AprilCal: Assisted and Repeatable Camera Calibration

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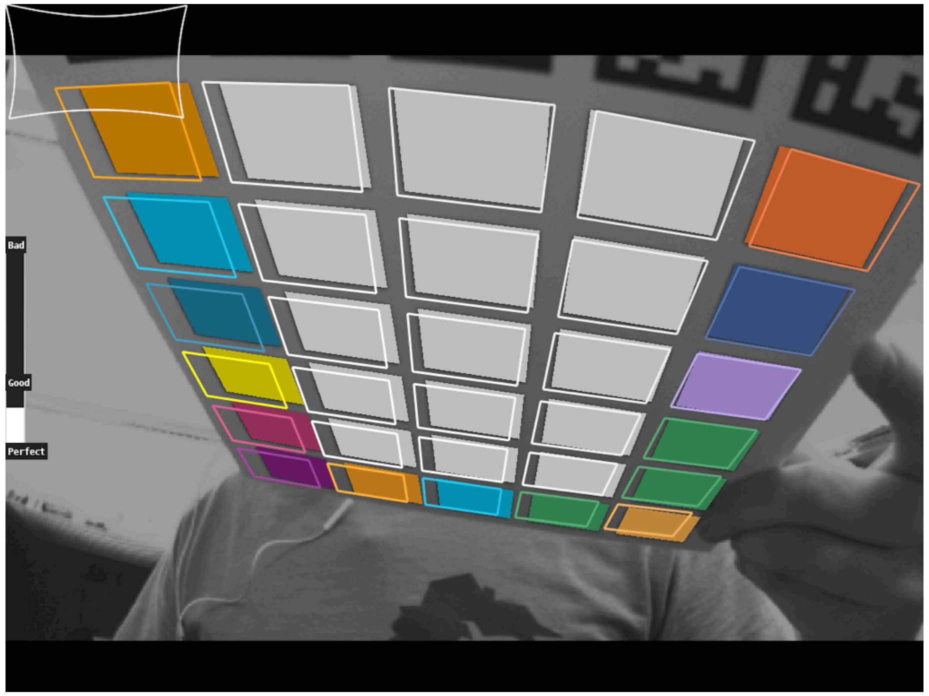

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Why do we need a new calibrator?

Repeatability

Calibration Target Design

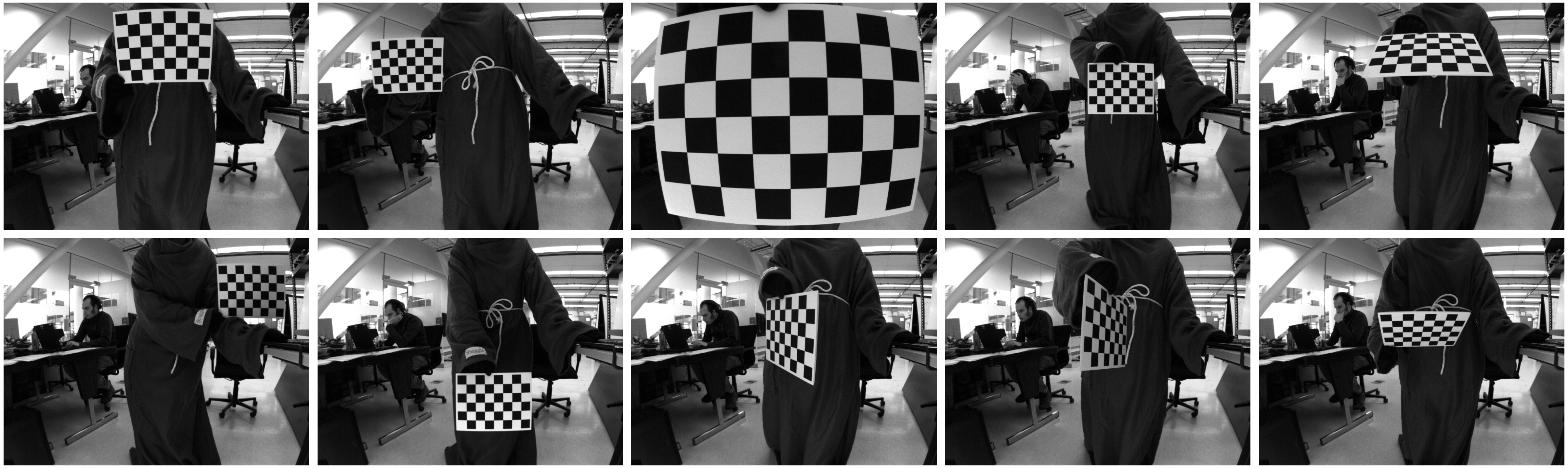
Evaluation Metrics

Feedback

Expert Calibration Knowledge

Repeatability

Why do we need a new calibrator?



