High performance tracking

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Overview of tracking

- Trackers have complementary properties
  - Robust, drift free, accurate, efficient, etc. . .
- Failures are also complementary
  - Fragile, drift, inaccurate, etc. . .
- Combining trackers combines strengths

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  - Robust, drift free, accurate, efficient, etc…
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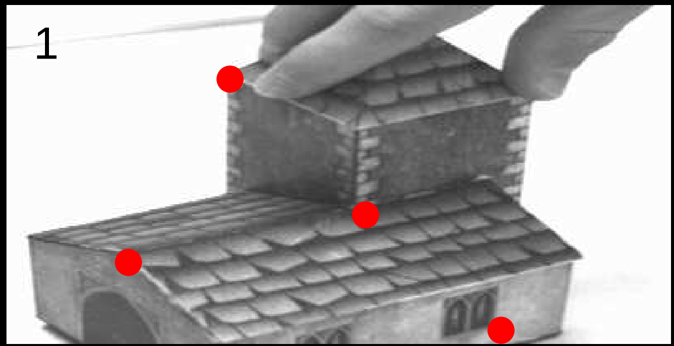
  - Fragile, drift, inaccurate, etc…
- Combining trackers combines strengths
- 6 DOF (degrees of freedom) tracking (position and orientation in 3D)
- Robust feature based tracker
  - New feature detector
- Edge based tracker
- Combining the trackers
  - Much better

Point based tracking

Point based tracking

Detect features



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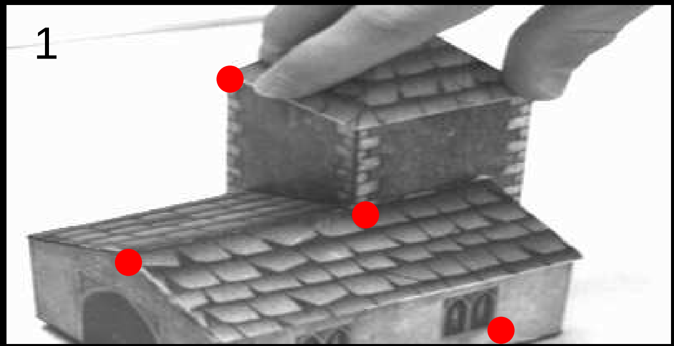
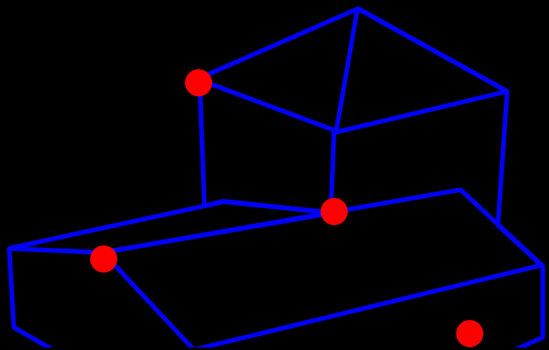


2



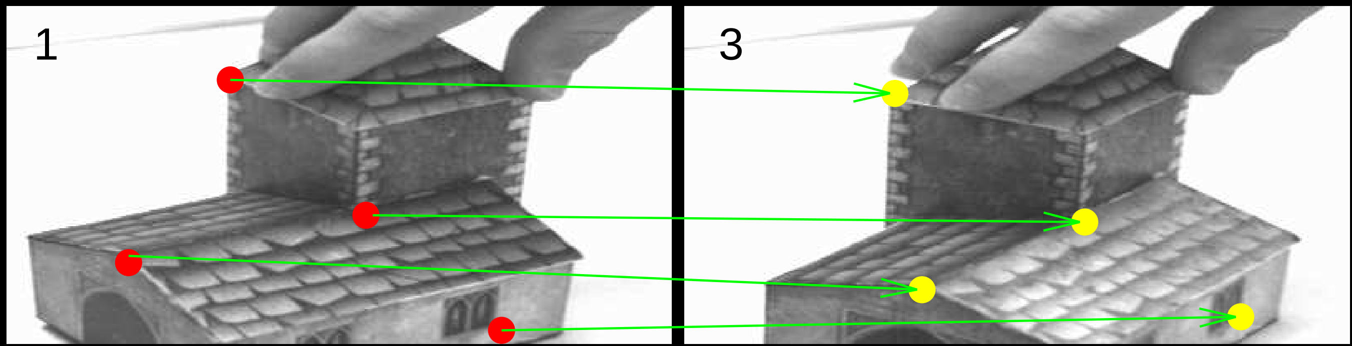
Project features on to model.

Drift occurs here

Point based tracking

Detect features

Detect and match features in next frame



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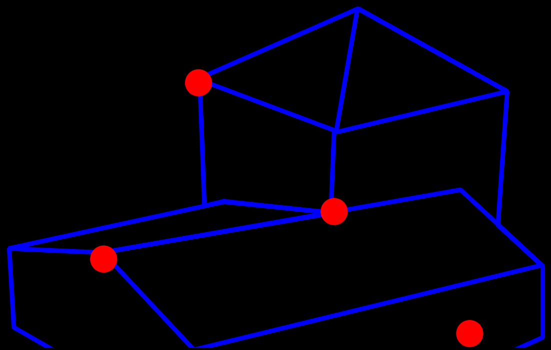

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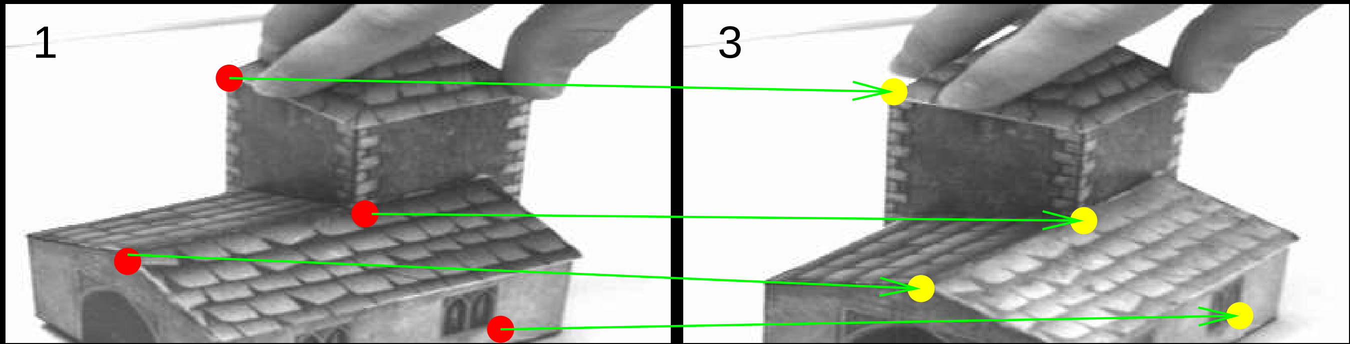

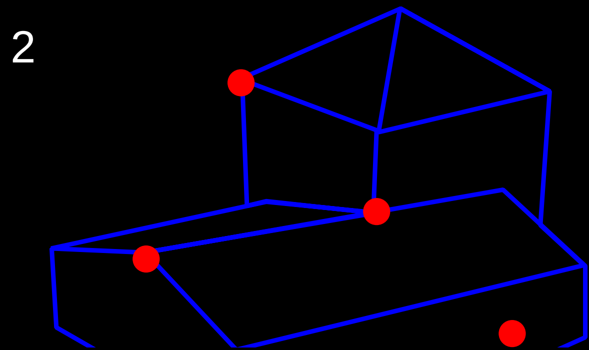

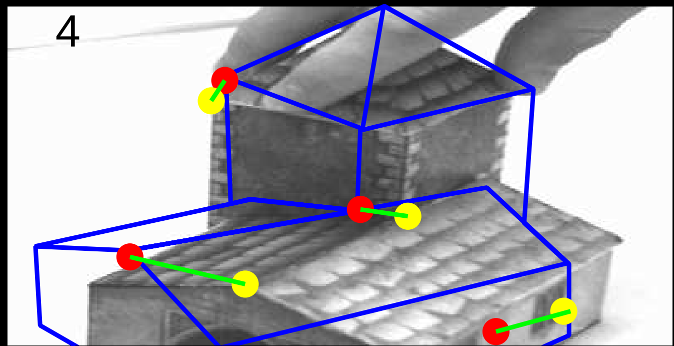

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Alter pose to minimize reprojection error

Point based tracking

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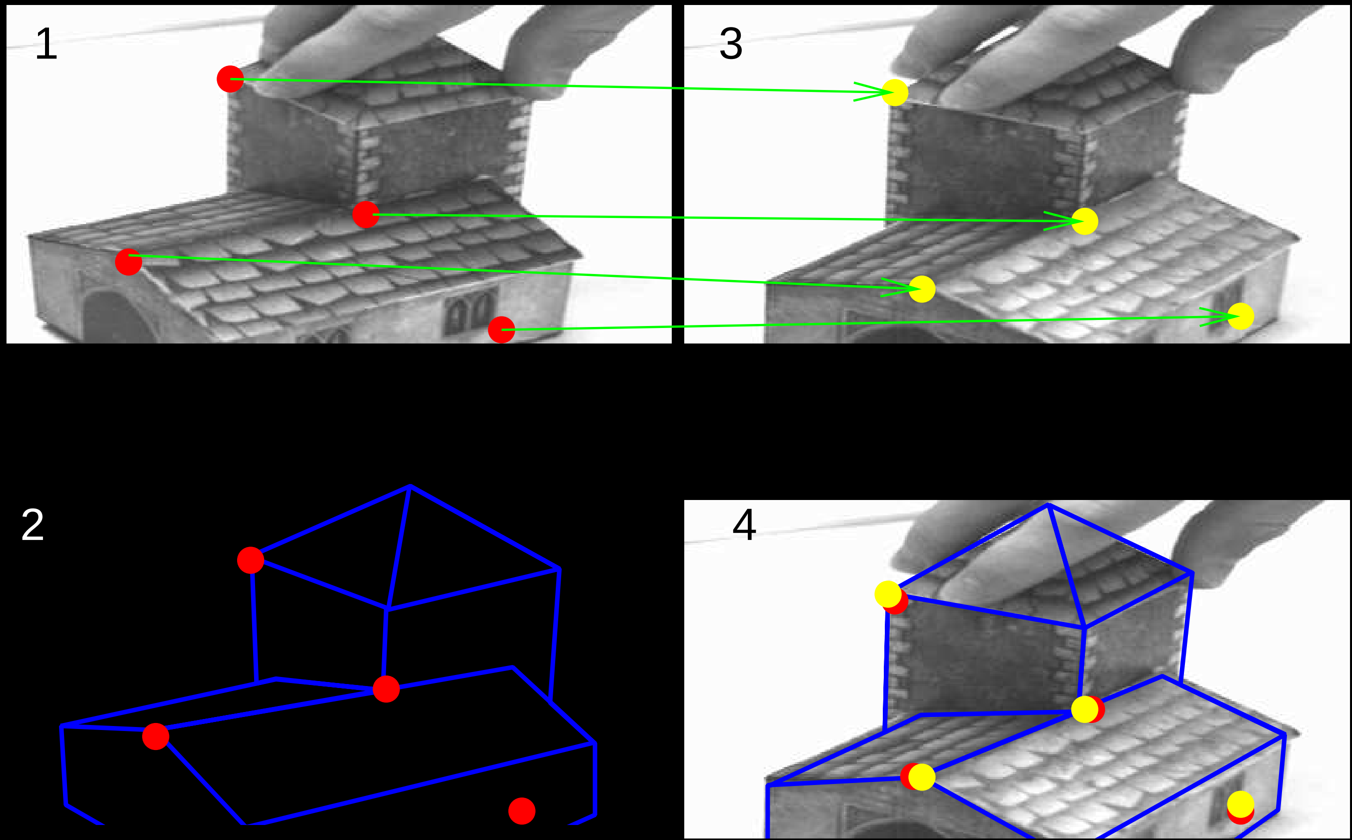

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Alter pose to minimize reprojection error

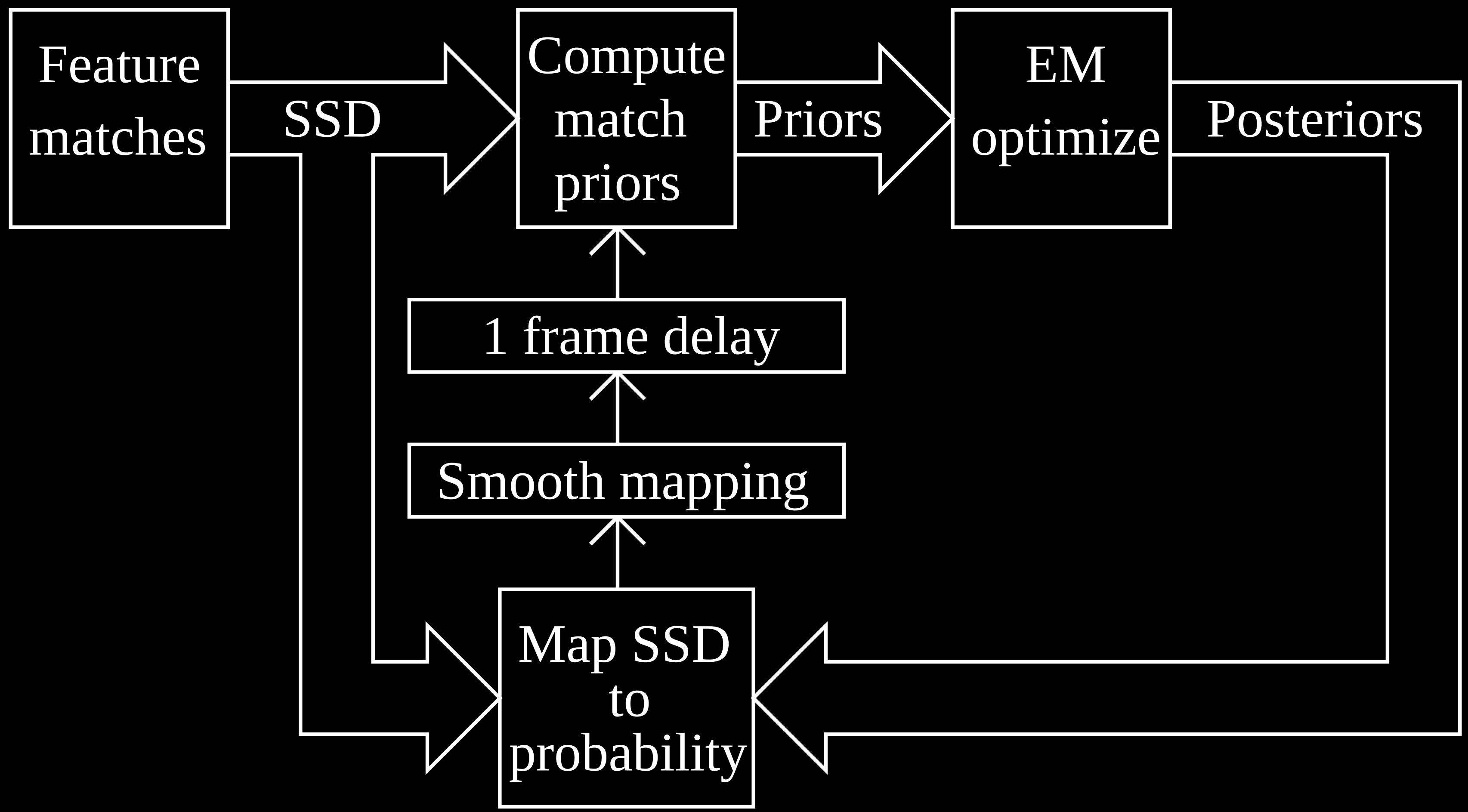
Position optimization

- Sometimes $> 90\%$ outliers (even with SIFT!)
  - Robust optimize required
- Use EM
  - Mixture model is
    Gaussian (inliers) + uniform (outliers)

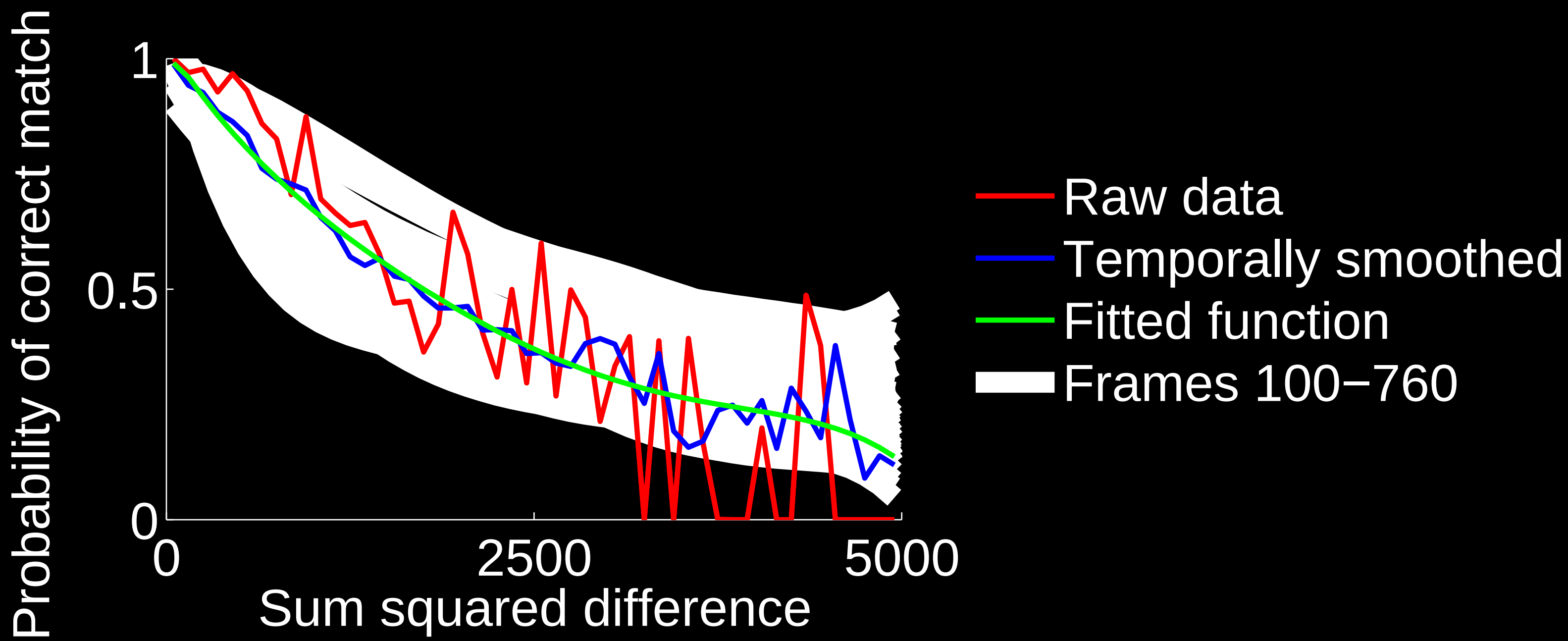
1. Compute $P(\text{match} \in \text{inliers} \mid \mu, \text{mixture model})$
2. Recompute μ (using Gauss-Newton)
3. Recompute mixture model

- SSD has some information about inlier probability
  - If only we knew the relationship...

Matching prior



Matching prior



- EM provides probability that a match is correct
- SSD for each match is known
- Compute smooth function mapping SSD to probability
- Use function to compute priors for each match next frame

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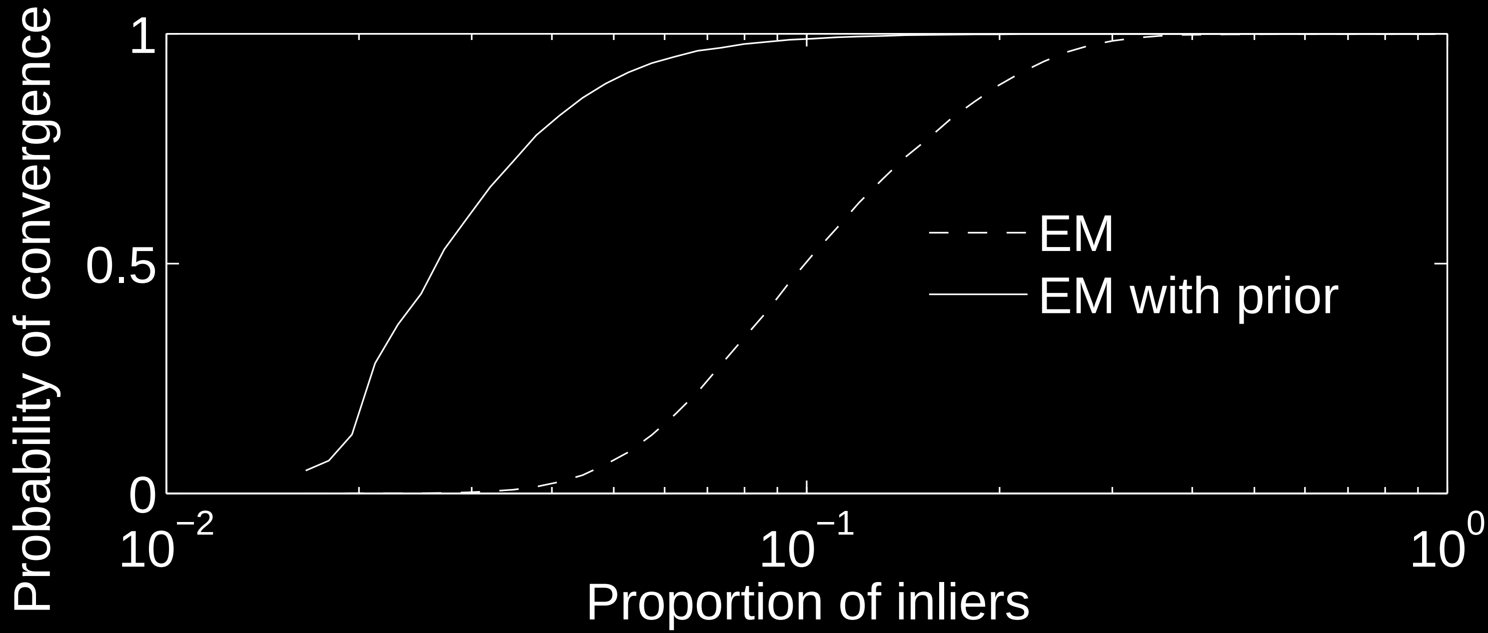

