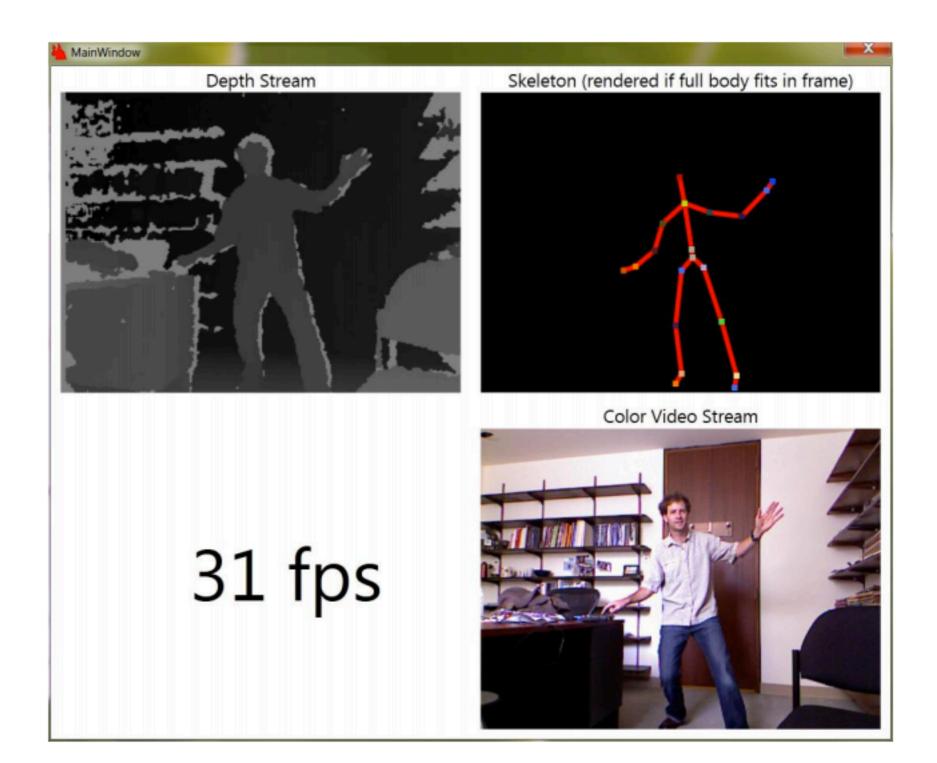
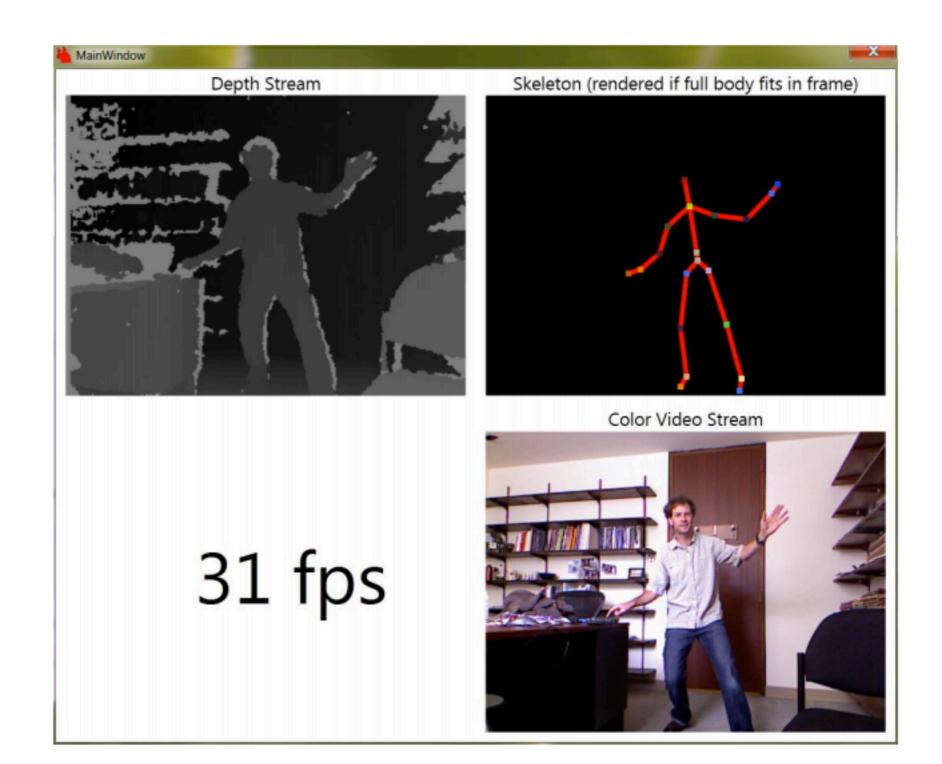
User Interface Software Projects: Intro to Kinect

Assoc. Professor Donald J. Patterson INF 134 Winter 2013

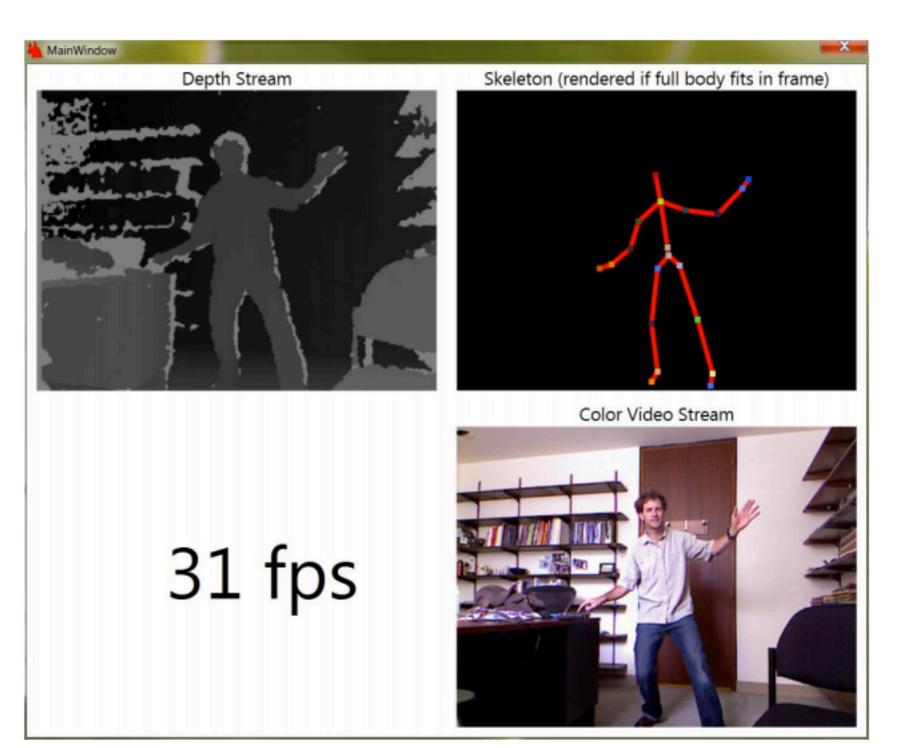
Slides adapted from John MacCormick, Guido Gerig: http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf http://www.sci.utah.edu/~gerig/CS6720 S2012/Materials/C\$6320-CV-



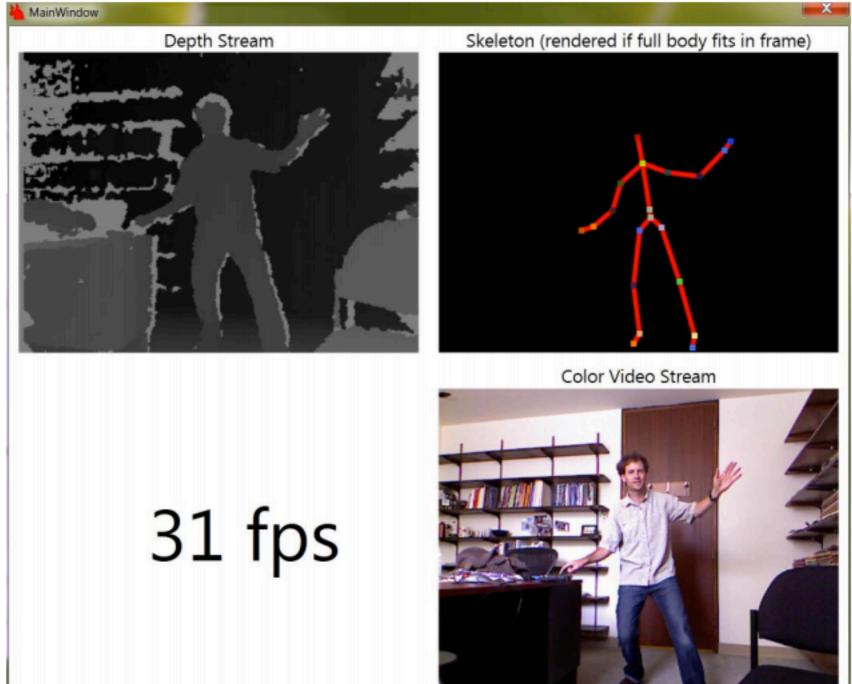
Depth Video Stream



- Depth Video Stream
- Skeleton detection



- Depth Video Stream
- Skeleton detection
- Color Video Stream



Several key technologies

- to compute a depth image
 - Structured light
 - Depth from focus
 - Depth from stereo
- Machine learning to infer skeleton position

Structured light

- The depth map is constructed by analyzing a projected speckle pattern of infrared laser light
 - Microsoft licensed this technology from PrimeSense
- The depth computation is done by the PrimeSense hardware in the Kinect
- Details are not public, the following is speculation based on patent applications

Structured light

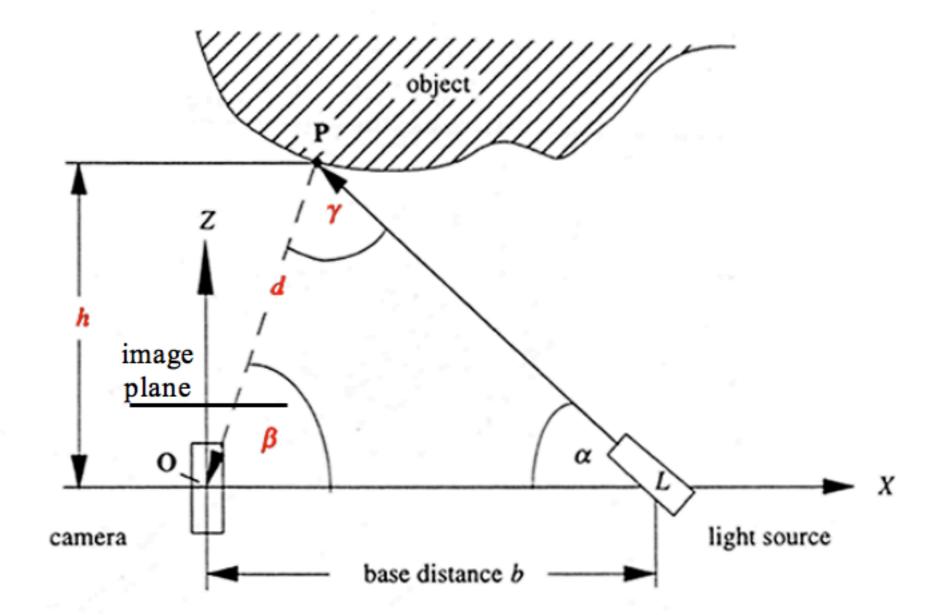
- A Computer Vision concept
- Based on projecting a known light pattern onto a scene
- Analyzing how the observed light differs from the known projection
- Assuming that the differences are due to the topology of the world

- Structured light
 - Technique #1



Light Spot Projection 2D

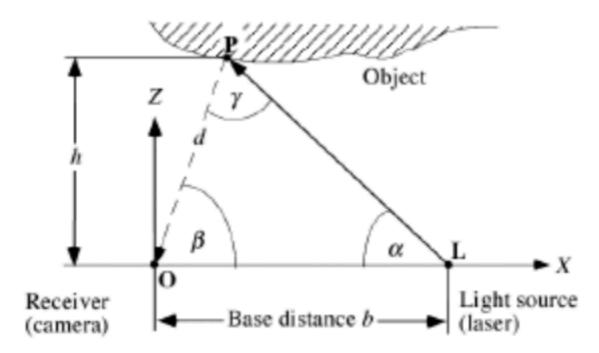
Assume point-wise illumination by laser beam, only 2D



http://www.sci.utah.edu/~gerig/CS6320-S2012/Materials/CS6320-CV-S2012-StructuredLight.pdf



Light Spot Projection 2D



O, L, and P define a triangle, and we determine the position of P by triangulation, using basic formulas about triangles such as the law of sines:

$$\frac{d}{\sin \alpha} = \frac{b}{\sin \gamma}$$

It follows that

$$d = \frac{b \cdot \sin \alpha}{\sin \gamma} = \frac{b \cdot \alpha}{\sin(\pi - \alpha - \beta)} = \frac{b \cdot \alpha}{\sin(\alpha + \beta)}$$

and, finally, $\mathbf{P} = (d \cdot \cos \beta, d \cdot \sin \beta)^T$. Note that β is determined by the position of the projected (illuminated) point \mathbf{P} in the 1D image.

http://www.sci.utah.edu/~gerig/CS6320-S2012/Materials/CS6320-CV-S2012-StructuredLight.pdf



Light Spot Projection 2D

- Coordinates found by triangulation
 - β can be found by projection geometry
 - $d = b*sin(\alpha)/sin(\alpha + \beta)$

$$-X_0 = d*\cos(\beta)$$

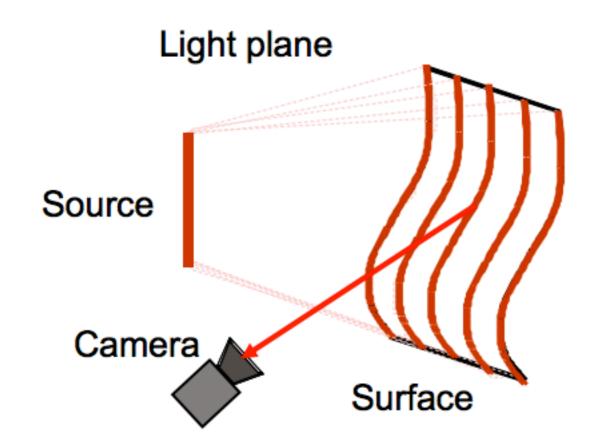
$$- Z_0 = h = d*sin(\beta)$$

- Concept:
 - known b and $\boldsymbol{\alpha}$
 - $-\beta$ defined by projection geometry
 - Given image coordinate u and focal length f -> calculate β
 - Given b, α , β -> <u>calculate d</u>

http://www.sci.utah.edu/~gerig/CS6320-S2012/Materials/CS6320-CV-S2012-StructuredLight.pdf

- Structured light
 - Technique #2

Light Stripe Scanning – Single Stripe





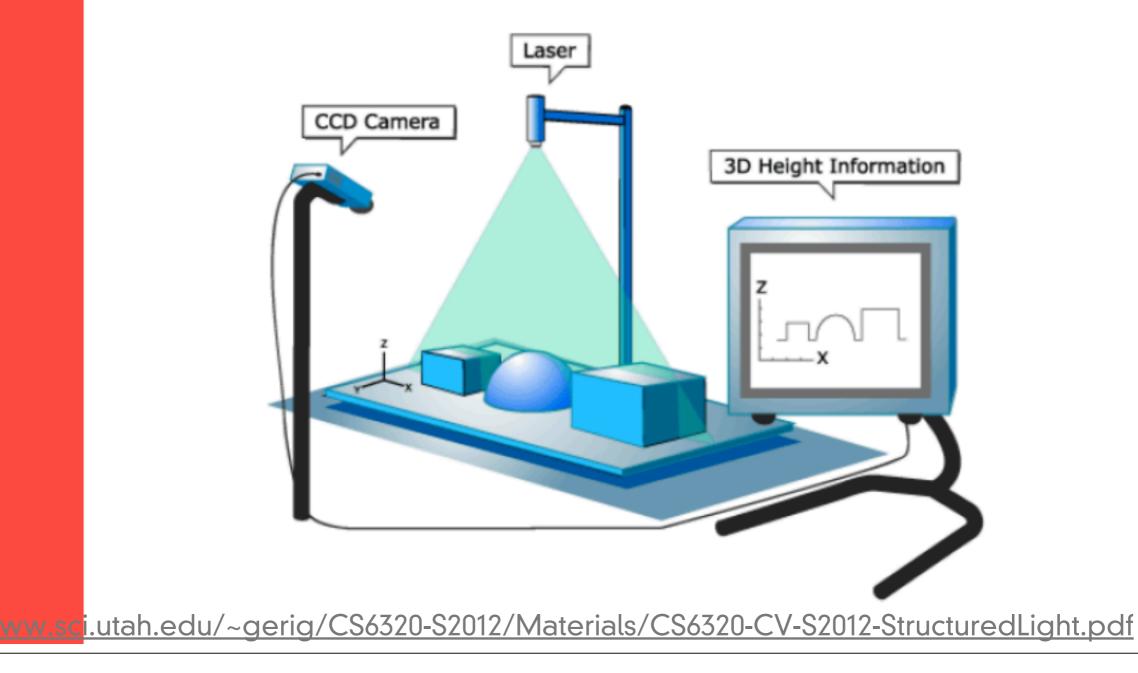
- Optical triangulation
 - Project a single stripe of laser light
 - Scan it across the surface of the object
 - This is a very precise version of structured light scanning
 - Good for high resolution 3D, but needs many images and takes time

http://www.sci.utah.edu/~gerig/CS6320-S2012/Materials/CS63204Cess/2612Narasimbang G.M.

