up to 30%
- Reconstruction accuracy falls-off almost linearly with coverage loss (A)
- Reconstruction accuracy is independent of dip up to about 80 degrees (B)



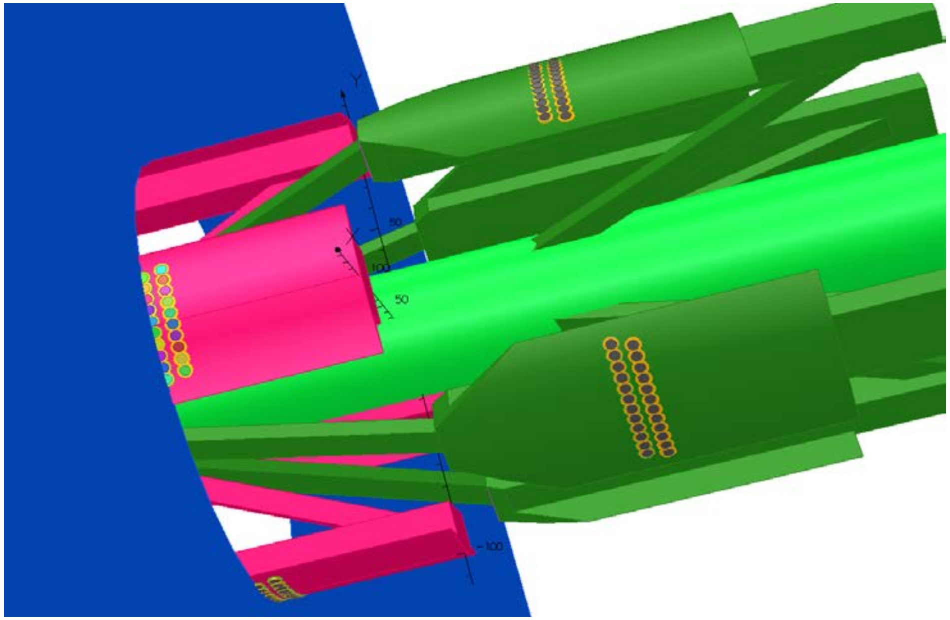

A. Field Data




B. Synthetic Images

# Quantitative Resistivity

- Image-driven petrophysics requires quantitative resistivity values
- Limitations of 1st & 2nd generation WBM tools led to ad-hoc normalizations
- High dynamic range is necessary but insufficient for quantitative resistivity
- Combination of calibrated measurement and high fidelity model allows characterization then exploitation of high dynamic range responses



