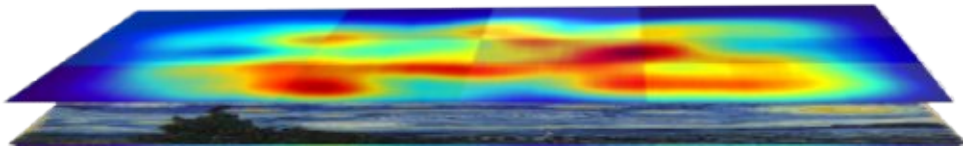
Machine Learning-based Indoor Localization for Micro Aerial Vehicles

Volker Strobel
volker.strobel87@gmail.com

14th July 2016



Radboud Universiteit

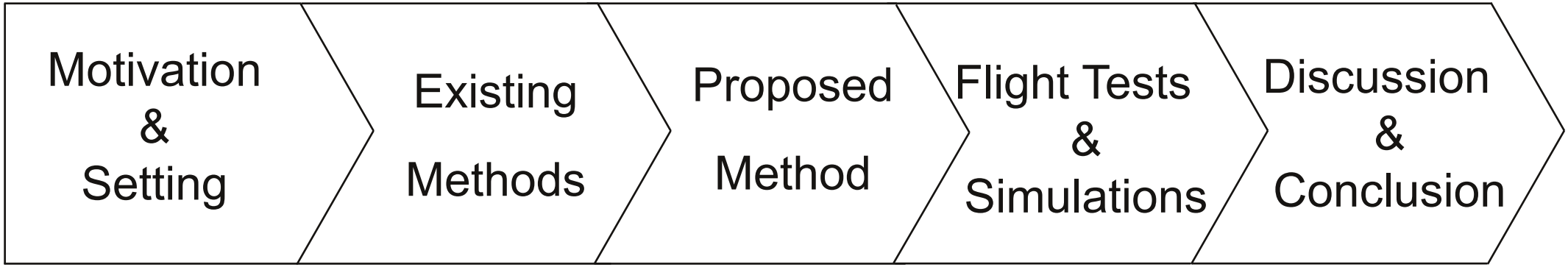
IN·DEI·NOMINE·FELICITER

TU Delft Delft University of Technology

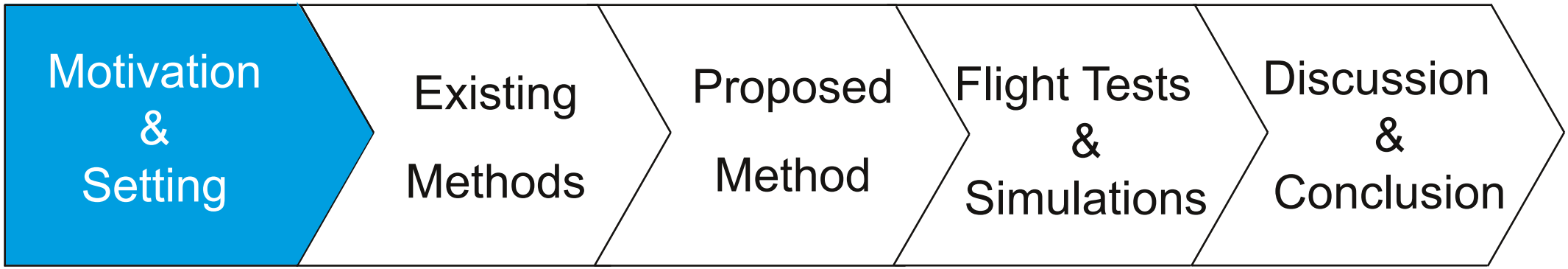
Louis Vuurpijl

Guido de Croon
Roland Meertens

OUTLINE


Motivation & Setting
Existing Methods
Proposed Method
Flight Tests & Simulations
Discussion & Conclusion

OUTLINE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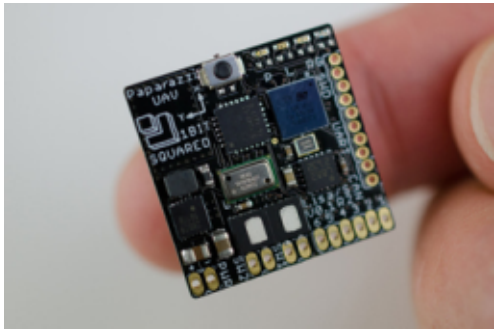
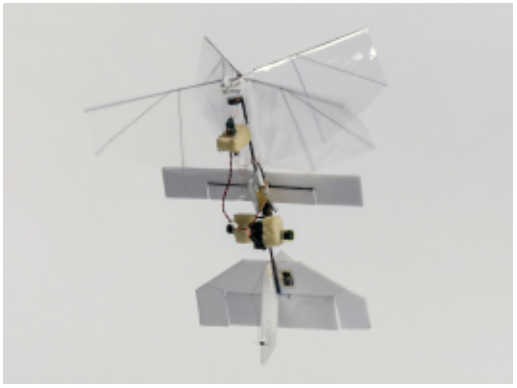
Micro Air Vehicle Lab

TU Delft Delft University of Technology

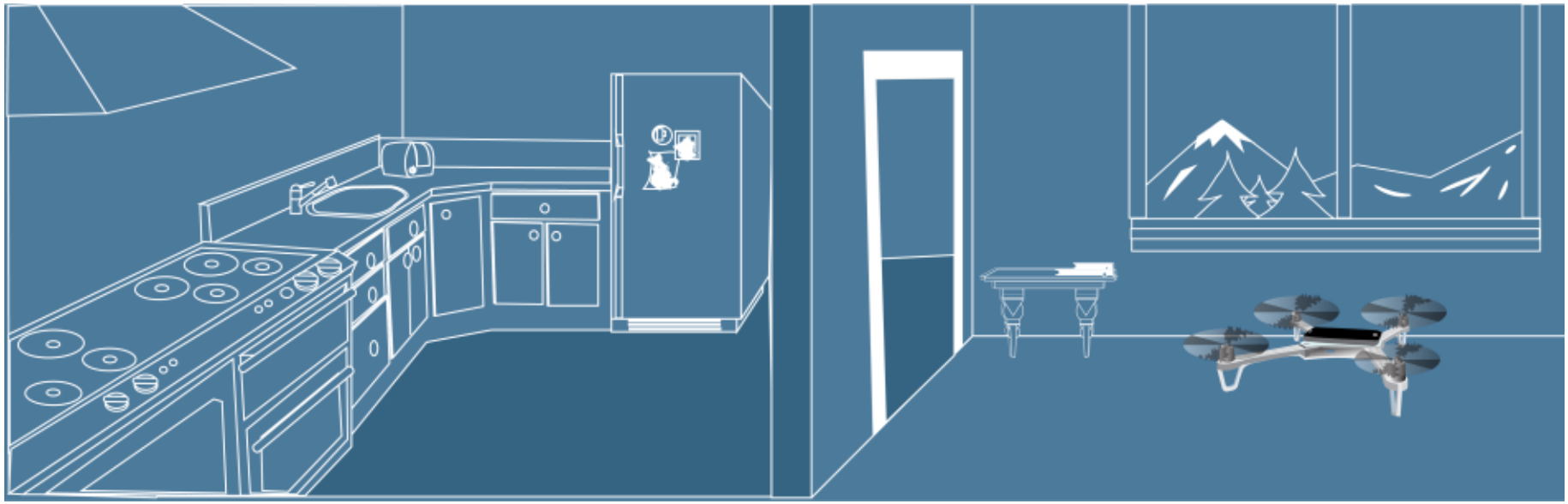
MAVLab





Miniaturization

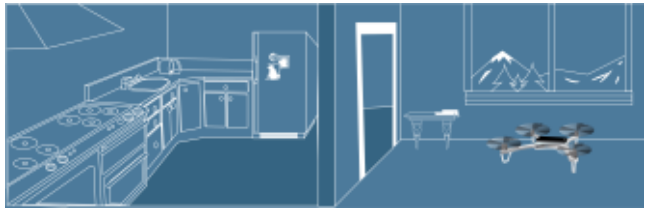
MOTIVATION



MOTIVATION

Tools

Environment

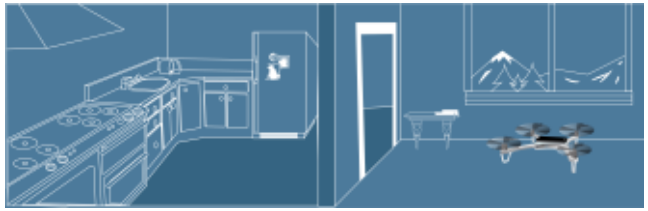


modifiable known fixed planar

MOTIVATION

Tools

Environment



known modifiable fixed flat

x,y-coordinates

real-time on-board fixed height

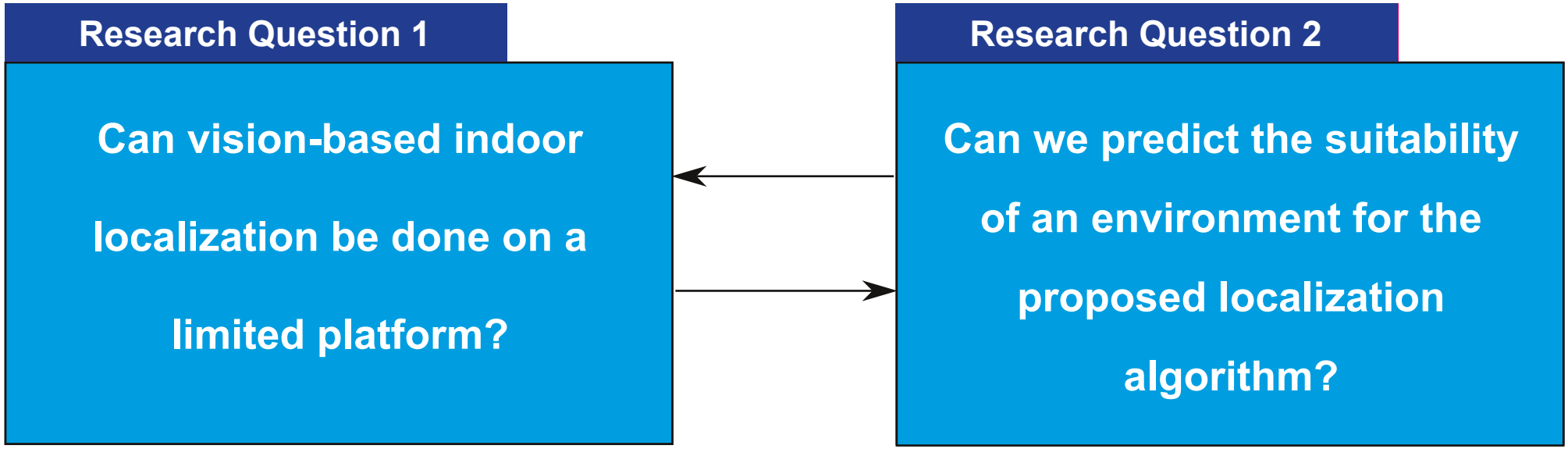
MOTIVATION

Research Question

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

accurate on-board real-time

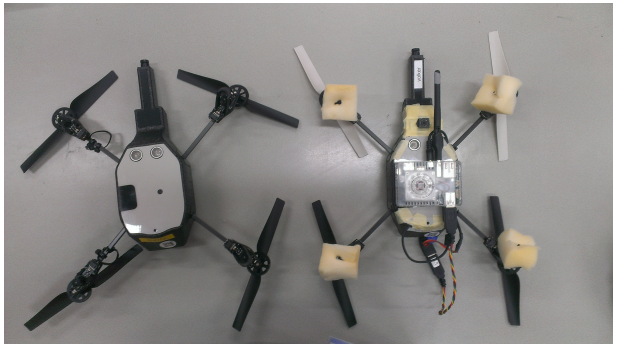
RESEARCH QUESTIONS



CHALLENGES

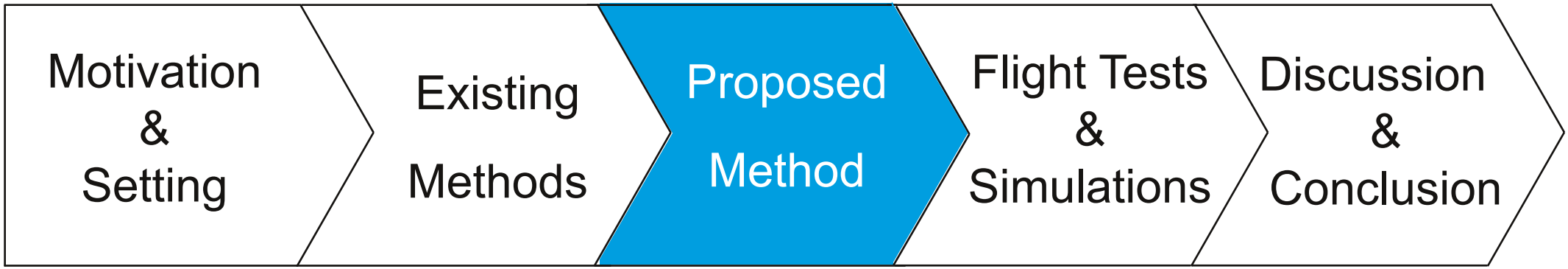
Low-performance platform

Low-level embedded programming (C)



