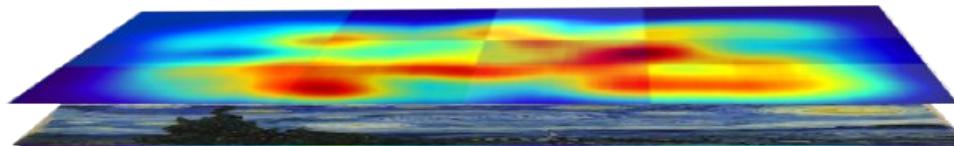


# Machine Learning-based Indoor Localization for Micro Aerial Vehicles



**Volker Strobel**  
[volker.strobel87@gmail.com](mailto:volker.strobel87@gmail.com)

**14th July 2016**

**Radboud Universiteit**

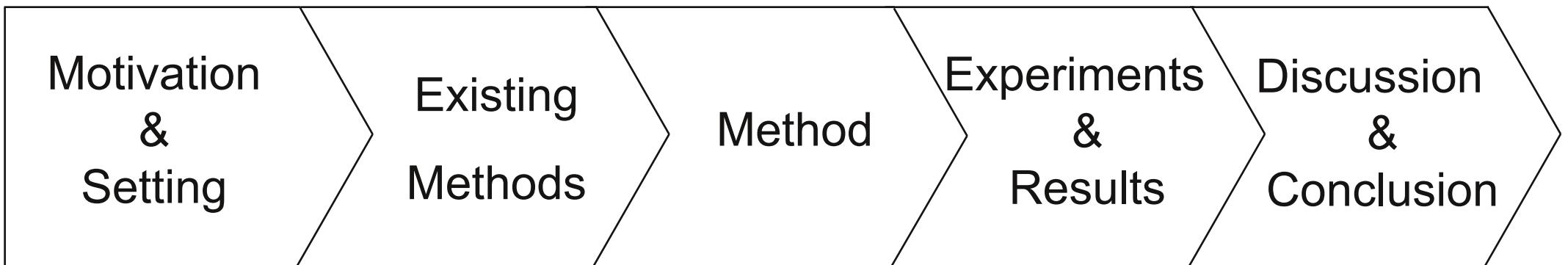


**Louis Vuurpijl**

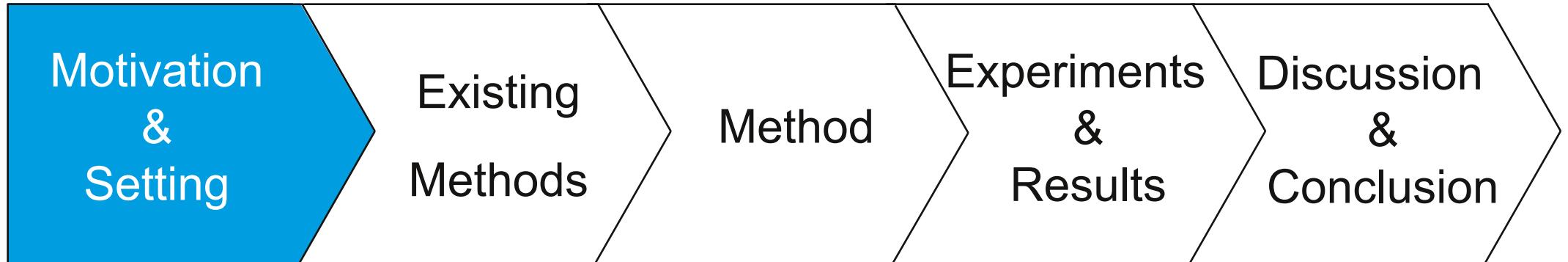
**TU Delft** Delft  
University of  
Technology

