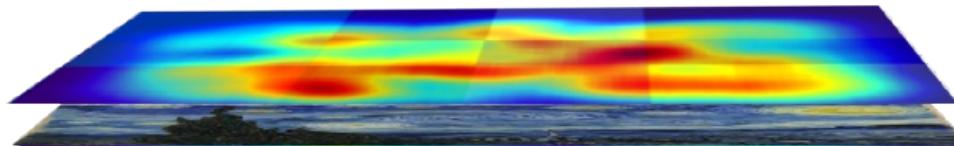


Machine Learning-based Indoor Localization for Micro Aerial Vehicles



Volker Strobel
volker.strobel87@gmail.com

14th July 2016

Radboud Universiteit

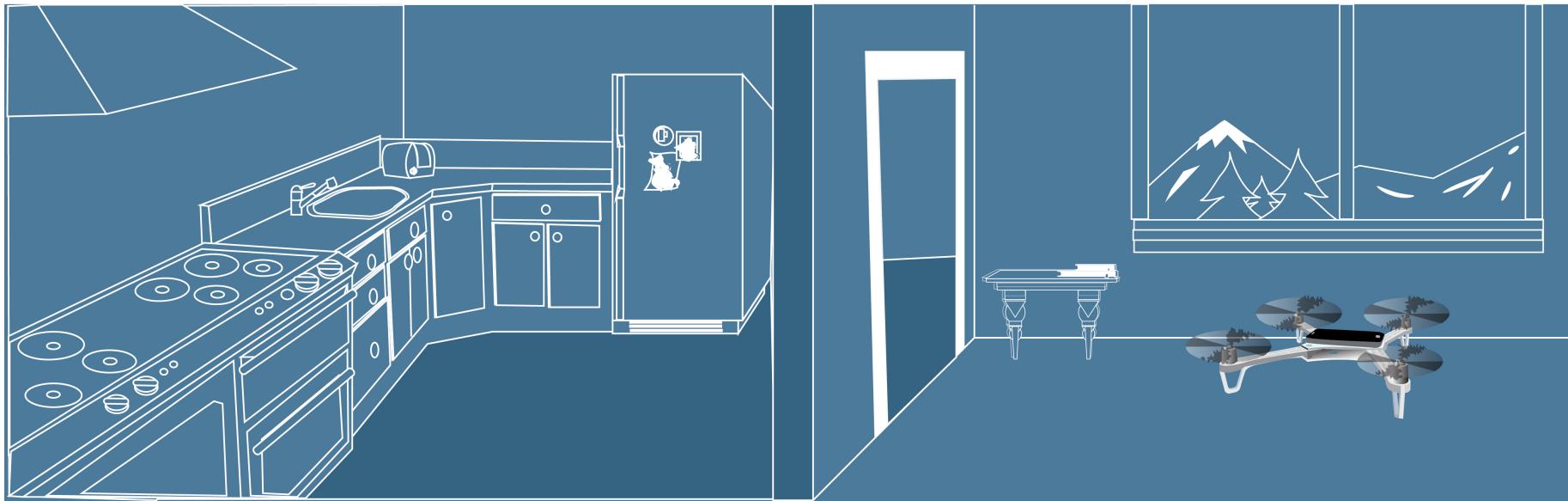


Louis Vuurpijl

TU Delft Delft
University of
Technology

Guido de Croon
Roland Meertens

MOTIVATION

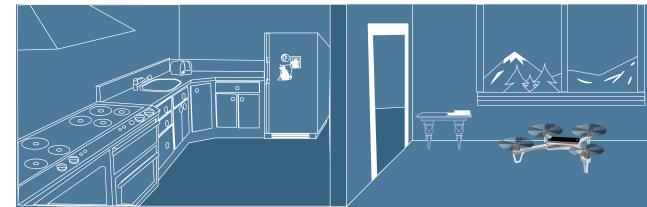


MOTIVATION

Tools



**x,y-coordinates
in real time
environment**



modifiable known fixed planar

MOTIVATION

Research Question

Can vision-based indoor localization be done on a very limited platform?

RESEARCH QUESTIONS

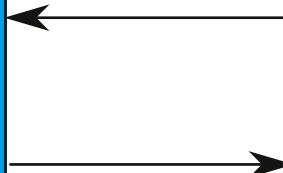
Research Question 1

Can vision-based indoor localization be done on a very limited platform?

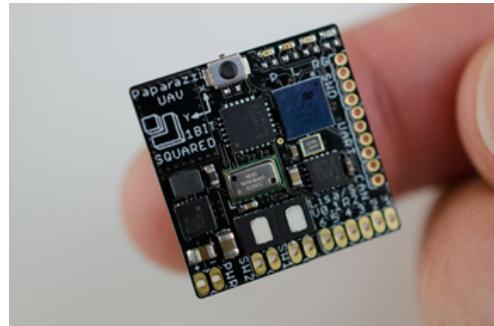
Research Question 2

Can we predict the suitability of an environment for the proposed localization algorithm?

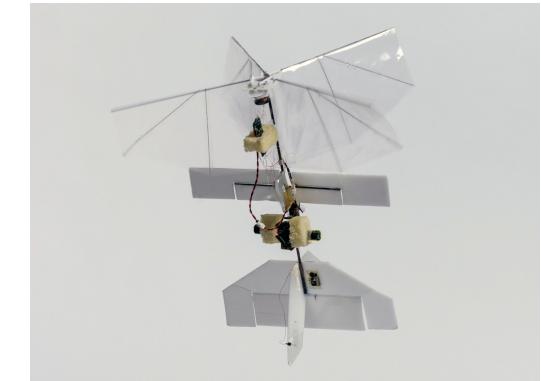
**x,y-coordinates
in real time**



Micro Air Vehicle Lab



Miniaturization



OUTLINE

- Existing Methods
- Machine Learning-based Approach
- Simulations & Flight Tests
- Discussion & Future Work

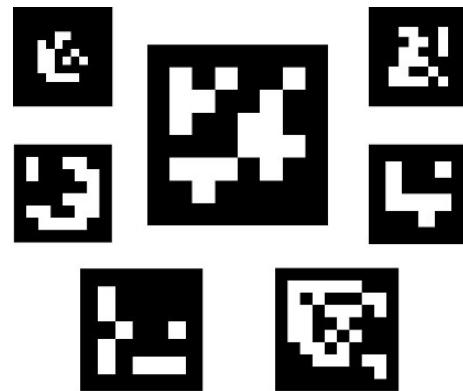
OUTLINE

- Existing Methods
- Methods
- Experiments and Results
- Discussion
- Conclusion

METHODS FOR INDOOR LOCALIZATION

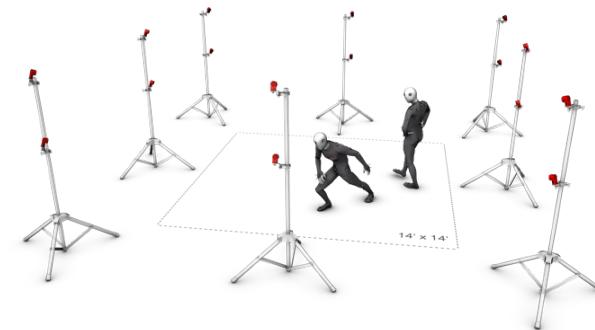


Laser range finder

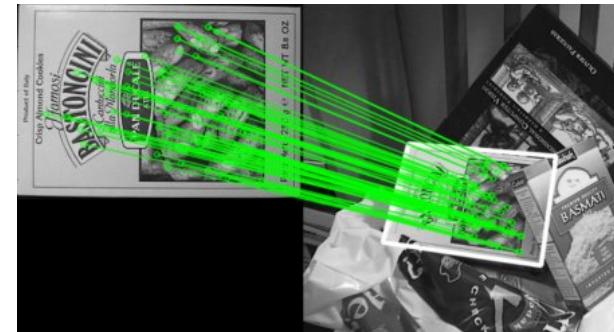


Markers

Visual odometry
(acumulating
error)



Motion tracking system



SIFT + homography finding

CHALLENGES / CONTRIBUTIONS

Low-performance platform

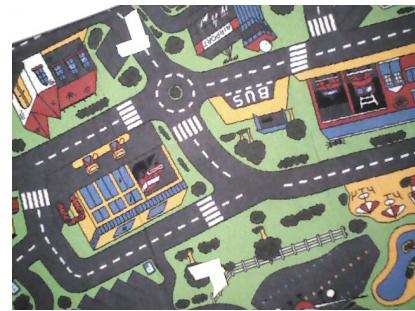


Low-level embedded
programming (C)

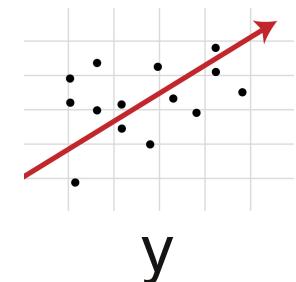
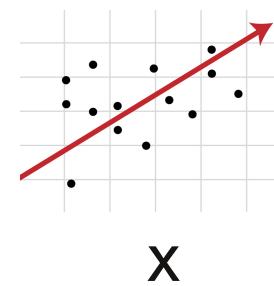


Ground truth estimation

x?
y?