Real-world

OUTLINE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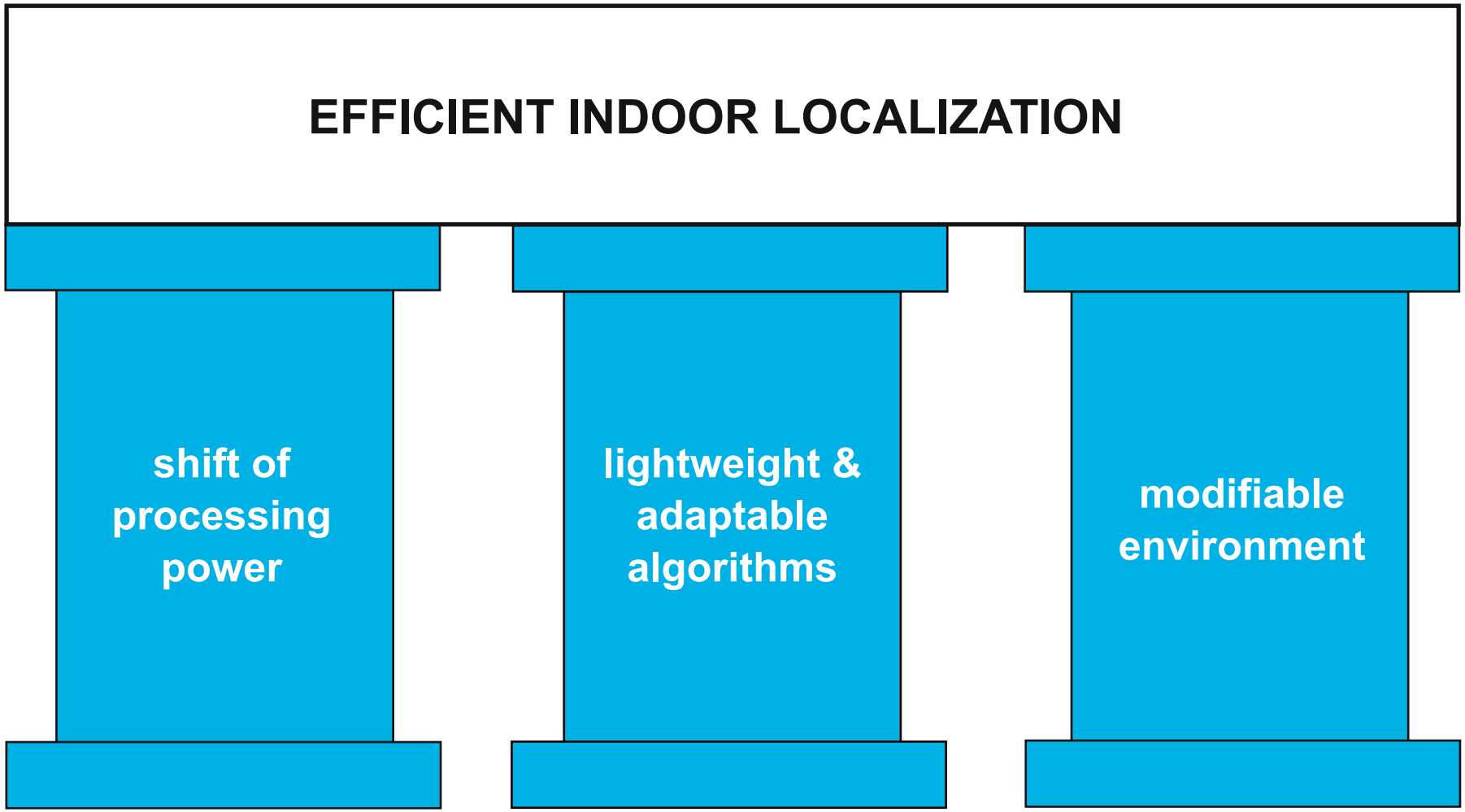

EFFICIENT INDOOR LOCALIZATION
shift of processing power
lightweight & adaptable algorithms
modifiable environment

APPROACH

Flight phase

APPROACH

Flight phase

1 Image / sec

APPROACH

~~Flight phase~~

Pre-flight phase

Dataset

	x	y
	200	300
	210	320
⋮	⋮	
	111	210

APPROACH

~~Flight phase~~

Pre-flight phase

Flight phase

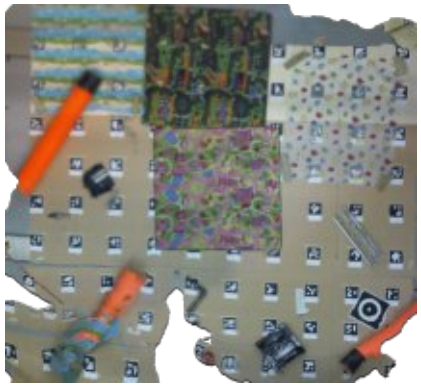
create

compare

Dataset

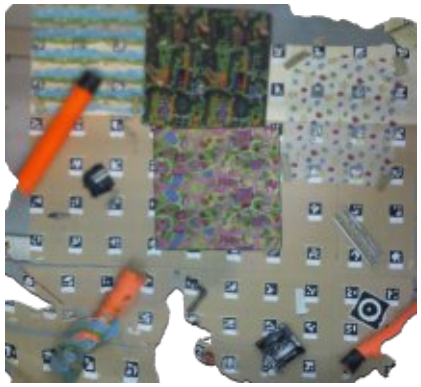
x	y
200	300
210	320
⋮	⋮
111	210

GROUND TRUTH ESTIMATION



Orthomap

GROUND TRUTH ESTIMATION

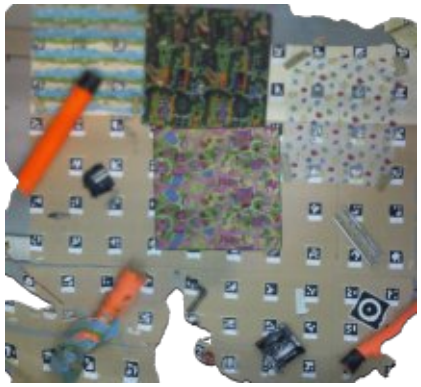


Orthomap

OR

Poster

GROUND TRUTH ESTIMATION

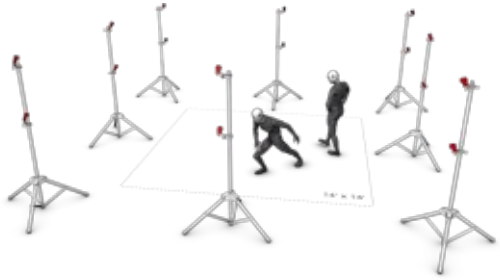


Orthomap

OR

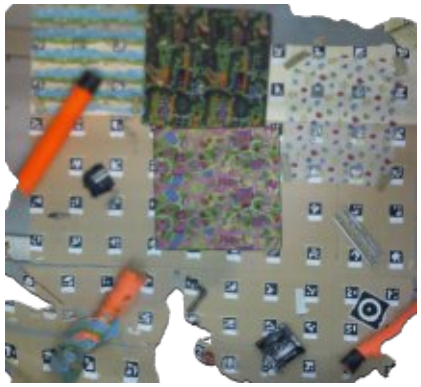
Poster

OR



Motion tracking

GROUND TRUTH ESTIMATION

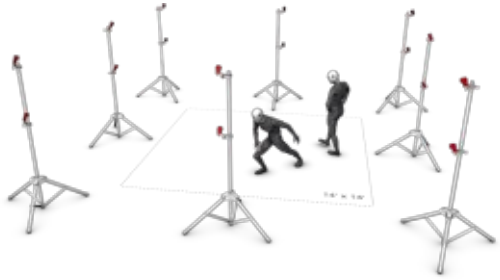


Orthomap

OR

Poster

OR



Motion tracking

Dataset

x	y
200	300
210	320
⋮	⋮

GROUND TRUTH ESTIMATION

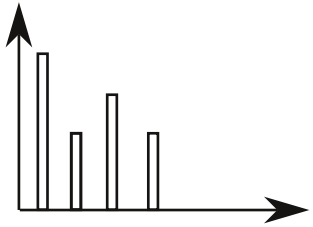
Orthomap

shift of processing power

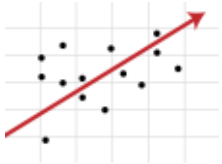
Motion tracking

CHALLENGES

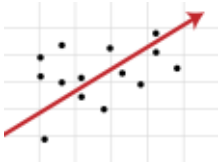
Image features?



2-dimensional regression

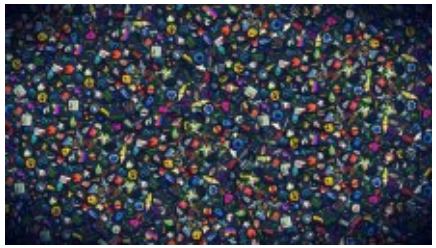


x

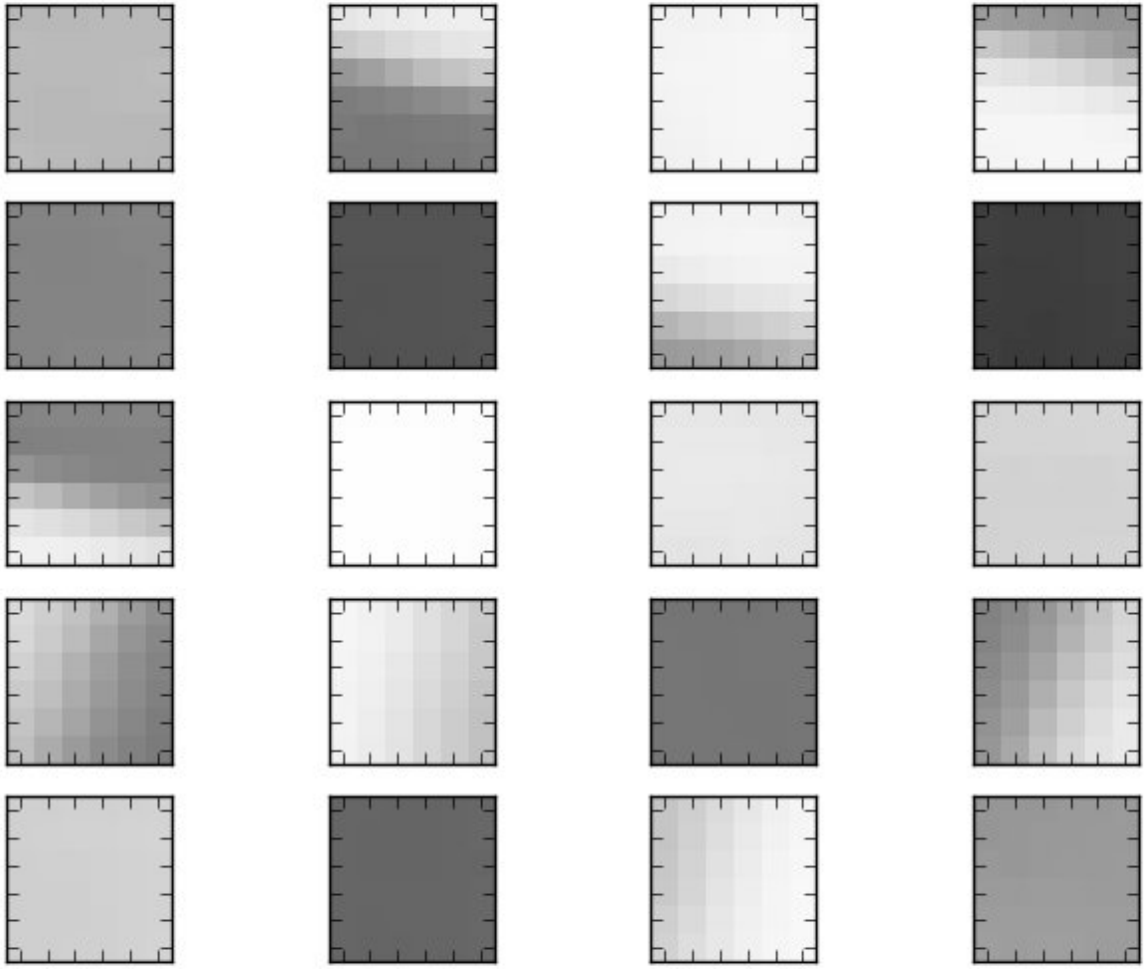


y

Which map is good?

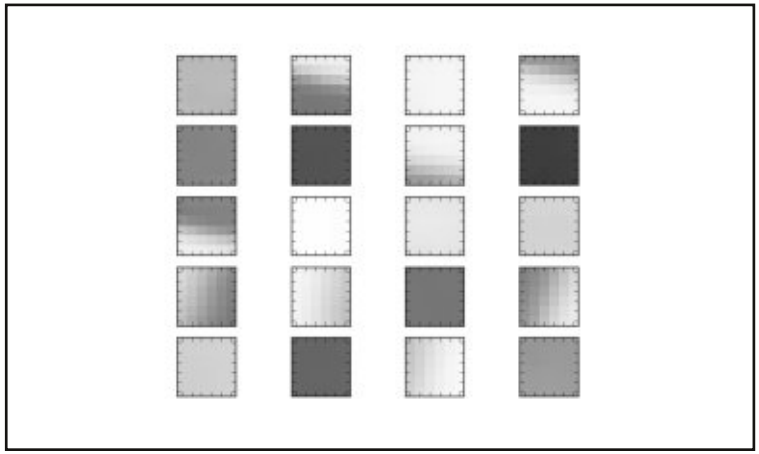


TEXTONS AS IMAGE FEATURES



MACHINE-LEARNING APPROACH

Dictionary of textons



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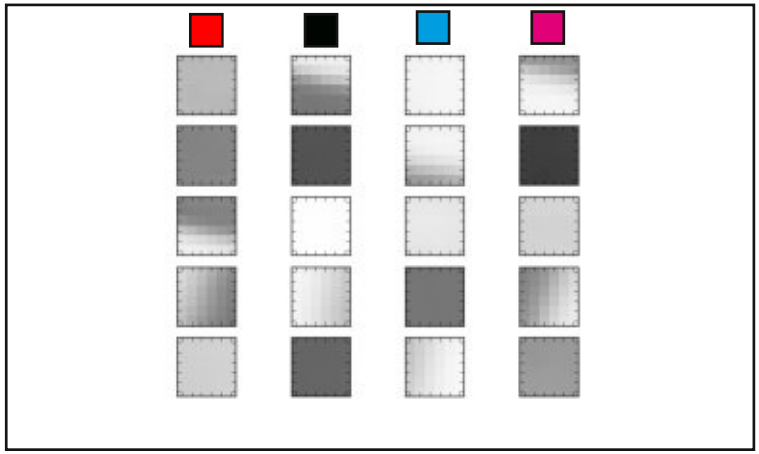

