Fusing points and lines for high performance real-time tracking

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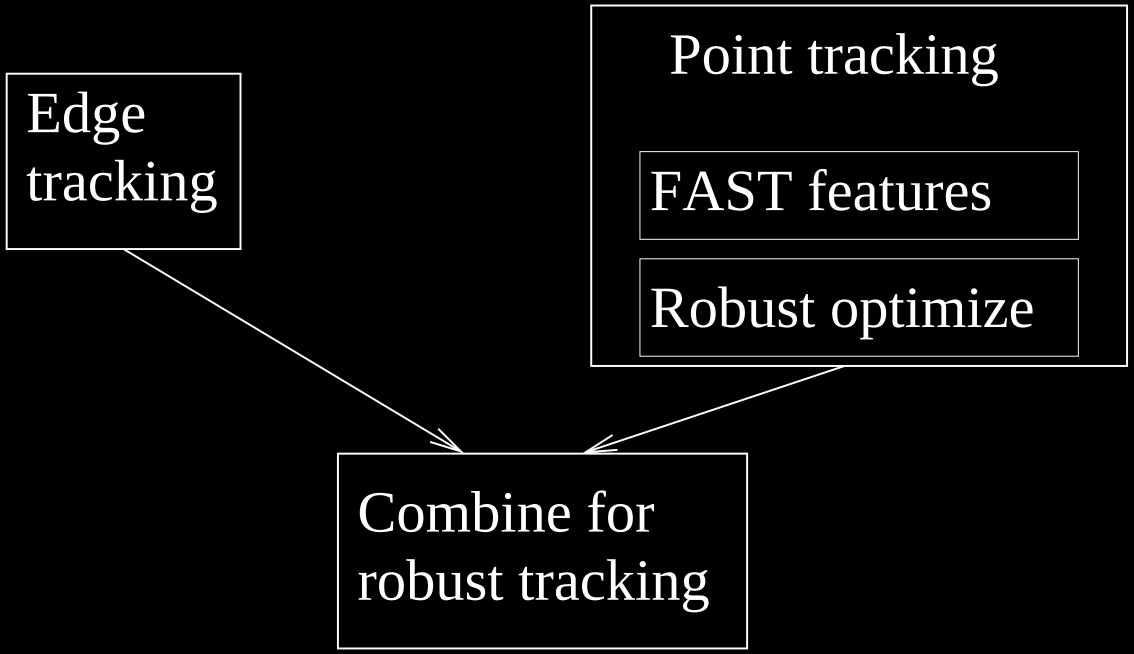
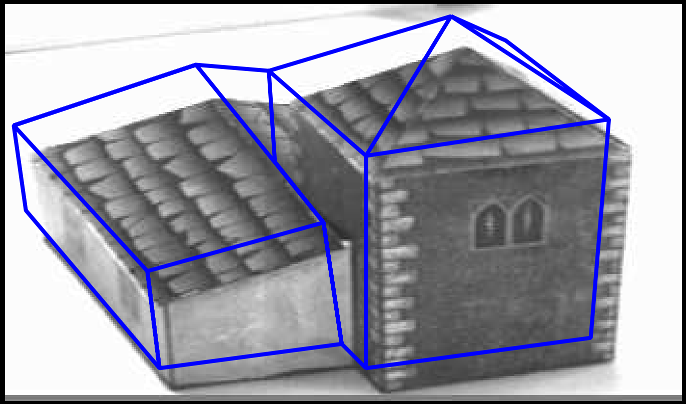
Model based tracking



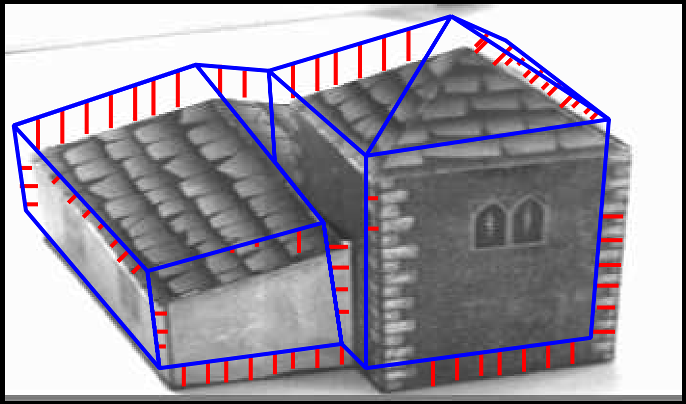
- Different failure modes
  - Combine for extra robusteness
  - Combination is difficult
    - ⋆ Statistics are non Gaussian

Edge based tracking



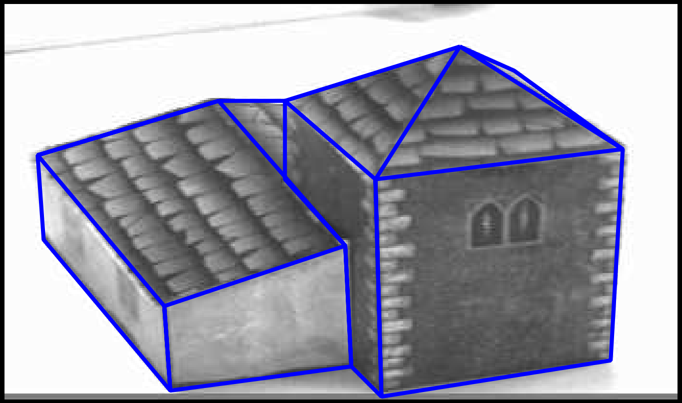
- Start from position prior

Edge based tracking



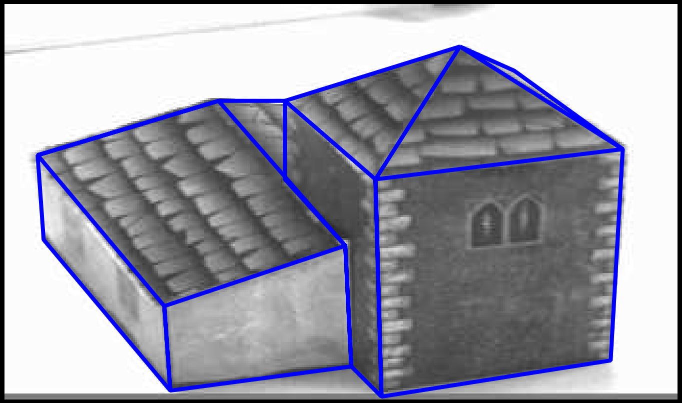
- Start from position prior
- Search along edge-normal lines

Edge based tracking



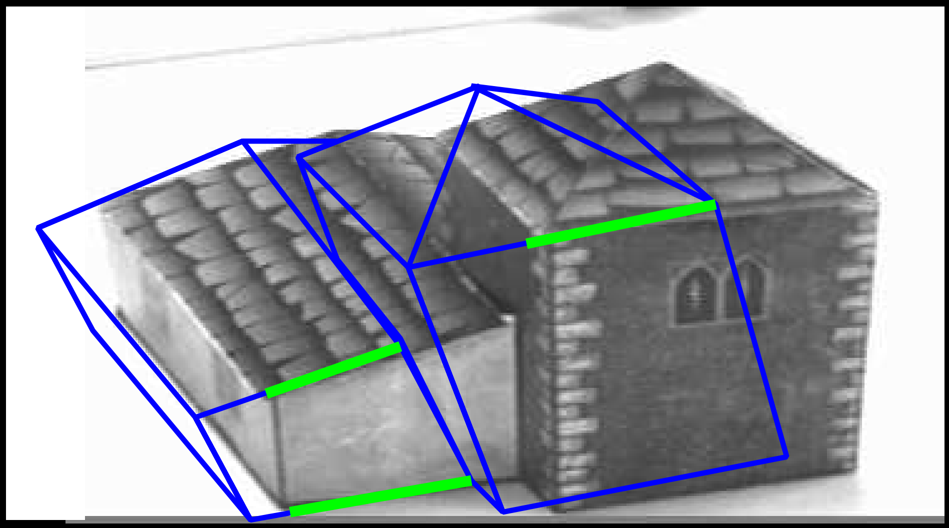
- Start from position prior
- Search along edge-normal lines
- Adjust position to minimize errors

Edge based tracking



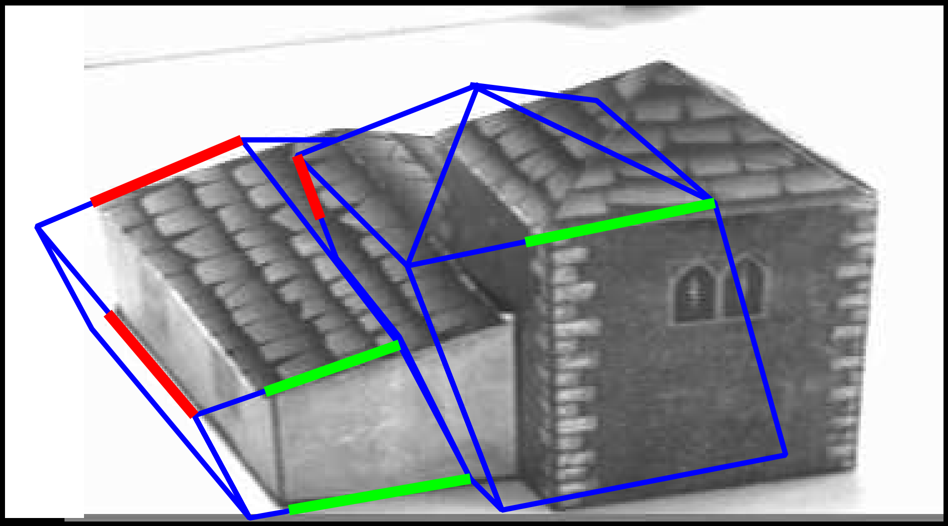
- Start from position prior
- Search along edge-normal lines
- Adjust position to minimize errors
- Gives drift free measurements
  - Model is static