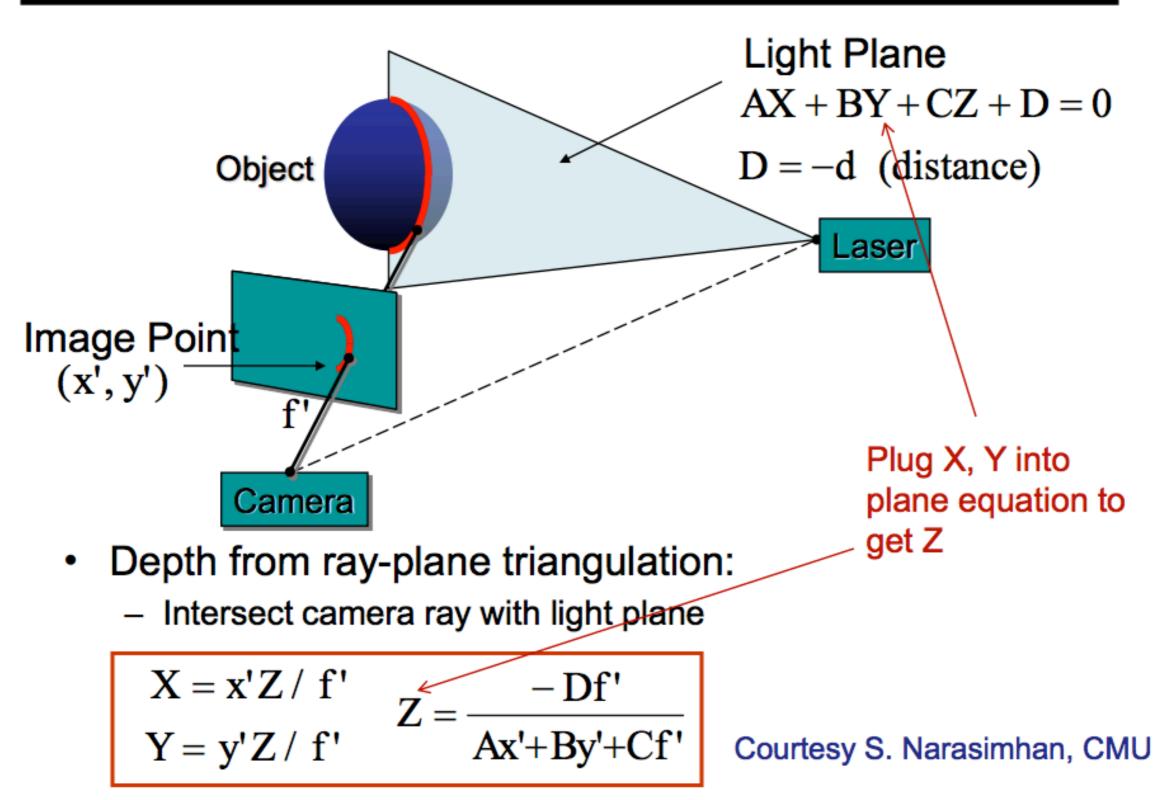


Light Stripe Projection

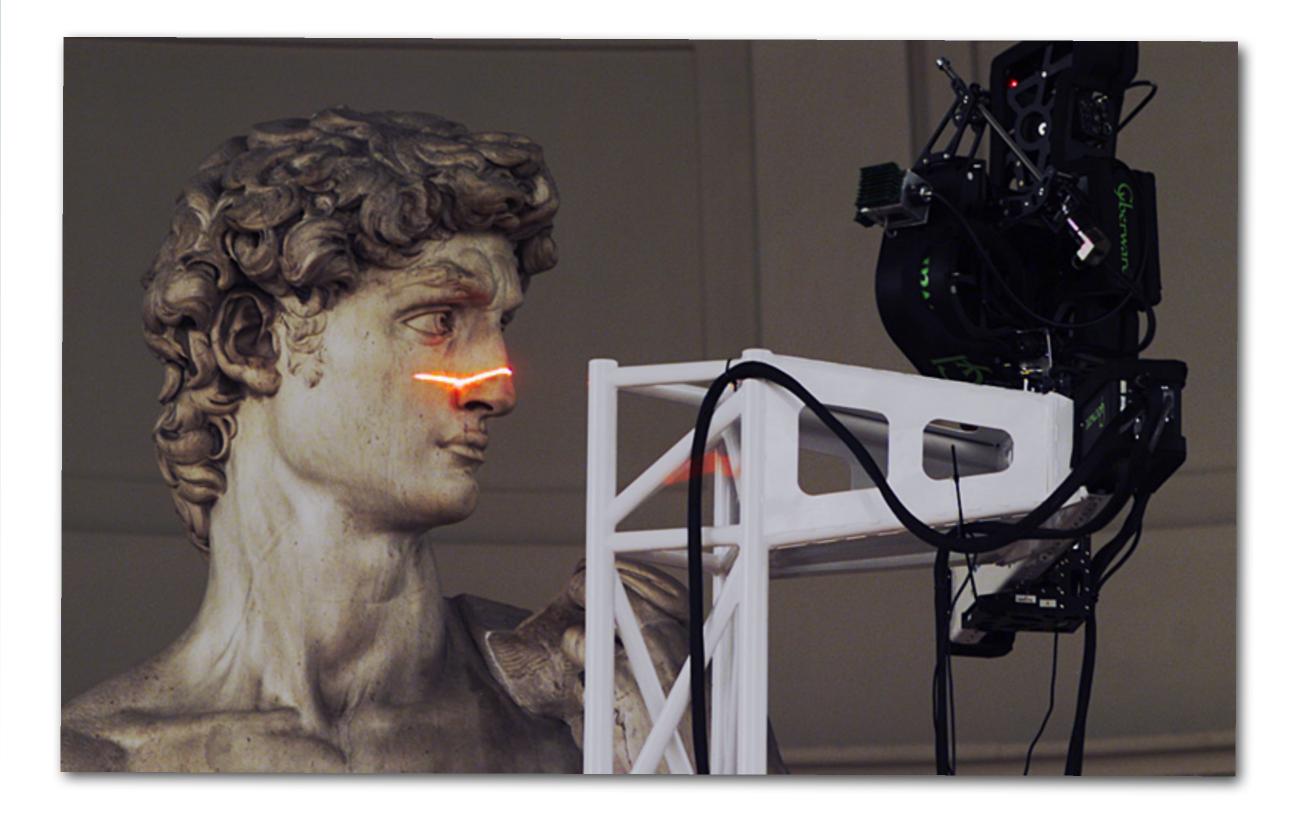
Structured light is the projection of a light pattern (ray, plane, grid, encoded light, and so forth) under calibrated geometric conditions onto an object whose shape needs to be recovered.



Triangulation



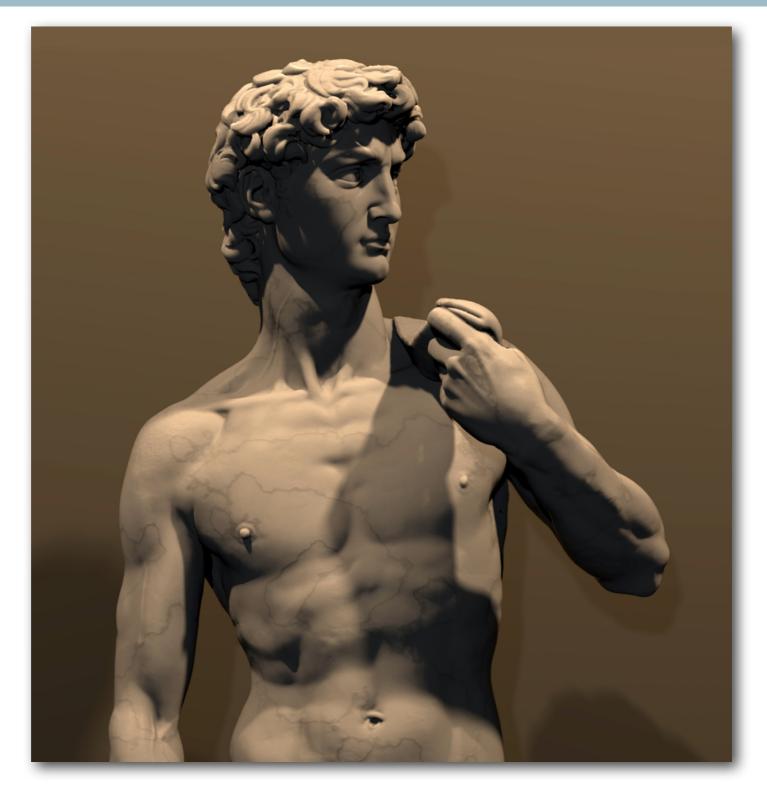
http://www.sci.utah.edu/~gerig/CS6320-S2012/Materials/CS6320-CV-S2012-StructuredLight.pdf



http://graphics.stanford.edu/projects/mich/more-david/scanner-head-and-david-head-s.jpg

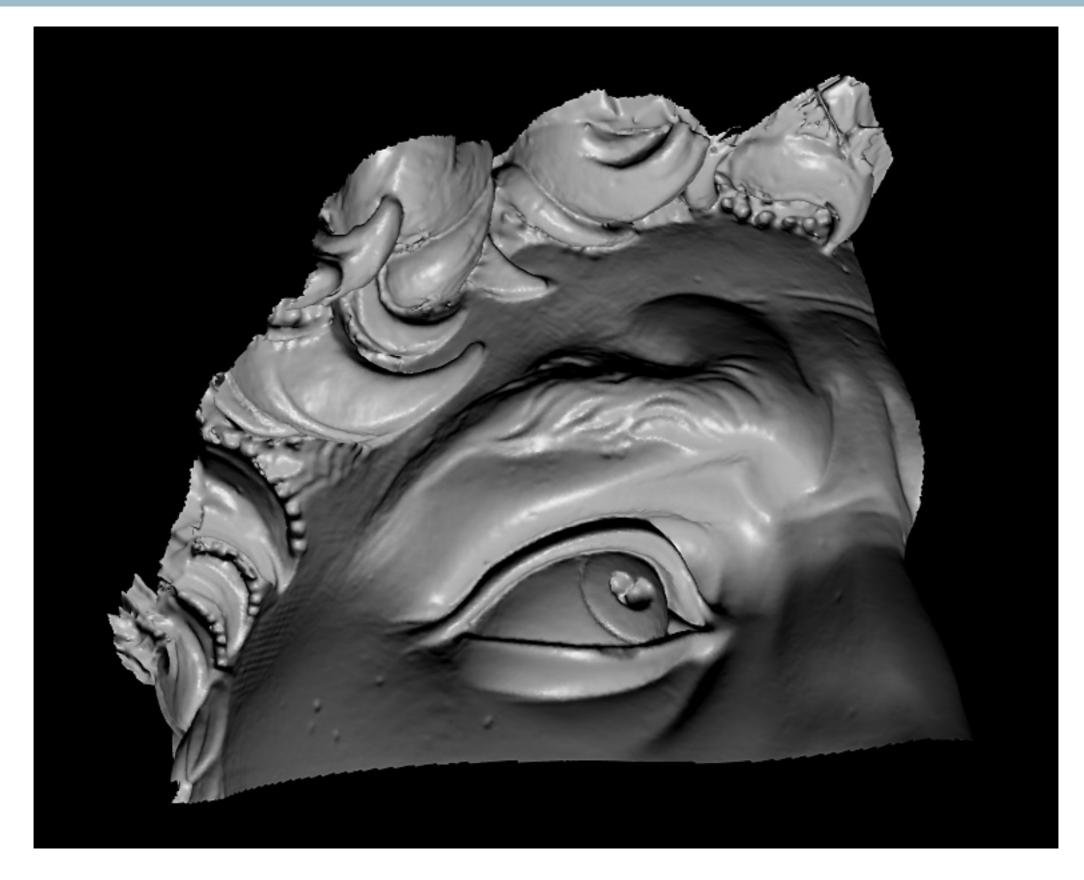


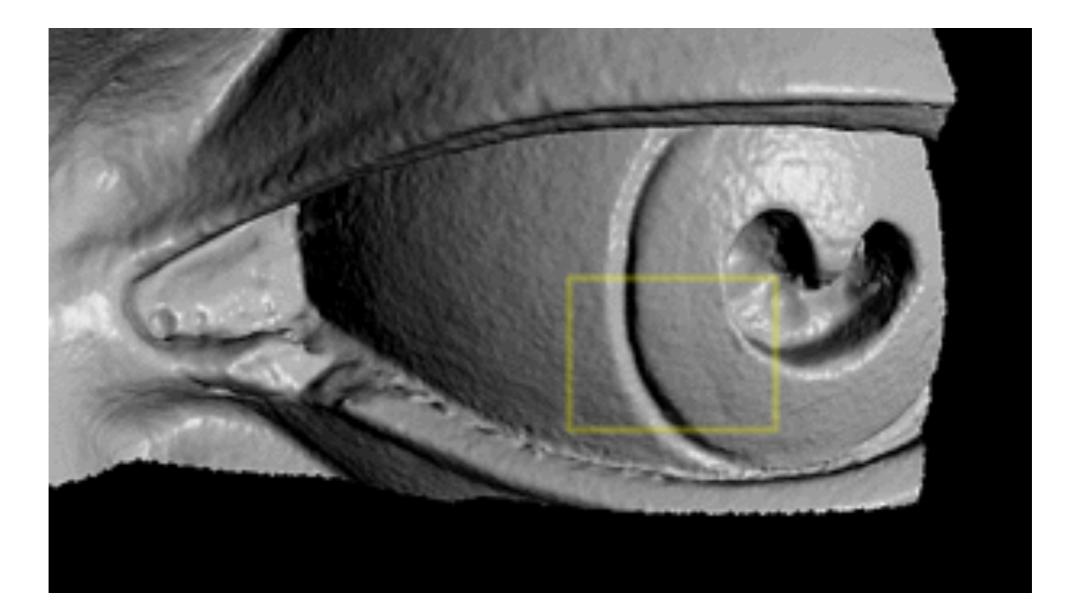
http://www.flickr.com/photos/nathaninsandiego/6165296066/sizes/z/in/photostream/

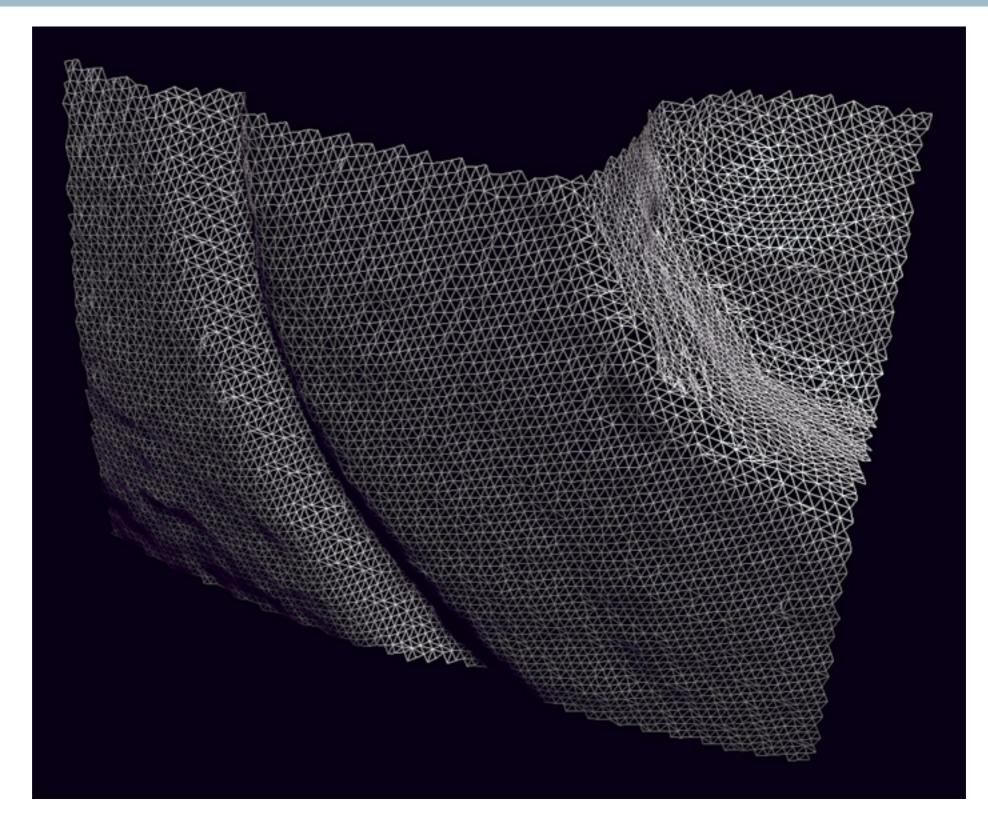


http://graphics.stanford.edu/projects/mich/head-of-david/head-of-david.html





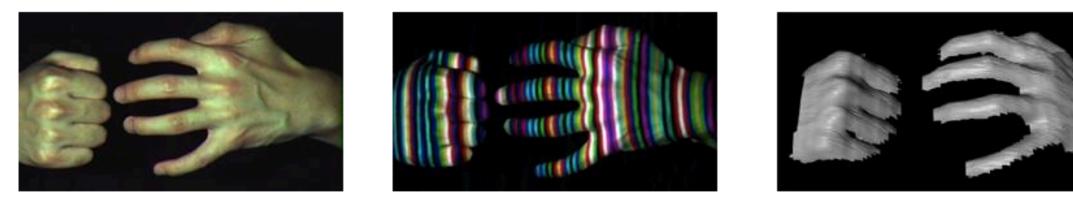




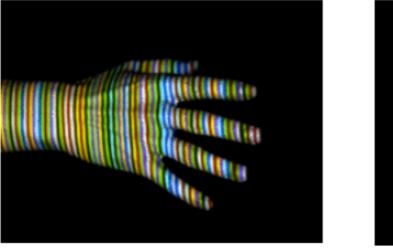
Digital Michelangelo Project: <u>http://graphics.stanford.edu/projects/mich/</u>

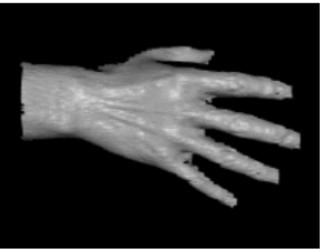
- Structured light
 - Technique #3

Real Time by Color Coding



Works despite complex appearances





Works in real-time and on dynamic scenes

- Need very few images (one or two).
- But needs a more complex correspondence algorithm

Zhang et al, 3DPVT 2002

http://www.sci.utah.edu/~gerig/CS6320-S2012/Materials/CS6320-CV-S2012-StructuredLight.pdf

- Structured light
 - Do it yourself

Build Your Own 3D Scanner: 3D Photography for Beginners



SIGGRAPH 2009 Course Notes Wednesday, August 5, 2009

Douglas Lanman Brown University dlanman@brown.edu

Gabriel Taubin Brown University taubin@brown.edu

- Course notes: <u>http://mesh.brown.edu/byo3d/notes/byo3D.pdf</u>
- Slides: <u>http://mesh.brown.edu/byo3d/slides.html</u>
- Source code: <u>http://mesh.brown.edu/byo3d/source.html</u>