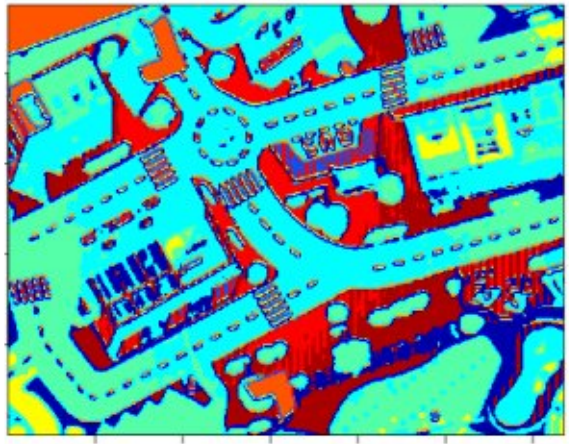

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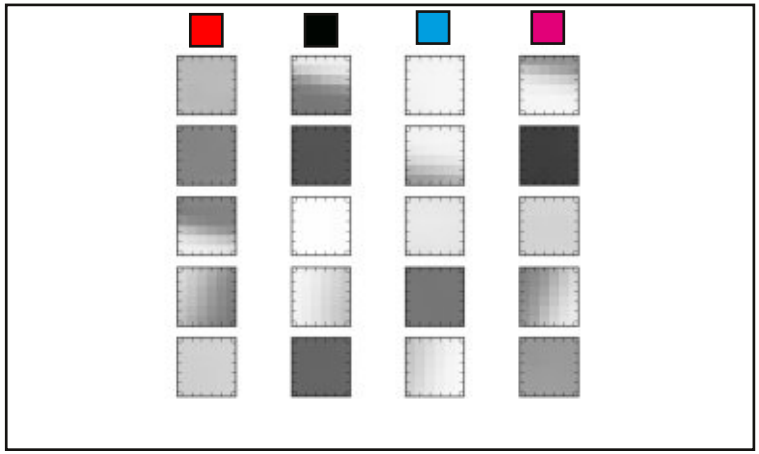
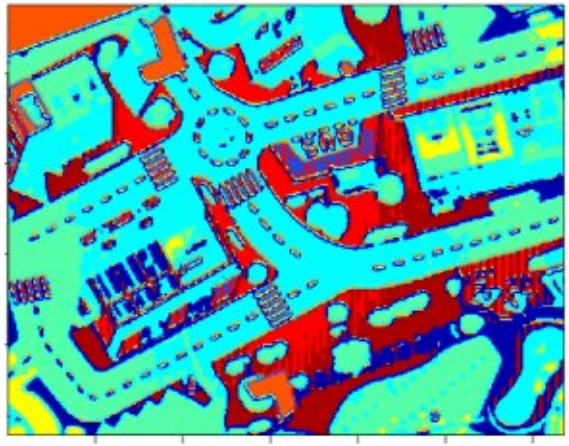
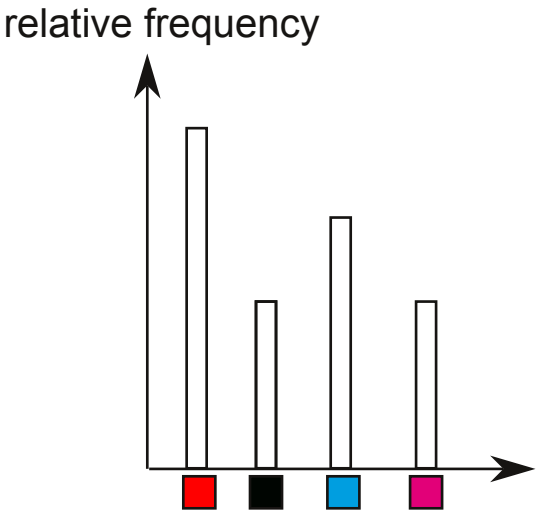




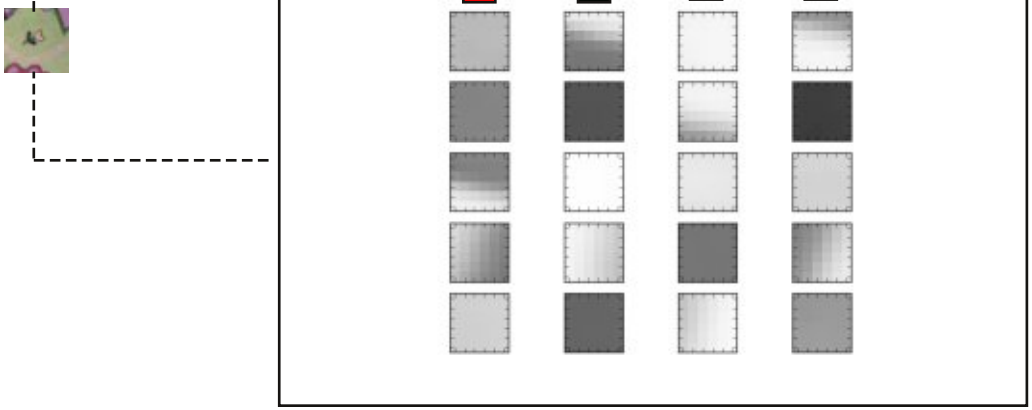
Texton Histogram



MACHINE-LEARNING APPROACH

Image

Dictionary of textons



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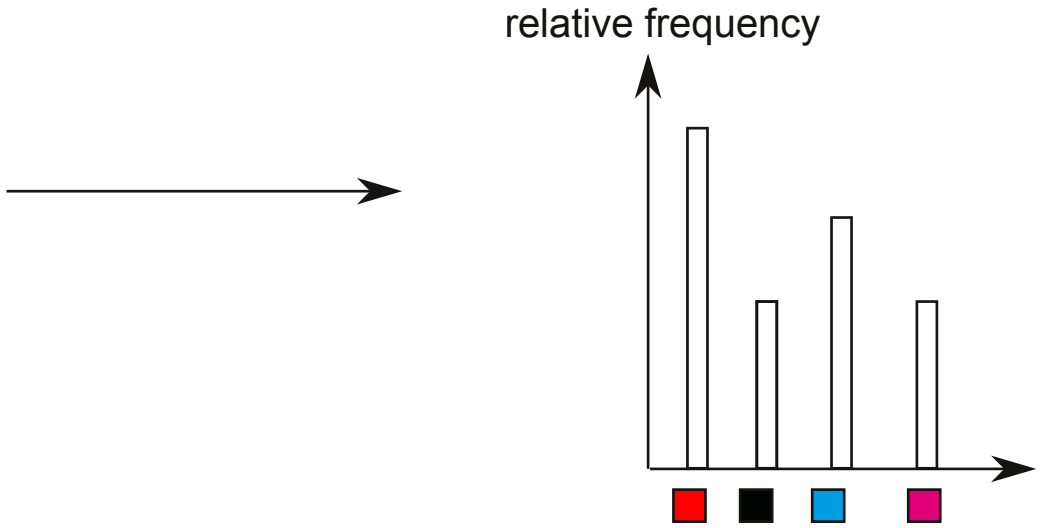
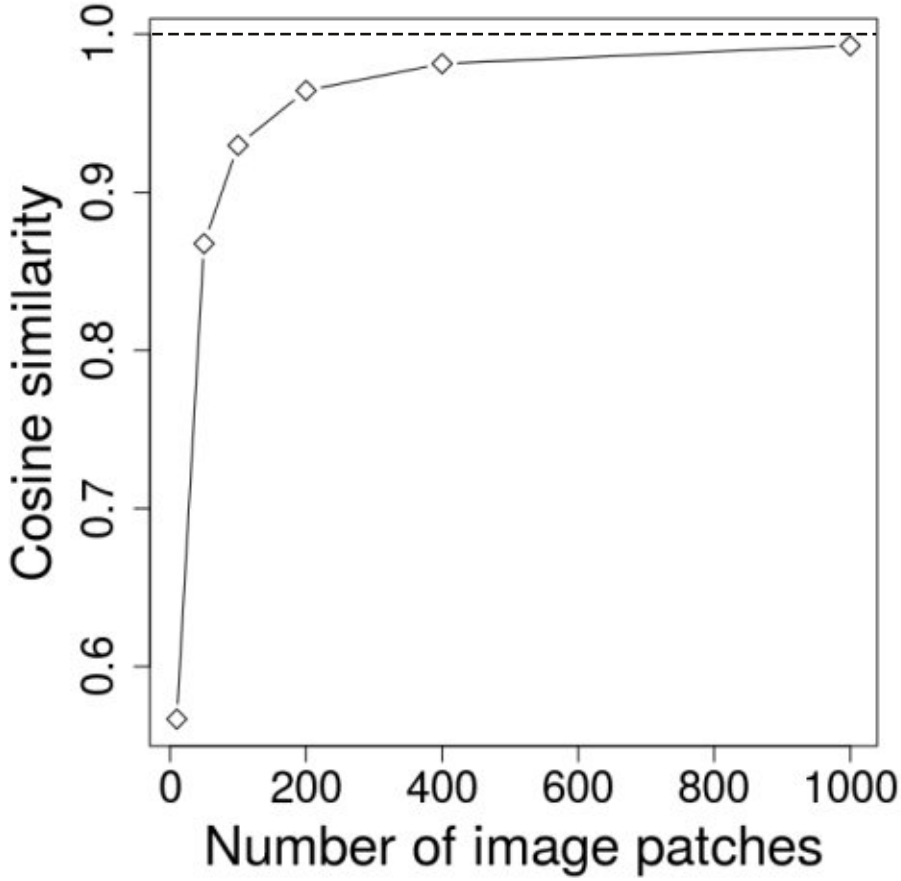


MACHINE-LEARNING APPROACH

307200!



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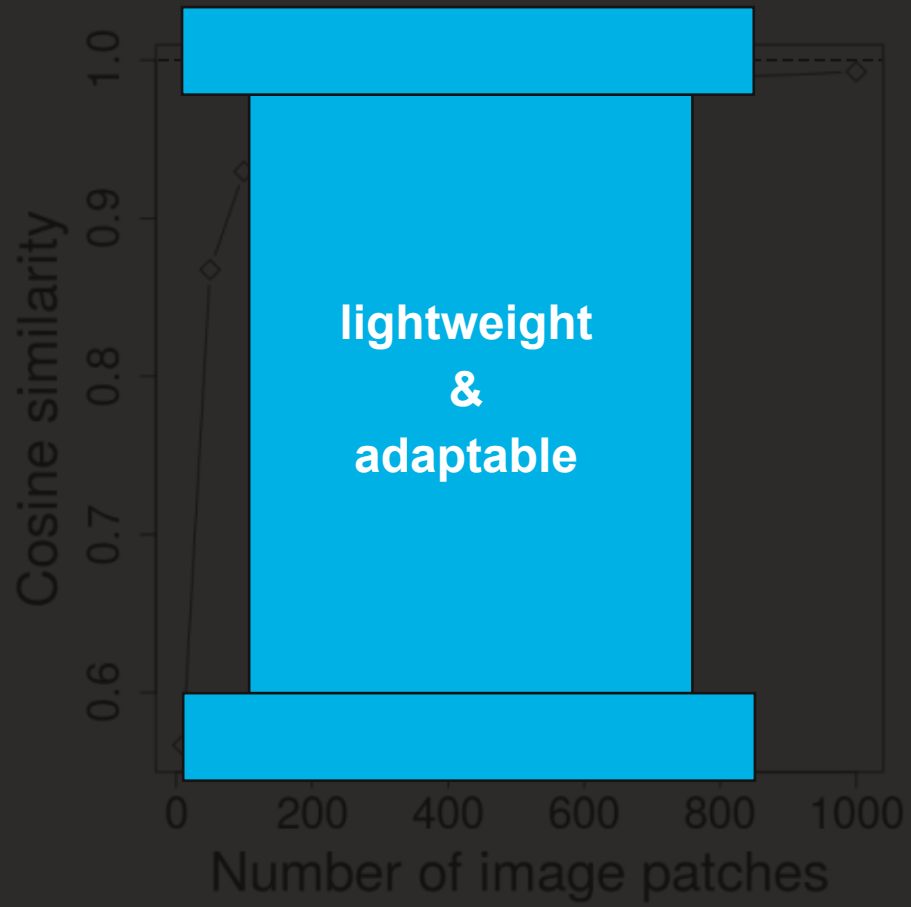

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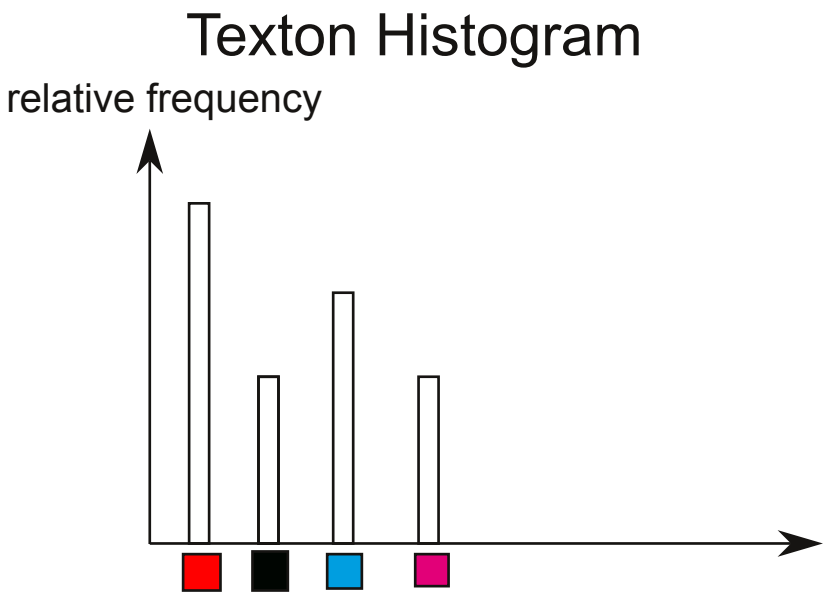

