Computer Vision
and Probabilistic Inference

Brian Potetz

Inference of Depth:

Ambiguous, Underconstrained, Difficult

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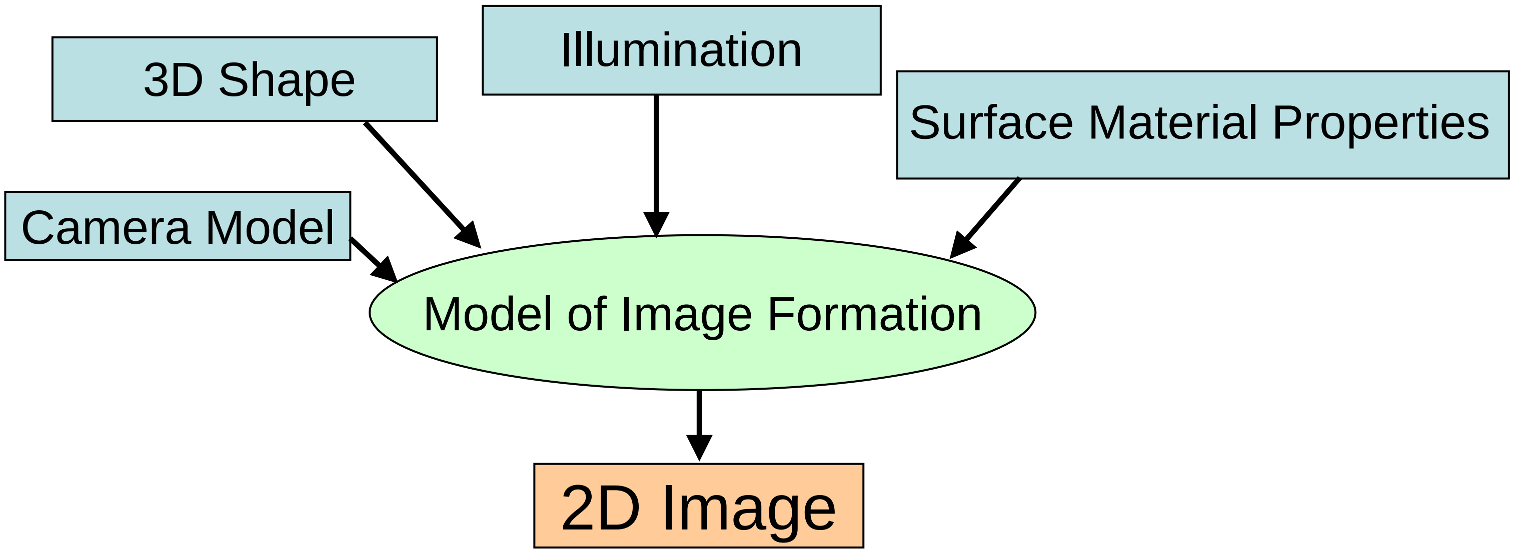

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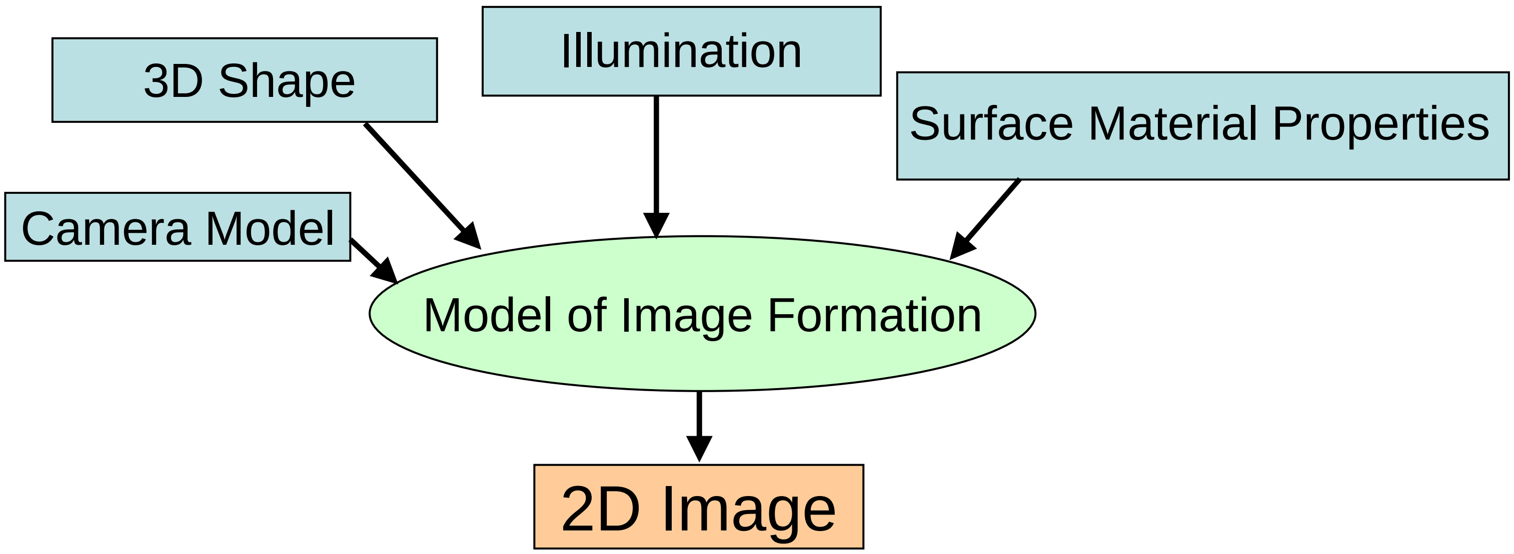

