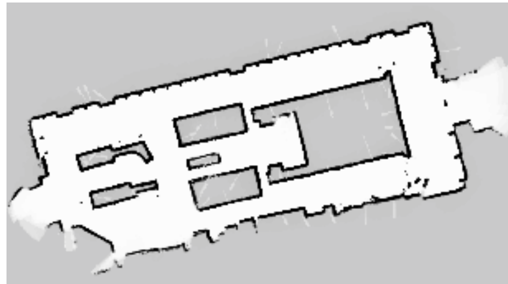
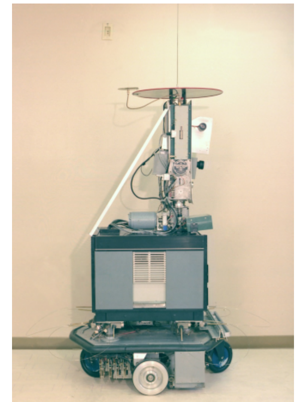
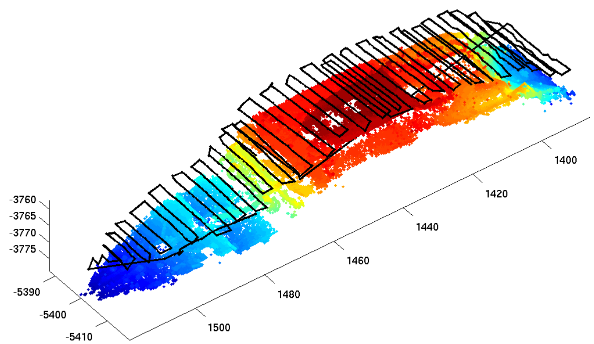
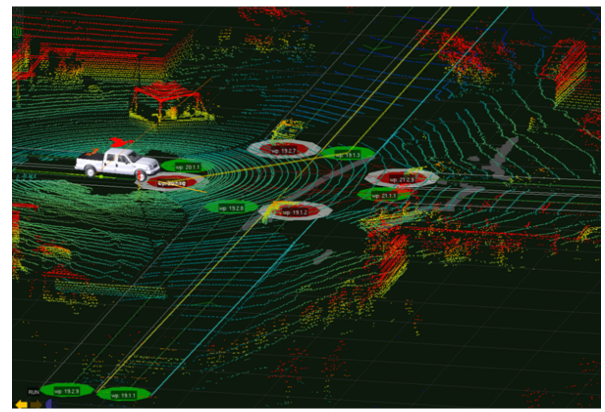








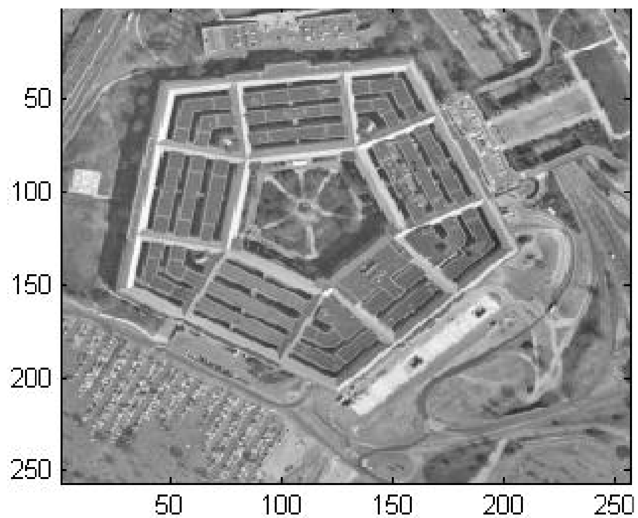
EECS568 Mobile Robotics: Methods and Principles

Prof. Edwin Olson

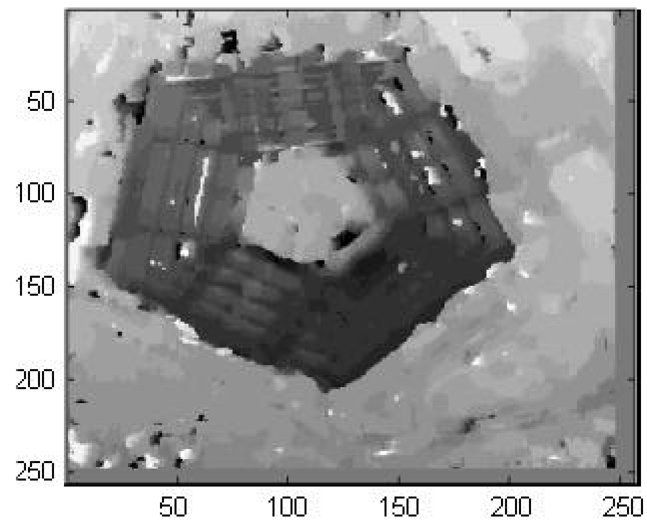
L22. A trip through the sensor zoo

Stereo

- Classic approach to stereo vision: matching pixel patches between left and right.



Left Image



Depth Map (8x8)

- Shortcoming: in low-detail areas, results are erratic. (How would we enforce local consistency?)