# Quantitative Resistivity

Resistance R = Voltage / Current

Requires high dynamic range

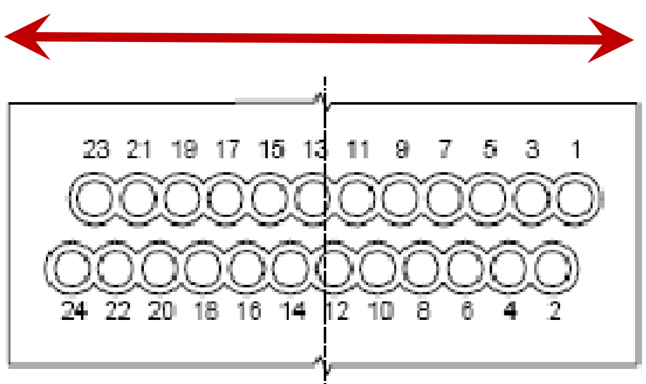
Resistivity ($\rho$) = K.R

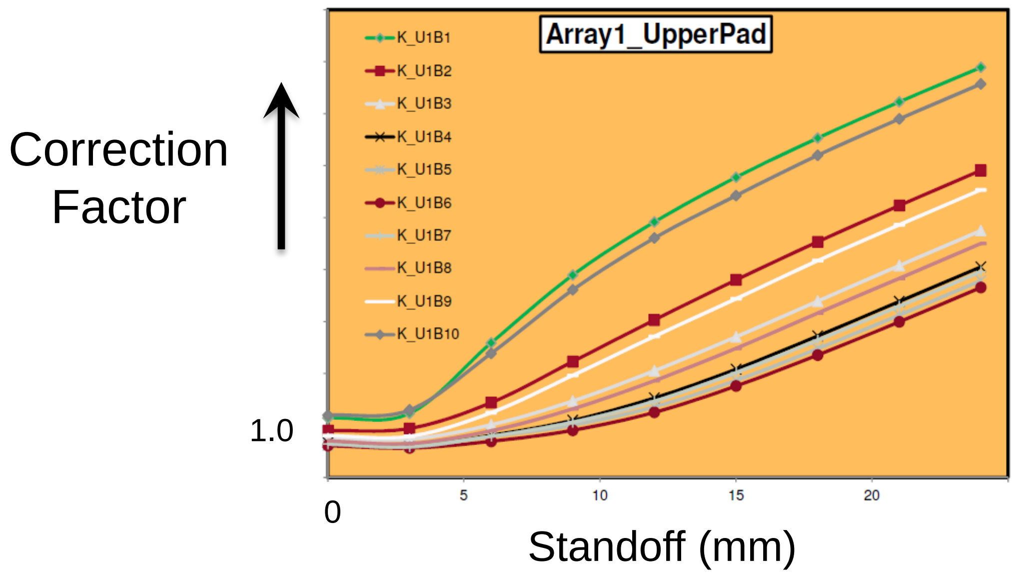
K = k-factor for standard conditions

BH Corrected Resistivity ($\rho_{corr}$) = $\rho.\Delta K$

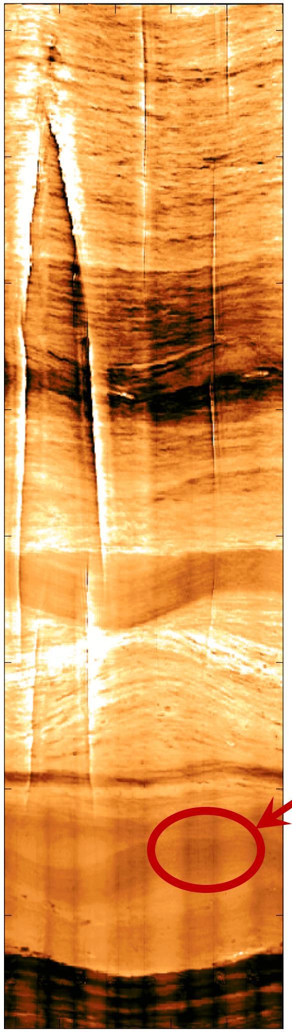
$\Delta K$ = BH correction factor

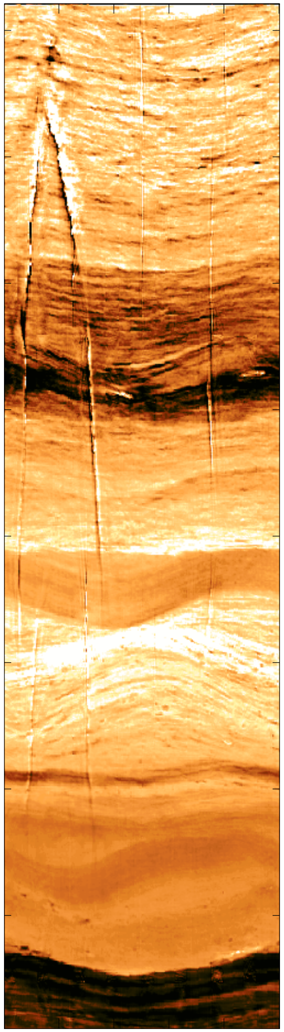
- K-factors vary systematically across the button array