Standard Past Approach:

1) Form a deterministic model of image formation
2) Invert it

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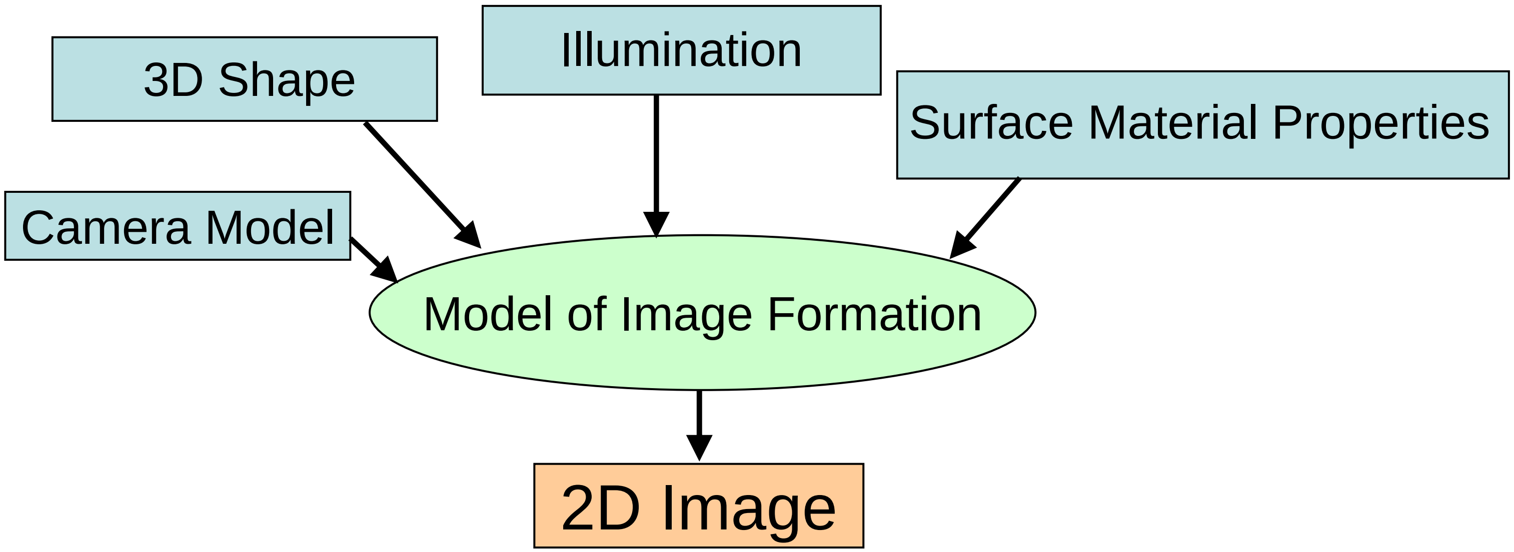

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<u>A Better Approach:</u>

1) Model the uncertainties directly
2) Solve the problem probabilistically

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Background: Statistical Inference