Block Matching

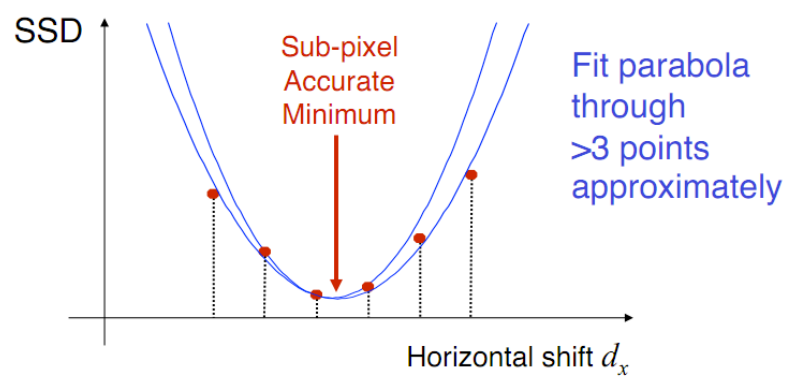
- Exploit epipolar geometry
  - A pixel in the left camera corresponds to a ray.
  - The image of a ray (in the right camera) is a line
  - Thus, if we know the geometry of the cameras, we only need to search for matches along a line.

$$\sum_{(i,j)\in W} |I_1(i,j) - I_2(x+i, y+j)|$$

$$\sum_{(i,j)\in W} \left(I_1(i,j) - I_2(x+i, y+j)\right)^2$$

- Matching procedure
  - Block size (5x5, 7x7, ...)
  - Comparison (SAD, SSE)

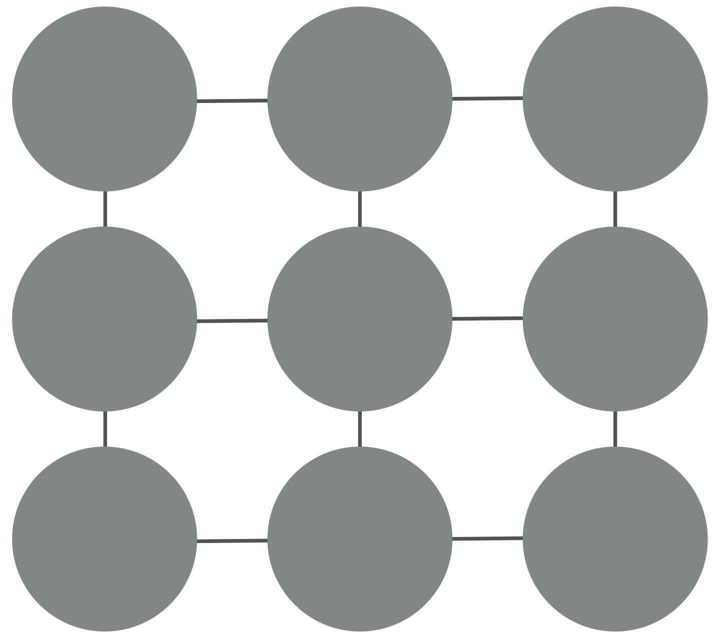
- Sub-pixel matching
  - Fractional translation of reference image
  - Polynomial interpolation of full-pixel data



Bernd Girod: EE398A Image and Video Compression

Stereo Vision: Graphical Model

- Label each pixel with a disparity
  - Maximize agreement between adjacent pixels (“discontinuity cost”)
  - Maximize agreement between left and right pixel (“data cost”)



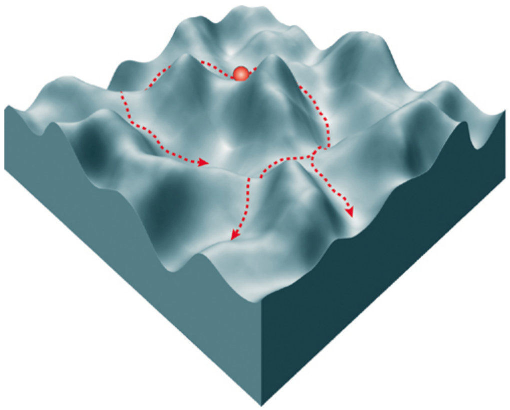
Stereo MRFs

- Could approach as a least-squares problem
  - State: disparity at each node (relax to continuous values)
  - Optimize product of function potentials (or equiv. sum of log of potentials... "log likelihood")

- Very difficult local minimum
  - Least-squares solves a local quadratic problem. If you're not in the right basin, you won't converge.
  - Least squares doesn't work well.

Iterated Conditional Modes

- Simple idea:
  - Consider a single node at a time. (i.e., fix the values of all other nodes)
  - Compute a new disparity for that node that minimizes the log likelihood
    - Only a function of the neighboring factor potentials... cheap!
    - Always reduces global error
- Not much better than least squares--- still get stuck in local minima.
- Need a method that can "look ahead", leaping out of local minima
  - Consider two nodes a=0, b=0. Cost f(a,b) has local minimum at 0,0, but global minimum at 1,1.



Nature Reviews | Molecular Cell Biology

Loopy Belief Propagation

- Each node passes messages to its neighbors:
  - "If you take on value *v*, the cost could be as low as m(v)."
  - All possible values of *v* are evaluated in a best-case sense, allowing the recipient to "teleport" to a new minimum

$$m^t_{p\to q}(f_q) = \min_{f_p}\left(V(f_p, f_q) + D(f_p) + \sum_{s\in N(p)\backslash q} m^{t-1}_{s\to p}(f_p) \right)$$

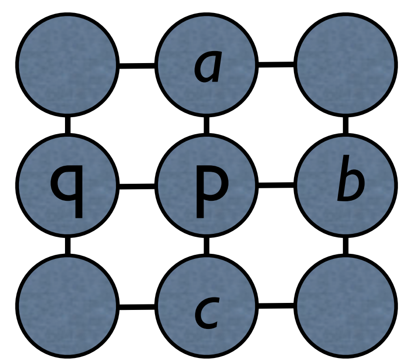
P's message to q specifies a "cost" for each value that q might take.

For every value fq, we'll report the cost for the best-case fp.

Cost of neighbors having different labels

Cost of assigning fp to pixel p

How much do *our* neighbors say it would cost for q to have value p



Isn’t this fun?

- With an almost trivial model, we can destroy block matching problems.
    - You can be competitive with Middlebury top 100 in a couple days’ effort!