Regression with 2 dependent
variables

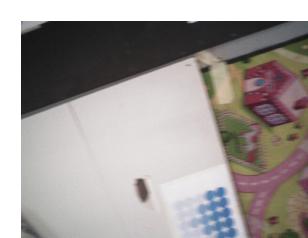
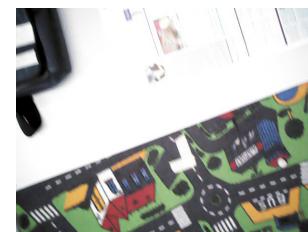


CHALLENGES / CONTRIBUTIONS

Which map is good?



GROUND TRUTH ESTIMATION



•

•

•

•

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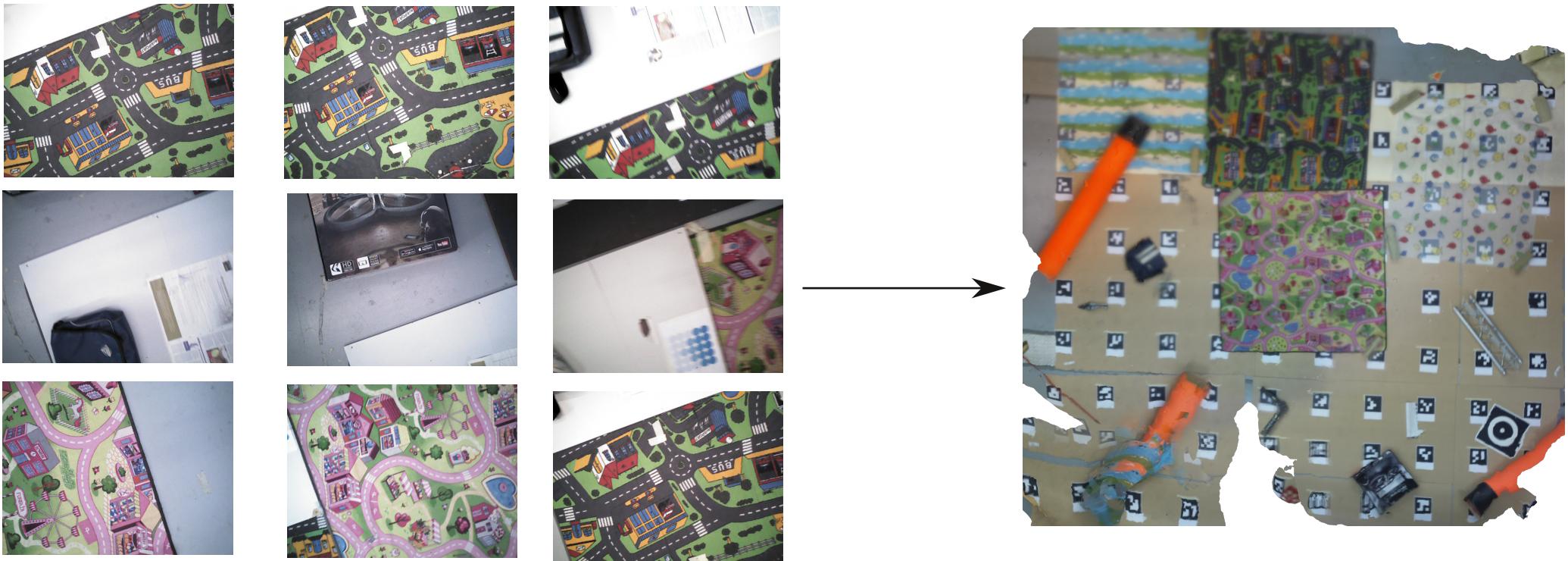
•

•

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•

GROUND TRUTH ESTIMATION



A horizontal line with six black dots. The dots are arranged in two columns of three. The left column has dots at approximately x=100, y=100 and x=100, y=300. The right column has dots at approximately x=500, y=100 and x=500, y=300.