Real human study calibration images (OpenCV + ‘web instructions’)

- Calibration is a fundamental prerequisite
- Accuracy is crucial
- Not all users are calibration experts

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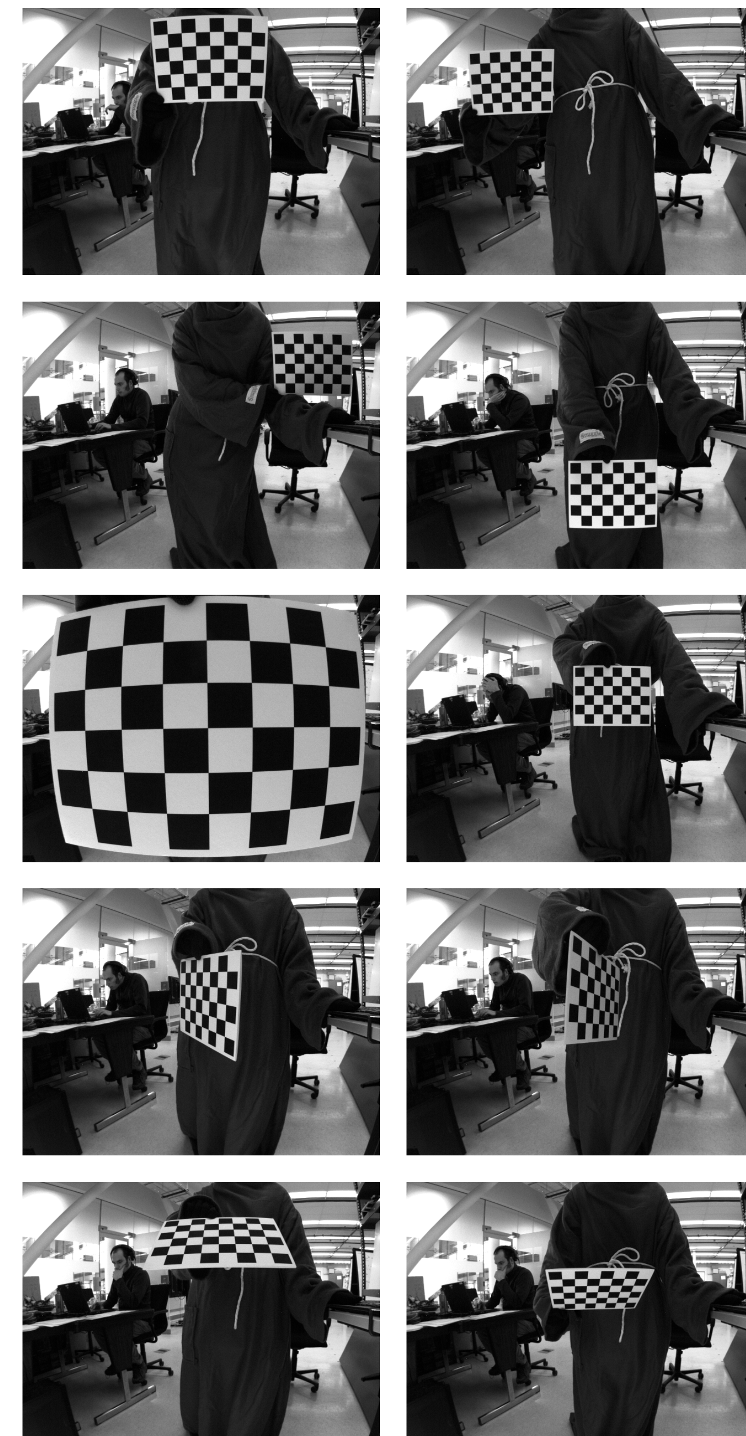
Common Calibrator Issues

- **Repeatability**: Lacking for many users
- **Calibration targets**: Hard to get any constraints in distorted corners
- **Evaluation metrics**: Training error reflects only seen data, parameter uncertainties very unintuitive
- **Little feedback**: User has to guess when the calibration is done
- **Experiment design**: User must understand which images are 'good'