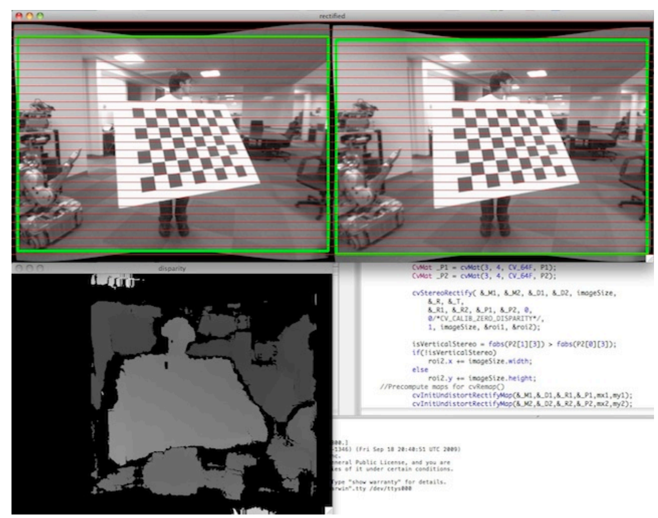
SSD+min-filter [scharstein szeliski], rank = 90

LBP [olson], rank* = 60

The disappointment

- MRF approaches are too slow for robots
  - #1. [Wang/Zheng]: 20s
  - #2. [Yang/Nister]: 62s

- Block matching is fast!
  - (unranked) [Konolige], 10ms



Why is LBP slow?

- Short answer: because computing messages is slow

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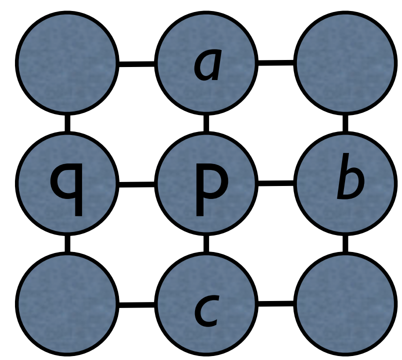
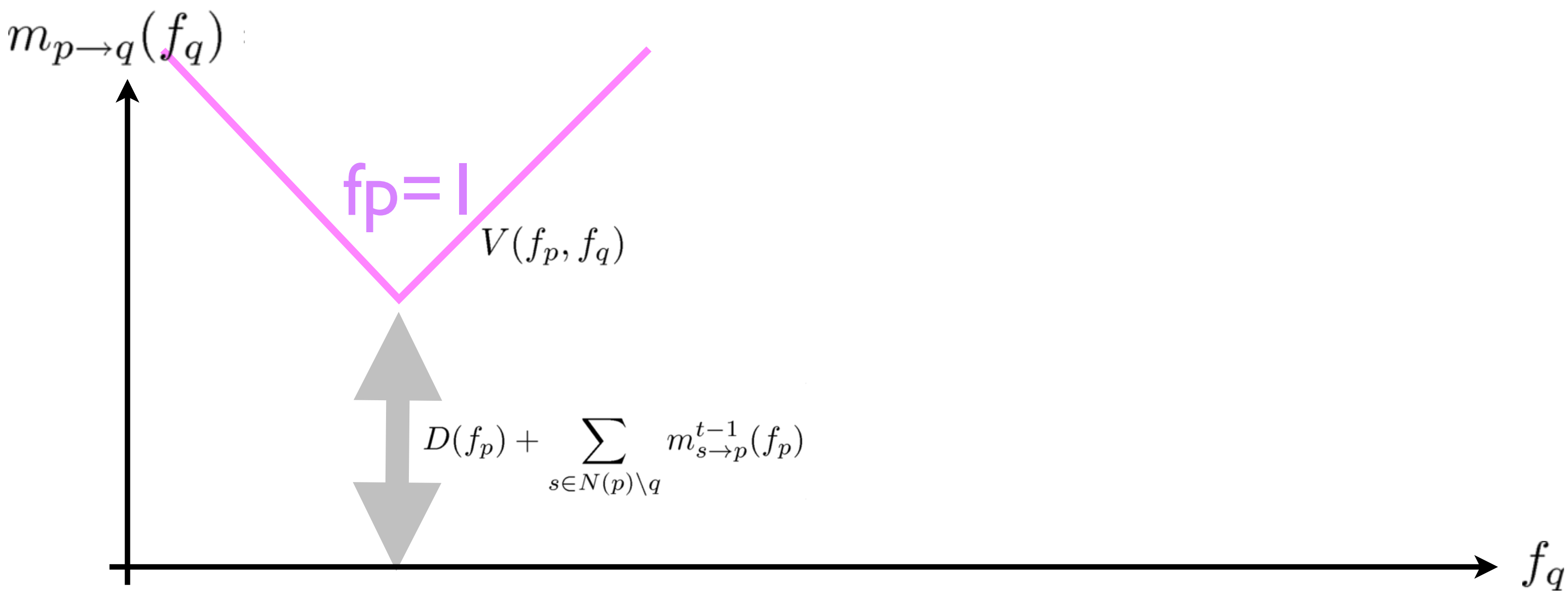



```
for x=1:width
  for y=1:height
    for n=1:neighbors
      for fq=1:labels
        for fp=1:labels
          ...
```

Cool trick #1: Min Convolution

[Felzenswalb/Huttenlocher 2004]

$$m_{p\to q}^{t}(f_q) = \min_{f_p}\left(V(f_p, f_q) + D(f_p) + \sum_{s\in N(p)\backslash q} m_{s\to p}^{t-1}(f_p)\right)$$