Good prior needed



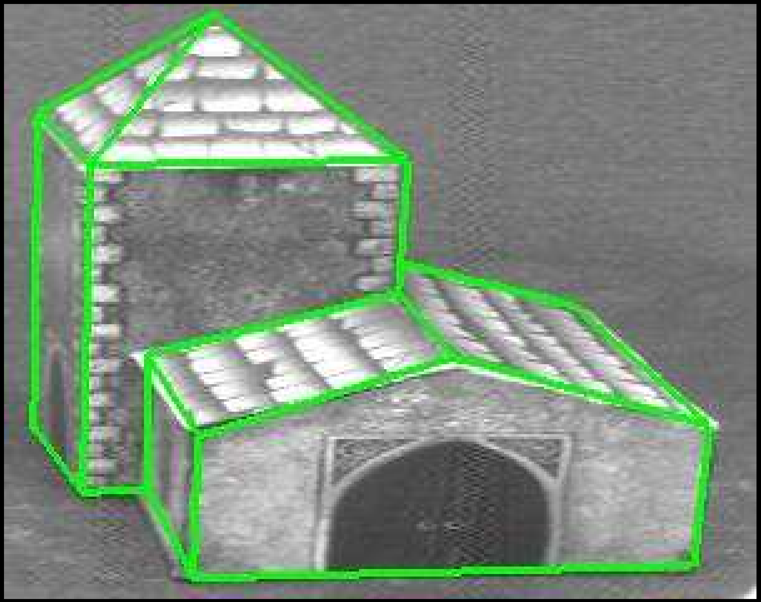
- Edges are a step change in intensity
- Correspondence is hard—pick closest edge

Good prior needed



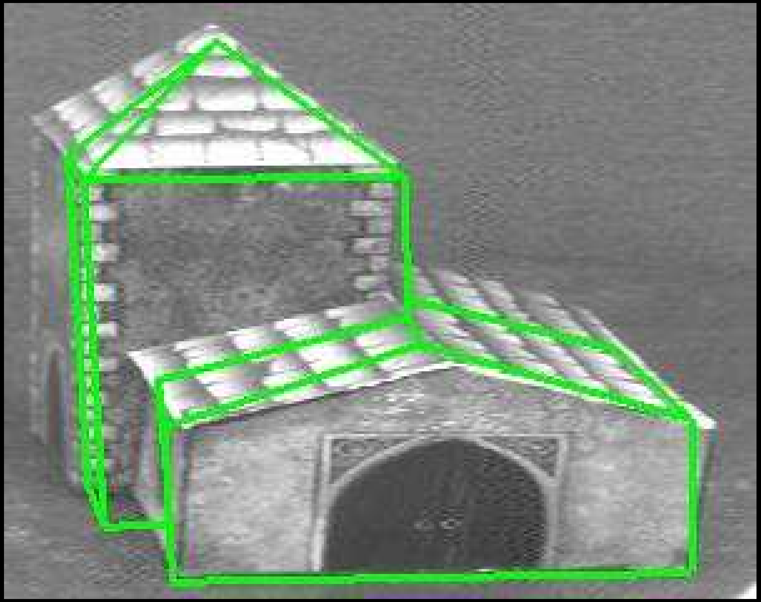
- Edges are a step change in intensity
- Correspondence is hard—pick closest edge
- Prior must be good, or the wrong edge will be found
  - Correct edge might be nowhere near

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
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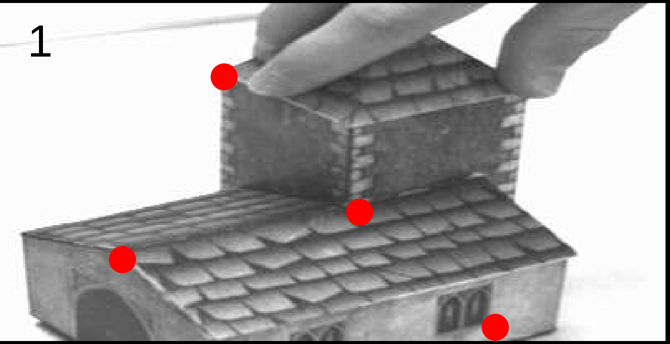
  - Tracking is inaccurate—even if prior is good

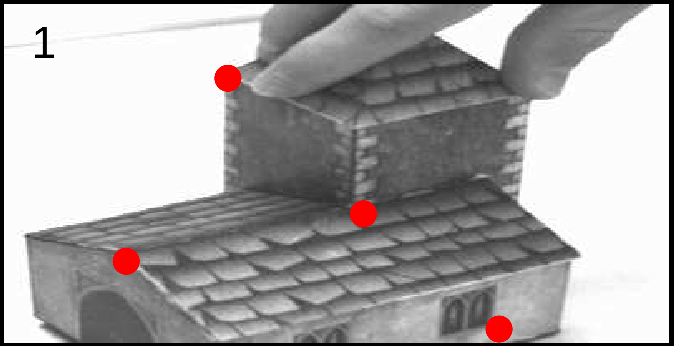
Point based tracking

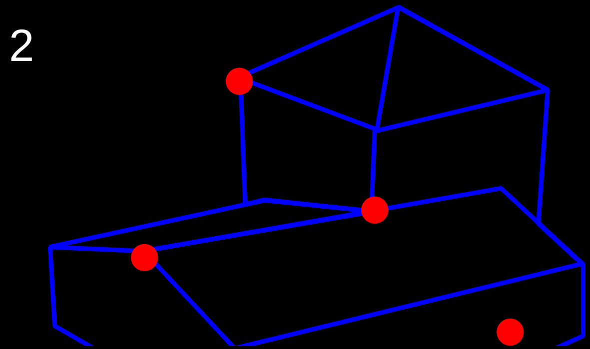
Detect features



Point based tracking

Detect features





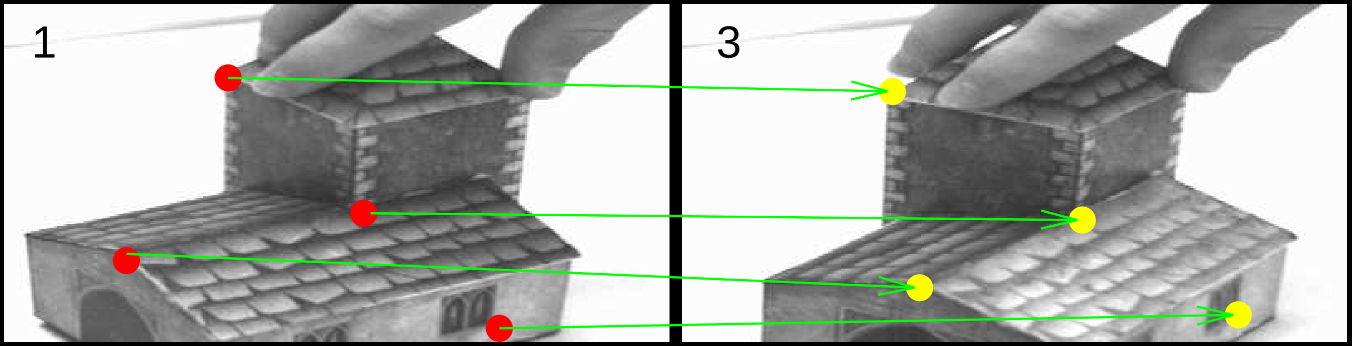
Project features on to model.