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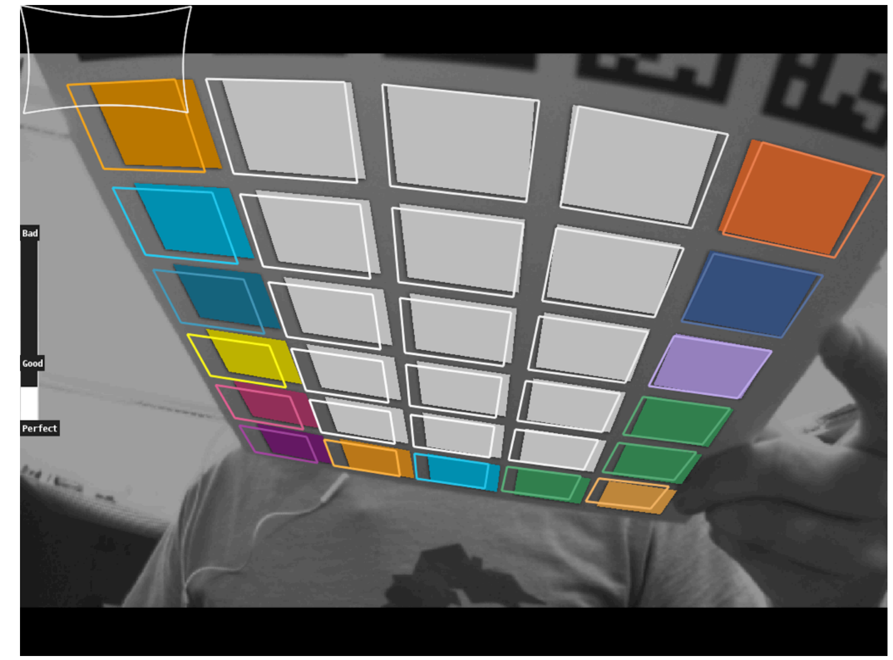
- Interactive, suggestion-based calibrator
- Realtime marker detection with fiducial markers (AprilTags)
- Intuitive worst-case error metric for generating suggestions and automatic completion



Two Biggest Takeaways

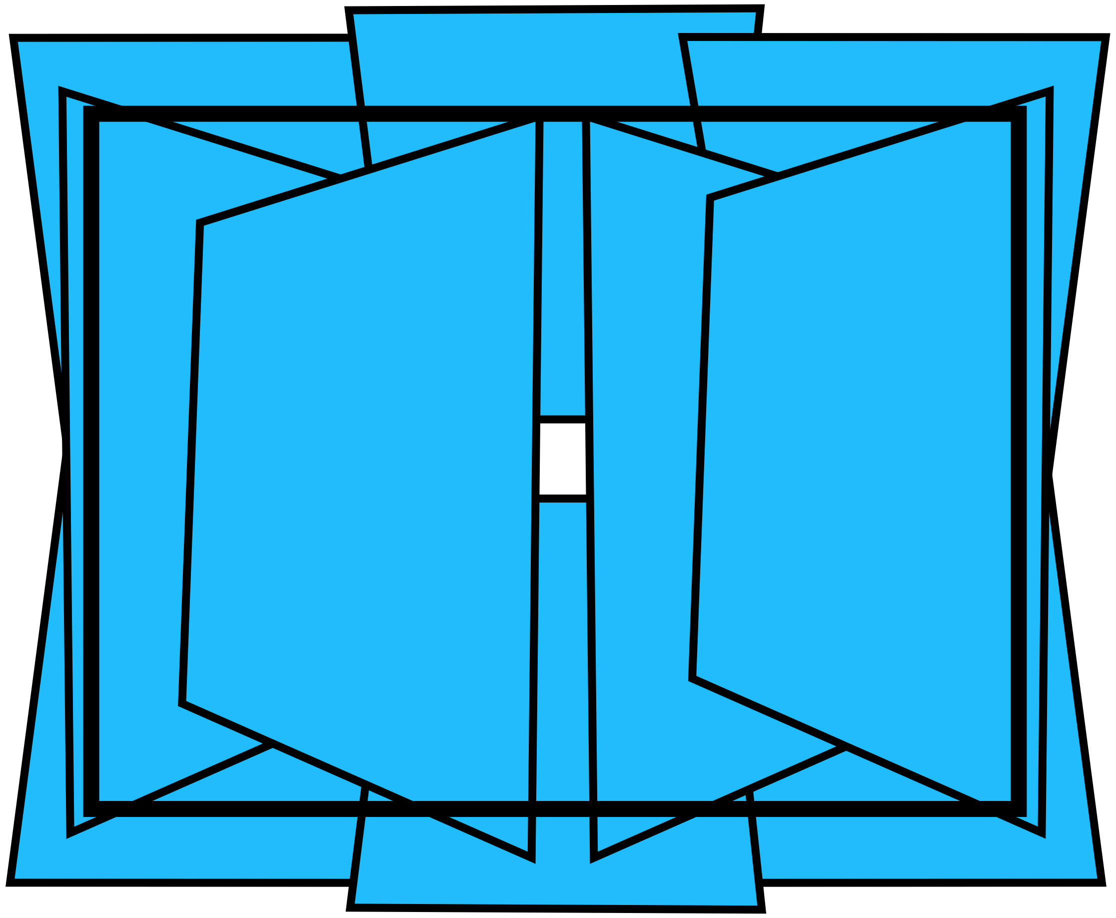
1. Suggestion-based calibration improves repeatability