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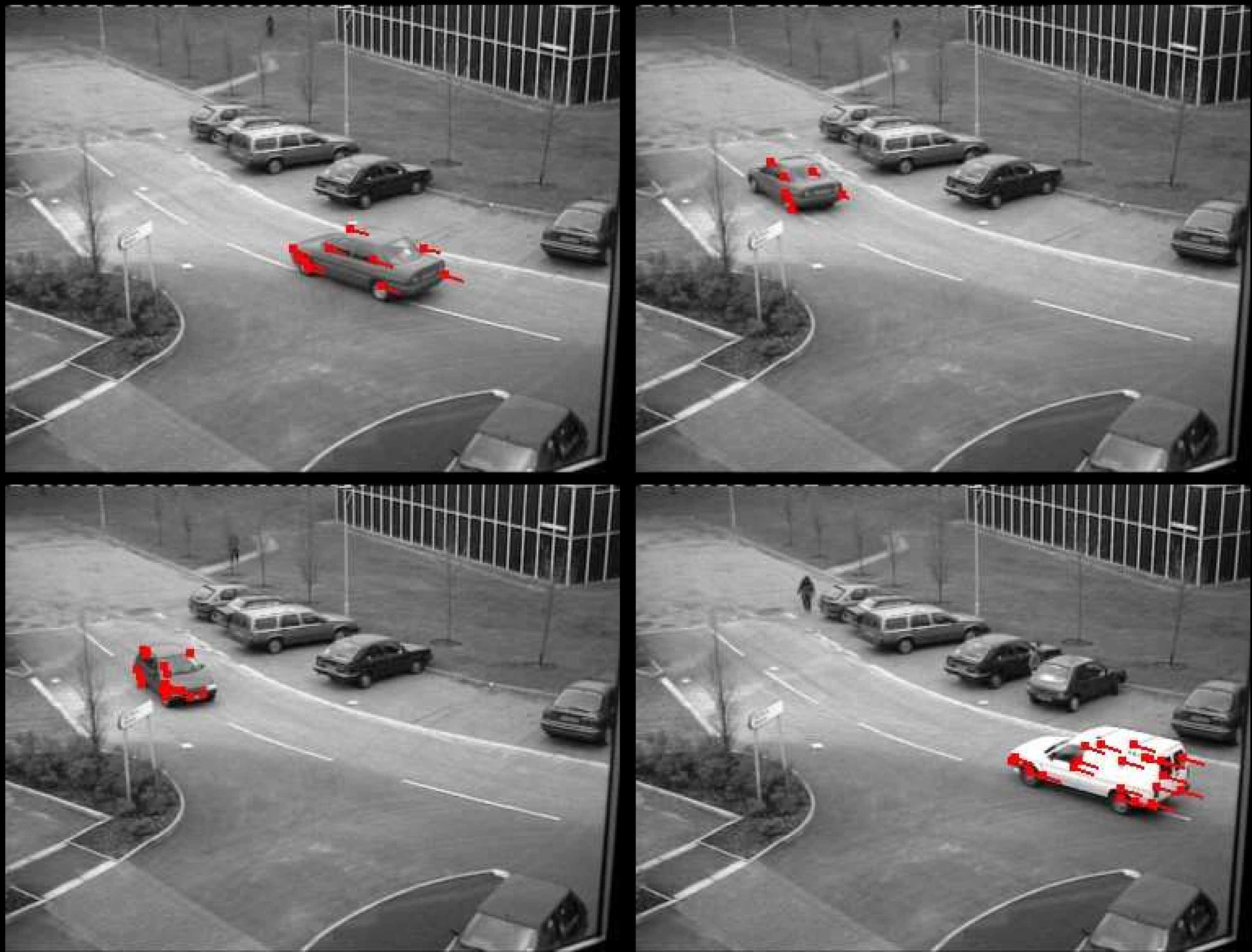
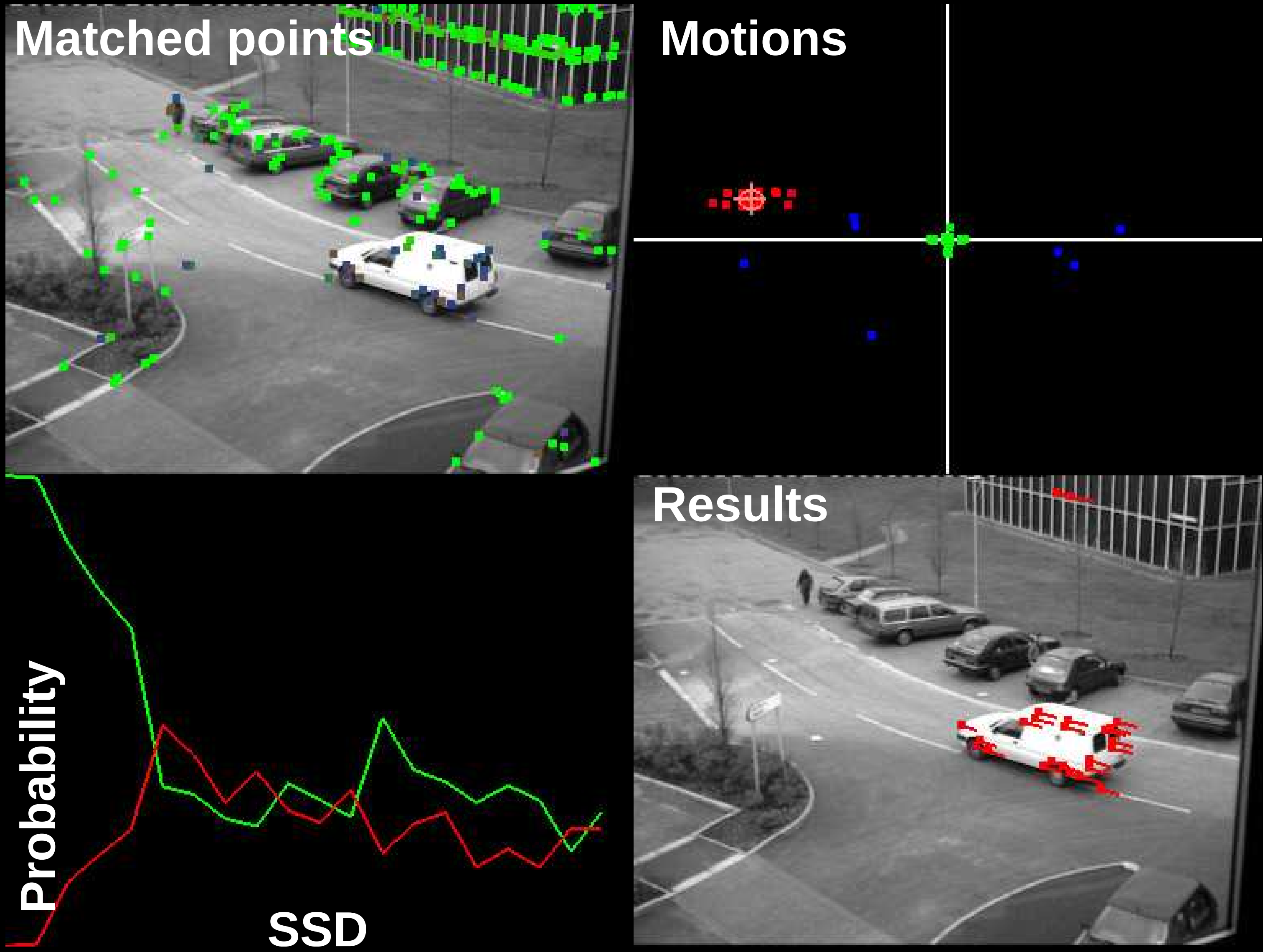
2D example - Motion tracking



Analysis

- Cel style animation - foreground and background can appear anywhere
- 3 kinds of match
  - Background (small offset)
  - Motion (many points with coherent offset)
  - Mismatch (ransom offset)
- Model offsets as GMM
- Compute $P(\text{match} \in \text{background} \mid \text{SSD})$, $P(\text{match} \in \text{motion} \mid \text{SSD})$, $P(\text{match} \in \text{mismatches} \mid \text{SSD})$

Video



2D example

- Not really tracking!
- Very simplistic:
  - No model of car
  - No motion model
  - No background model
  - Exactly one motion per frame modelled
- ...but it still works
- Possible improvements
  - Better modelling
  - Combining with other trackers

Back to 6 DOF tracking...

Measurement Properties

- Point based tracking
  - Requires
    - 3D point cloud
  - Provides
    - Robust differential measurements...
    - ...with approximately Gaussian posterior

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- Point based tracking
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  - Provides
    - Robust differential measurements...
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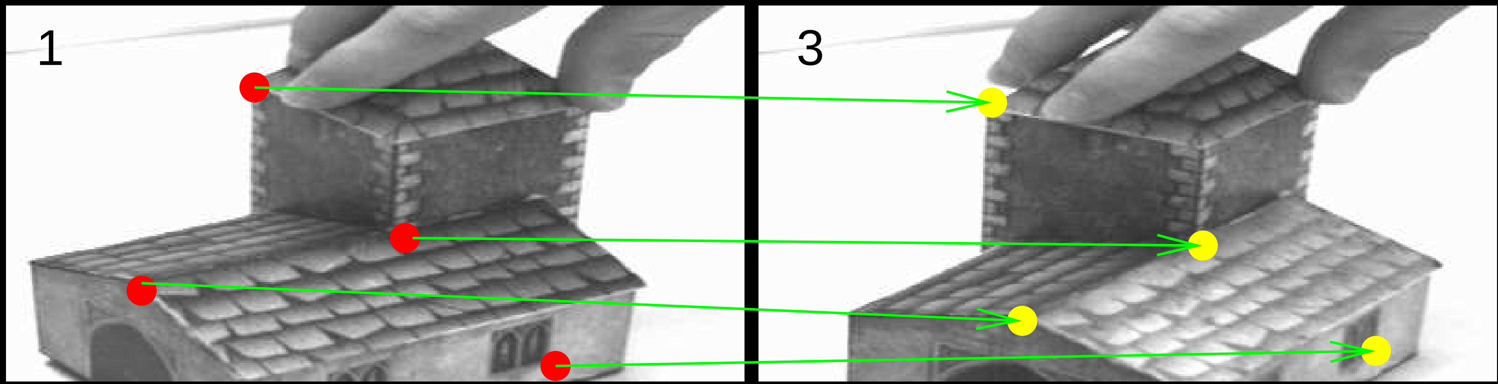
- Relies on full frame matching

Robust differential measurements

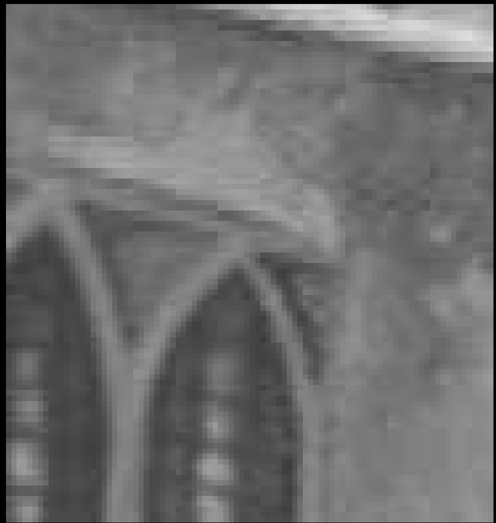
Detect and match features in next frame



- Full frame matching makes it robust to large motions
- Detecting features in a whole frame is slow
- Matching can be $O(n^2)$
- Solution to detection is...

FAST feature detection

The FAST feature detector



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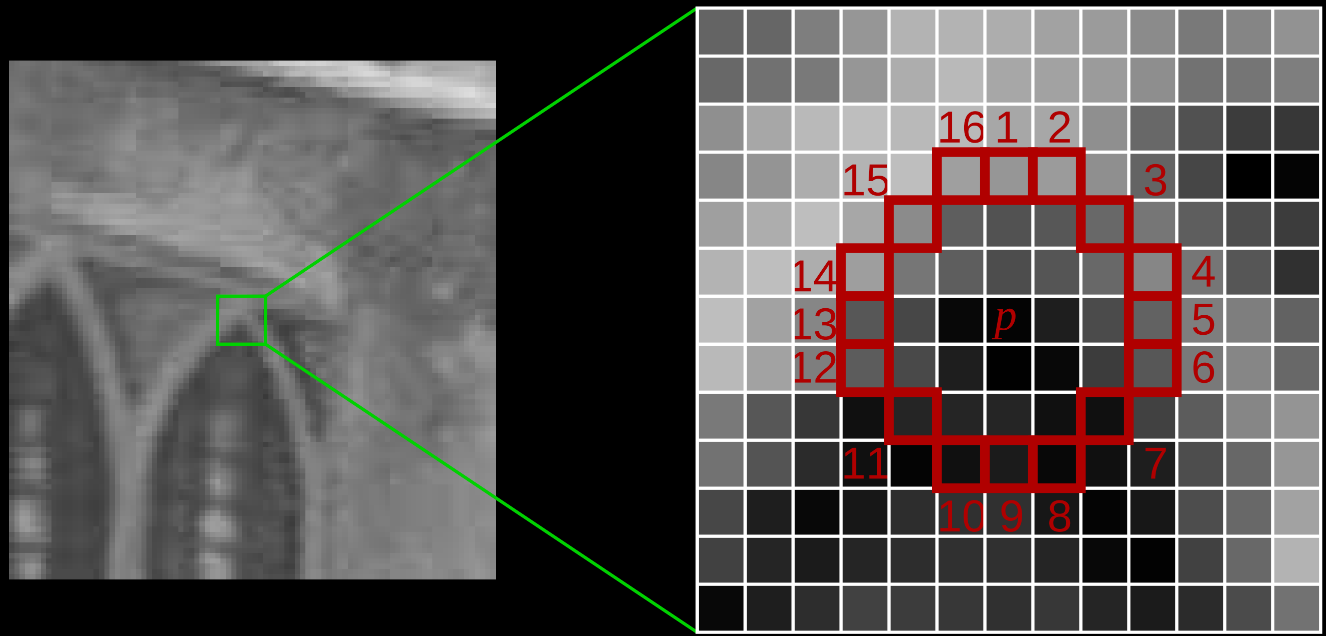

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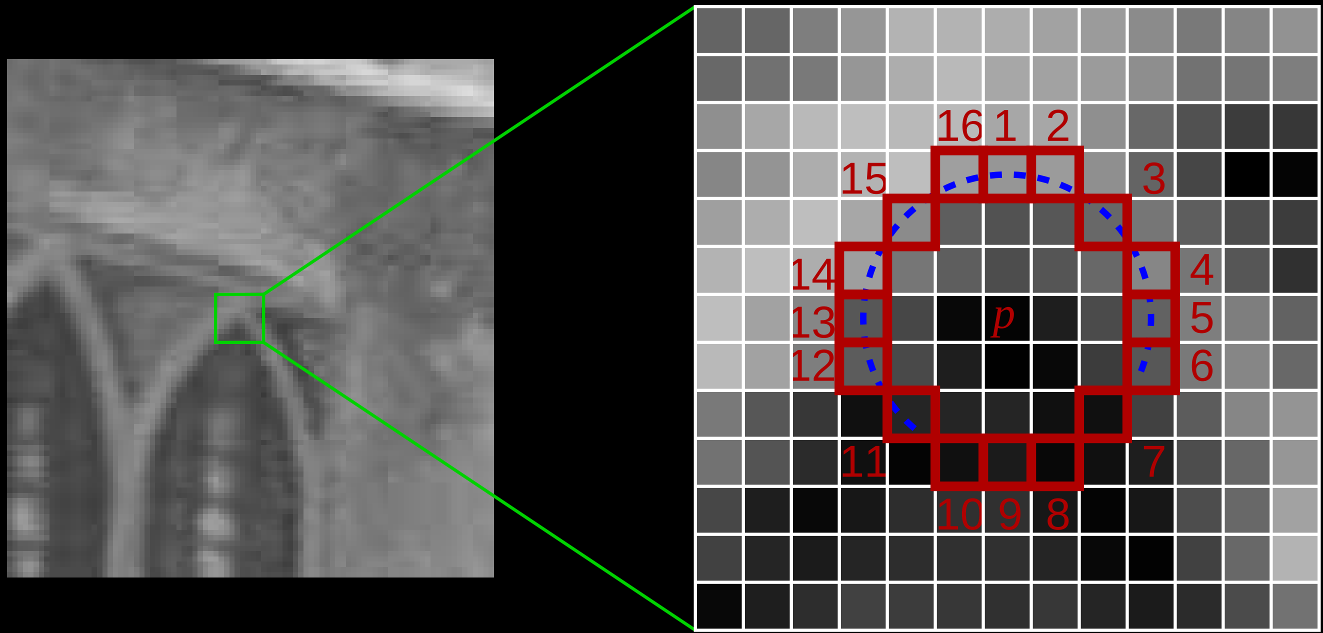
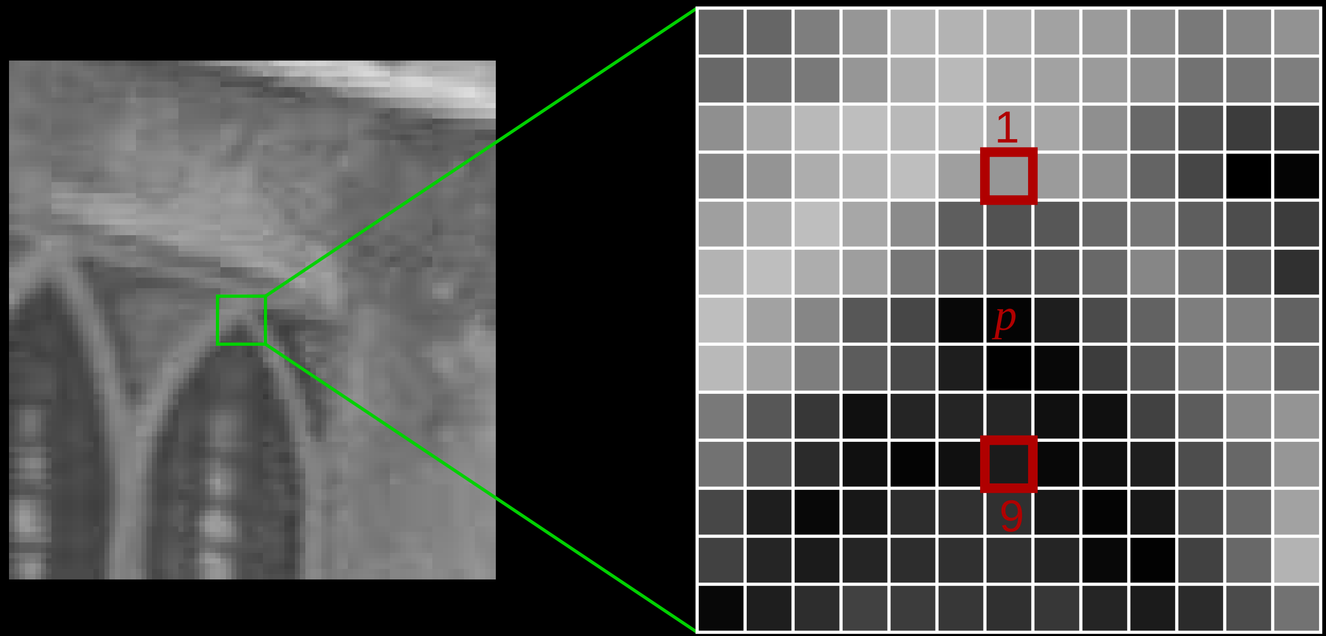


- $\geq$ 12 contiguous pixels brighter than p+*threshold*

The FAST feature detector



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- Rapid rejection by testing 1, 9

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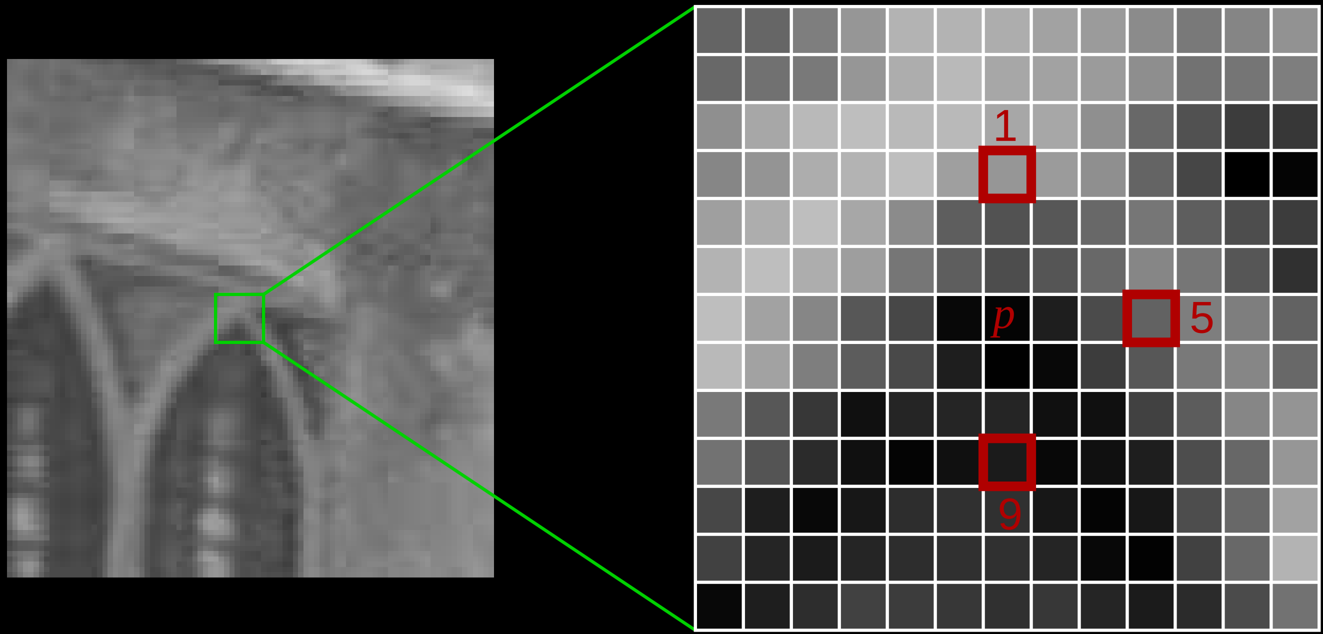

- $\geq$ 12 contiguous pixels brighter than *p+threshold*
- Rapid rejection by testing 1, 9, 5