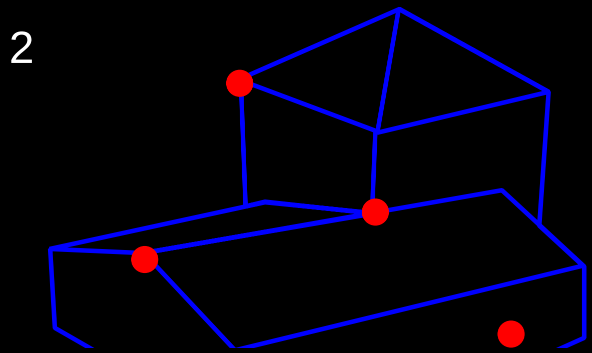
Drift occurs here

Point based tracking

Detect features

Detect and match features in next frame





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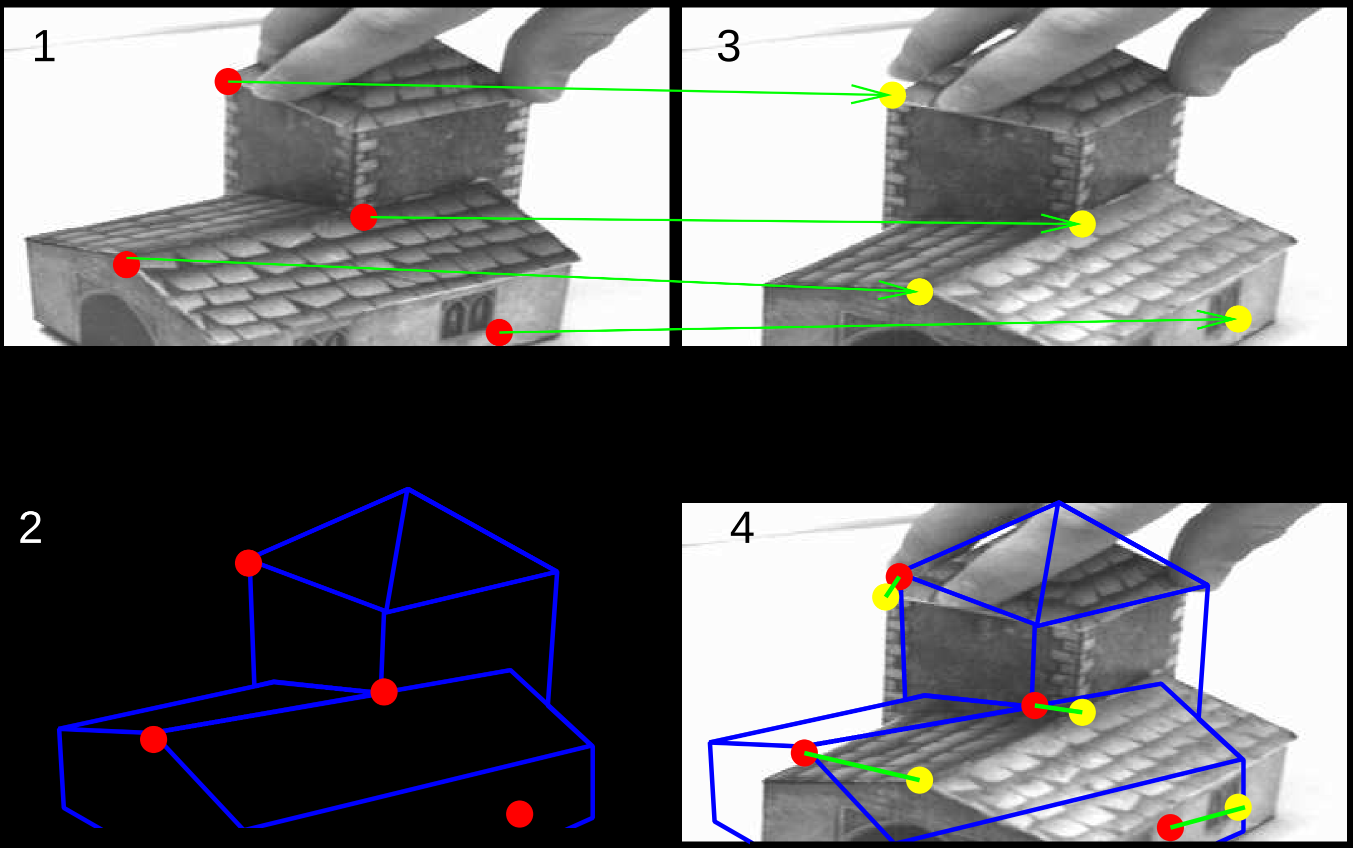


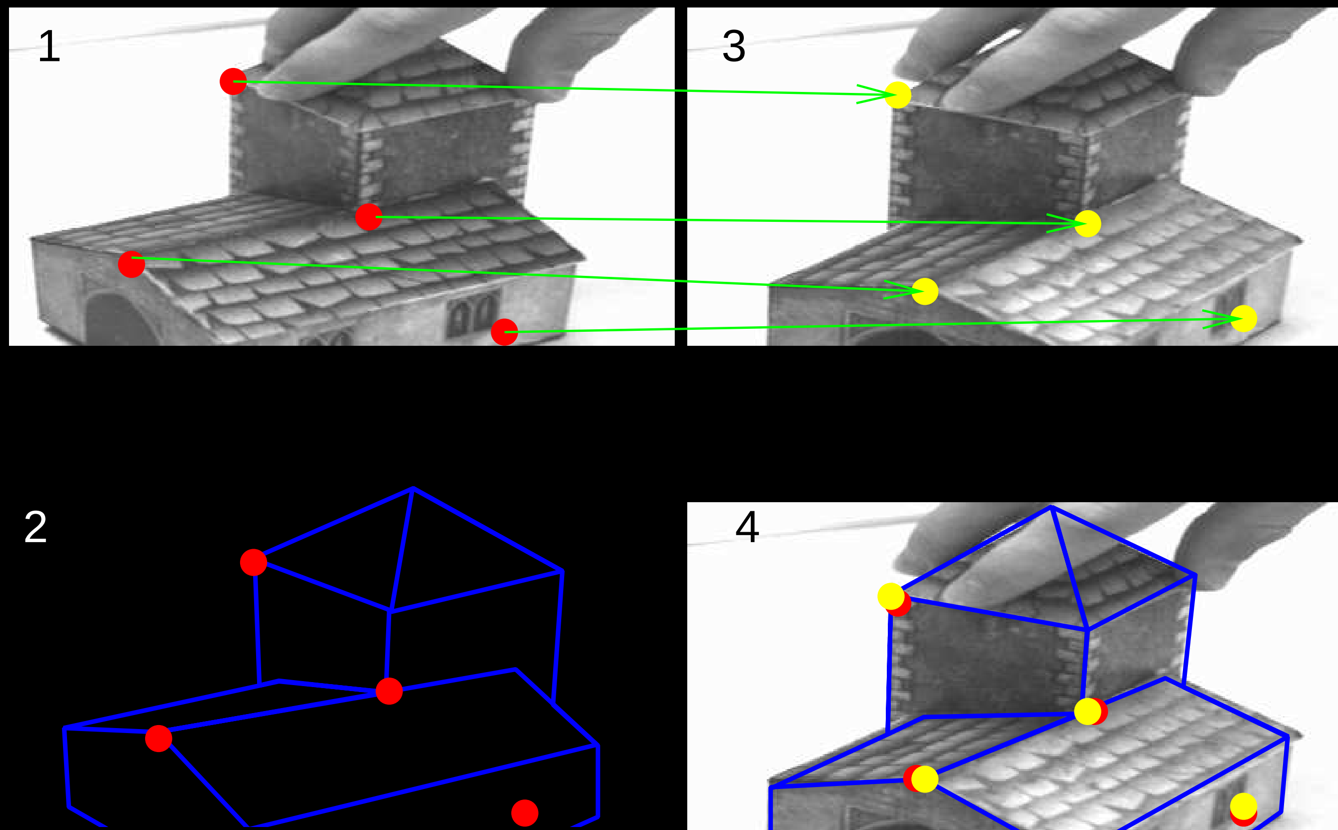
Project features on to model. Drift occurs here