2. New evaluation metric summarizes calibration uncertainty intuitively, can be used as stopping criterion
   - Suggestions not required to use this metric

How can we generate suggestions?

Generating Suggestions

- Live, adaptive suggestions (not choreography)
- Concepts:
  - **Candidate poses**: database of candidate target positions spread over working area



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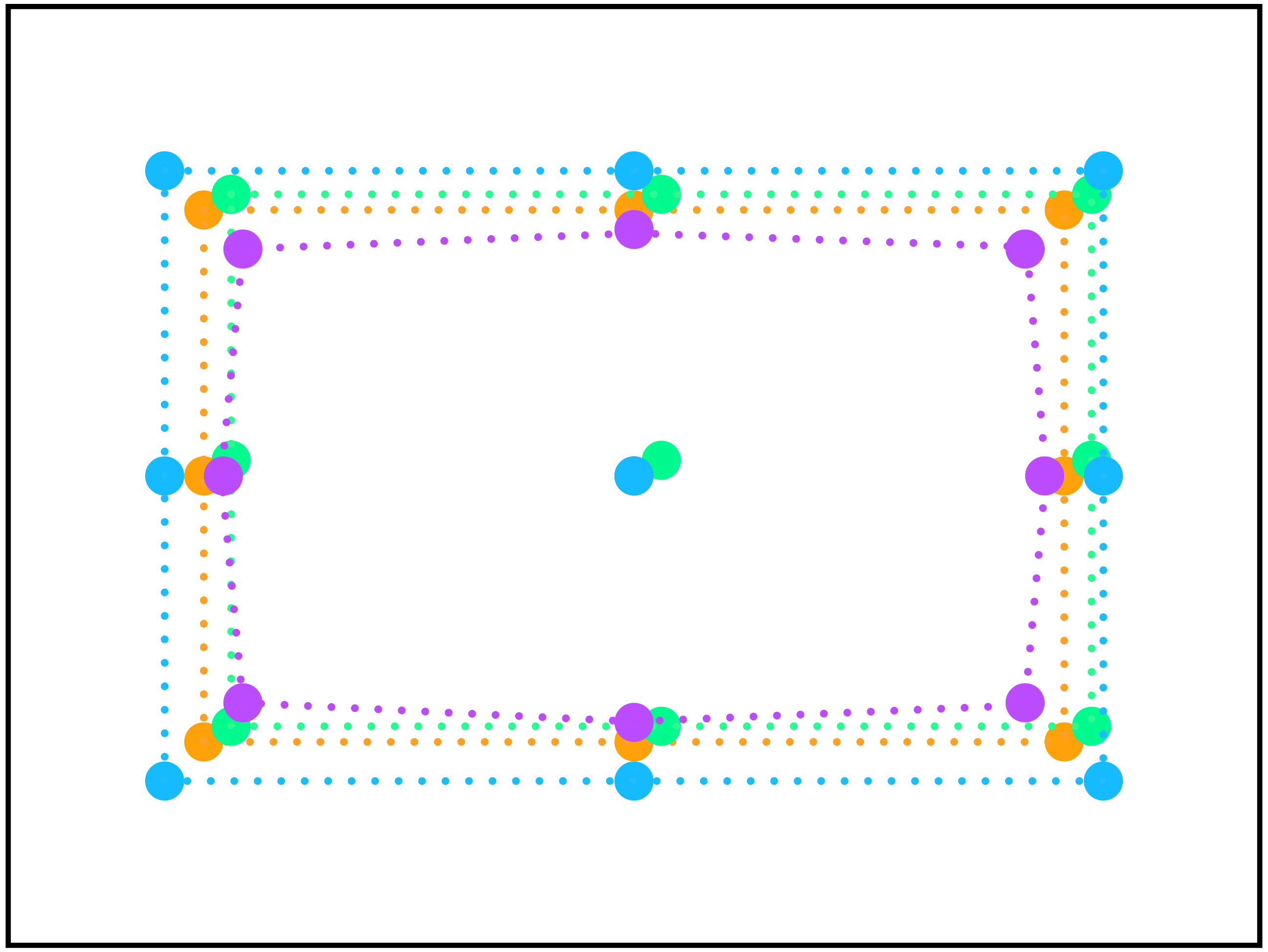
Generating Suggestions

