Fast vision-based relocalization for MAVs

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Introduction

- New major roles for MAVs
- Operations in GPS denied environments
- Semi-direct Visual Odometry [1]
  - 300 frames per second

Problem

Tracking failure

- Rapid camera motions
- Image occlusion
- Motion blur

A fast and accurate relocalization method is important.

Scenario

- Area recognition. Training stage.
- Tracking is lost. Drone makes a flip.
- Fast 6 DoF relocalization.
  - Provide the pose after relocalization
  - SVO can accept it or not

Implementation

- Independent, extendible, no dependencies from SVO
- Fast, C++
- ROS

Outline

PTAM method

- PTAM is based on keyframes
- The PTAM [2] relocalization method has two main steps
  - **Place Finder**: Given a new frame, it finds the closest keyframe
  - **Relative Pose Finder**: Once the closest frame is found, its transformation to the new frame is calculated

Outline

PTAM Place Finder

The squared difference between *Small Blurry image* is taken as a measure of distance. Cross Correlation distance.

Small Blurry image

- Size 40×30
- Zero mean
- Blurred with Gaussian $\sigma = 2.5$

$$d_{CC} = \sum_{x,y} [(I(x,y) - \bar{I}) - (G(x,y) - \bar{G})]^2 \quad (1)$$

PTAM Place Finder

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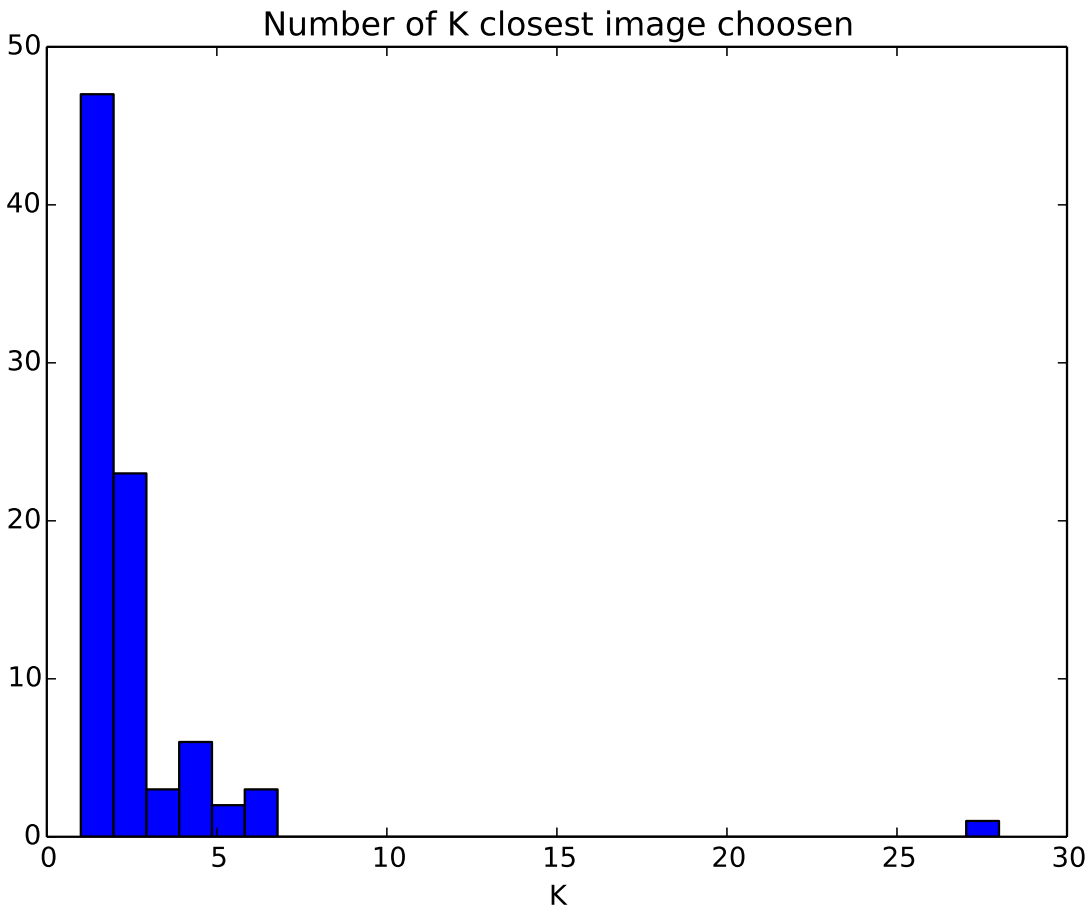

Outline

PTAM Rrelative Pose Finder

Image Alignment

The found keyframe and the new image are aligned over translation and rotation, $SE(2)$. Extended Second-Order Minimization (ESM) [3] is used.

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$$W(x;p) = \begin{bmatrix} cos(\alpha) & sin(\alpha) & t_x \\ -sin(\alpha) & cos(\alpha) & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} xcos(\alpha) + ysin(\alpha) + t_x \\ -xsin(\alpha) + ycos(\alpha) + t_y \end{bmatrix} \quad (1)$$

