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Learning Systems Lab

Örebro Universitet

SIFT, SURF and Seasons: Long-term Outdoor Localization Using Local Features

Christoffer Valgren, Achim J. Lilienthal

AASS Research Centre, Dept. of Technology, Örebro University

Appearance Based Localization

Matching images to find out where you are ...

... should be easy?

Appearance Based Localization

- Appearance Based Localization Over Time
  - for localization (single image localization)
  - for loop closing

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Background

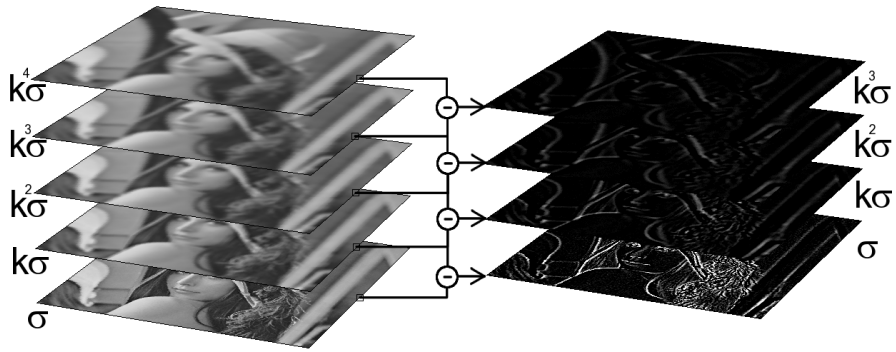
1 Appearance Based Localization

- Comparing (Omni-)Images
  - colour histograms [Ulrich & Nourbakhsh 2000]
  - eigenimages [Kröse et al 2001]
  - Fourier signatures [Menegatti et al 2004]
  - scale-invariant feature transform (SIFT) features [many authors]
- Advantages of Local Features
  - robust against many variations in appearance
    - rotation, scaling, lighting to some extent
  - SIFT is the de facto standard

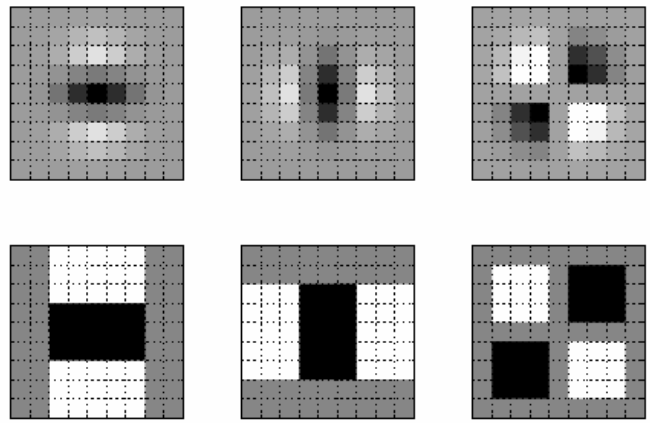
1 SIFT and SURF

- Scale-Invariant Feature Transform
  - SIFT [Lowe 2004]
- Speeded Up Robust Features
  - SURF [Bay et al 2006]

1 SIFT and SURF



L(x,y,σ) D(x,y,σ)



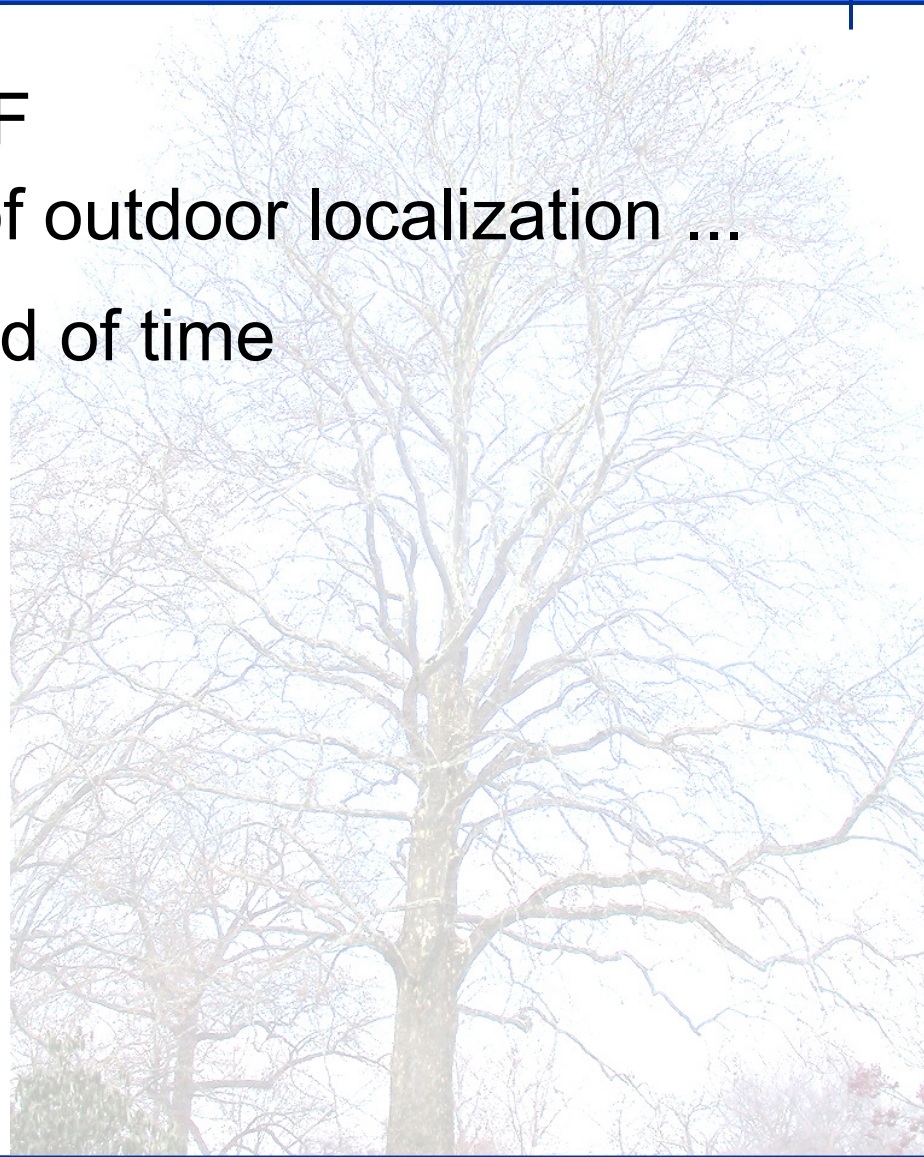
	SIFT	SURF
Scale-space	Difference of Gaussians (approximates trace of Hessian)	Box filters (approximate determinant of Hessian)
Detector	Maxima & Minima (discard low-intensity extrema and points on edges)	Maxima (blob-detector), stores sign of the trace of Hessian for matching stage
Descriptor	Based on gradient magnitude	Based on Haar wavelet response