**Guido de Croon**  
**Roland Meertens**

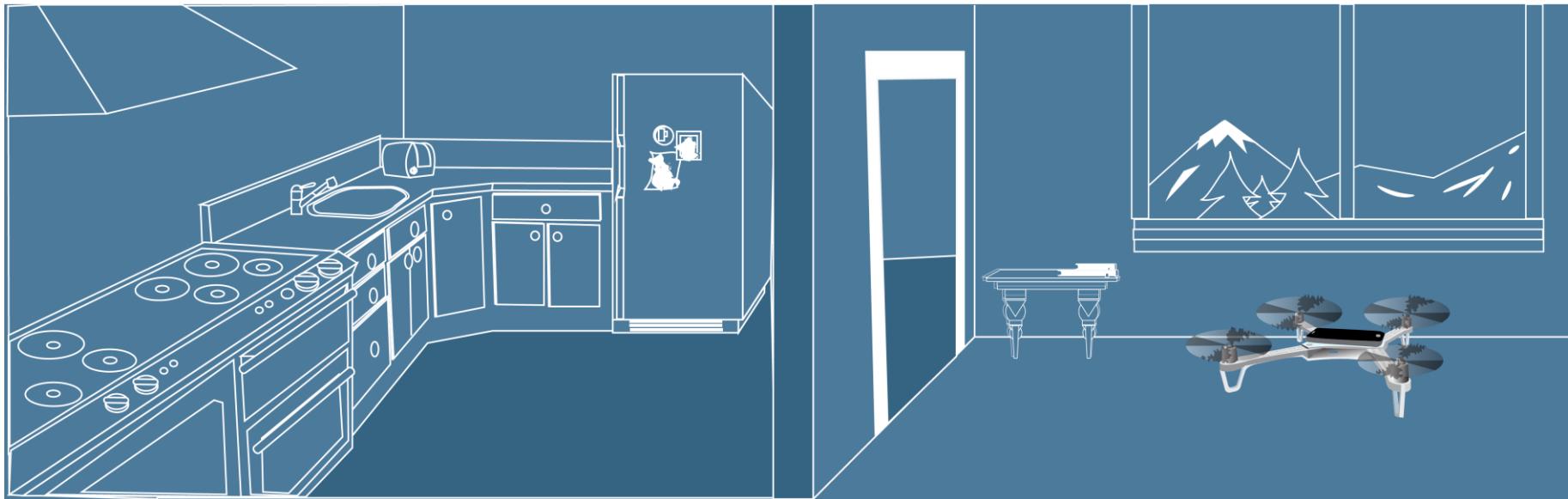
# OUTLINE



# OUTLINE



# MOTIVATION



# MOTIVATION

## Tools



## Environment



modifiable

known

fixed

planar

## x,y-coordinates

accurate

on-board

real-time

# MOTIVATION

## Research Question

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

accurate

on-board

real-time

# RESEARCH QUESTIONS

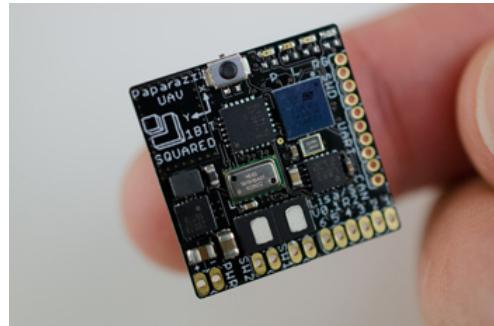
## Research Question 1

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

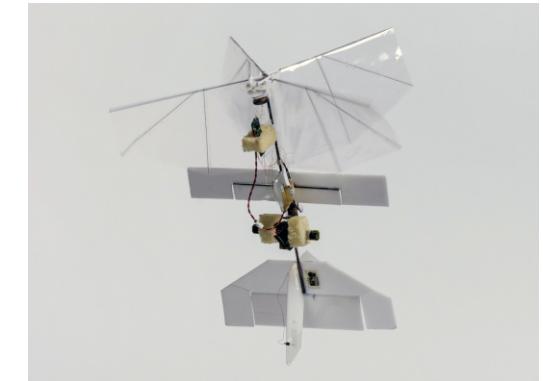
## Research Question 2

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

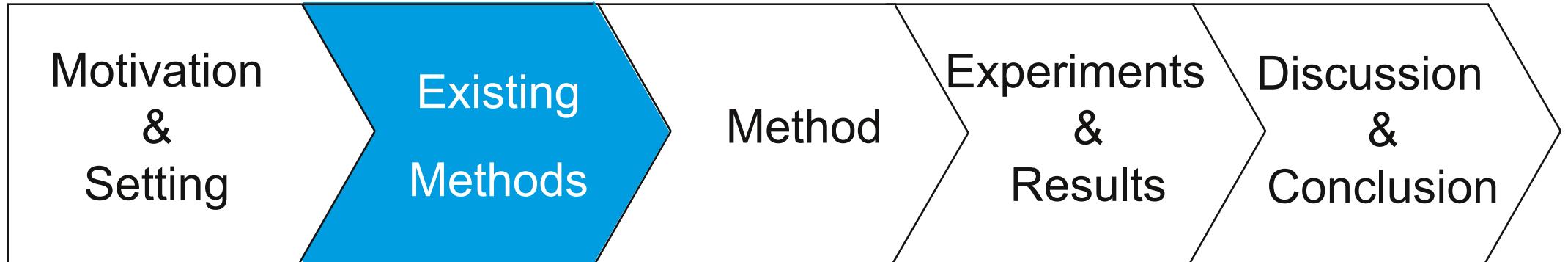
# Micro Air Vehicle Lab



## Miniaturization



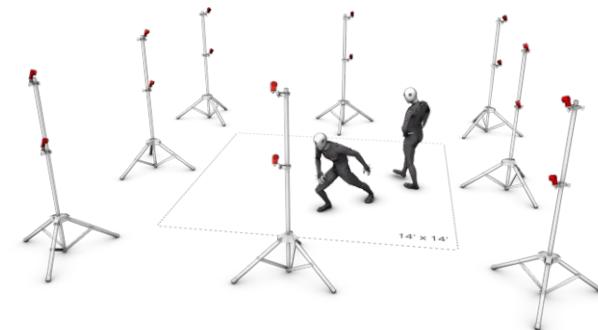
# OUTLINE



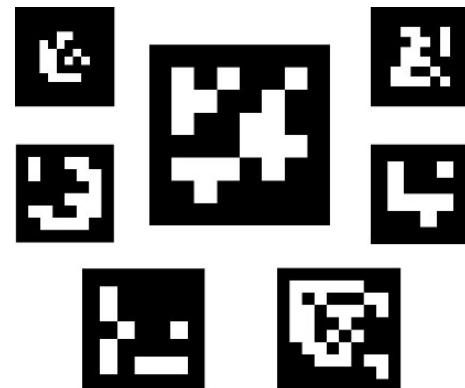
# METHODS FOR INDOOR LOCALIZATION



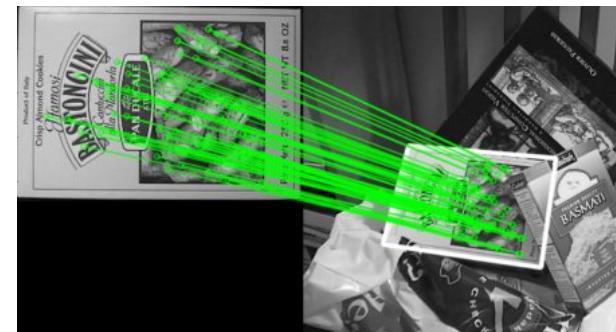
Laser range finder



Motion tracking system



Markers



SIFT + homography finding

**DUMMY: INSERT SIFT VIDEO**

# APPROACH

## Flight phase



1 Image / sec

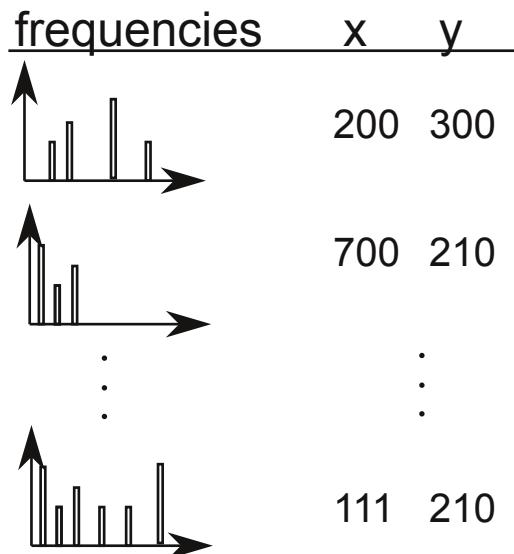


# IDEA

## Preflight phase

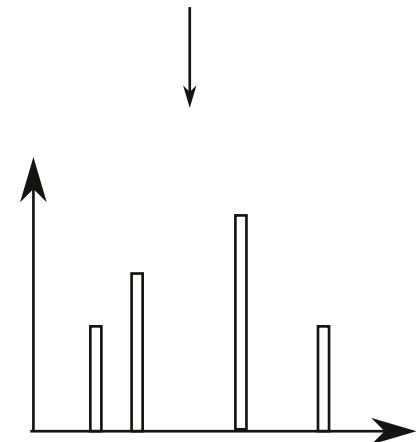


## Training Data



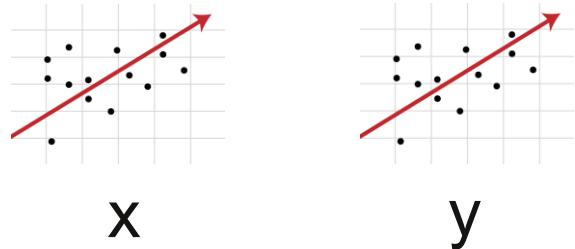
(computational)  
effort

## Flight phase



# CHALLENGES / CONTRIBUTIONS

2-dimensional  
regression



Ground truth estimation

x?  
y?



Which map is good?



# CHALLENGES / CONTRIBUTIONS

Low-performance  
platform

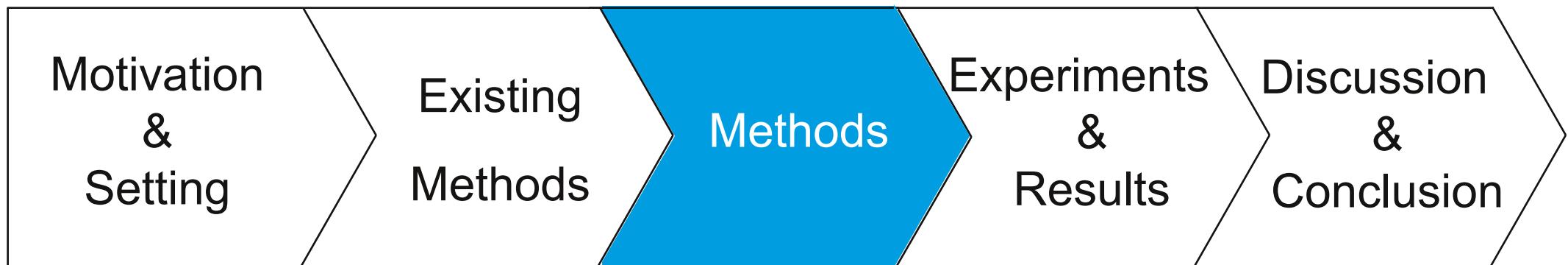


Low-level embedded  
programming (C)



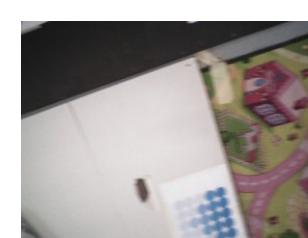
## Real-world

# OUTLINE



- Ground truth estimation
- Texton-based approach
- Particle Filter
- Map Evaluation

# GROUND TRUTH ESTIMATION



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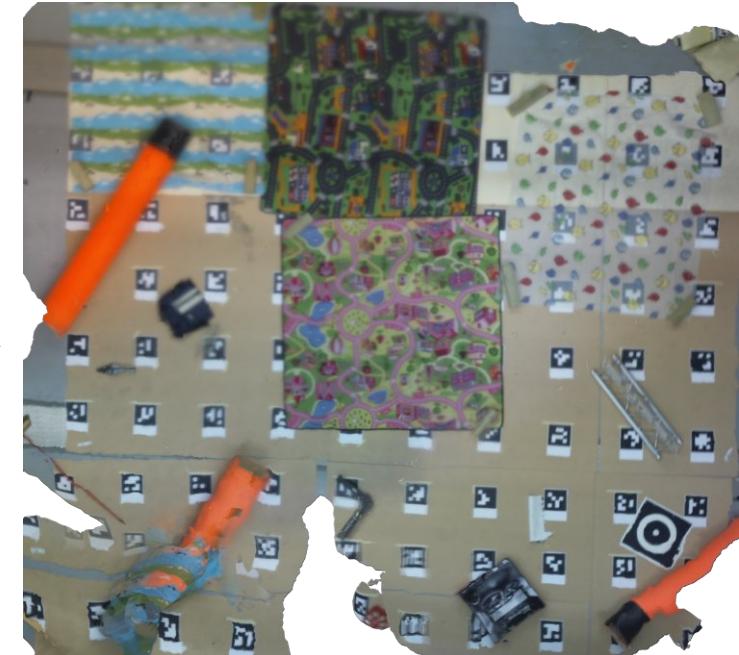
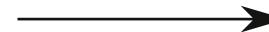
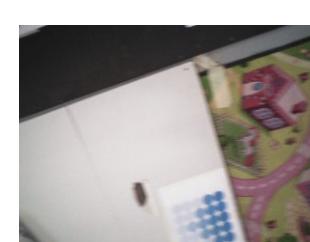
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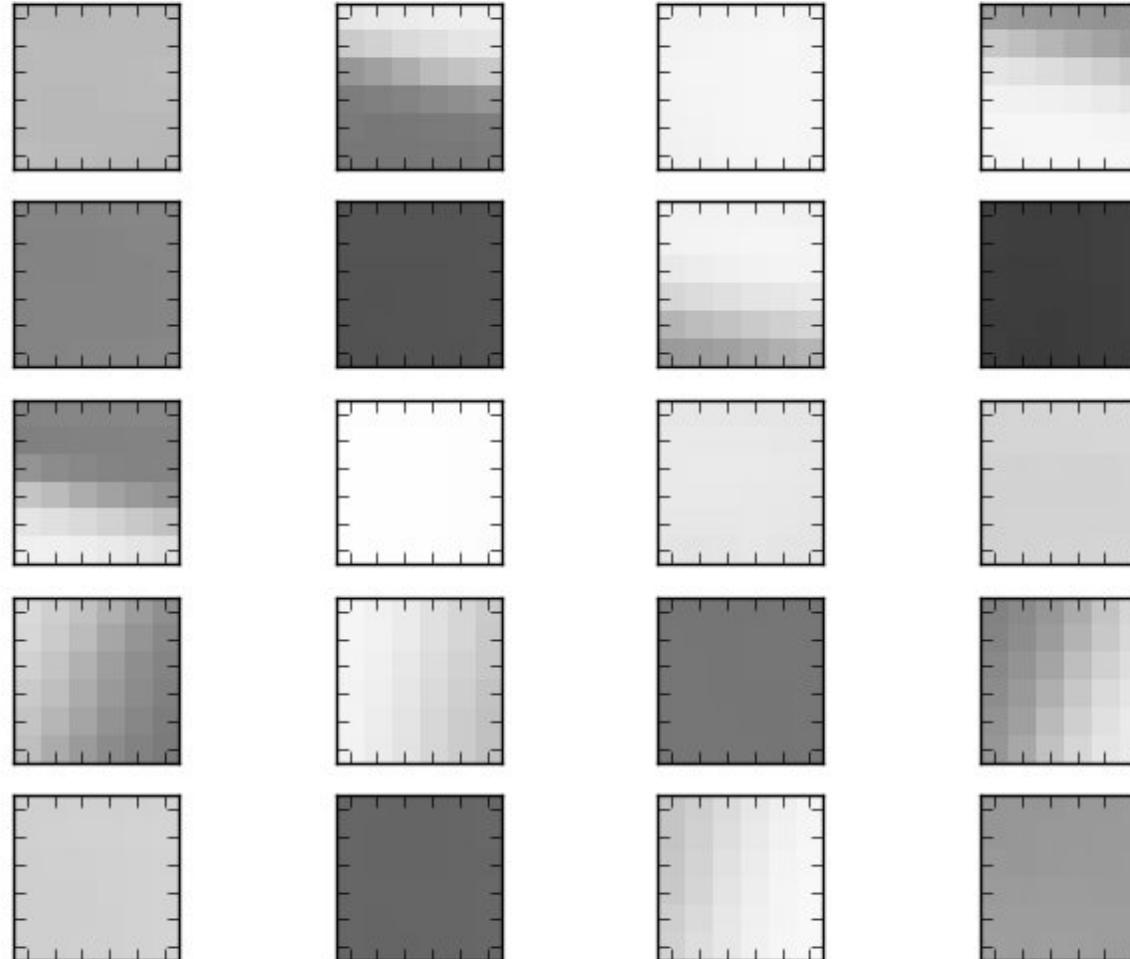
# GROUND TRUTH ESTIMATION