A Better Approach to infer shape:

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Requires finding the most likely point of a complex, high-dimensional probability distribution:

$$P(Shape|Image)$$

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- In general, statistical inference is NP-Hard
- Gradient ascent often struggles with local maxima
- Key insight: exploit local *structure* of the problem. Many probability distributions can be factorized:

$$p(\vec{X}) = \prod f_i(\vec{x_i}) \qquad \vec{x_i} \subset \vec{X}$$

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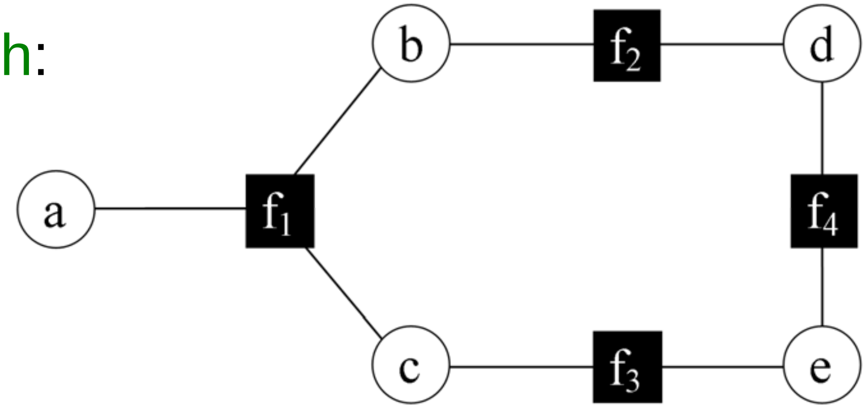
Example:

$$P(a,b,c,d,e) \propto f_1(a,b,c) f_2(b,d) f_3(c,e) f_4(d,e)$$

Drawn as a Factor Graph:

solve using graph based algorithms



Applications:

- speech recognition
- disease diagnosis
- fraud detection
- genetic linkage analysis
- error-correcting codes
- data compression
- computer vision

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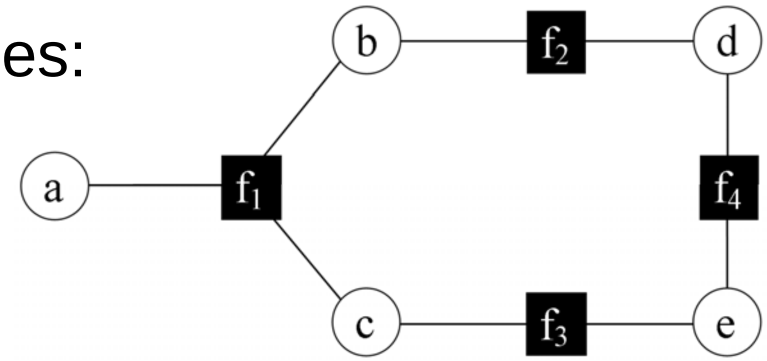
Belief Propagation

Ex: $P(a,b,c,d,e) \propto f_1(a,b,c) f_2(b,d) f_3(c,e) f_4(d,e)$

Great empirical successes:

- Error-correcting codes,
- Image super-resolution,
- Shape from stereo,
- Photometric stereo, etc.



Slow for highly connected graphs

– Takes *exponential* time to compute

– Especially slow for continuous variables

– Loopy Belief Propagation for continuous variables is historically limited to pairwise-connected graphs

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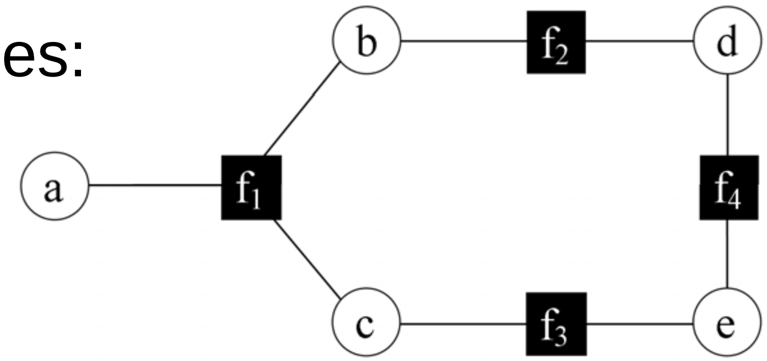

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I have developed a method to reduce complexity (run-time) from exponential to linear.