1 SIFT and SURF

- Scale-Invariant Feature Transform [Lowe 2004]
- Speeded Up Robust Features [Bay et al 2006]
  - similar approaches;
    SURF takes additional shortcuts and is faster
  - SURF produces fewer features than SIFT
  - SURF has several variations:
    (regular) SURF, U-SURF, SURF-128, etc.
  - U-SURF
    - ignore the computation of the dominant orientation
    - no rotation of the neighbourhood of the interest point

1 Objective

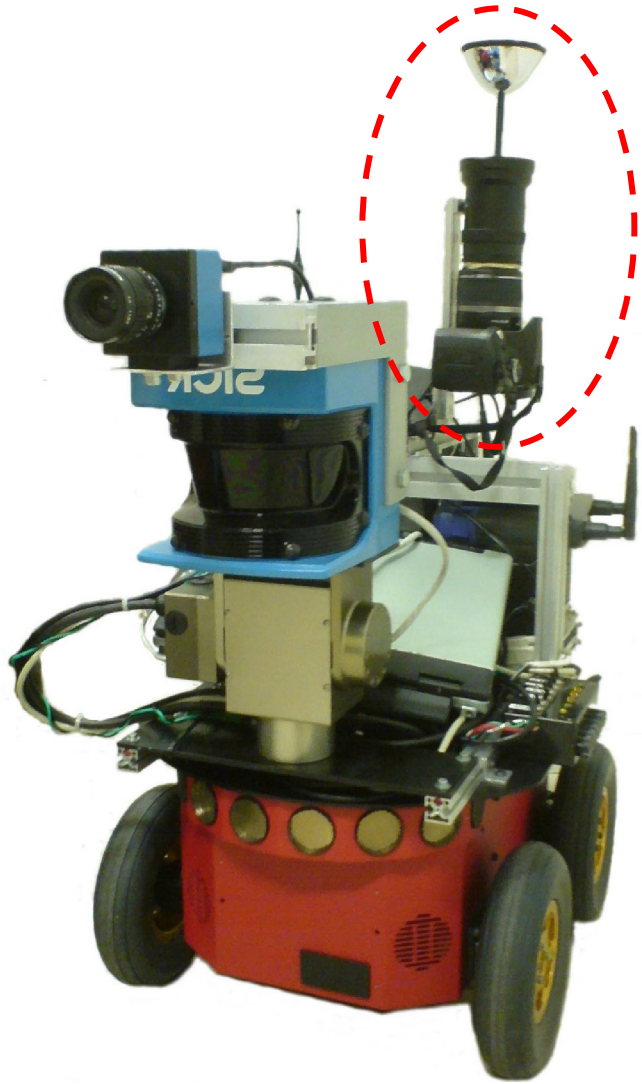
- Compare SIFT and SURF
  for the challenging task of outdoor localization ...
- ...over an extended period of time



Experiments

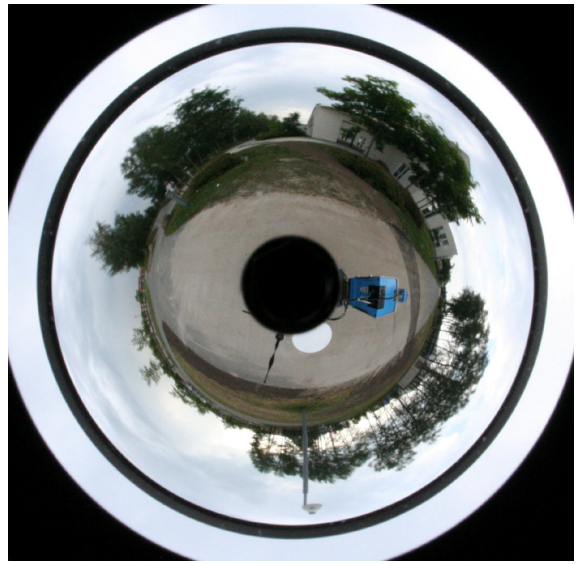
2 Experiments

- Data Acquisition
  - Canon EOS350D (8 megapixels)
  - mirror from 0-360.com
  - teleoperated ActivMedia P3-AT
  - snapshot every few meters (interval varies)



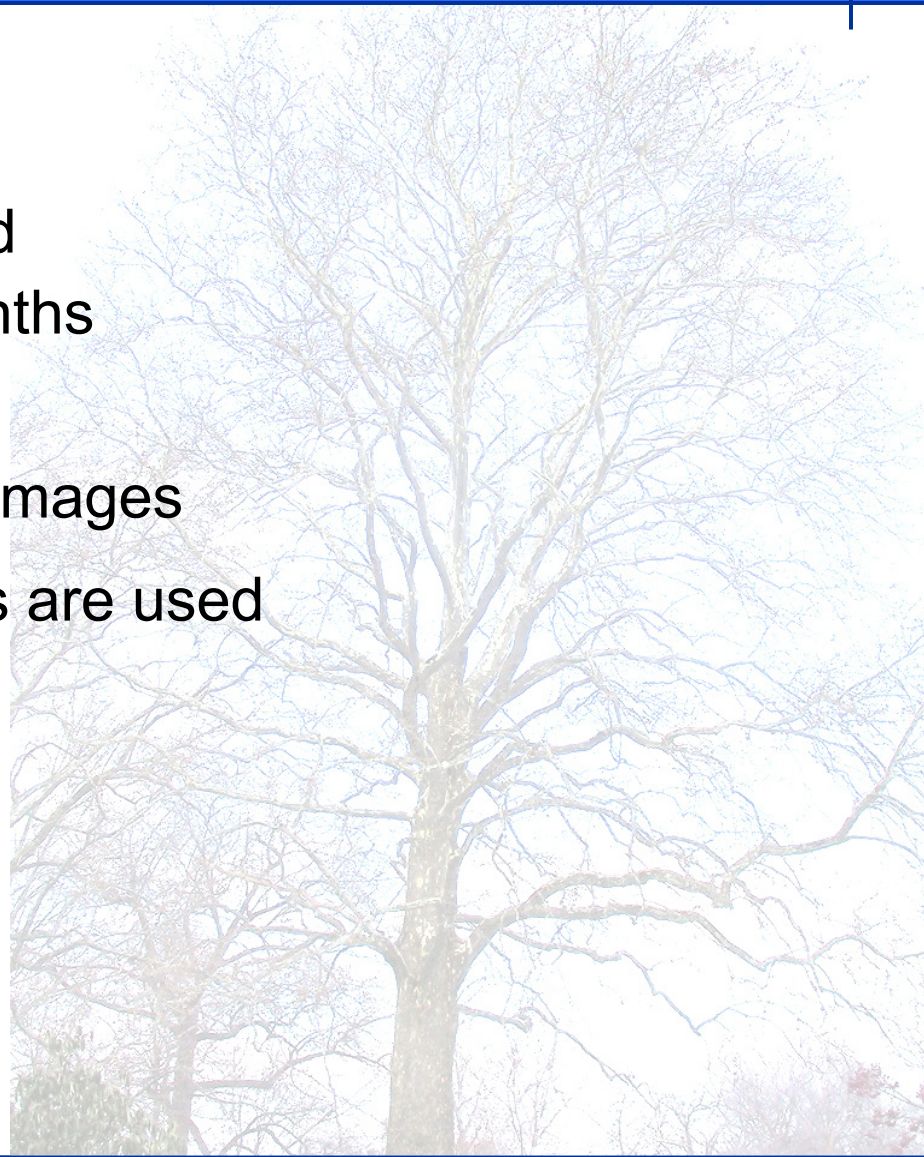
2 Experiments

- Input
  - omnidirectional images
  - → conversion to panoramic images
  - resize to 800 x 240 pixels (~ 1/3)