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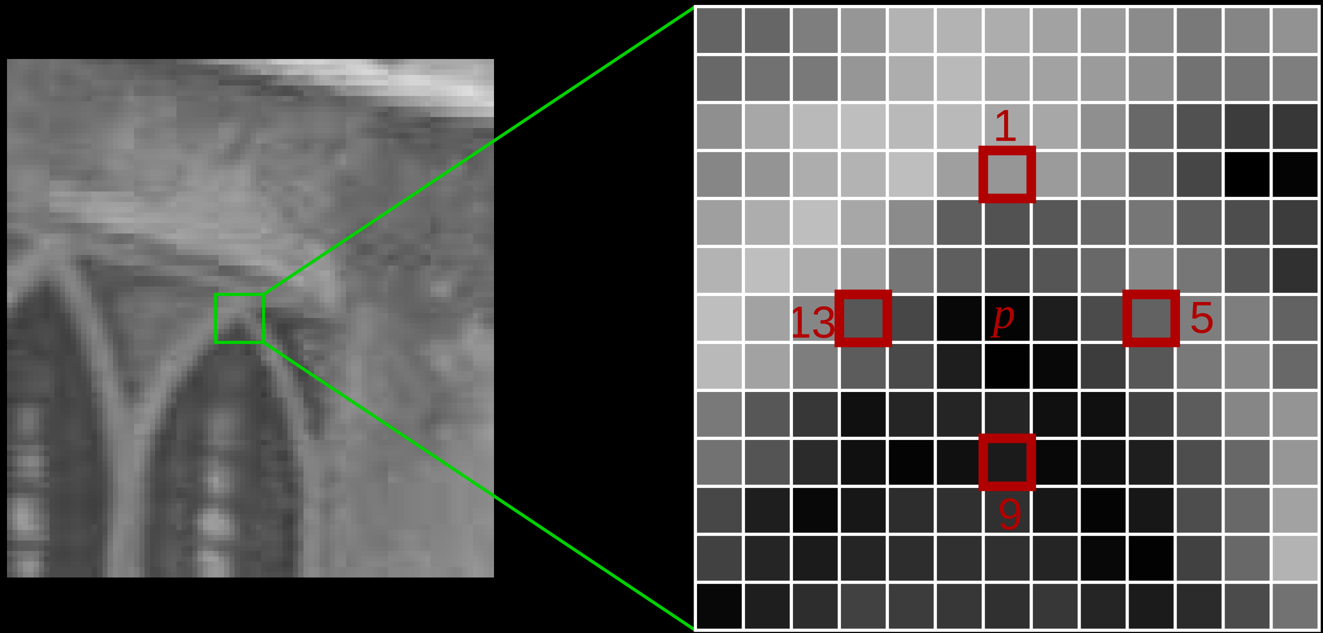
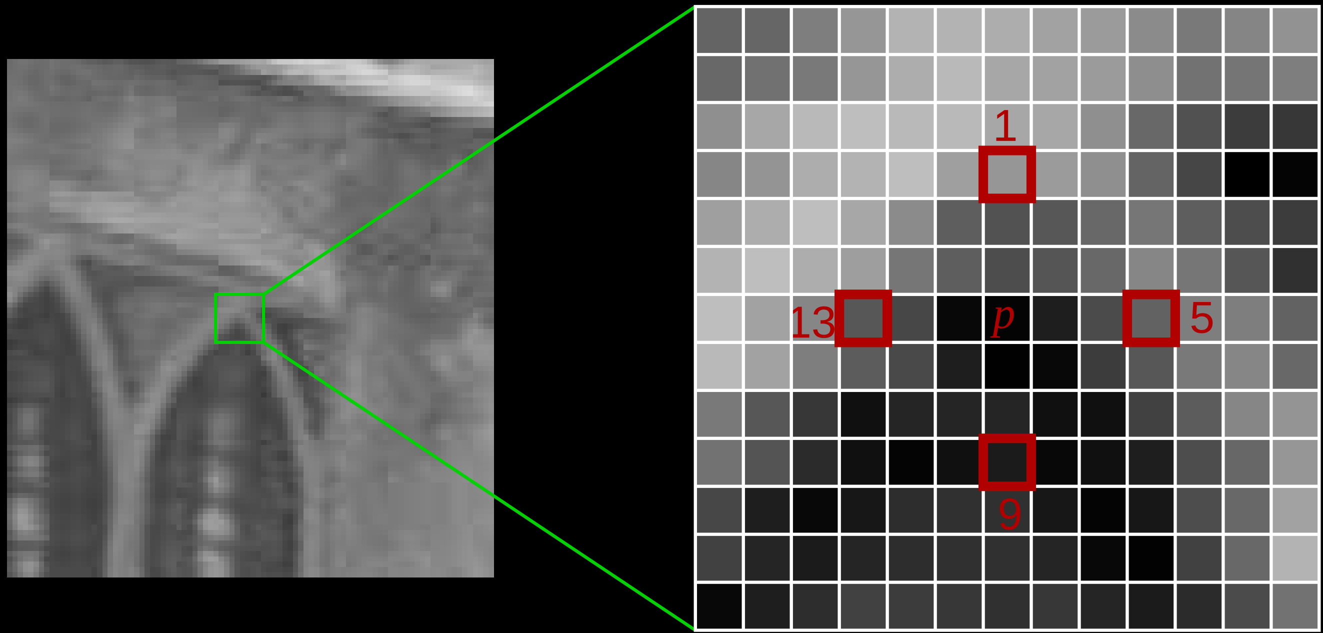


- $\geq$ 12 contiguous pixels brighter than *p+threshold*
- Rapid rejection by testing 1, 9, 5 then 13

The FAST feature detector



- $\geq$ 12 contiguous pixels brighter than *p+threshold*
- Rapid rejection by testing 1, 9, 5 then 13
- 1.59ms (Opteron 2.6GHz) - 8% of available CPU time
- Source code available
- `http://savannah.nongnu.org/projects/libcvd`

Problems

- Corners are clustered together
  - Use non maximal suppression

$$V = \max \begin{cases} \sum(\text{pixel values} - p) \text{ if } (\text{value} - p) > t \\ \sum(p - \text{pixel values}) \text{ if } (p - \text{value}) > t \end{cases}$$

  - Bias bigger differences over more points

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- Choice of high speed test is not optimal
- Results of test are thrown away

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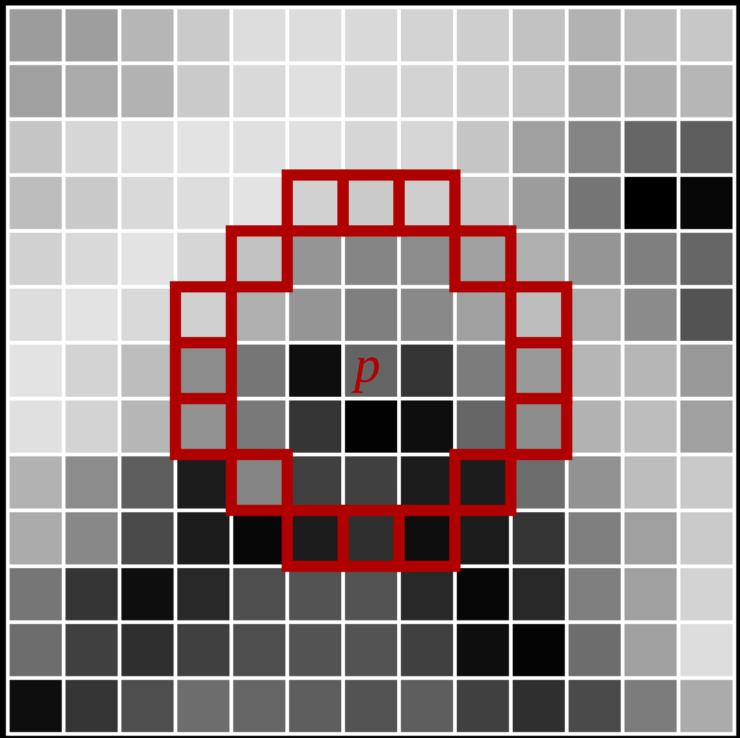
  - Bias bigger differences over more points
- High speed test does not generalize well to $n < 12$
- Choice of high speed test is not optimal
- Results of test are thrown away
- Learn question ordering

Analysis of pixels



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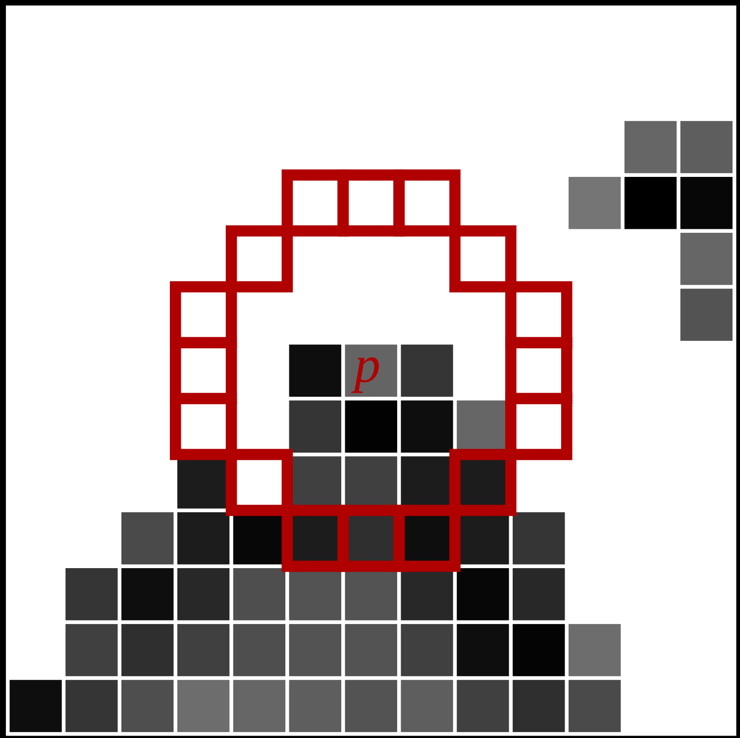
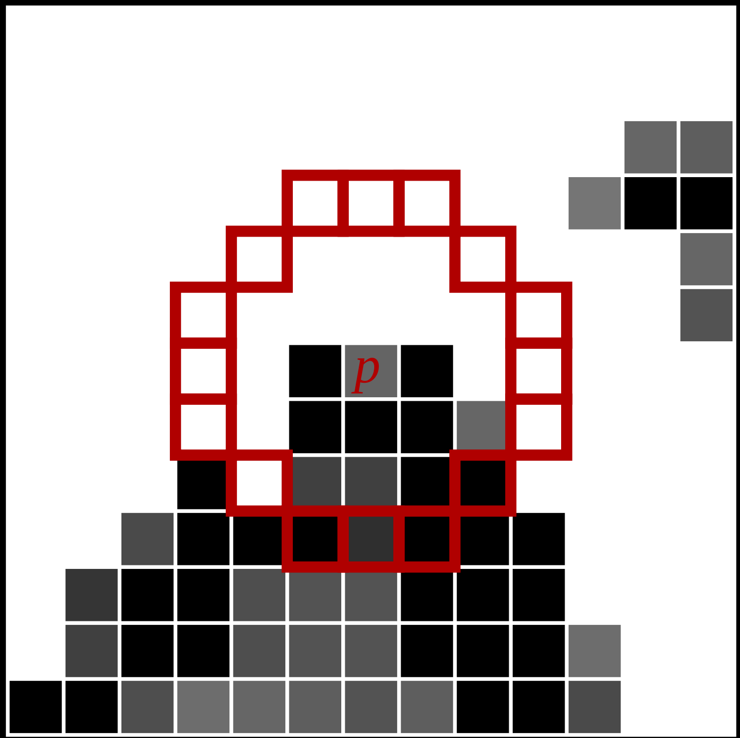


- Pixels are either:
    - Much brighter

Analysis of pixels



- Pixels are either:
  - Much brighter
  - Much darker

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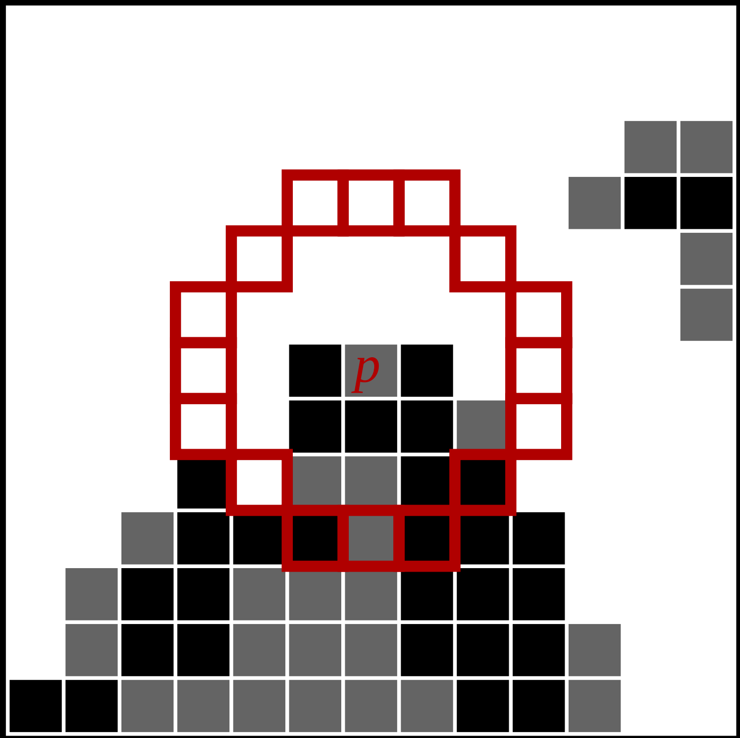
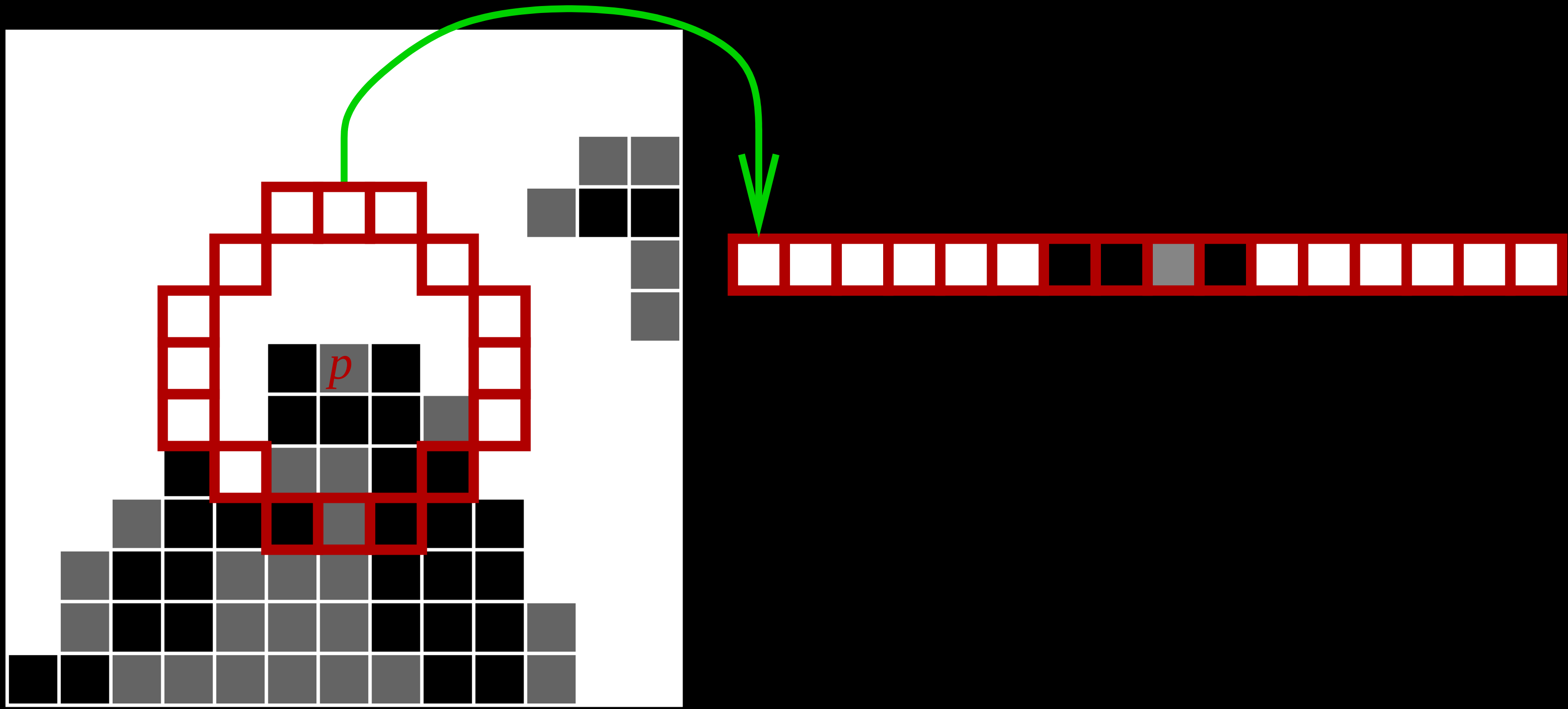


- Pixels are either:
  - Much brighter
  - Much darker
  - Similar

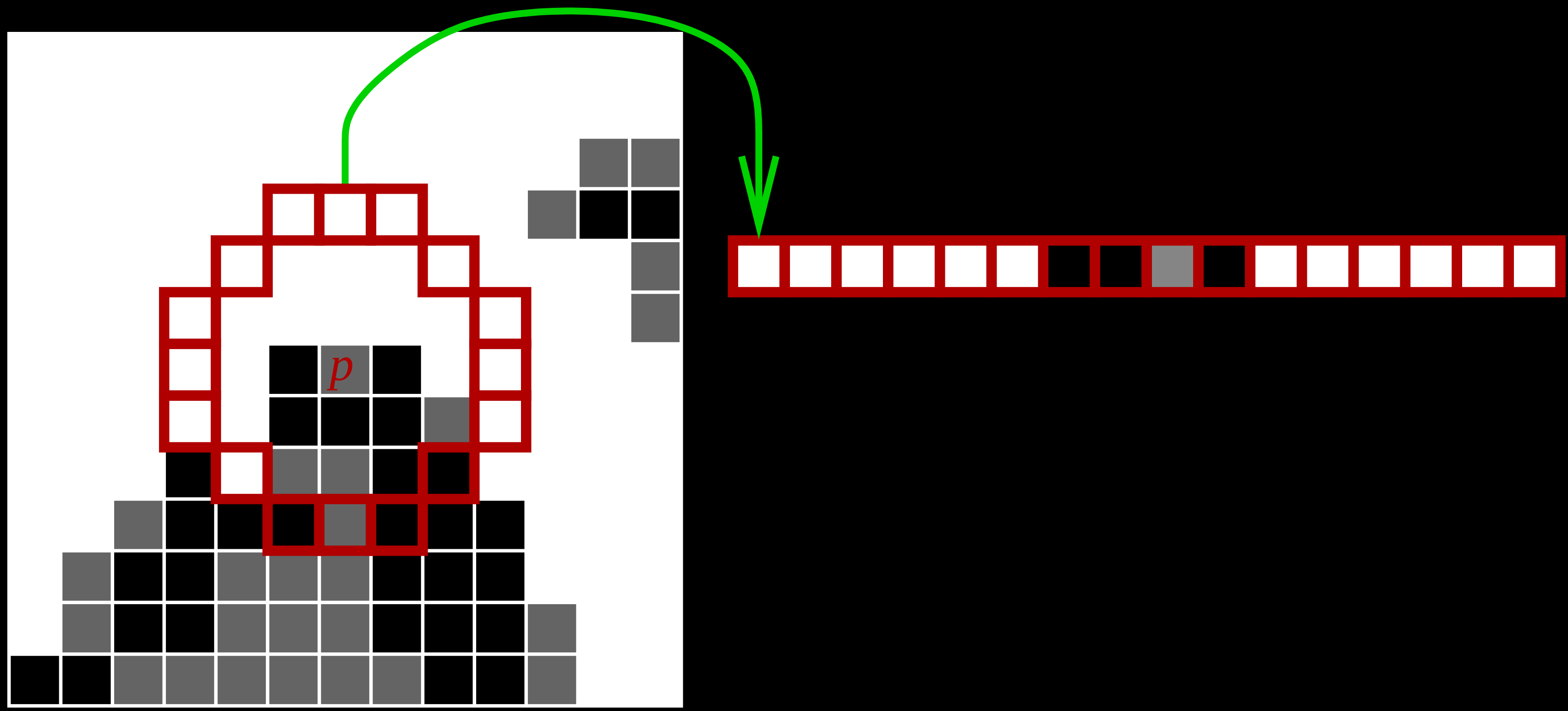
Analysis of pixels



- Pixels are either:
    - Much brighter
    - Much darker
    - Similar

- Ring represented as ternary vector

Analysis of pixels



- Pixels are either:
  - Much brighter
  - Much darker
  - Similar
- Ring represented as ternary vector
- Extract vectors for **ALL** pixels

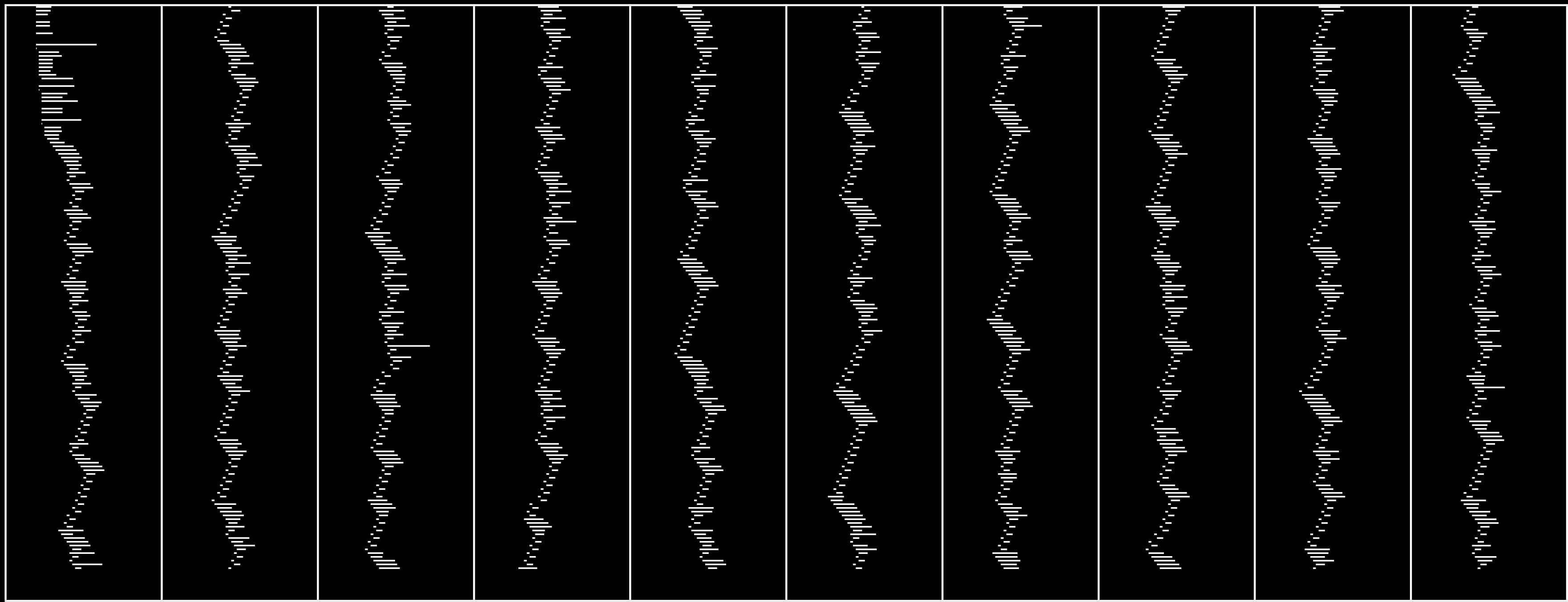
Ask ternary questions

- List of all potential features:
    - Ternary vector
    - Is it a feature?
- Question splits list in to 3 sublists
- Query each sublist
- Recurse until list contains all features or all non features

- Use questions on new feature

Output C++ code

A long string of nested if-else statements:



. . . which continues for 2 more pages.