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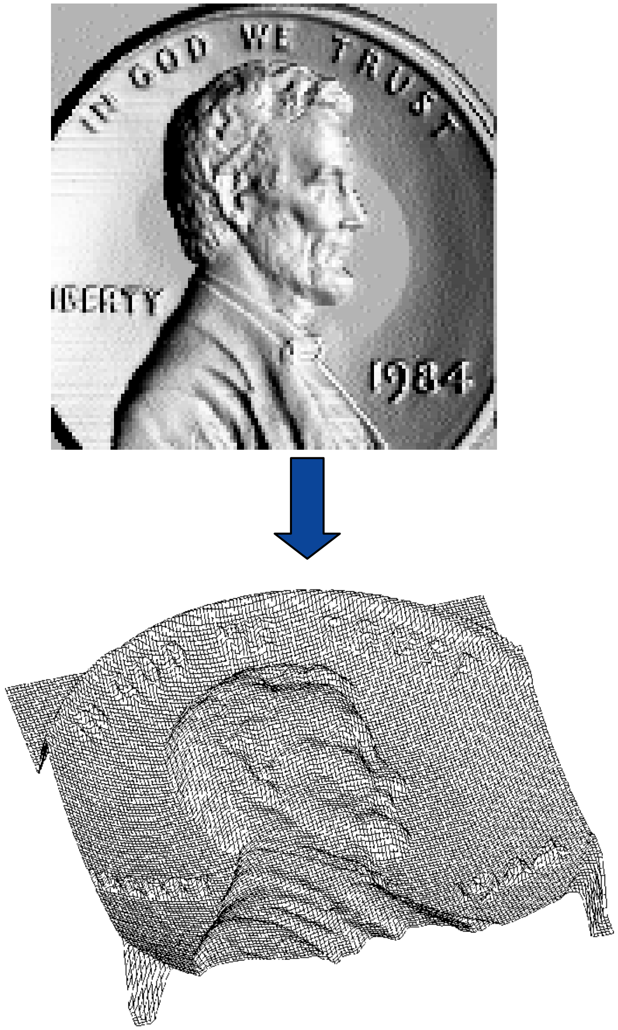
Shape-From-Shading