$$\min_p \sum_x [I(W(x;p)) - T(x)]^2 \quad (2)$$

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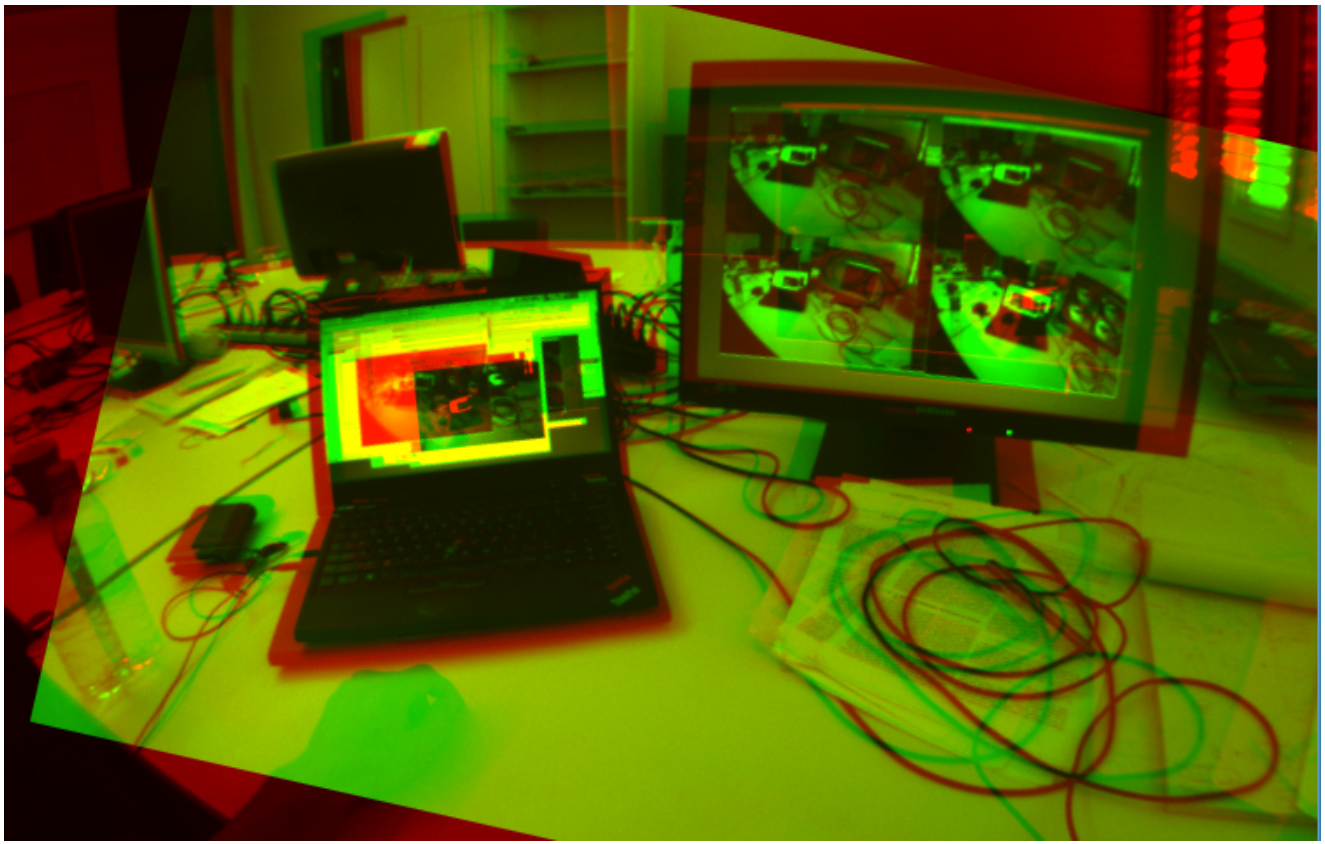

3D Interpretations

- The found transformation can be interpreted in different ways from the world frame.
- It is interpreted as world frame rotations, $SO(3)$.
- An optimization framework is used to find the best approximations.

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$$\delta_i(\xi) = T_{SE(2)} u_i - \pi(T_{SO(3)}(\xi) p_i) \qquad \text{where} \quad u_i = \pi(p_i) \qquad (1)$$

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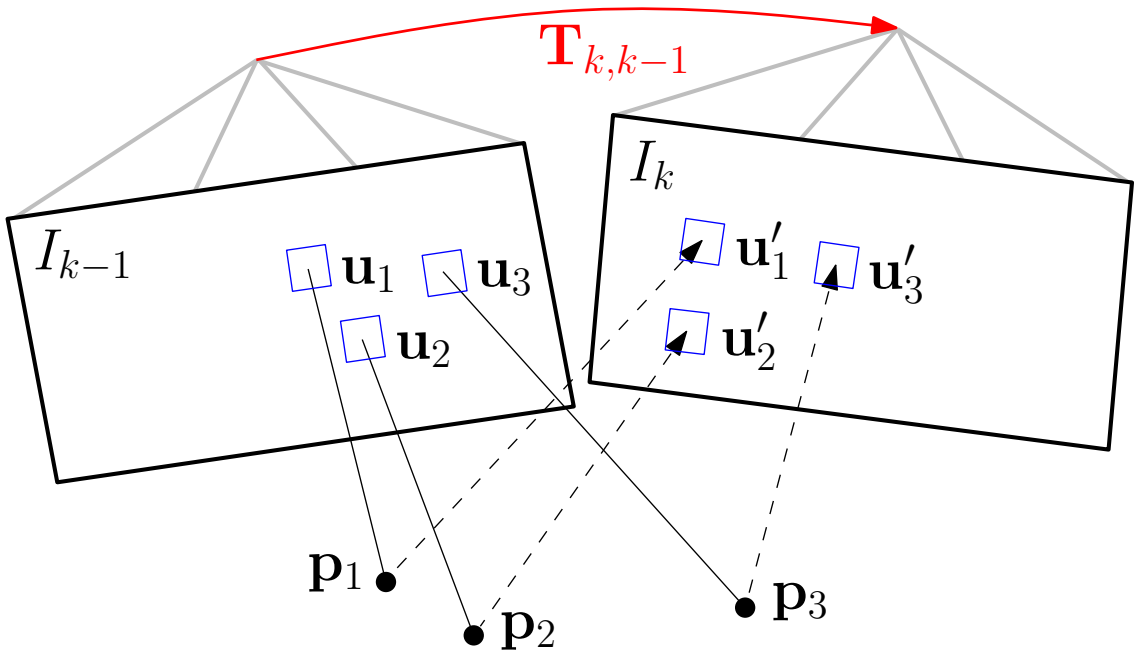
Figure: $SE(2)$ transformed image. $SO(3)$ transformed image