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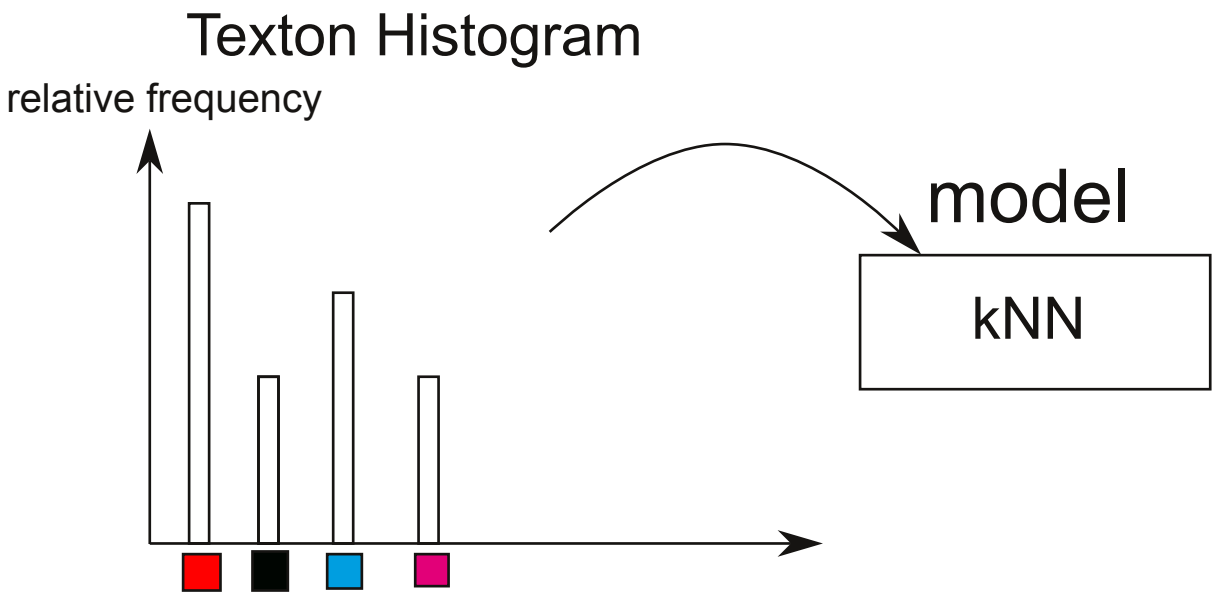

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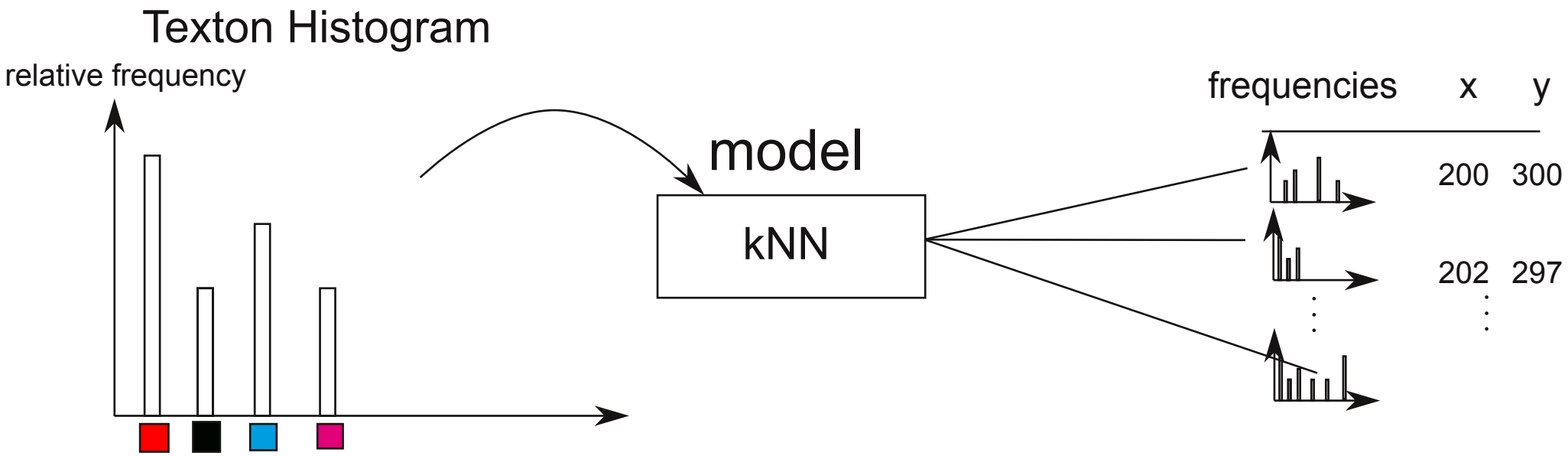
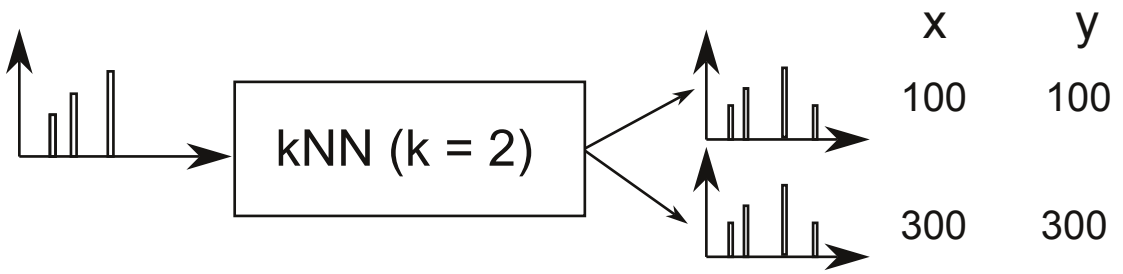
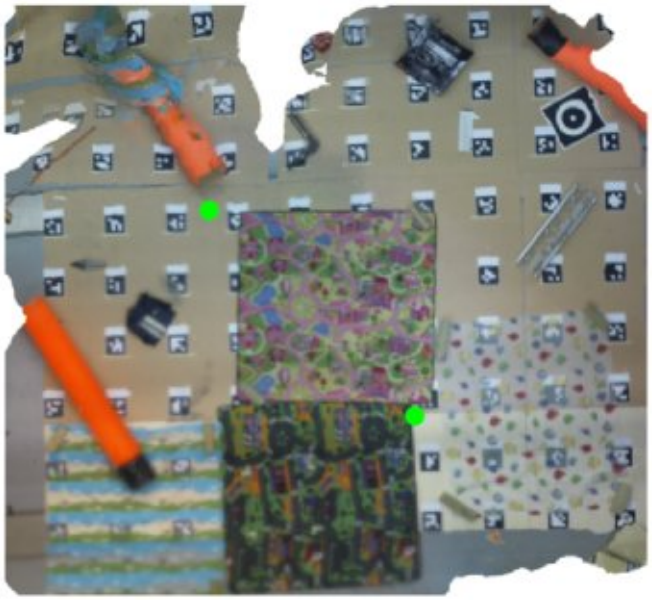


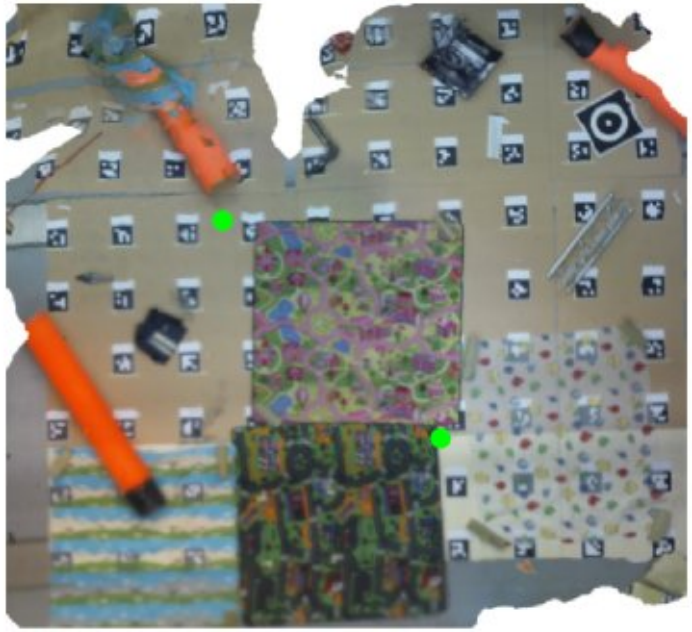
FILTERING





FILTERING

Sensor model (Likelihood)



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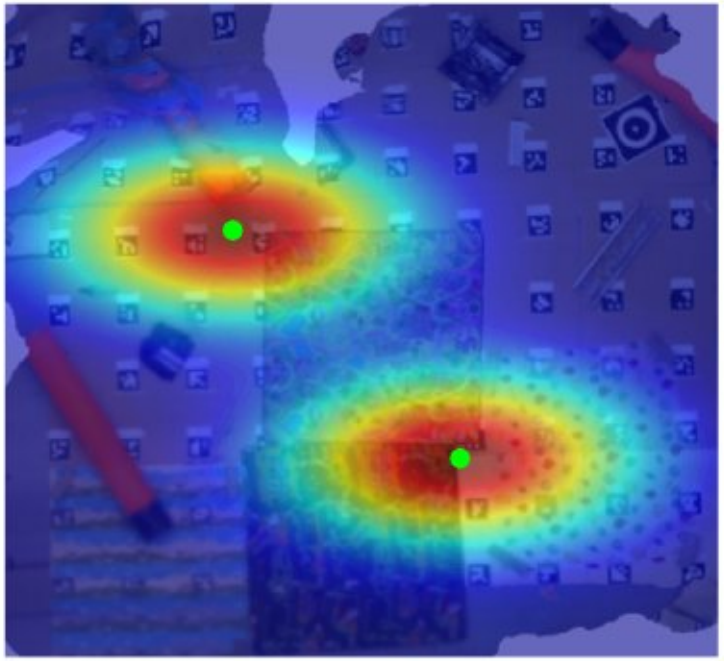
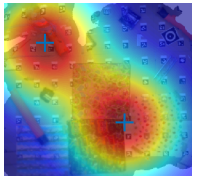


2-D Gaussian mixture model

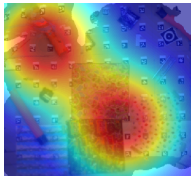
FILTERING

Prior (t = 1)

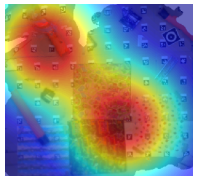
Likelihood (t = 1)



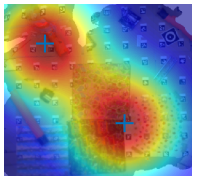
Posterior (t = 1)



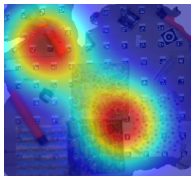
Prior (t = 2)



Likelihood (t = 2)



Posterior (t = 2)



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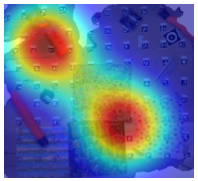
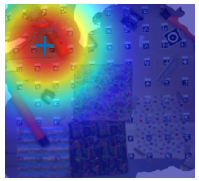
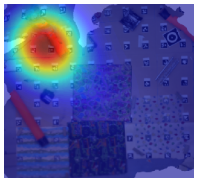


Likelihood (t = 3)



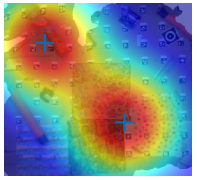
Posterior (t = 3)



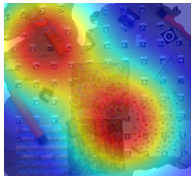
FILTERING

Prior (t = 1)

Likelihood (t = 1)



Posterior (t = 1)



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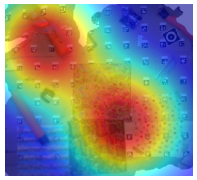
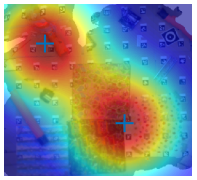
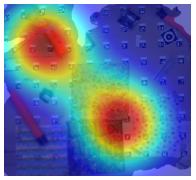


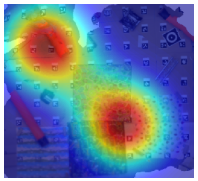
Likelihood (t = 2)



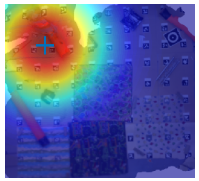
Posterior (t = 2)



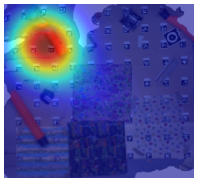
Prior (t = 3)



Likelihood (t = 3)

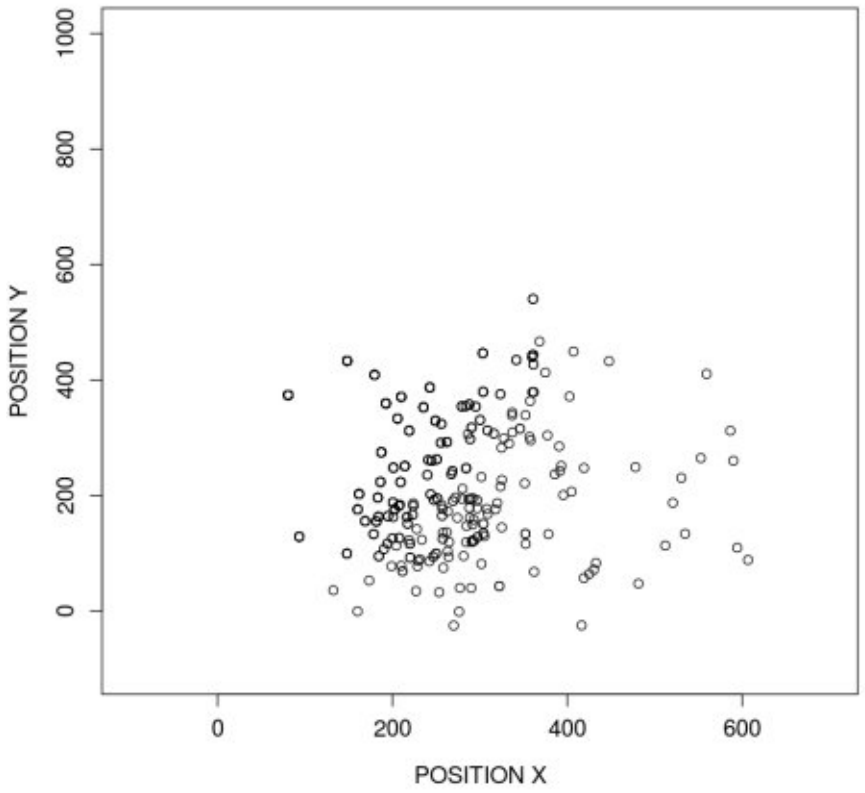


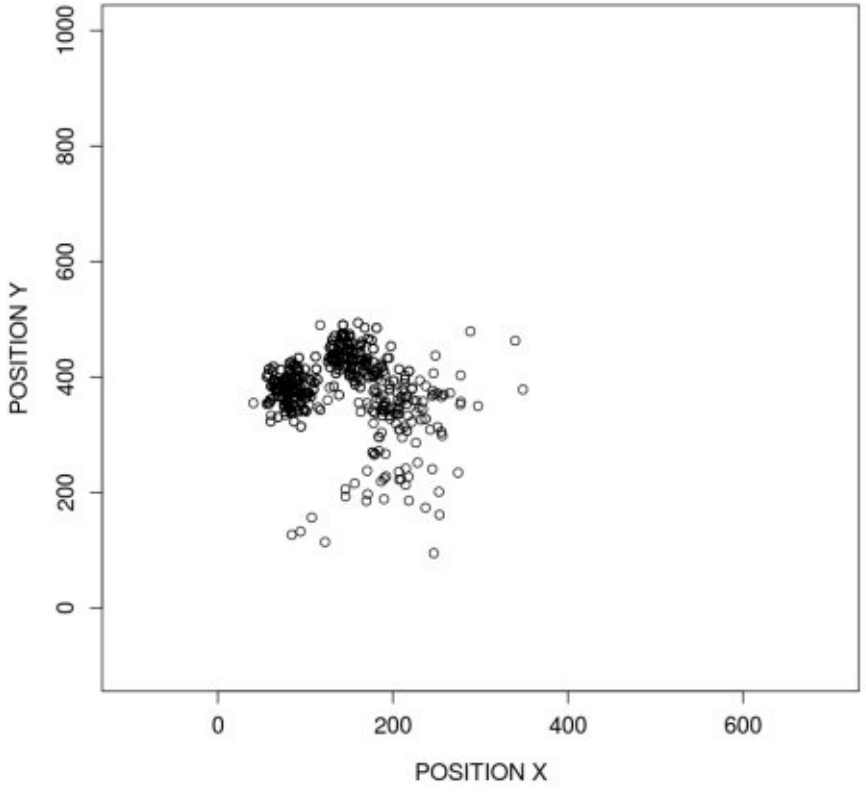
Posterior (t = 3)