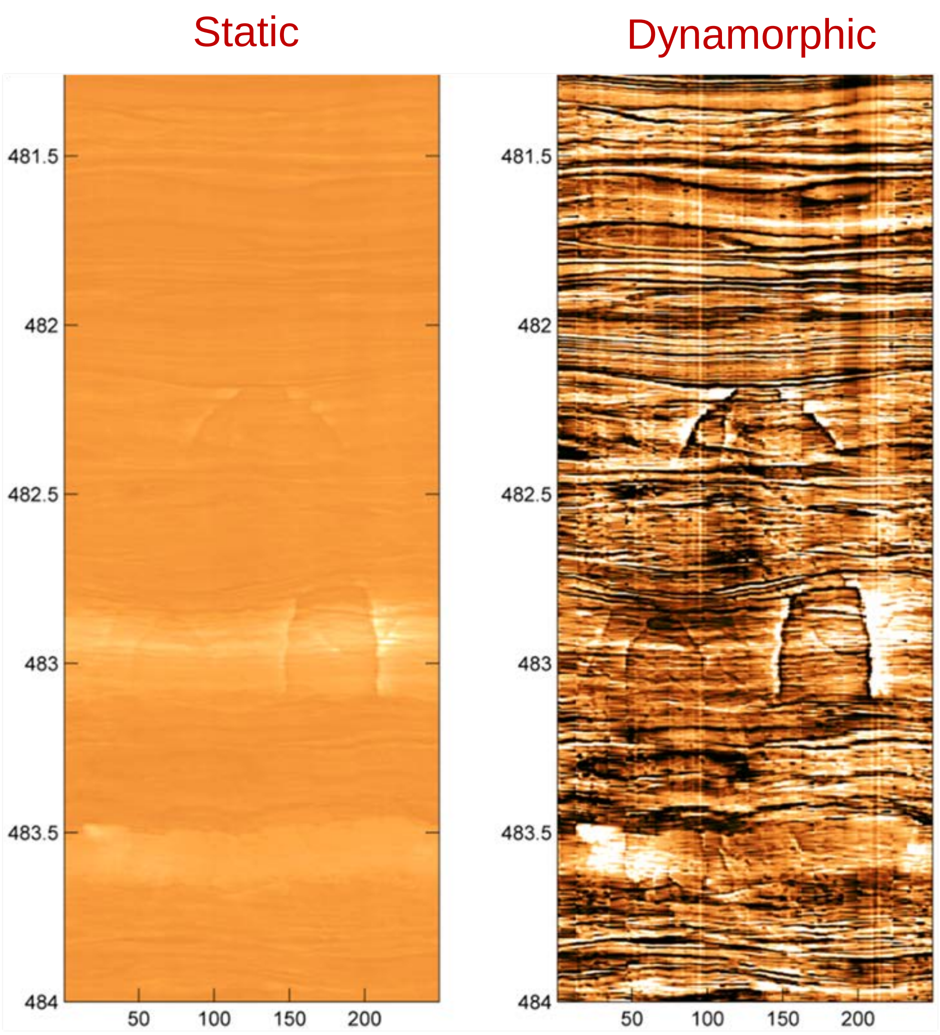



# Quantitative Resistivity - Results

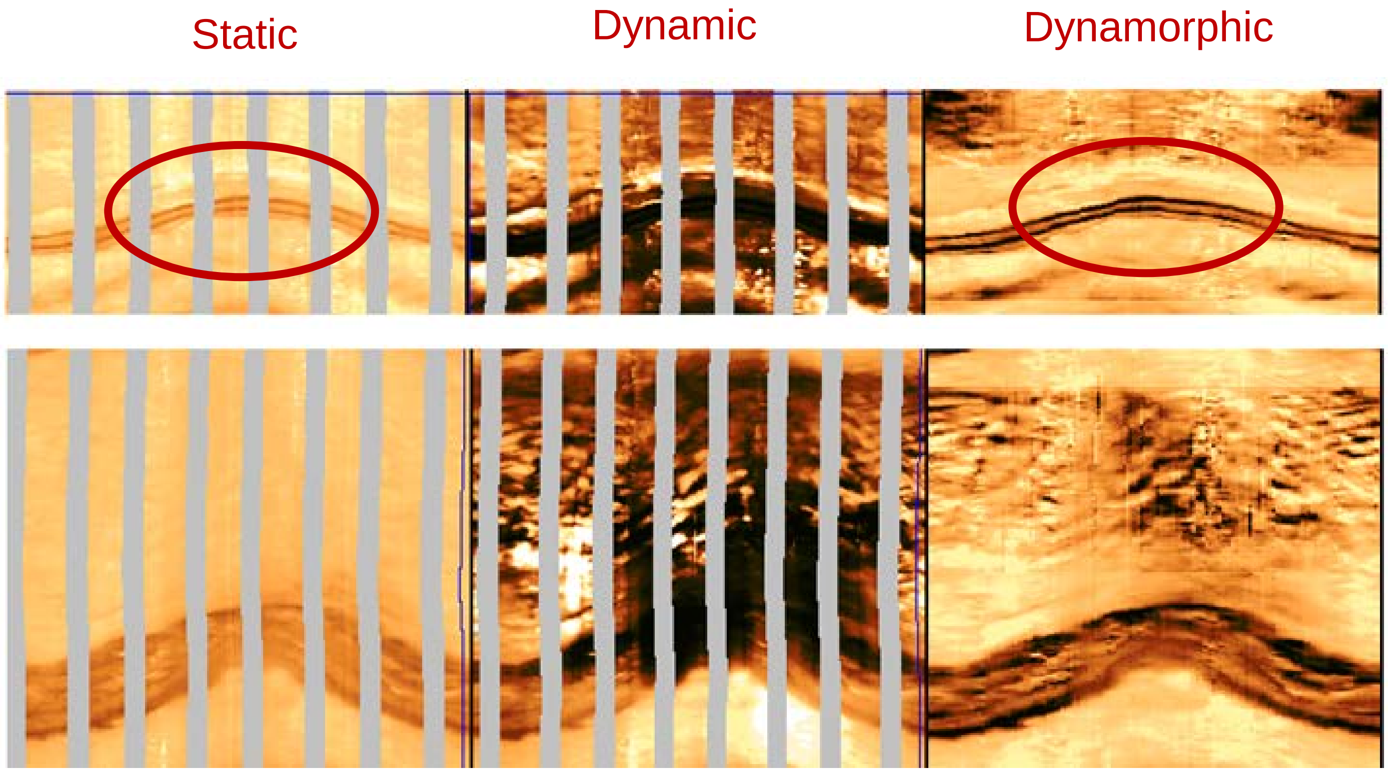



# Appropriate Visualization



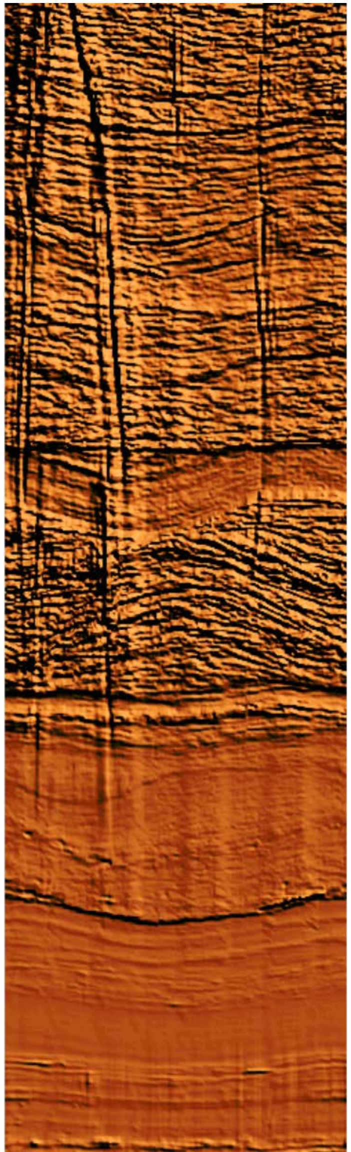

- Data must be visualized optimally to give machines the best opportunity to pick features
- High Dynamic range of CMI is a challenge from a rendering perspective