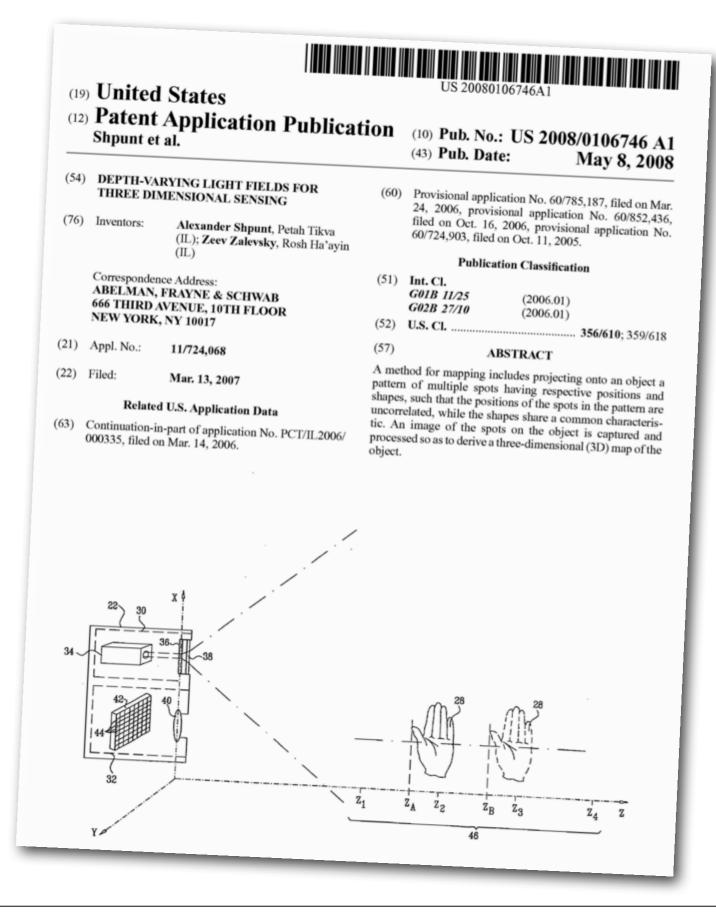
Dual Photography

Pradeep Sen* Billy Chen* Gaurav Garg* Stephen R. Marschner† Mark Horowitz* Marc Levoy* Hendrik P.A. Lensch*

*Stanford University

†Cornell University





Structured light

Kinect Style

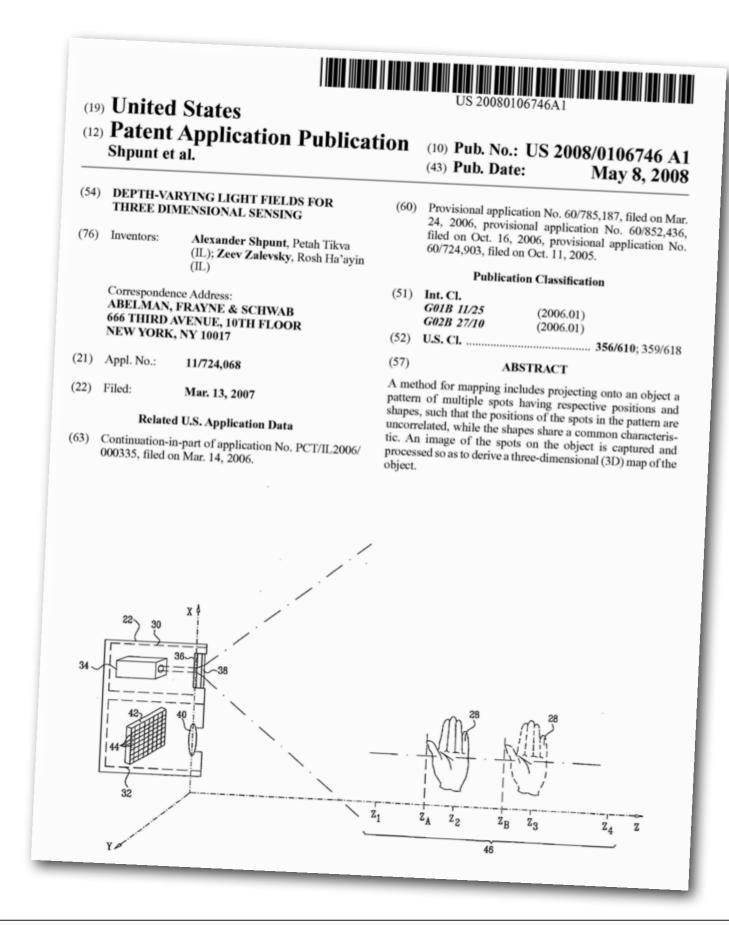


FIG. 3A

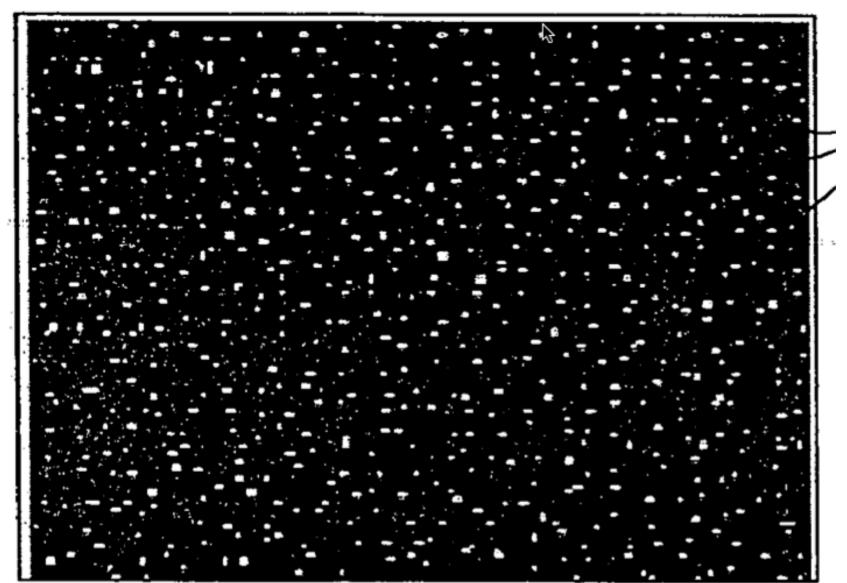
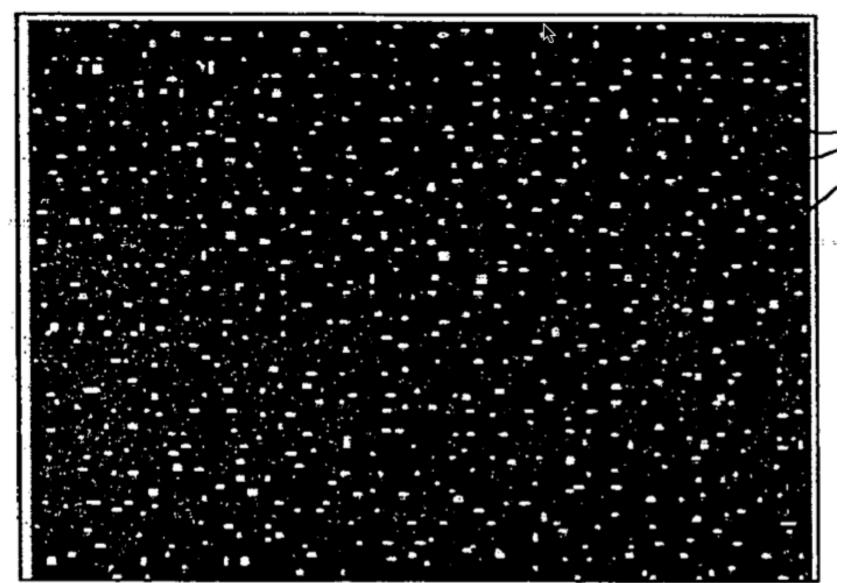
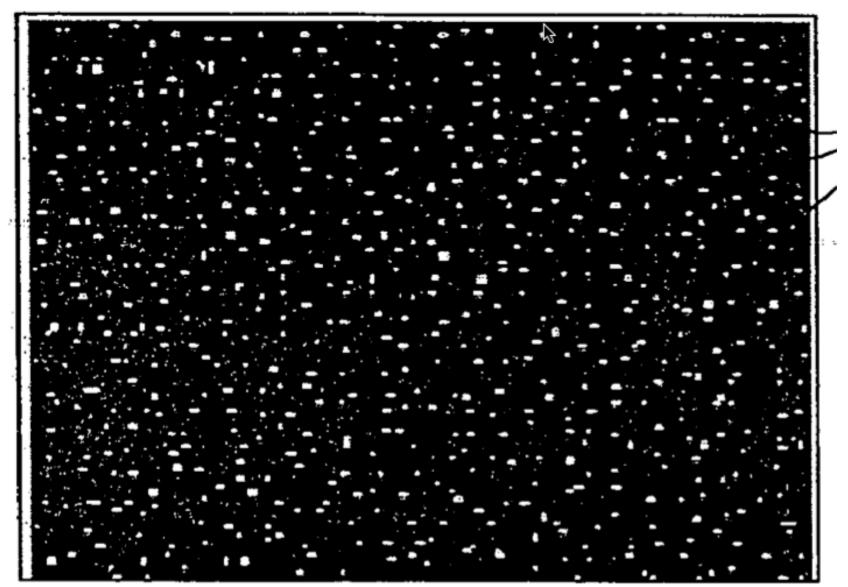


FIG. 3A



Structured light

FIG. 3A



Structured light

• The kinect uses random spots created by an infrared laser



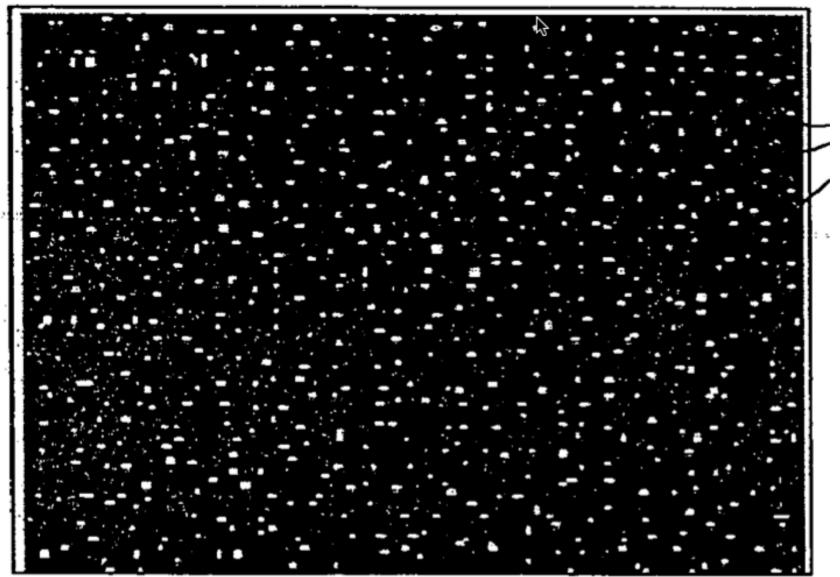
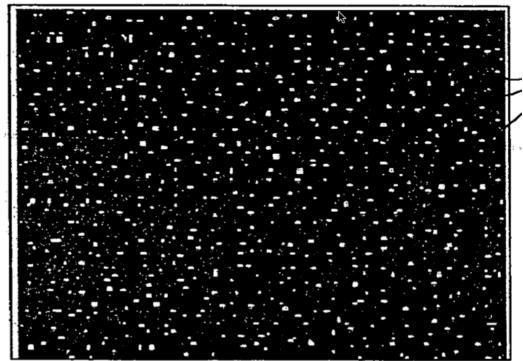
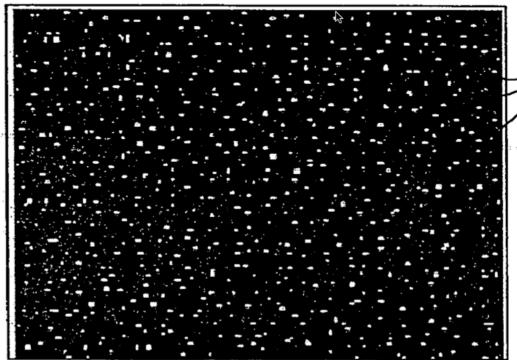


FIG. 3A

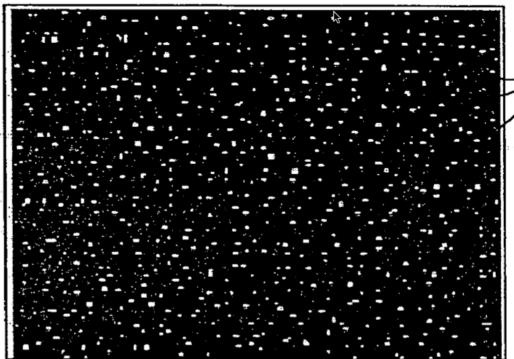






Structured light

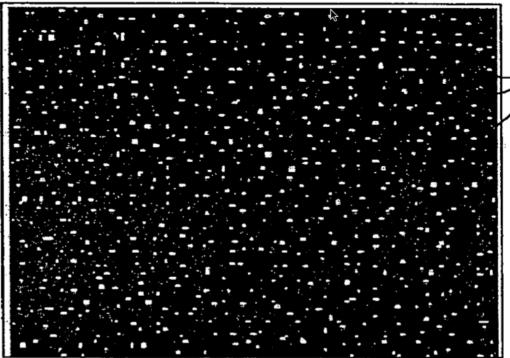




Structured light

• The kinect uses random spots created by an infrared laser

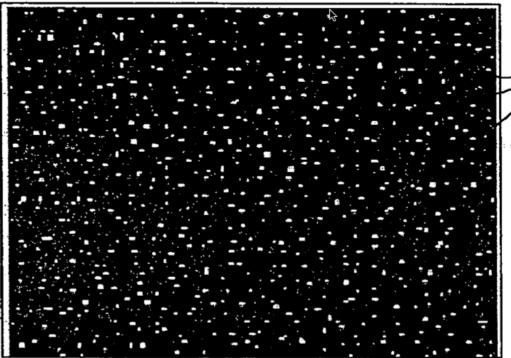


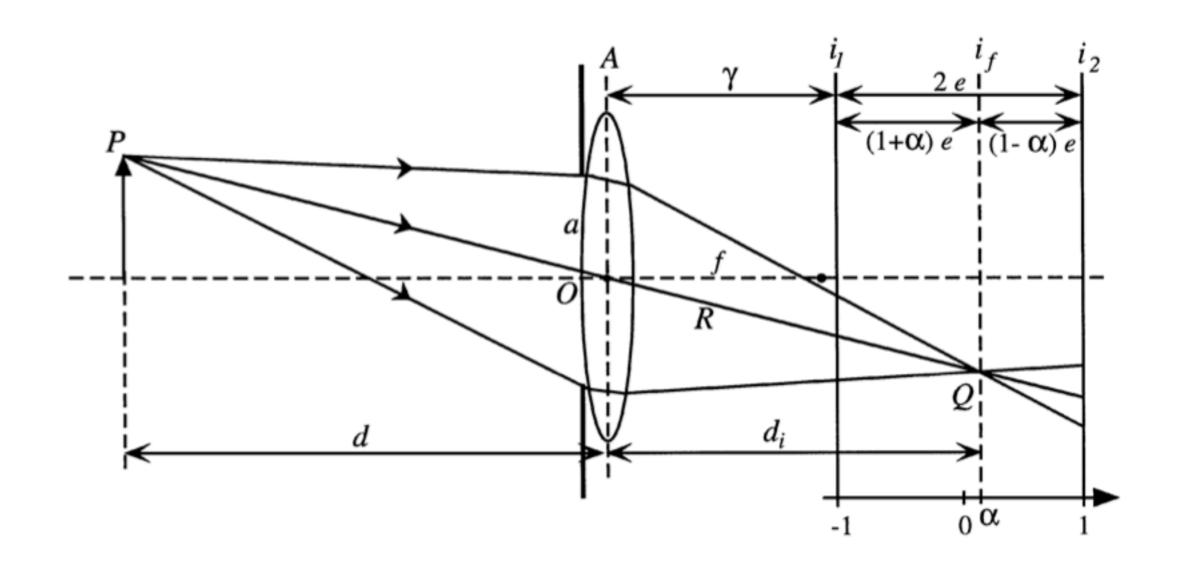


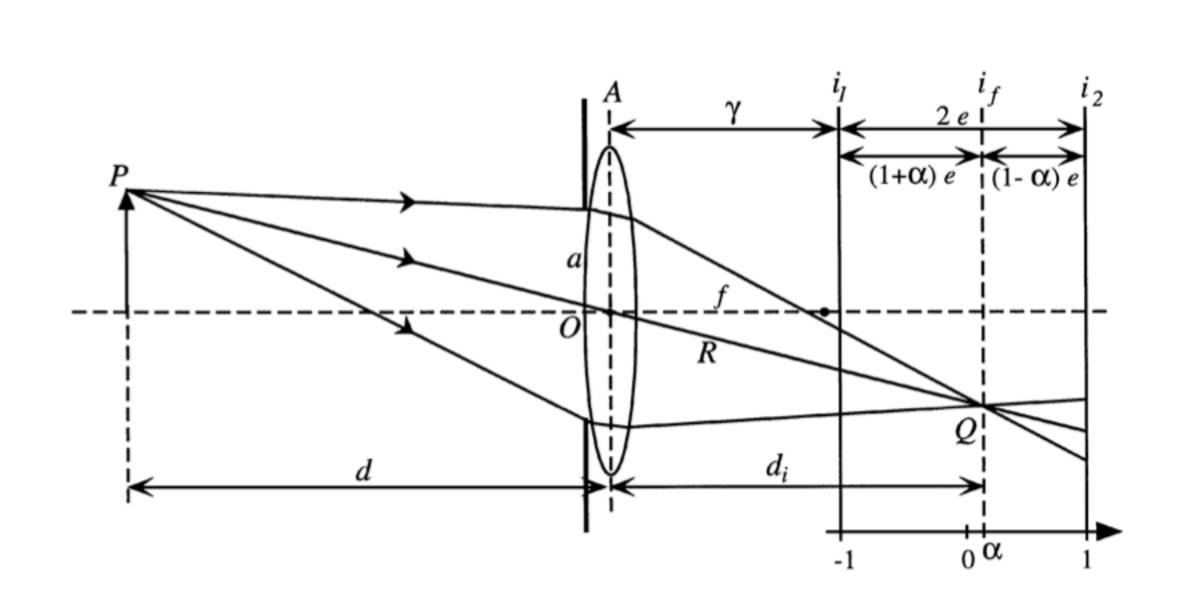
Structured light

- The kinect uses random spots created by an infrared laser
- The RGB camera is not used for depth computation