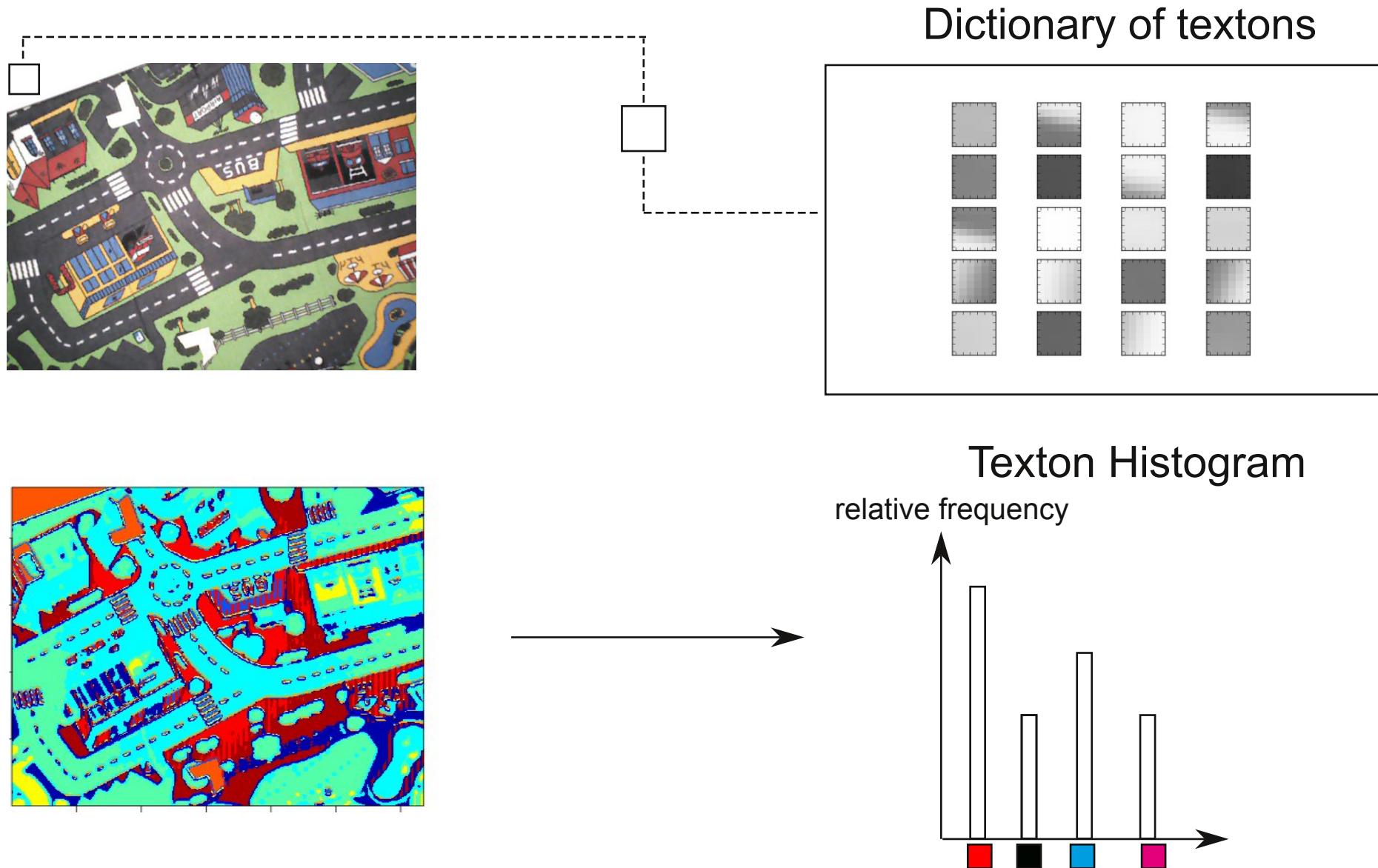
Orthomap

- 
- 
- 
- 
- 
- 
- 
-

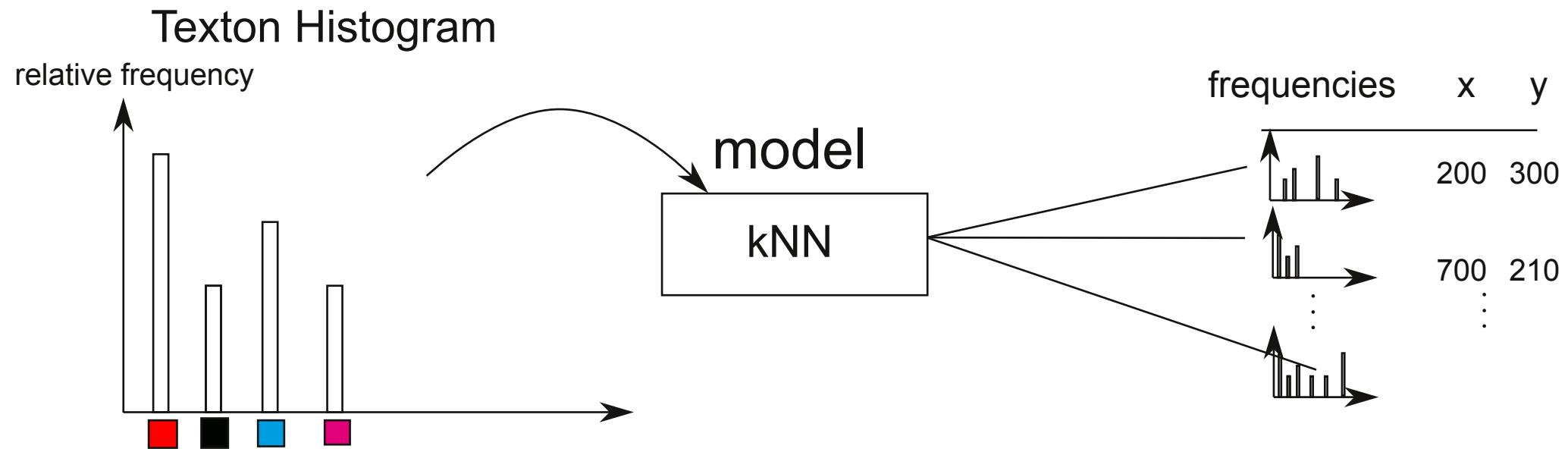
# TEXTONS



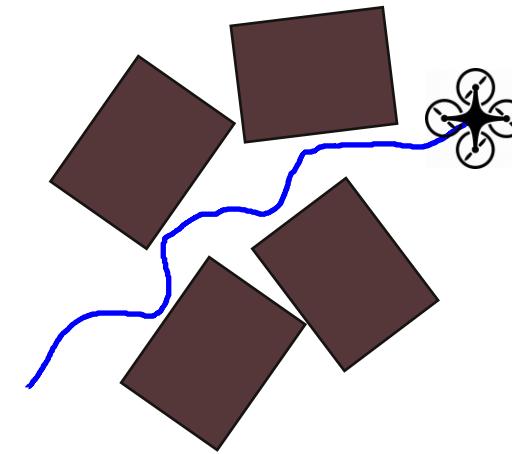
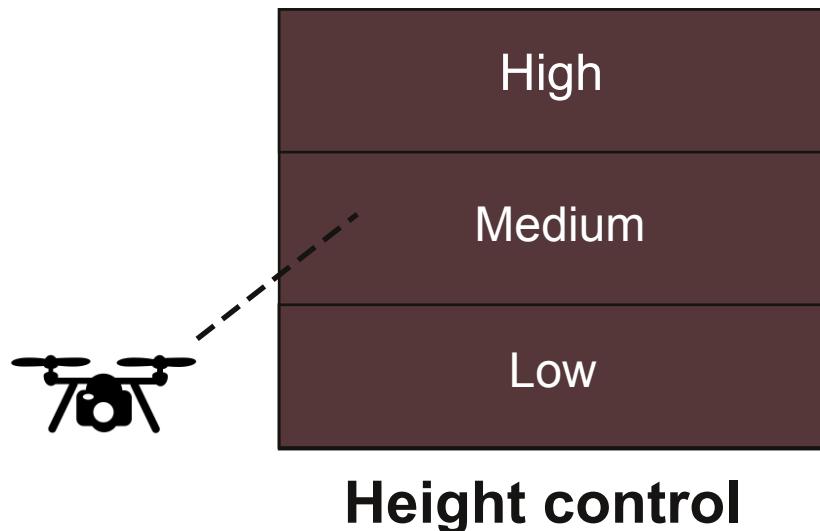
# MACHINE-LEARNING APPROACH