2 Experiments

- Cross Season Dataset
  - 7 sets of images acquired over a period of nine months (February to October)
  - both indoor and outdoor images
  - here only outdoor images are used (about 1800 in total)



2 Cross Season Dataset

Winter (A)

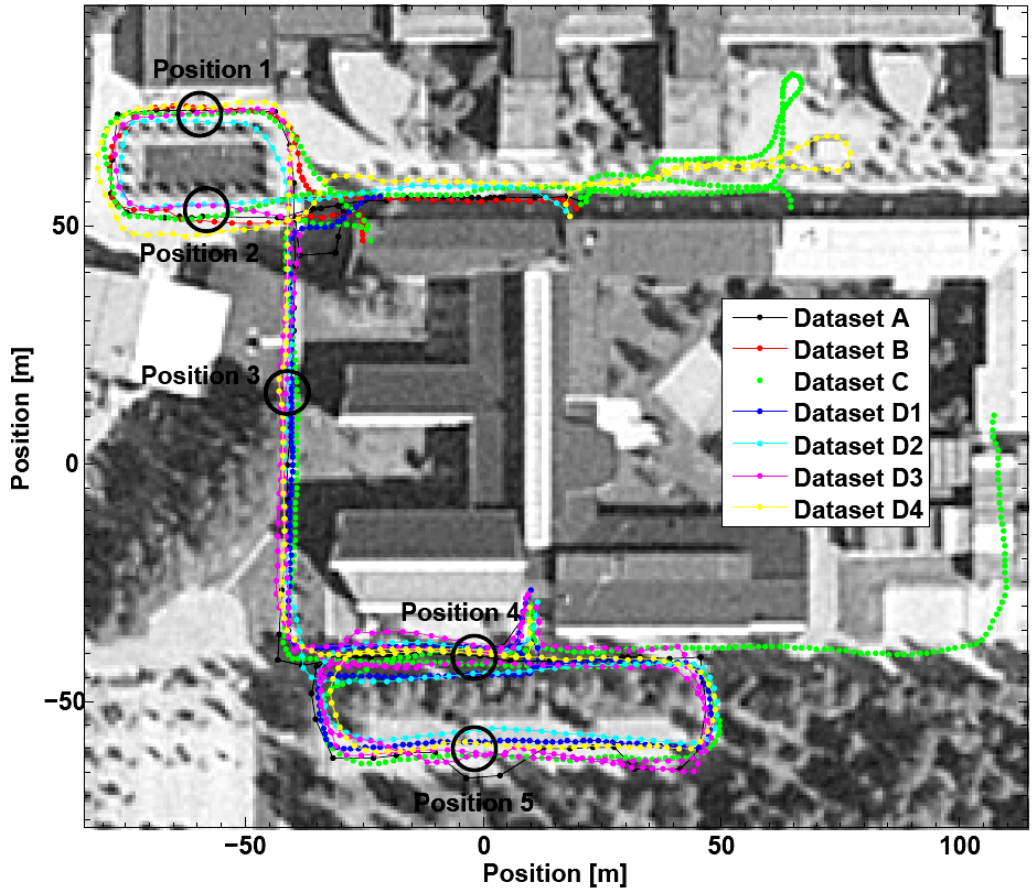
Spring (B)

Summer (C)

Autumn (D1 – D4)

2 Cross Season Dataset

- Coverage

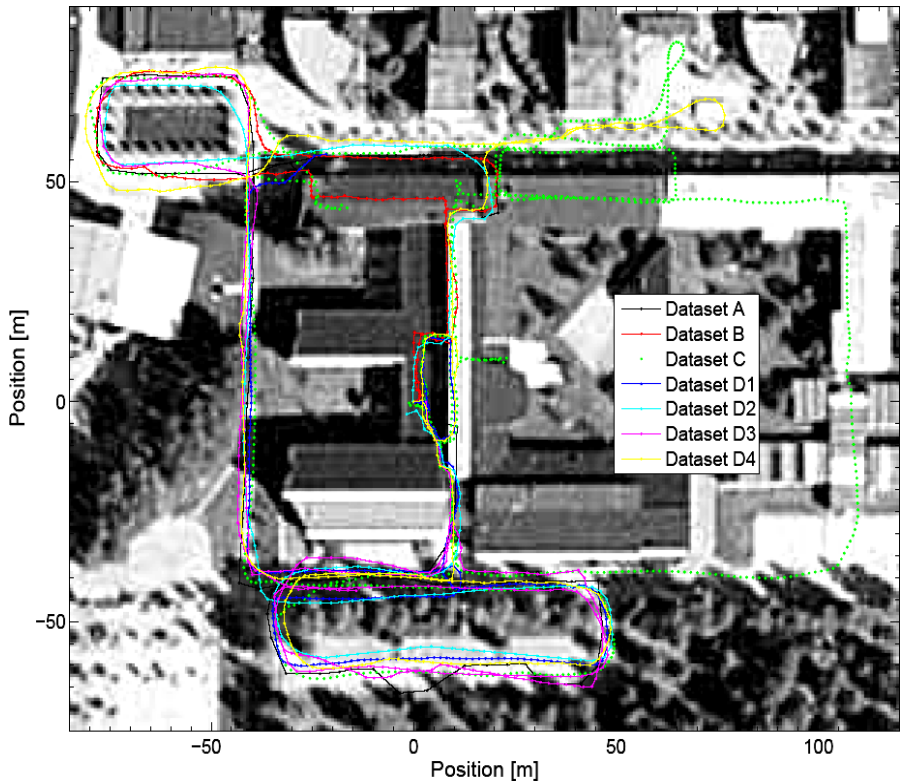


- max. path length: 1.1 km.
- trajectories from corrected odometry

Evaluation

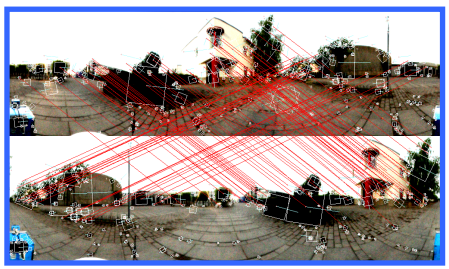
3 Evaluation

- Experiment 1 – global topological localization
  - localization against data set C (597 images)
    - 40 images selected randomly from each dataset and matched against dataset C
    - localisation at the image with the highest number of matched features
    - considered to be succesful if the distance between the images was < 10 m