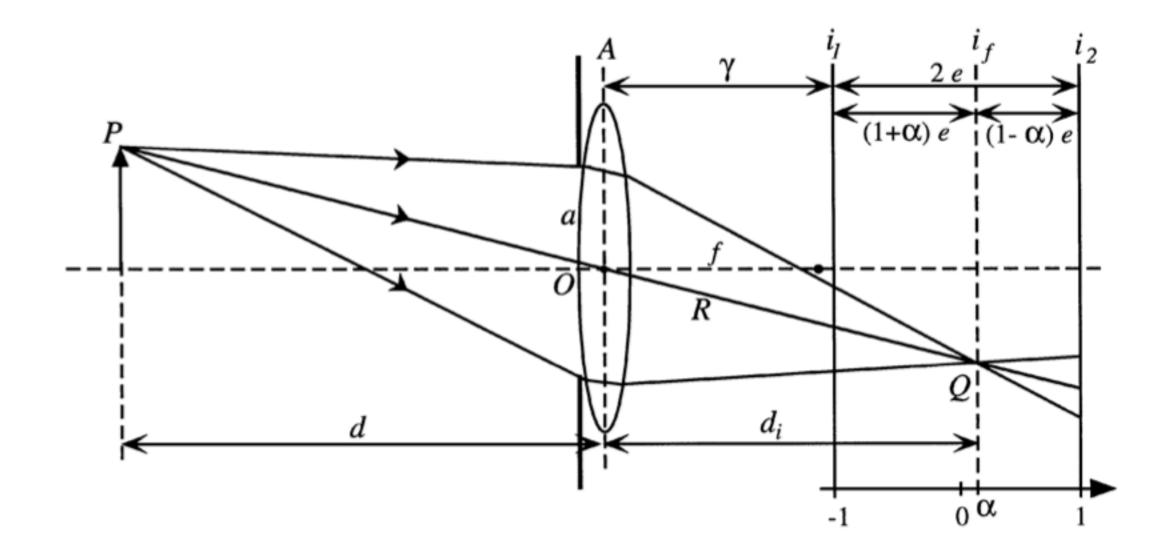






Rational Filters for Passive Depth from Defocus by Watanabe, Nayar

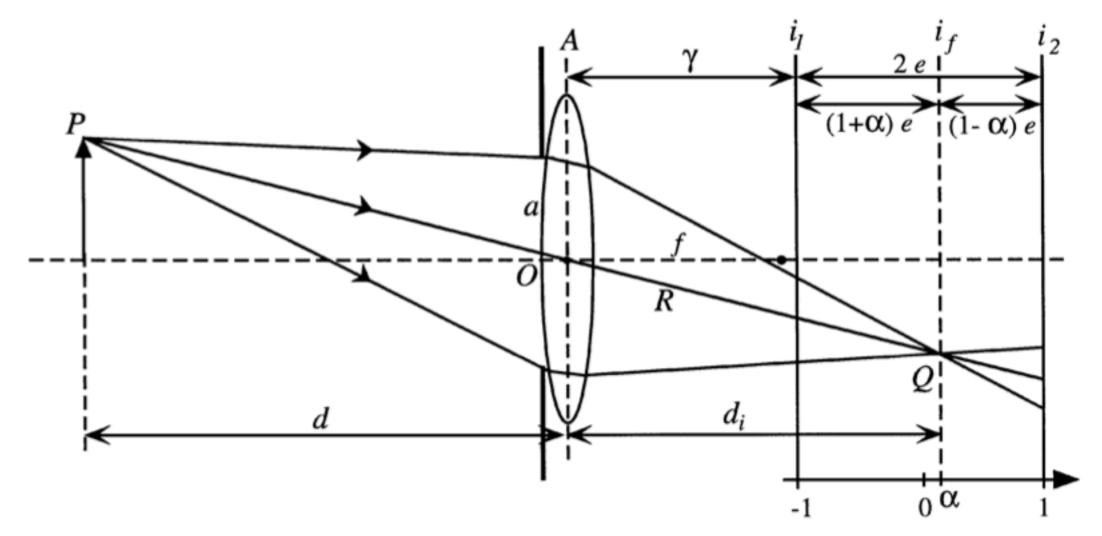
Depth from focus



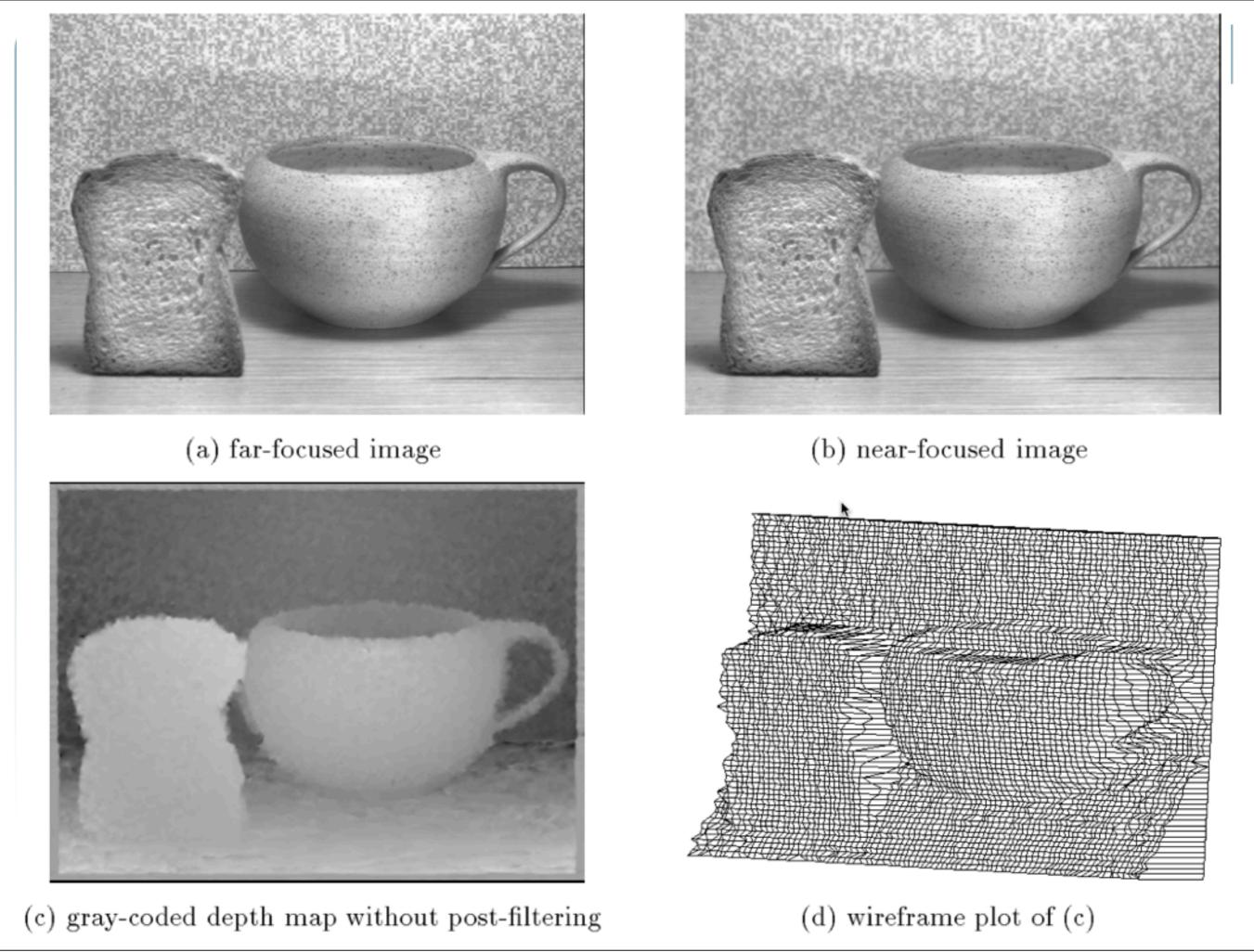
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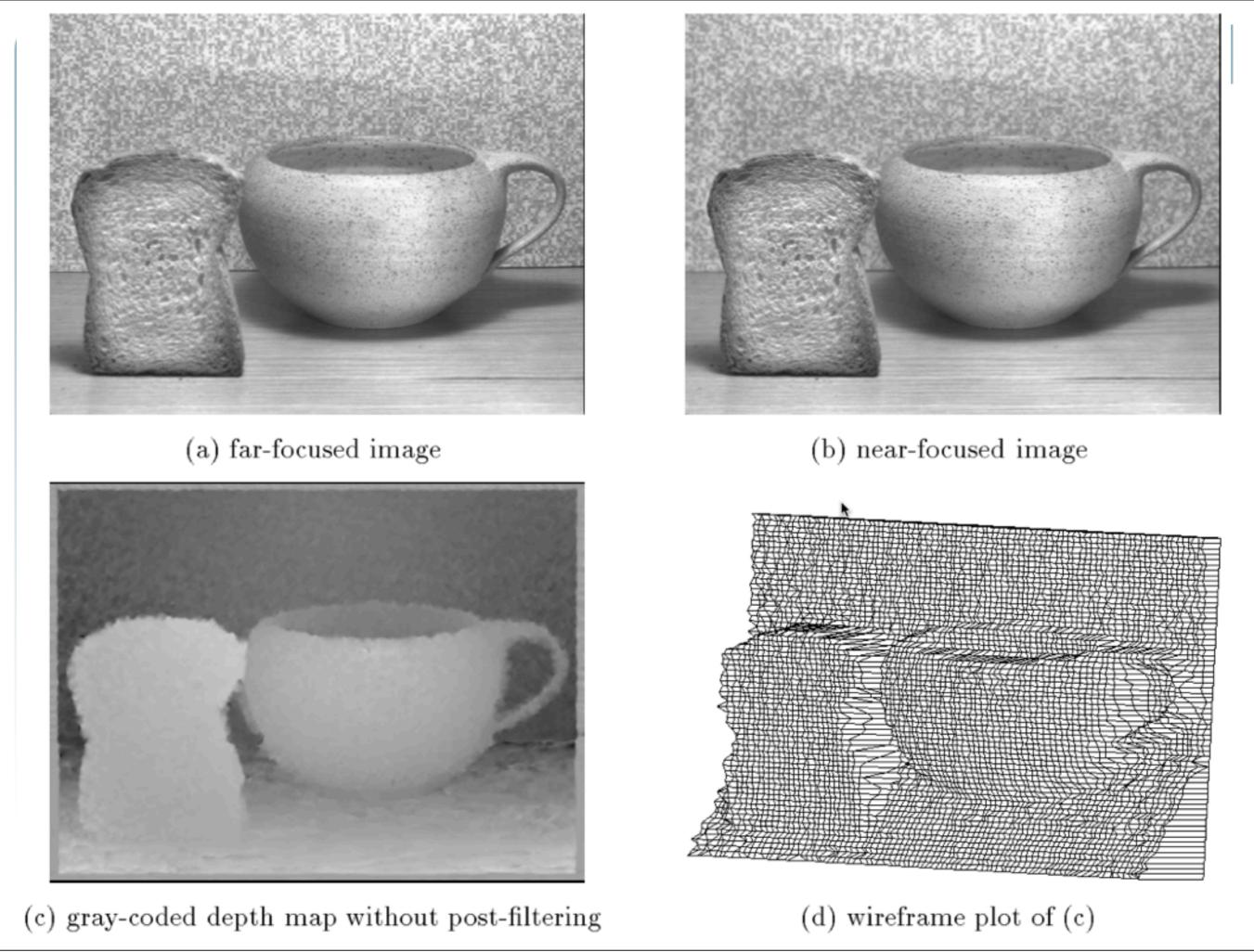
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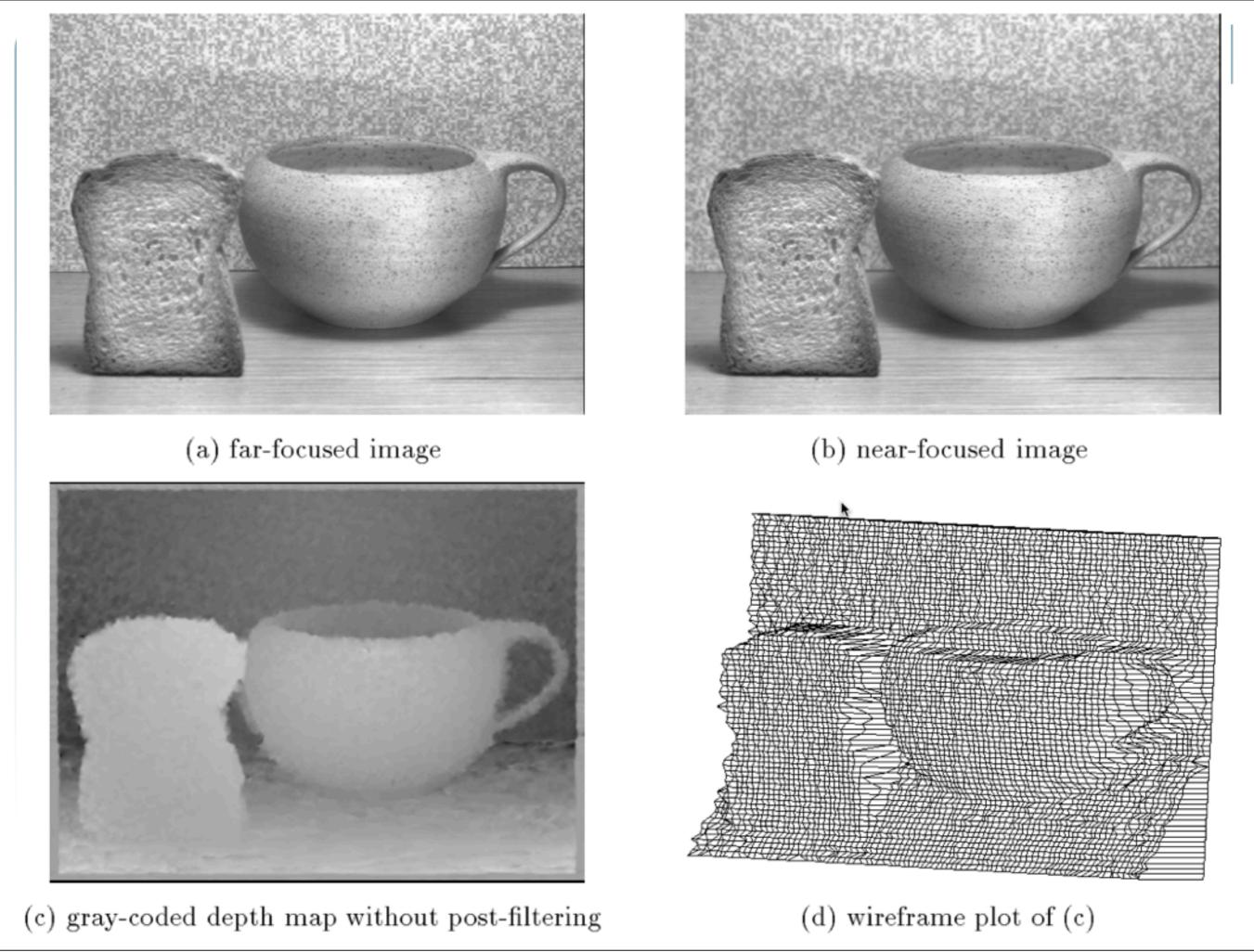
• Blurry things are further away