- Live, adaptive suggestions (not choreography)
- Concepts:
  - **Candidate poses**: database of candidate target positions spread over working area
  - **Frame scorer**: algorithm to rank a candidate pose. Two scorers (Intrinsics variance and Max Expected Reprojection Error)
- Method:
  - For each candidate pose
    - Copy the calibration state
    - Observe target using mean model
    - Update model estimate
    - Evaluate frame score
  - Return pose with best score

Max Expected Reprojection Error (Max ERE)

- Worst-case expected error across the image, computed empirically via sampling
- Algorithm:
  - Marginalize-out observations
  - For N trials:
    - Sample calibration parameters from distribution
    - Observe a set of control points
    - Update Local ERE for each control point
  - Compute Max ERE

Max ERE Animation



Reference:

Mean

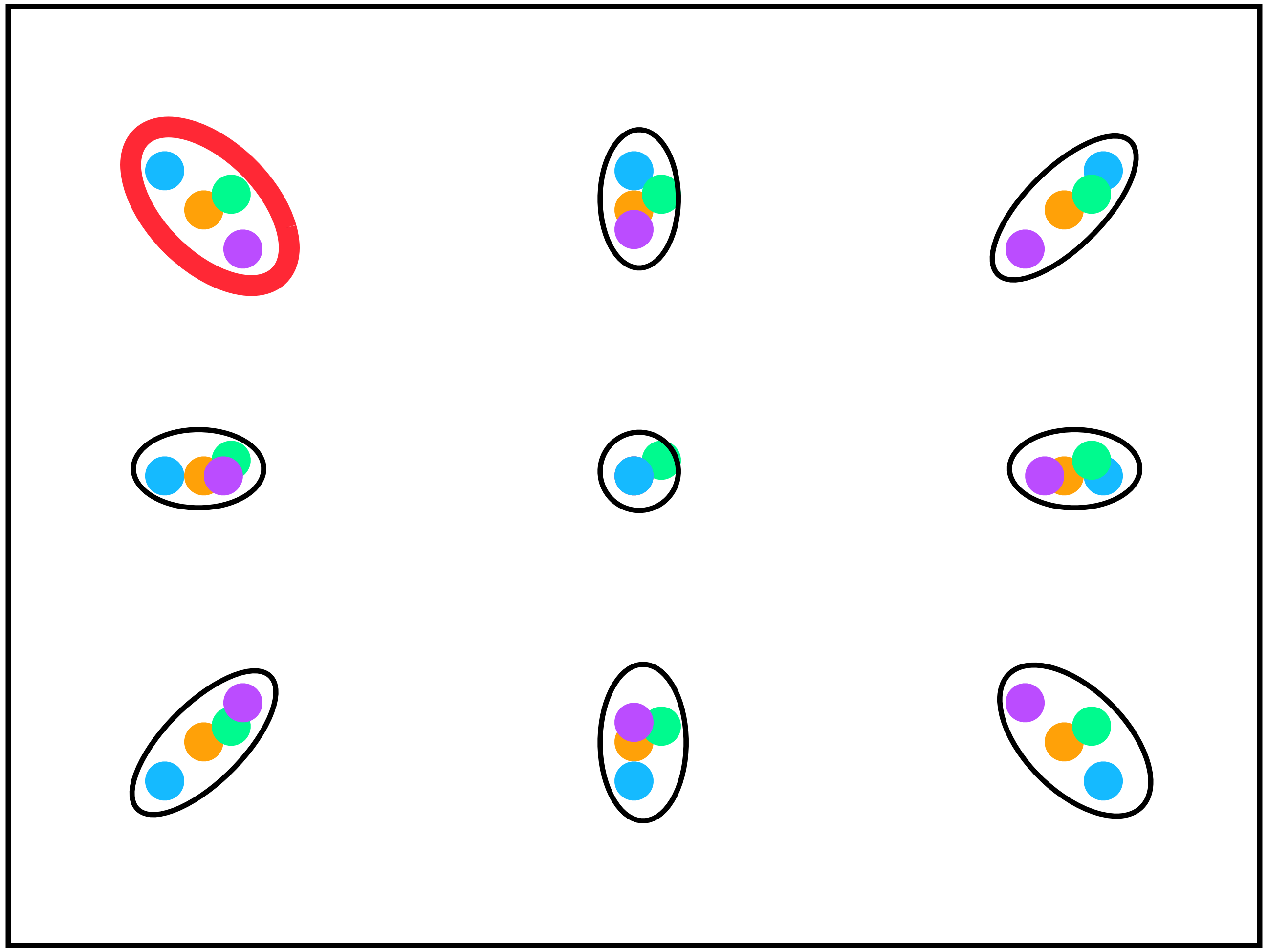
Samples:

Focal length

Focal center

Distortion

Max ERE Animation



Reference:

Mean

Samples:

Focal length

Focal center

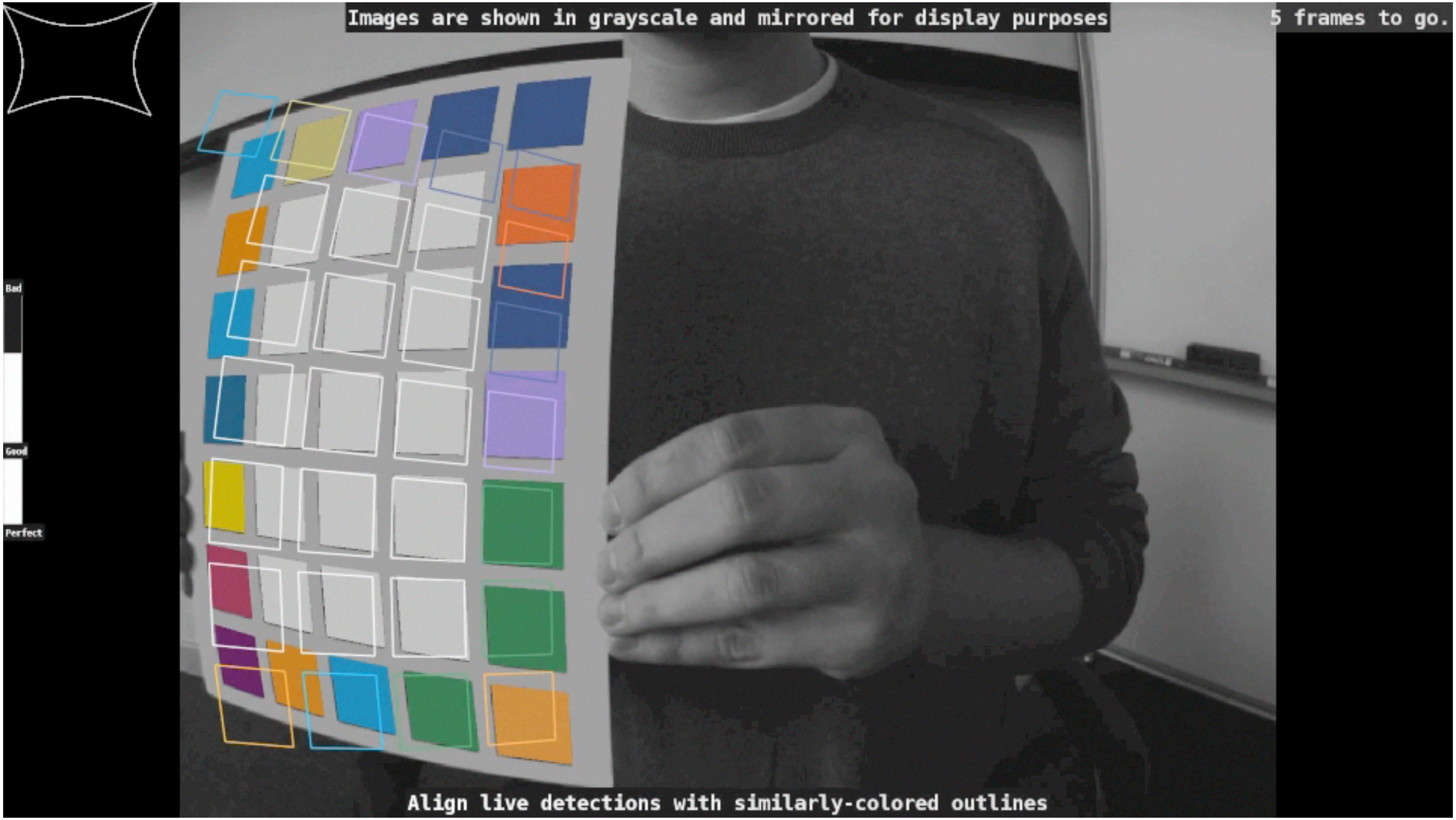
Distortion

Metrics:

Local ERE

Max ERE

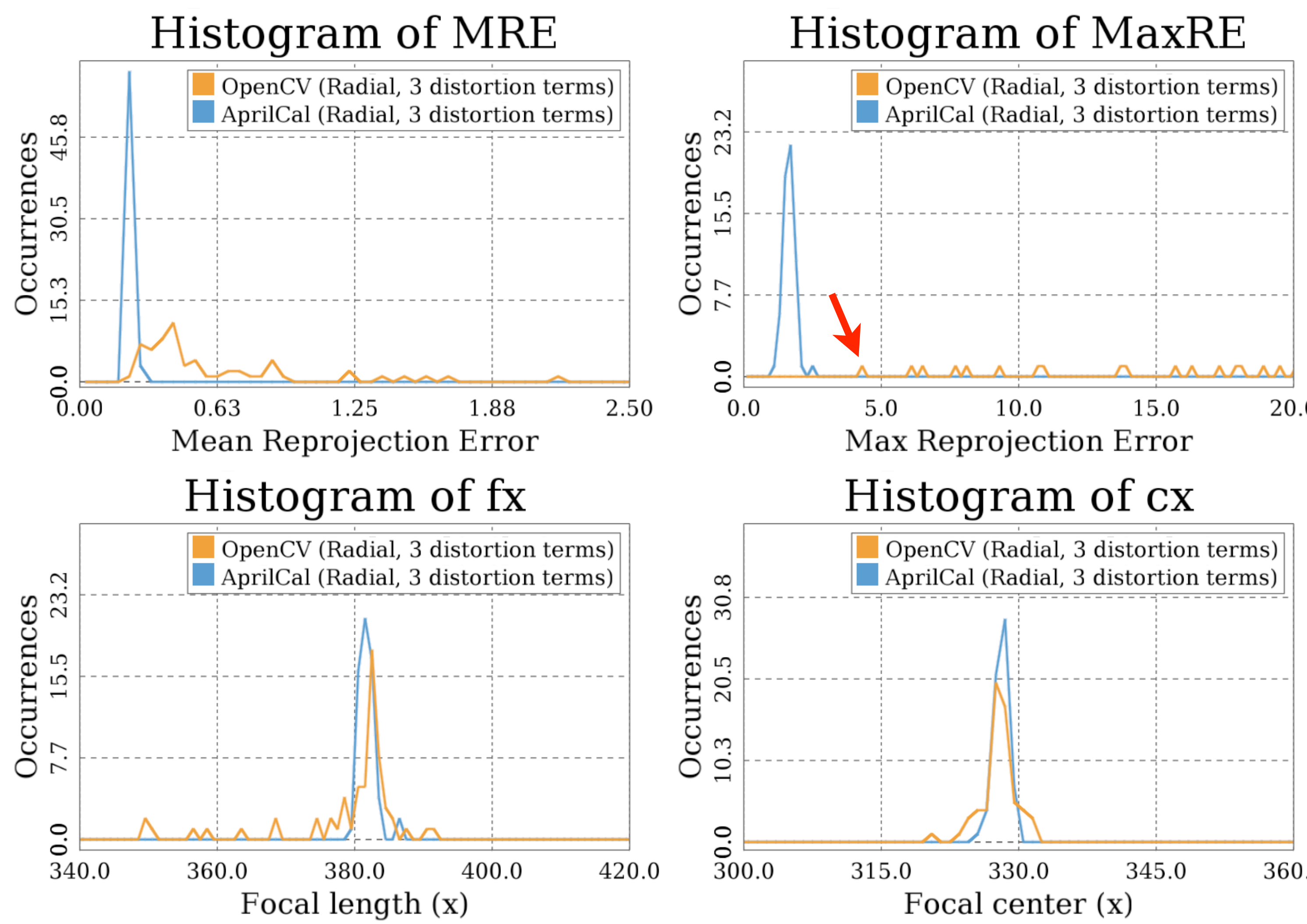
Video


Images are shown in grayscale and mirrored for display purposes
5 frames to go.
Bad
Good
Perfect
Align live detections with similarly-colored outlines

Evaluation Preview

- 16-participant user study vs. OpenCV
- *Best* OpenCV MaxRE worse than *worst* AprilCal MaxRE
- Very accurate, very repeatable

Mean & Max reprojection errors against testing set



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Thanks!