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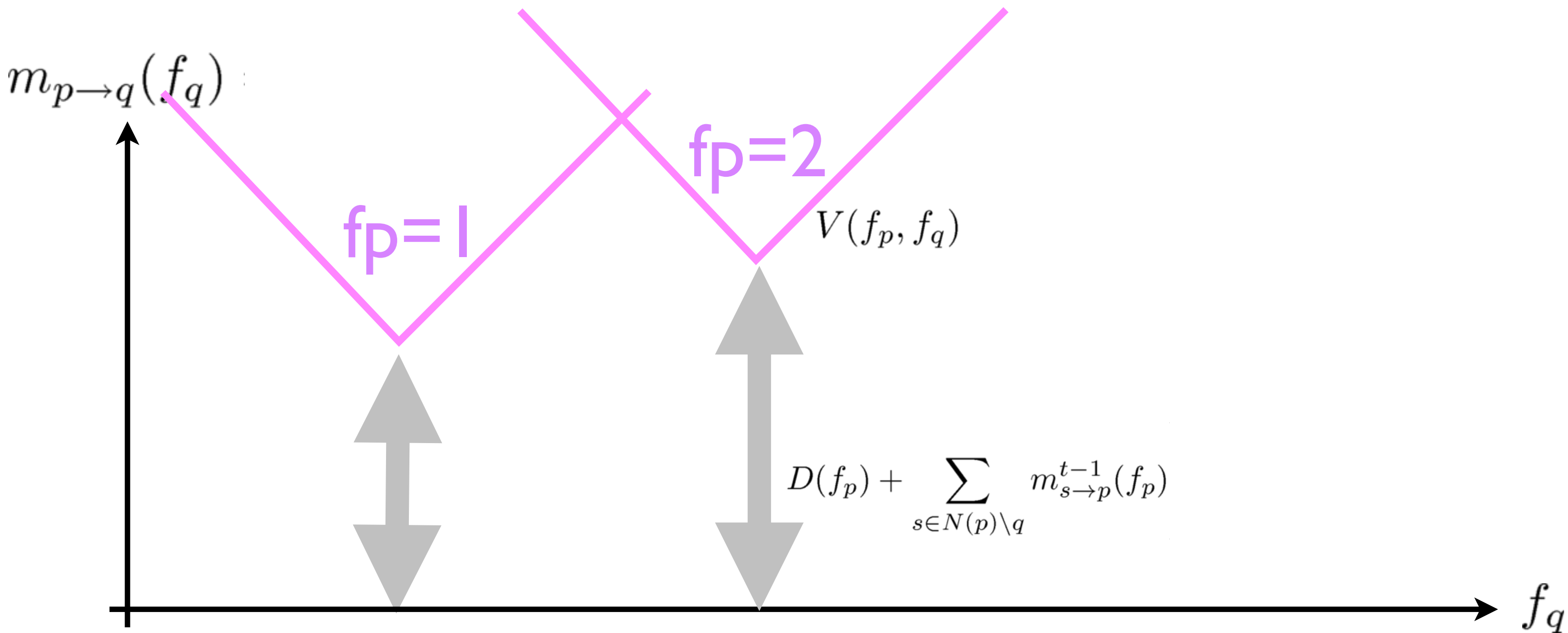

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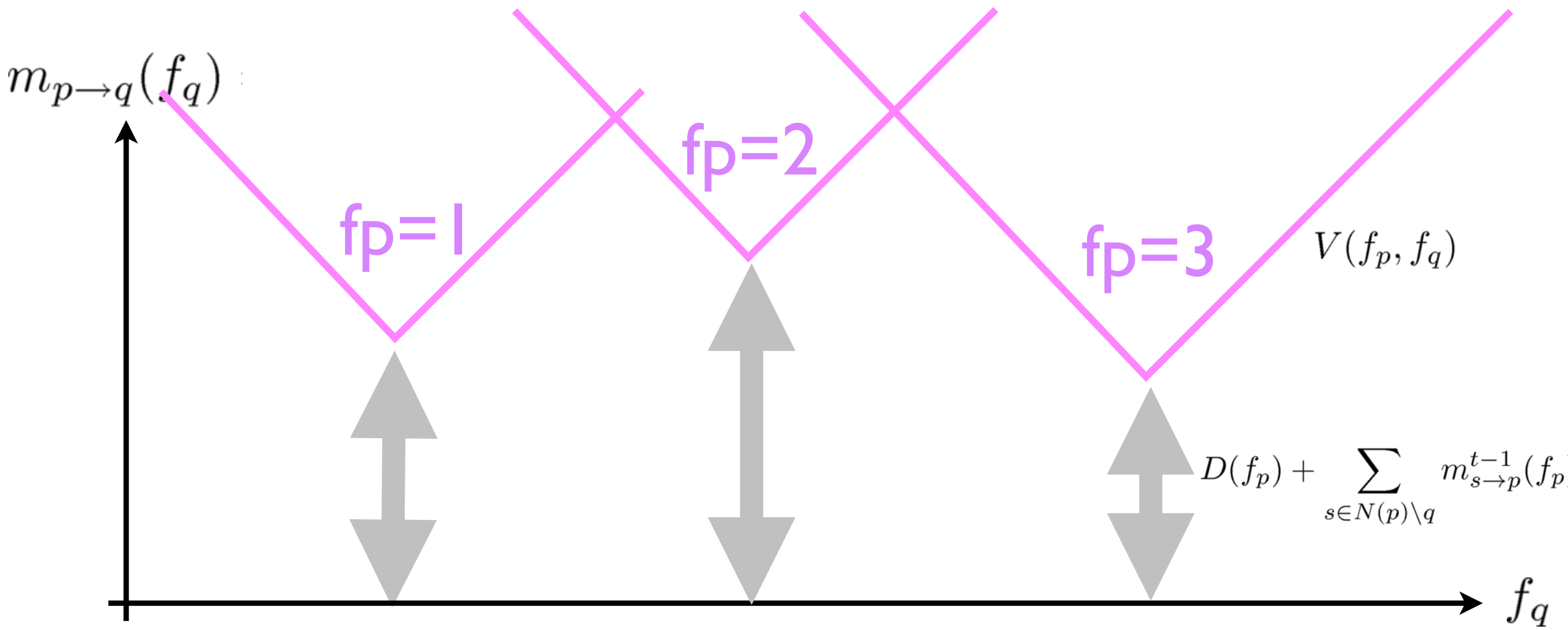