Choosing questions

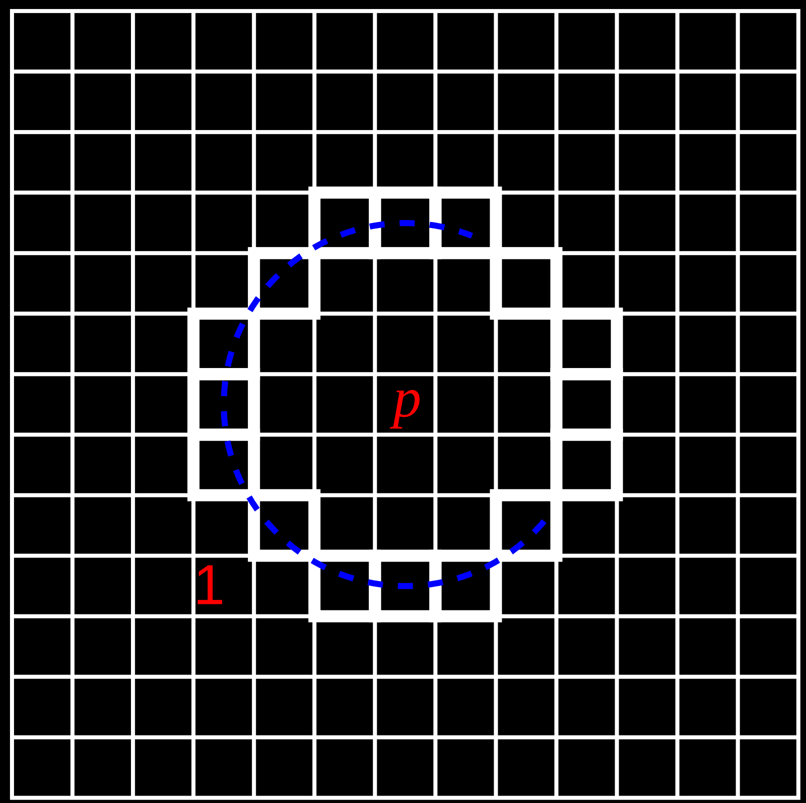
- Minimize average number of questions per feature
- Choose question to eliminate largest number of features

Or

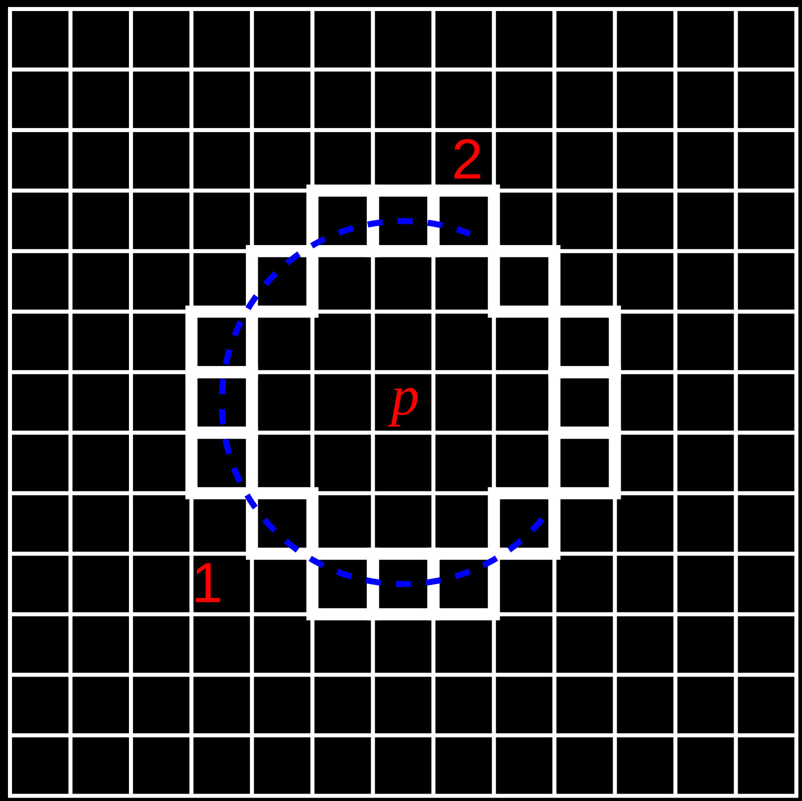
- Use entropy
    - Entropy of a list depends on distribution of features
    - Questions yield information
    - Total entropy of sublists is less
- Choose questions to maximize entropy gain
  (This is the ID3 algorithm)

Using entropy is better

Example tree



Example tree



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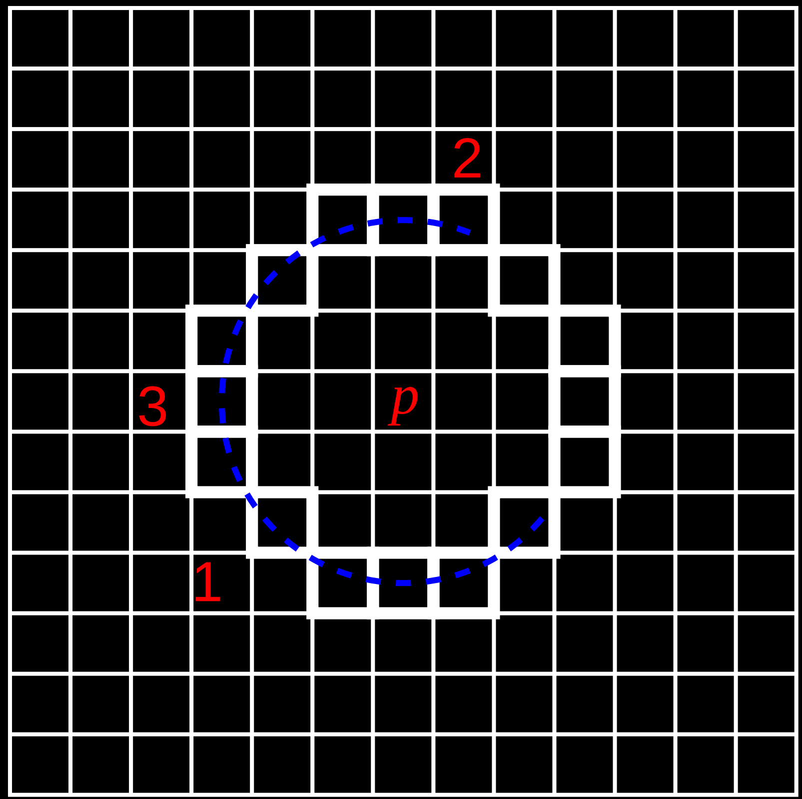

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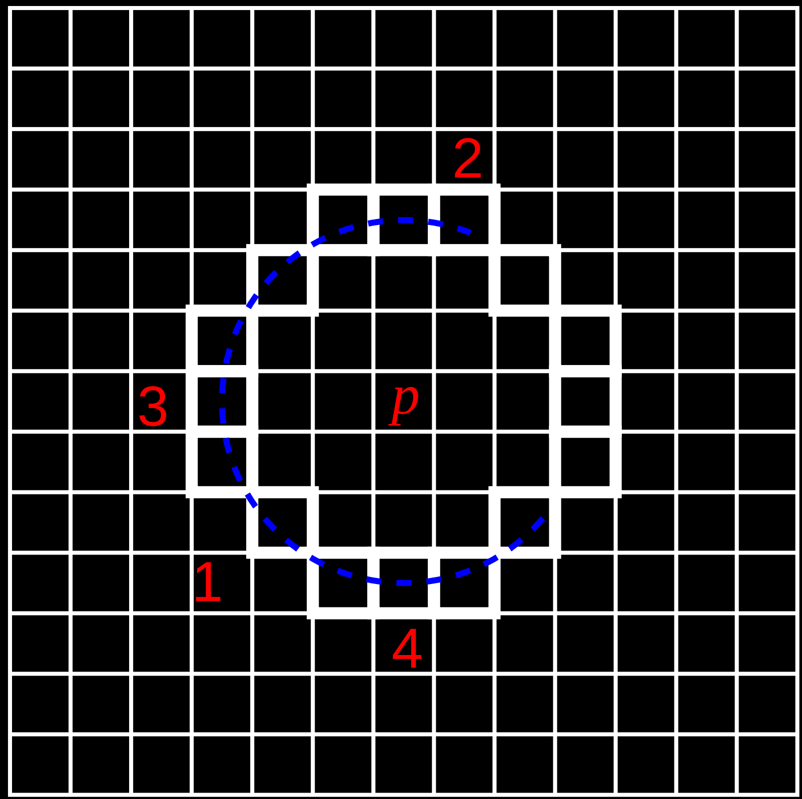

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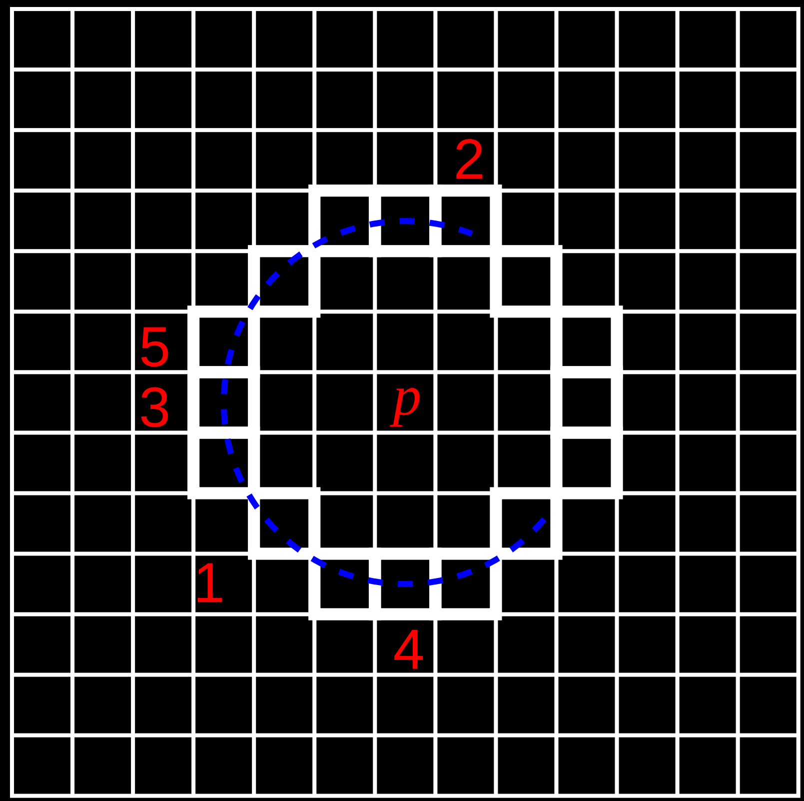

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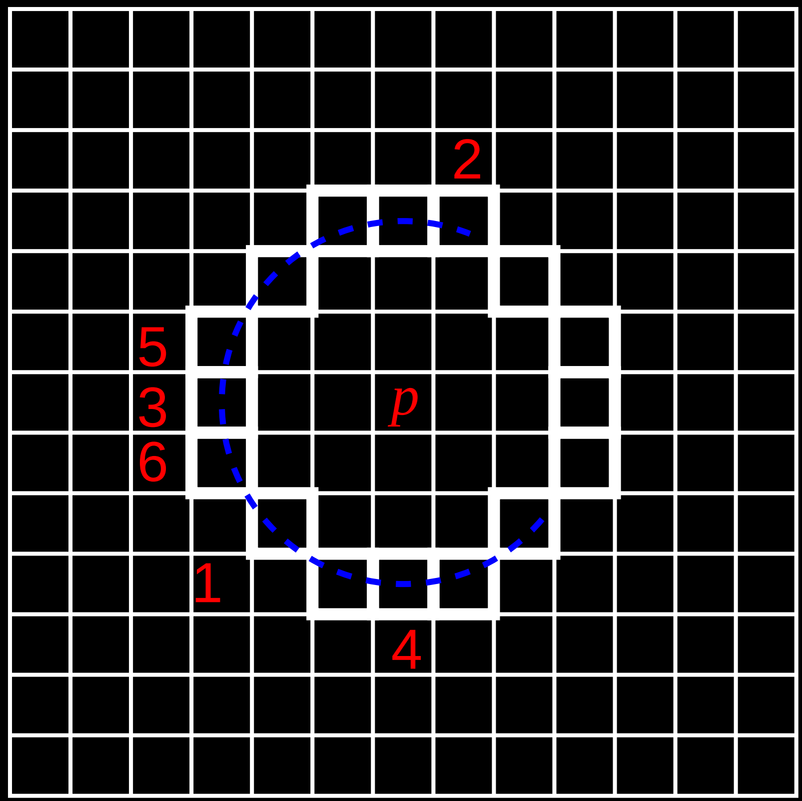

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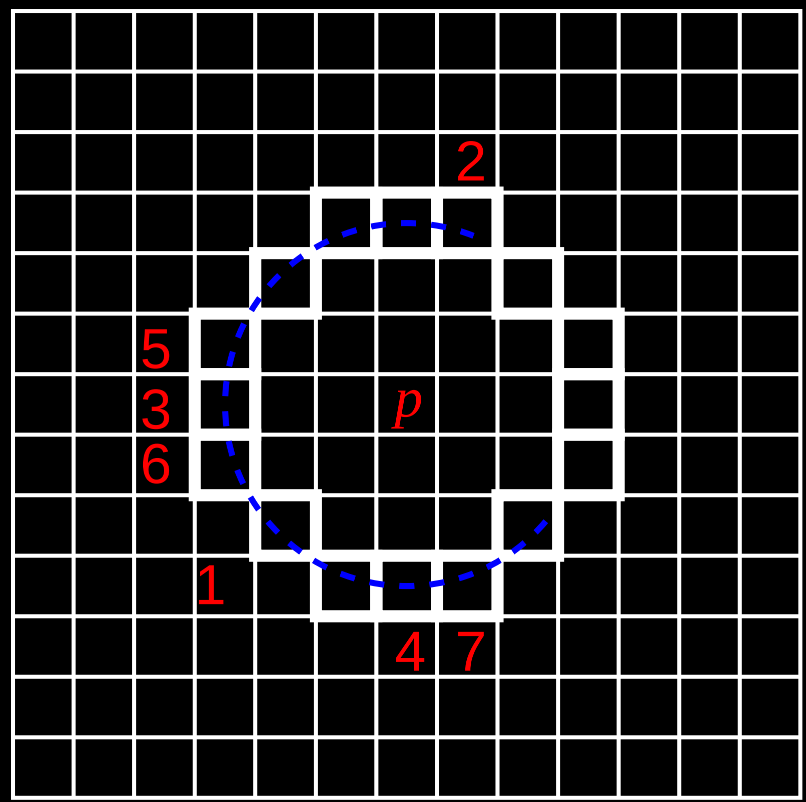

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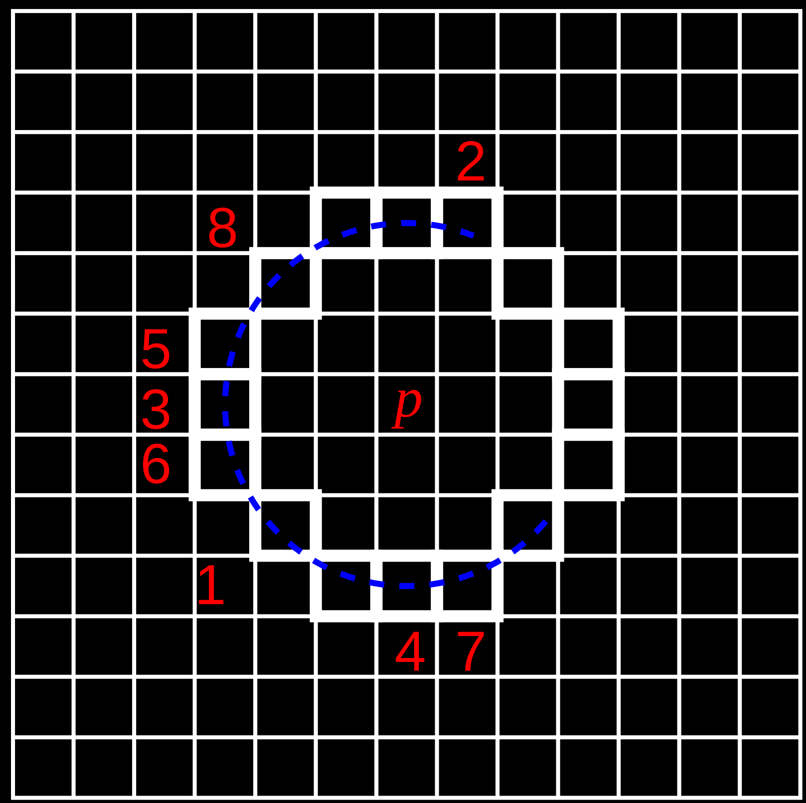

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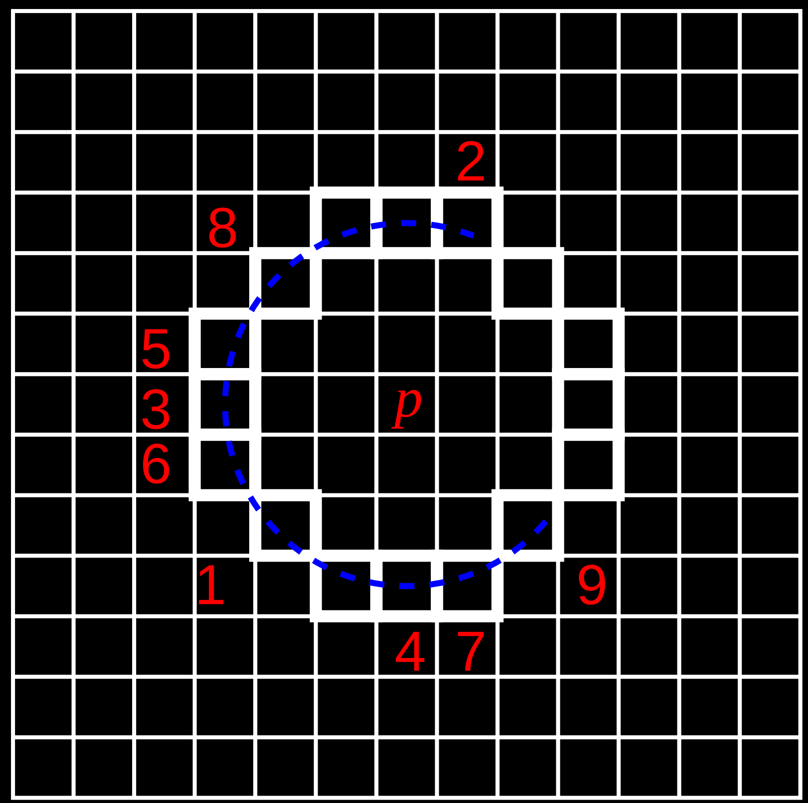

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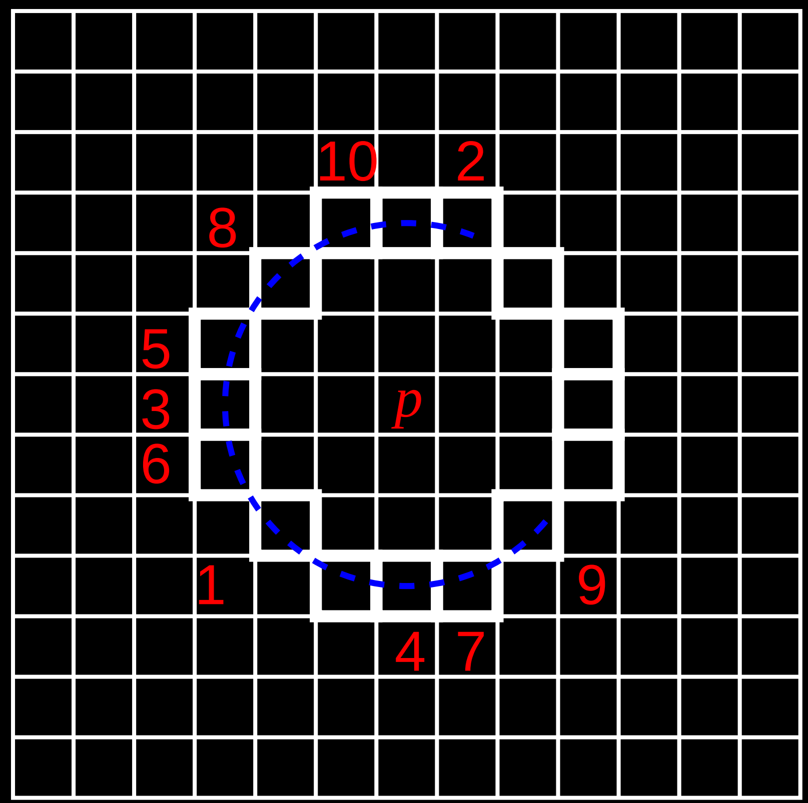

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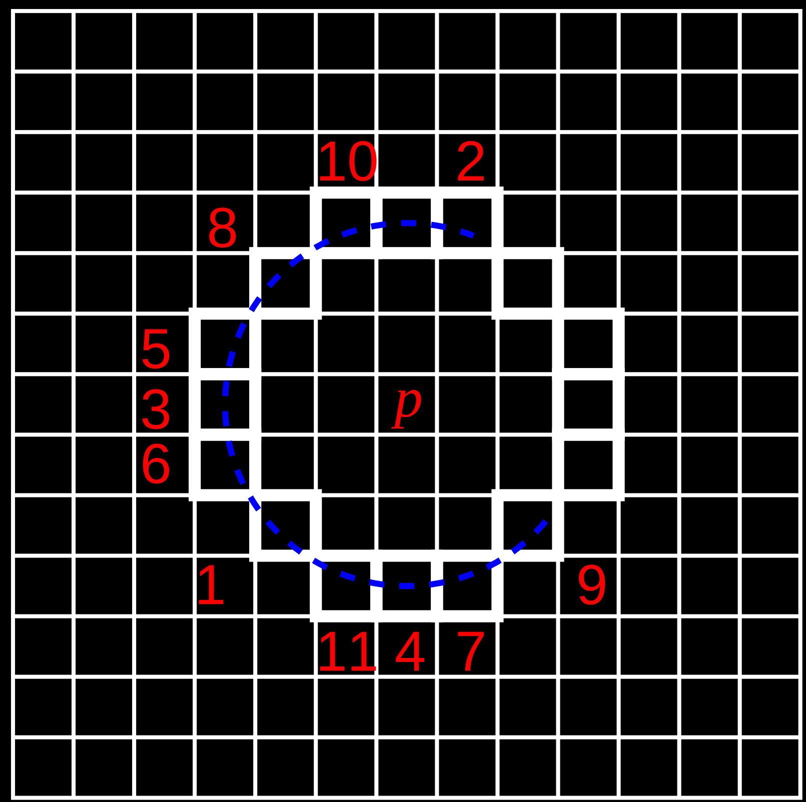

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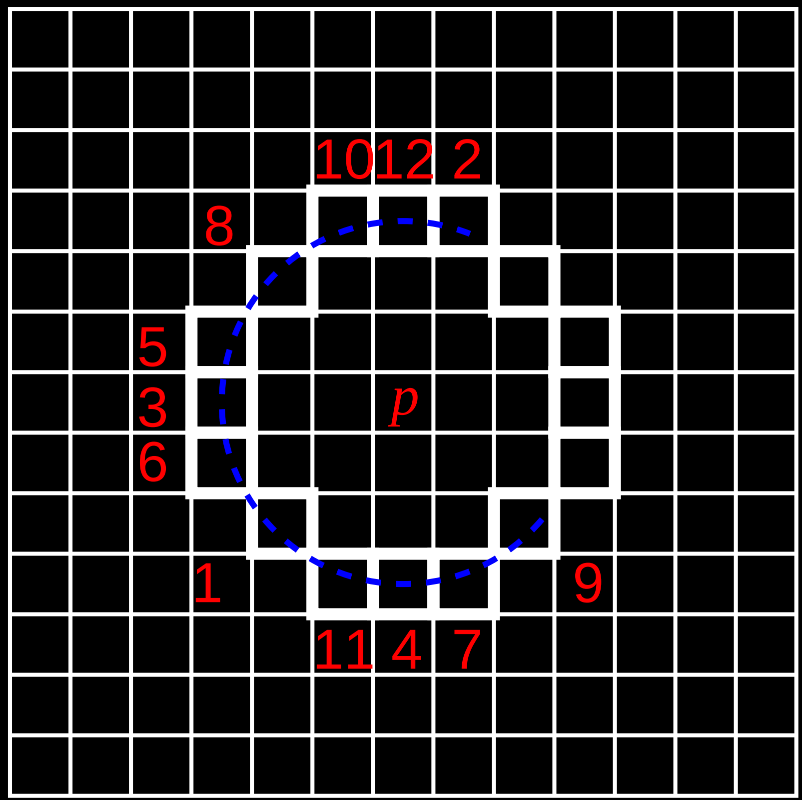