# MACHINE-LEARNING APPROACH



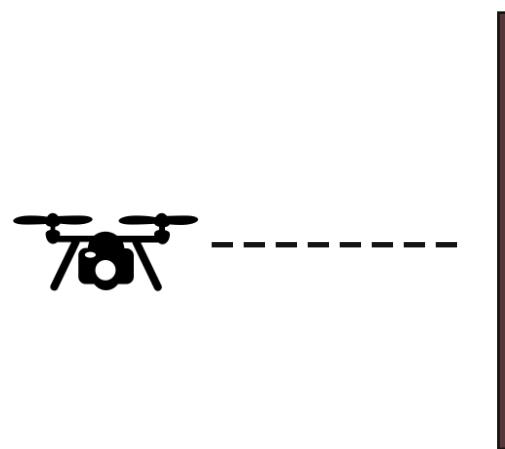
# FOUNDATION



**Obstacle Avoidance**



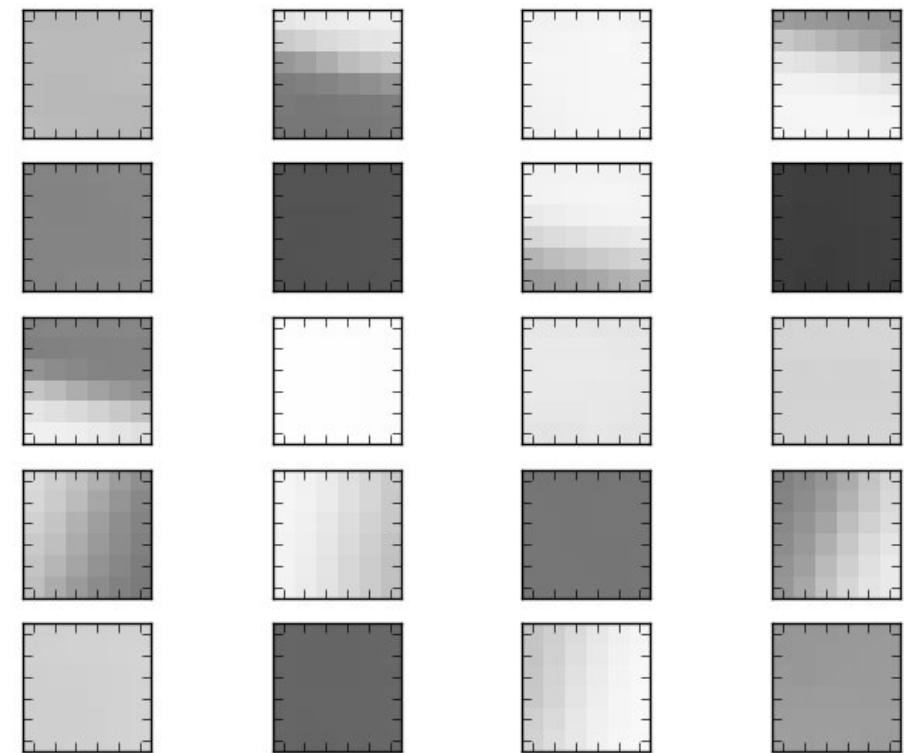
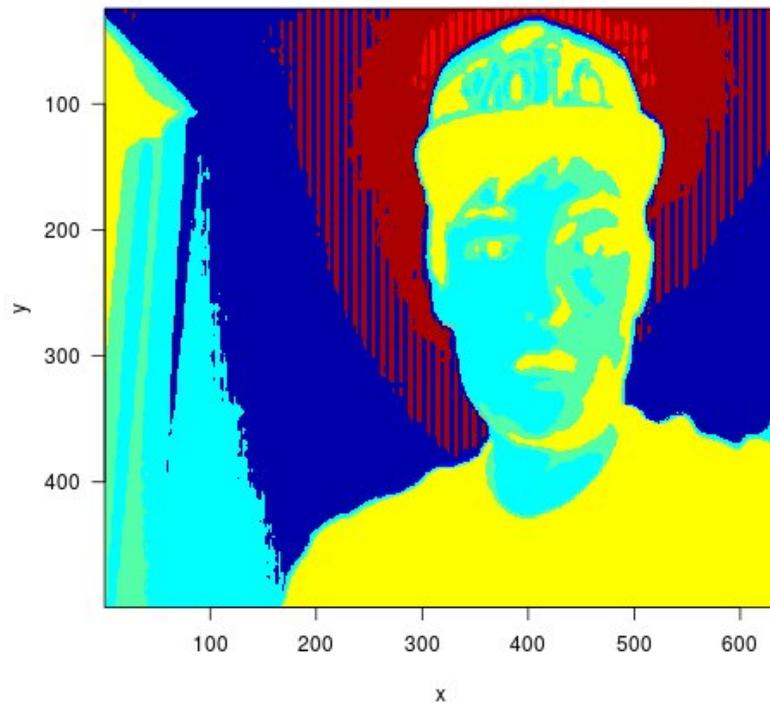
**Safe Landing Spot Detection**