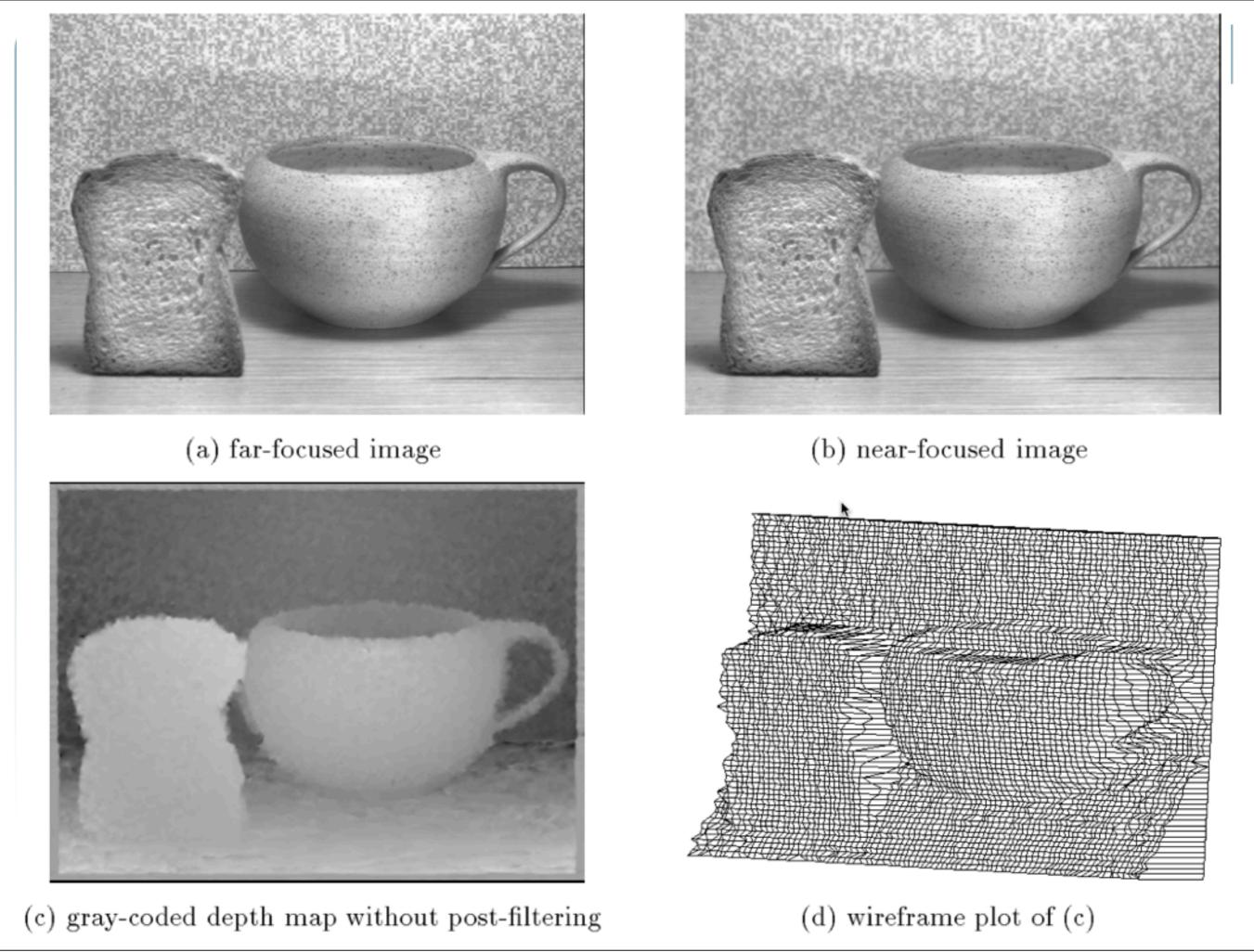


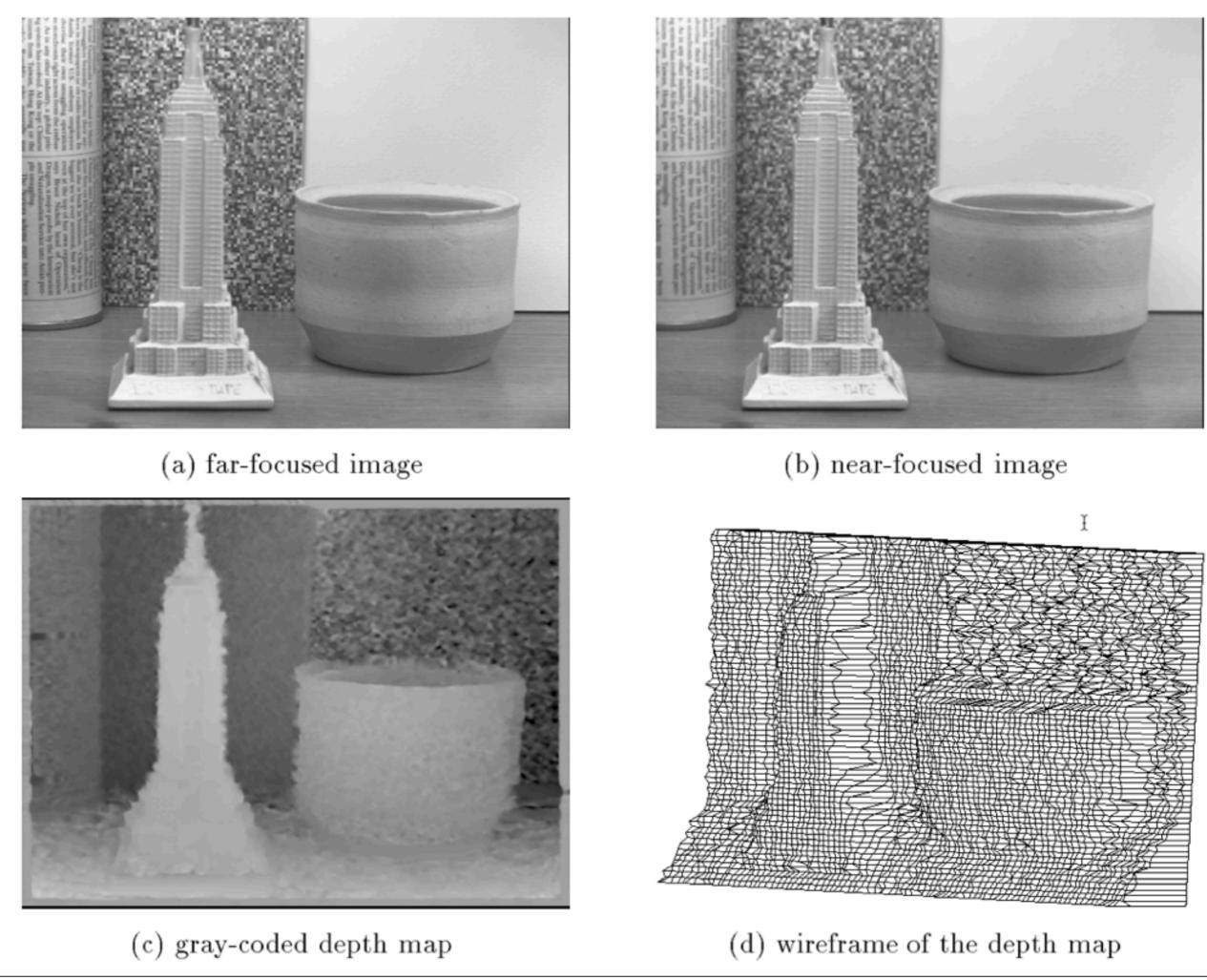
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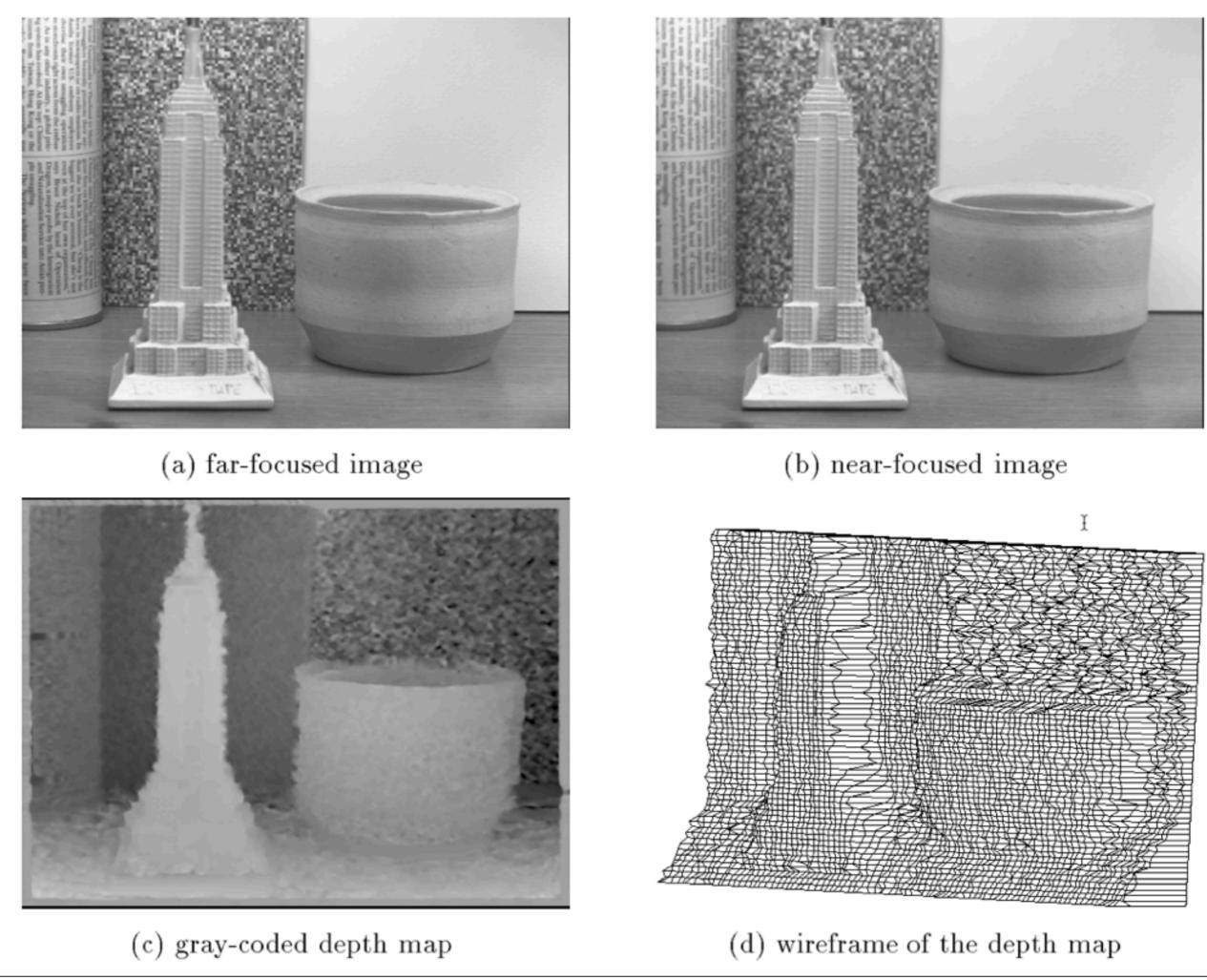