Outline

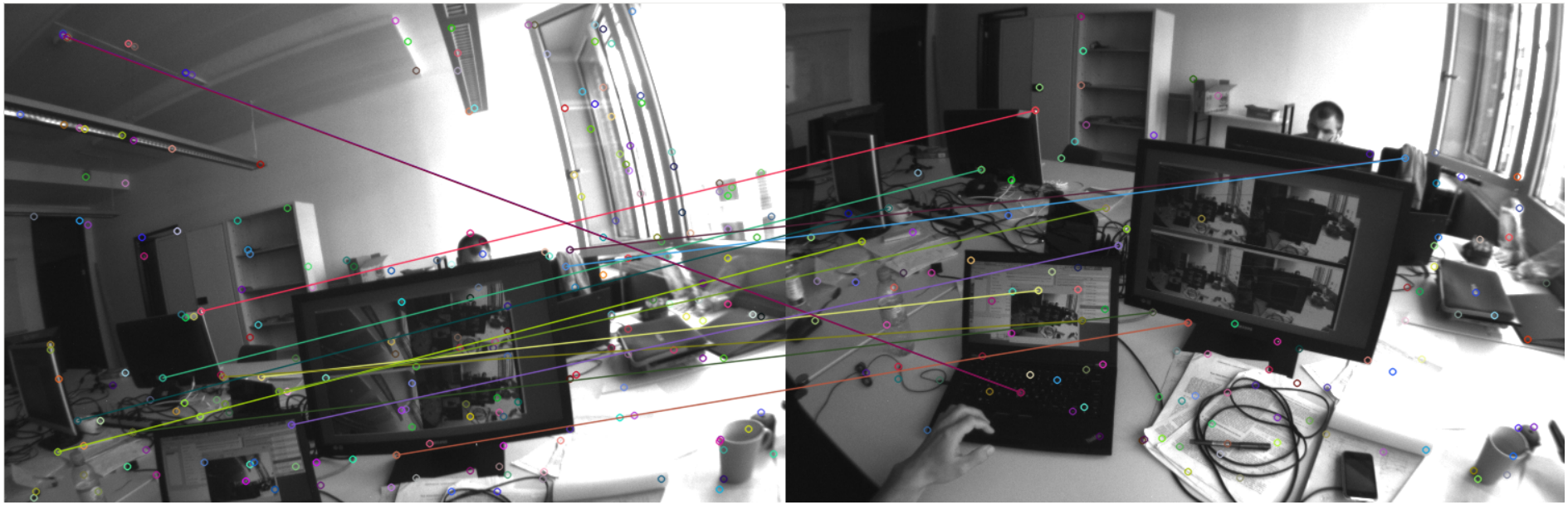
Geometric Relative Pose Finder

- Every keyframe has a world frame point associated to every featured point



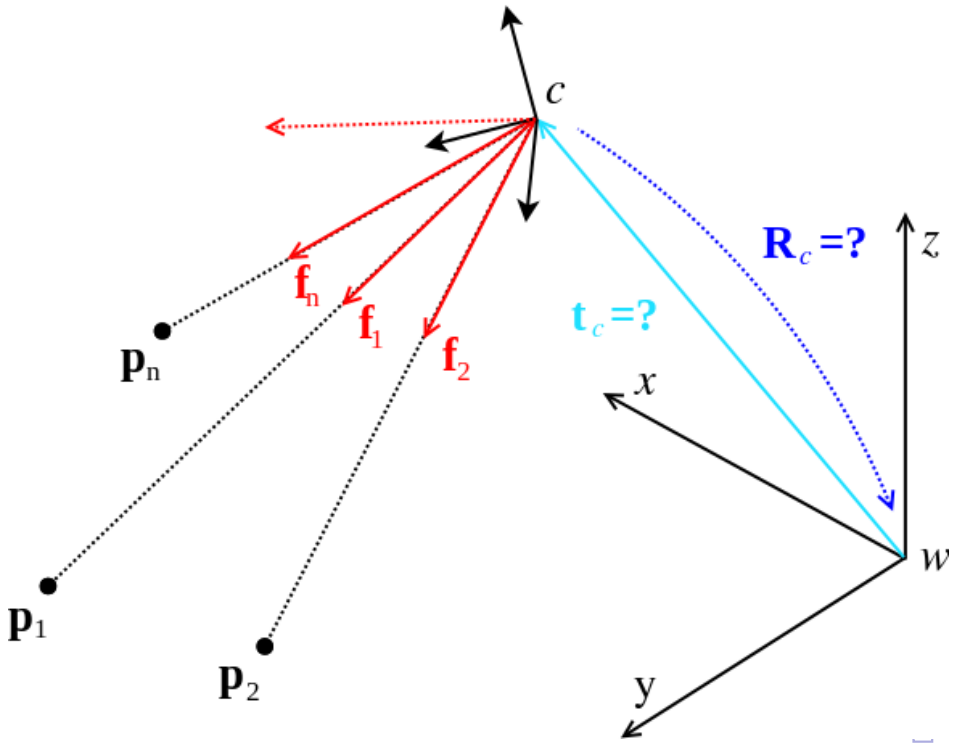
Geometric Relative Pose Finder

- Every keyframe has a world frame point associated to every featured point
- Relate featured points from the new frame to featured points from the keyframe



Geometric Relative Pose Finder

- Every keyframe has a world frame point associated to every featured point
- Relate featured points from the new frame to featured points from the keyframe
- Use P3P to find the camera pose