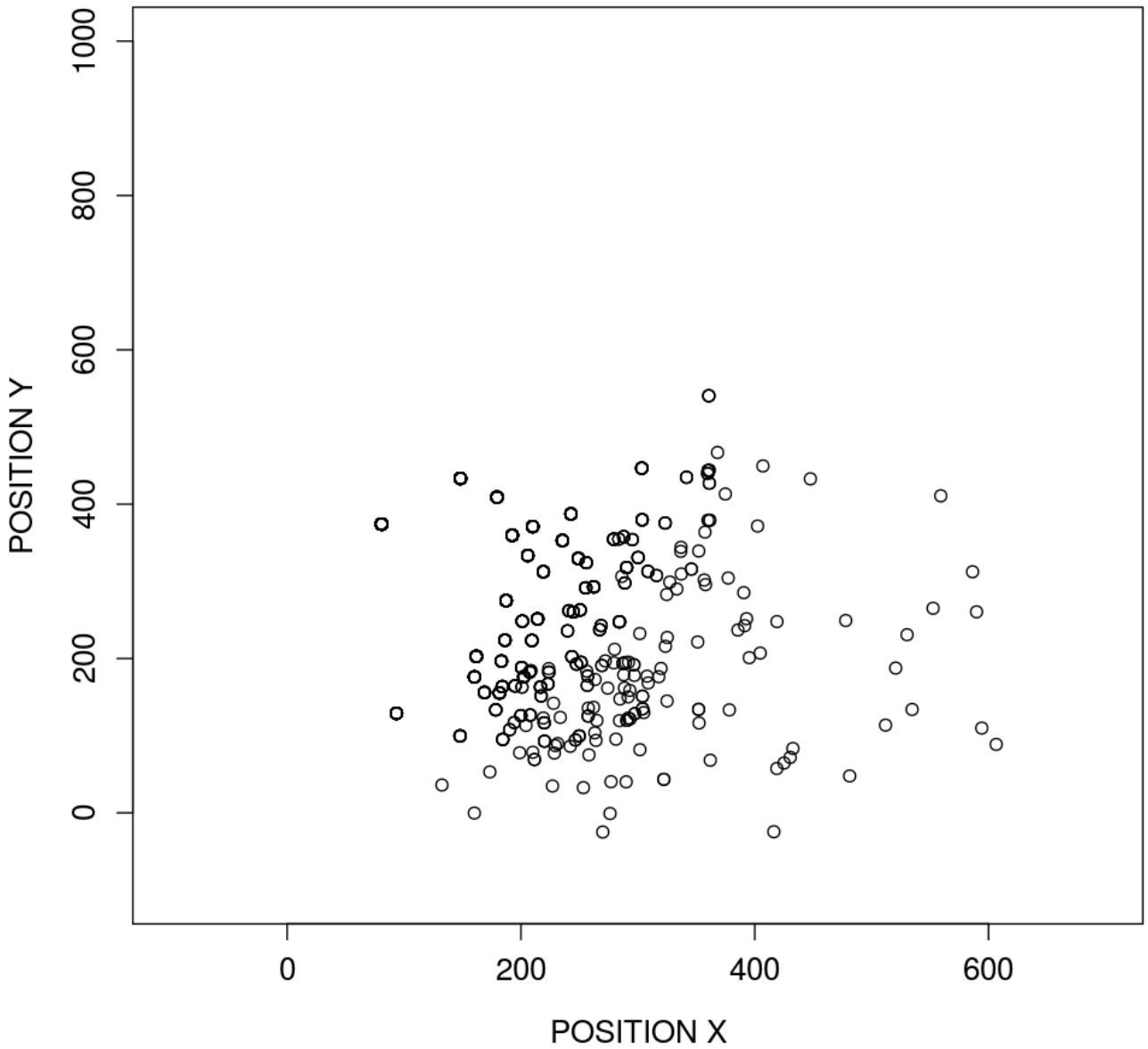


+ proximity-based motion model

PARTICLE FILTER






POSITION Y
0
200
400
600
800
1000
0
200
400
600
POSITION X


lightweight
&
adaptable

MAP EVALUATION

MAP EVALUATION

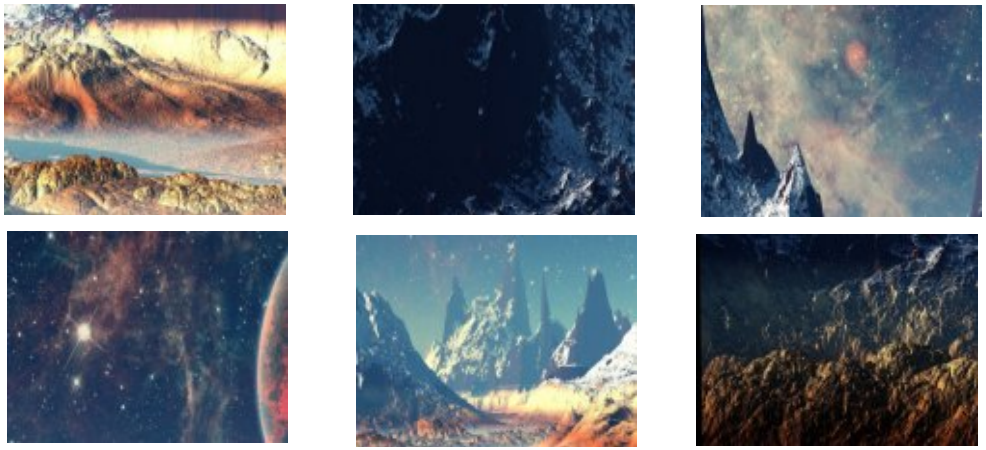
IDEAL SIMILARITY OF HISTOGRAMS FOR FIXED POSITION

MAP EVALUATION - SYNTHETIC FLIGHT

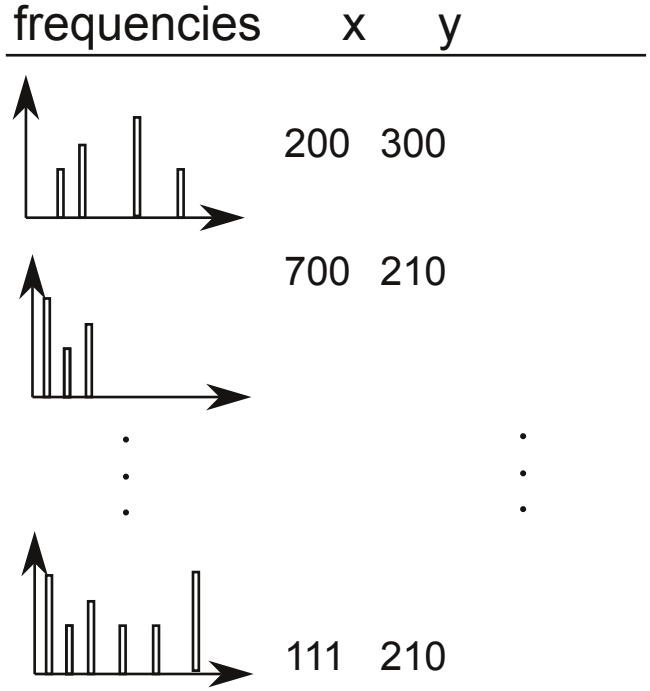
MAP EVALUATION - SYNTHETIC FLIGHT

synthetic flight

MAP EVALUATION – SYNTHETIC FLIGHT



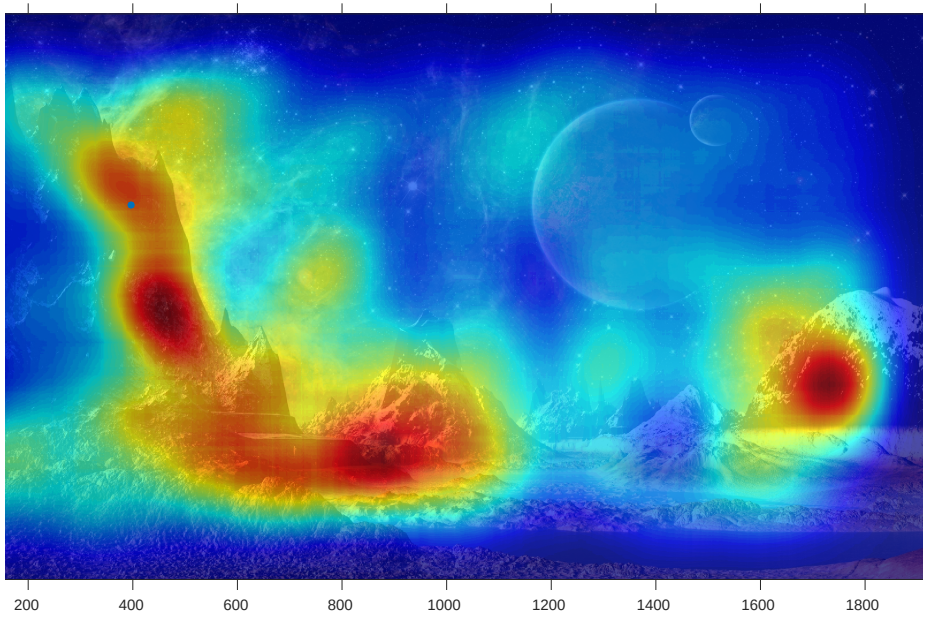
1000 patches



Training Data

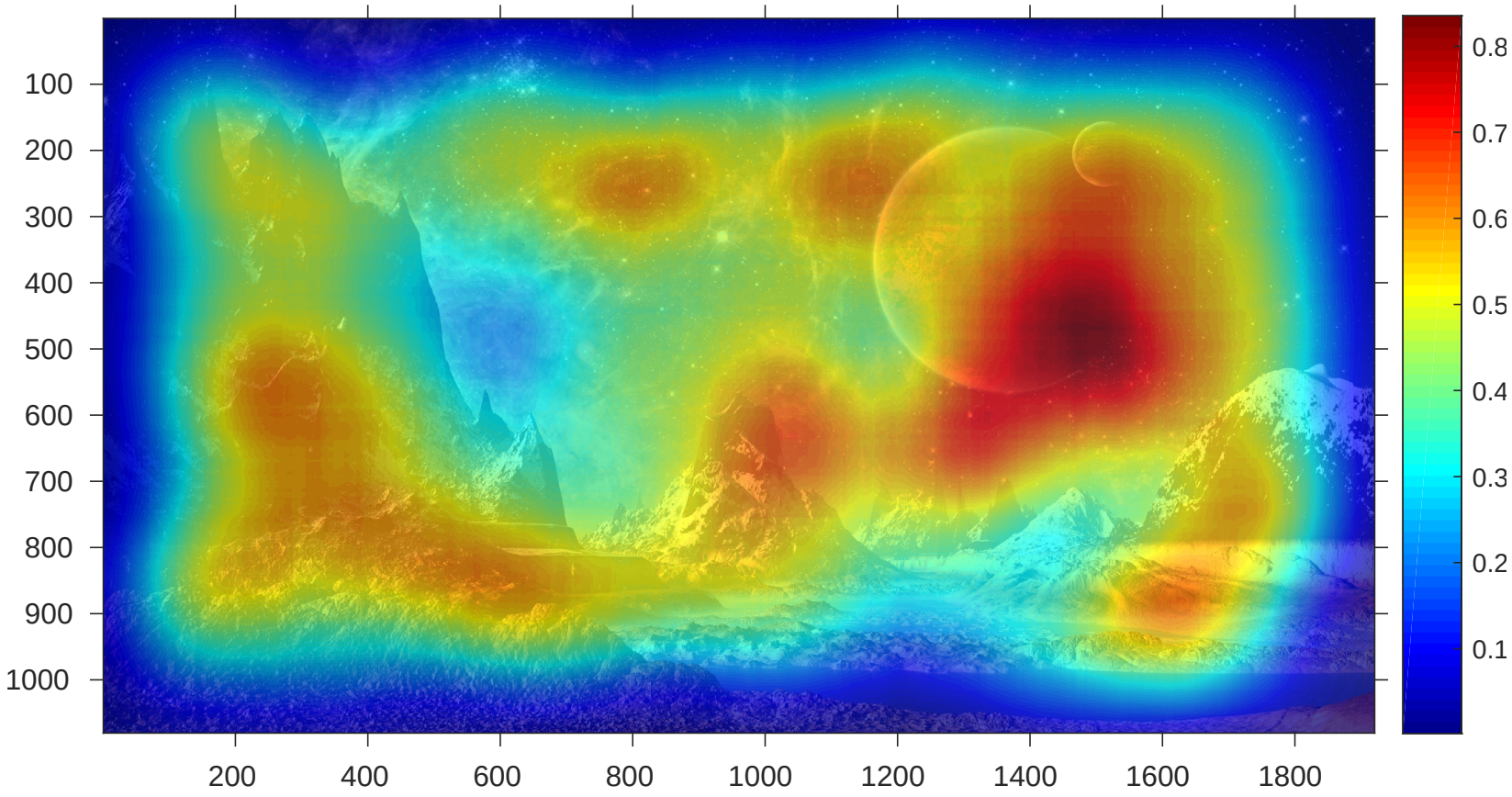
MAP EVALUATION

IDEAL SIMILARITY OF HISTOGRAMS FOR FIXED POSITION



ACTUAL SIMILARITY
(Gaussian smoothing)