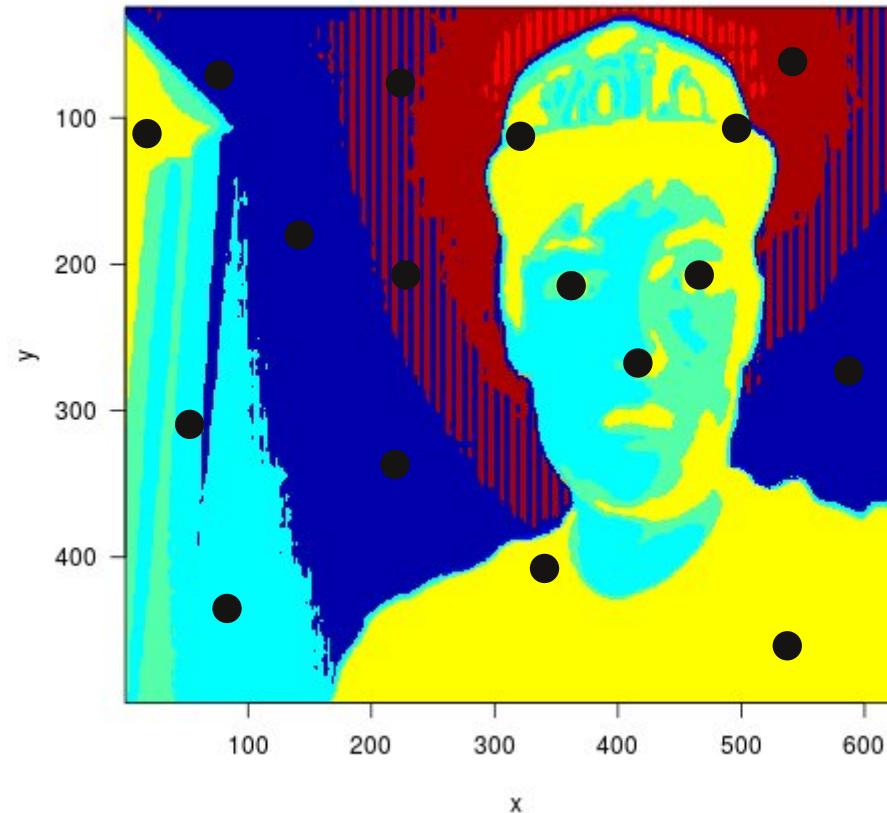
**Distance Measurement**

**DUMMY: INSERT CYBERZOO\_FLIGHT**

# MACHINE-LEARNING APPROACH

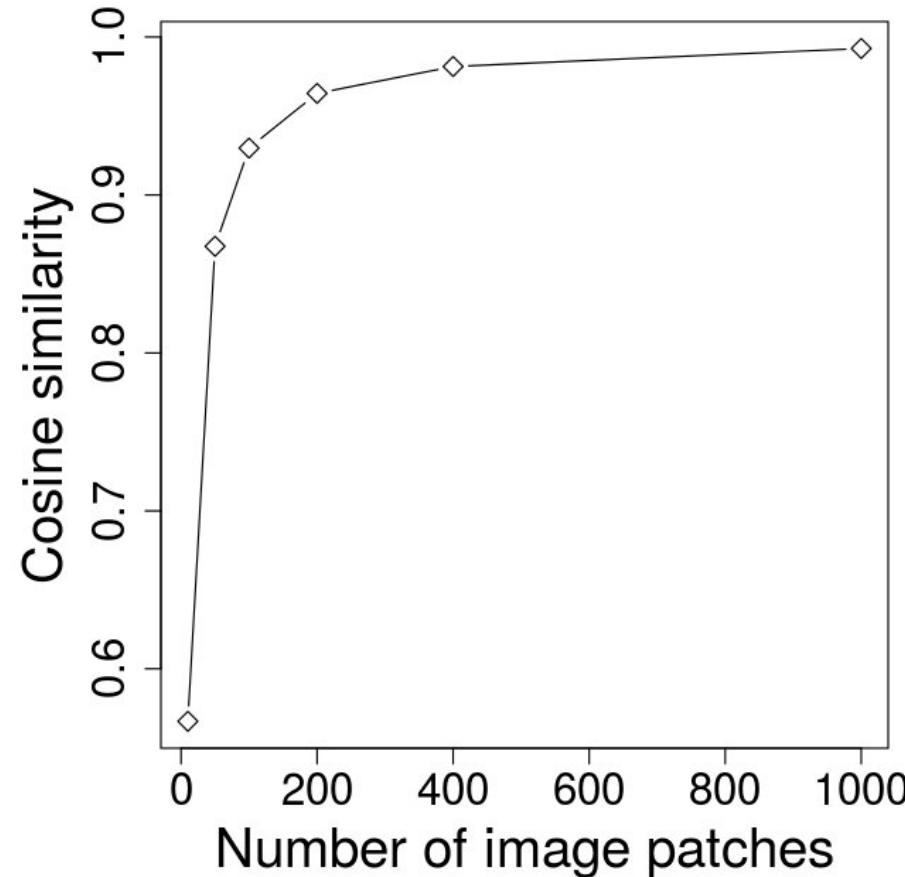


# MACHINE-LEARNING APPROACH



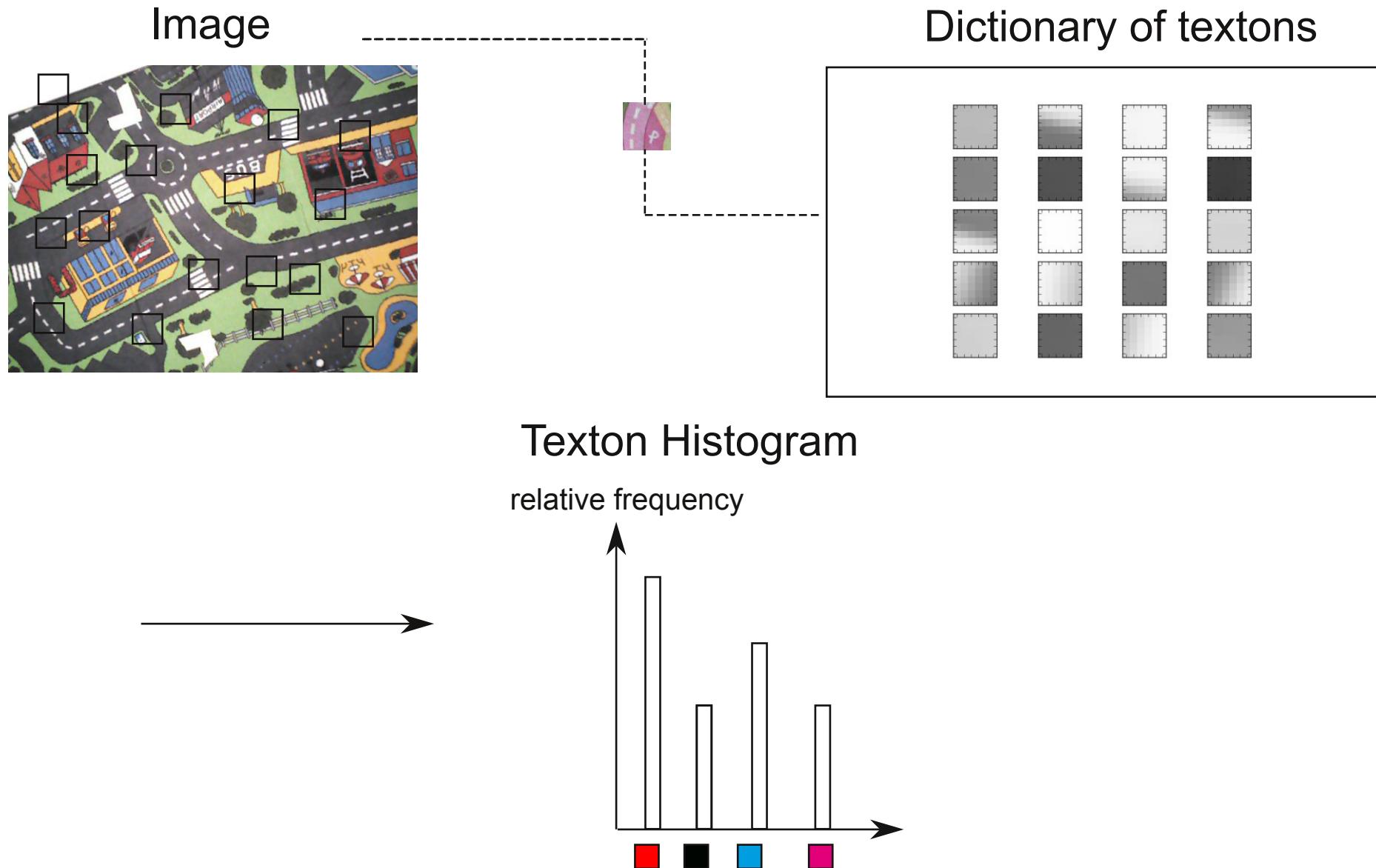
# MACHINE-LEARNING APPROACH

307200!

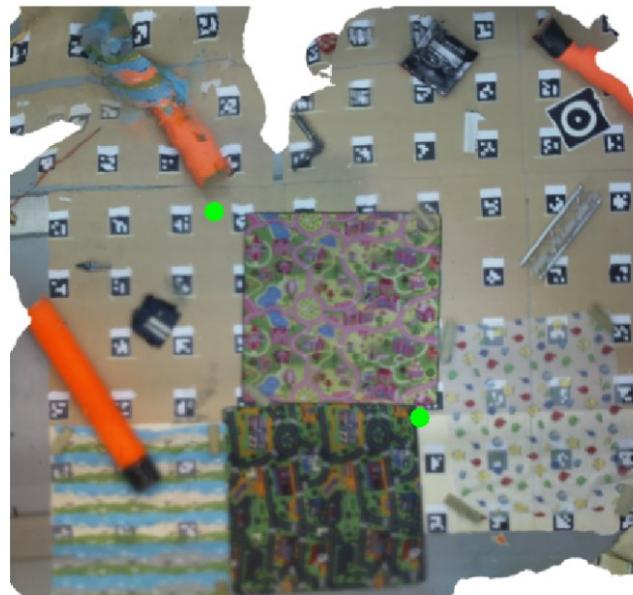
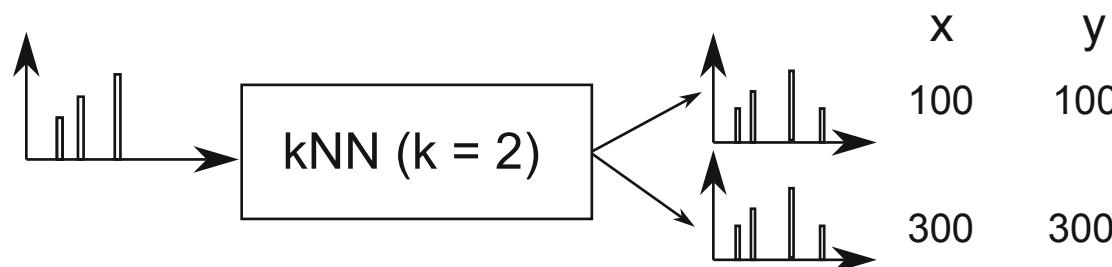


**TODO: Standard deviations**

# MACHINE-LEARNING APPROACH

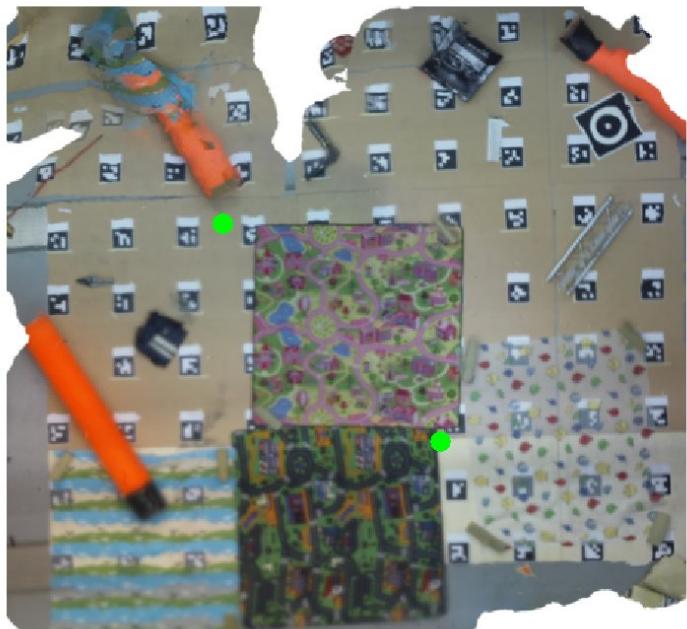


# FILTERING



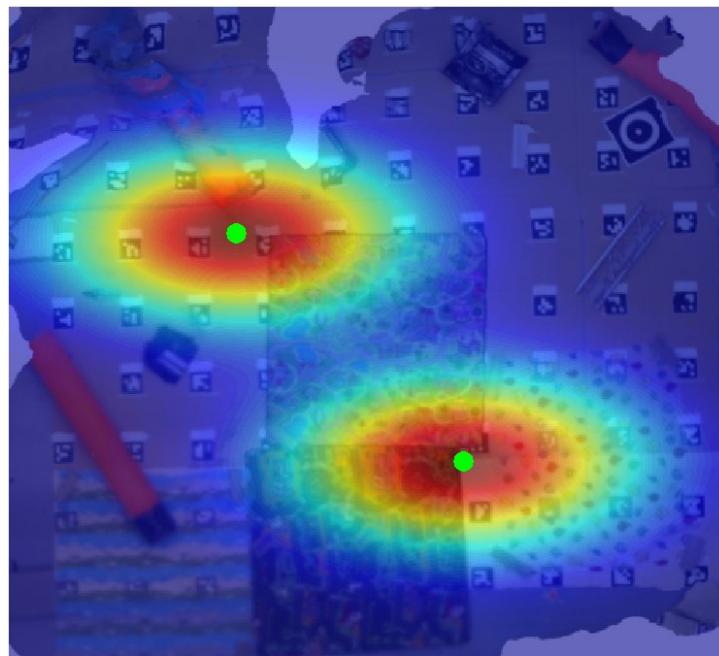
# FILTERING

## Sensor model



# FILTERING

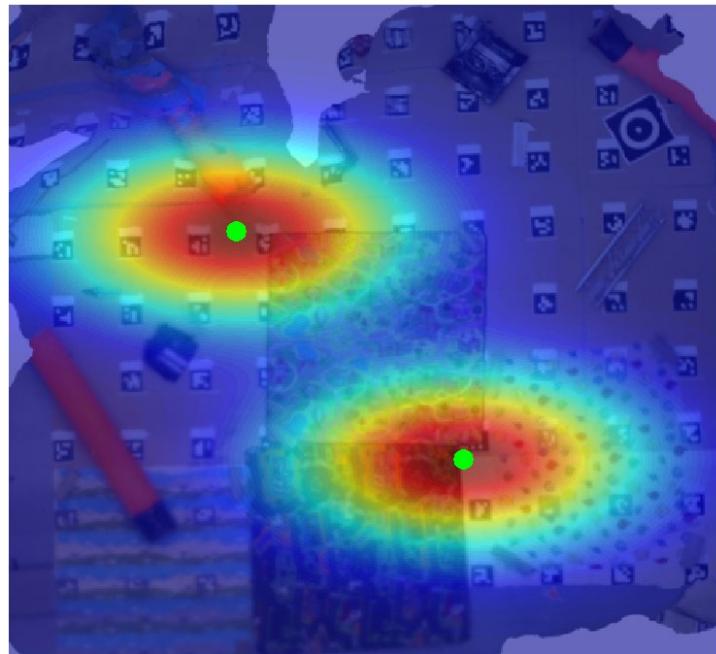
## Sensor model



2-D Gaussian mixture model

# FILTERING

## Sensor model



2-D Gaussian mixture model

## Motion model

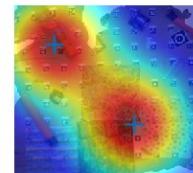
Gaussian noise

# FILTERING

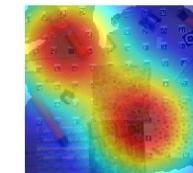
Prior ( $t = 1$ )