- Dynamorphic Processing splits images into low and high spatial frequencies, renders them separately, then recombines

# The Problem with Dynamic Normalization




- Dynamic normalization can create phantom features
- Static images reflect the true structures, but only if optimally scaled
- Dynamorphic images have the desirable attributes of a Dynamic image but without the phantoms

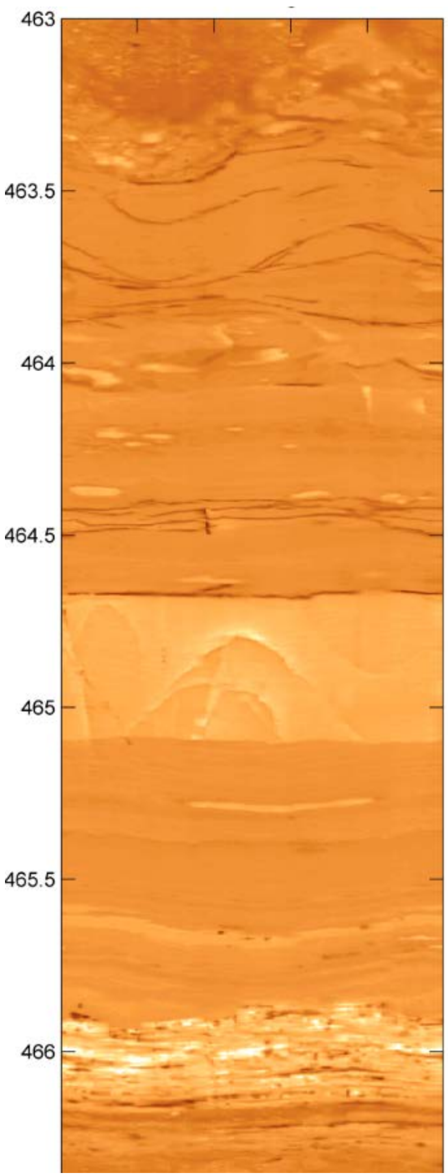
# Appropriate Visualization – Virtual Light Source