DUMMY: INSERT SIFT

APPROACH

Flight phase



1 Image / sec

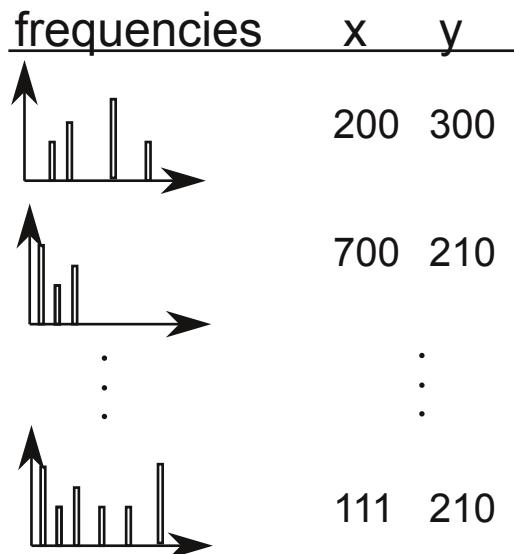


IDEA

Preflight phase

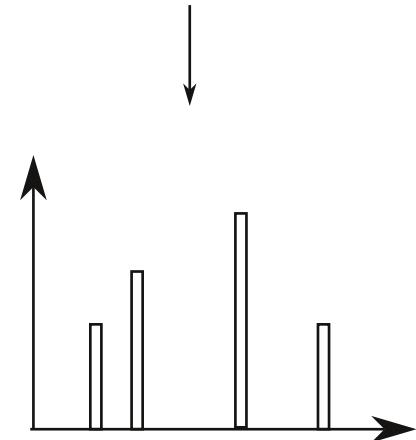


Training Data



(computational)
effort

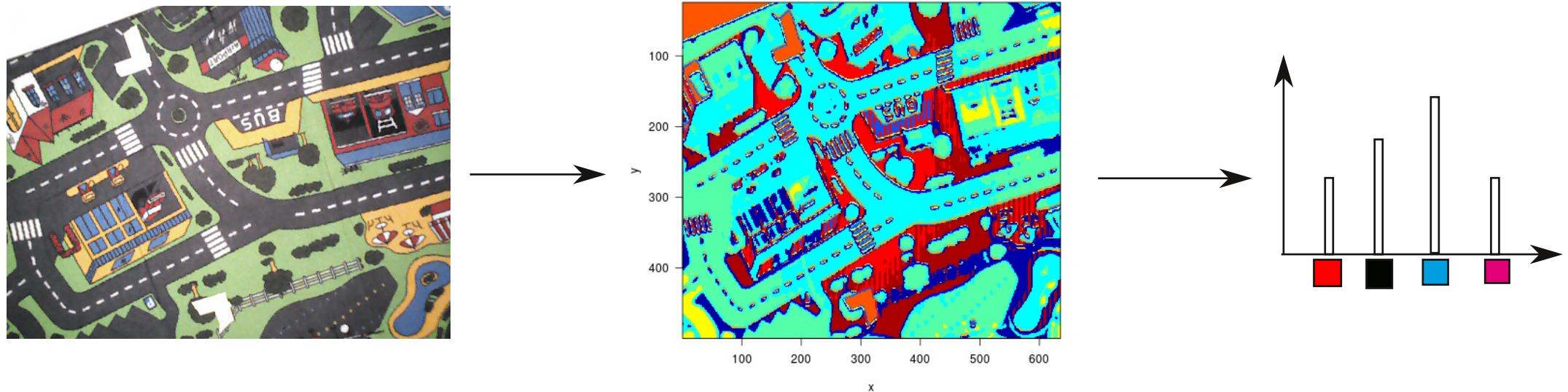
Flight phase



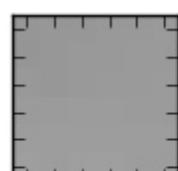
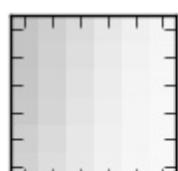
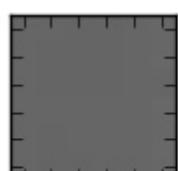
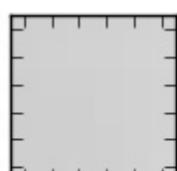
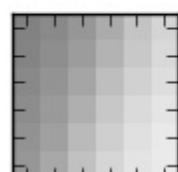
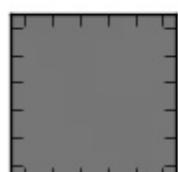
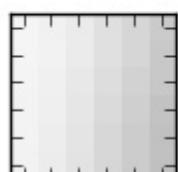
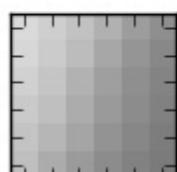
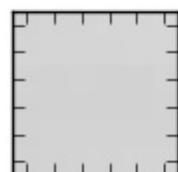
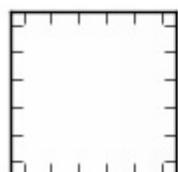
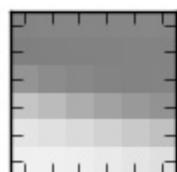
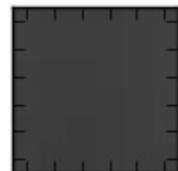
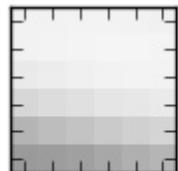
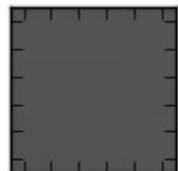
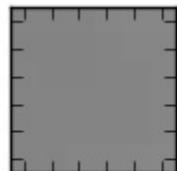
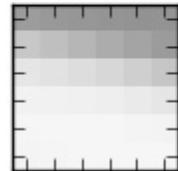
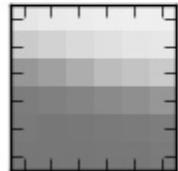
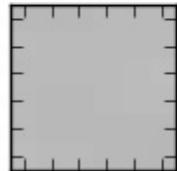
OUTLINE

- Related Work
- Methods
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- Conclusion

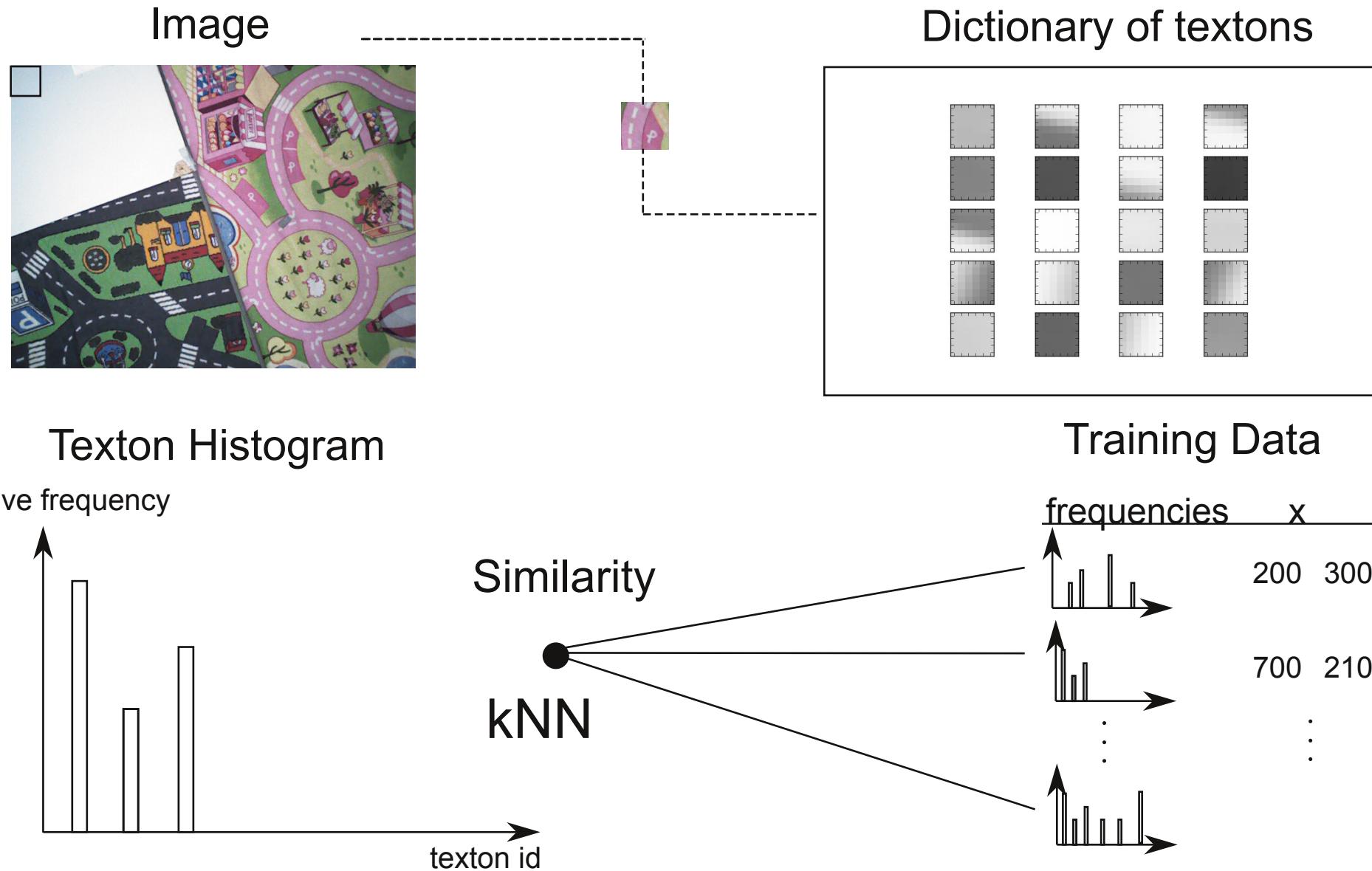
TEXTONS



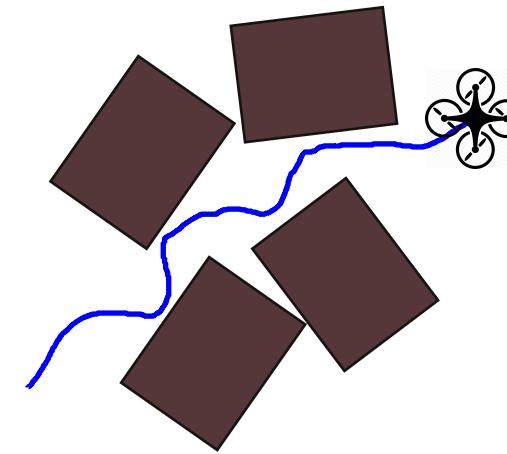
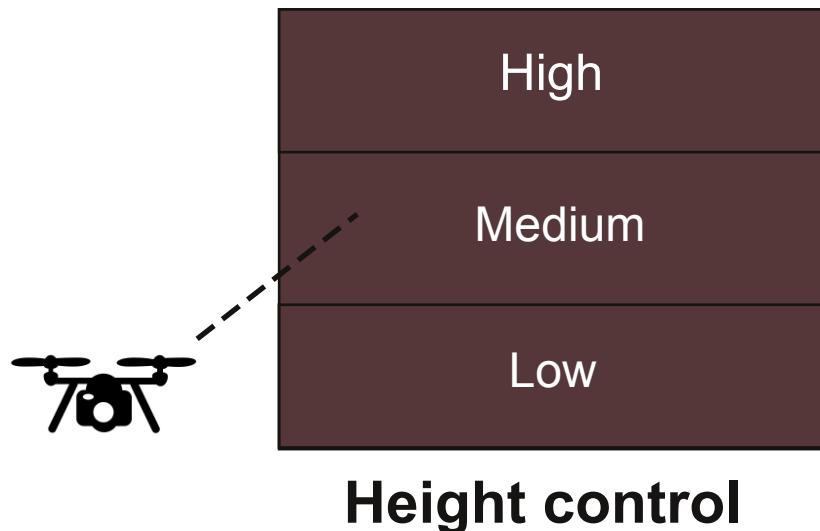
TEXTONS