MAP EVALUATION

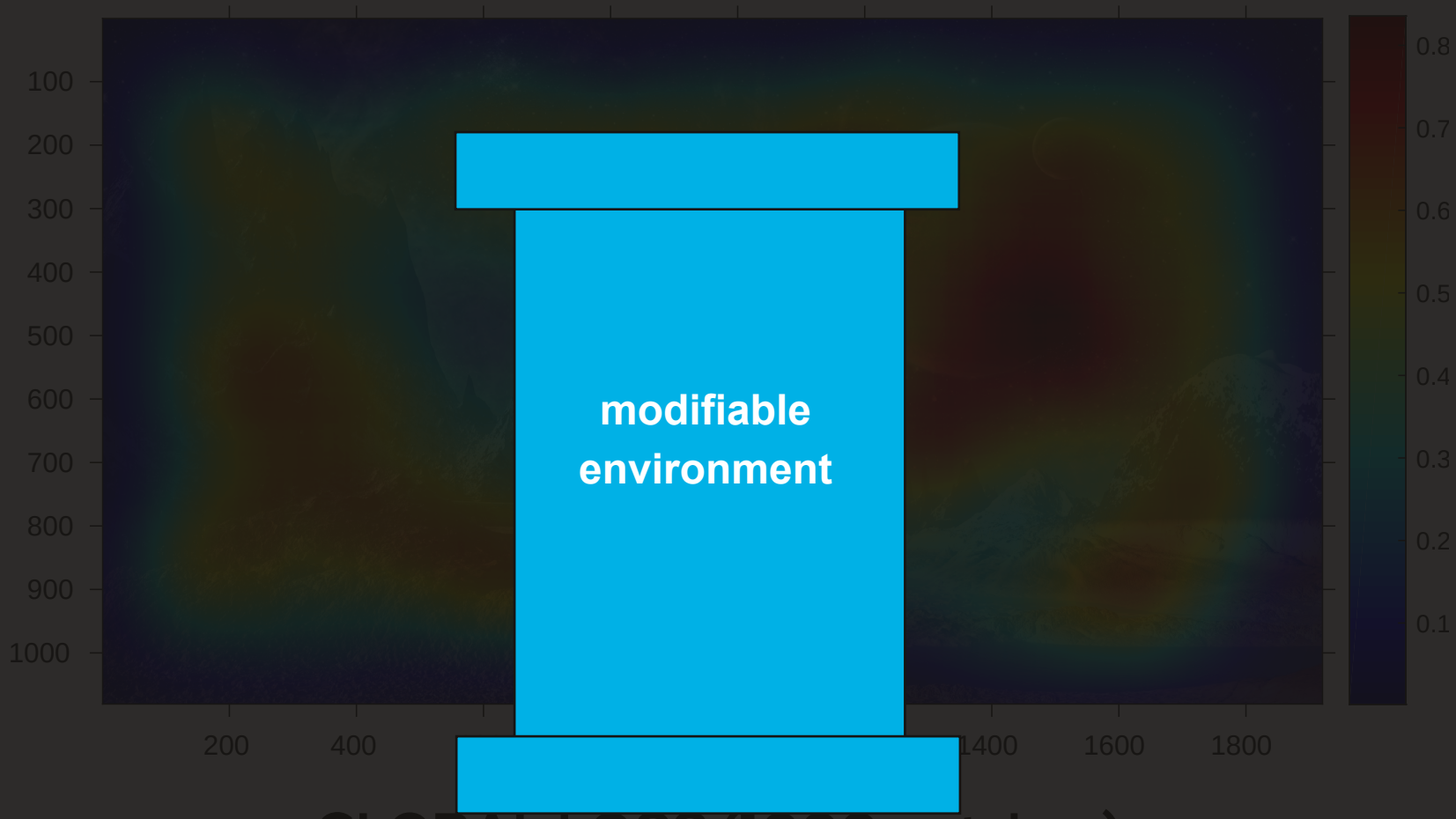


GLOBAL LOSS (1000 patches)

0 < global loss < 1

MAP EVALUATION

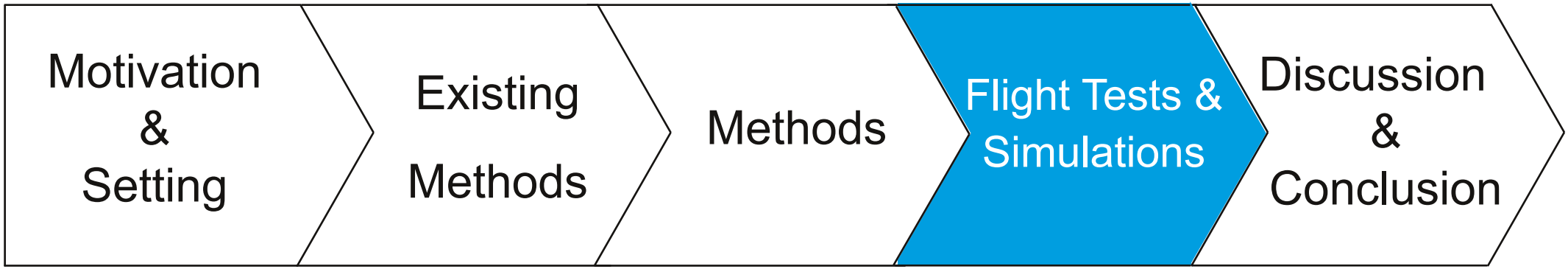
MAP EVALUATION



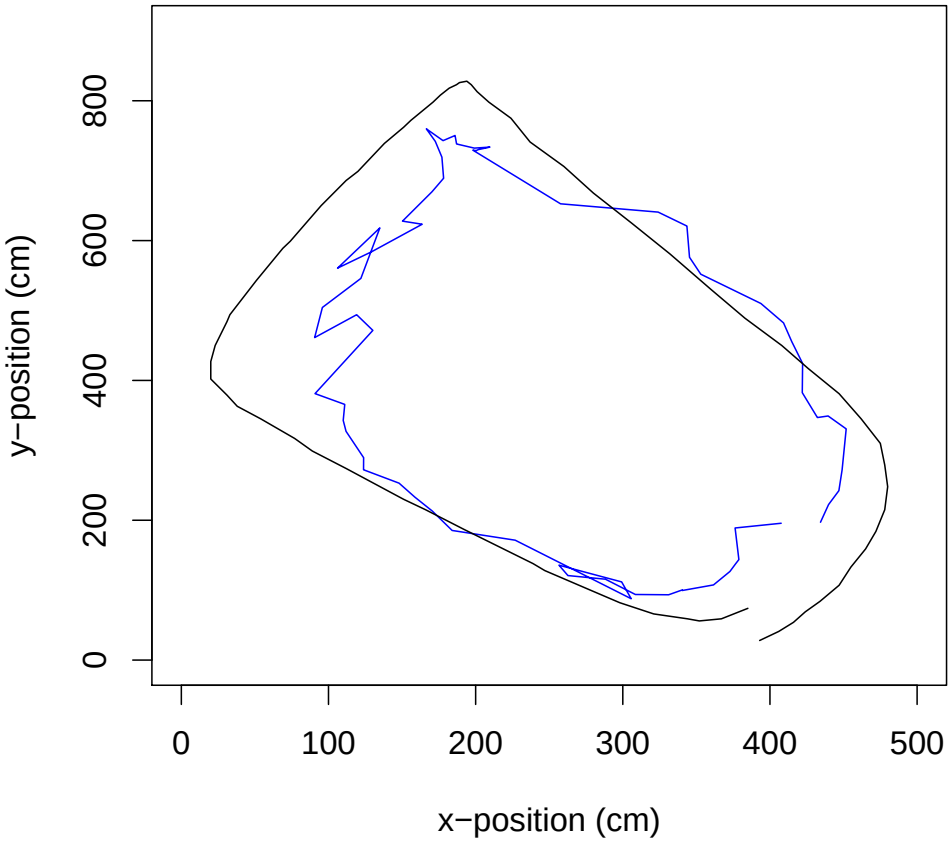
GLOBAL LOSS (1000 patches)

0 < global loss < 1

OUTLINE


Motivation & Setting
Existing Methods
Methods
Flight Tests & Simulations
Discussion & Conclusion