Outline

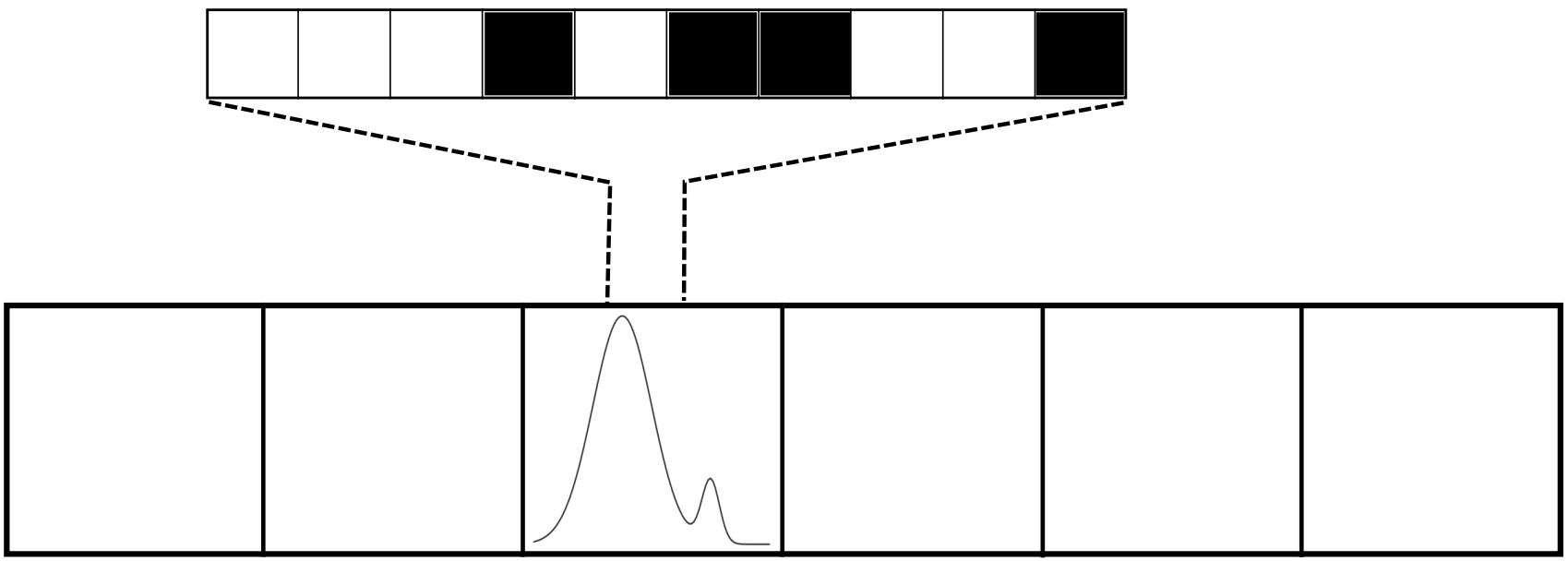
Ferns relocalizer

- Use classifier to model every world frame point with all its views
- Every world frame point is a class
- Multiple views of the point are used to train
  - Artificially generated views are used as well
- Finally, P3P is applied to the found points to find the camera transformation

Ferns relocalizer

- A *fern* [4] is a set of randomly generated binary tests on a patch

$$f_j = \begin{cases} 1, & \text{if } I(d_j, 1) < I(d_j, 2) \\ 0, & \text{otherwise} \end{cases} \quad (1)$$