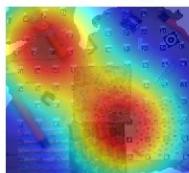
Likelihood ( $t = 1$ )



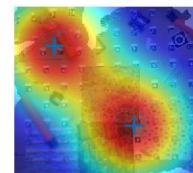
Posterior ( $t = 1$ )



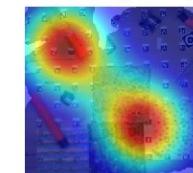
Prior ( $t = 2$ )



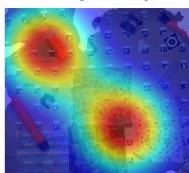
Likelihood ( $t = 2$ )



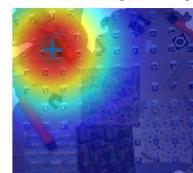
Posterior ( $t = 2$ )



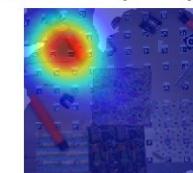
Prior ( $t = 3$ )



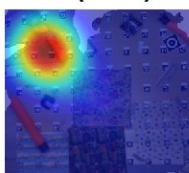
Likelihood ( $t = 3$ )



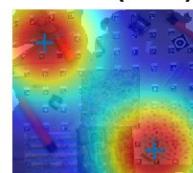
Posterior ( $t = 3$ )



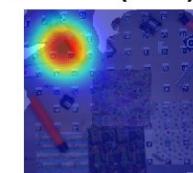
Prior ( $t = 4$ )



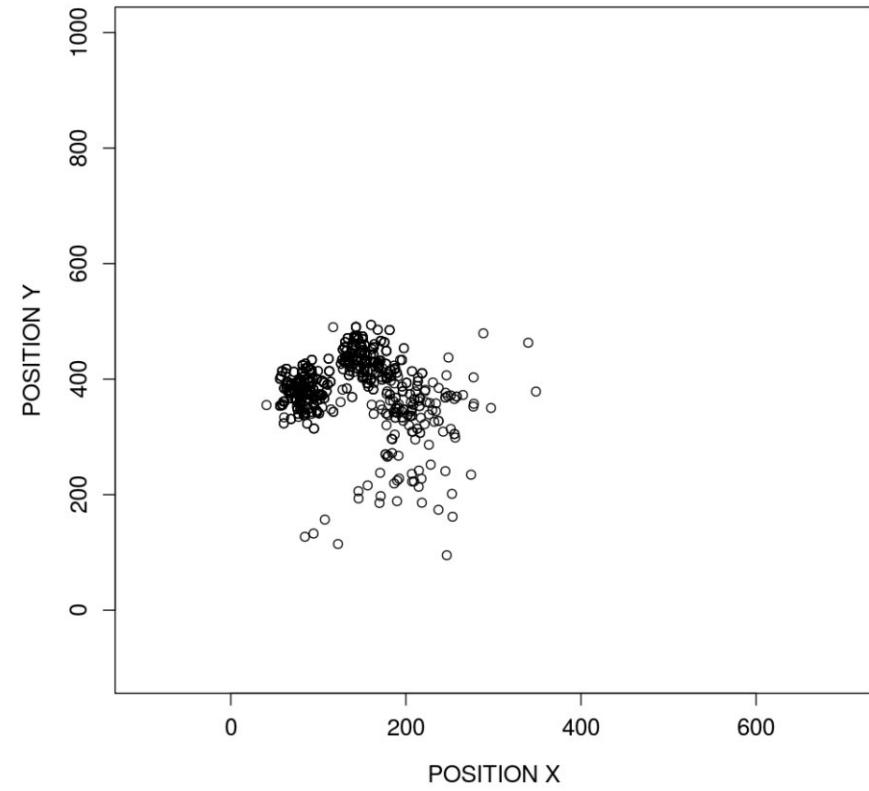
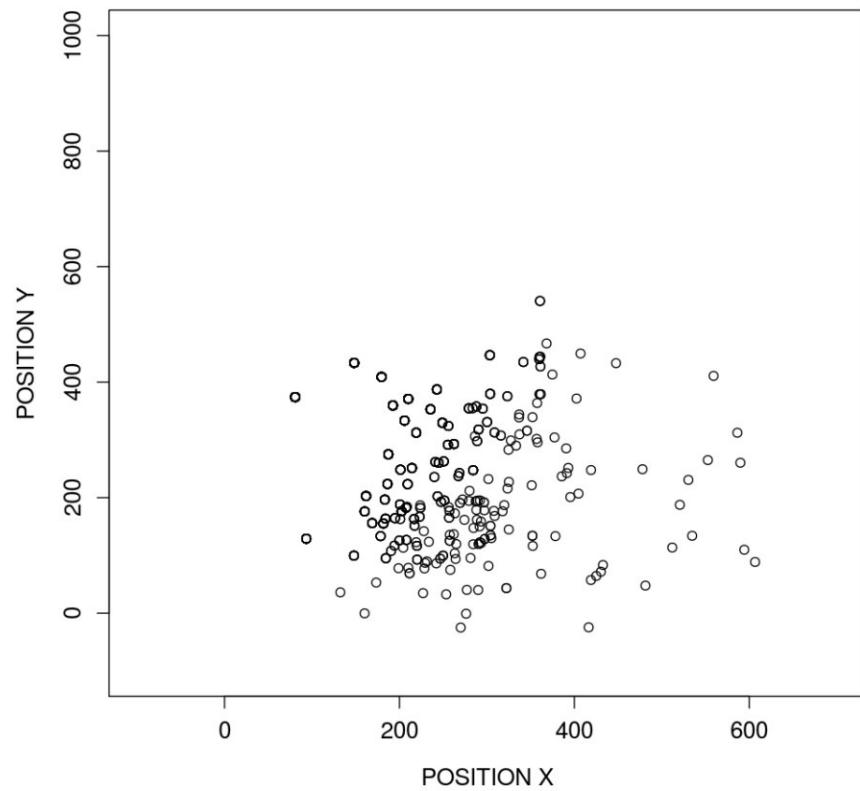
Likelihood ( $t = 4$ )



Posterior ( $t = 4$ )