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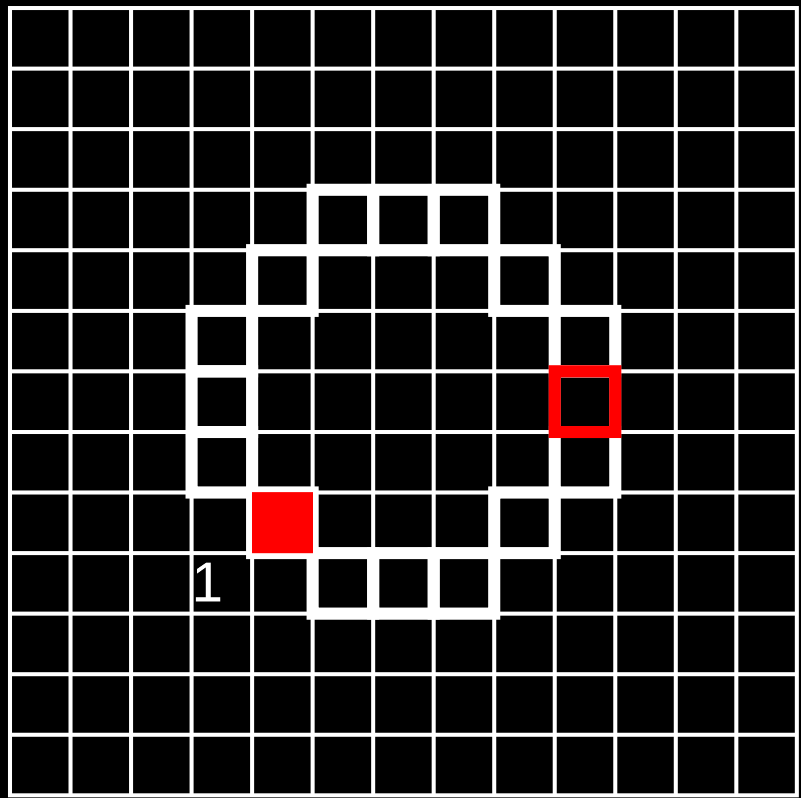

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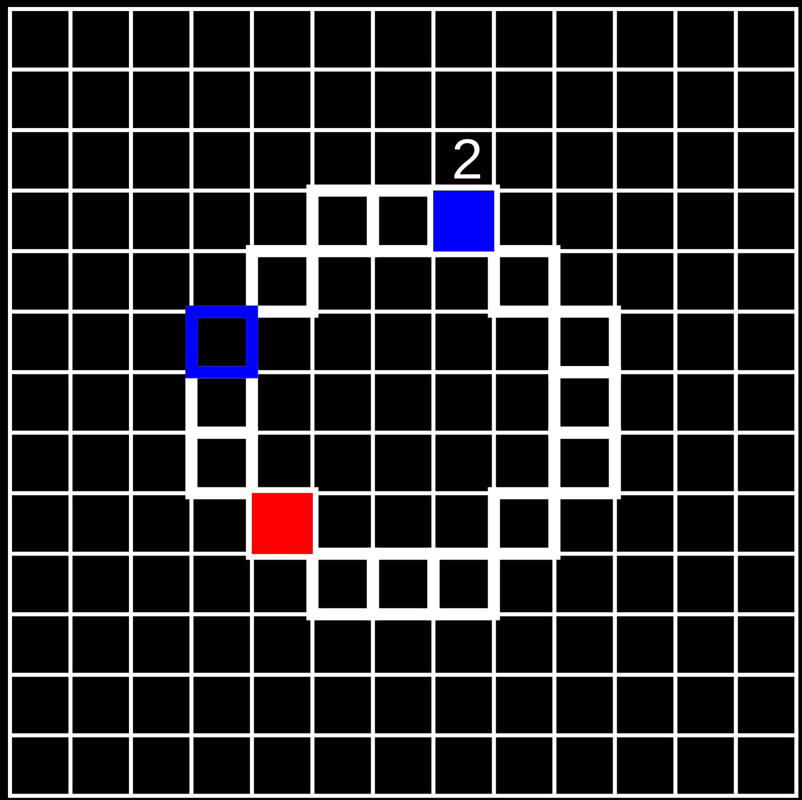

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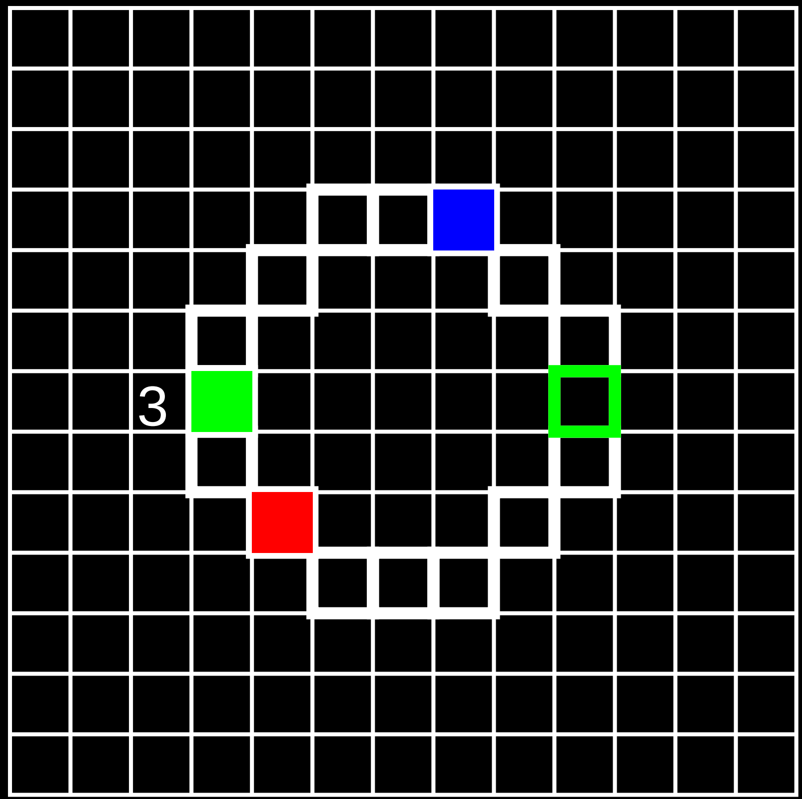

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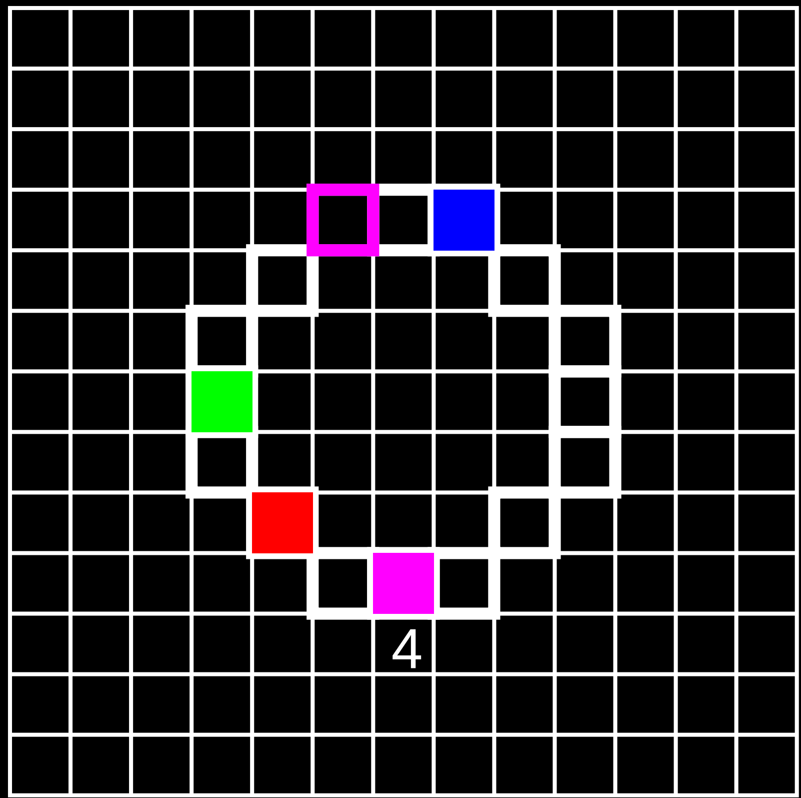


How FAST?

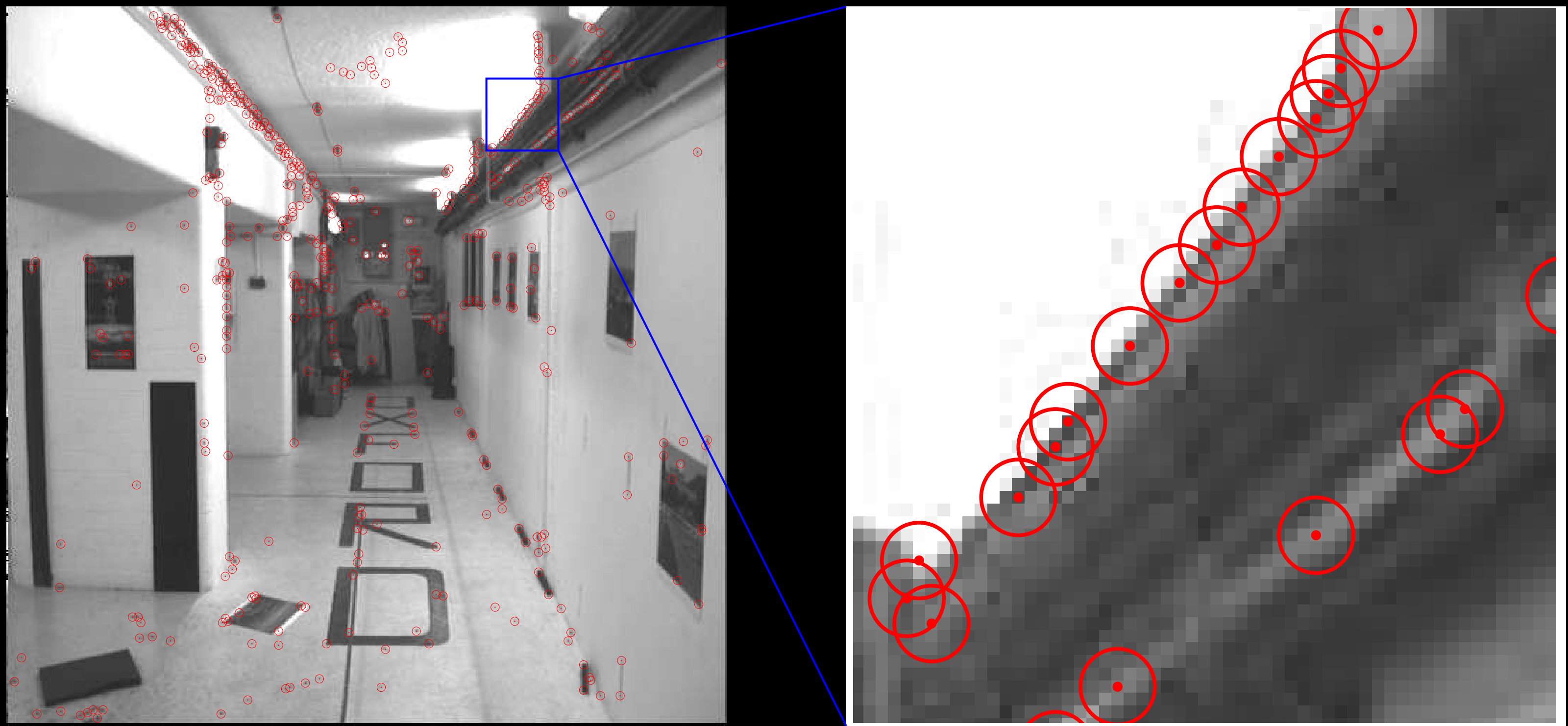
Percentage of available CPU time (typical video)

Detector	2.6 GHz (%)	850 MHz (%)
New FAST	5.4	21.7
FAST	7.45	48.5
DoG	301	1280
SUSAN	37.9	137.5
Harris	120	830

- New FAST: 2.2 questions per feature

Is it any good...?

An example failure mode:



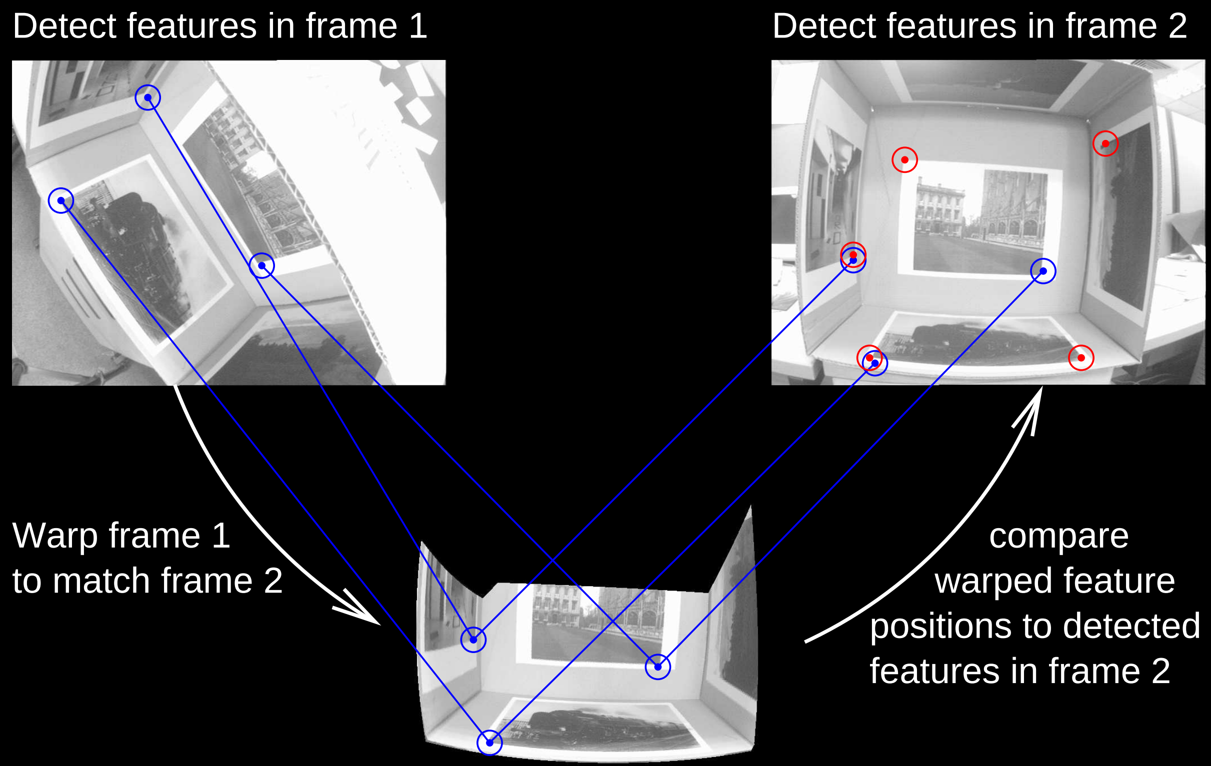
- Ring misses thin quantized lines
- ‘Obvious’ corners missed

Compare against others

- Harris
- Shi/Kanade and Tomasi
- SUSAN
- Multiscale DoG (used by SIFT)
- Harris-Laplace

Comparison methodology

Is the same real-world 3D point detected from multiple views?

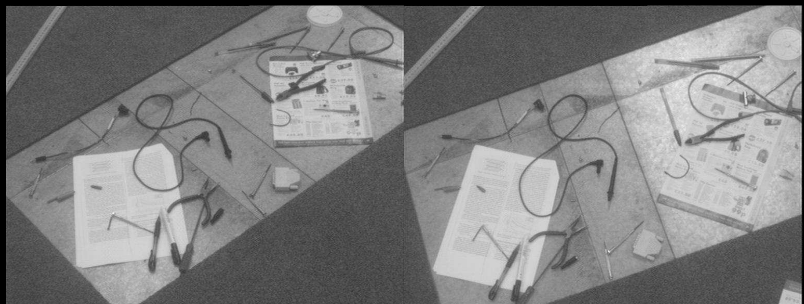


Repeat for all pairs in a sequence

Data sets

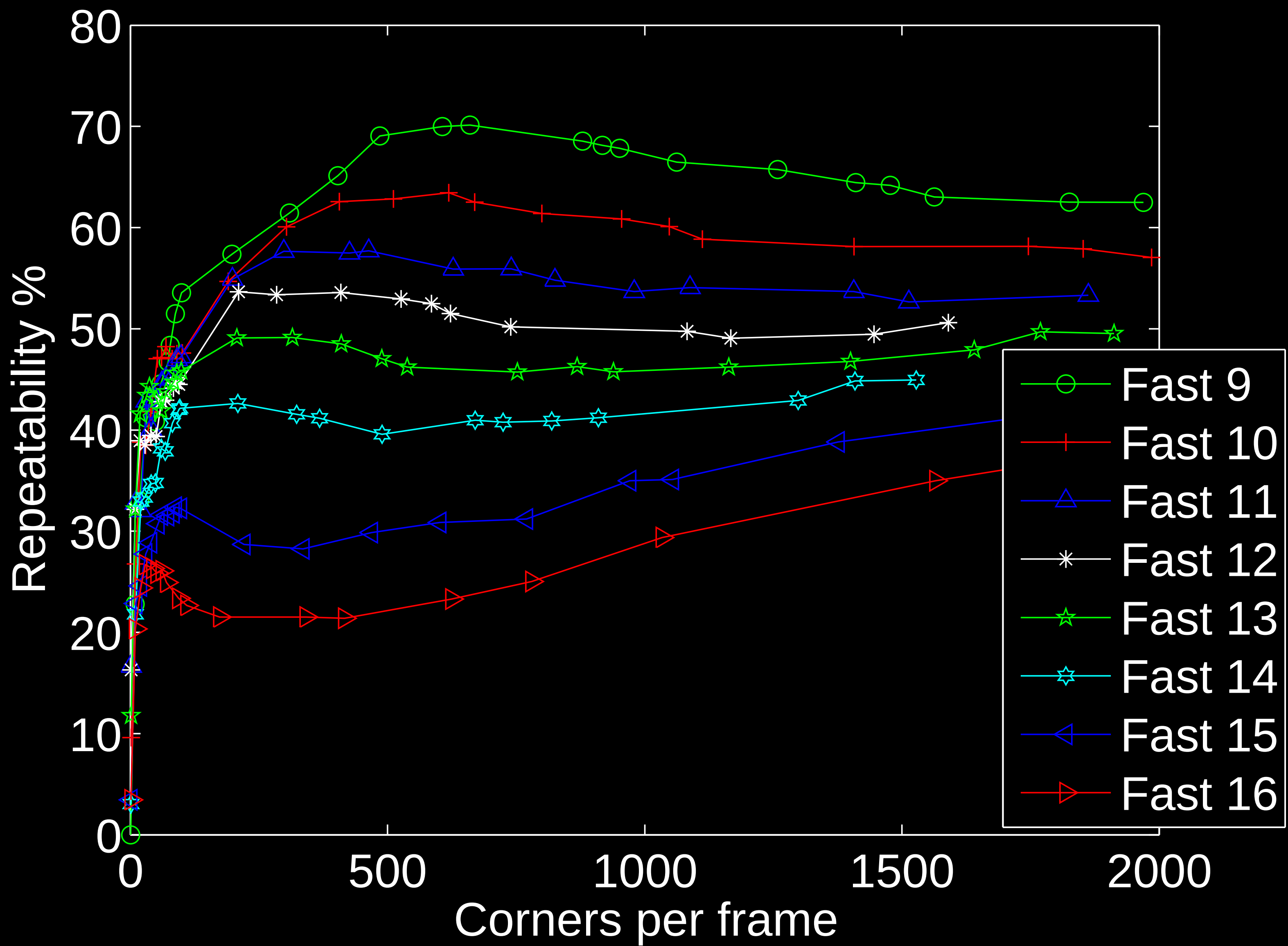
Affine (14 images)

Geometric (15 images)

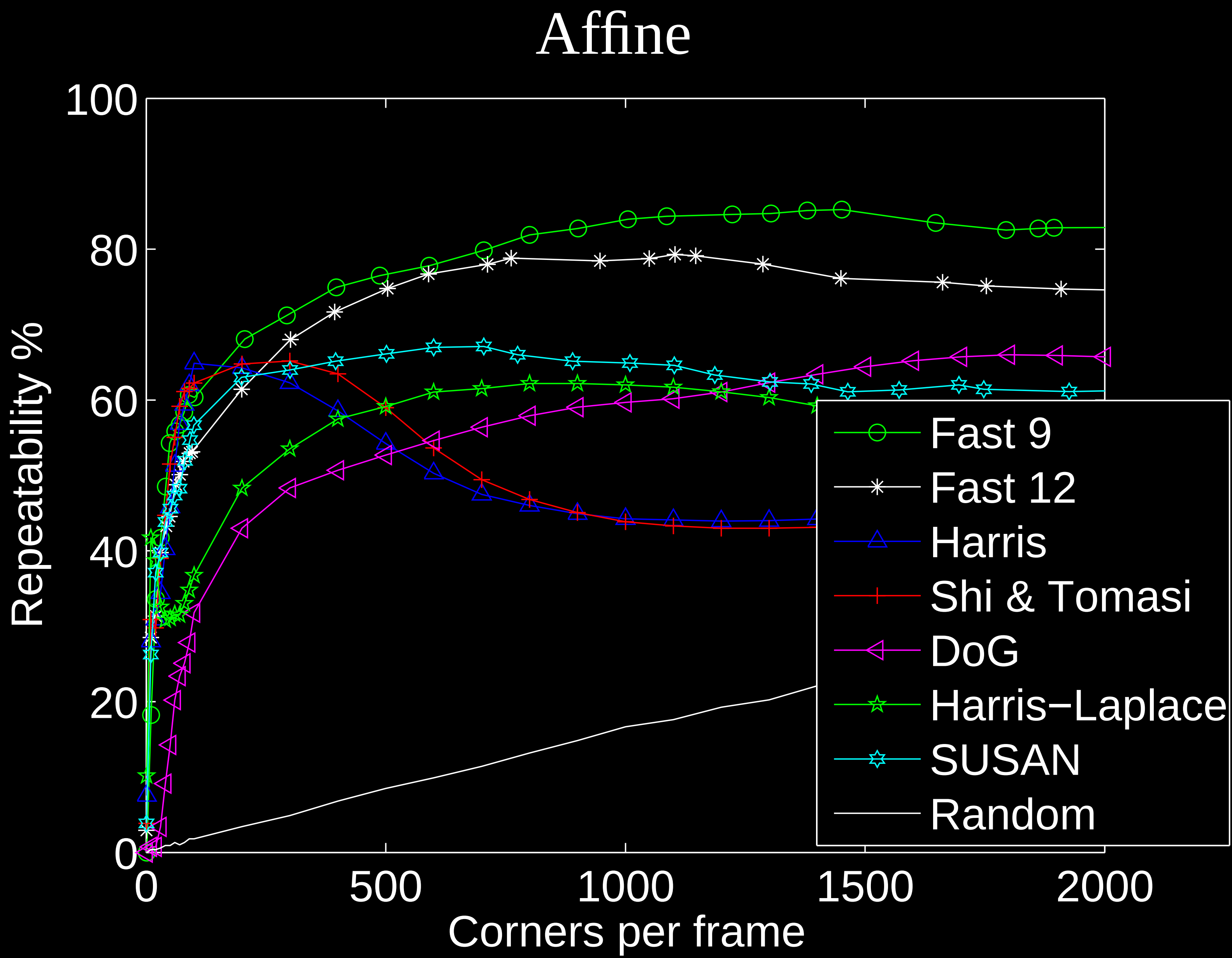


Bas-relief (8 images)

Which FAST is the best?