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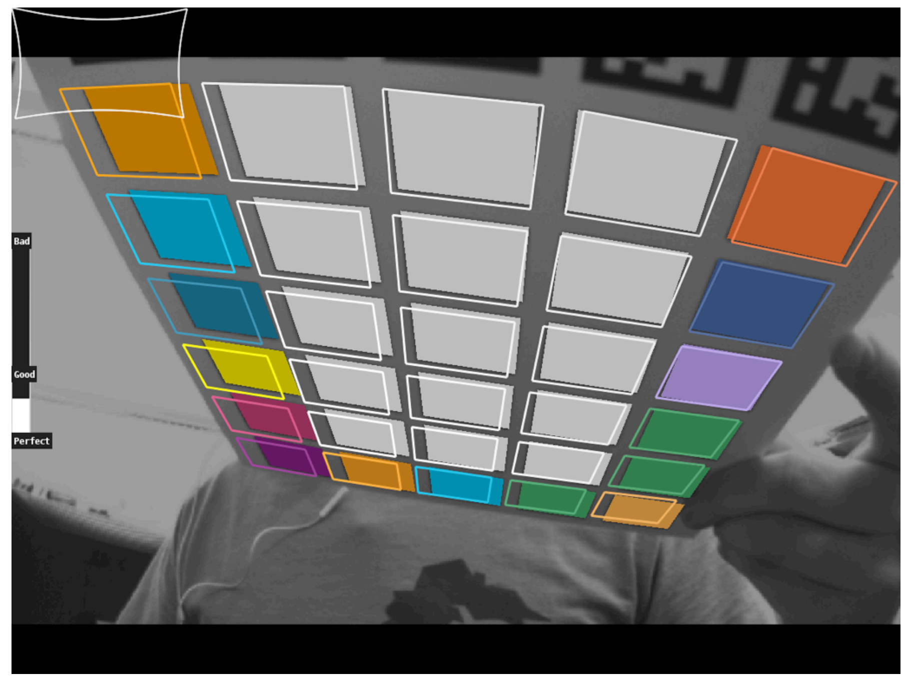

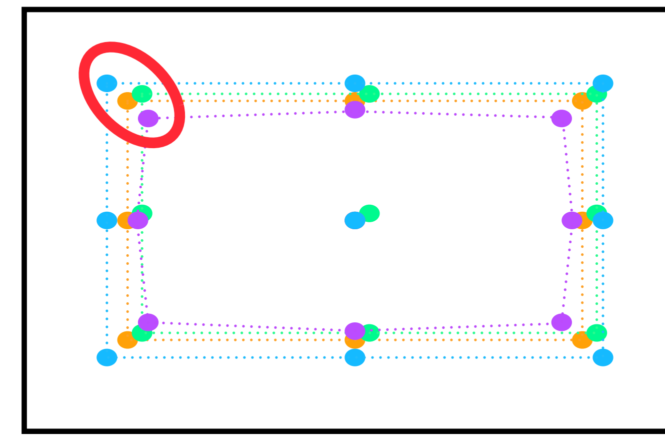

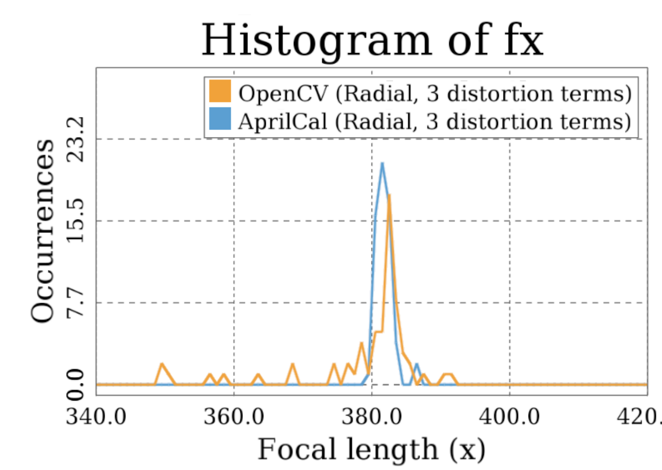

Software online:

april.eecs.umich.edu

See me for a demo!

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Error Distribution

(a) OpenCV (Radial, 3 dist. terms) (b) AprilCal (Radial, 3 dist. terms)