FLIGHT ACCURACY

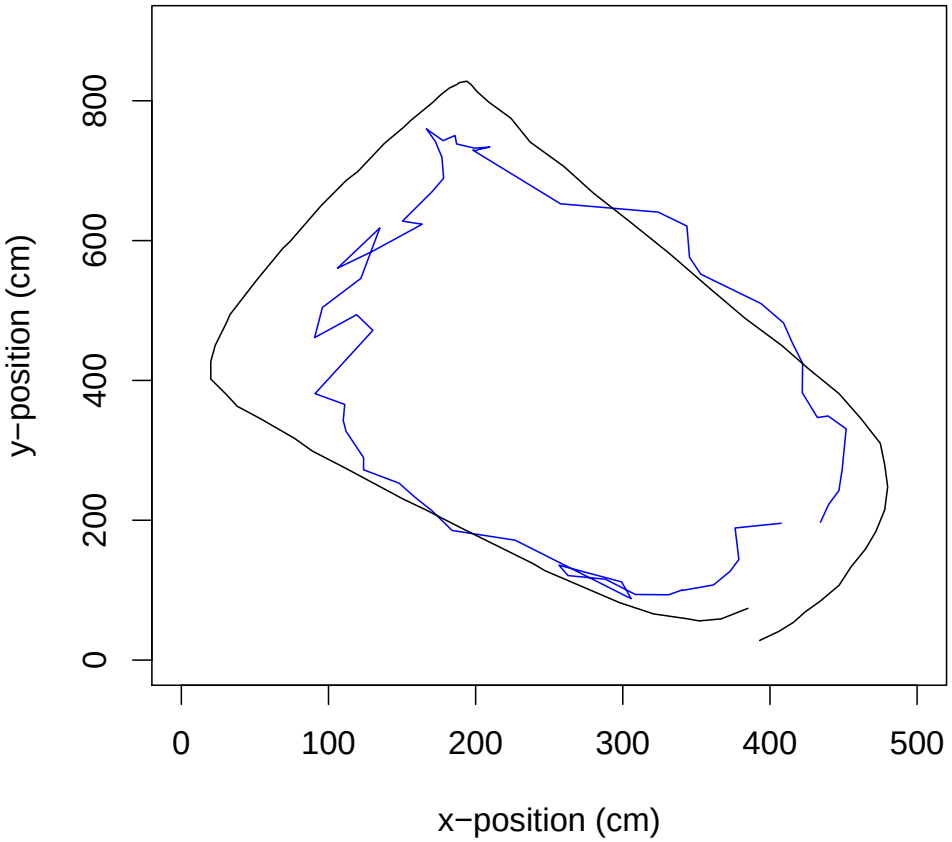


Flight with 400 images

Mean distance x: 46 cm

Mean distance y: 54 cm

FLIGHT ACCURACY



Flight with 400 images

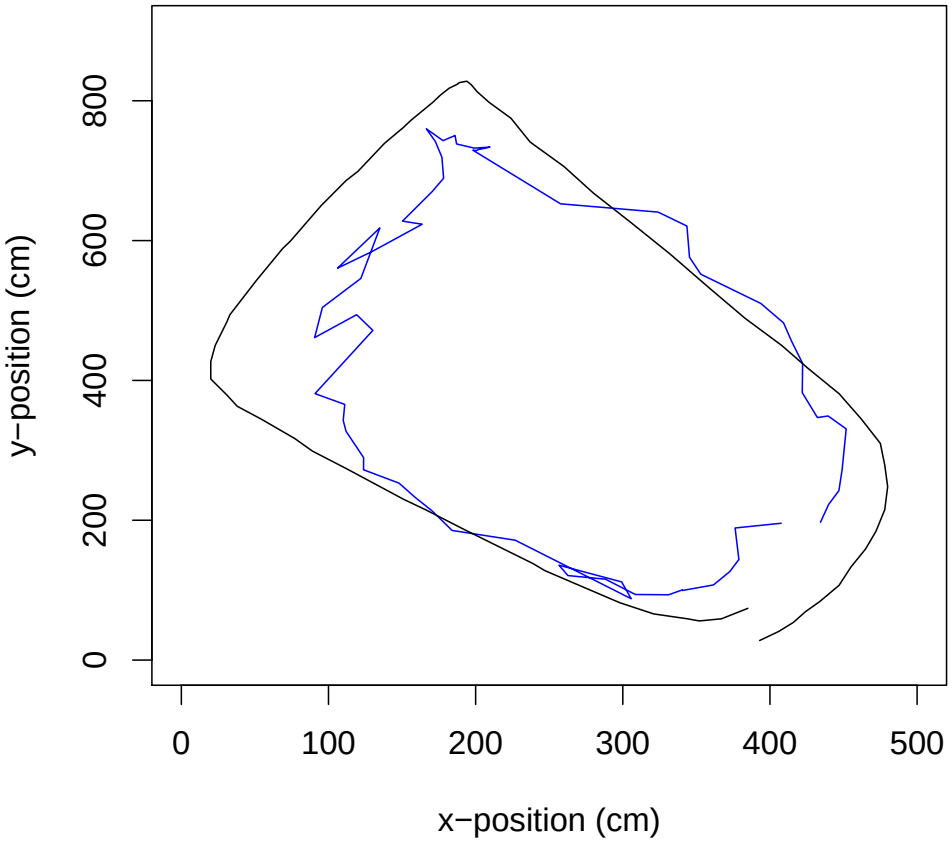
Mean distance x: 46 cm

Mean distance y: 54 cm

SD distance x: 56 cm

SD distance y: 71 cm

FLIGHT ACCURACY



Flight with 400 images

Mean distance x: 46 cm

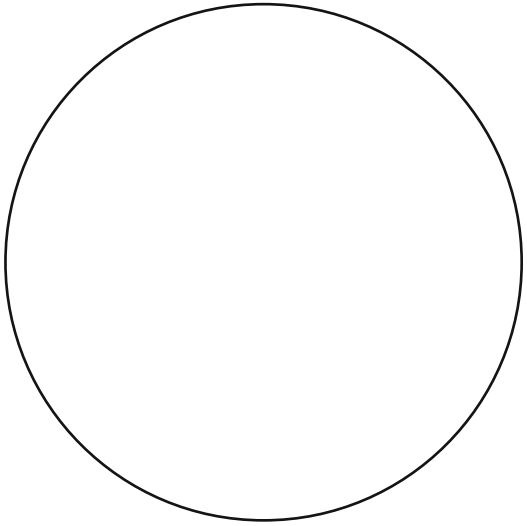
Mean distance y: 54 cm

SD distance x: 56 cm

SD distance y: 71 cm

Frequency: 12 Hz

TRIGGERED LANDING

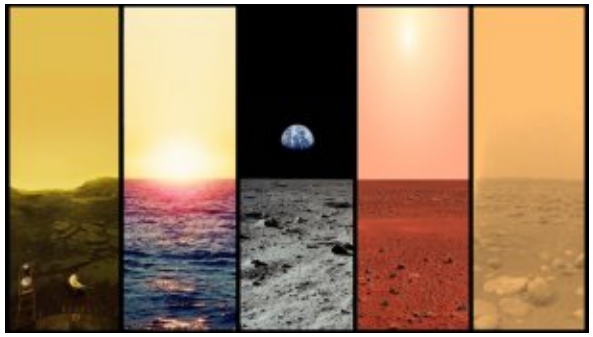


6 Landings

criterion:
distance < 60 cm

safety criterion:
low variance of particles

MAP EVALUATION





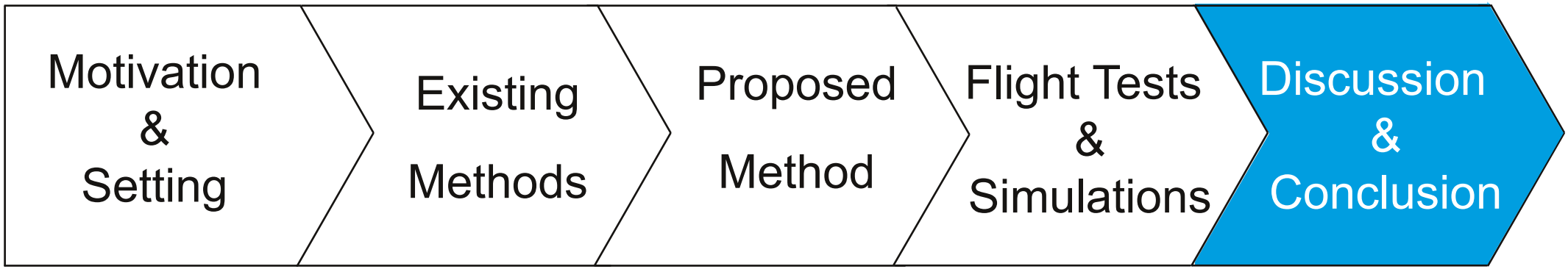




46 images

MAP EVALUATION - LOSSES

OUTLINE


Motivation & Setting
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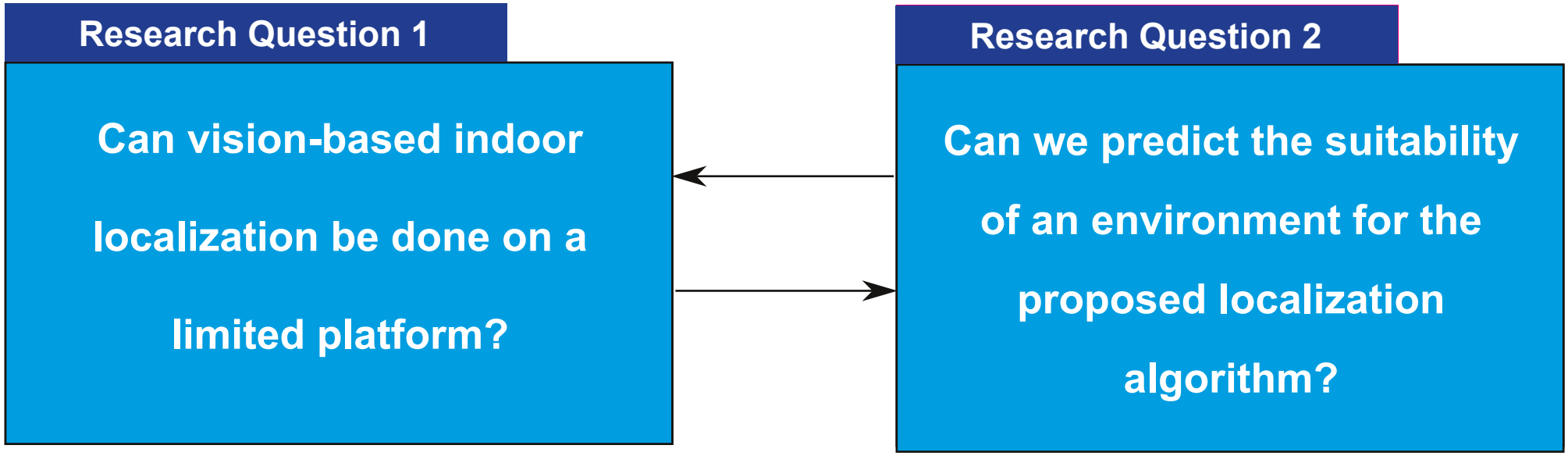
RESEARCH QUESTIONS

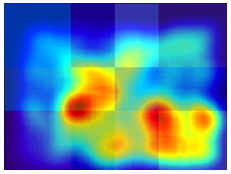


DISCUSSION

Implications:

- paves the way to indoor flight
- adaptable to different platforms

- detect safe landing spots



DISCUSSION

Limitations:

- assumes constant height and no rotations

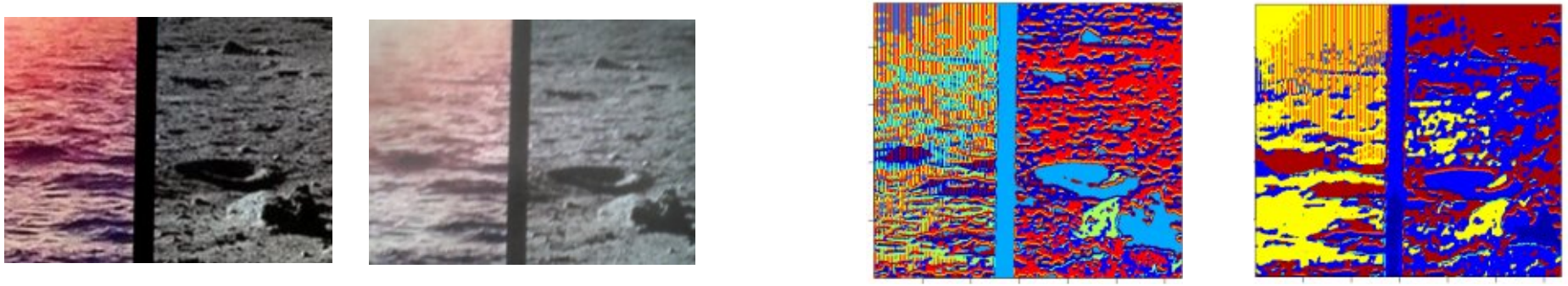
- robustness to differerent lighting conditions

- particle filter does not include velocity or heading

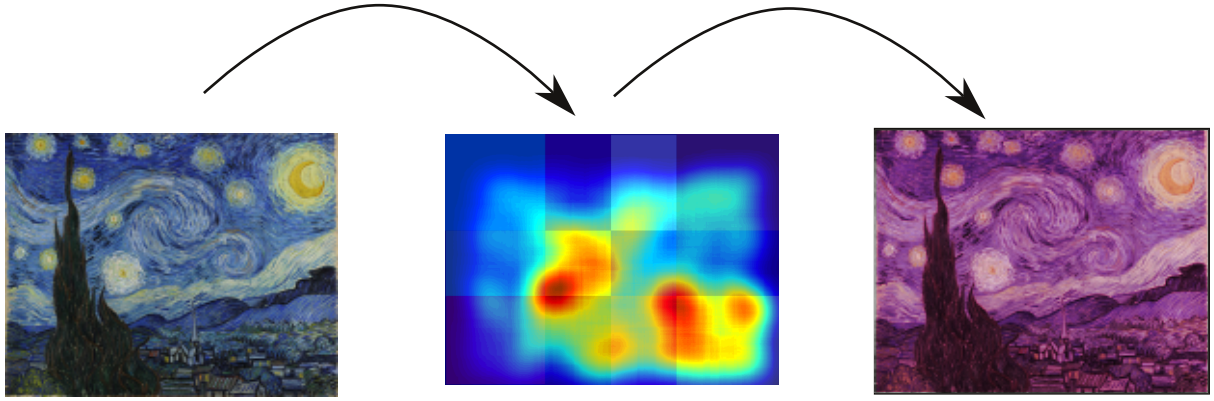
DISCUSSION

Future research:

- bridge reality gap



- automatic map generation (evolutionary algorithm)



CODE CONTRIBUTIONS

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

  https://github.com/Pold87/draug

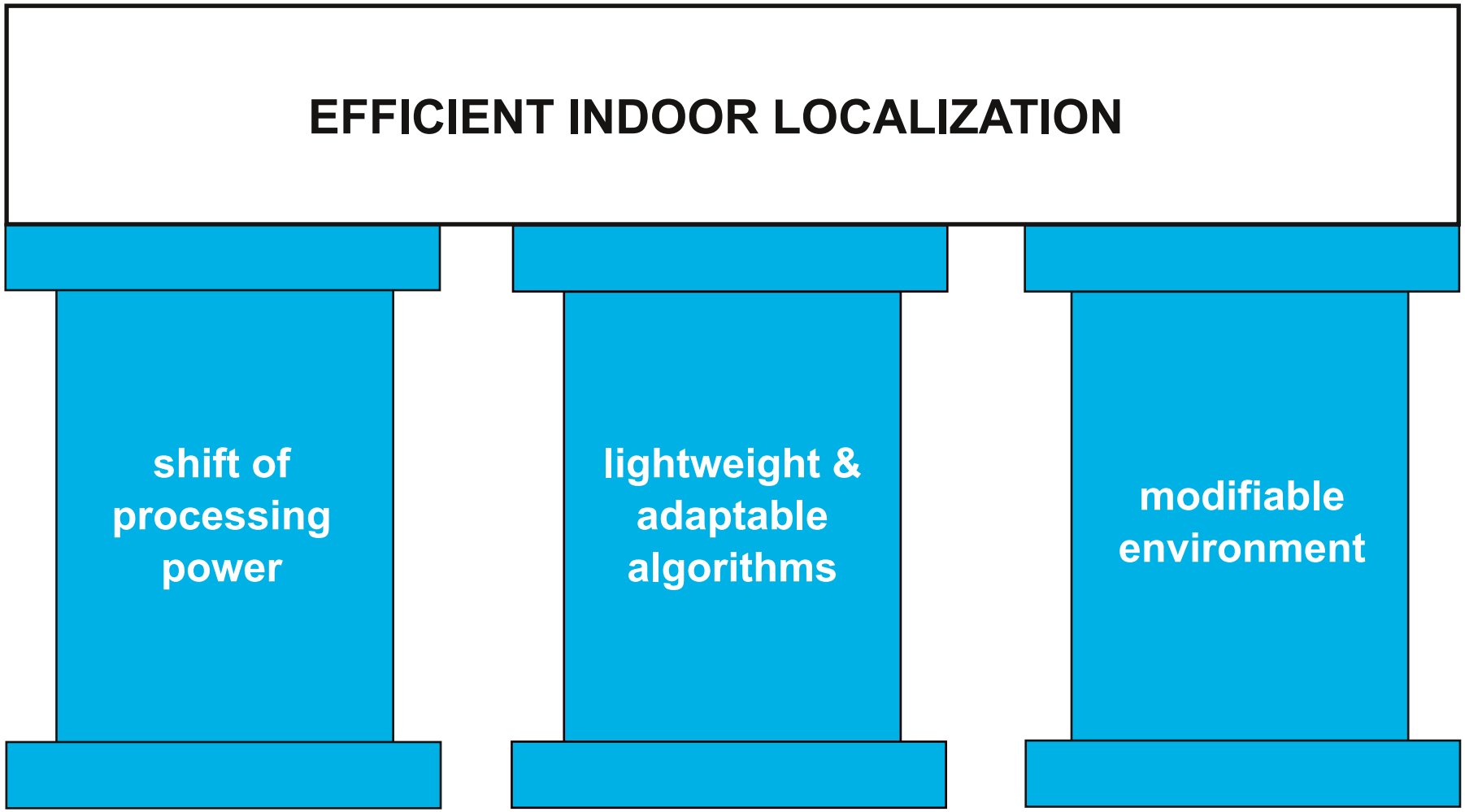
- Map evaluation (MATLAB)

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

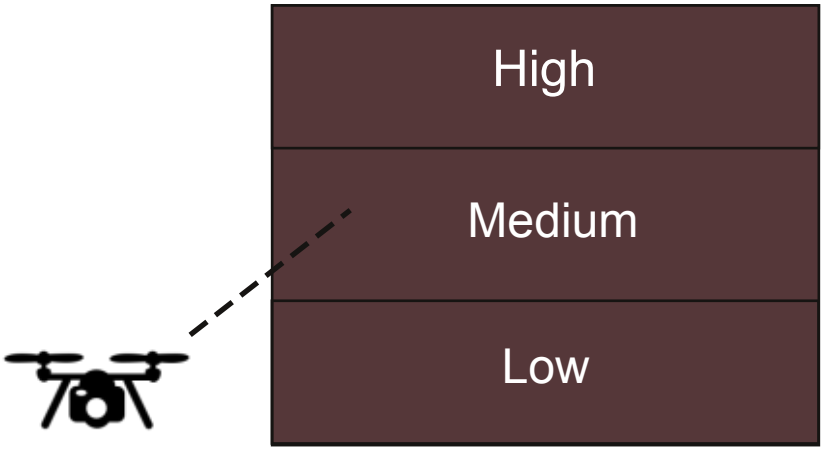
- Localization: SIFT matching (C++), particle filter (C), texton-based approach (C)