How good is FAST?



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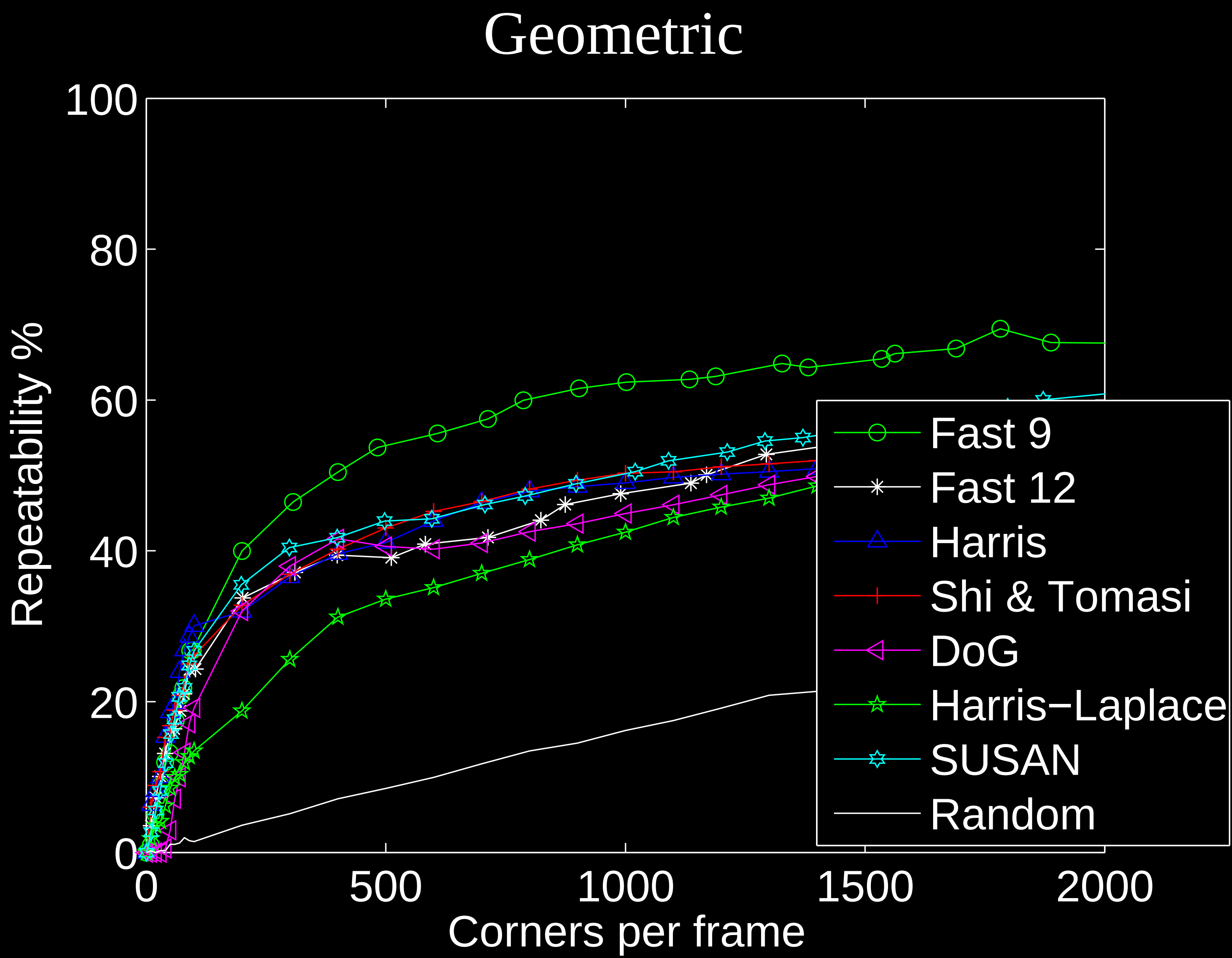

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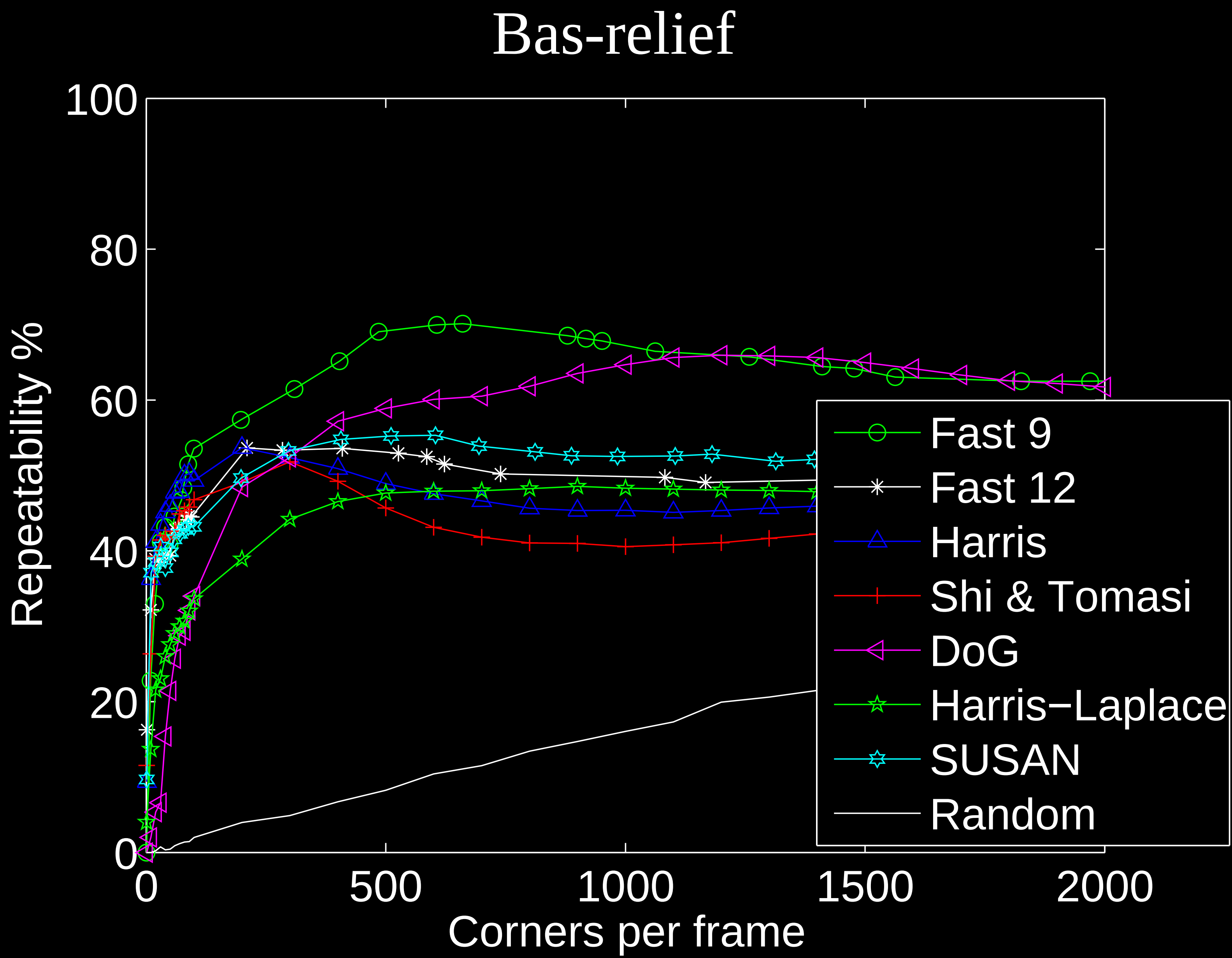
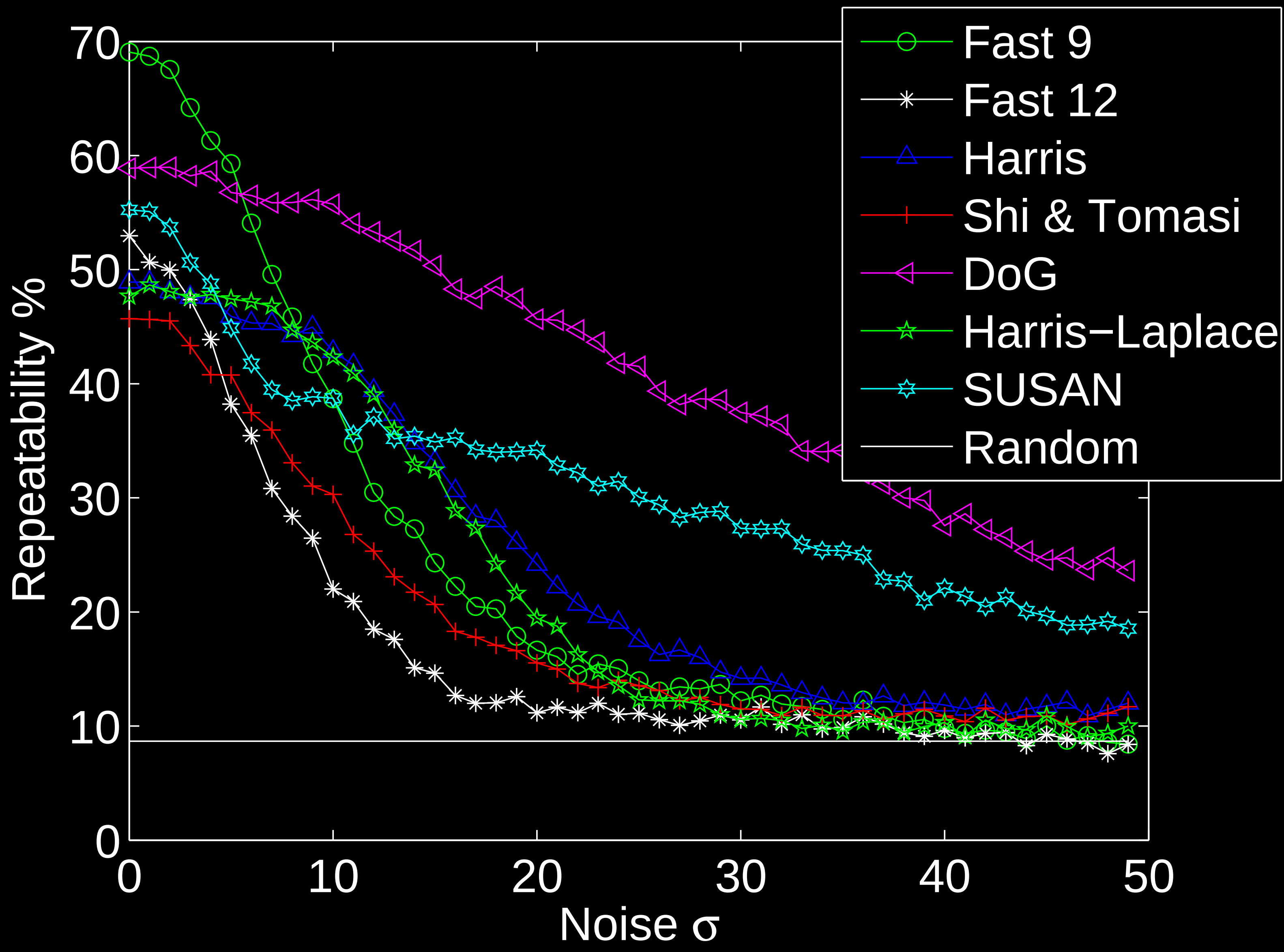


Noise performance



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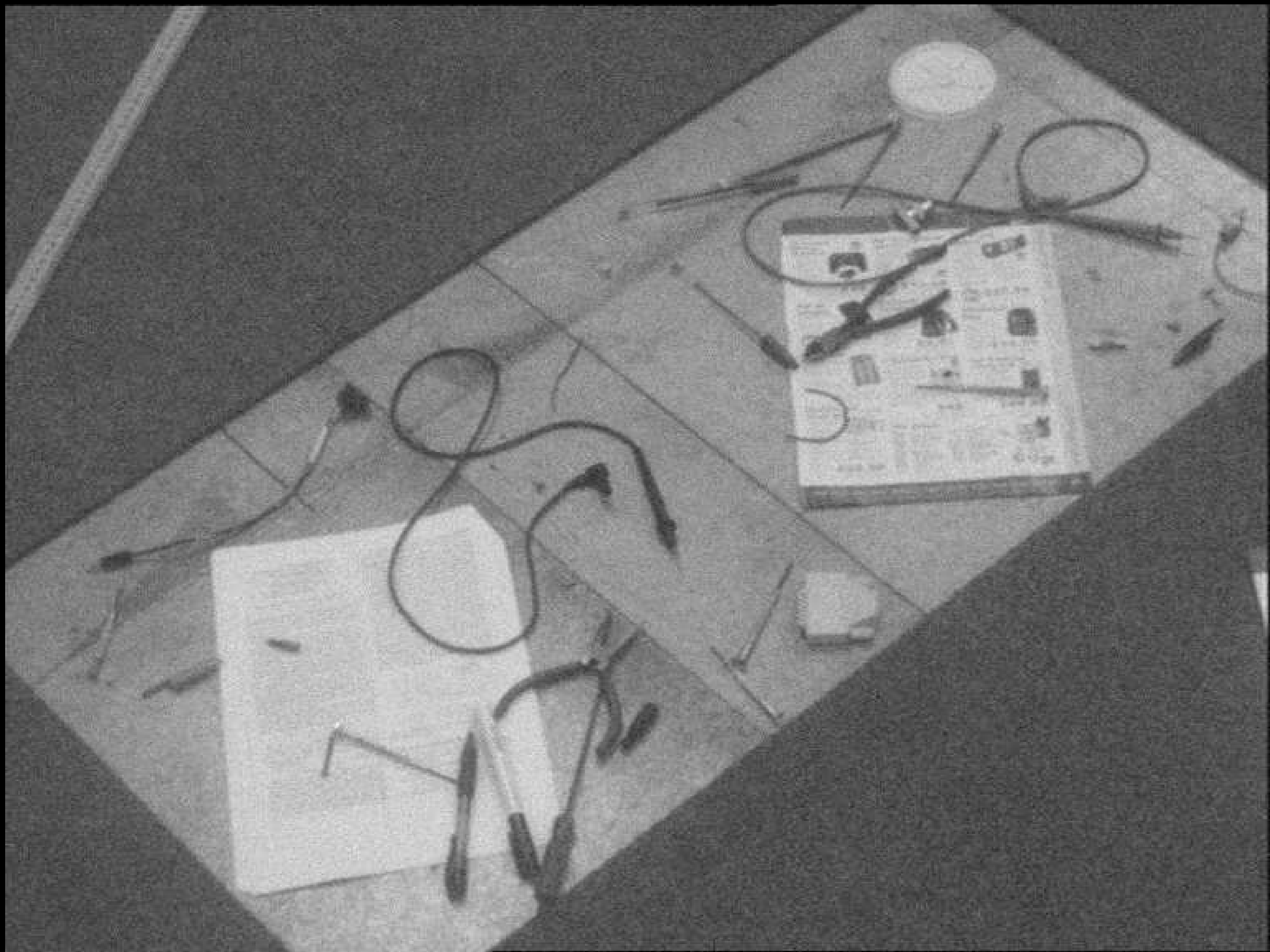


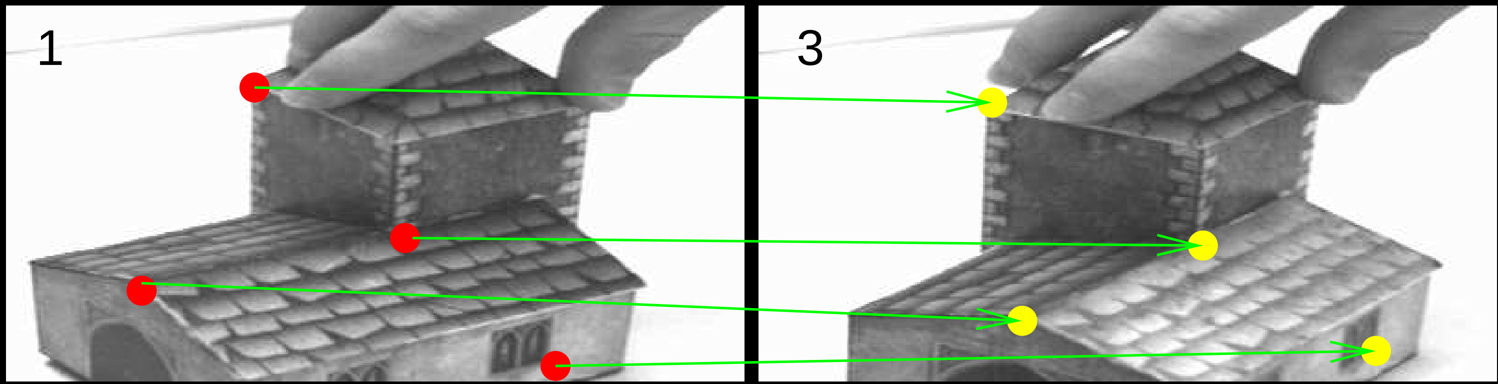
Conclusions on FAST

- Very fast
  - 190 MPixels/s (1.48 Gi b/s)!
  - Used machine learning to learn for speed
- Produces high quality features
  - Results from real features from representative images

Back to tracking

Robust differential measurements

Detect and match features in next frame



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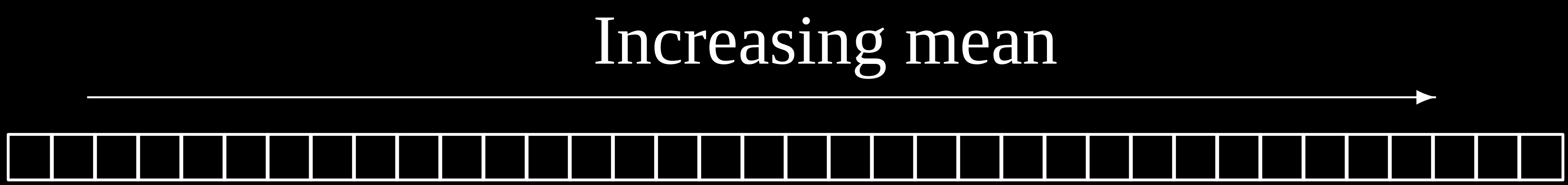
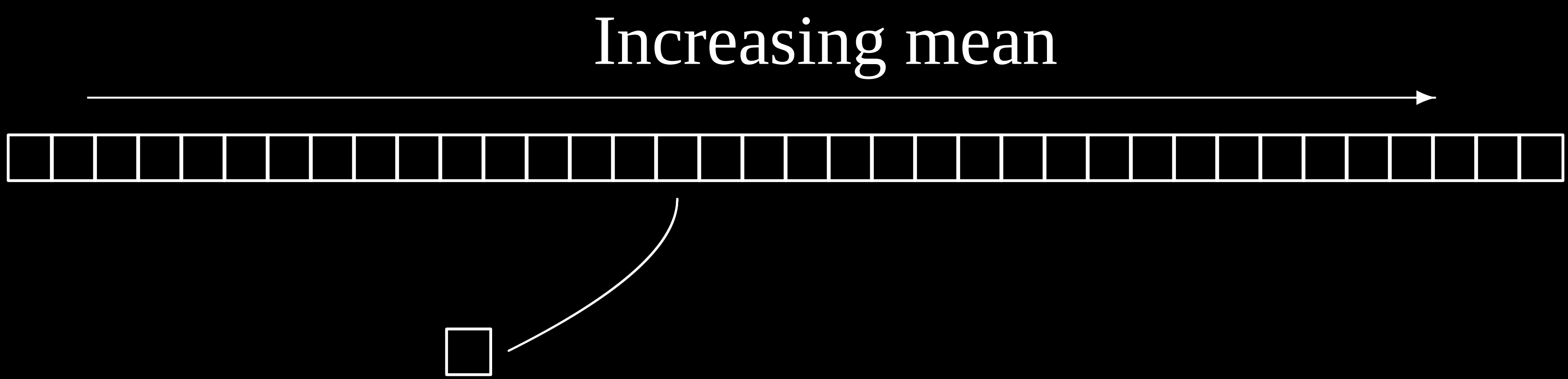
- Detecting features in a whole frame is slow
- Matching can be $O(n^2)$

Efficient feature matching



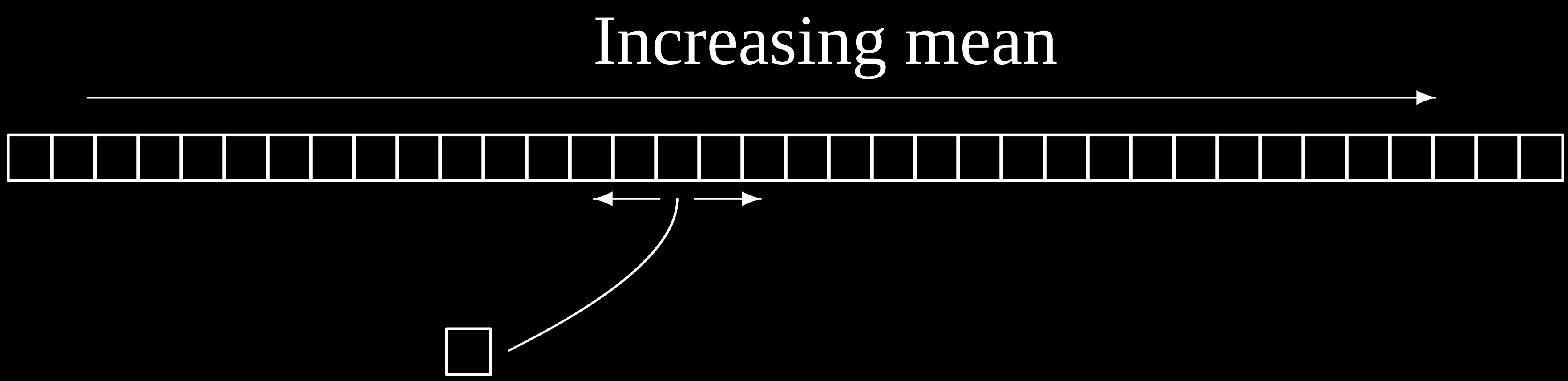
- Sort features by mean value of feature vectors