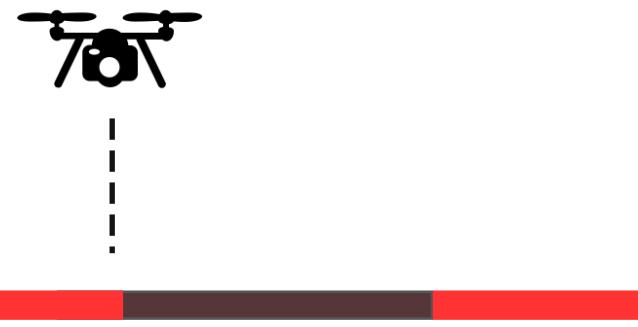
MACHINE-LEARNING APPROACH



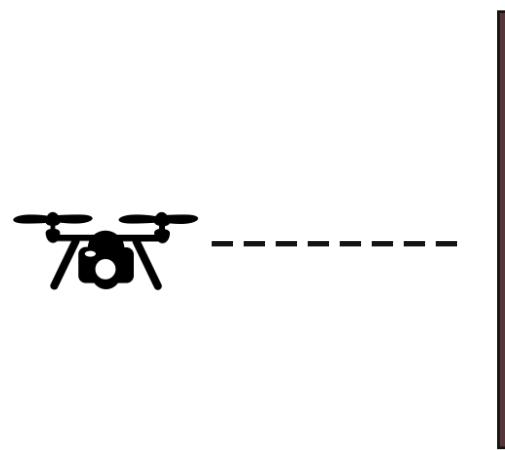
FOUNDATION



Obstacle Avoidance



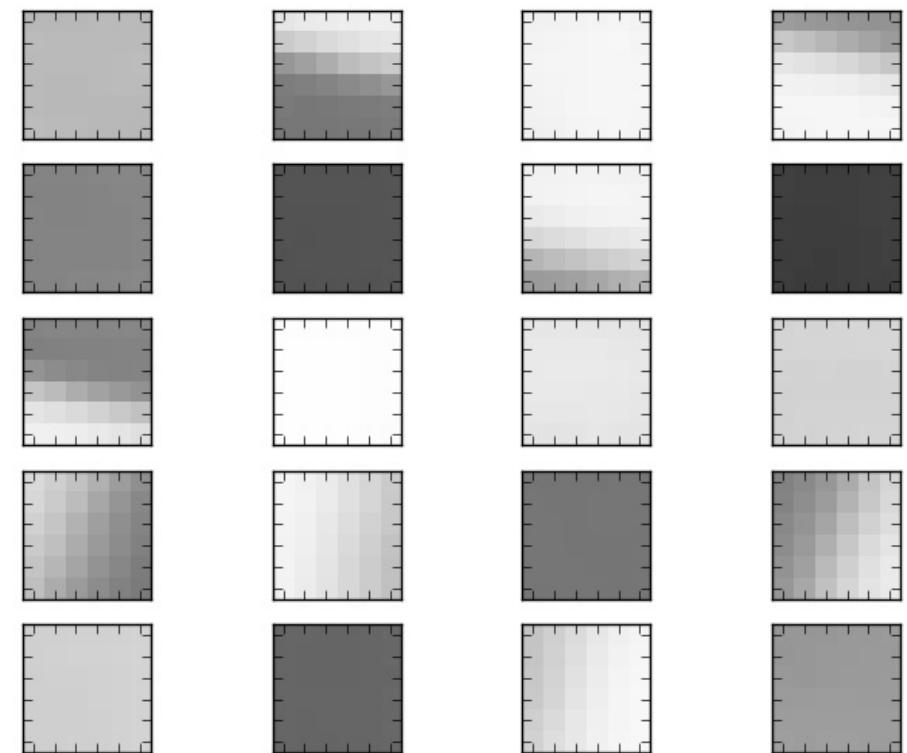
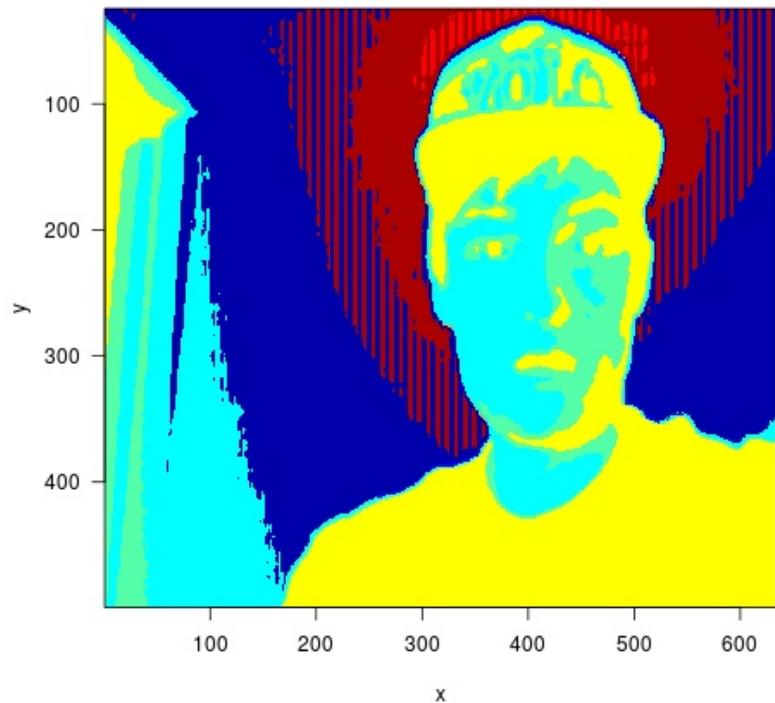
Safe Landing Spot Detection