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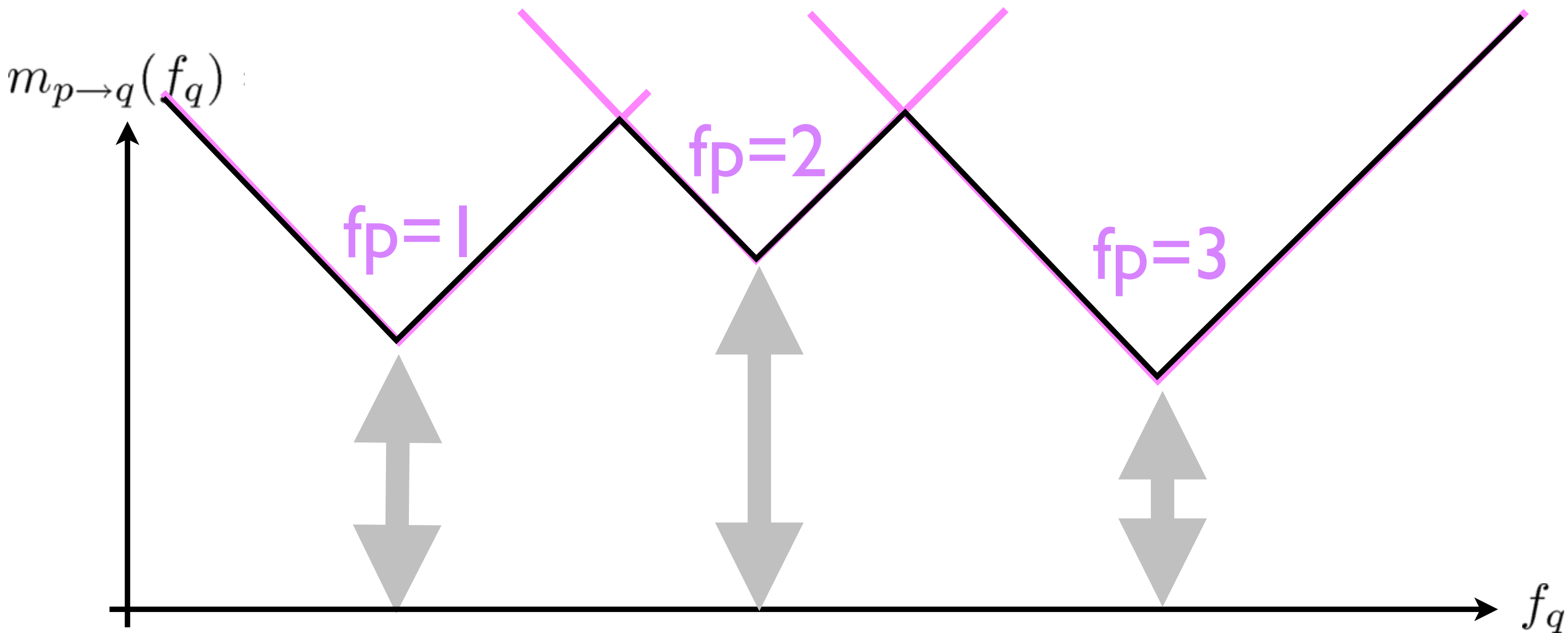
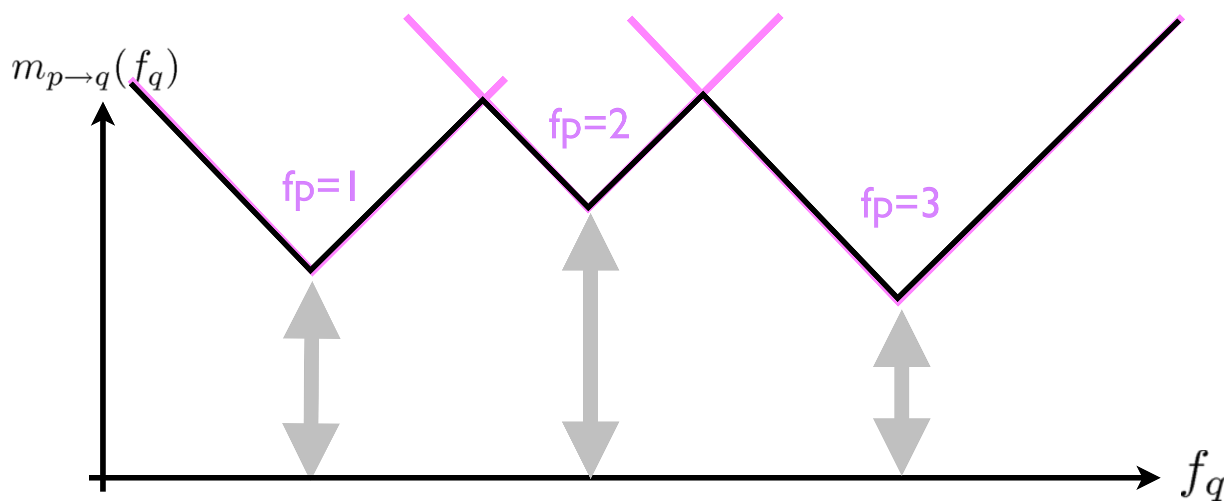
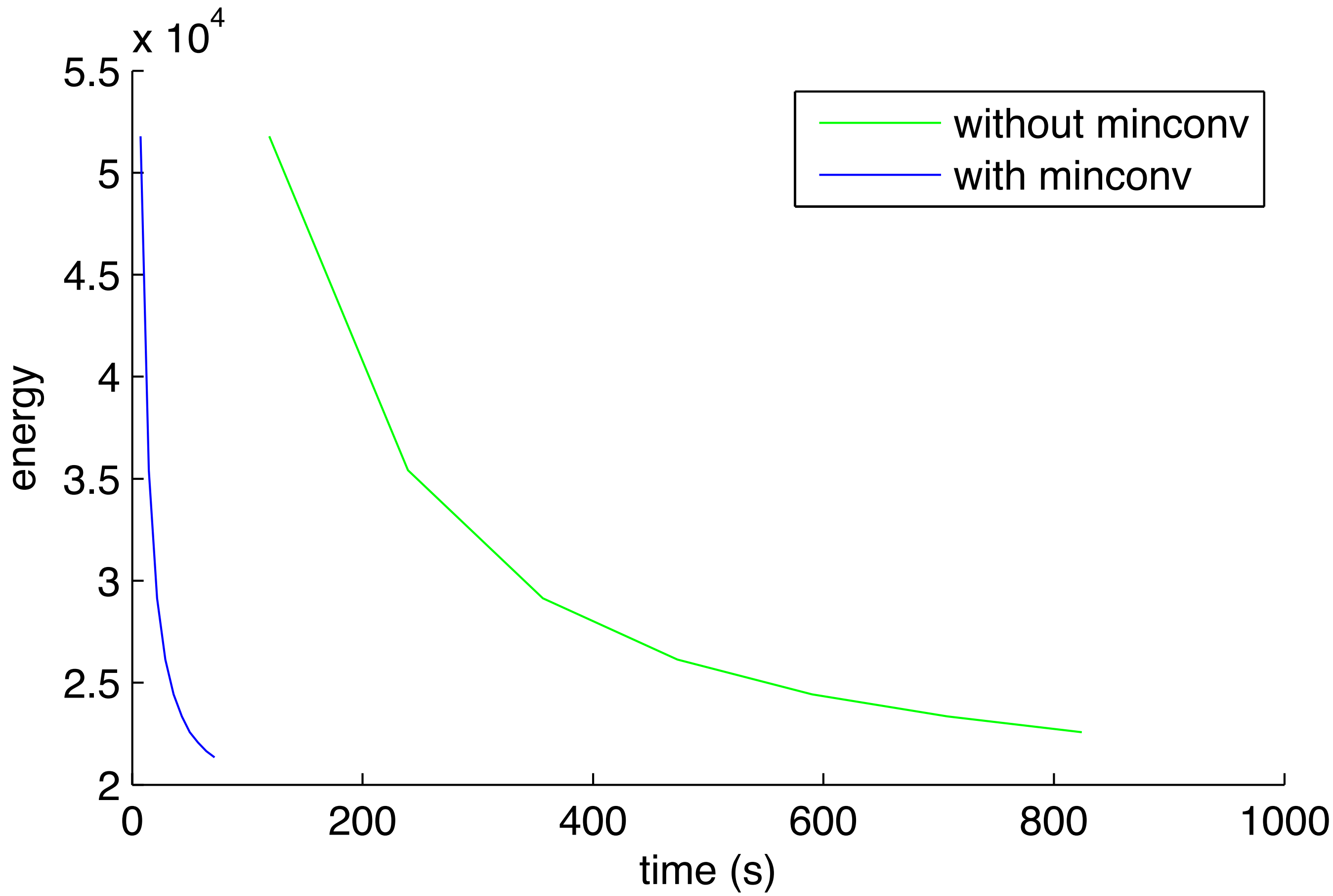