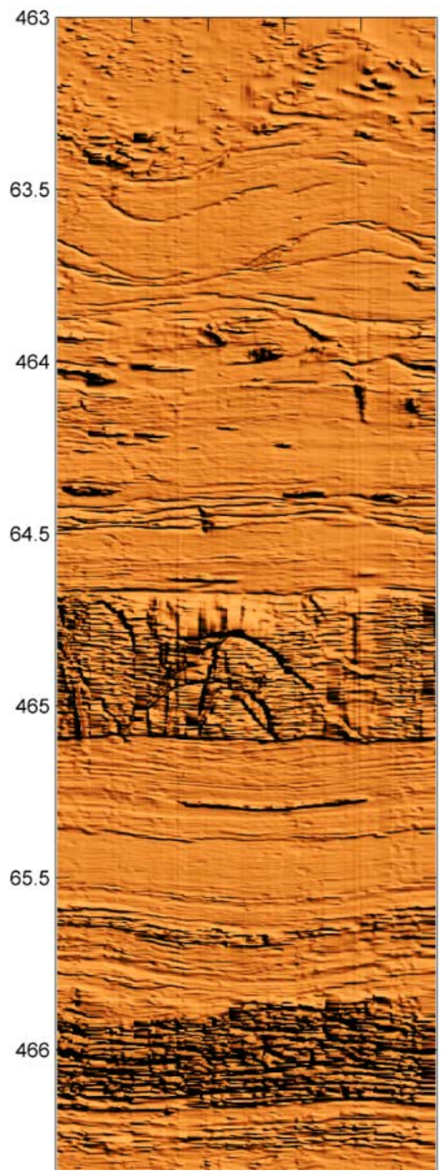


- VLS visualization shines a virtual light onto a landscape constructed from resistivity values
- Features at particular orientations of interest are preferentially enhanced by changing the elevation and azimuth of the light