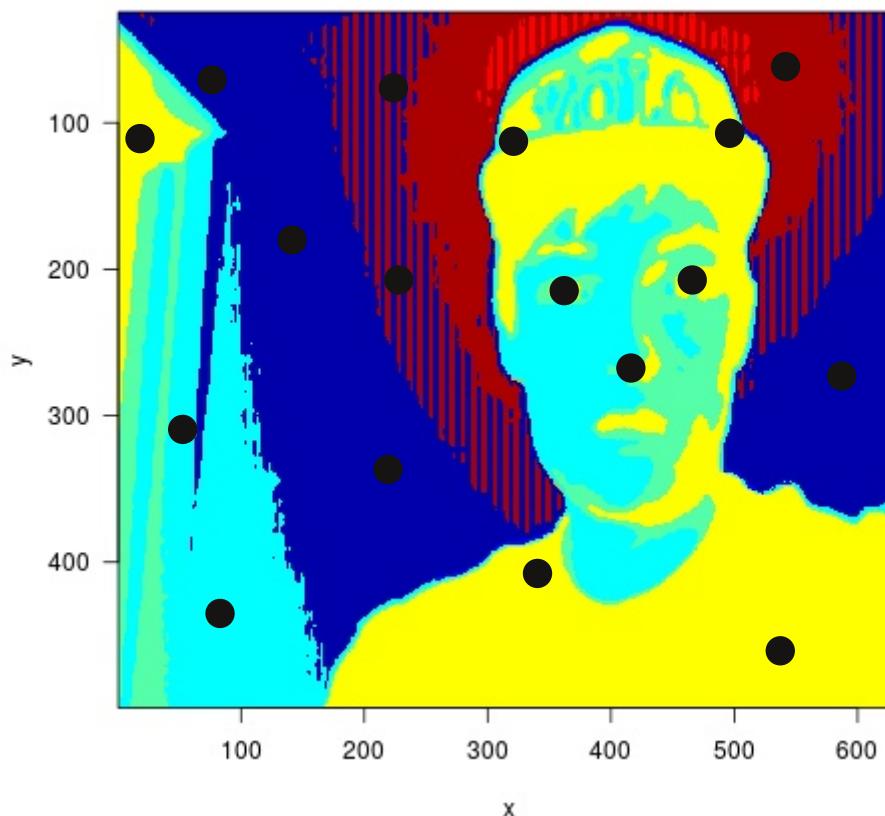
Distance Measurement

DUMMY: INSERT CYBERZOO_FLIGHT

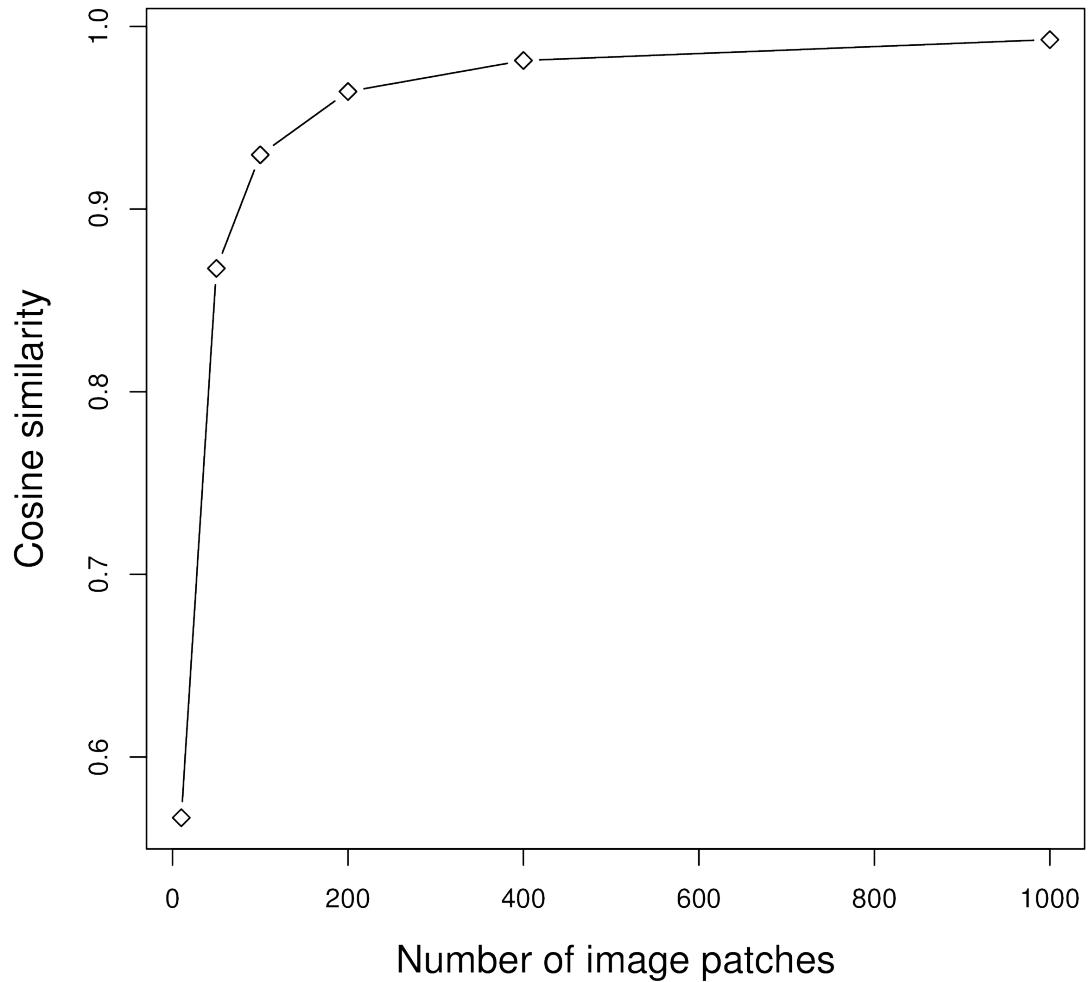
MACHINE-LEARNING APPROACH



MACHINE-LEARNING APPROACH

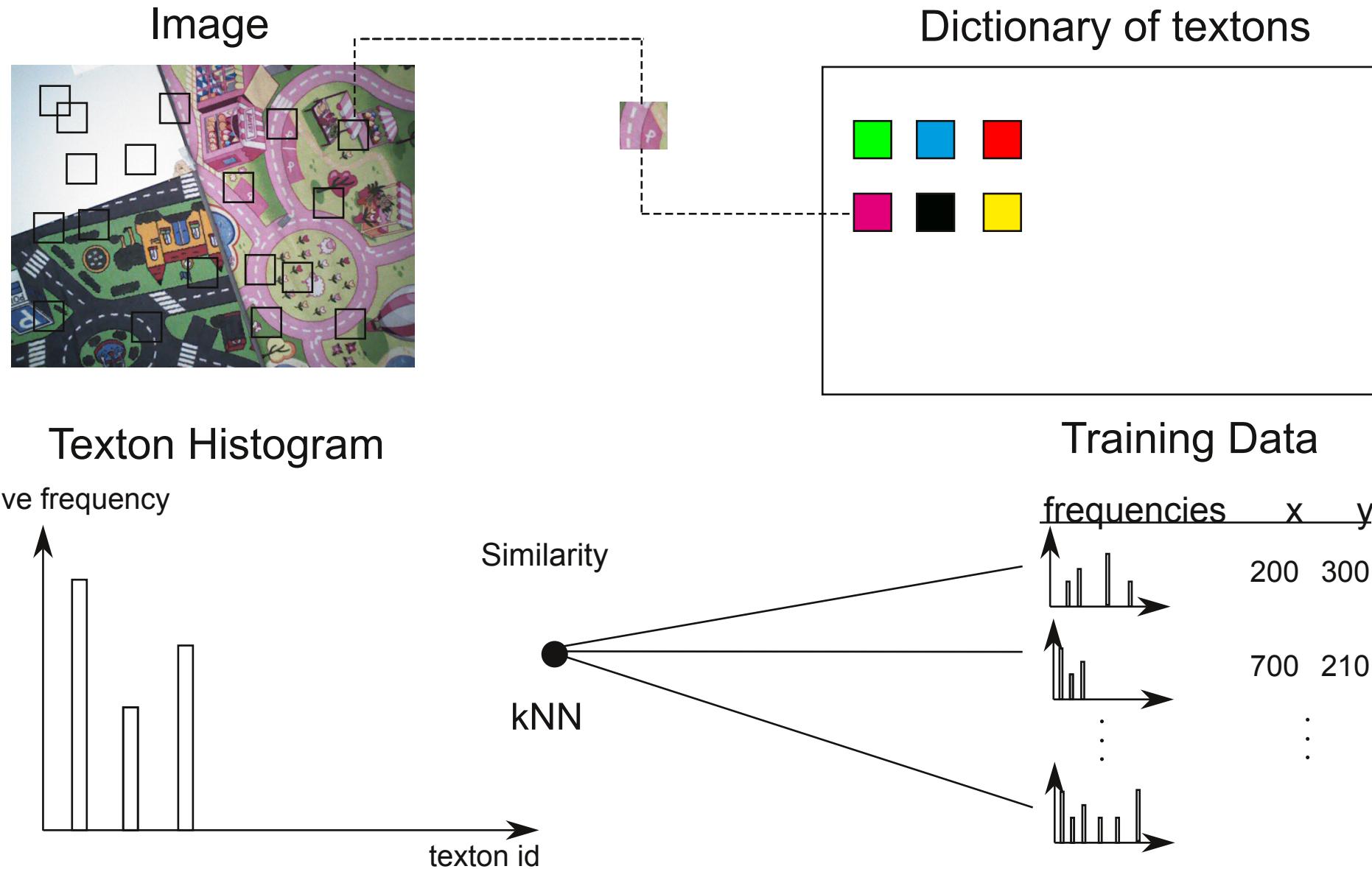


MACHINE-LEARNING APPROACH

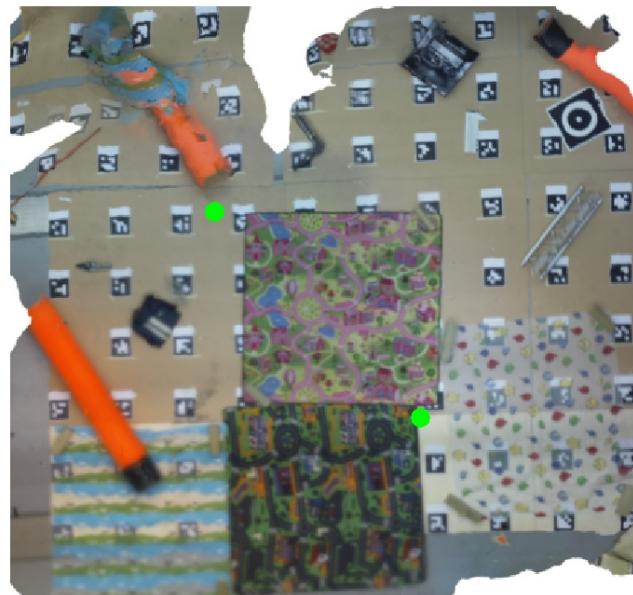
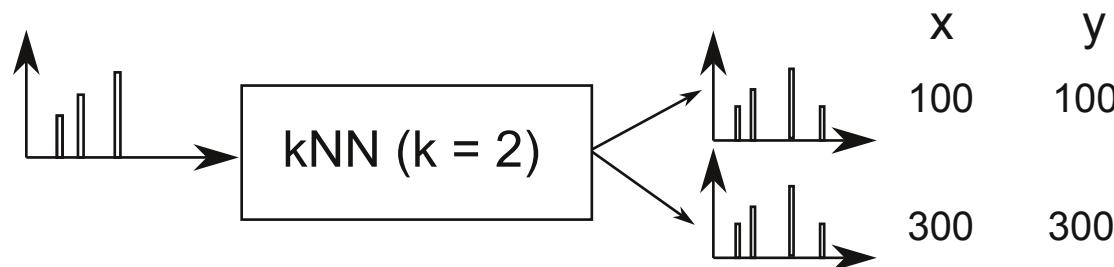


307200!