Cool trick #1: Min Convolution

- This is a min-convolution operation
  - Naive implementation is $O(k^2)$
- Efficient algorithms exist for special cases!
  - In linear case, forward-backwards algorithm O(k)
  - Quadratic case also has a method... a bit messier, but still O(k)
- Exact!



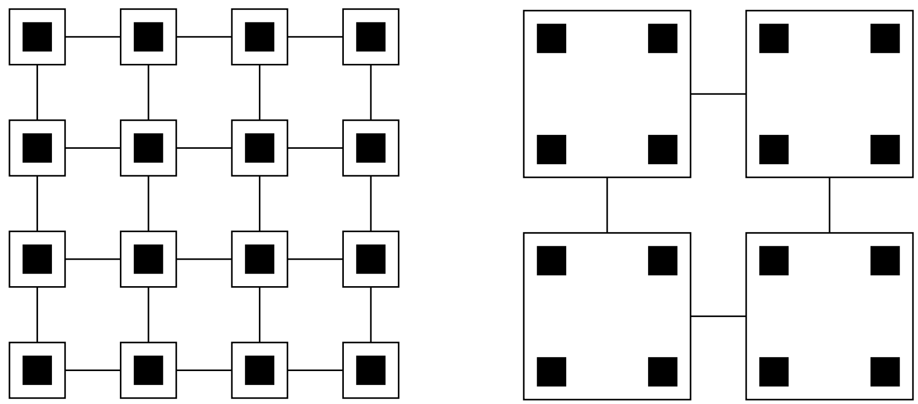
Performance



tsukuba (384 x 288), 16x subpixel, nlabels=256

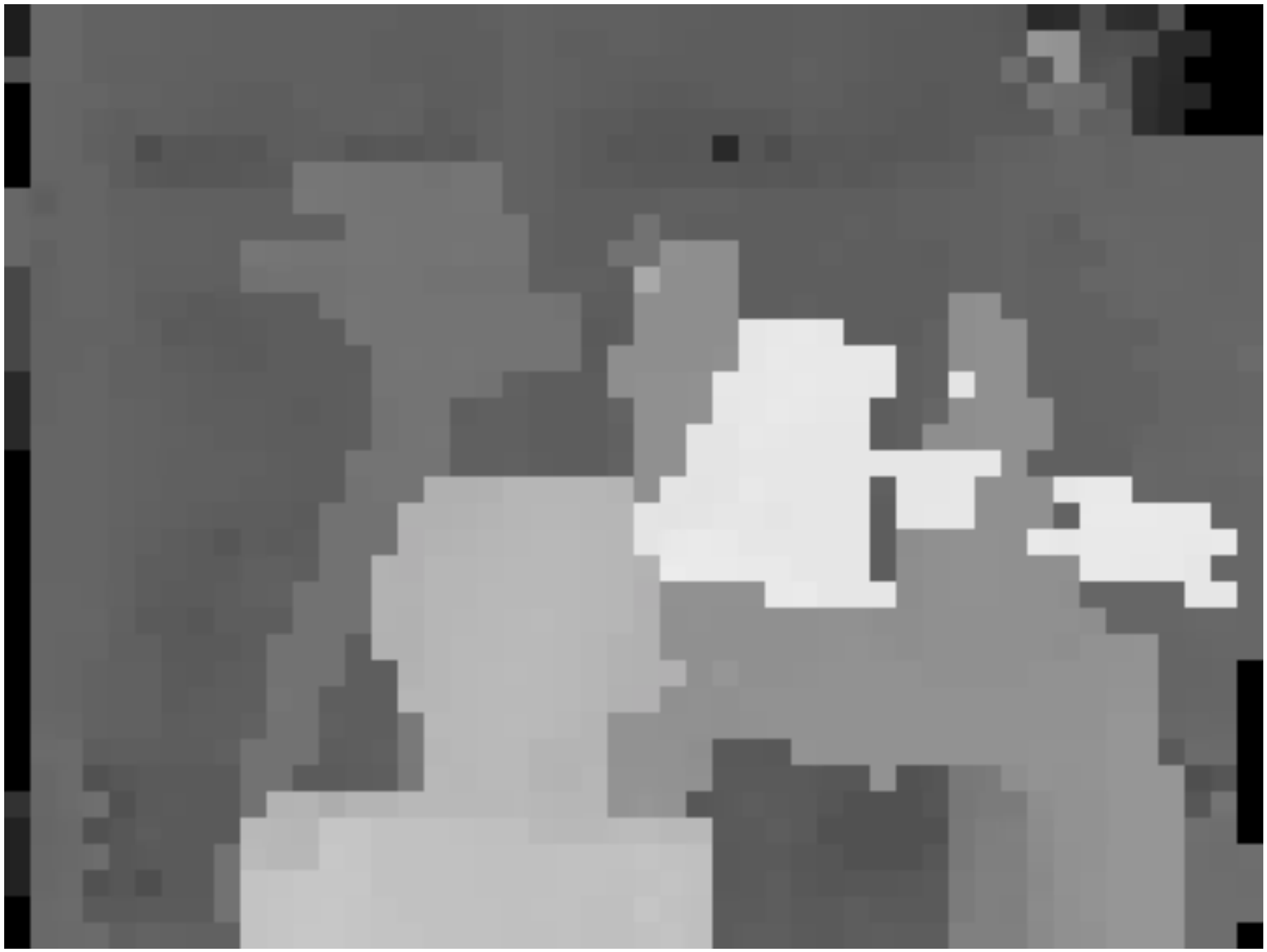