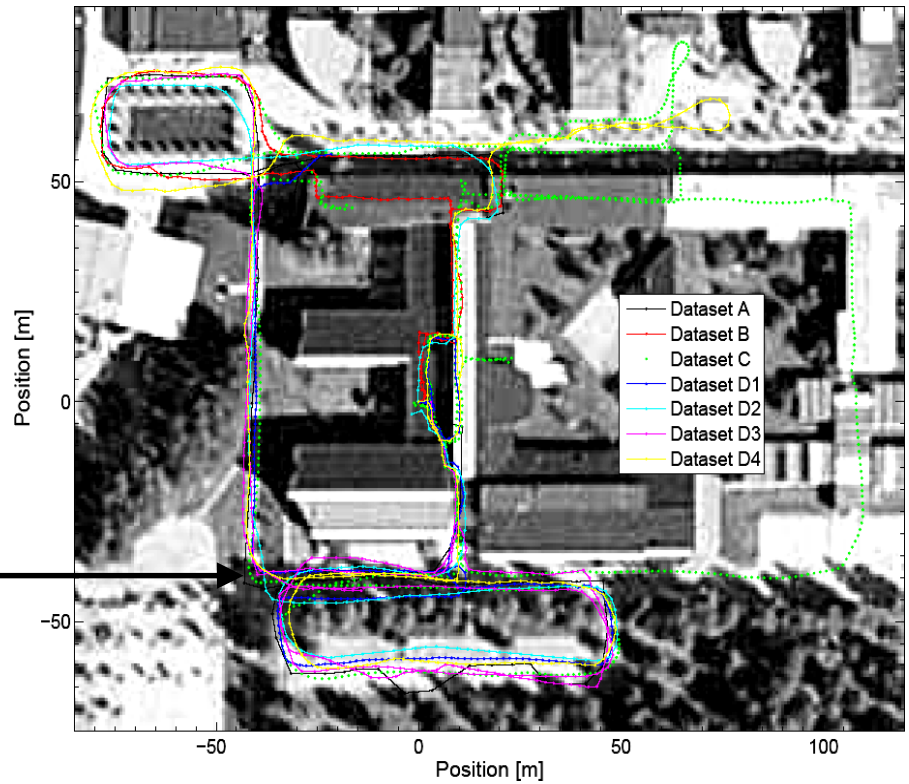


3 Evaluation

- Experiment 1 – global topological localization
  - localization against data set C (597 images)

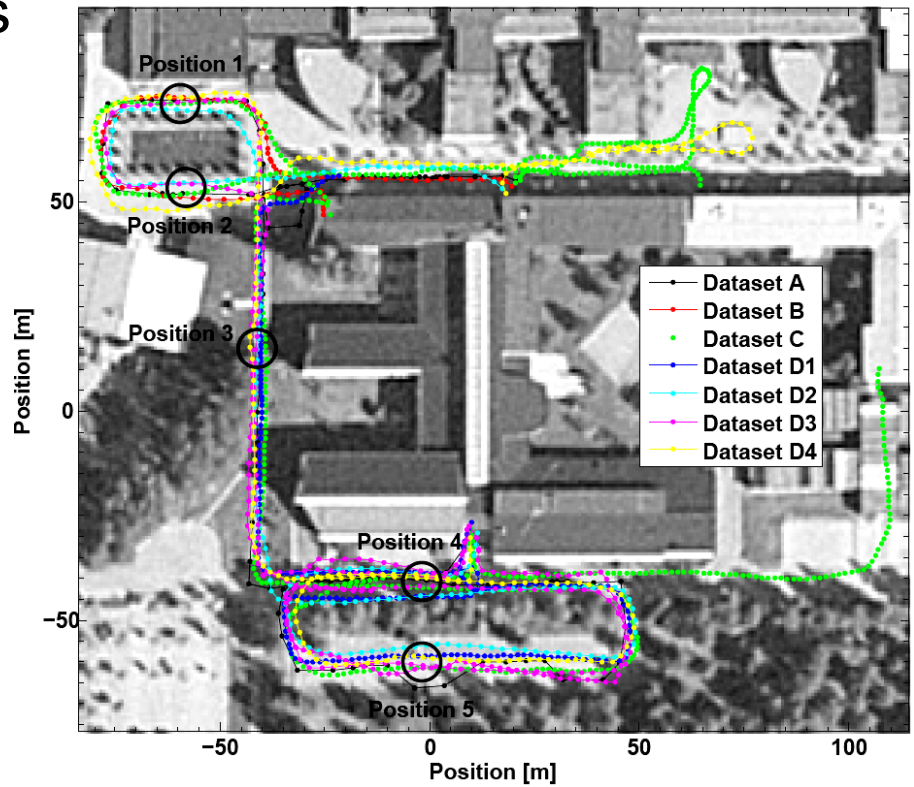


?



3 Evaluation

- Experiment 1 – global topological localization
- Experiment 2 – image comparison over seasons
  - selection of 5 viewpoints that occured in several data sets
  - number of correct correspondences / total number of correspondences recorded (human judge)



3 Evaluation

- Experiment 1 – global topological localization
- Experiment 2 – image comparison over seasons
- Binaries for SIFT and SURF (from the Web sites) to compute the feature descriptors
- Same code for feature matching
  - simple brute force nearest neighbour search
  - match if closest neighbour is closer than x times the second closest neighbour
    - SIFT: x = 0.8
    - SURF: x = 0.7