MACHINE-LEARNING APPROACH

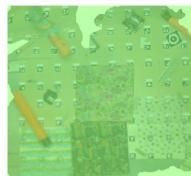


FILTERING

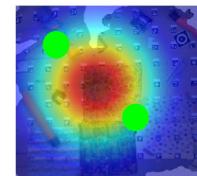


FILTERING

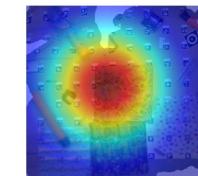
Prior ($t = 1$)



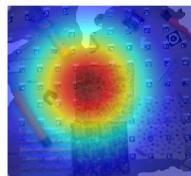
Likelihood ($t = 1$)



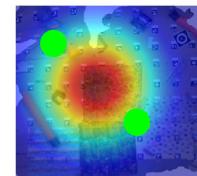
Posterior ($t = 1$)



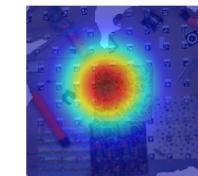
Prior ($t = 2$)



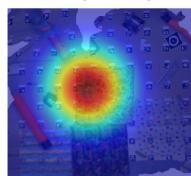
Likelihood ($t = 2$)



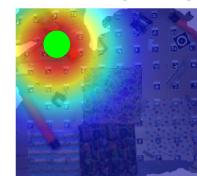
Posterior ($t = 2$)



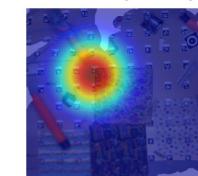
Prior ($t = 3$)



Likelihood ($t = 3$)

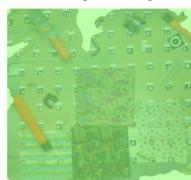


Posterior ($t = 3$)

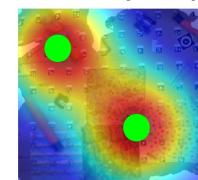


FILTERING

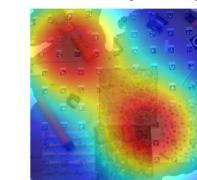
Prior ($t = 1$)



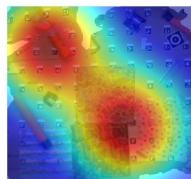
Likelihood ($t = 1$)



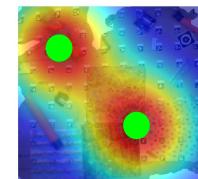
Posterior ($t = 1$)



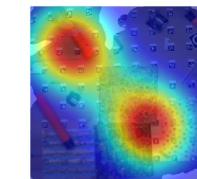
Prior ($t = 2$)



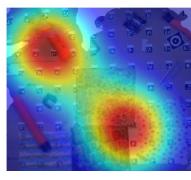
Likelihood ($t = 2$)



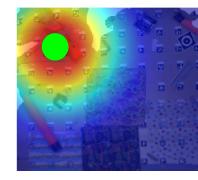
Posterior ($t = 2$)



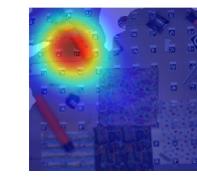
Prior ($t = 3$)



Likelihood ($t = 3$)

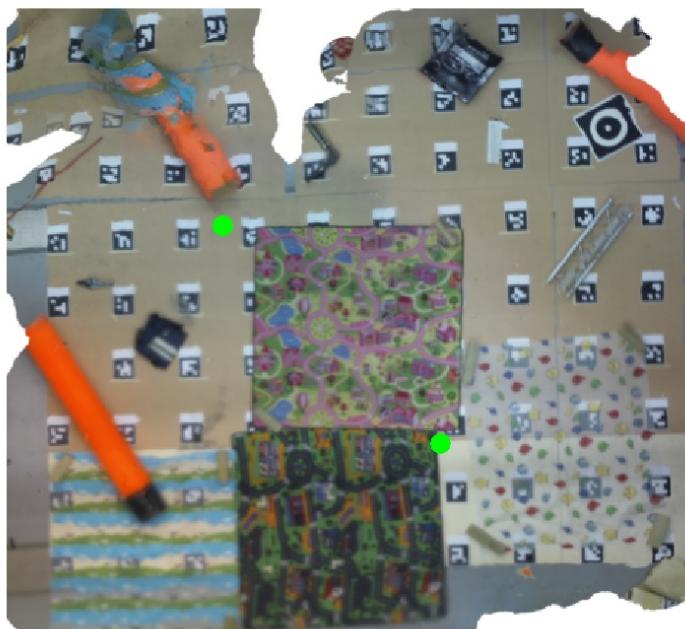


Posterior ($t = 3$)