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

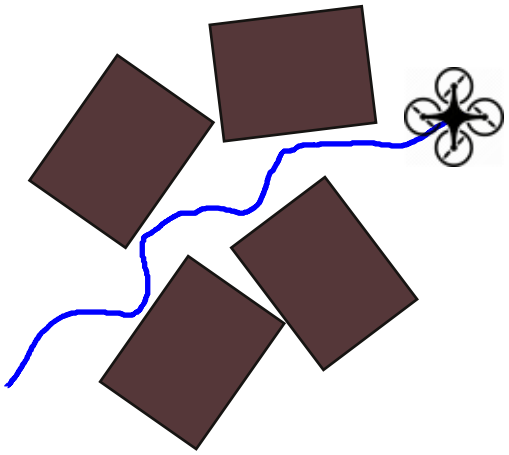
CONCLUSION


EFFICIENT INDOOR LOCALIZATION
shift of processing power
lightweight & adaptable algorithms
modifiable environment

FOUNDATION

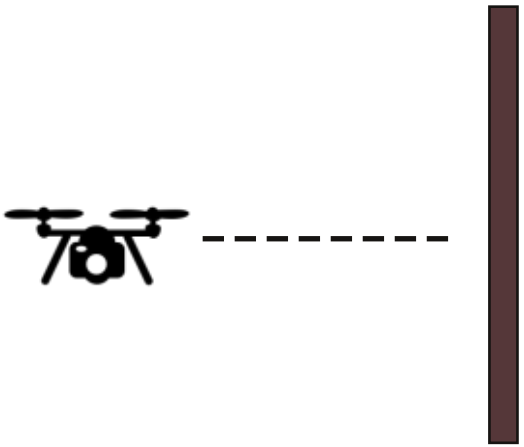


Height control



Obstacle Avoidance

Safe Landing Spot Detection



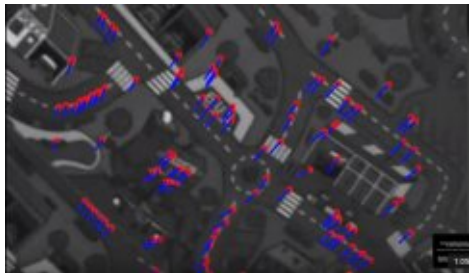
Distance Measurement

METHODS FOR ONBOARD LOCALIZATION

Laser range finder

METHODS FOR ONBOARD LOCALIZATION

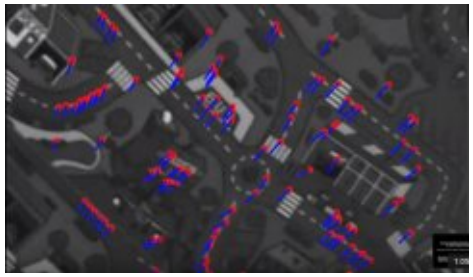
Laser range finder



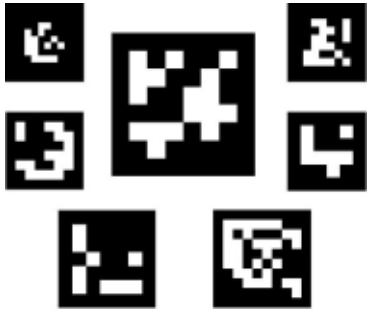
Optical flow

METHODS FOR ONBOARD LOCALIZATION

Laser range finder



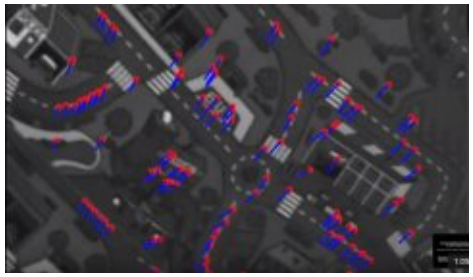
Optical flow



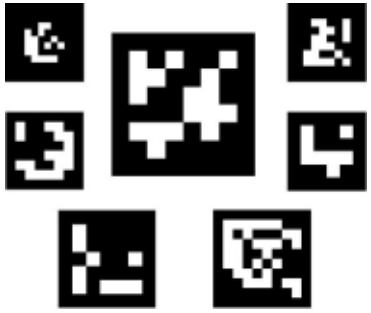
Markers

METHODS FOR ONBOARD LOCALIZATION

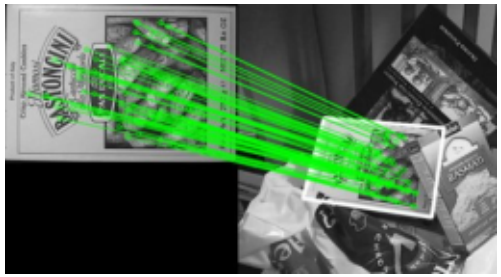
Laser range finder



Optical flow

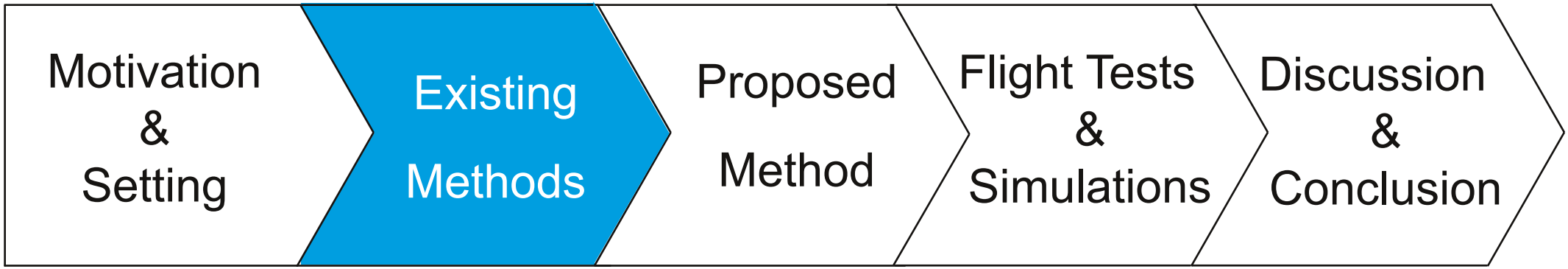


Markers



Homography finding

OUTLINE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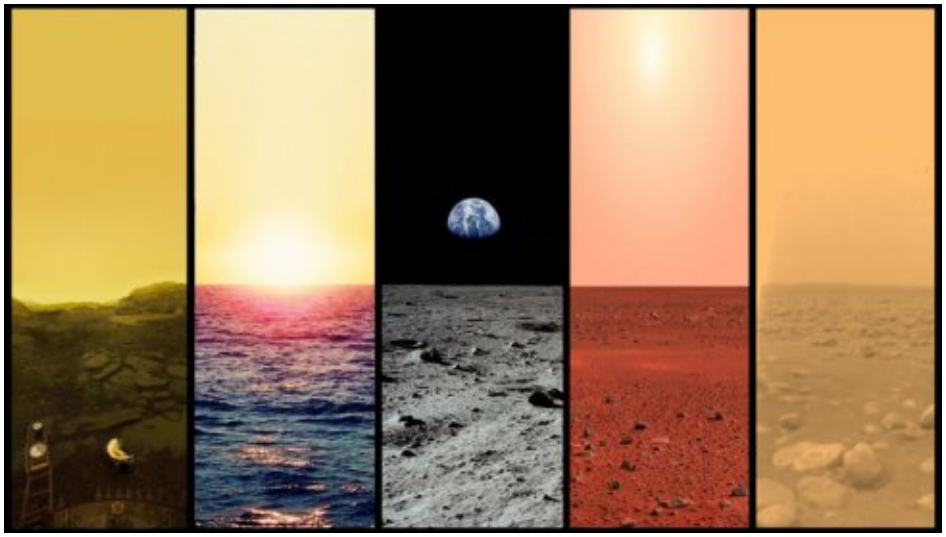
MAP EVALUATION

GOOD



0.57

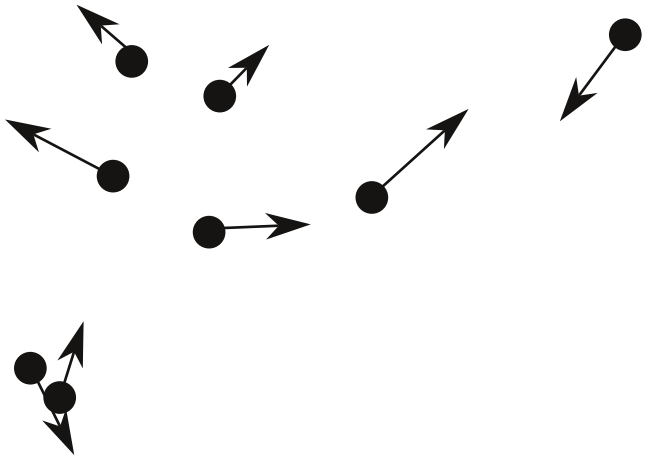
BAD

0.98

PARTICLE FILTER

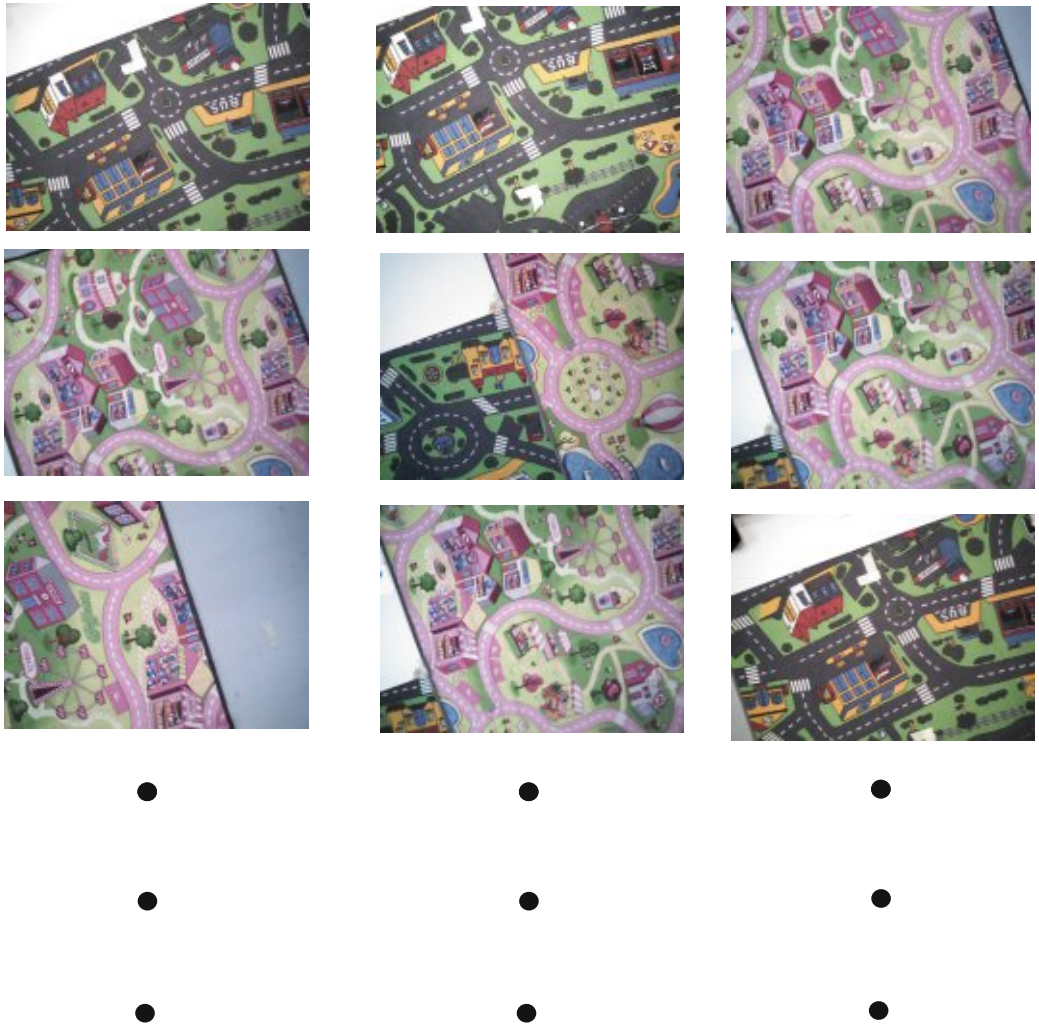
Motion model

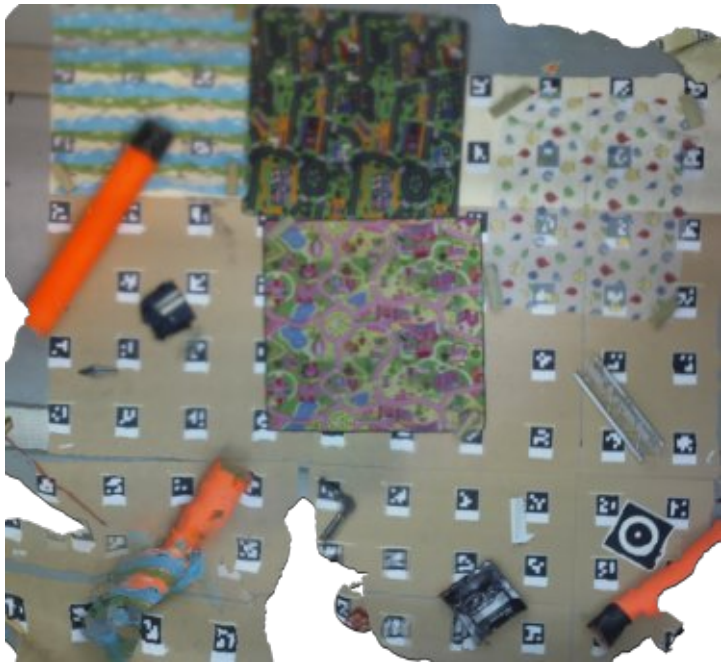
2D-Gaussian noise



SCALABILITY

SCALABILITY





Orthomap