# Appropriate Visualization – Virtual Light Source

In-Painted

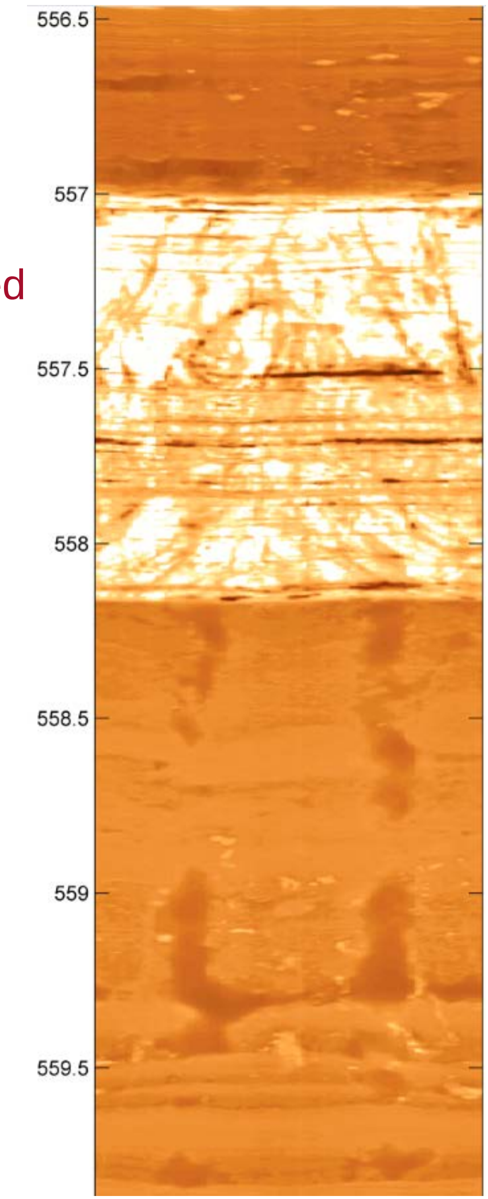


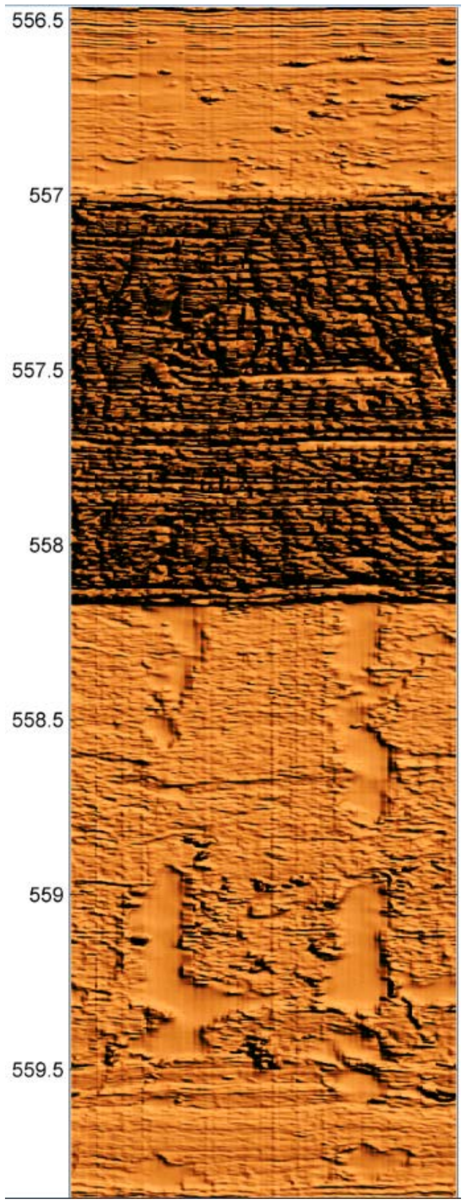




Virtual Light Source

# Appropriate Visualization – Virtual Light Source

In-Painted



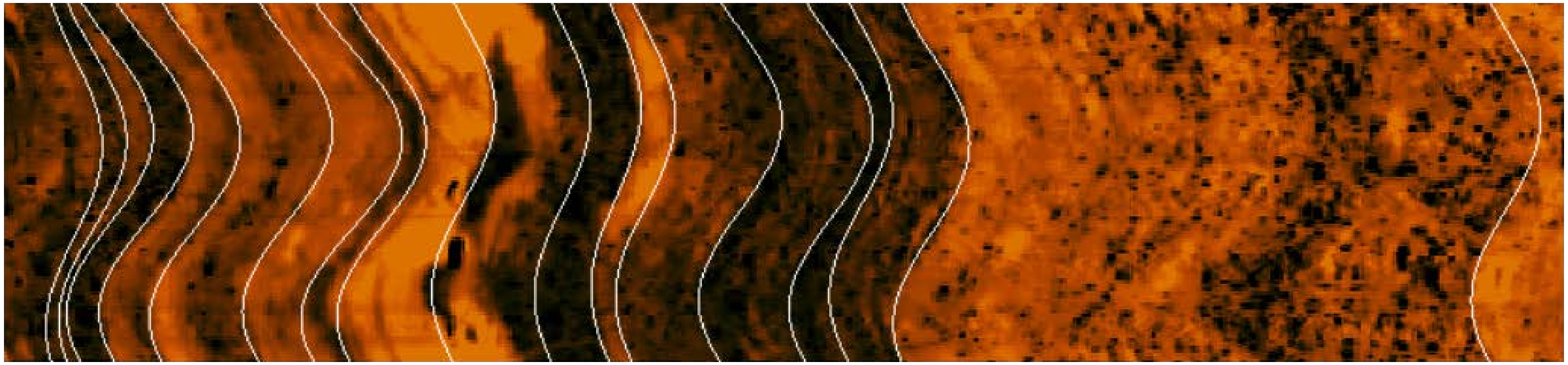




Virtual Light Source

# Automation Example – Picking Planar Features

- It takes many hours to pick features manually from a long image
- Most common task is the detection of planar geological boundaries
- Multiple methods exist for machine picking, but utility limited by high rates of false positives

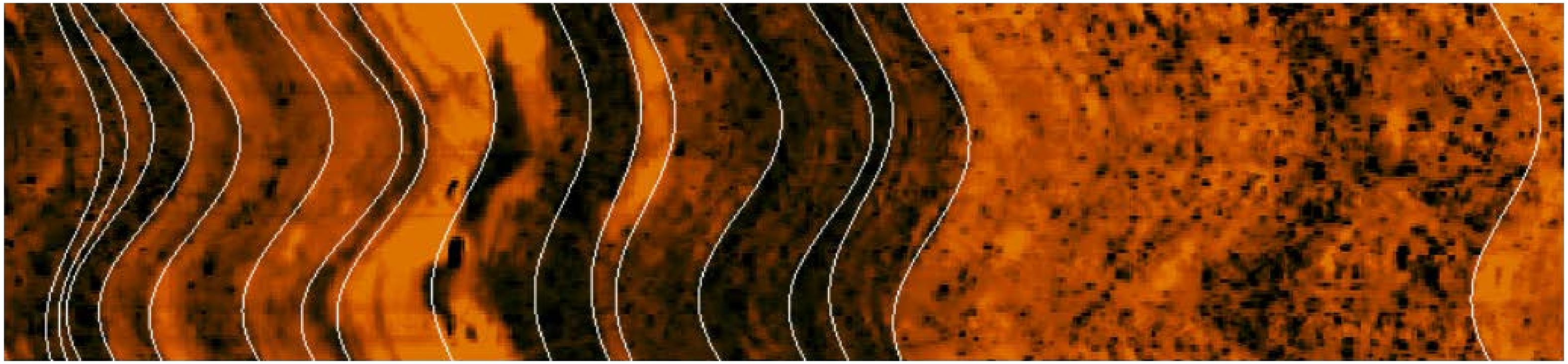
Multi-agent picking example



# Automation Example – Picking Planar Features

- Old methods are prone to false picks associated with:
  - Background noise
  - Connected segments that belong to different features
  - One feature being detected multiple times
- Dramatic reduction in false positives achieved using multiple "agents" applied to inpainted images