Cool Trick #2: Multi-Grid

[Felzenszwalb/Huttenlocher 2004]



- Advantages:
  - Information spreads rapidly around graph
- Disadvantages:
  - Have to come up with function potentials for other levels of the image pyramid
  - Can lead to artifacts due to the arbitrary alignment of the grid cells

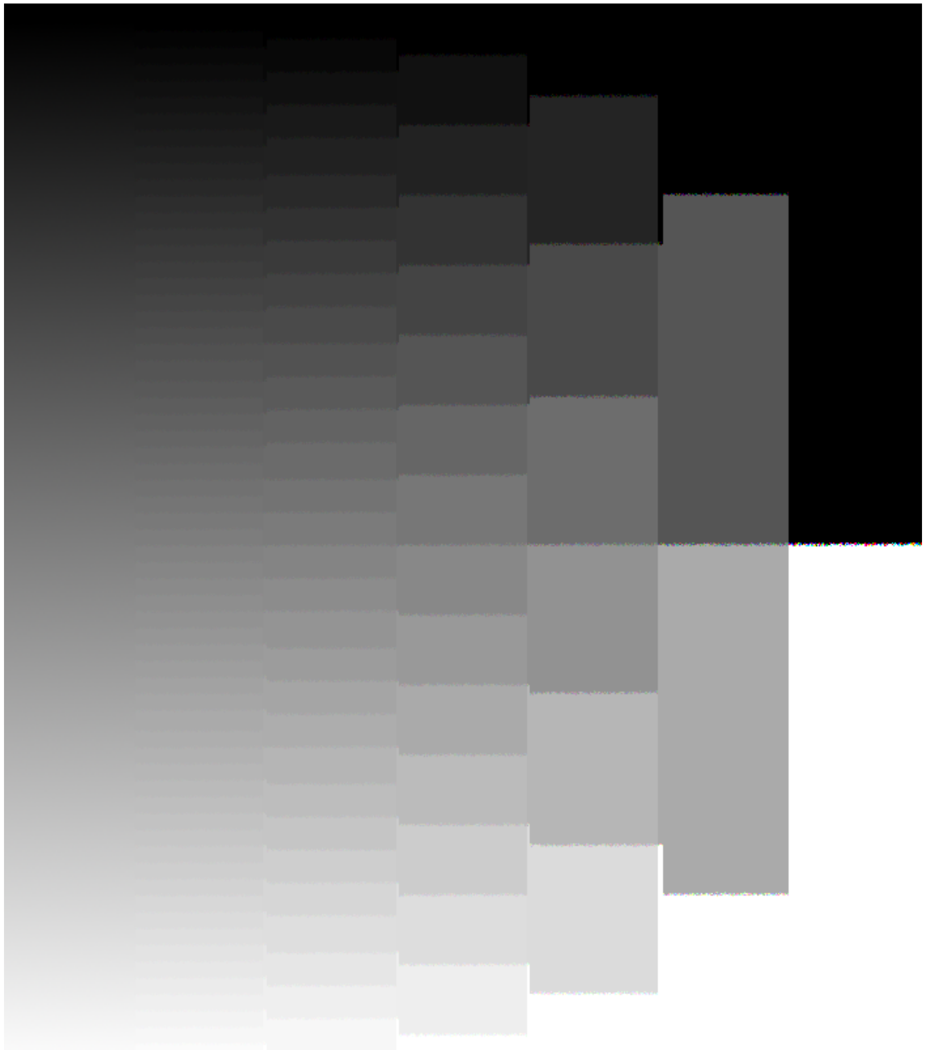
Multi-resolution LBP



Cool Trick #3: Quantized labels

[Strom, Olson 2010*]