Goal: Recover 3D surface shape from a single image



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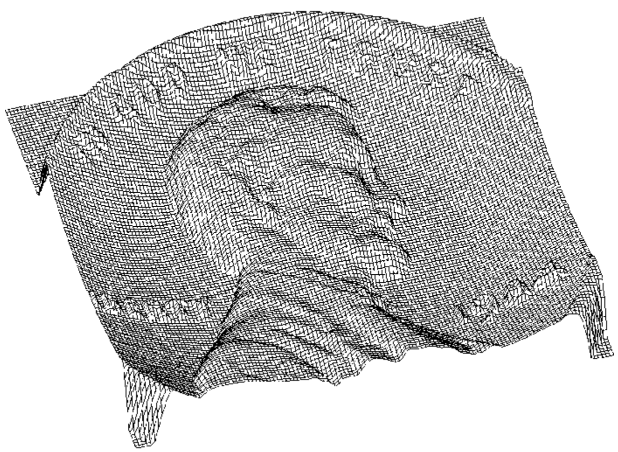
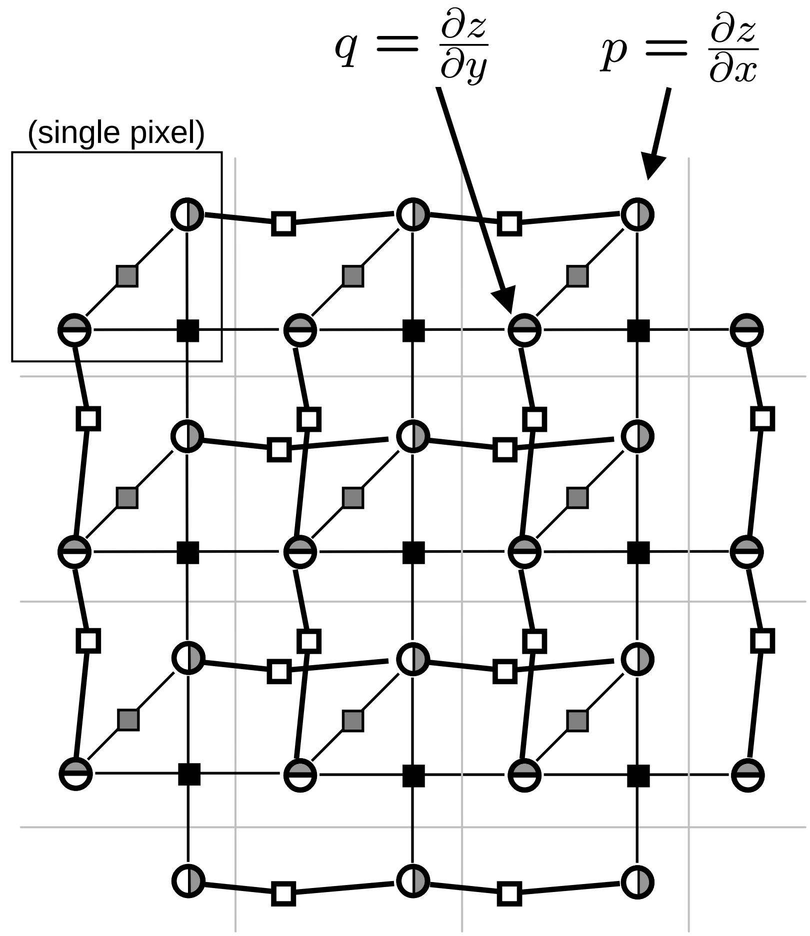
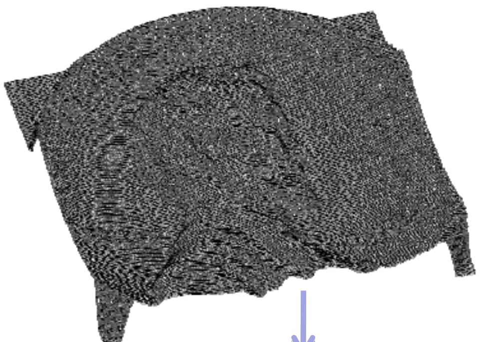




A factorized probability distribution for shape-from-shading

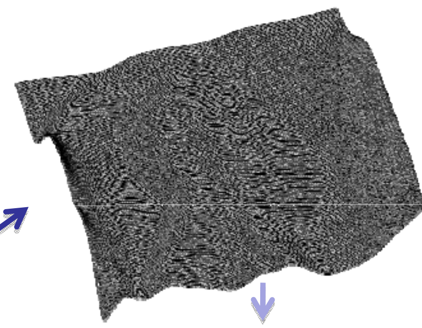
Shape-From-Shading Results

Ground-truth
3D shape:

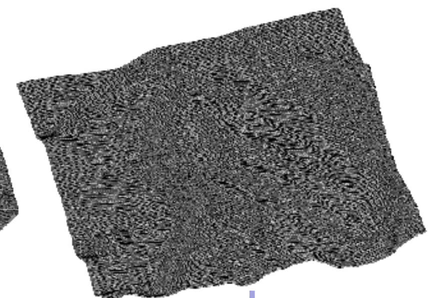


2D Input image

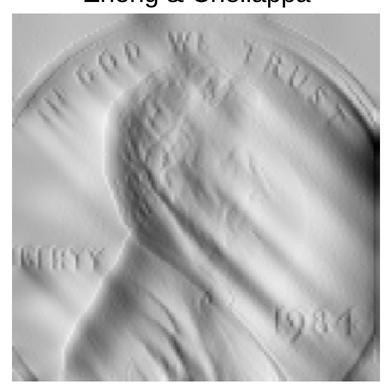
Previous state-of-the-art
algorithms performed poorly:

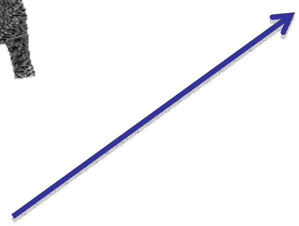


Lee & Kuo



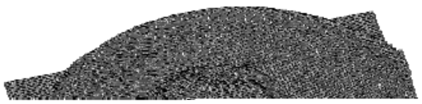
Zheng & Chellappa





2D images generated by illuminating the reconstructed 3D shapes.

Ground-truth
3D shape:



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