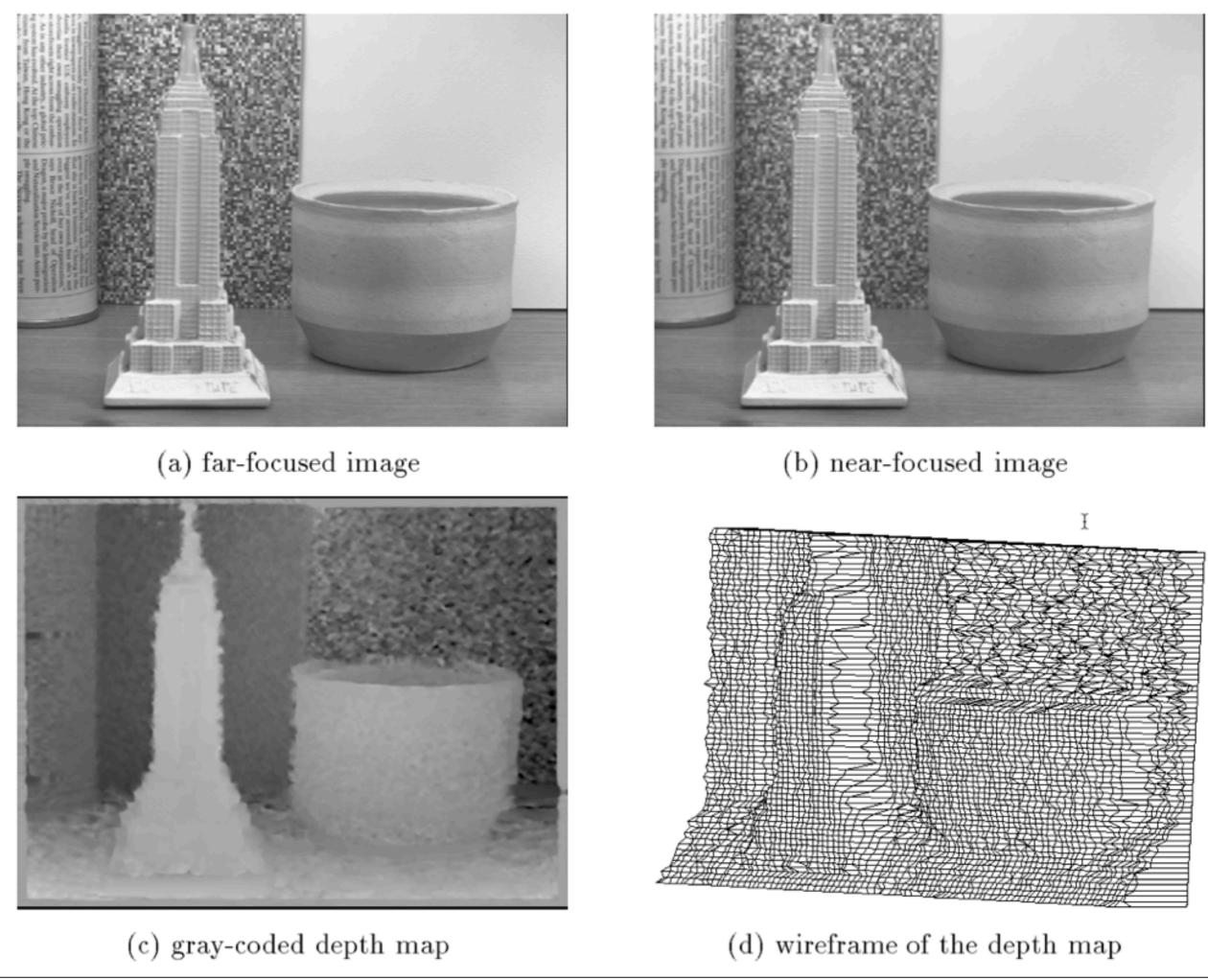


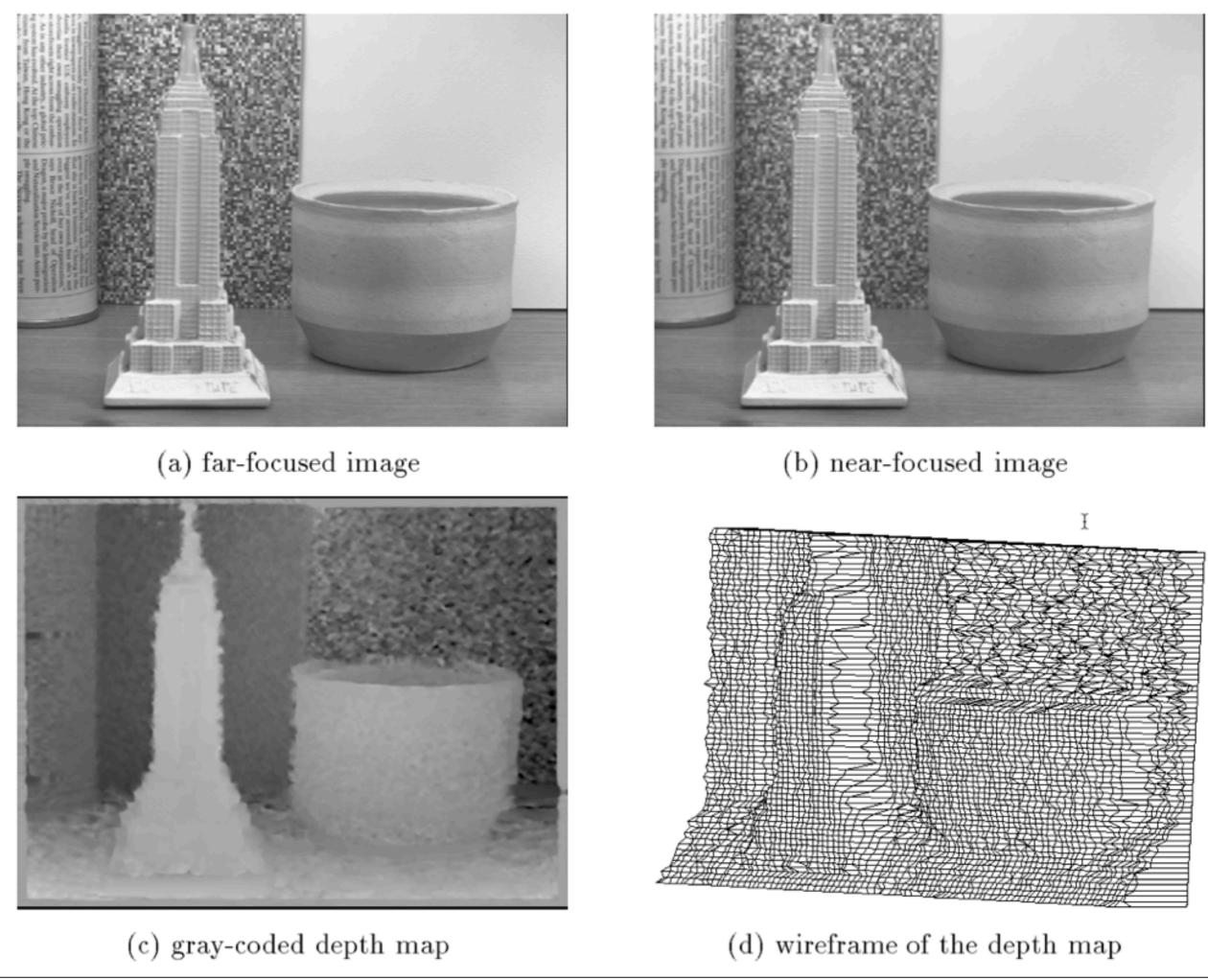


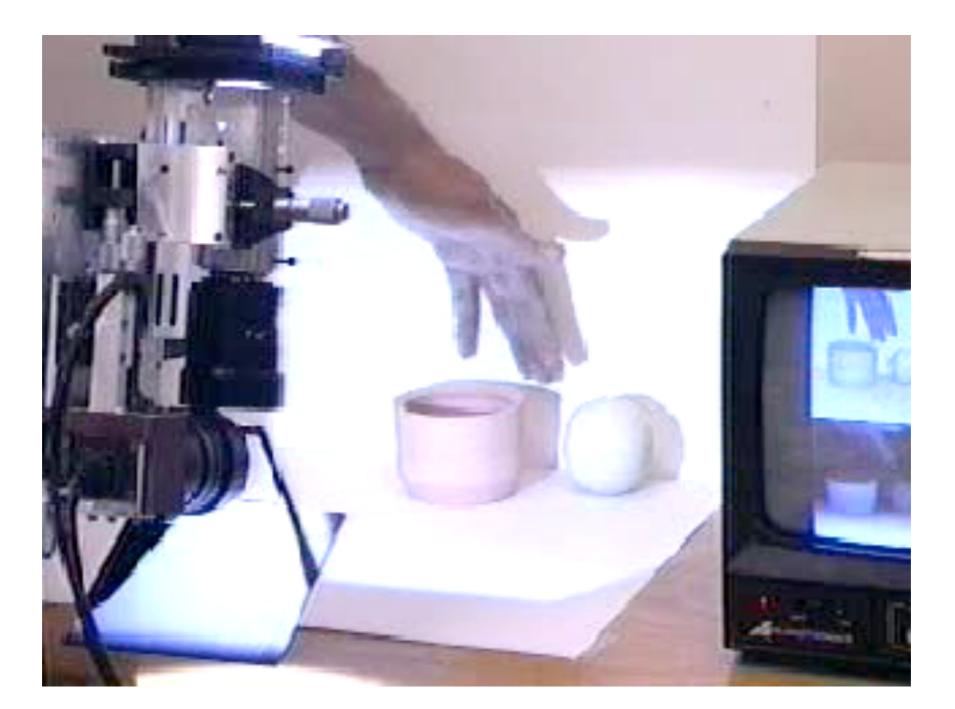


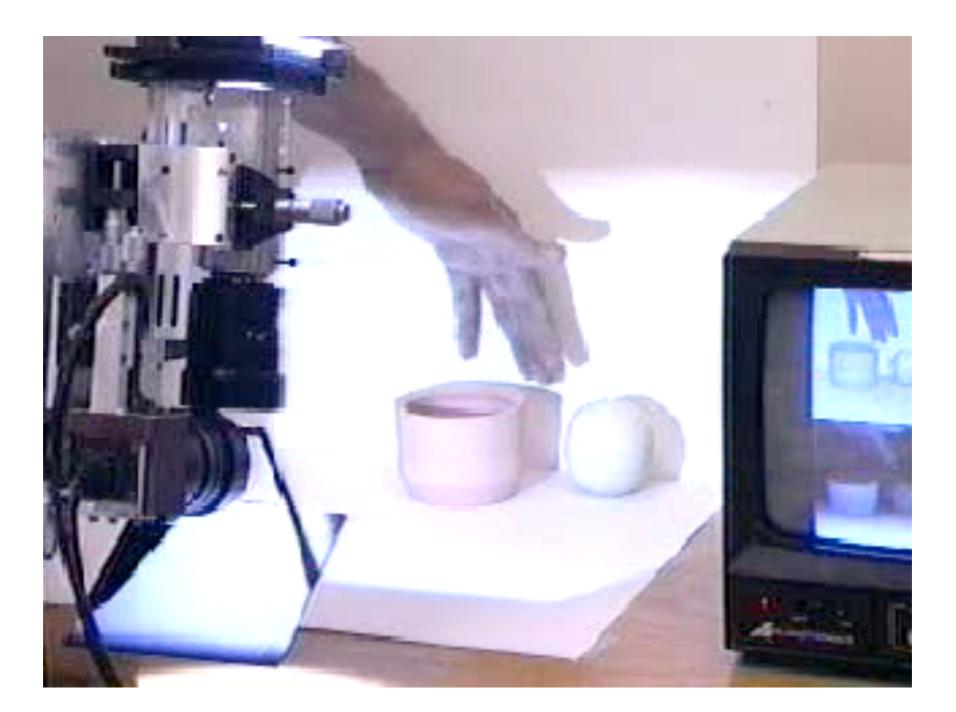












http://www.cs.columbia.edu/CAVE/projects/depth_defocus/images/defocus_ball.mpg

Depth from focus



http://www.cs.columbia.edu/CAVE/projects/depth_defocus/images/defocus_ball.mpg

Depth from focus

• Blurry things are further away



http://www.cs.columbia.edu/CAVE/projects/depth_defocus/images/defocus_ball.mpg

http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Depth from focus

http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Depth from focus

• The Kinect dramatically improves the accuracy of traditional depth from focus

http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Depth from focus

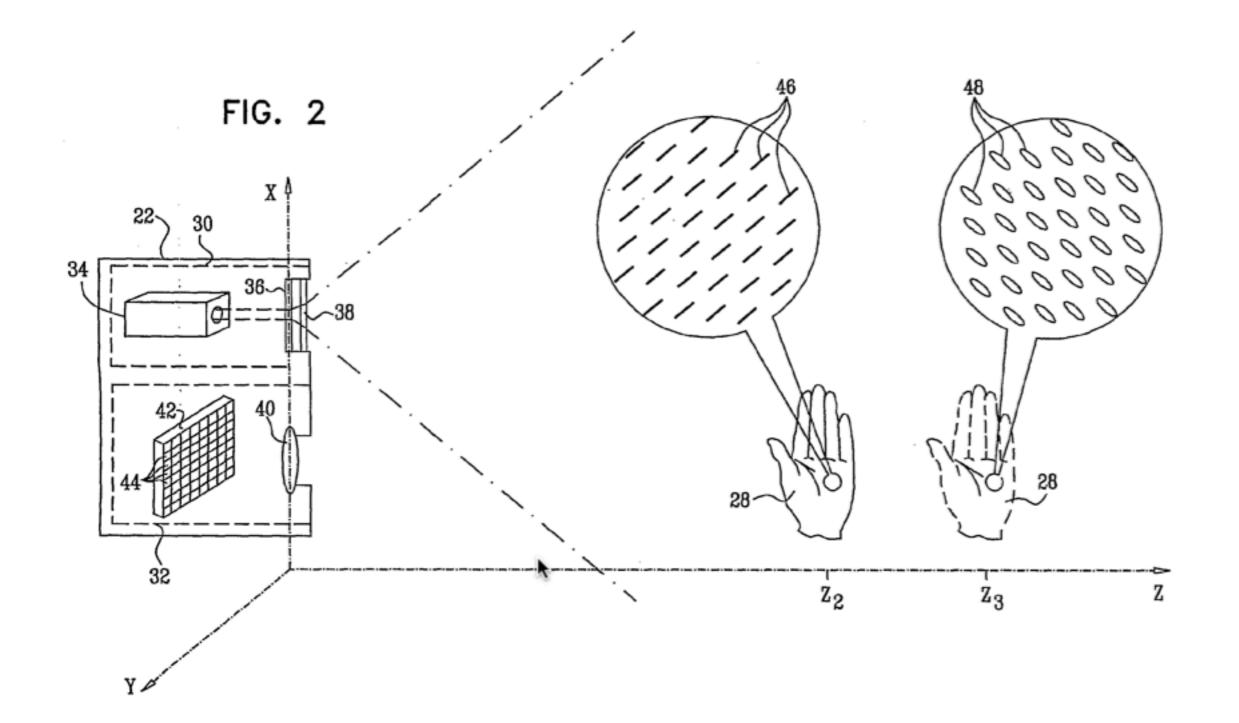
- The Kinect dramatically improves the accuracy of traditional depth from focus
- The Kinect uses a special ("astigmatic") lens with different focal length in x and y directions

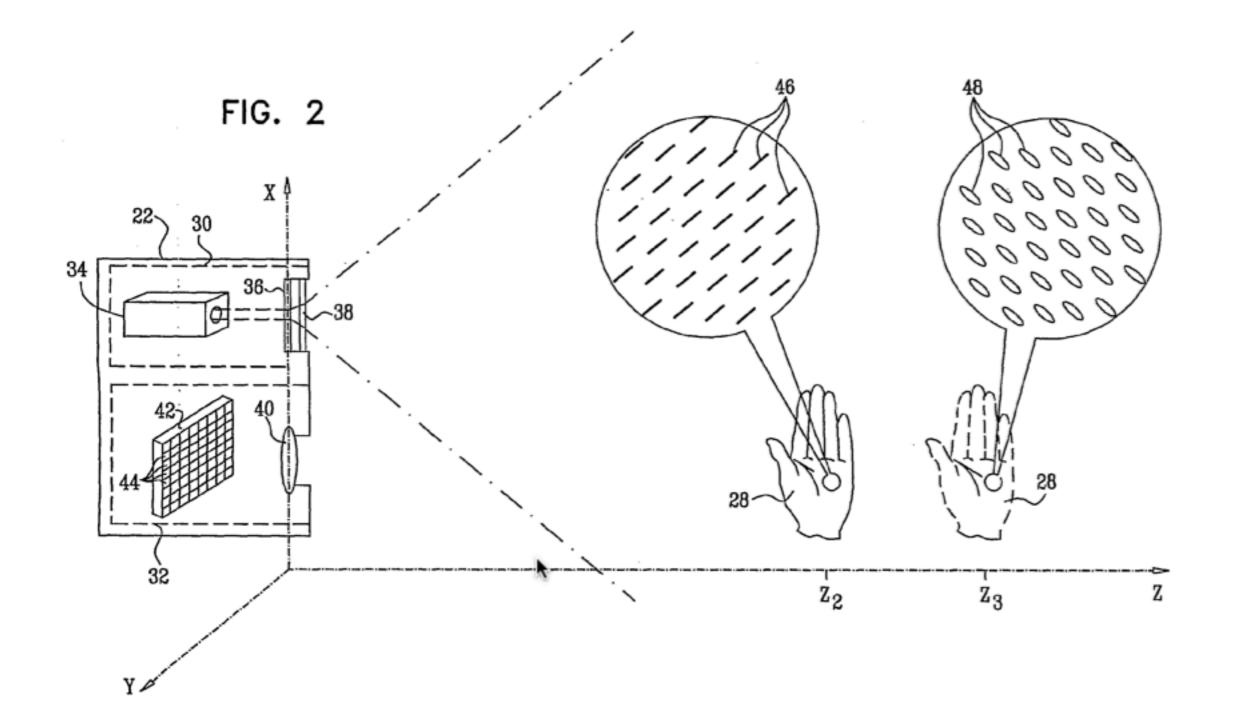
http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Depth from focus

- The Kinect dramatically improves the accuracy of traditional depth from focus
- The Kinect uses a special ("astigmatic") lens with different focal length in x and y directions
- A projected circle then becomes an ellipse whose orientation depends on depth

http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf





Patent: US 2010/0290698 A1

http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Depth from stereo

http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Depth from stereo

Based on parallax

http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

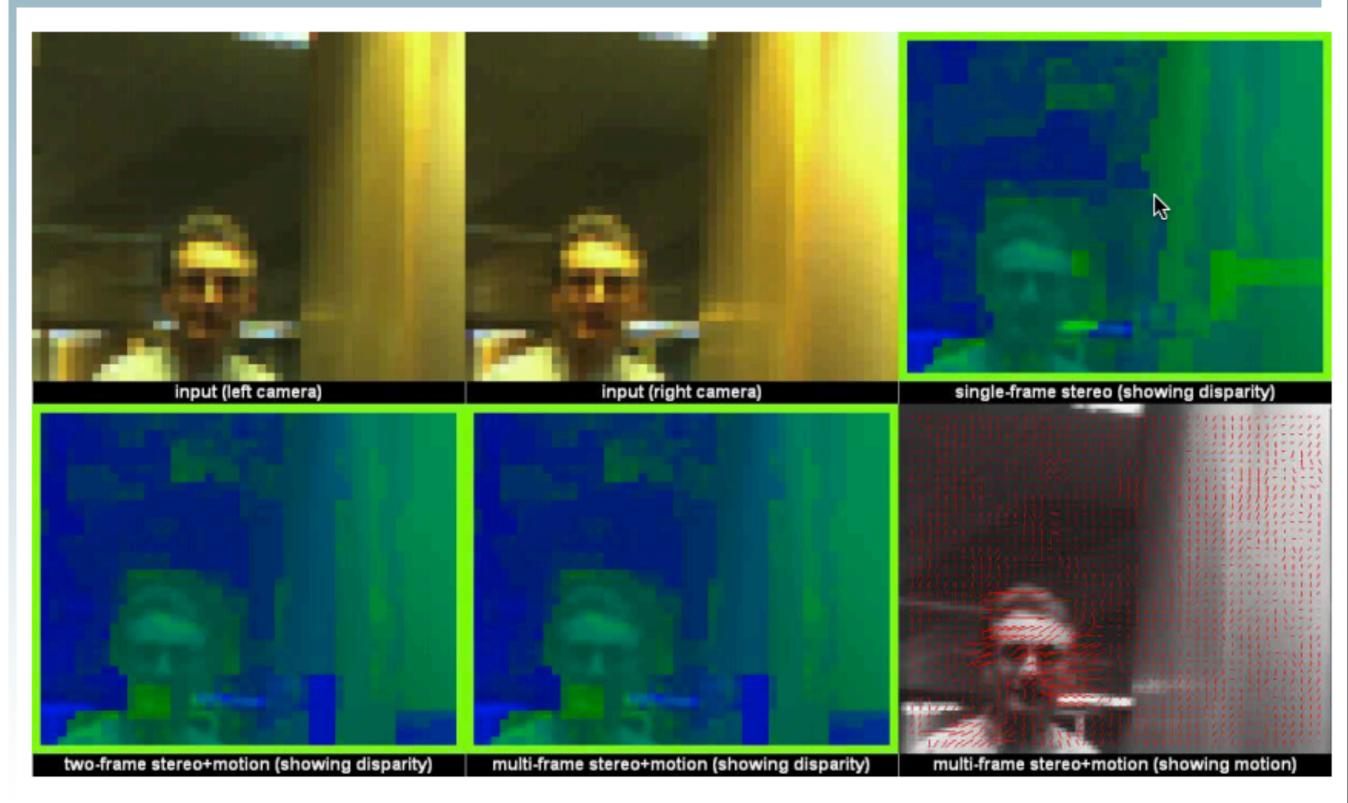
Depth from stereo

- Based on parallax
- If you look at the scene from two angles, objects that are close get shifted to the side more than objects that are far away

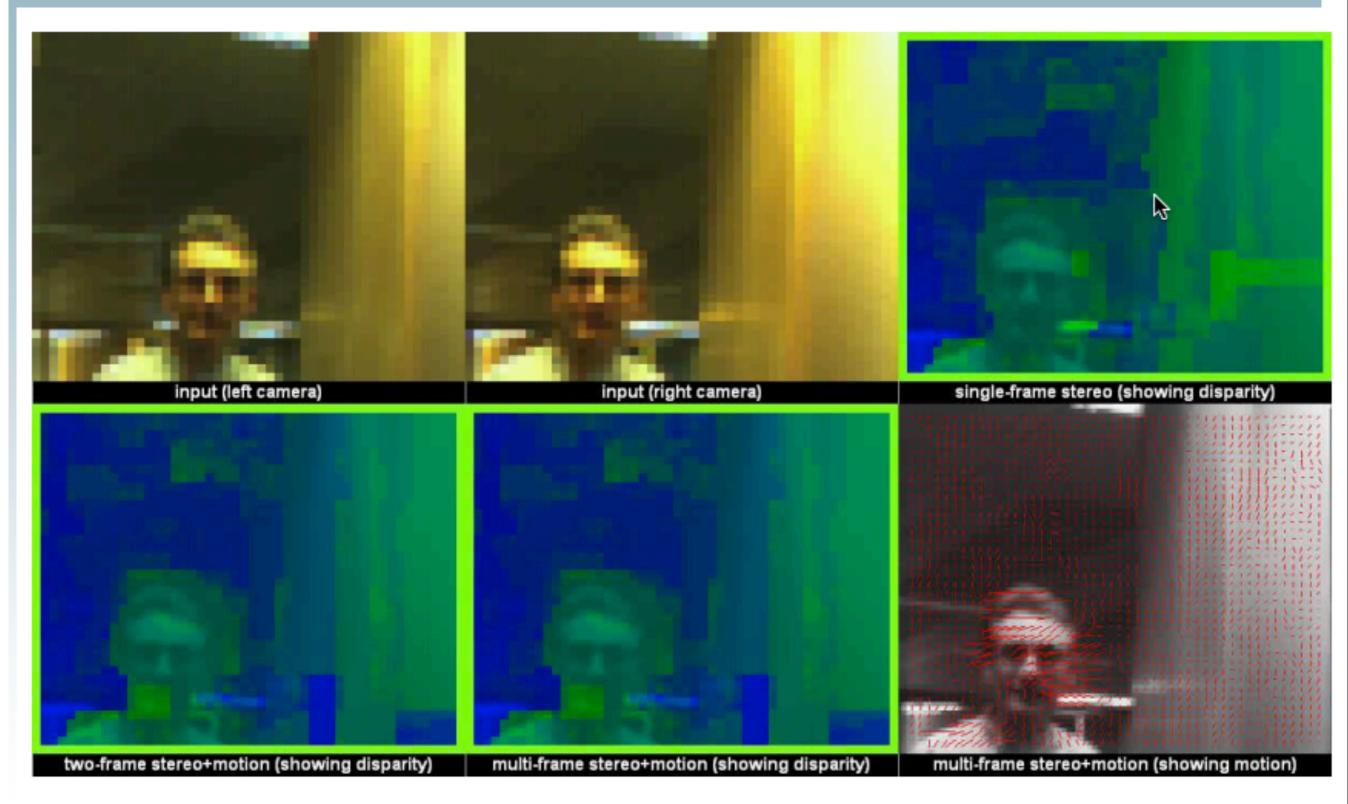
http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Depth from stereo

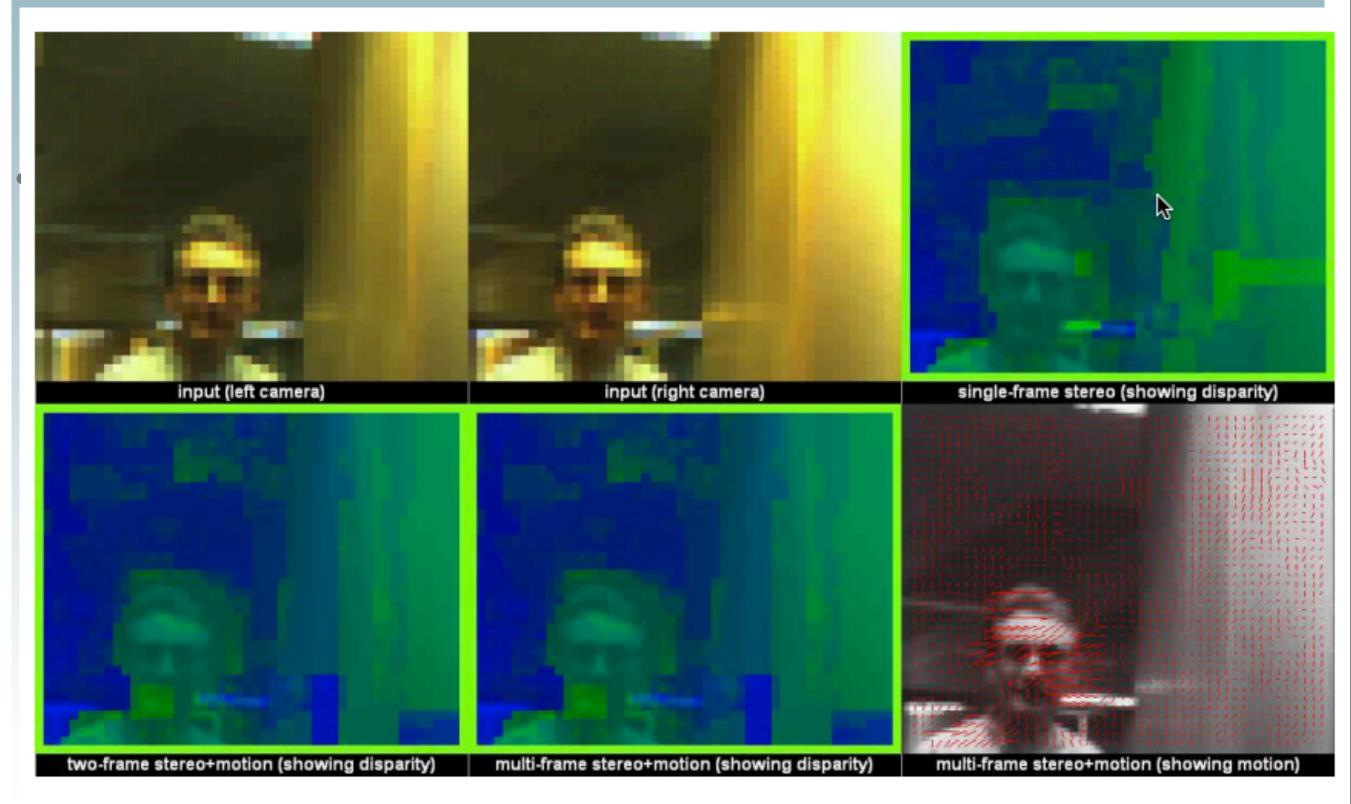
- Based on parallax
- If you look at the scene from two angles, objects that are close get shifted to the side more than objects that are far away
- The Kinect analyzes the shift of the speckle pattern by projecting from one location and observing from another