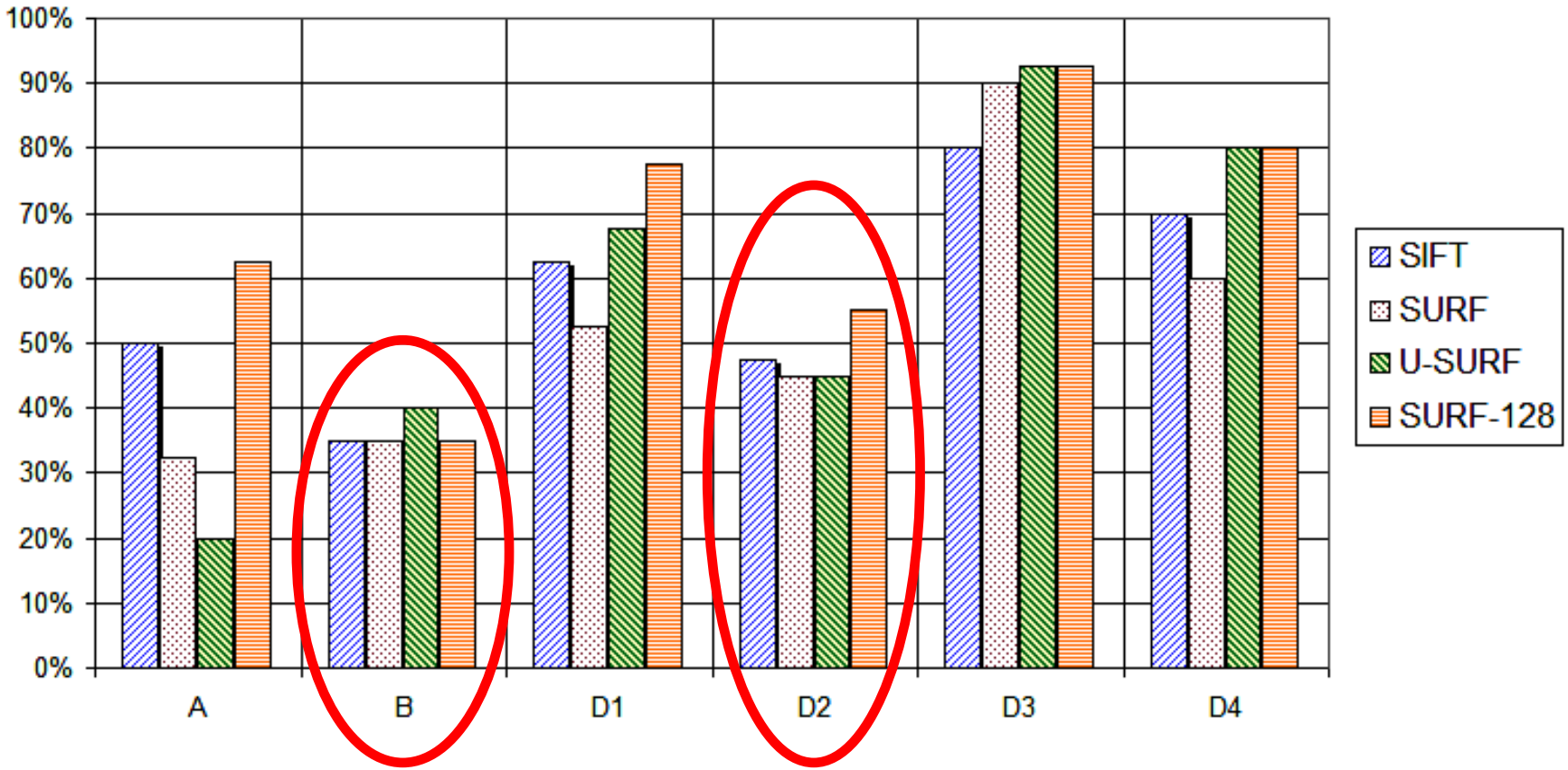
Results

4 Results – Experiment 1

- Experiment 1 – global topological localization
  - compare images with images from data set C
  - use SIFT, SURF, U-SURF and SURF-128
  - count the number of feature matches
  - the image in C with most matches is the winner

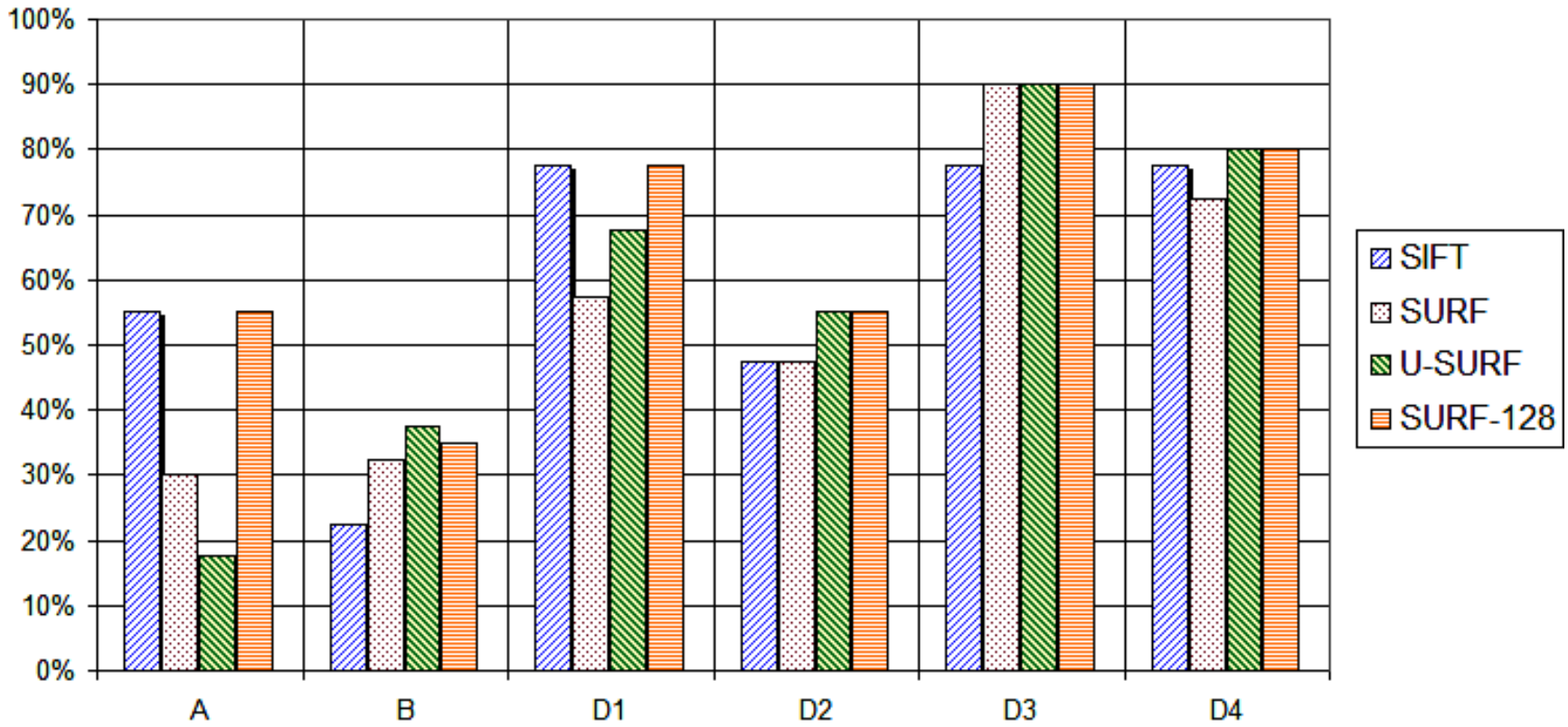
4 Results – Experiment 1

- x = 0.8



4 Results – Experiment 1

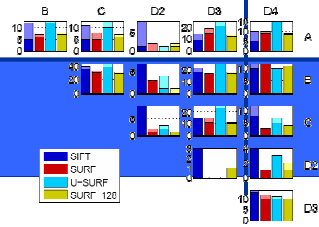
- x = 0.7



4 Results – Experiment 1

- Experiment 1 – global topological localization
  - no method can handle data sets B and D2 (sun and distinct shadows)
  - U-SURF and SURF-128 have overall best performance
  - SIFT performs worst for two of the data sets and never is (exclusively) best!