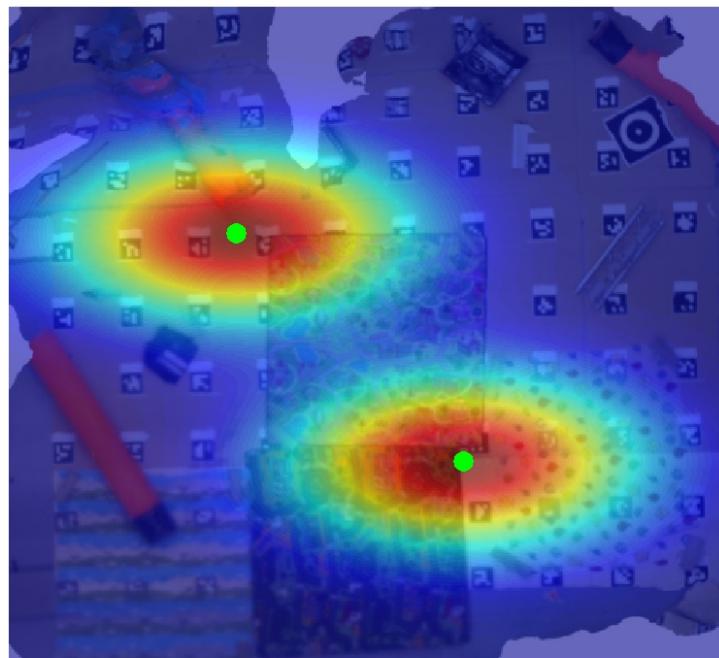
FILTERING

Sensor model



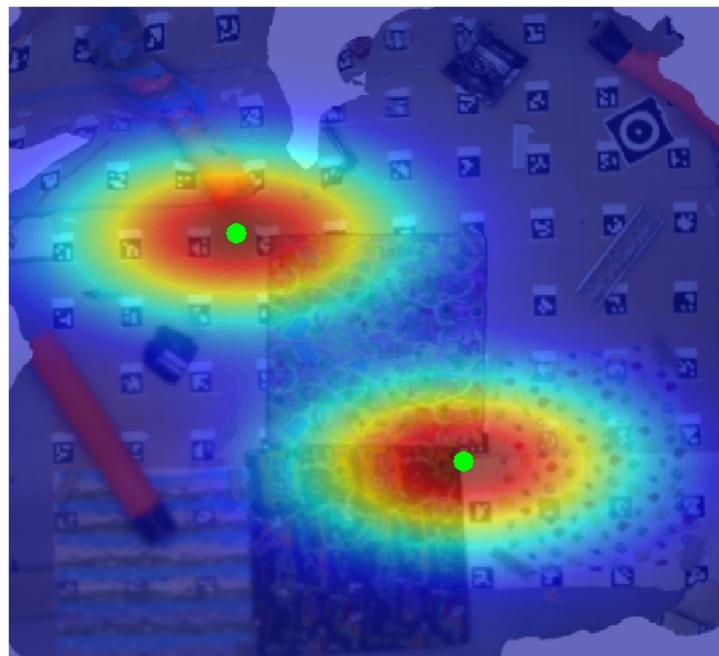
FILTERING

Sensor model



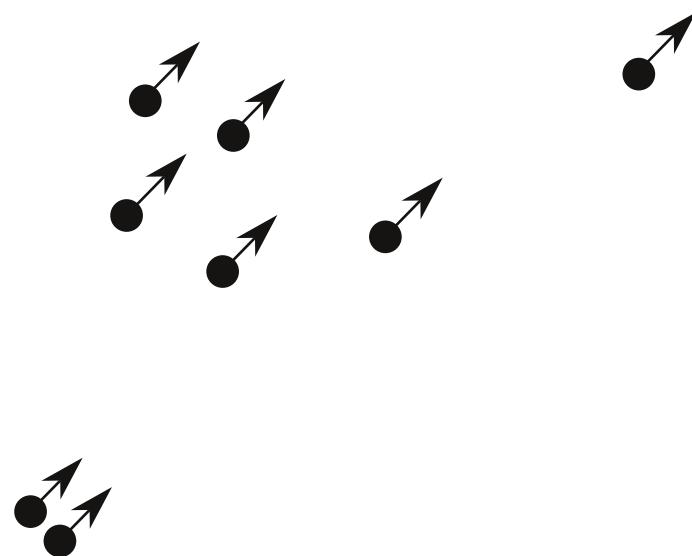
FILTERING

Sensor model



Motion model

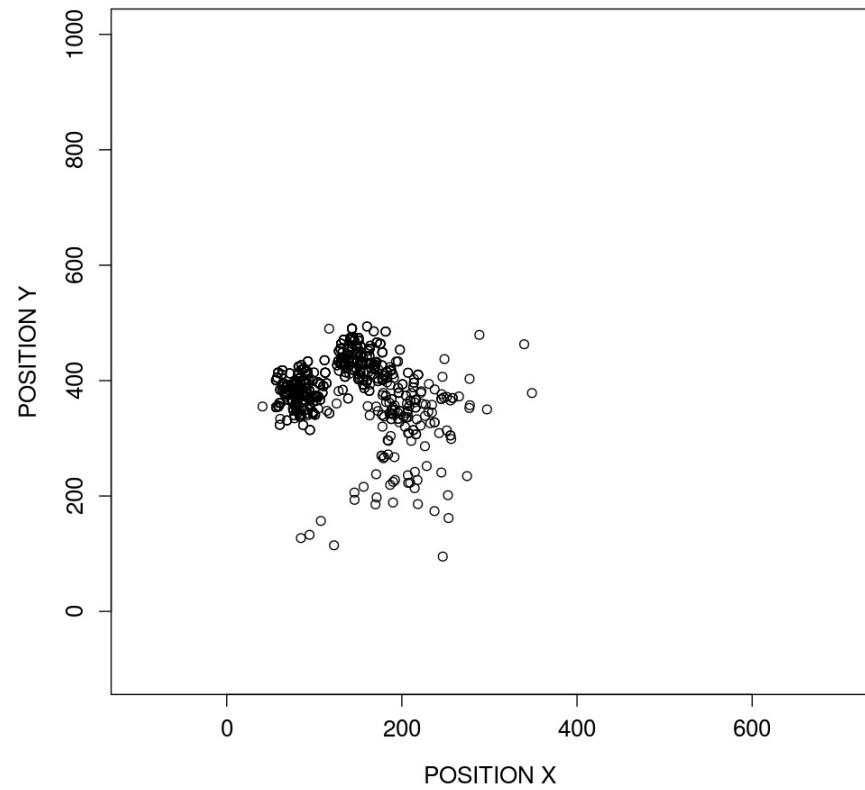
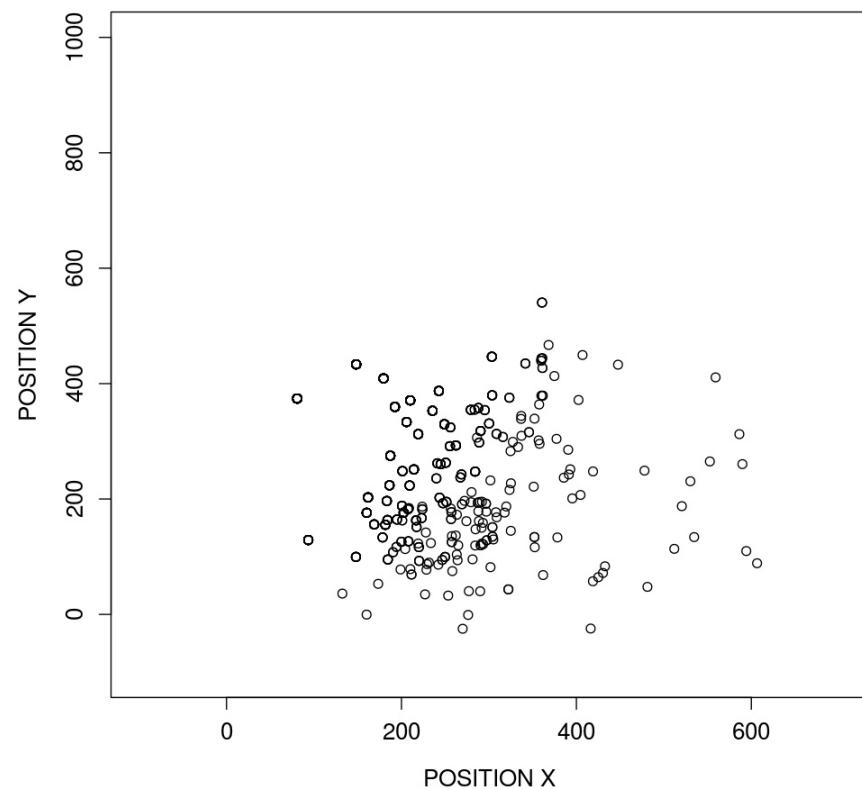
Determine optical flow and
add noise $\sim N(0, 10)$