Alter pose to minimize reprojection error

Point based tracking

Detect features

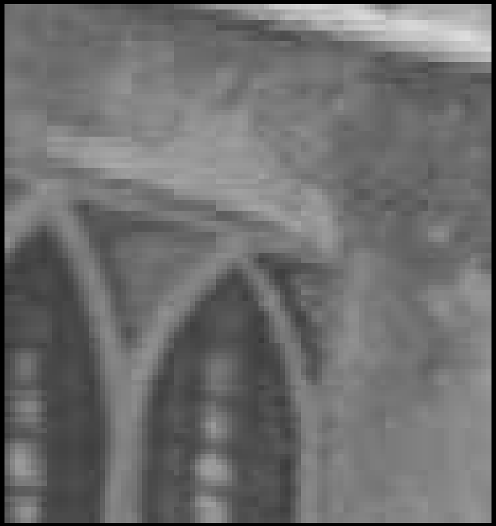
Detect and match features in next frame



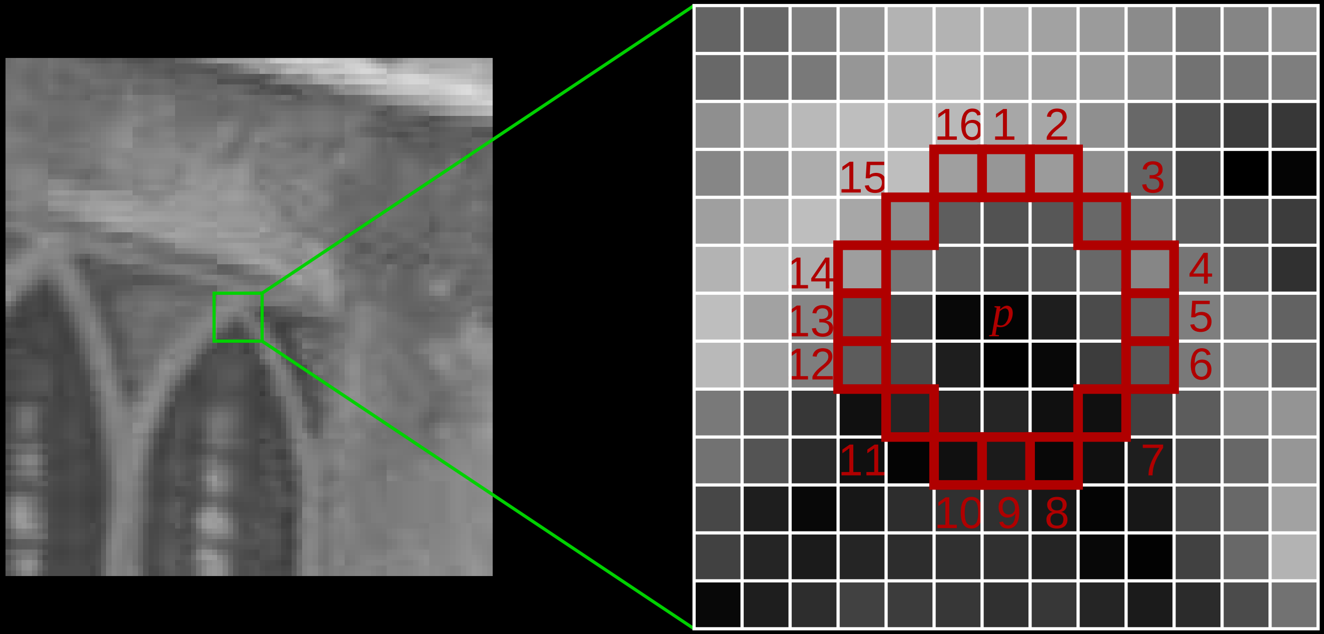
Project features on to model. Drift occurs here

Alter pose to minimize reprojection error

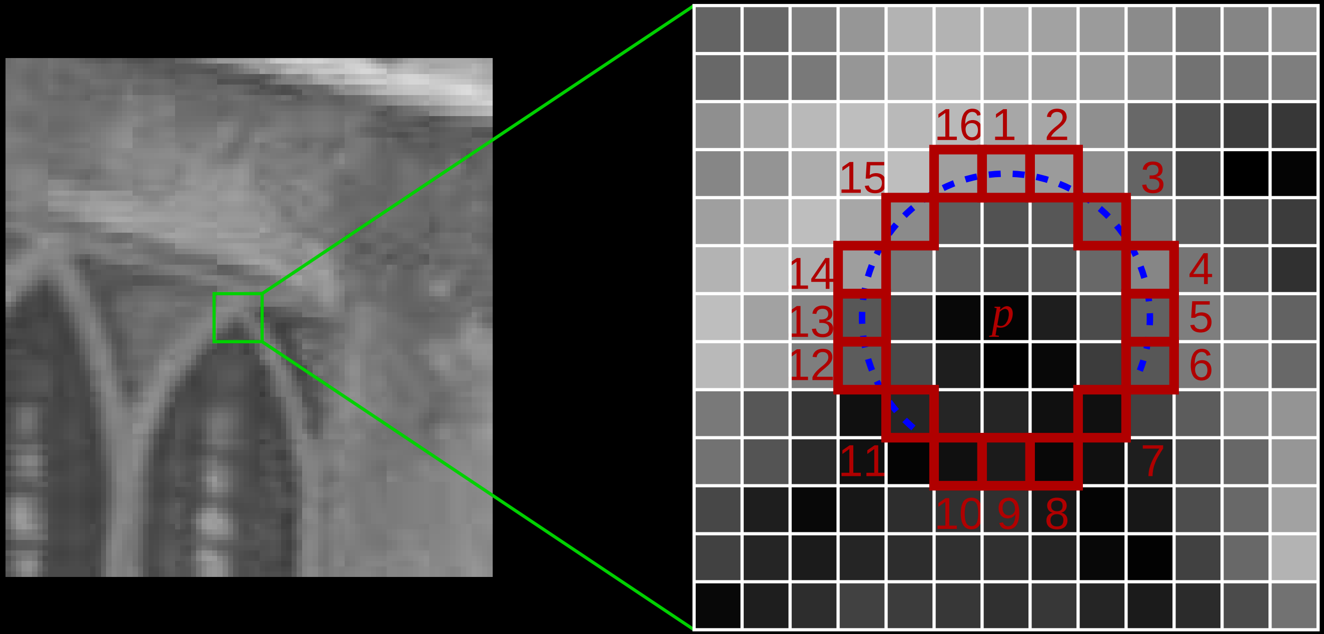
The FAST feature detector



The FAST feature detector

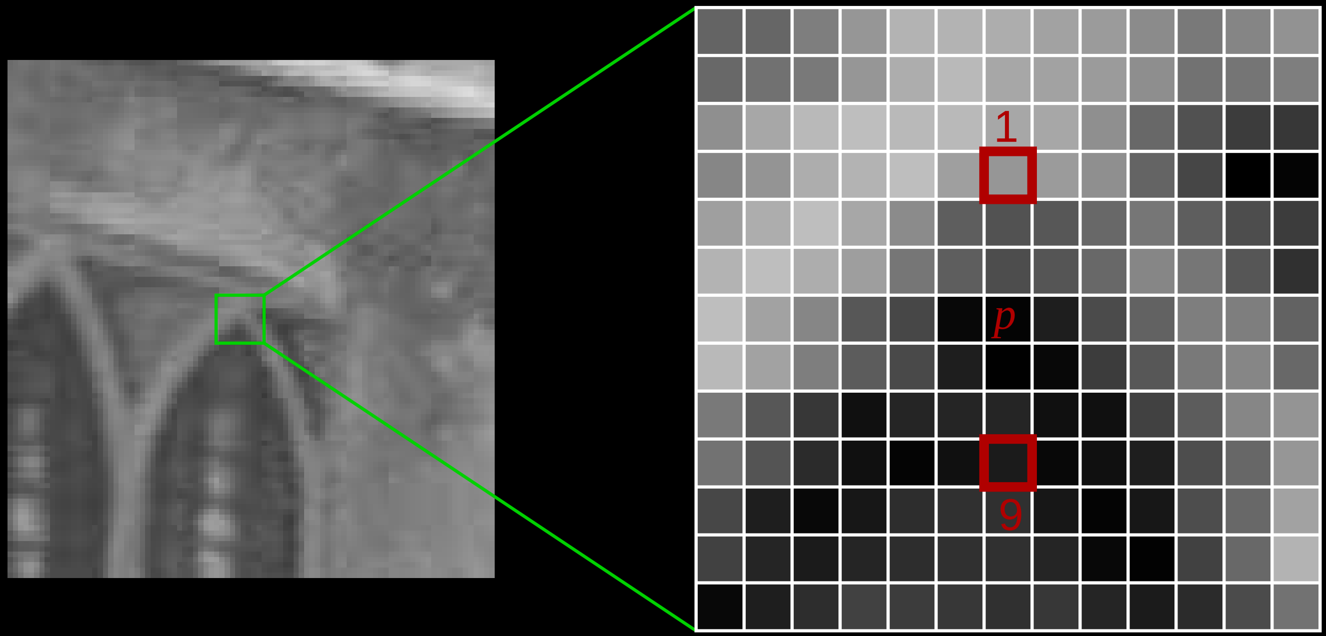


The FAST feature detector



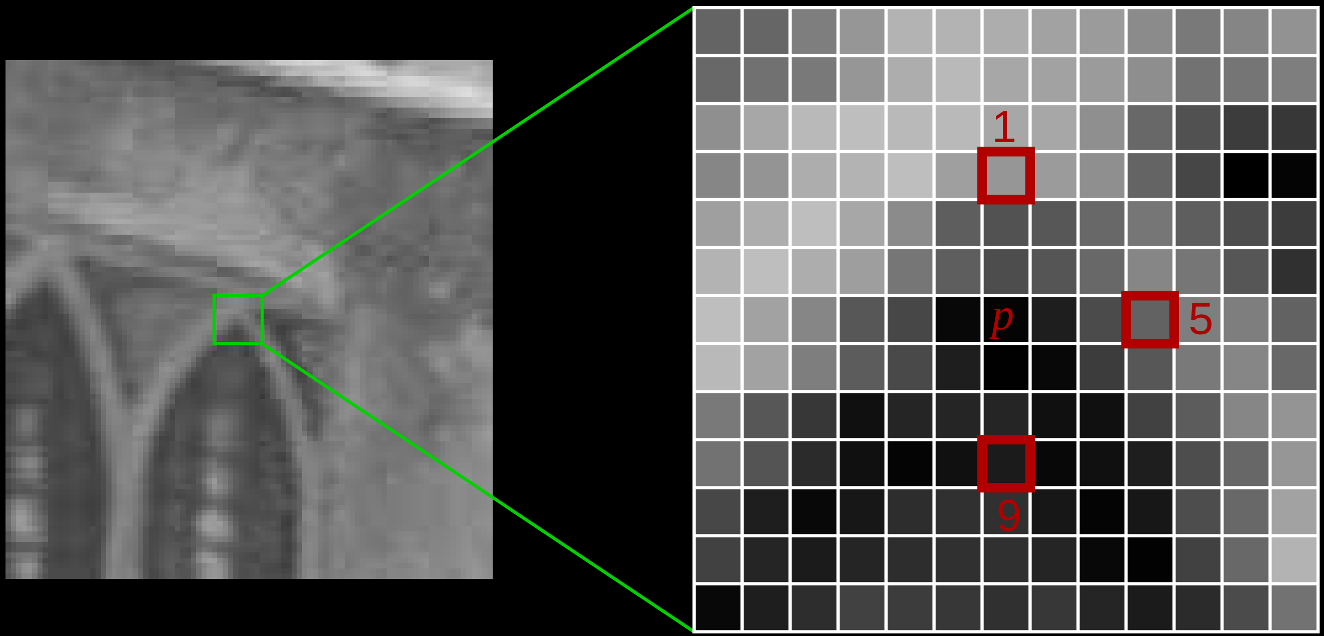
- $\geq$ 12 contiguous pixels brighter than p+*threshold*