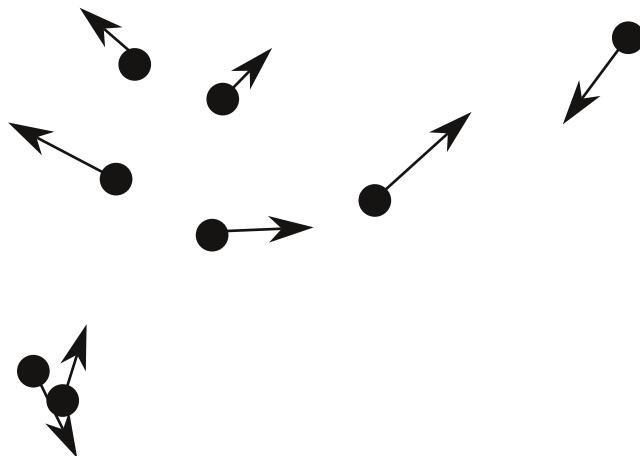
# PARTICLE FILTER



# PARTICLE FILTER

## Motion model

2D-Gaussian noise



**TODO: Improve explanation  
of particle filter**

# DUMMY: VIDEO FAST FLIGHT

# DUMMY: PARTICLE FILTER

# MAP EVALUATION



# MAP EVALUATION



**IDEAL SIMILARITY OF  
HISTOGRAMS FOR FIXED  
POSITION**

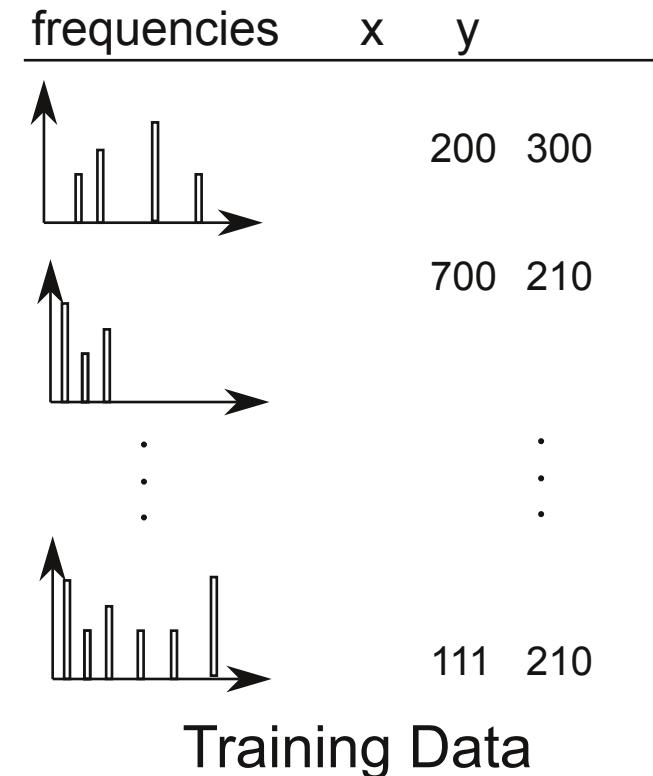
# MAP EVALUATION - SYNTHETIC FLIGHT



draug



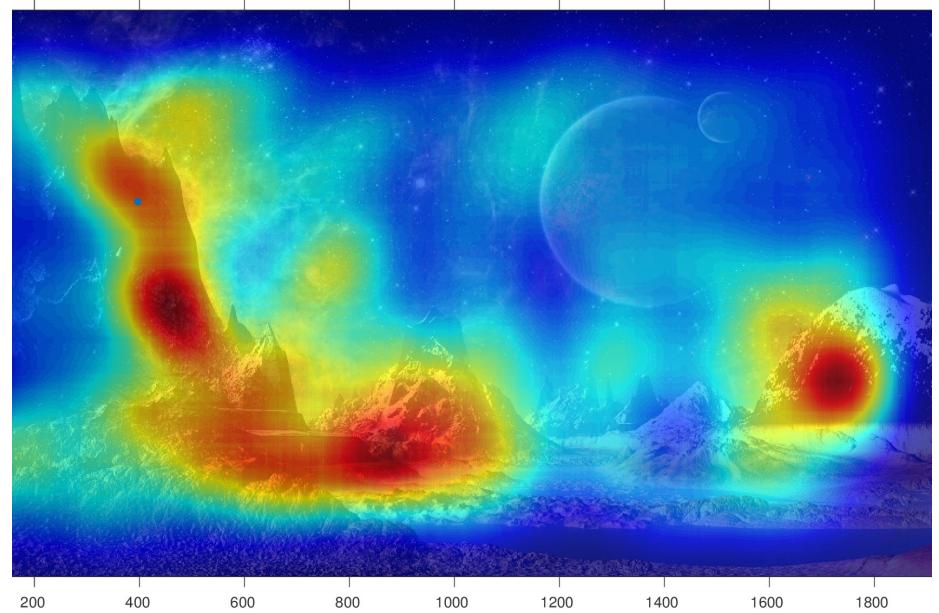
1000 patches



# MAP EVALUATION

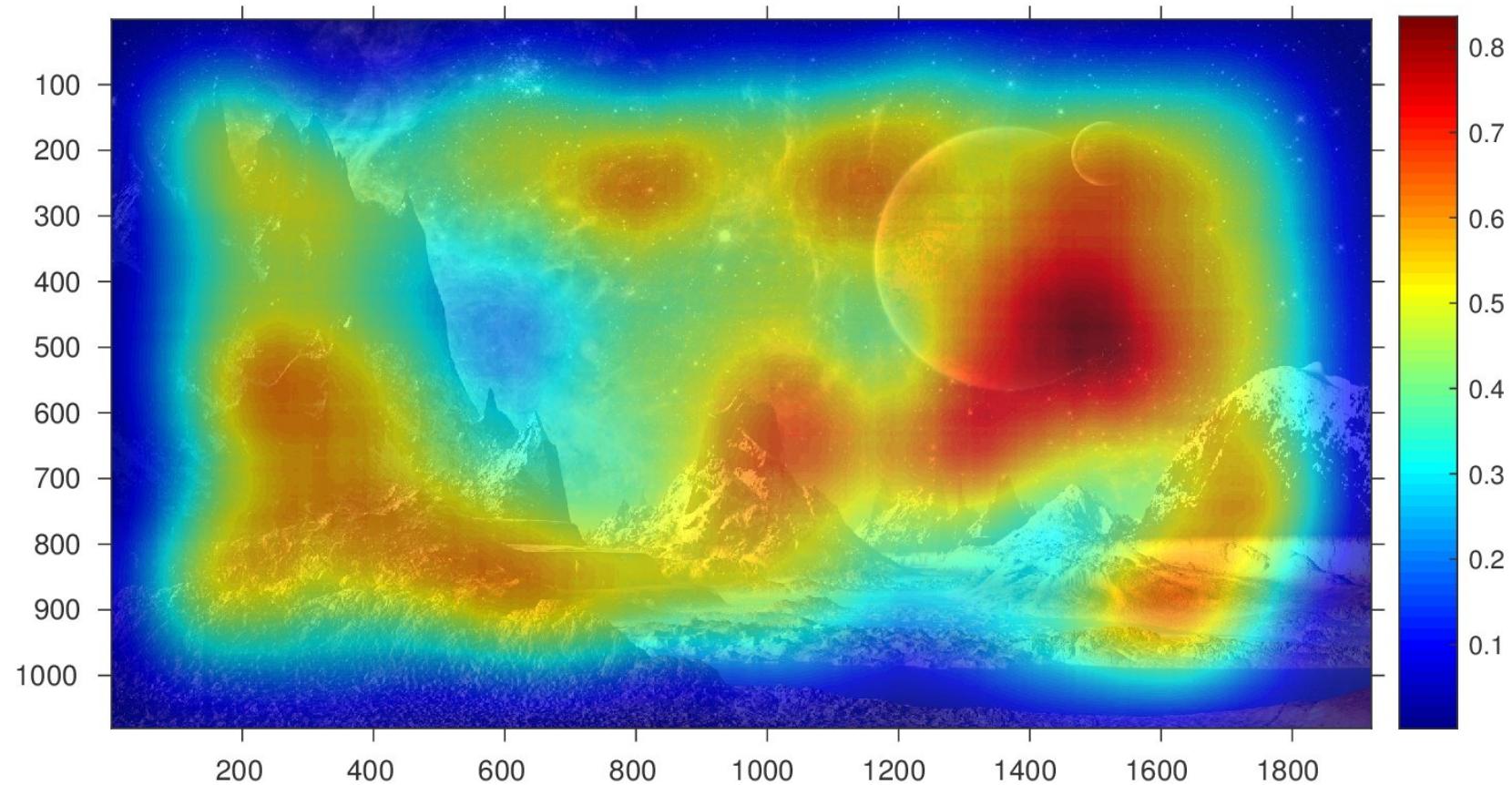


**IDEAL SIMILARITY OF  
HISTOGRAMS FOR FIXED  
POSITION**



**ACTUAL SIMILARITY  
(Gaussian smoothing)**

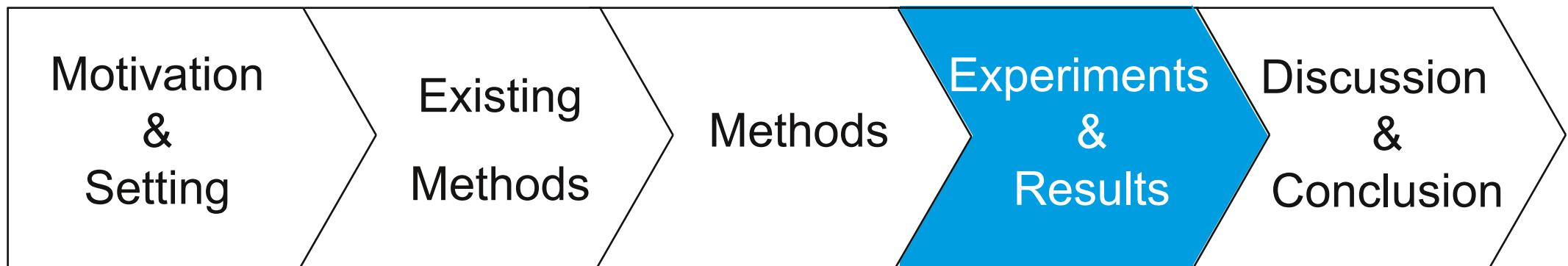
# MAP EVALUATION



**GLOBAL LOSS (1000 patches)**

$0 < \text{global loss} < 1$

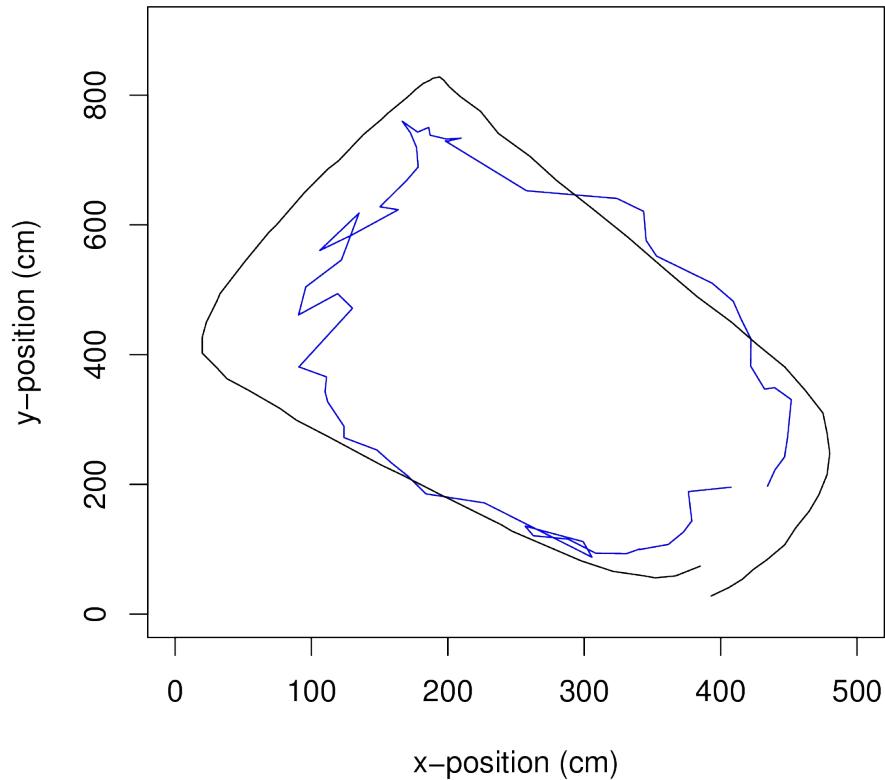
# OUTLINE



- OptiTrack vs. Textons
- Triggered Landing
- Map evaluation

# FLIGHT ACCURACY

4 Flights (400 images each)



OptiTrack vs. treXton

Mean distance x: **46 cm**

Mean distance y: **54 cm**

SD distance x: **56 cm**

SD distance y: **71 cm**

Frequency: **10 Hz**

**TODO: split up into filter,  
texton, etc.**

# TRIGGERED LANDING

MAYBE:

PLOT DELTA X Y OF  
SINGLE RUNS  
OR USE TABLE

6 Landings

criterion:  
distance < 60 cm

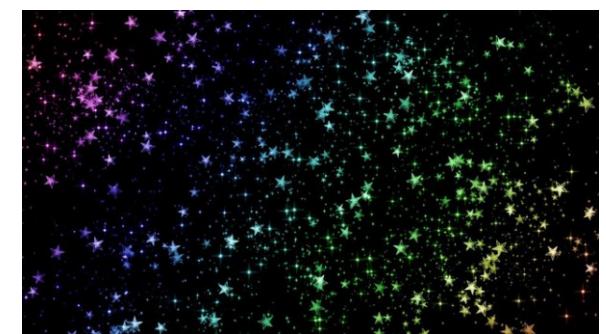
safety criterion:  
low variance of particles

Mean distance: 51 cm

SD distance: 17 cm

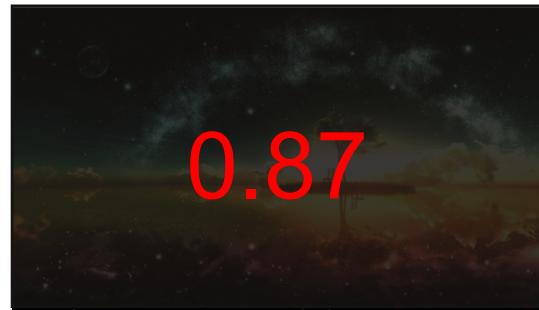
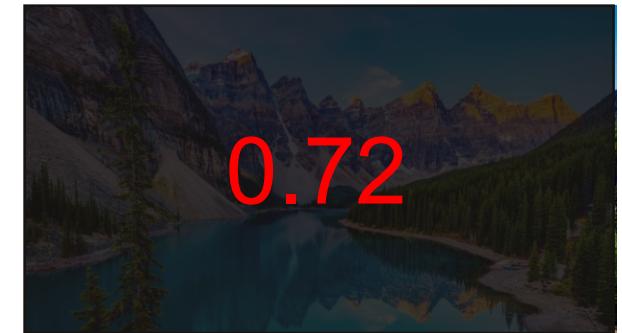
# DUMMY: VIDEO TRIGGERED LANDING

# MAP EVALUATION



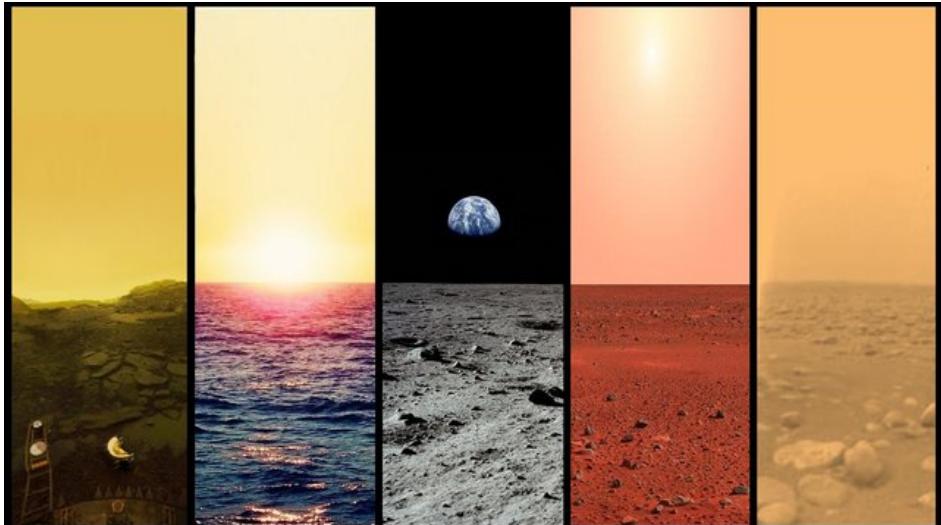
47 images

# MAP EVALUATION - LOSSES



# MAP EVALUATION

GOOD



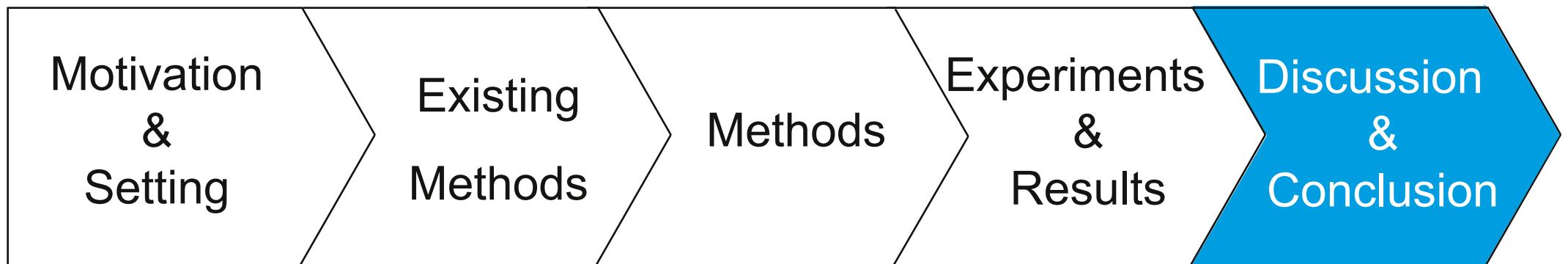
0.57

BAD



0.98

# OUTLINE



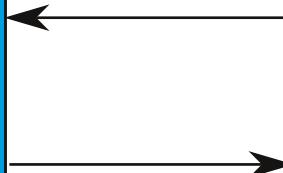
# RESEARCH QUESTIONS

## Research Question 1

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

## Research Question 2

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



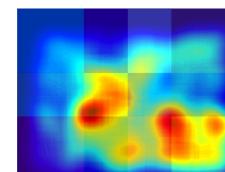
# DISCUSSION

## Implications:

- paves the way to indoor flight
- adaptable to different platforms
- detect safe landing spots



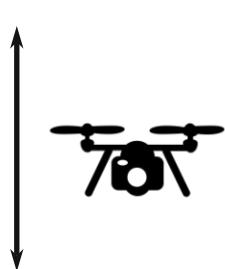
?



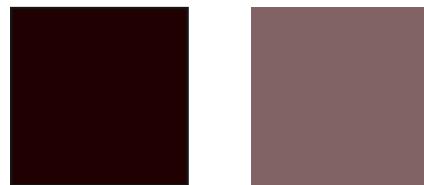
# DISCUSSION

## Limitations:

- assumes constant height and no rotations



- robustness to different lighting conditions

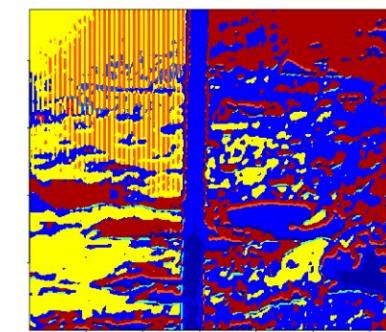
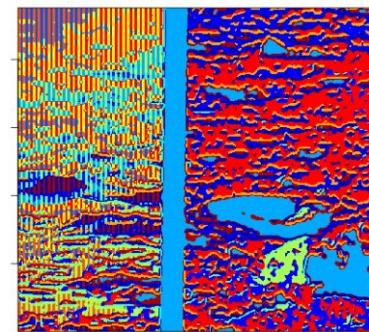
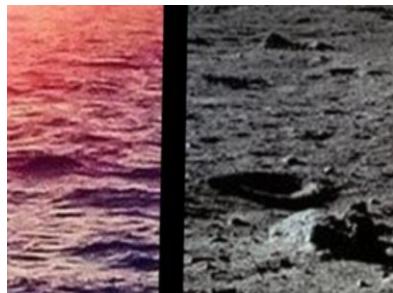


- Particle filter does not include velocity or heading

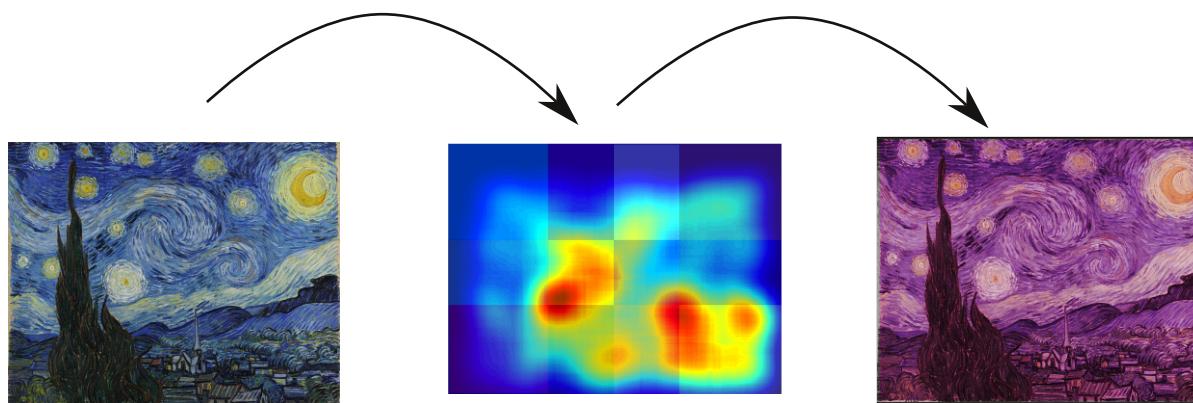
# DISCUSSION

## Future research:

- bridge reality gap



- automatic map generation (evolutionary algorithm)



# CODE CONTRIBUTIONS

- draug: Image augmentation with synthetic views (C++)

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

- Map evaluation (MATLAB)

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

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

TODO: PULL REQUEST C: <https://github.com/Pold87/paparazzi>      Python: <https://github.com/Pold87/treXton>



# CONCLUSION

## EFFICIENT INDOOR LOCALIZATION