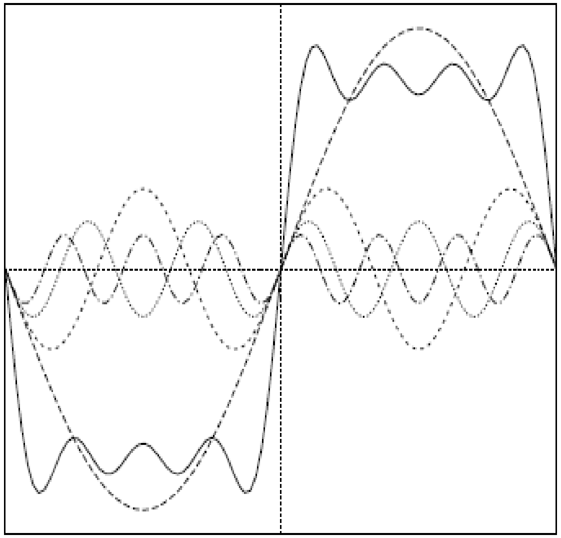
Multi-agent picking example



# Automation Example – Picking Planar Features

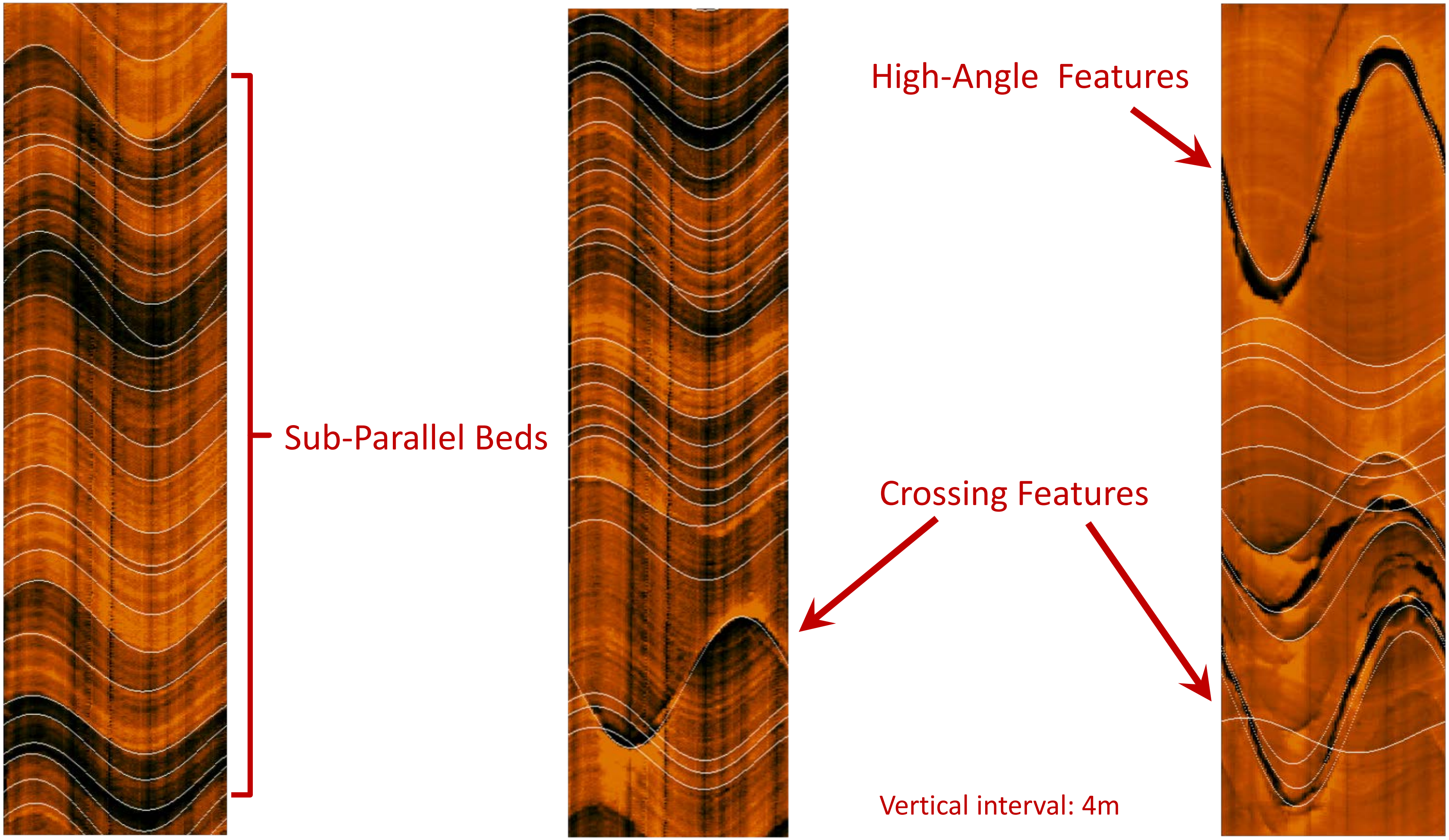
## Robust Method

- **Create** inpainted, dynamorphic image
- **Detect** edges using Lindeberg algorithm extended to include non-maxima suppression and edge cleaning
- **Validate** using Phase Congruency (insensitive to amplitude contrast)
- **Detect** sinusoids by searching validated edges
- **Sinusoid** parameters estimated exploit the assumption that valid sinusoids occur as one cycle in an image
- **Fully automatic** – no parameter selections