Isard and M, ACCV (2006)



Isard and M, ACCV (2006)



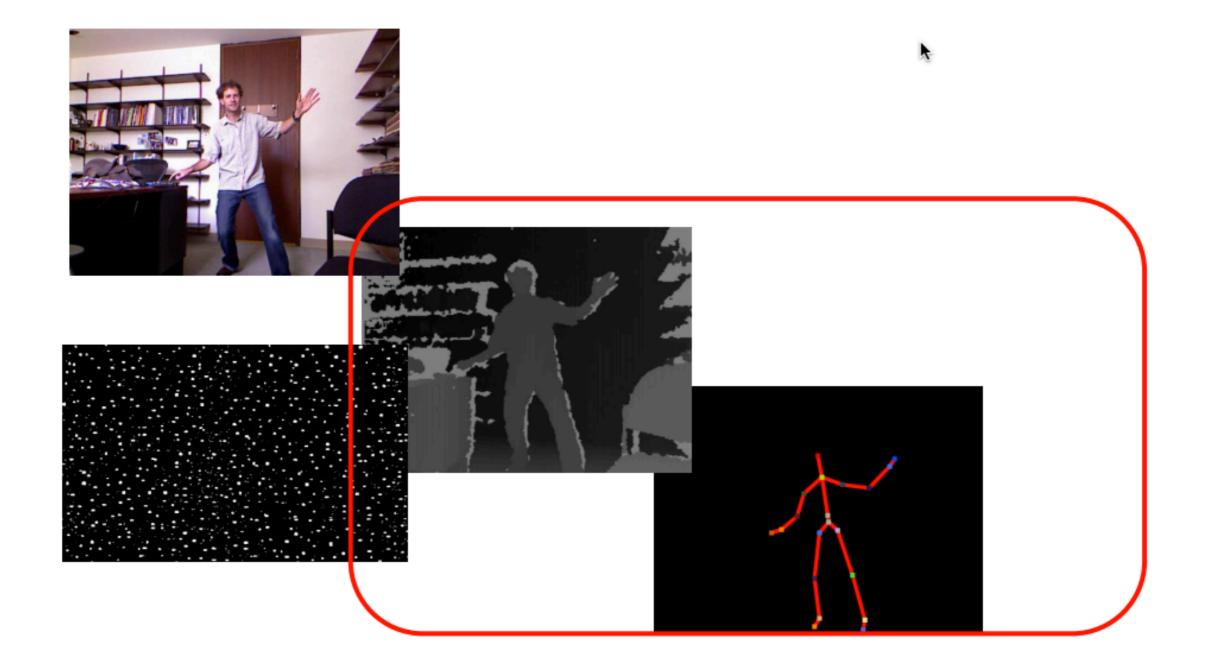
Isard and M, ACCV (2006)

Structured light

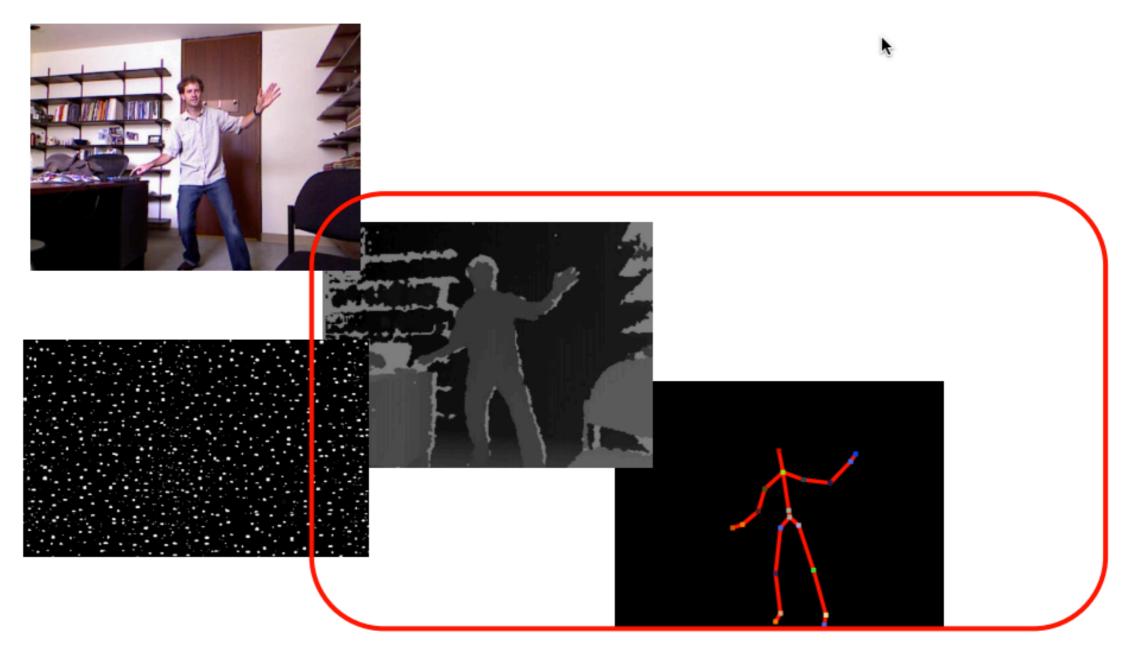
- Kinect Style
 - The Kinect uses an infrared projector and sensor
 - It does not use the RGB camera for depth computation
- Depth from focus
- Depth from parallax
- This creates a depth map

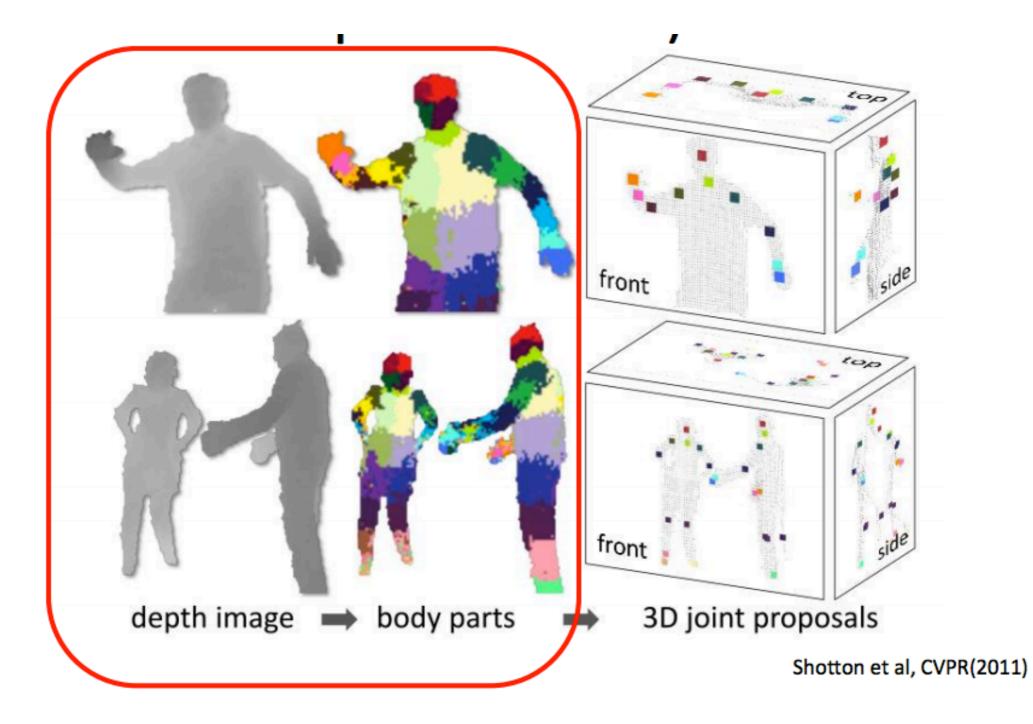
• Demo

• Explain "point cloud"

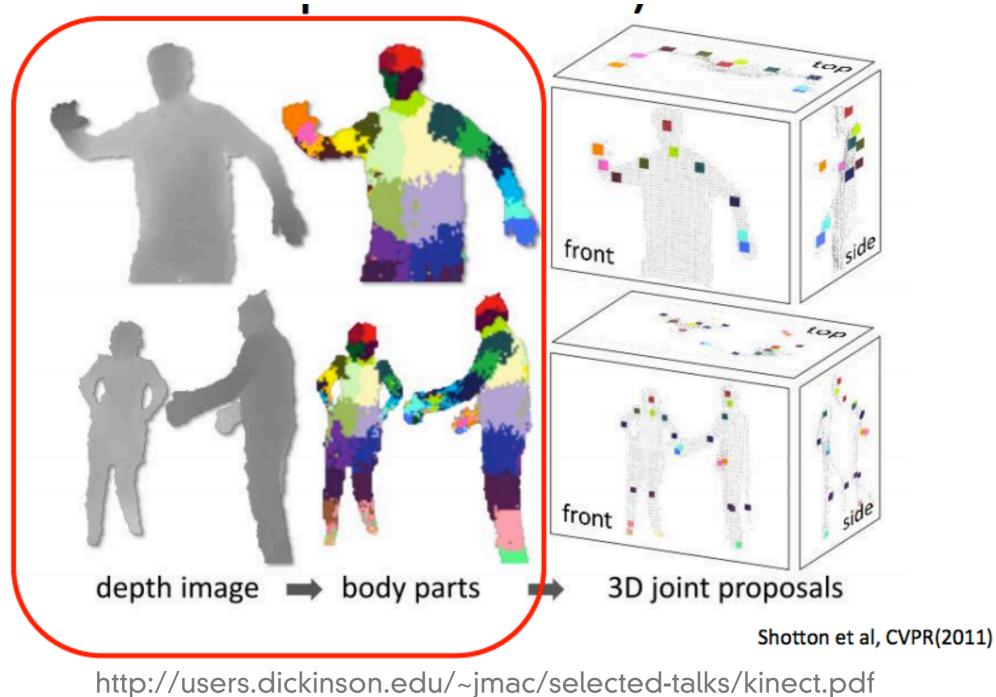


- Inferring body position is a two-stage process
 - First, Depth-map
 - Then Body Position

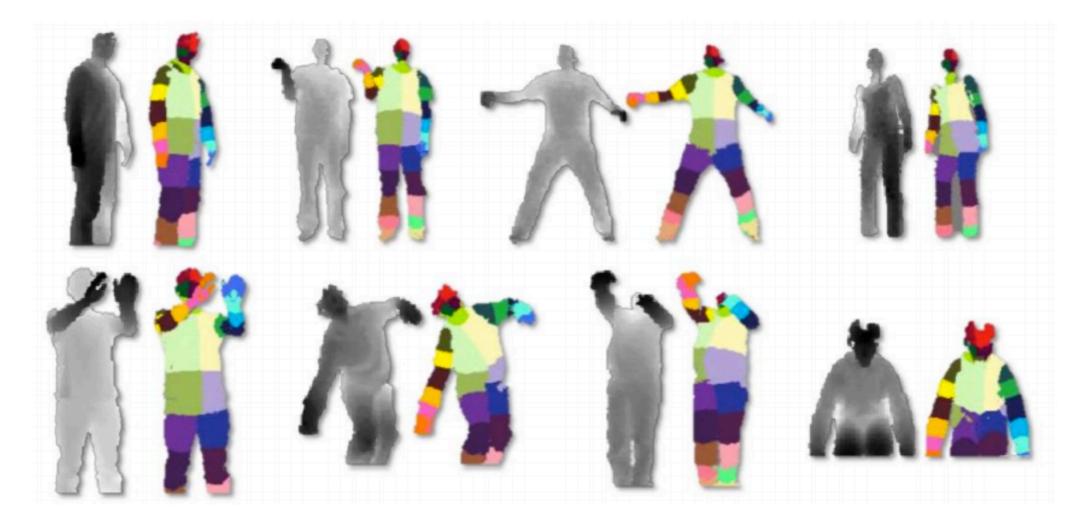




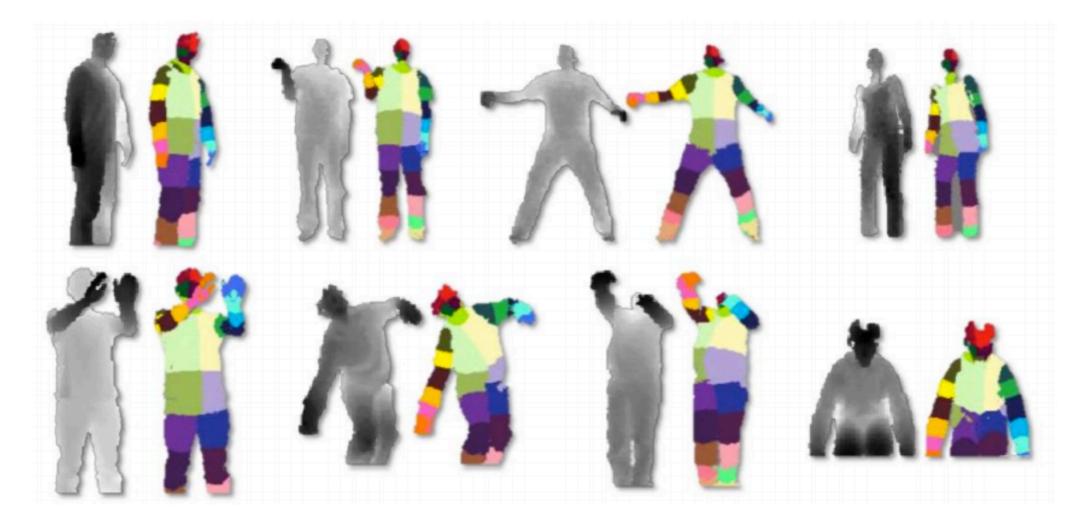
- Stage 2 has 2 substages
 - Map the depth-map to body-parts
 - map body-parts to 3d Joint proposals



Stage 2.1 starts with 100,000 depth images with known skeletons (from a motion capture system)



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For each real image, render dozens more using computer graphics techniques

- Use computer graphics to render all sequences for 15 different body types, and vary several other parameters
- Thus obtain over a million training examples

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Stage 2.1 transforms depth image to body part image

- Start with 100,000 depth images with known skeleton (from a motion capture system)
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- Learn a randomized decision forest, mapping depth images to body parts

Stage 2.1 transforms depth image to body part image

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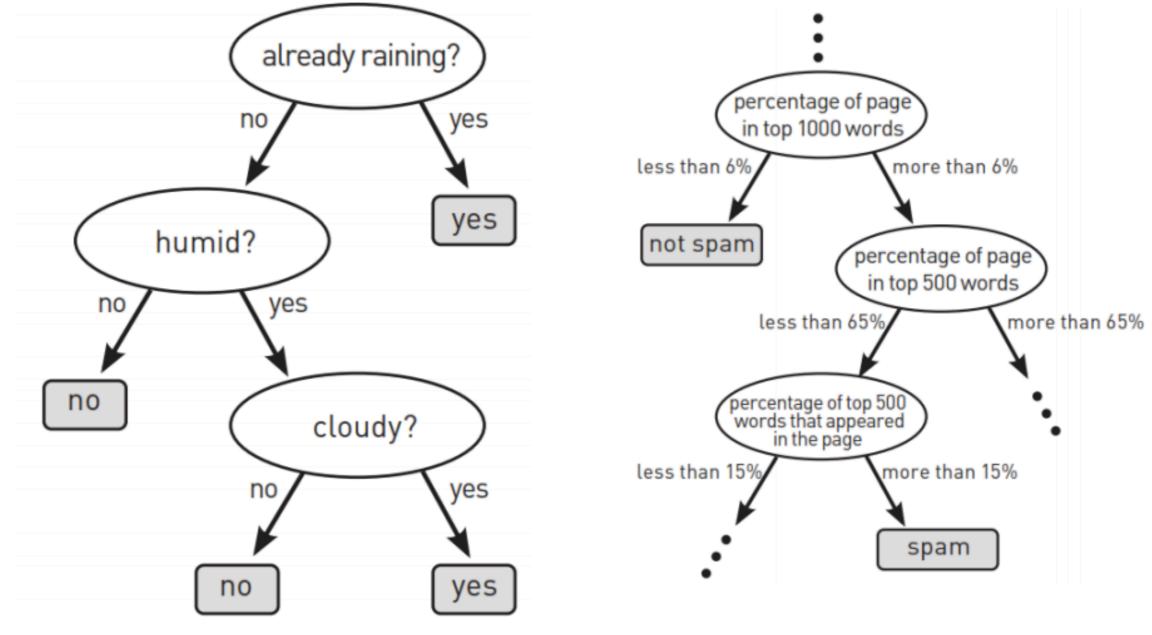
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A randomized decision forest is a more sophisticated version of the classic *decision tree*

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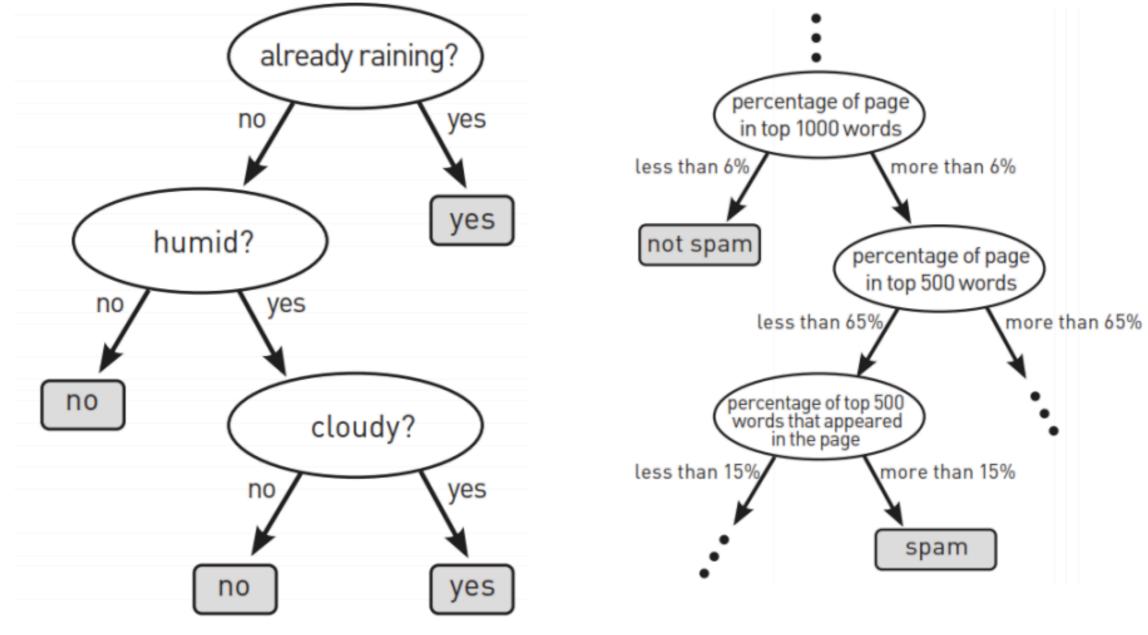
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A decision tree is like a pre-planned game of "twenty questions"