4 Results – Experiment 2



- Experiment 2 – image comparison over seasons
  - selection of 5 viewpoints (occured in several data sets)
  - use SIFT, SURF, U-SURF and SURF-128
  - count the number of feature matches
    and use human judge to say which ones are correct

Algorithm	Total matches	Total correct matches	Percentage correct
SIFT	1222	824	67%
SURF	598	473	79%
U-SURF	760	648	85%
SURF-128	531	452	85%

  - data sets B, D2 (visible sun, overcast) and A (snow)
    were the hardest to match (parking lot not so difficult)

Summary and Conclusions

5 Summary and Conclusions

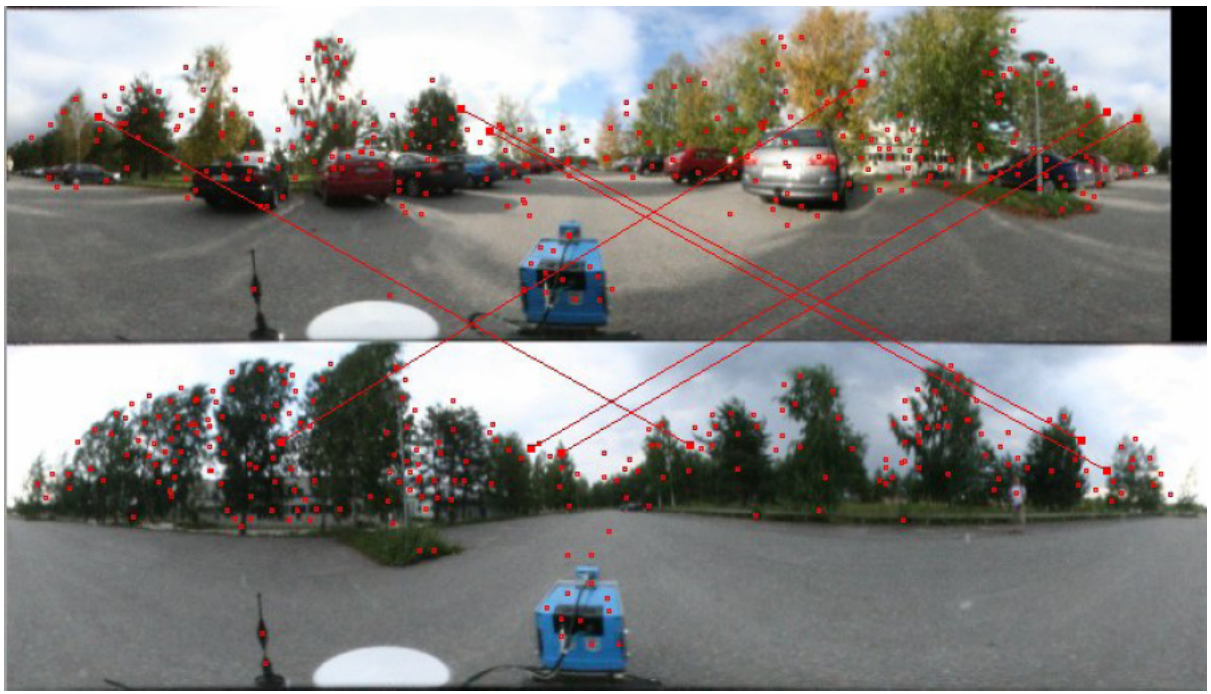
- Summary
  - evaluation of how local features can cope with large outdoor environments including seasonal variations
  - global topological localization (Experiment 1)
  - detailed analysis of the feature matches (Experiment 2)
  - SIFT, SURF, SURF-128, U-SURF
- Conclusions
  - no local feature based algorithm could be used directly for single shot localization over seasons
  - SURF-128 and U-SURF outperform the competition (faster and higher or equivalent accuracy)

Outlook

6 Outlook

- Future Work 1
  - include epipolar constraint, RANSAC

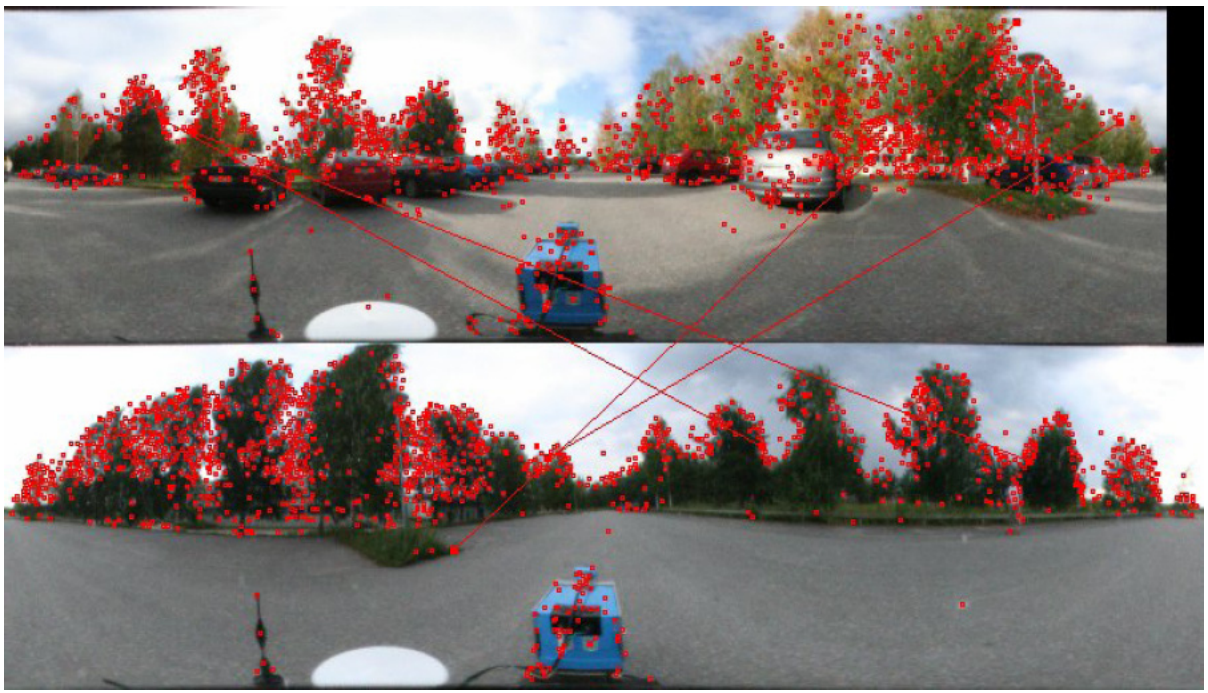
  $\Rightarrow$ problem: not enough feature matches