FILTERING

GREAT
BUT
SLOW

PARTICLE FILTER

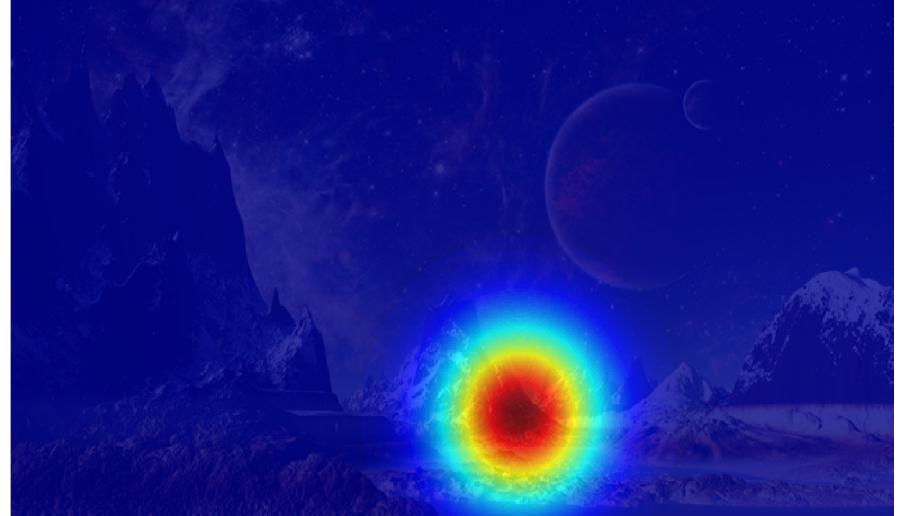


DUMMY: PARTICLE FILTER

ENVIRONMENTAL MODIFICATION

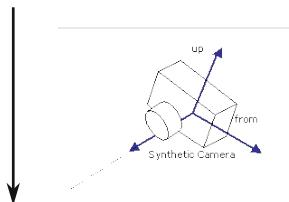


MAP EVALUATION

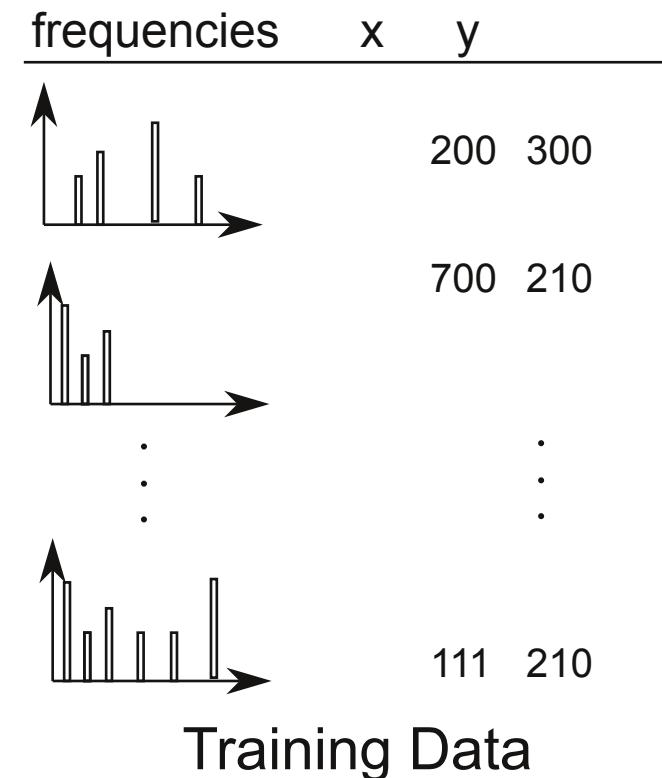


**IDEAL SIMILARITY OF
HISTOGRAMS FOR FIXED
POSITION**

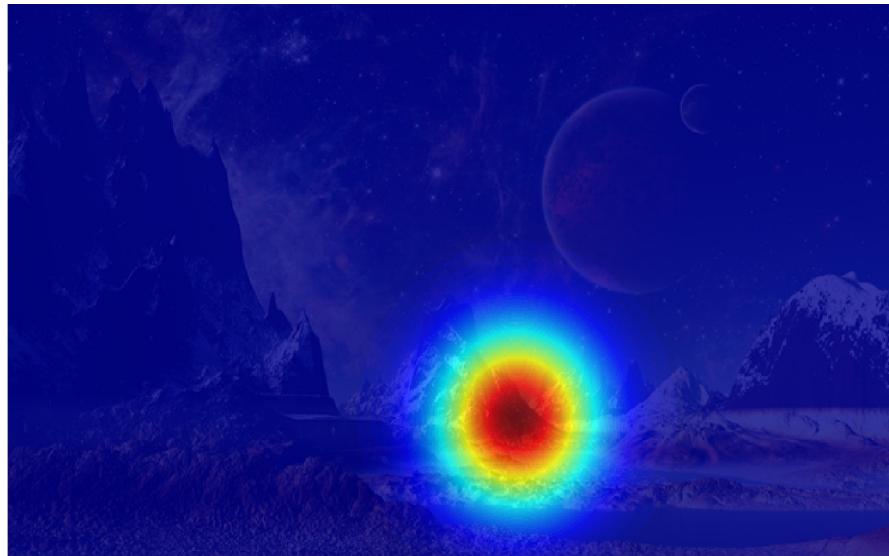
MAP EVALUATION - SYNTHETIC FLIGHT



1000 patches



MAP EVALUATION



**IDEAL SIMILARITY OF
HISTOGRAMS FOR FIXED
POSITION**

TODO

ACTUAL SIMILARITY

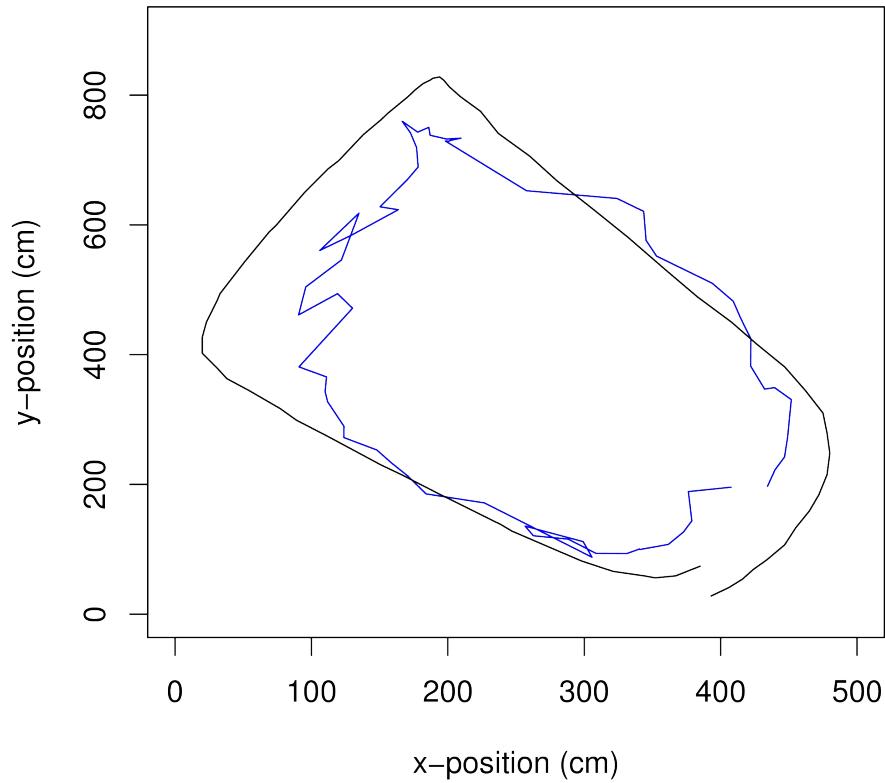
OUTLINE

- Related Work
- Methods
- Experiments and Results
- Discussion
- Conclusion

EXPERIMENTS

- Simulated flights
- Map evaluation
- Real-world Target Landing
- Real-world Navigation

FLIGHT ACCURACY



OptiTrack vs. treXton

Average distance

Standard deviation of errors

TRIGGERED LANDING

PLOT DELTA X Y OF SINGLE RUNS
OR USE TABLE

DUMMY: VIDEO TARGET LANDING

MAP EVALUATION



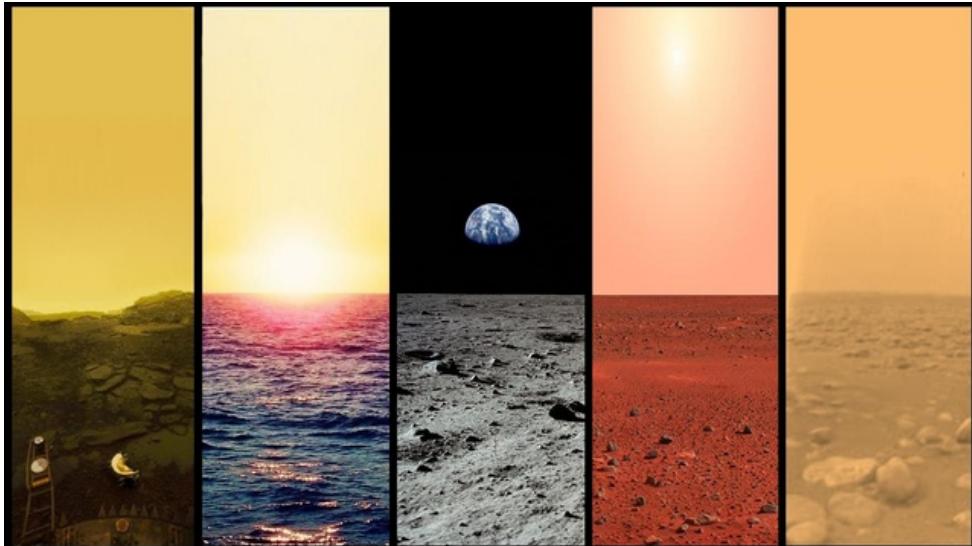
47 images

MAP EVALUATION



MAP EVALUATION

GOOD



BAD



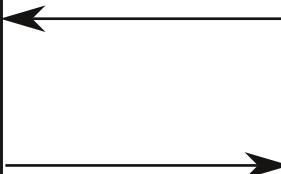
RESEARCH QUESTIONS

Research Question 1

**Can accurate indoor
localization be done on a very
limited platform?**

Research Question 2

**Can we predict the suitability
of a given map for the
proposed localization
algorithm?**



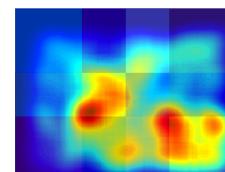
DISCUSSION

Implications:

- adaptable to different platforms
- robustness to motion blur
- detect safe landing spots



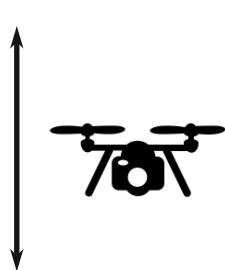
?



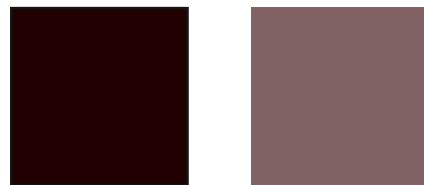
DISCUSSION

Limitations:

- assumes constant height and no rotations



- robustness to different lighting conditions



- Particle filter does not include velocity or heading

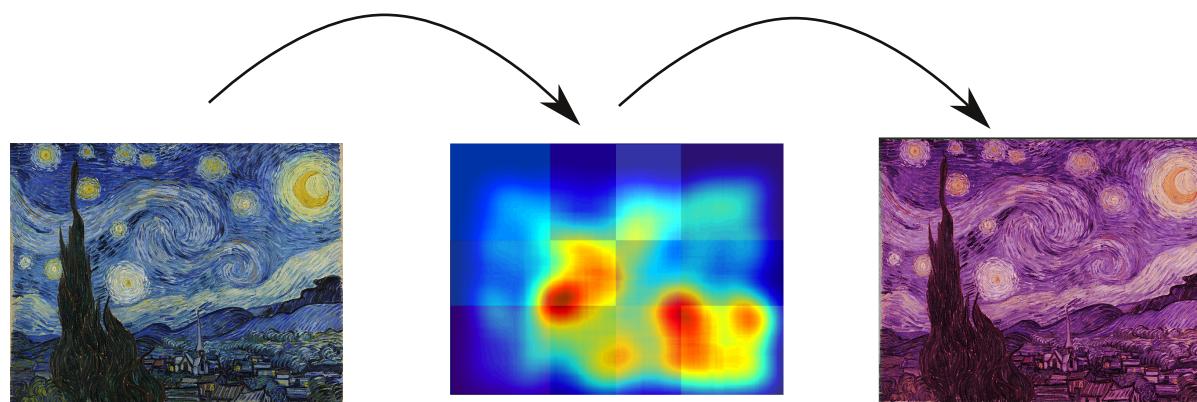
DISCUSSION

Future research:

- bridge reality gap



- automatic map generation (evolutionary algorithm)



CODE CONTRIBUTIONS

- Image augmentation with synthetic views (C++)

<https://github.com/Pold87/draug>

- Map evaluation (MATLAB)

<https://github.com/Pold87/evaluation-thesis>

- Localization: SIFT matching, particle filter, texton-based approach (C)

C: <https://github.com/Pold87/paparazzi>

Python: <https://github.com/Pold87/treXton>



CONCLUSION

EFFICIENT INDOOR LOCALIZATION