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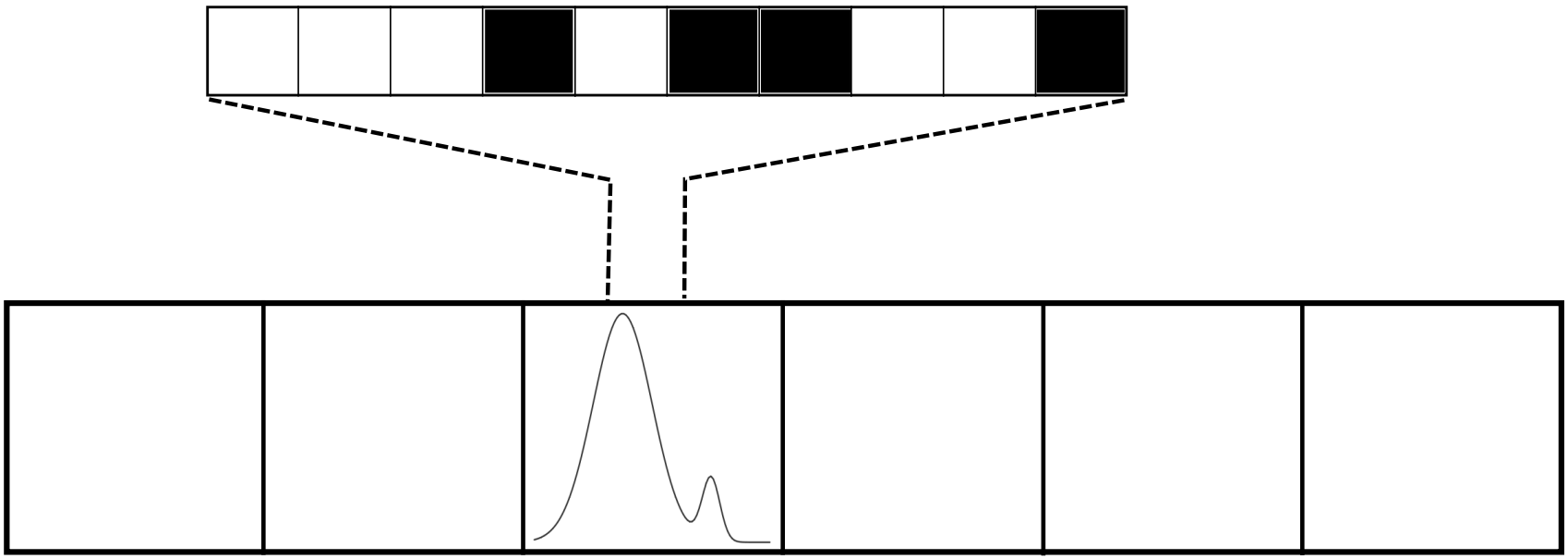
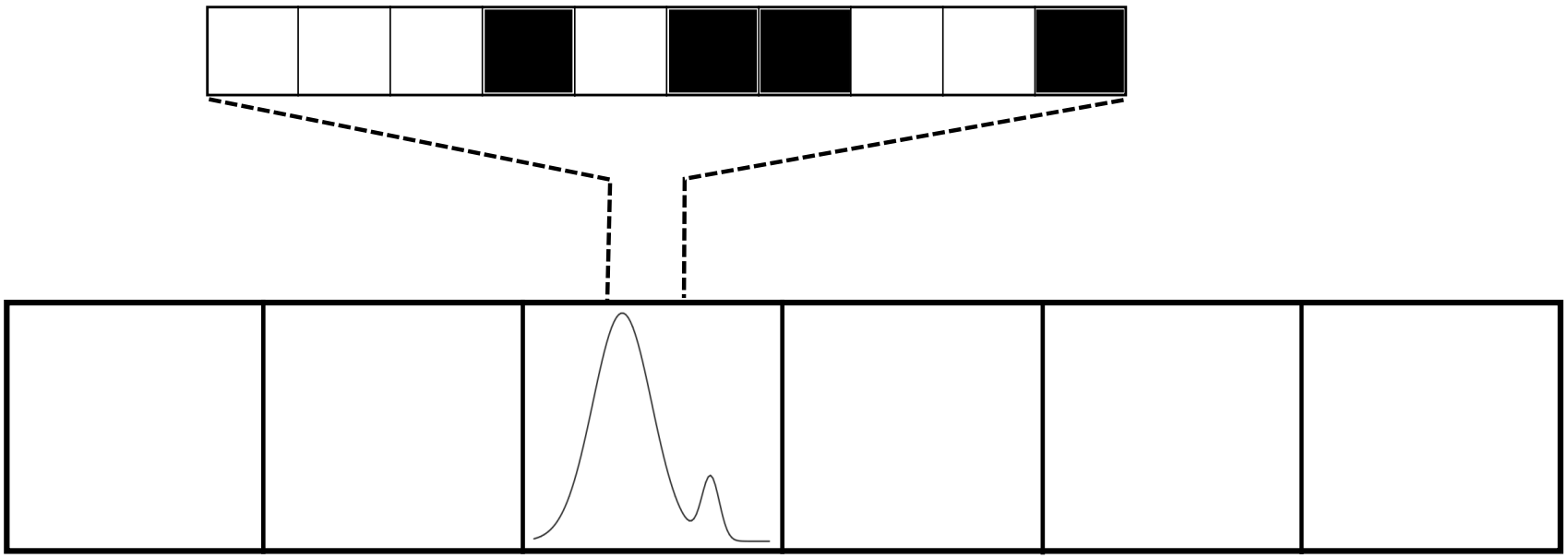


Ferns relocalizer

- A *fern* [4] is a set of randomly generated binary tests on a patch
- Every *fern* evaluation refers to a class posterior probability distribution
- Many *ferns* are used in a classifier

$$f_j = \begin{cases} 1, & \text{if } I(d_j,1) < I(d_j,2) \\ 0, & \text{otherwise} \end{cases} \quad (1)$$



Outline

Test Description

- Training set and testing set
  - Initialize with training set
  - Try to relocalize frames in testing set
- Ground Truth Baseline
  - Use GT data to find optimal Place Finder
- Performance showed histogram of translation error