6 Inclusion of the Epipolar Constraint

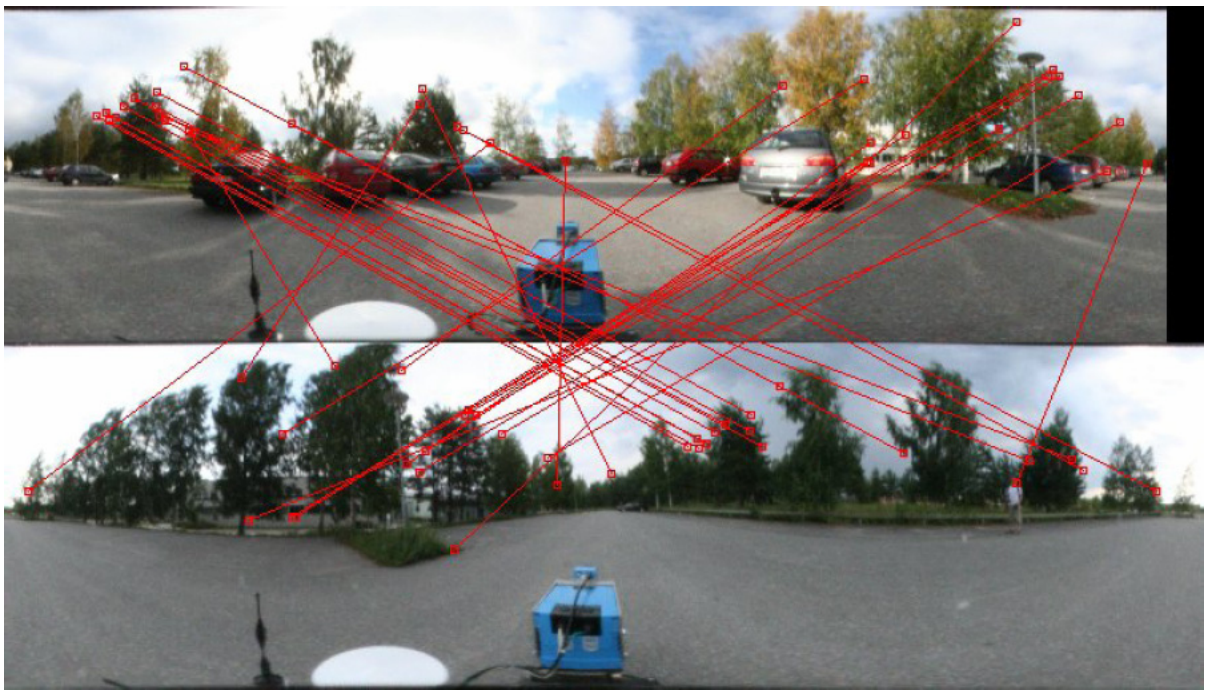
- Problem: Not Enough Feature Matches

  $\Rightarrow$ use high resolution images



6 Inclusion of the Epipolar Constraint

- Problem: Not Enough Feature Matches
  - ⇒ use high resolution images
  - ⇒ optimize (U-SURF) threshold to get more matches

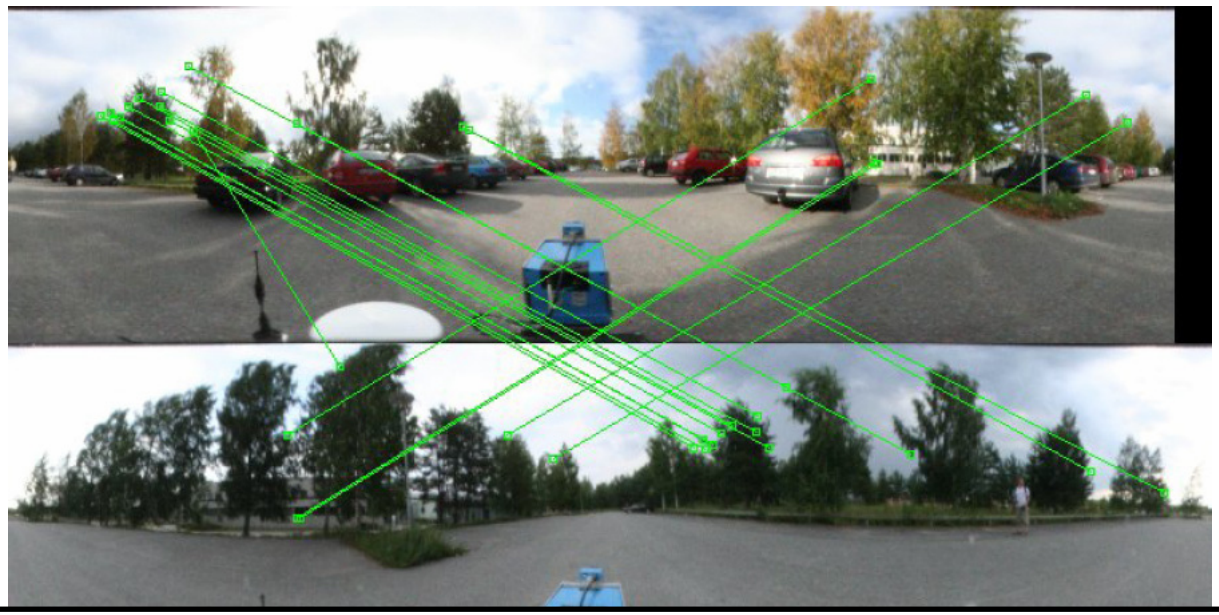


6 Inclusion of the Epipolar Constraint

Inclusion of the Epipolar Constraint

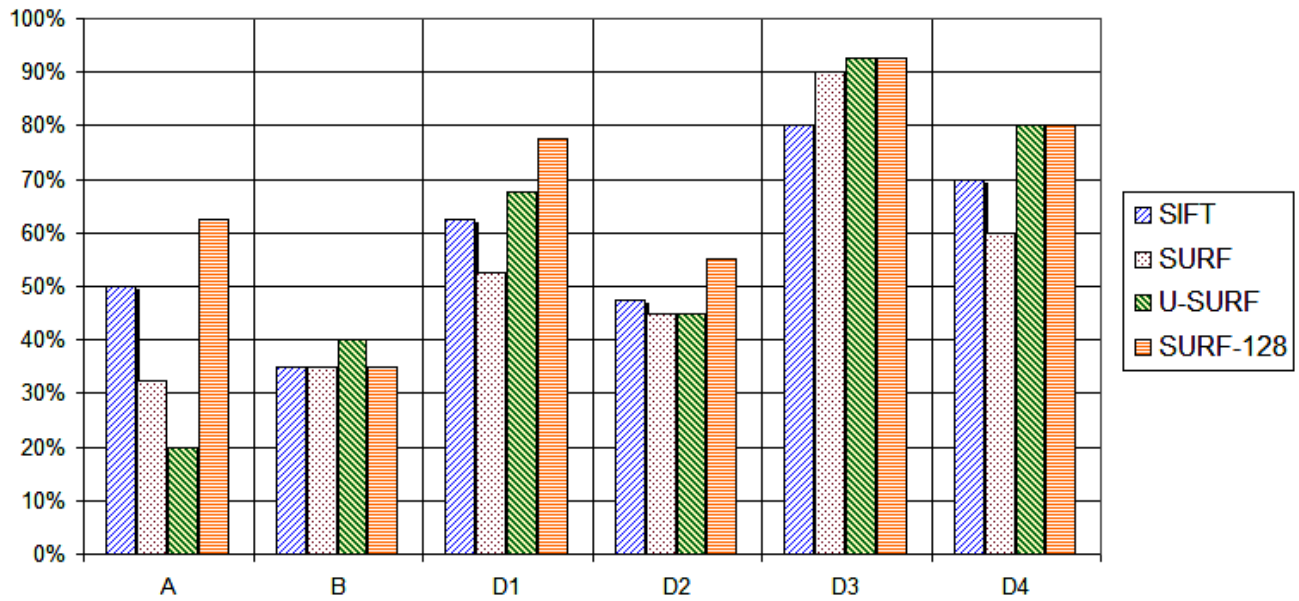
⇒ enough feature matches

⇒ apply epipolar constraint (RANSAC)



→ "A geometrically constrained image similarity measure for visual mapping ..." (Ben Kröse)