Efficient feature matching



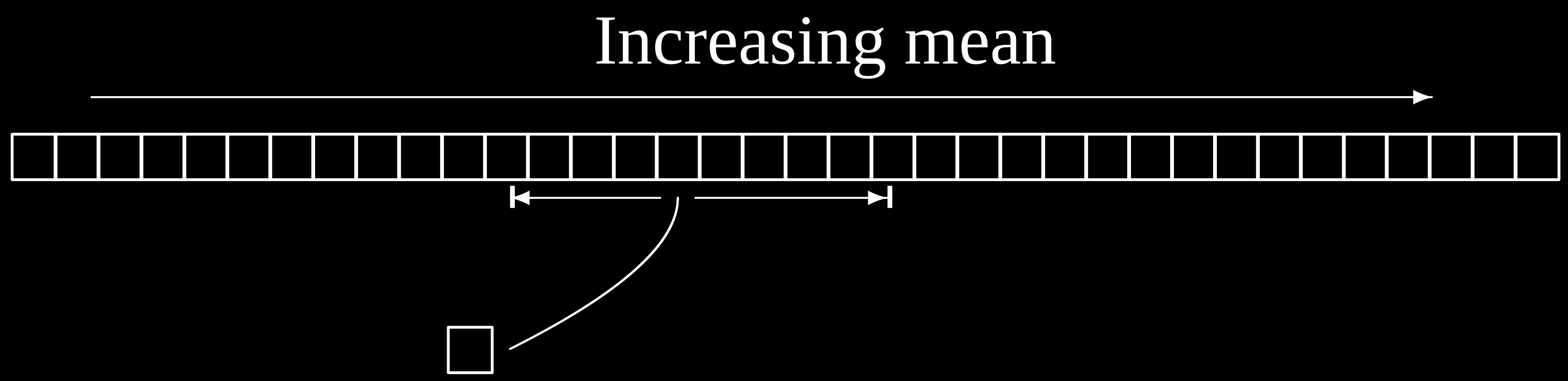
- Sort features by mean value of feature vectors
- Find closest mean by binary search

Efficient feature matching



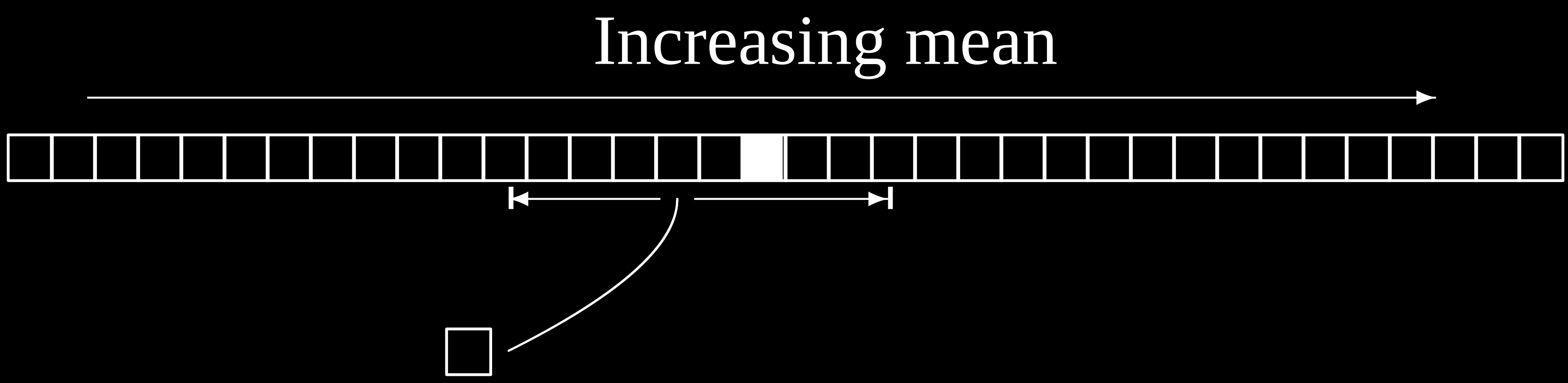
- Sort features by mean value of feature vectors
- Find closest mean by binary search
- Search outwards

Efficient feature matching



- Sort features by mean value of feature vectors
- Find closest mean by binary search
- Search outwards
- SSD between means bounds search

Efficient feature matching



- Sort features by mean value of feature vectors
- Find closest mean by binary search
- Search outwards
- SSD between means bounds search
- Best match has lowest SSD

Conclusions on point tracking

Statistical properties:

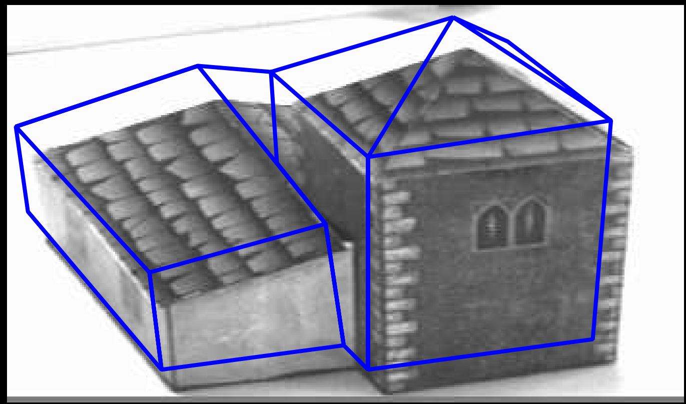
- Point based tracking
  - Requires
    - 3D point cloud
  - Provides
    - Robust *differential* measurements...
    - ...with approximately Gaussian posterior

Conclusion:

- Useful, but incomplete.

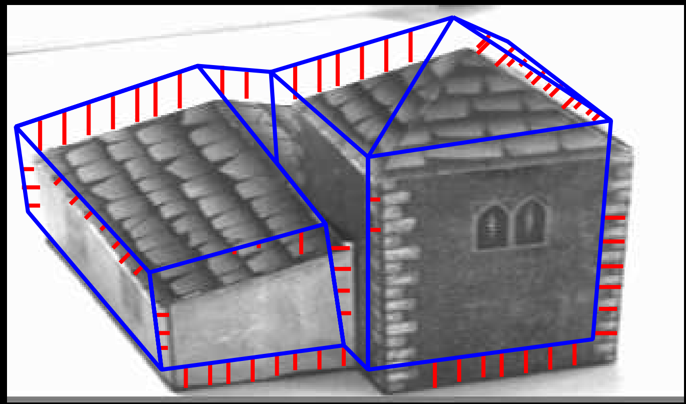
Edge based tracking

Edge based tracking



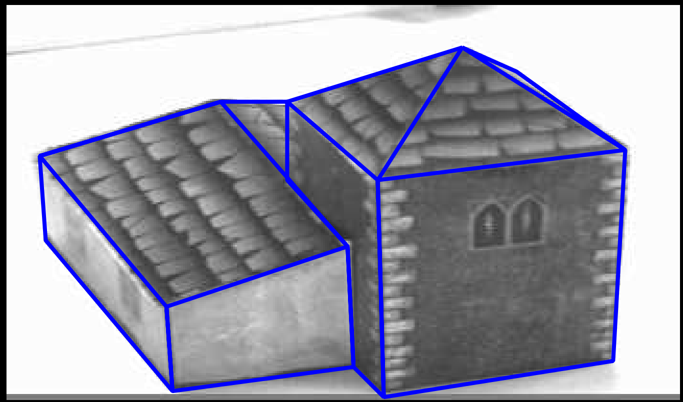
- Start from position prior

Edge based tracking



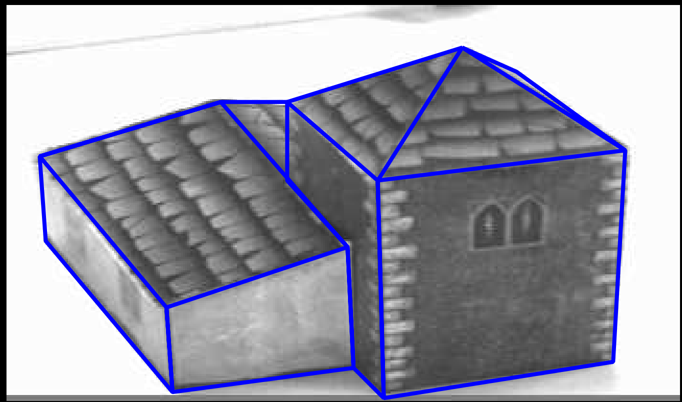
- Start from position prior
- Search along edge-normal lines

Edge based tracking



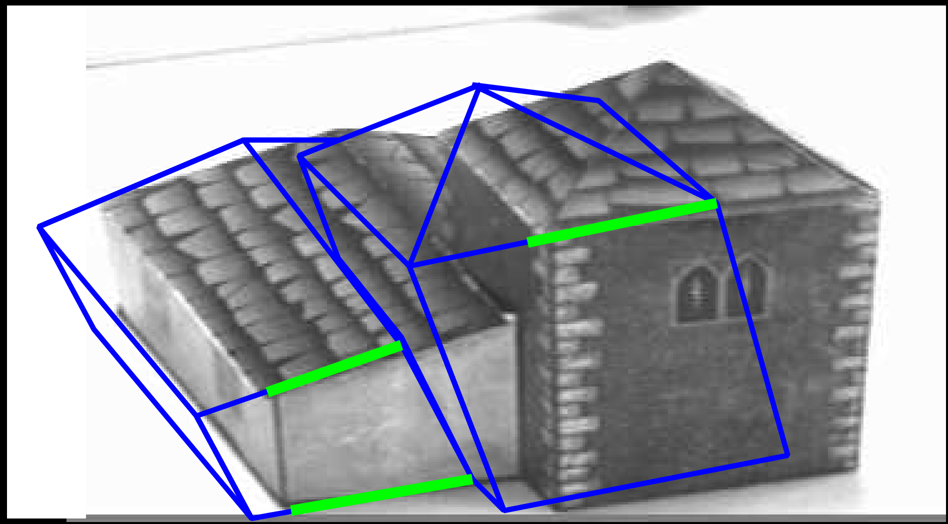
- Start from position prior
- Search along edge-normal lines
- Adjust position to minimize errors

Edge based tracking



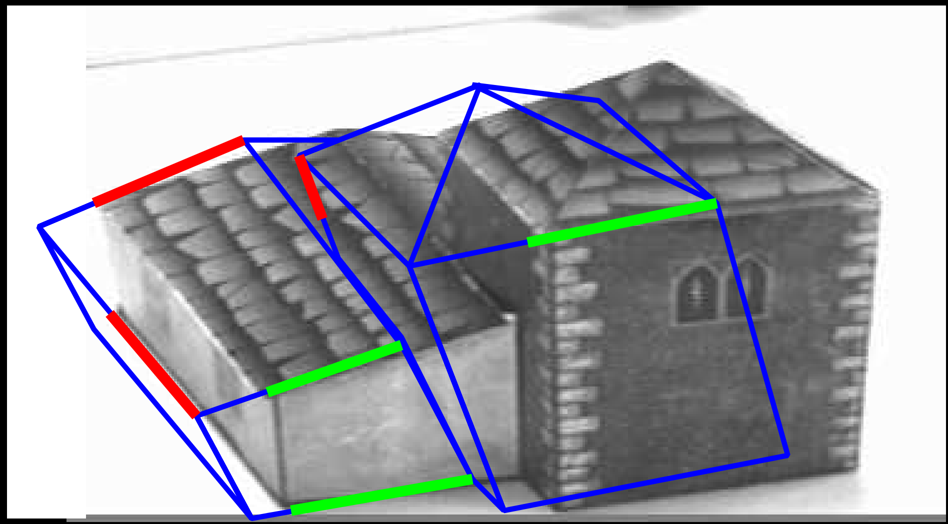
- Start from position prior
- Search along edge-normal lines
- Adjust position to minimize errors
- Gives drift free measurements
    - Model is static

Good prior needed



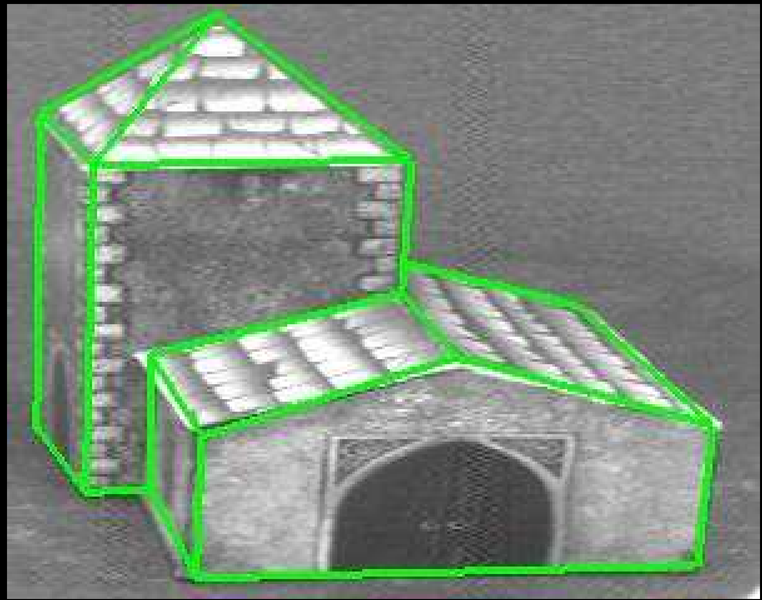
- Edges are a step change in intensity
- Correspondence is hard—pick closest edge

Good prior needed



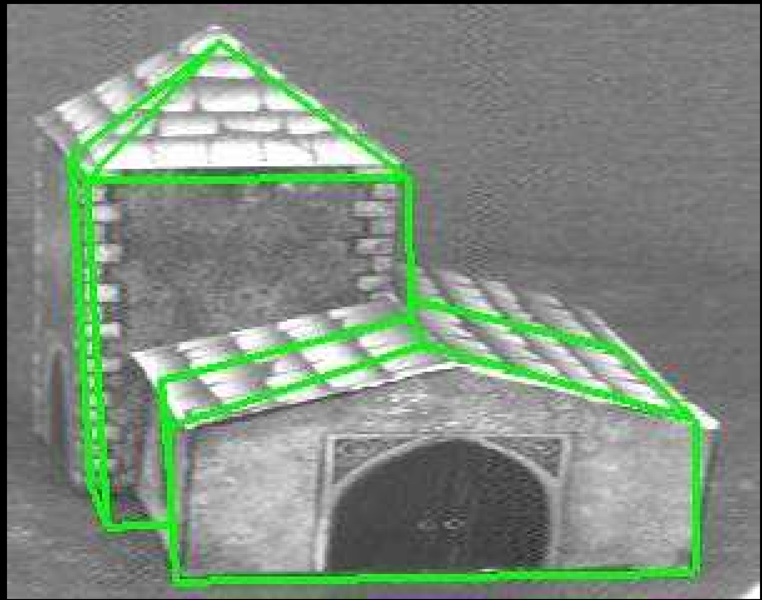
- Edges are a step change in intensity
- Correspondence is hard—pick closest edge
- Prior must be good, or the wrong edge will be found
  - Correct edge might be nowhere near

Non Gaussian posterior



- Correct correspondences
  - Tracking is accurate
- Incorrect correspondences
  - Tracking is inaccurate—even if prior is good

Non Gaussian posterior



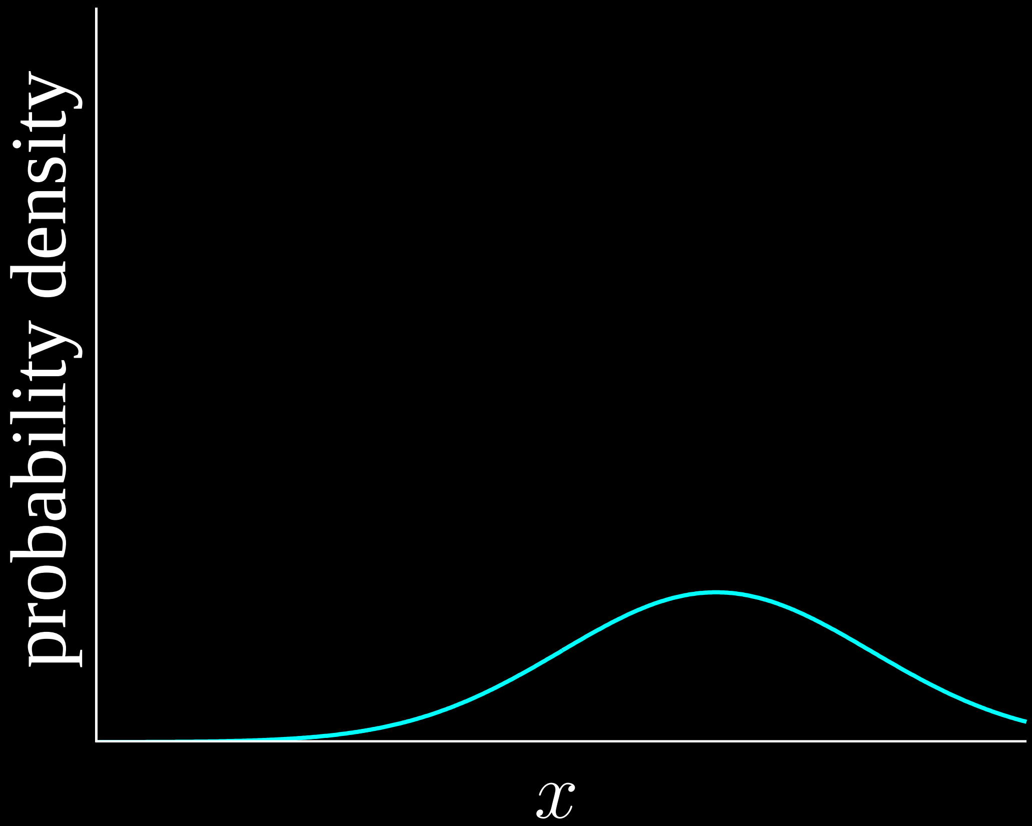
- Correct correspondences
  - Tracking is accurate
- Incorrect correspondences
  - Tracking is inaccurate—even if prior is good

Summary

- Edge based tracking
  - Requires
    - ⋆ 3D geometric model
    - ⋆ Good pose prior
  - Provides
    - ⋆ Drift free measurements
    - ⋆ Non Gaussian posterior
- Point based tracking
  - Requires
    - ⋆ 3D point cloud
  - Provides
    - ⋆ Robust differential measurements...
    - ⋆ ...with approximately Gaussian posterior