Ntoulas et al, WWW (2006)

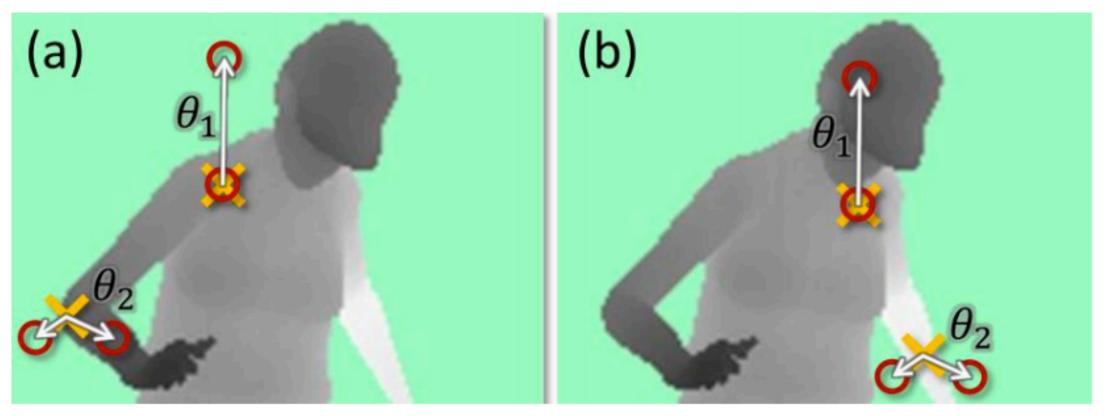
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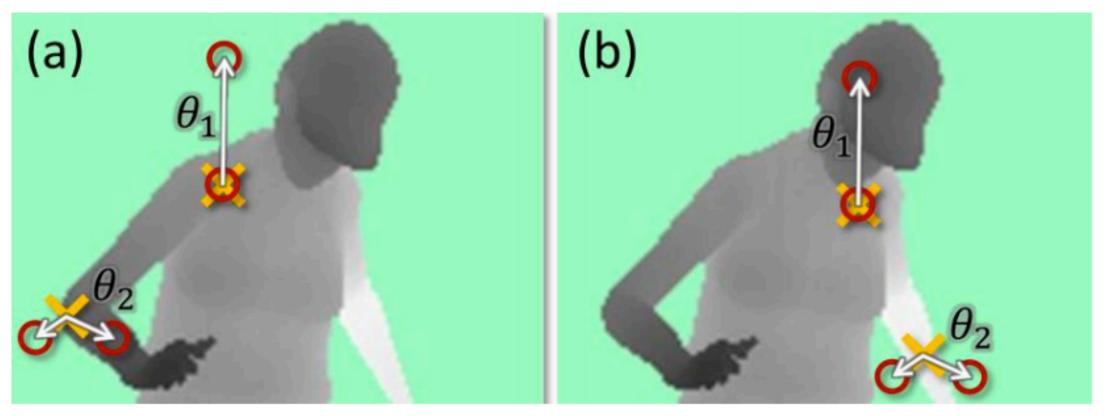
What kind of "questions" can the Kinect ask in its twenty questions?

- Simplified version:
 - "is the pixel at that offset in the background?"
- Real version:
 - "how does the (normalized) depth at that pixel compare to this pixel?" [see Shotton et al, equation 1]



What kind of "questions" can the Kinect ask in its twenty questions?

- Simplified version:
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 - "how does the (normalized) depth at that pixel compare to this pixel?" [see Shotton et al, equation 1]



To learn a decision tree, you choose as the next question the one that is most "useful" on (the relevant part of) the training data

- E.g. for umbrella tree, is "raining?" or "cloudy?" more useful?
- In practice, "useful" = information gain G (which is derived from entropy H):

$$G(\phi) = H(Q) - \sum_{s \in \{1, r\}} \frac{|Q_s(\phi)|}{|Q|} H(Q_s(\phi))$$

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Shotton et al, CVPR(2011)

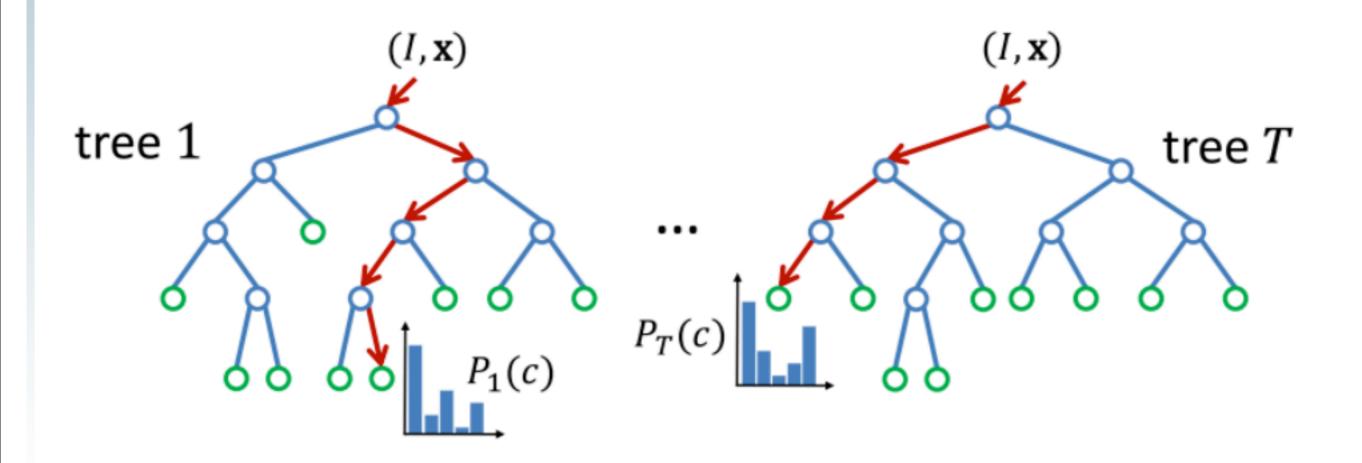
Kinect actually uses a *randomized* decision *forest*

- Randomized:
 - Too many possible questions, so use a random selection of 2000 questions each time
- Forest:
 - learn multiple trees
 - to classify, add outputs of the trees
 - outputs are actually probability distributions, not single decisions

Kinect actually uses a *randomized* decision *forest*

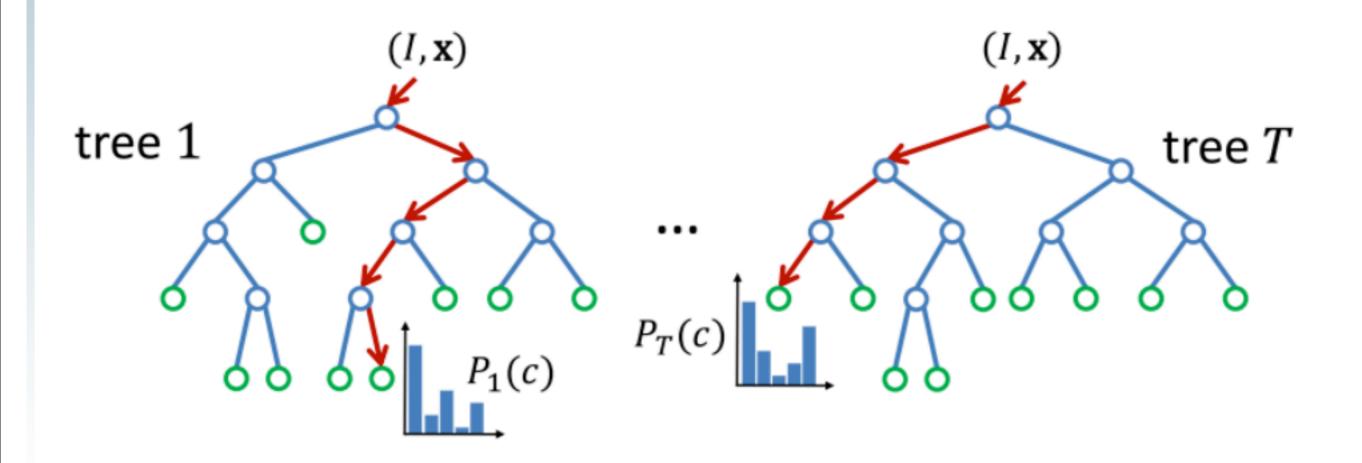
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Learning the Kinect decision forest requires 24,000 CPU-hours, but takes only a day using hundreds of computers simultaneously

"To keep the training times down we employ a distributed implementation. Training 3 trees to depth 20 from 1 million images takes about a day on a 1000 core cluster."

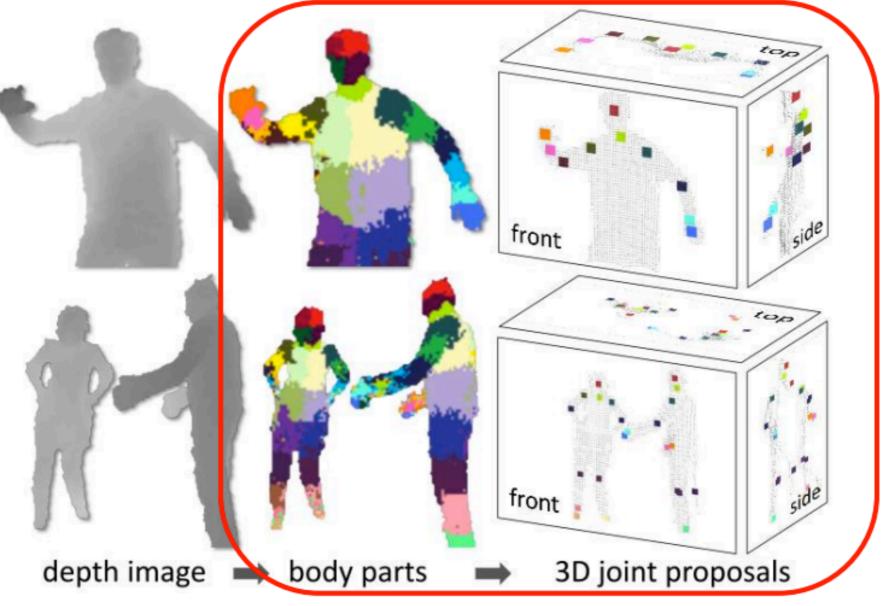
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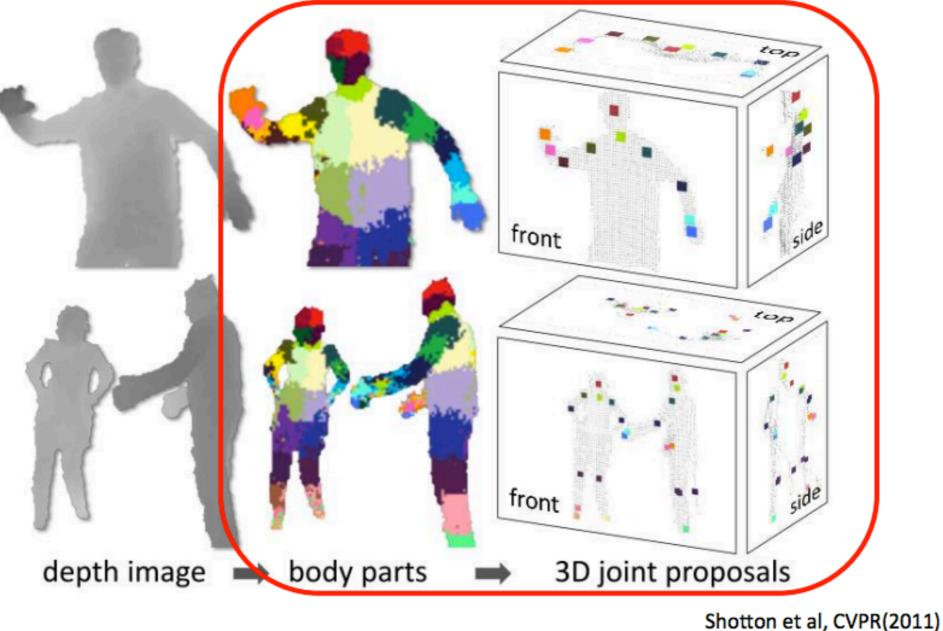
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http://users.dickinson.edu/~jmac/selected-talks/kinect.pdf

Tuesday, March 5, 13

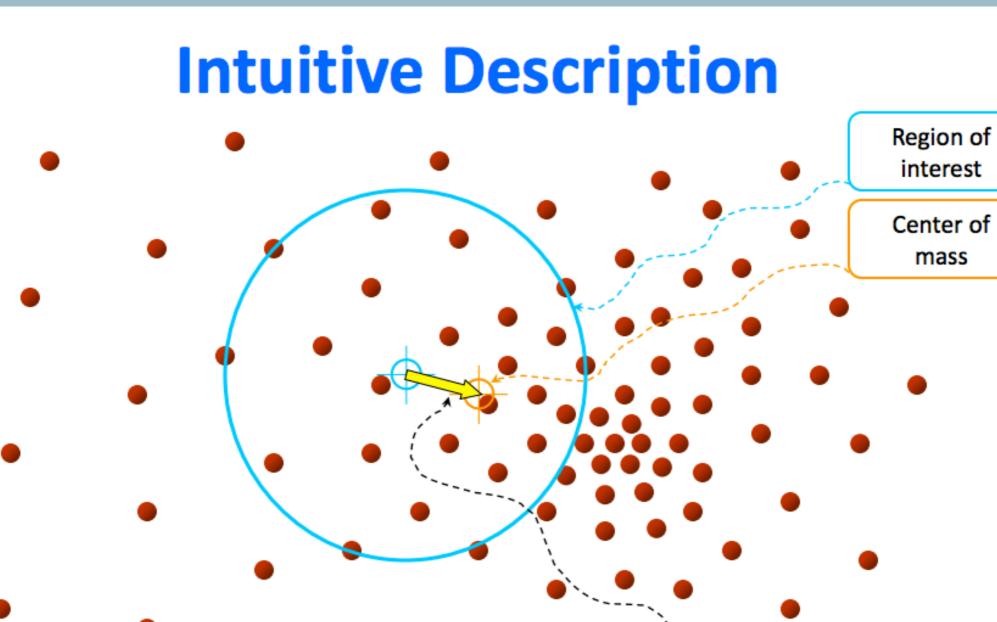
Stage 2.2 transforms the body part image into a skeleton

- The *mean shift* algorithm is used to robustly compute modes of probability distributions
- Mean shift is simple, fast, and effective

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IIIIp.//useis.uickinsun.euu/~jinuc/selecieu-luiks/kineci.pui

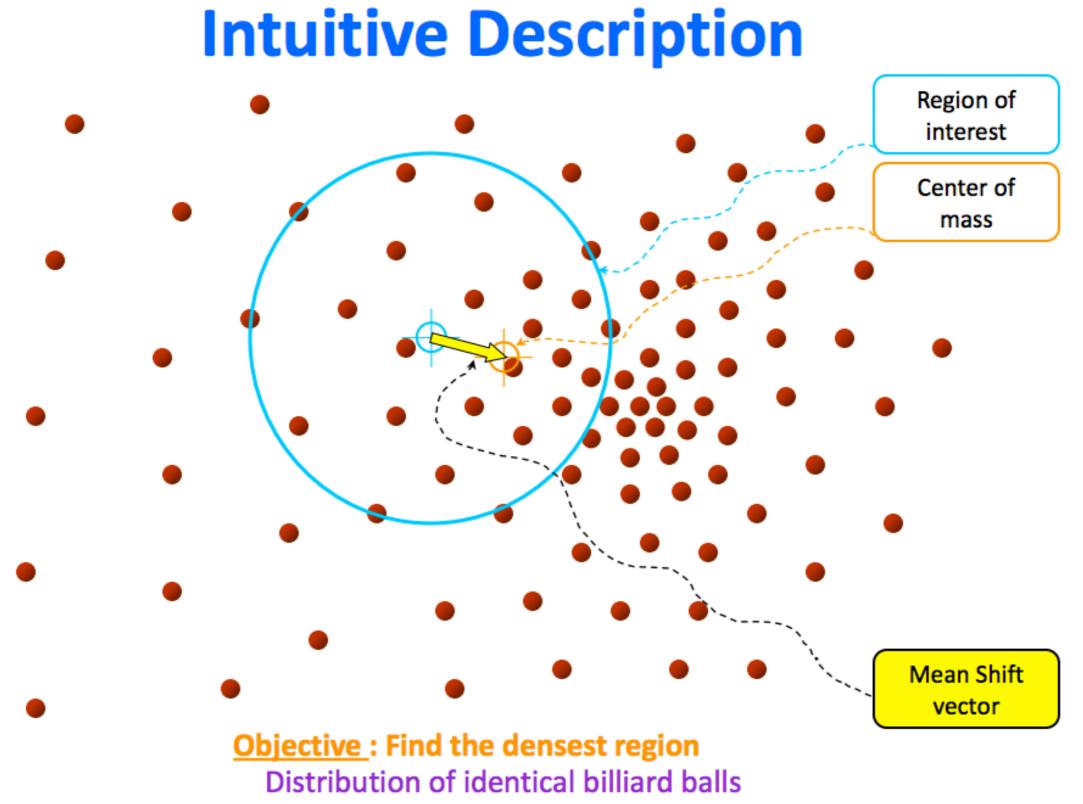


<u>Objective</u>: Find the densest region Distribution of identical billiard balls

Slide taken from Ukrainitz & Sarel

Mean Shift

vector



Slide taken from Ukrainitz & Sarel

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The Kinect uses *structured light* and *machine learning*

- Inferring body position is a two-stage process: first compute a depth map (using structured light), then infer body position (using machine learning)
- The results are great!
- The system uses many college-level math concepts, and demonstrates the remarkable advances in computer vision in the last 20 years

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http://youtu.be/abS7G5ZT17c

http://youtu.be/a0mdgdQfa-Q

http://vimeo.com/16985224

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