The FAST feature detector



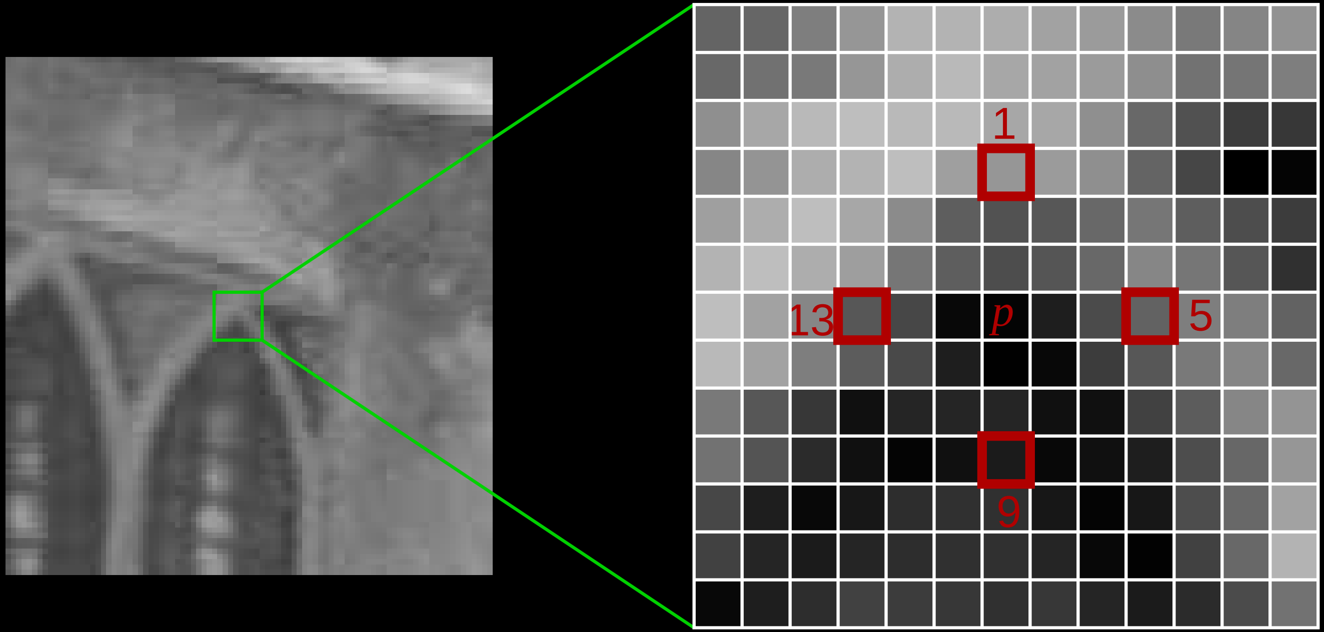
- $\geq$ 12 contiguous pixels brighter than p+*threshold*
- Rapid rejection by testing 1, 9

The FAST feature detector



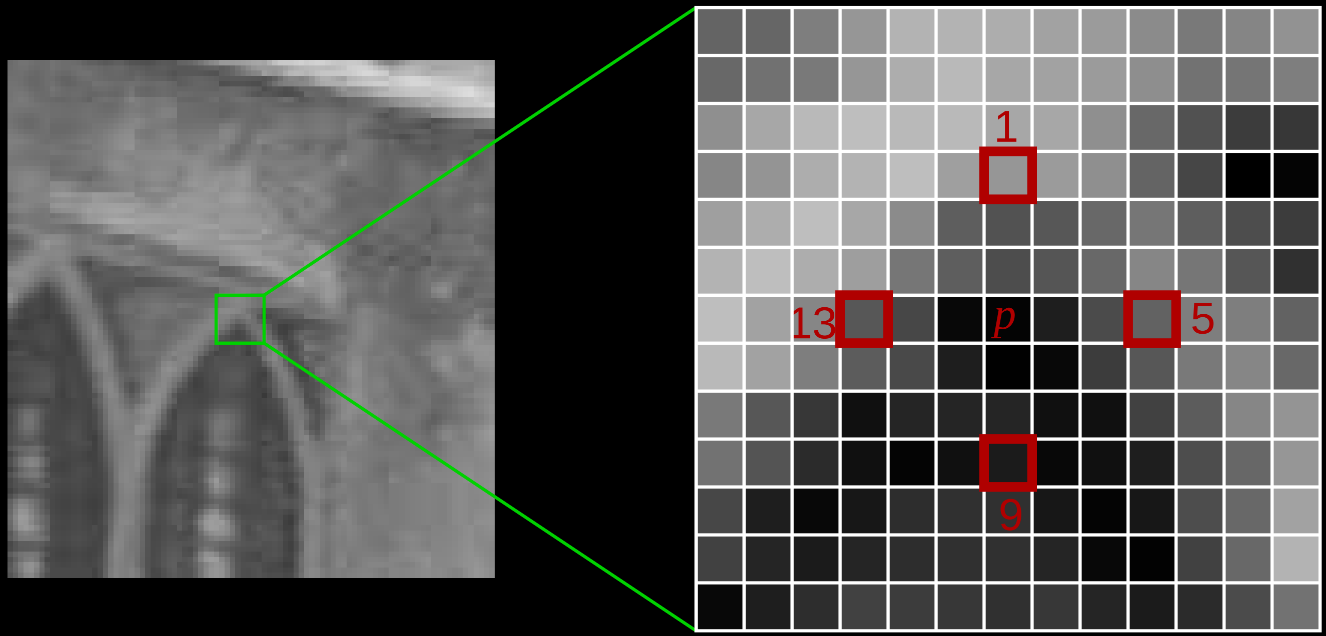
- $\geq$ 12 contiguous pixels brighter than *p+threshold*
- Rapid rejection by testing 1, 9, 5

The FAST feature detector



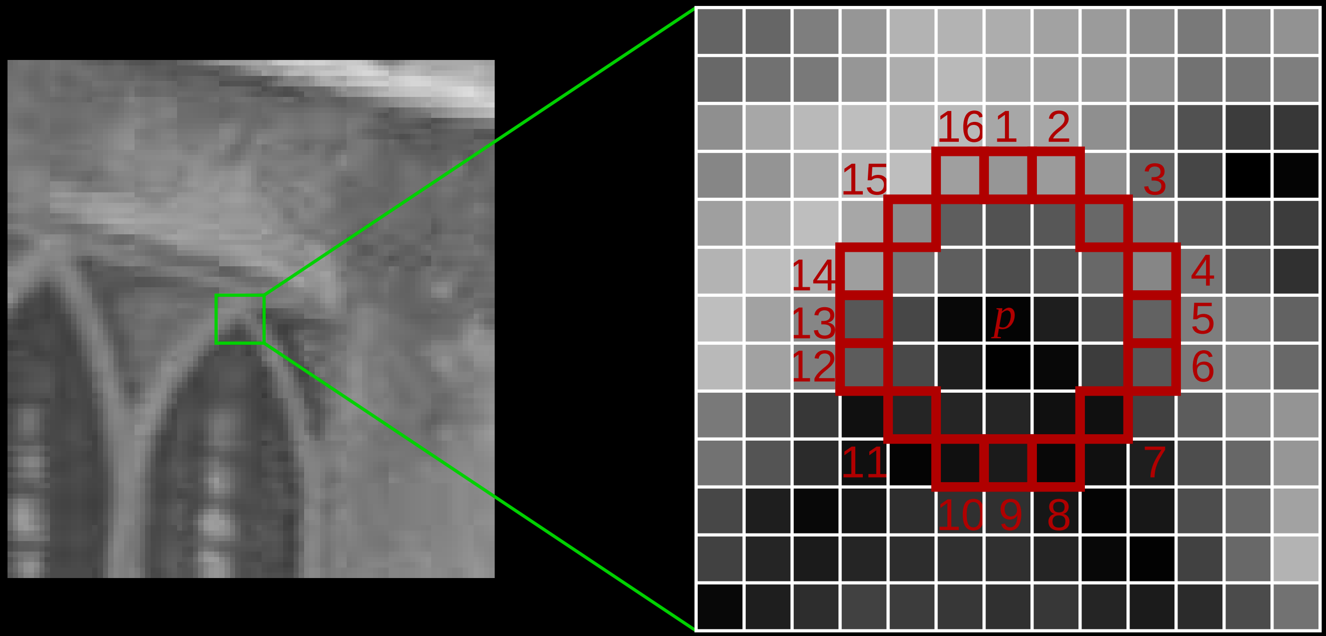
- $\geq$ 12 contiguous pixels brighter than *p+threshold*
- Rapid rejection by testing 1, 9, 5 then 13