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  - Initialize with training set
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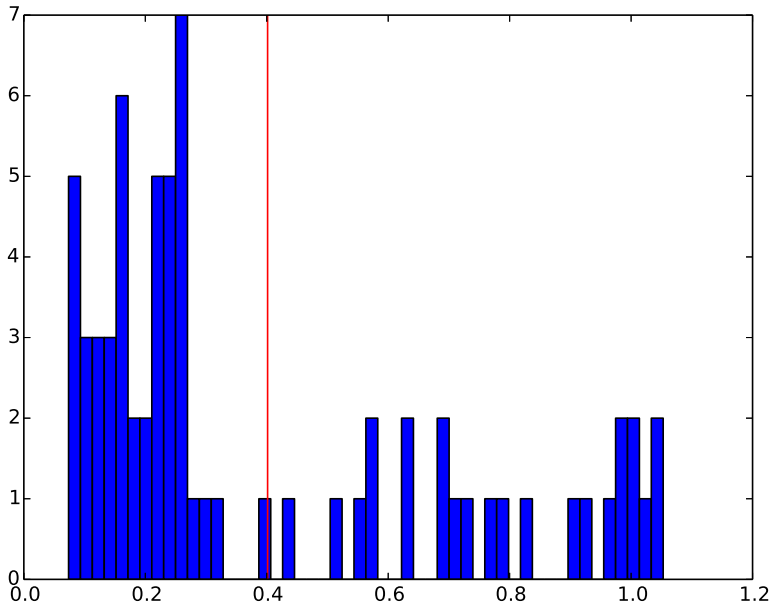
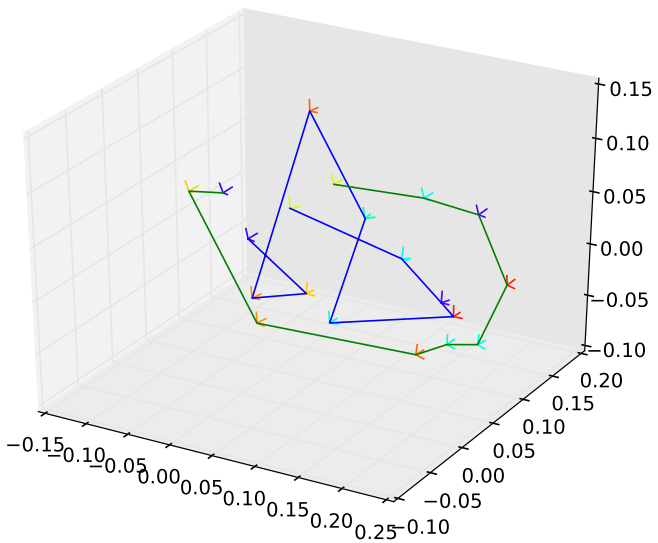
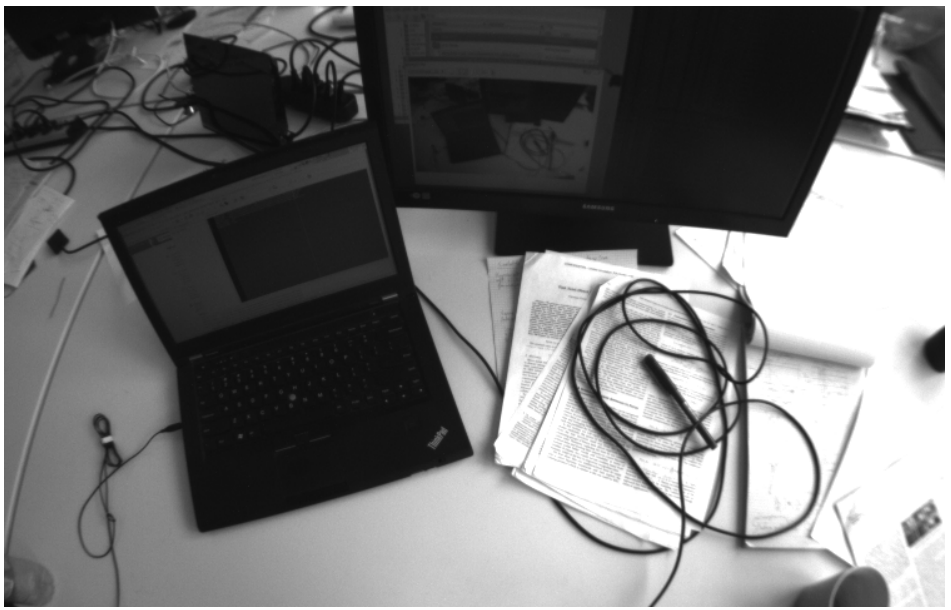
- Ground Truth Baseline
  - Use GT data to find optimal Place Finder
- Performance showed histogram of translation error



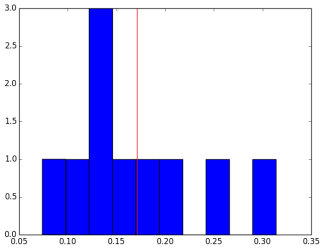
Results small dataset

- 10 images for training and 10 images for testing
- 237 world points
- 2 square meters area