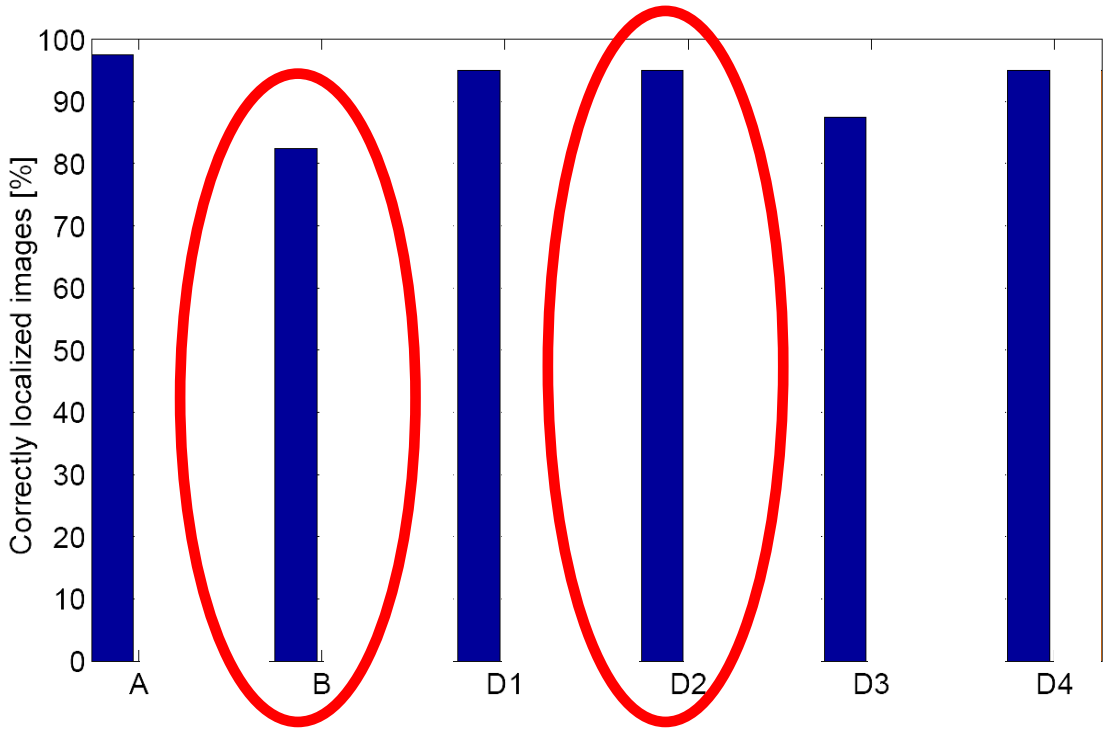
Inclusion of the Epipolar Constraint



6 Inclusion of the Epipolar Constraint

- Inclusion of the Epipolar Constraint

  $\Rightarrow$ now it works!



6 Outlook

- Future Work 2
  - build topological map incrementally (ISC)

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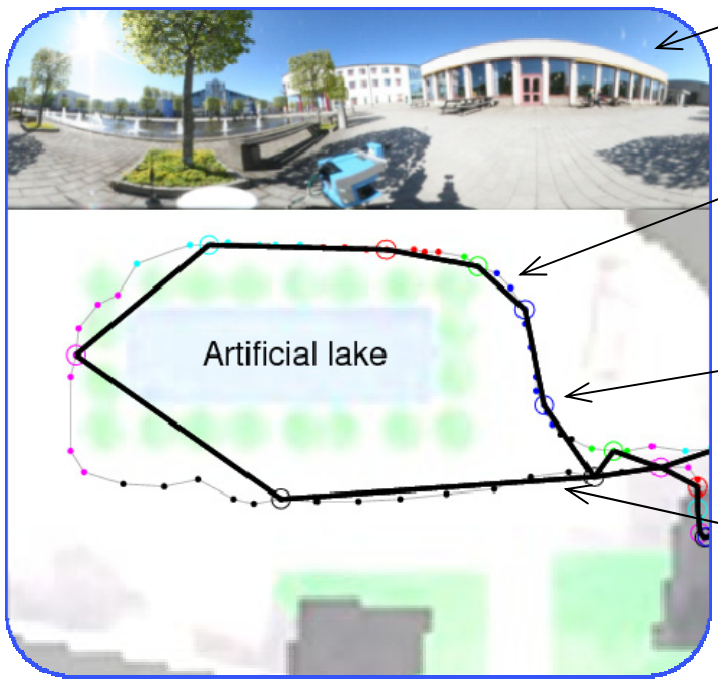
- Future Work 2
  - build topological map incrementally (ISC)

video on the next slide



current panoramic image

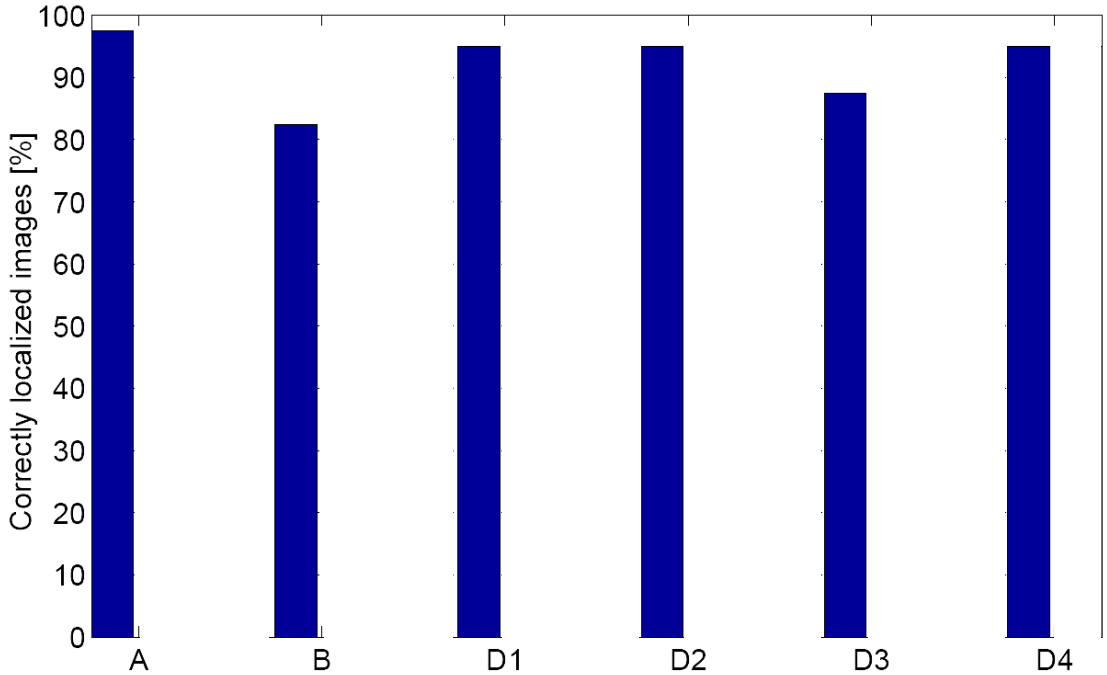
dot = images

circle = cluster representative

lines = links between clusters

6 Outlook

- Future Work 2
  - localize against the incrementally built topological map



SIFT, SURF and Seasons: Long-term Outdoor Localization Using Local Features

Thank you!