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 (see paper for URL)

The FAST feature detector

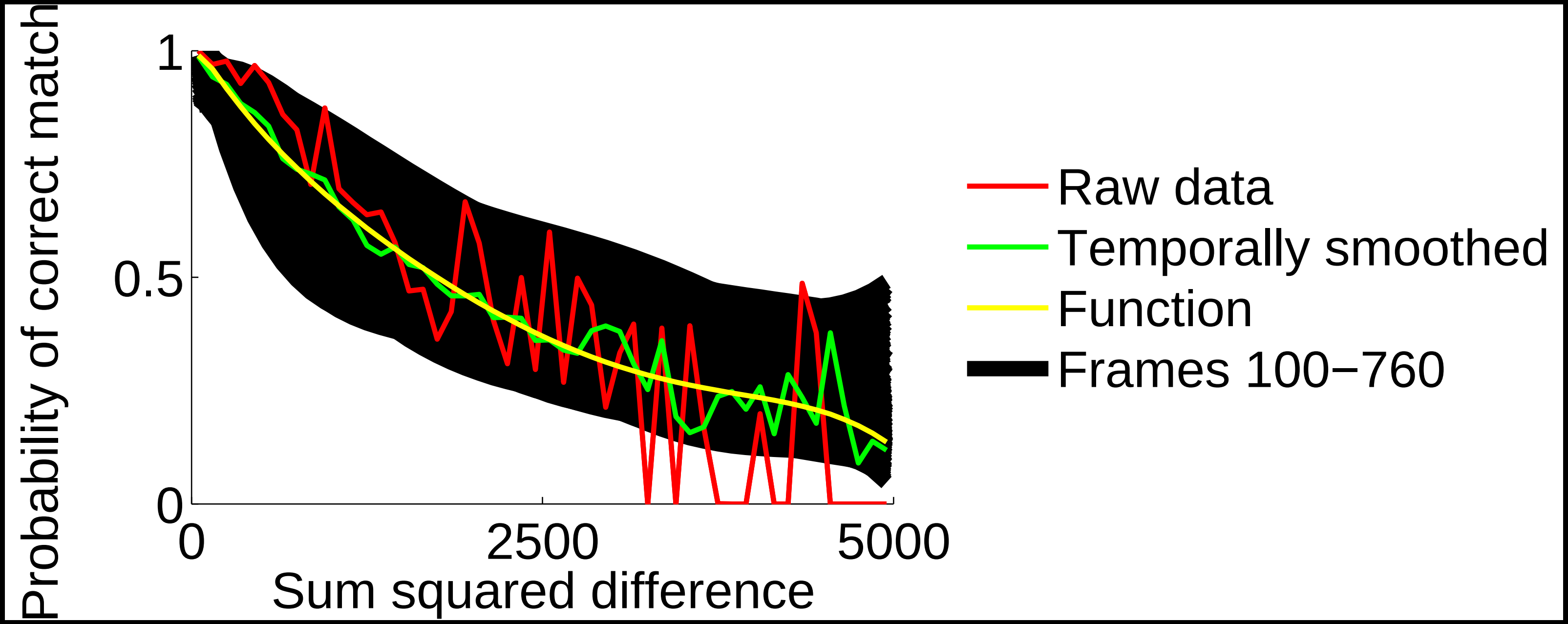


- $\geq$ 12 contiguous pixels brighter than *p+threshold*
- Rapid rejection by testing 1, 9, 5 then 13
- 1.59ms (Opteron 2.6GHz) - 8% of available CPU time
- Source code available (see paper for URL)
- 16 test pixels used for feature vector
- SSD used for matching between frames

Position optimization

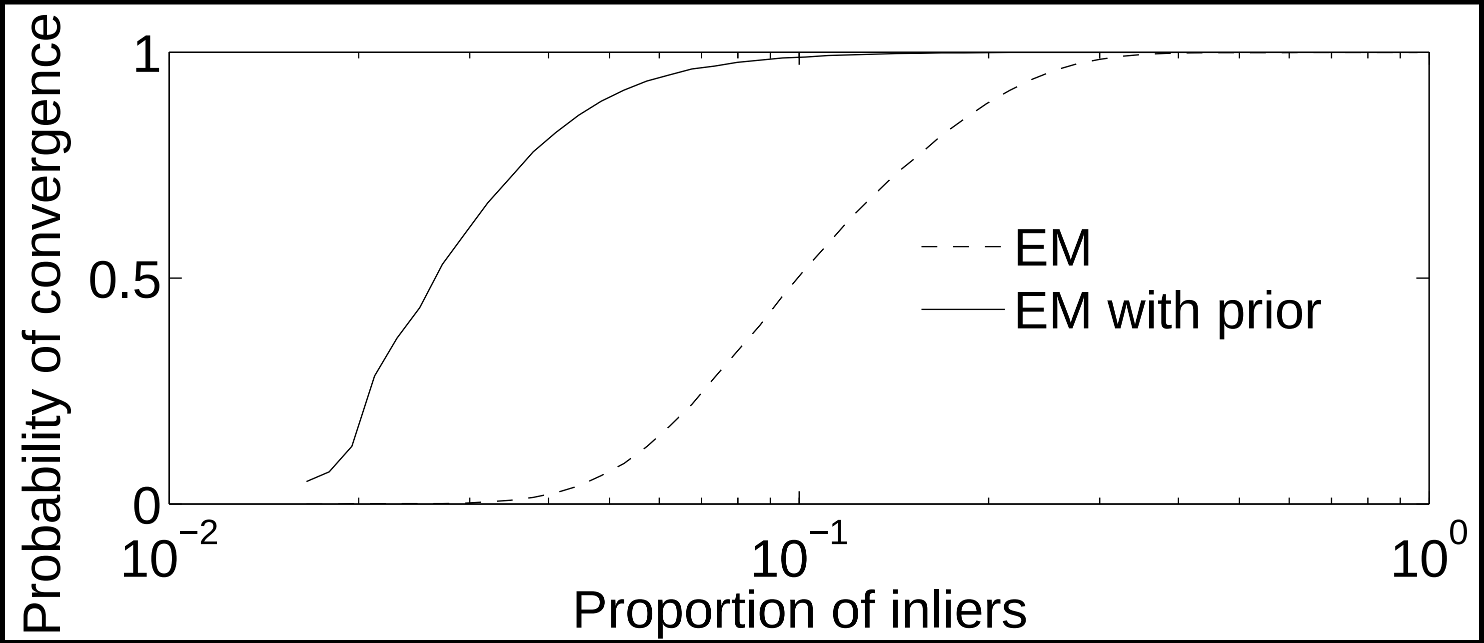
- Sometimes $> 90\%$ outliers (even with SIFT!)
  - Robust optimize required
- Use EM
  - Mixture model is
    Gaussian (inliers) + uniform (outliers)
- SSD has some information about inlier probability
  - If only we knew the relationship...

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

Matching prior



- EM provides probability that a match is correct
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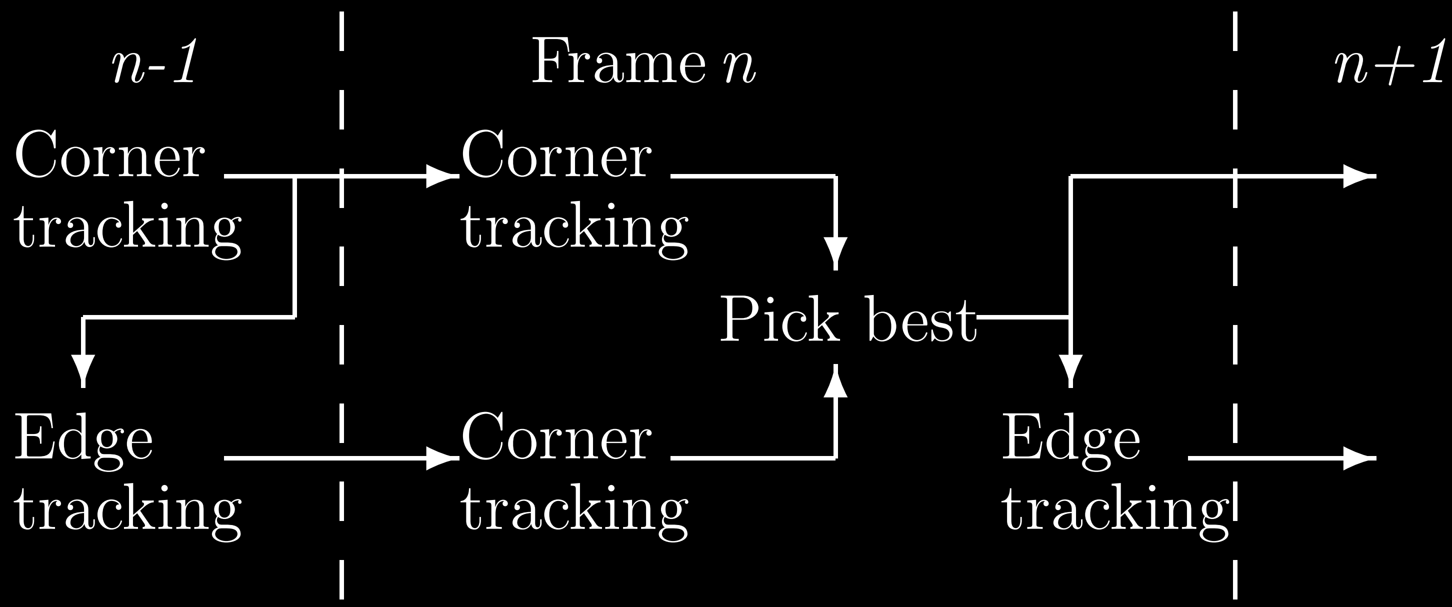
Measurement Properties