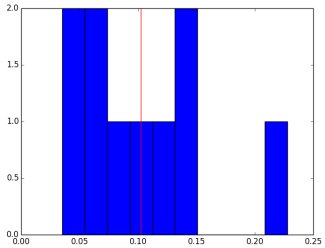




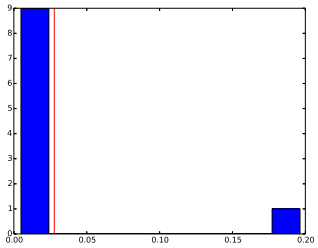
Results small dataset



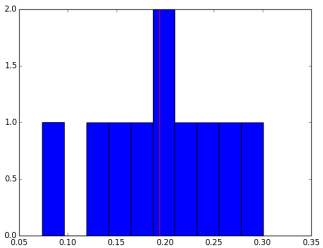
Only GT mean error = 0.17



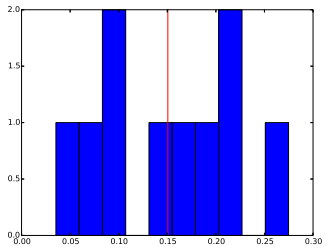
GT and ESM mean error = 0.10



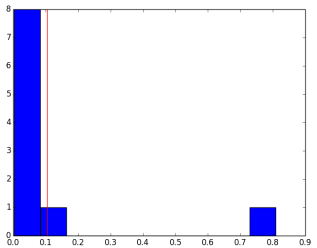
GT and P3P mean error = 0.02



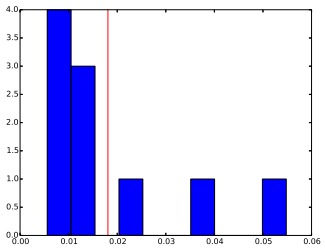
Only CC mean error = 0.19



CC and ESM mean error = 0.15



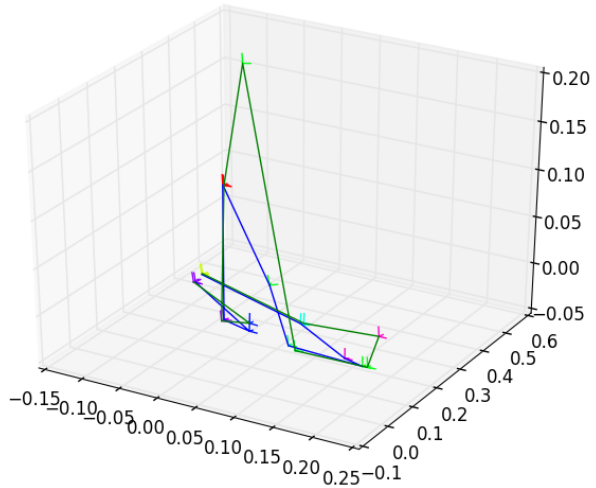
CC and P3P mean error = 0.11



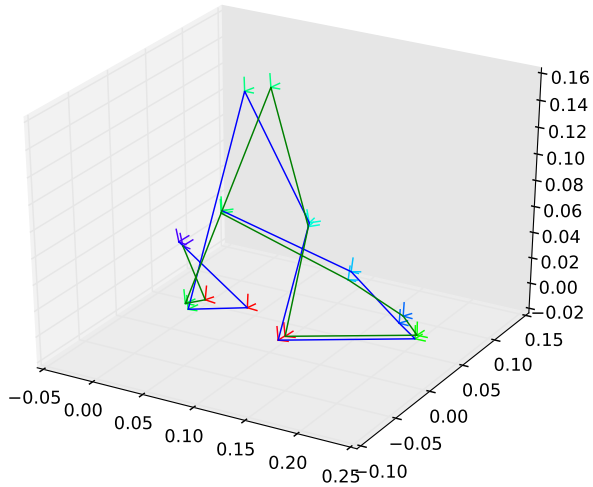
ferns mean error = 0.02

Figure: Translation error histograms

Results small dataset



Path found with CC and P3P

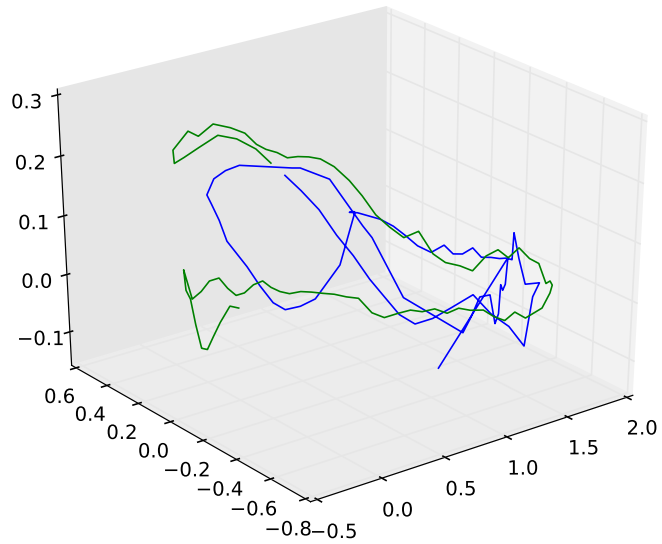


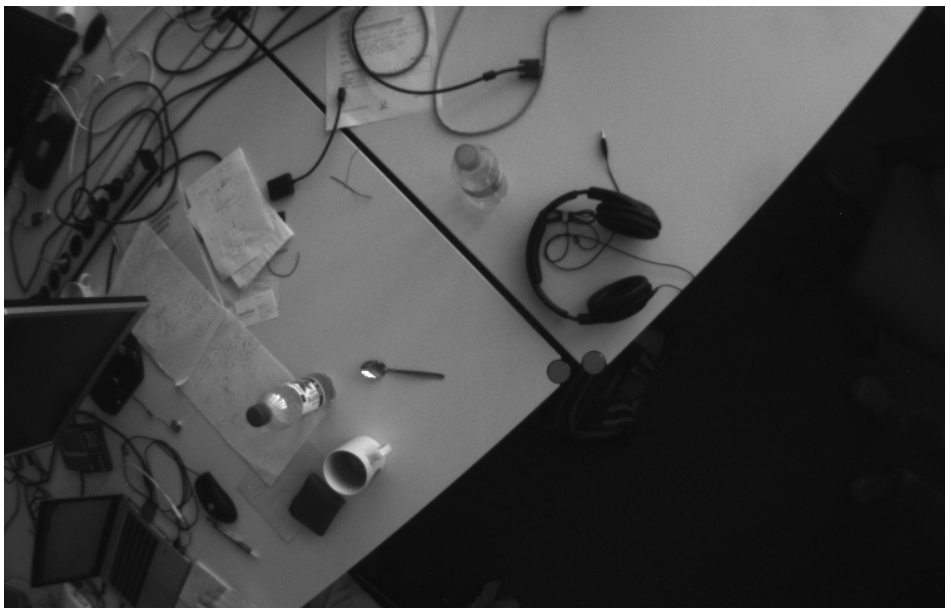
Path found with *ferns*

Outline

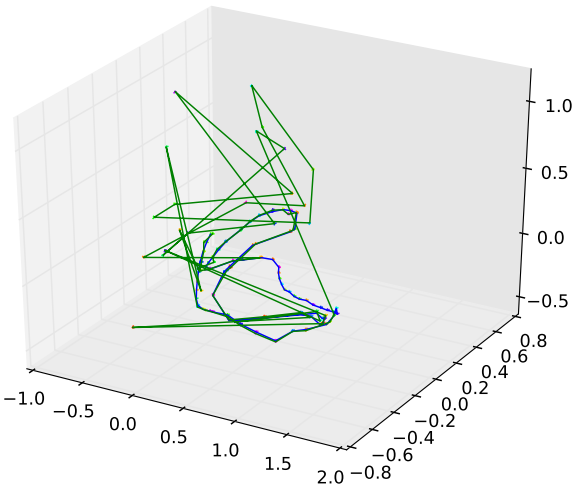
Results large dataset

- 84 images for training and 69 images for testing
- 1730 world points
- 7x3 meters area