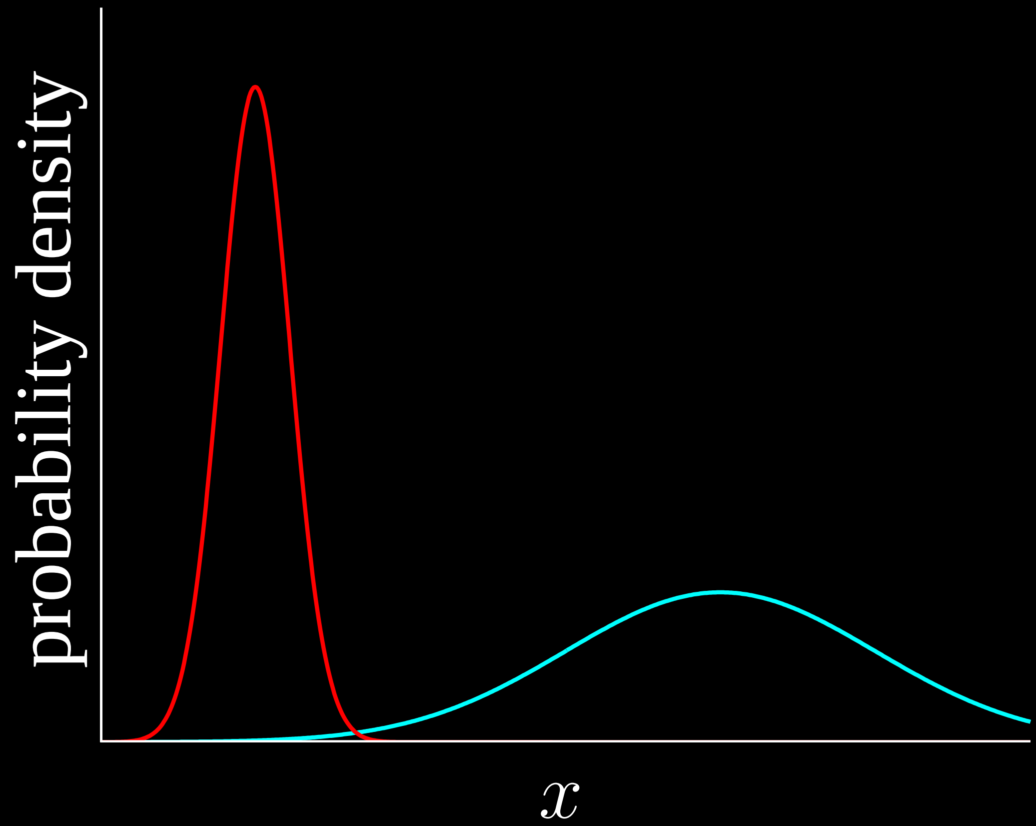
Sensor fusion

Combining measurements



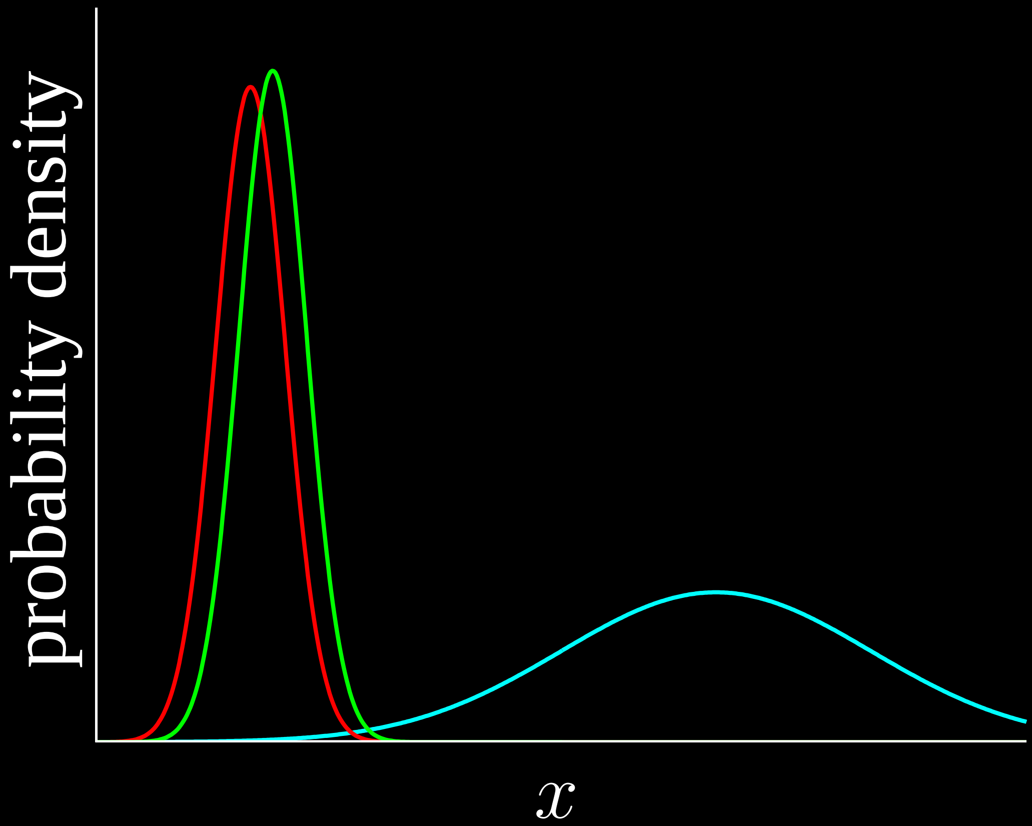
prior

Combining measurements



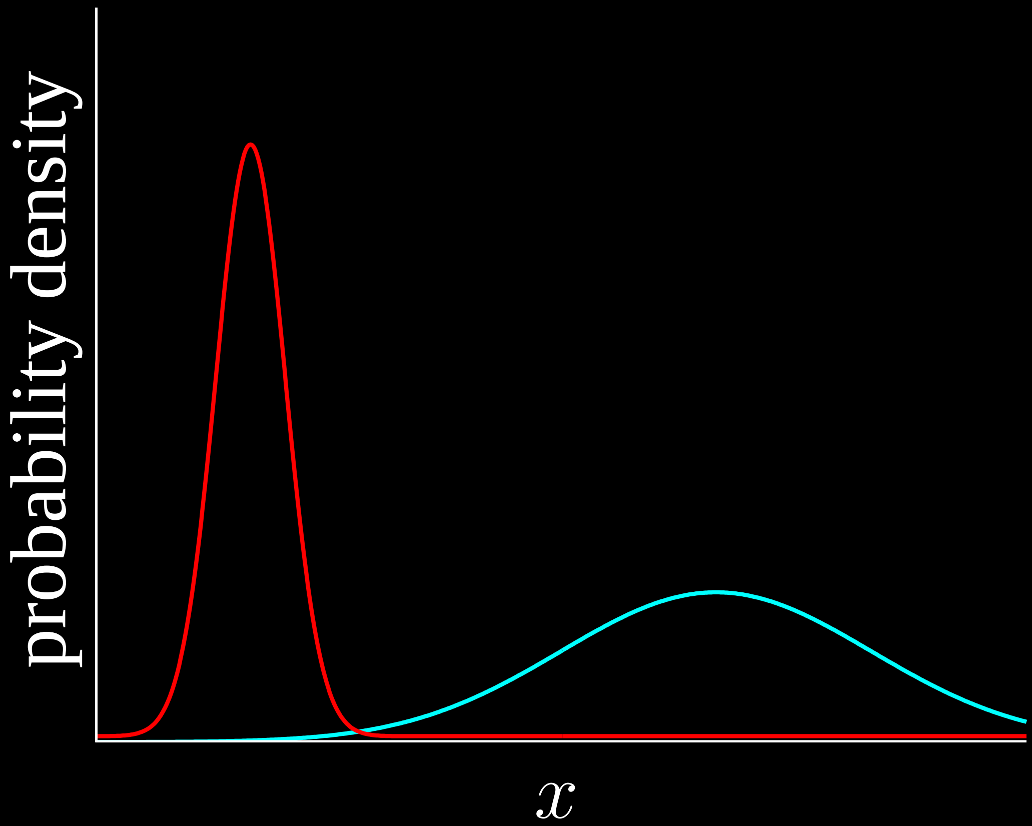
prior $\times$ liklihood

Combining measurements



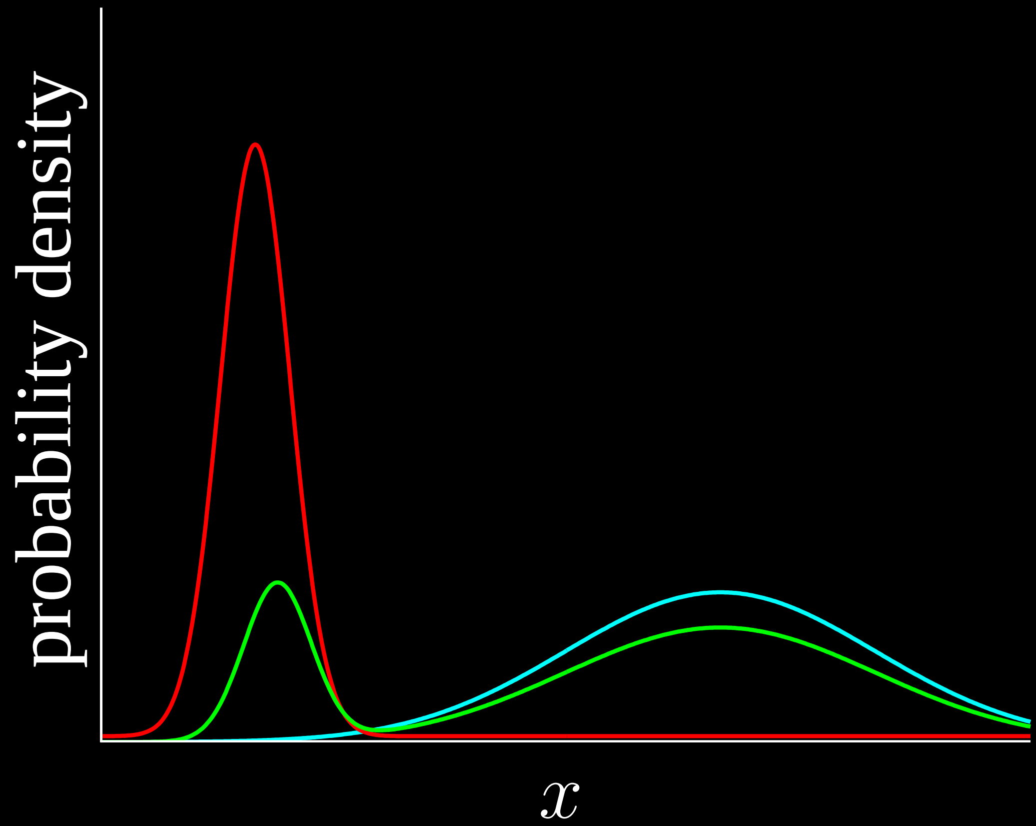
prior $\times$ liklihood $=$ posterior

Combining measurements



prior $\times$ liklihood (with outliers)

Combining measurements

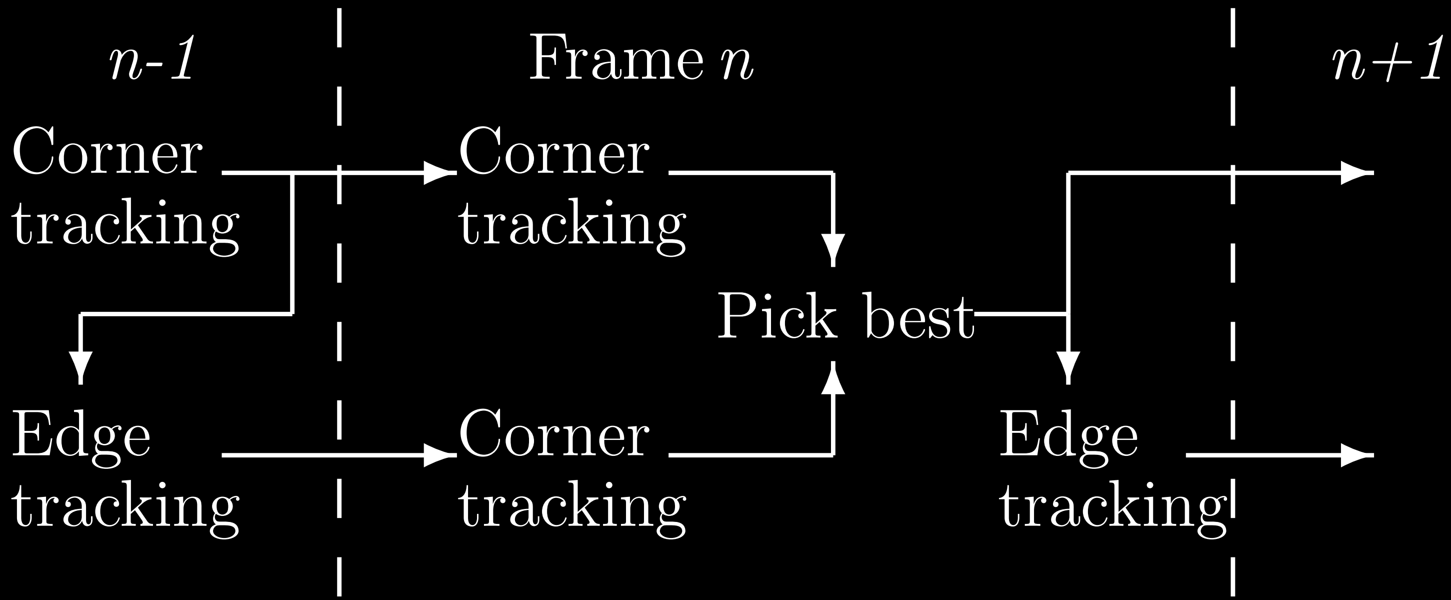


prior $\times$ liklihood (with outliers) $=$ multimodal posterior

Multimodal posterior propagation

- Either tracker can be wrong
  - Edge tracker can get correspondence wrong
  - Point based tracker can drift
- Posterior can be multimodal
  - Simple solutions do not work

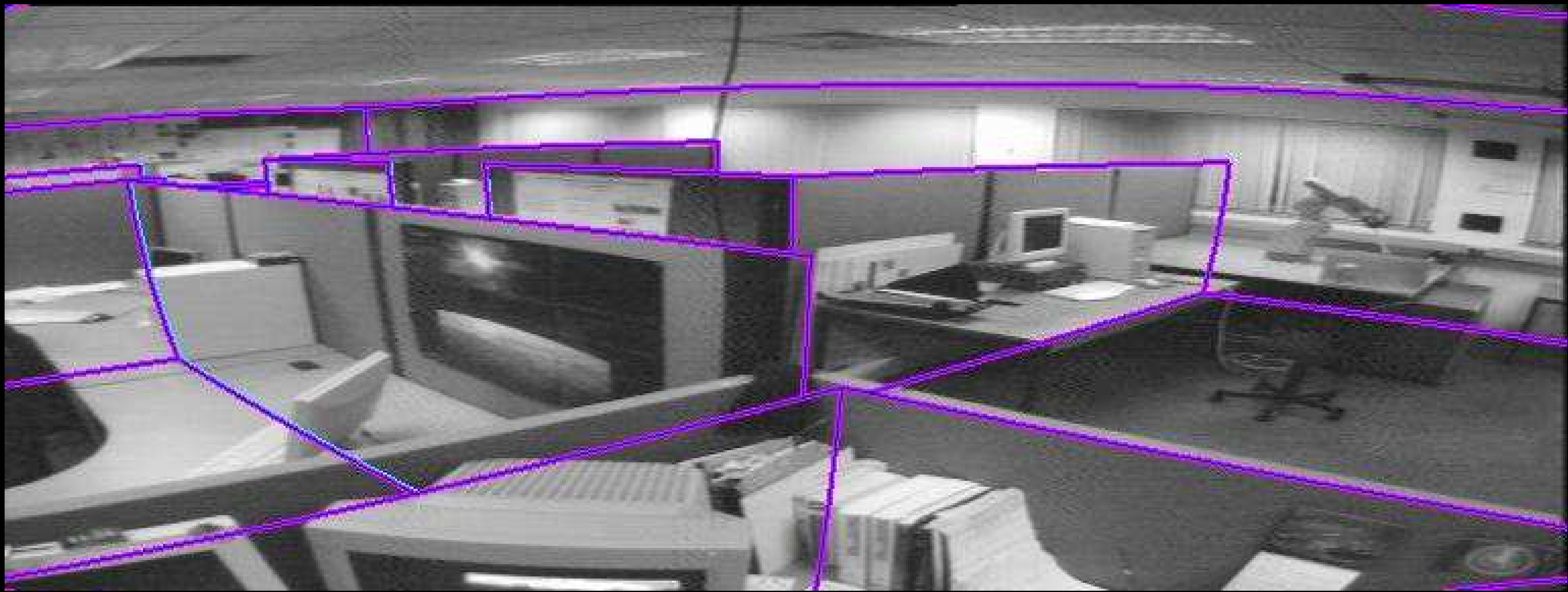
Multimodal posterior propagation



- Either tracker can be wrong
  - Edge tracker can get correspondence wrong
  - Point based tracker can drift
- Posterior can be multimodal
- Evaluate modes *next* frame when more data arrives

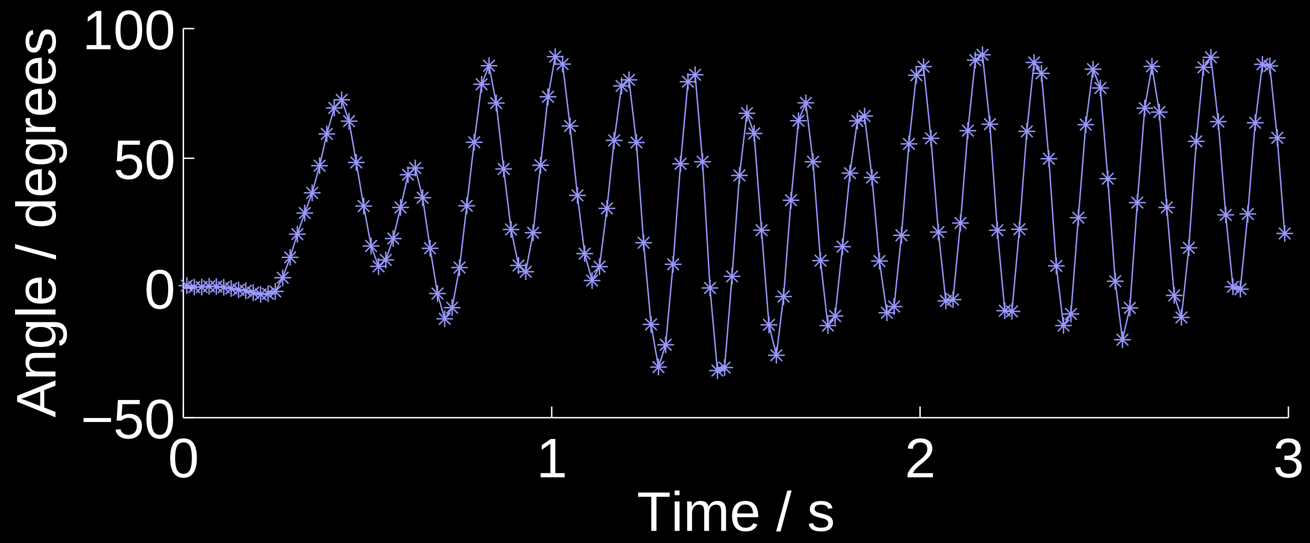
Results

Results - Camera shake



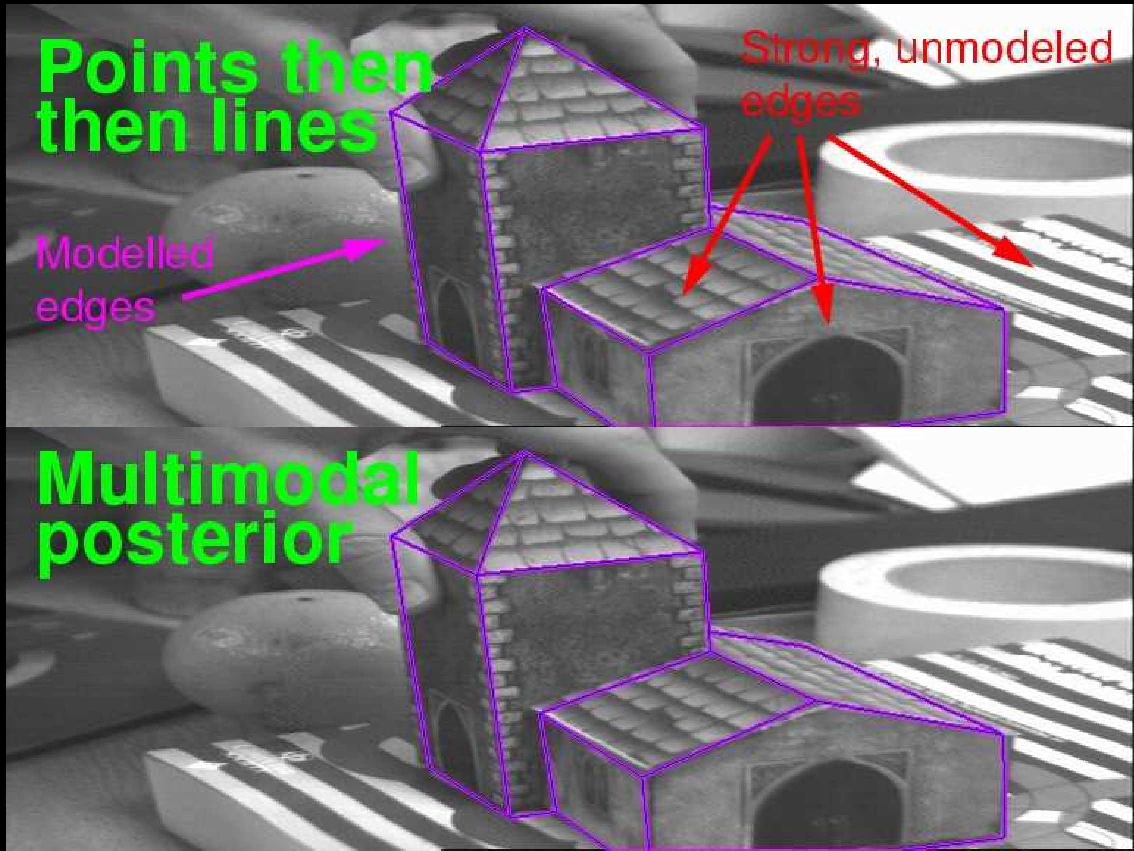
- Pick up camera and shake *really* hard
- Mainly tests point tracker
- Can you follow the video? I can’t (but my tracker can)

Results - Camera shake



- 6Hz Camera shake
- Up to 204 pixels prediction error (89 average)

Results - Strong unmodelled edges



- Strong unmodelled edges frequently break the edge tracker
- Breaks without proper sensor fusion

Results - Handheld camera

Pick up the camera and run around the lab

Summary

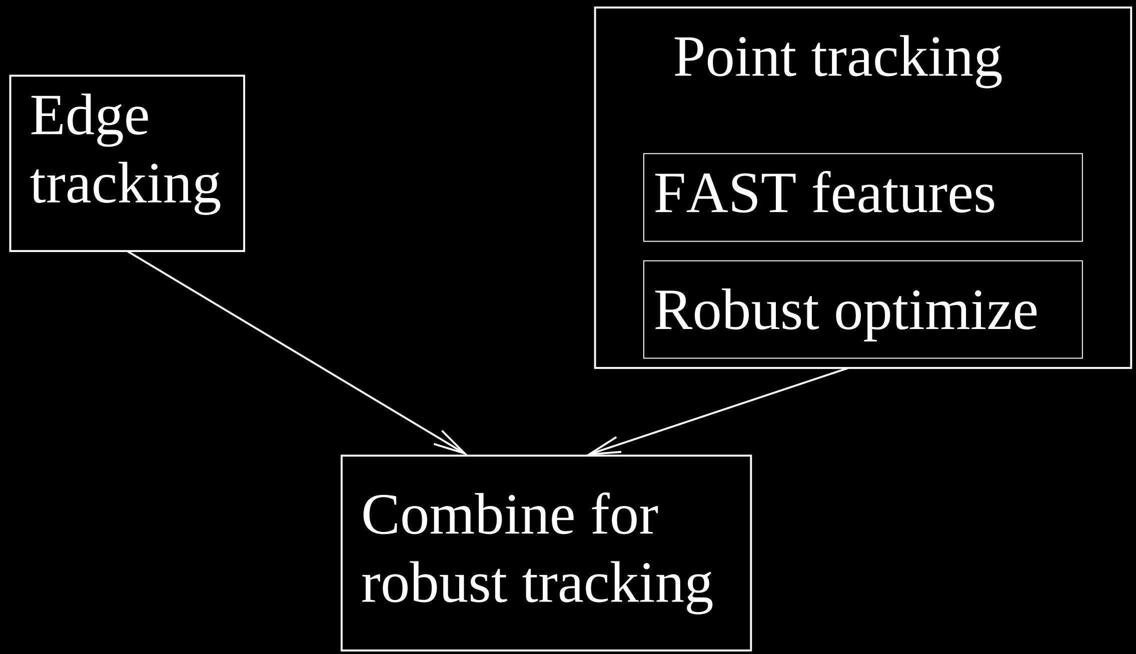
- An efficient, robust point based tracker

  Built using:

  - A *very* fast, repeatable feature detector
    - ⋆ Now used in crowd tracking, SLAM, localisation...
  - Online learning of match quality
- Careful modelling allows combination of trackers for extra robustness
- Technologies described apply more widely than to 6 DOF tracking

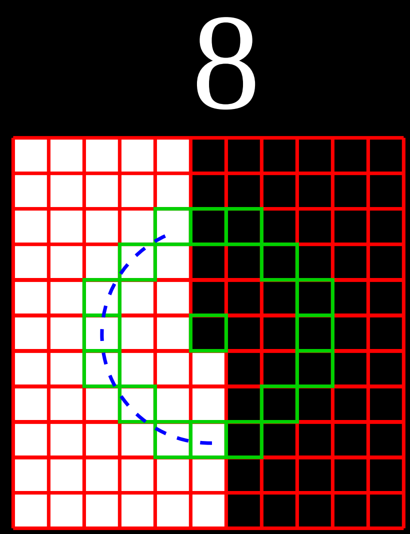
Any questions?

Model based tracking

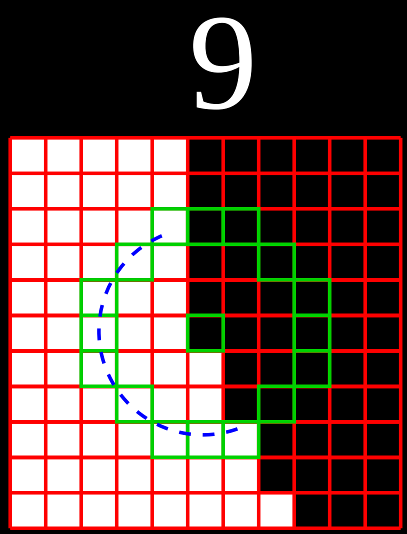


- Different failure modes
  - Combine for extra robusteness
  - Combination is difficult
    - ⋆ Statistics are non Gaussian

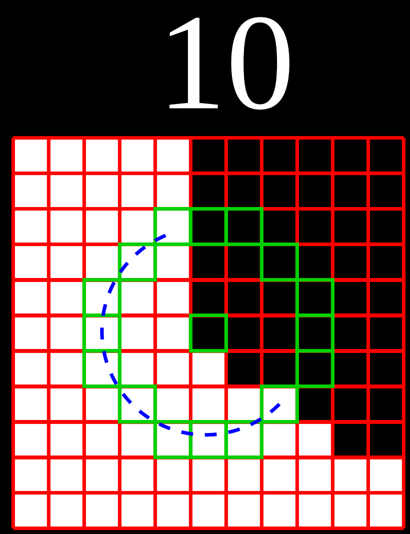
Example detectors



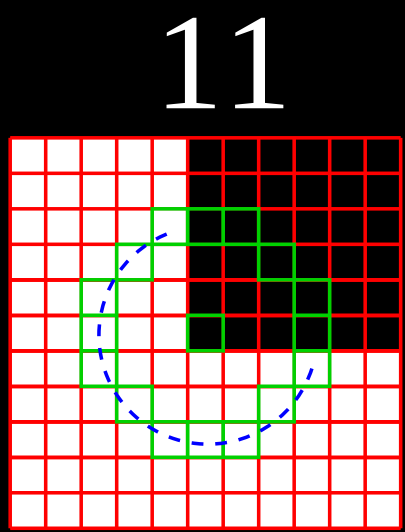
Example detectors



Example detectors



Example detectors



Example detectors

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