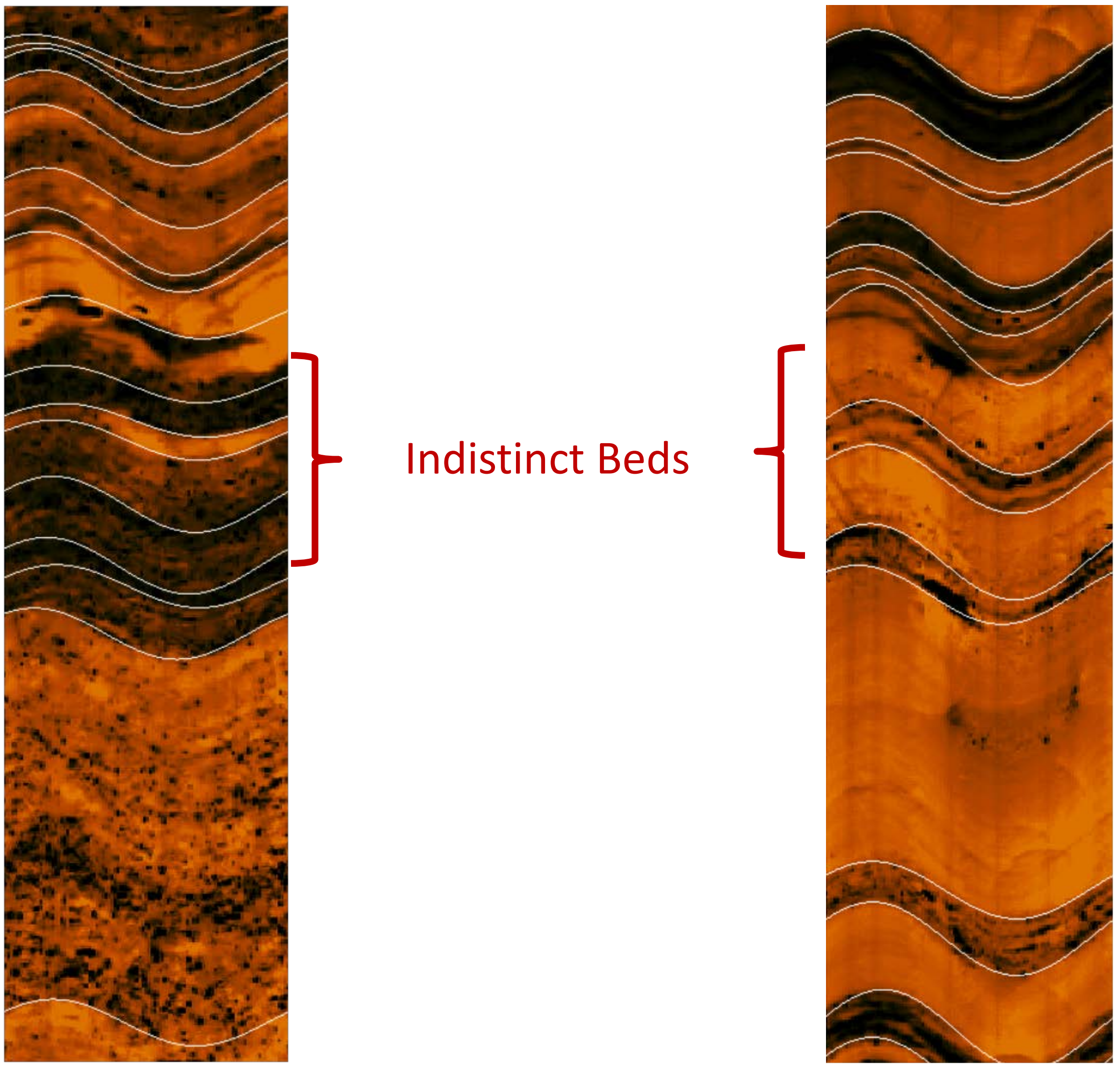


Edge exists where frequency components are in phase

# Feature Picking – Results (1 of 2)



# Feature Picking – Results (2 of 2)




Vertical interval: 4m

# Wrap-Up

- MCA inpainting reconstructs the whole image, including missing data, in a way that honours the information in the measured parts
- Design calibration factors unique to each button enable quantitative resistivity for use in image-driven petrophysical applications
- Dynamorphic processing allows images to be rendered with wide dynamic range
- The Virtual Light Source illuminates features at orientations of interest.
- Robust multi-agent detection reduces sinusoid pick times from the order of many hours to a few minutes, and the results are reliable and wholly reproducible.