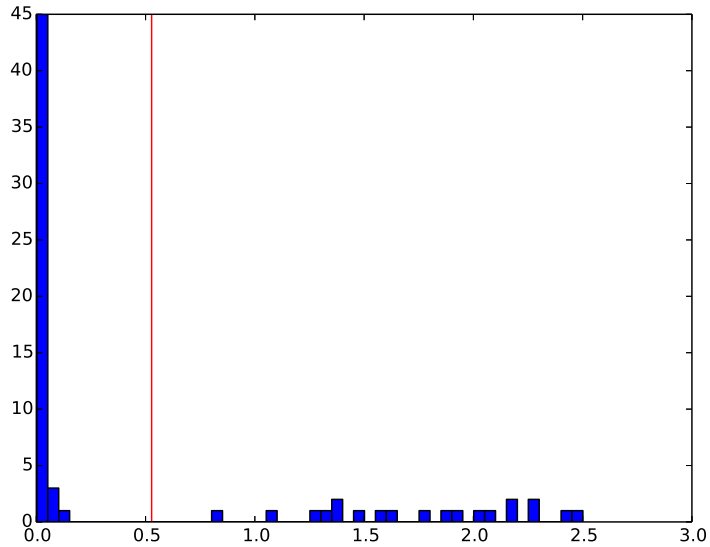




Results large dataset with *ferns*



Path found with *ferns*



ferns error histogram. 45/69

Timing

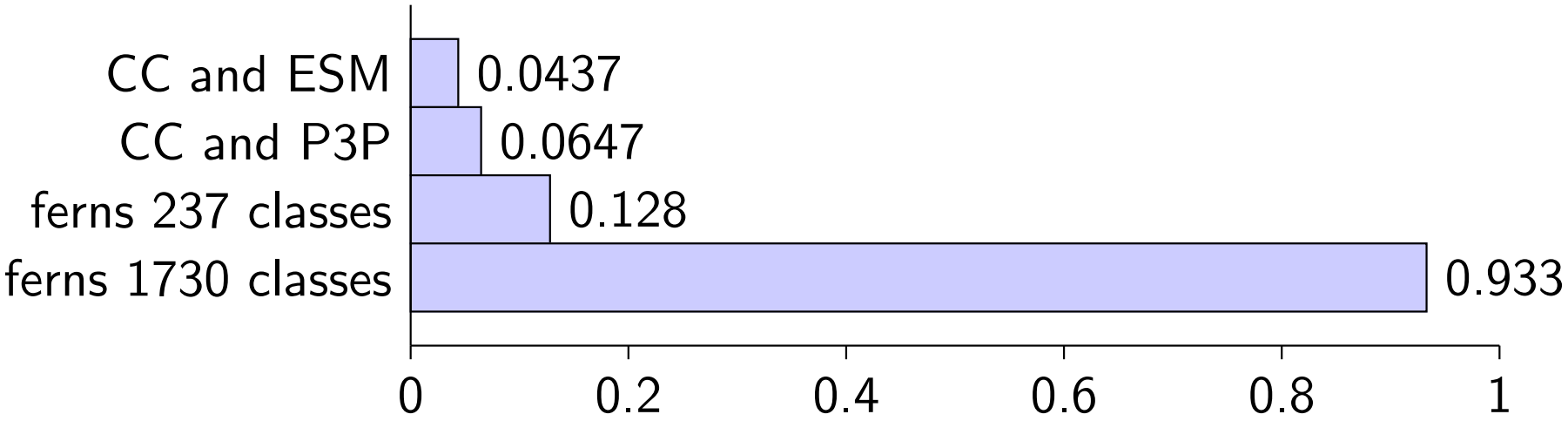


Figure: Single relocalization execution time in seconds

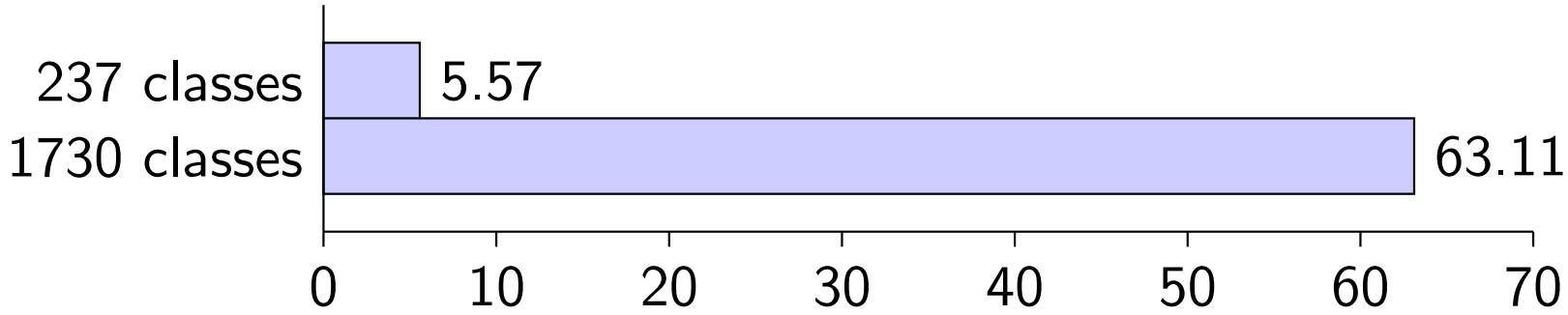


Figure: *ferns* classifier training time in seconds

Outline

Conclusions

Work done

- We have addressed one of the missing parts of SVO
- Different methods have been studied an evaluated
- An independent framework and library have been implemented

Future work

- Further tests on board
- Use image retrieval techniques like bag of word as Place Finder
- Test performance on rectified images

Thank you!

Questions?

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