- 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

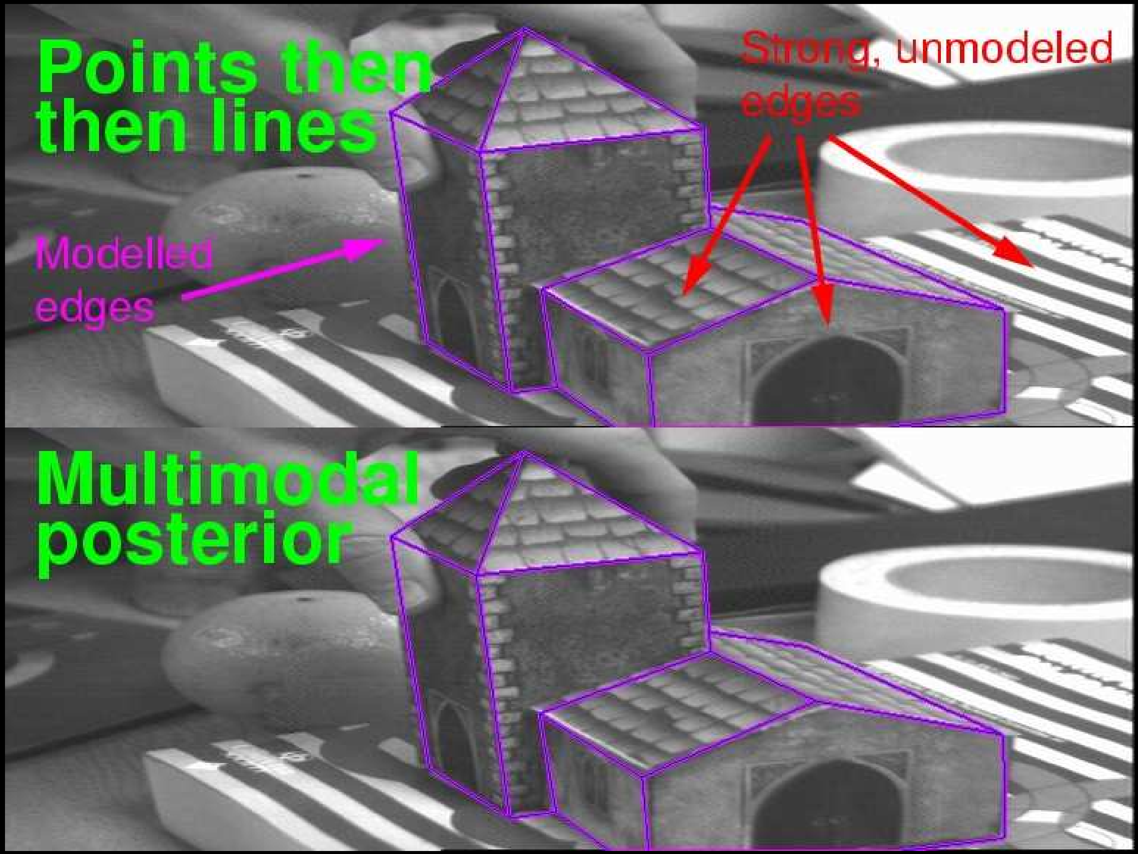
- Either tracker can be wrong
  - Edge tracker can get correspondence wrong
  - Point based tracker can drift
- Posterior can be multimodal
  - Simple solutions do not work

Sensor fusion



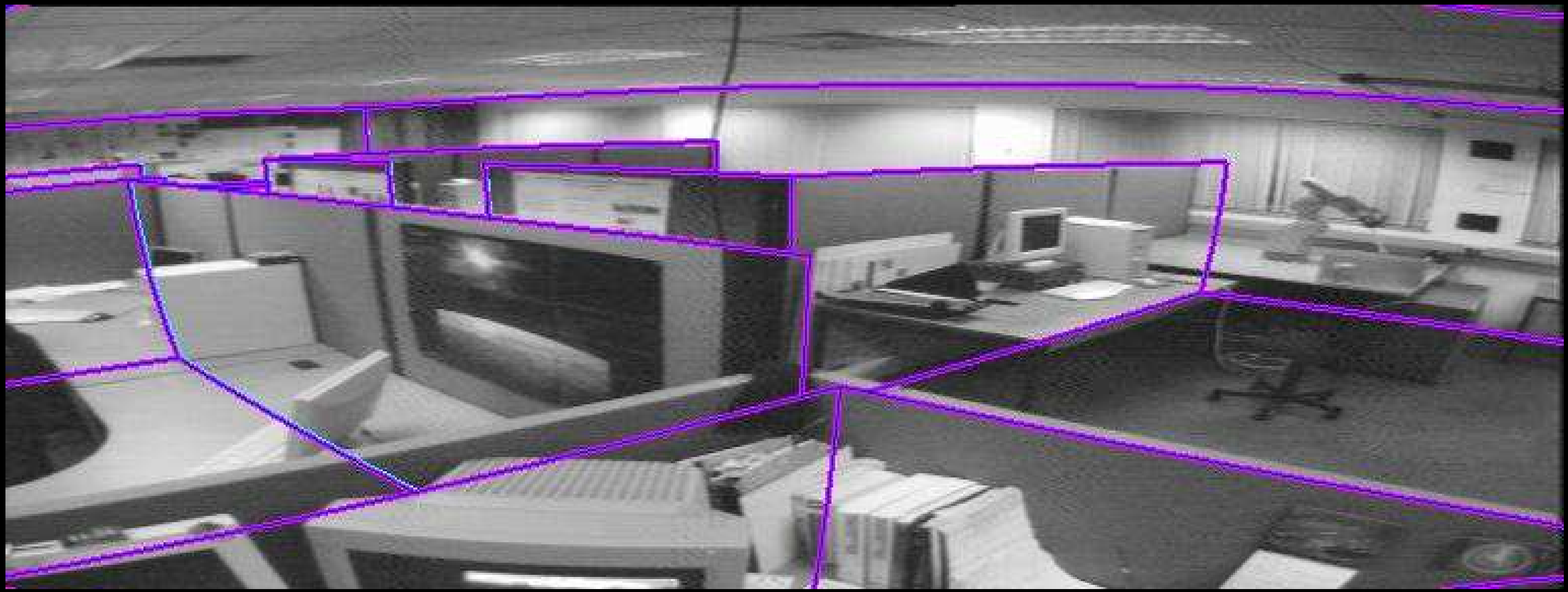
- Either tracker can be wrong
  - Edge tracker can get correspondence wrong
  - Point based tracker can drift
- Posterior can be multimodal
- Evaluate modes *next* frame when more data arrives

Results - Strong unmodelled edges



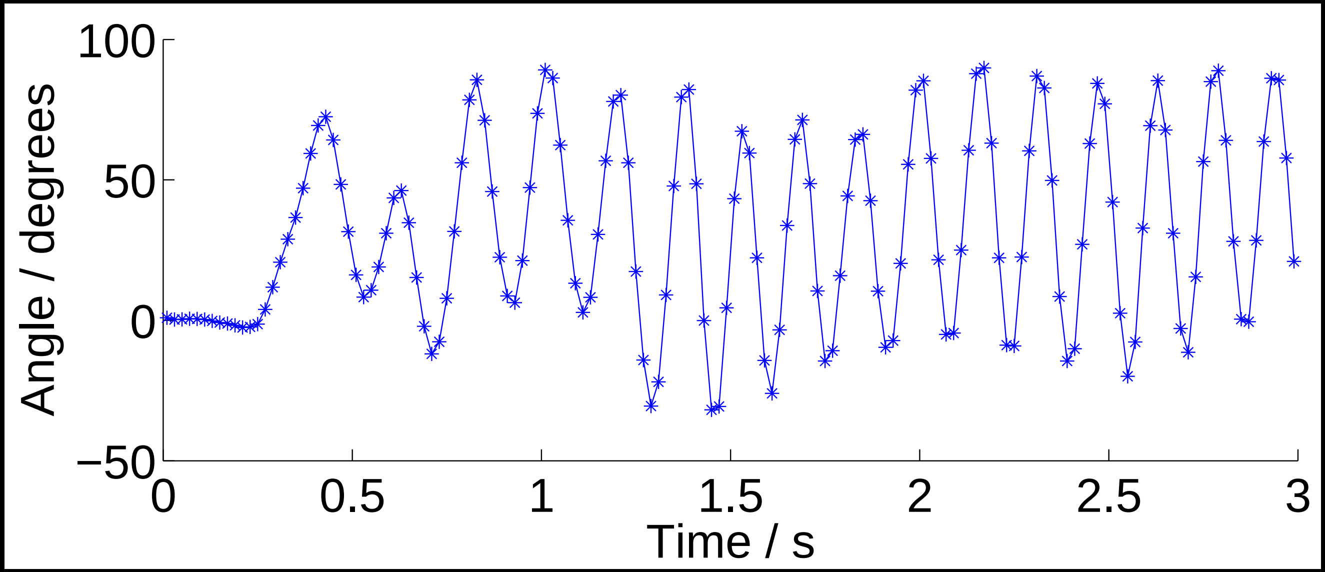
Strong unmodelled edges frequently break the edge tracker

Results - Camera shake



- Pick up camera and shake *really* hard
- 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 - Handheld camera

Pick up the camera and run around the lab

Summary

- A *very* fast feature detector
- An efficient, robust point based tracker
- Online modelling of match quality
- Careful modelling resulting in robust combination of trackers.