- Idea: Start iterating with fewer labels, slowly increase number of labels
- Advantages:
  - Information spreads rapidly around graph
  - No spatial blocking artifacts
- Disadvantage:
  - Not as fast as multi-grid



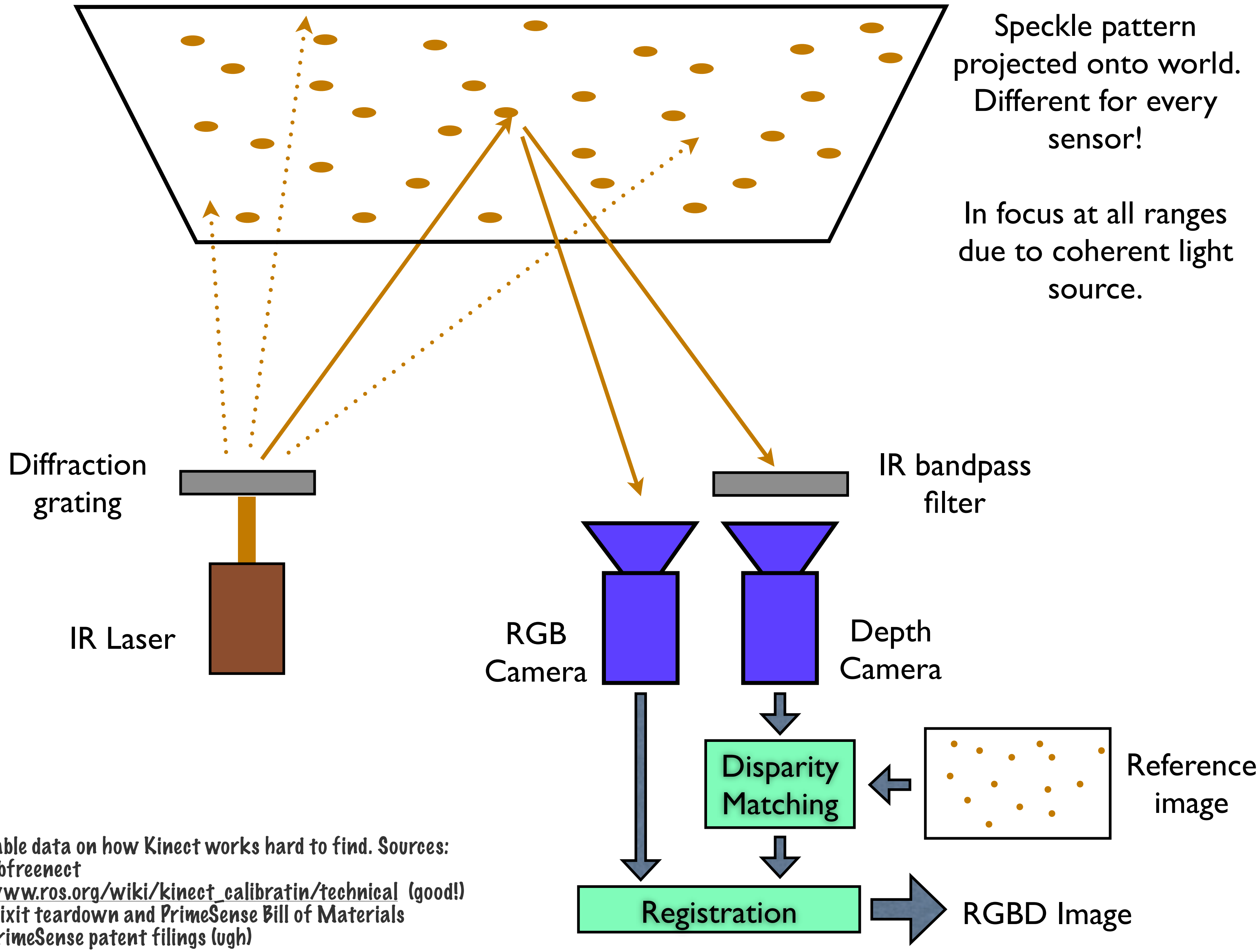
Quantized LBP

PrimeSense/Kinect

- Similar to a stereo camera in concept
    - But replace one camera with a *projector*
    - Second camera detects projected camera.

- Why is this a good idea?
    - It works even when the environment is devoid of distinguishing features (e.g. white walls)
    - Under favorable conditions, very good results

- What are the shortcomings?
    - Brightness of projector limits effectiveness at long ranges and outdoors
    - Power consumption / stealth



reliable data on how Kinect works hard to find. Sources:
-- libfreenect
-- www.ros.org/wiki/kinect_calibratin/technical (good!)
-- iFixit teardown and PrimeSense Bill of Materials
-- PrimeSense patent filings (ugh)

Kinect Particulars

- Produces 640x480 RGBD Image
  - IR Camera is 1280x1024 @ 15Hz
    - Uses 2x2 binning to increase sensitivity and frame rate to 30Hz
    - Monochrome... 16 bit?
- Matching
  - Calibration image stored in device at factory
  - Repeatedly "streamed" in sync with acquired IR image, fed into matching engine
  - Block based matching
    - 9x9 blocks
    - 1/8 pixel interpolation
    - 64 (?) pixel search range (Kinect returns 11 bit range values)
- Registration
  - Corrects for parallax of RGB and depth sensor. (Could be eliminated by using a single sensor with both RGB and IR pixels in an RGBI "Bayer" pattern).