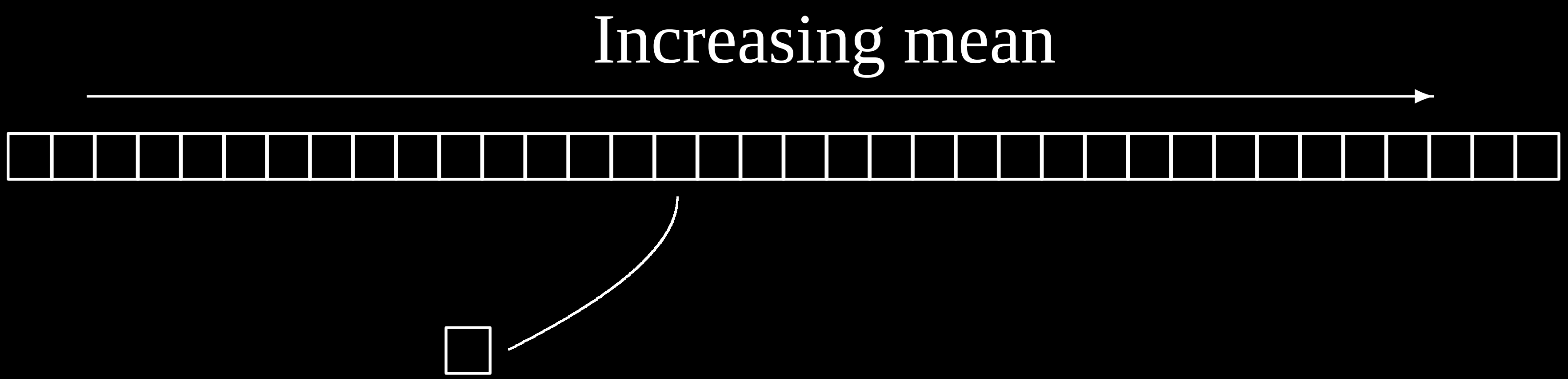
Any questions?

Efficient feature matching

Increasing mean

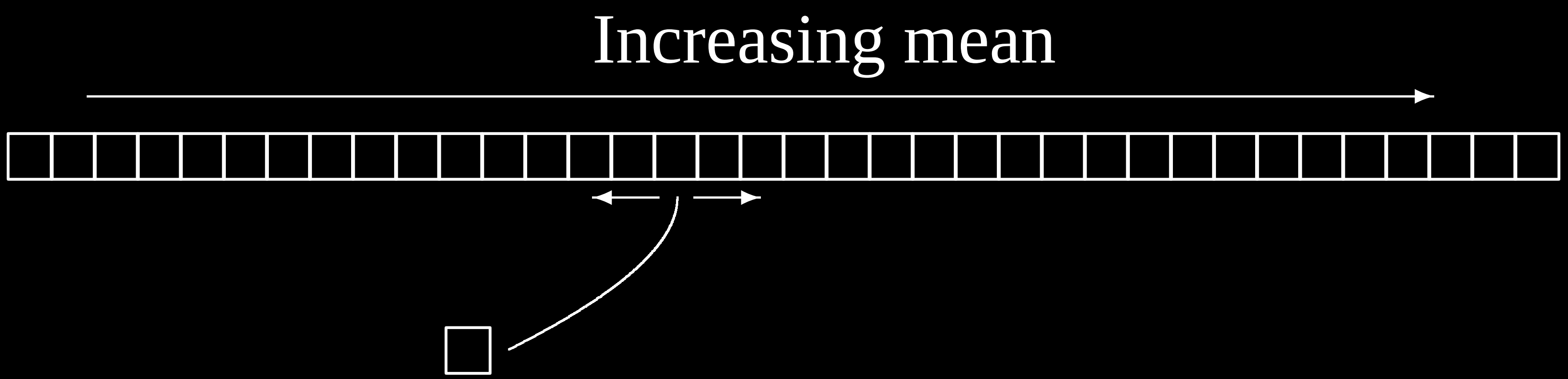
- Sort features by mean value of feature vectors

Efficient feature matching



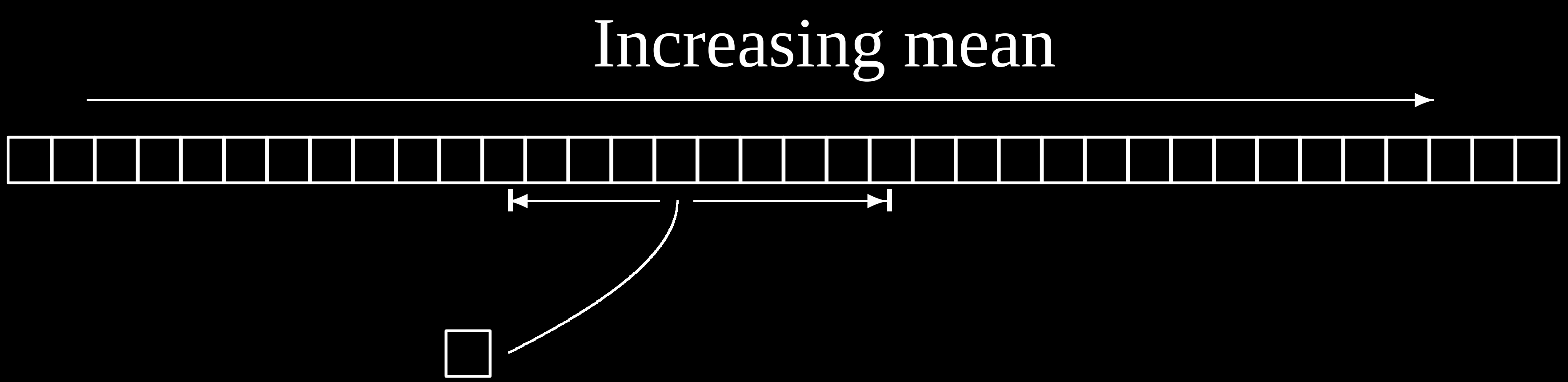
- Sort features by mean value of feature vectors
- Find closest mean by binary search

Efficient feature matching



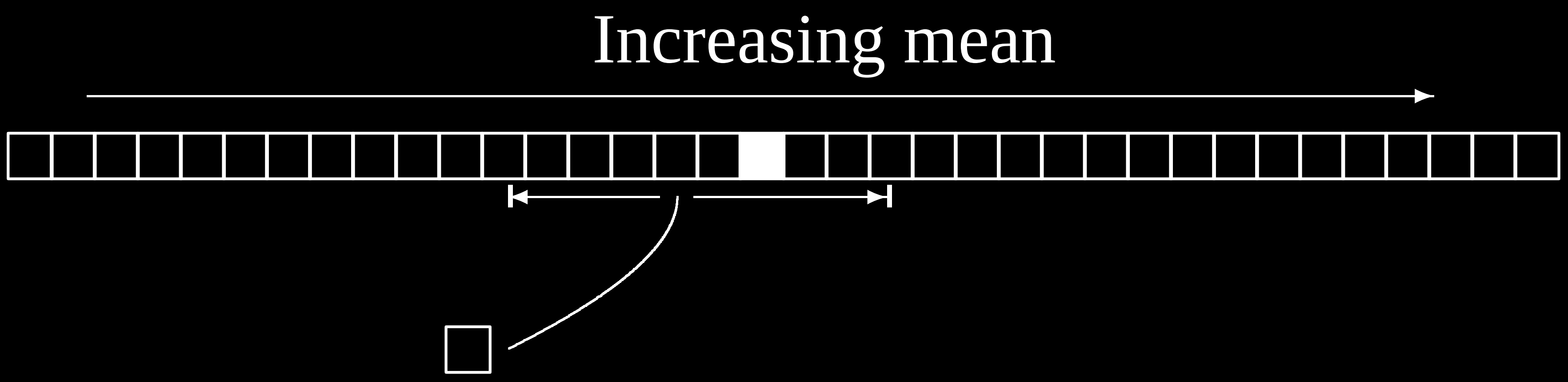
- Sort features by mean value of feature vectors
- Find closest mean by binary search
- Search outwards

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

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