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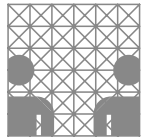

Position Estimation on Image-Based Heat Map Input using Particle Filters in Cartesian Space

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Technical Aspects of Multimodal Systems

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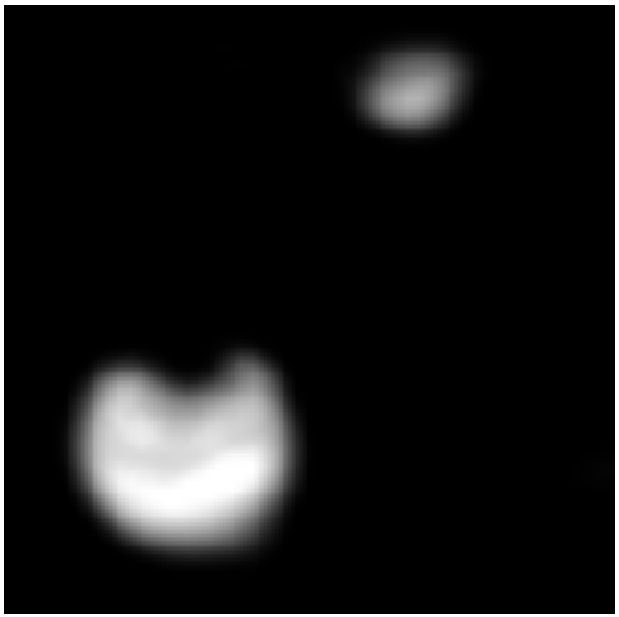
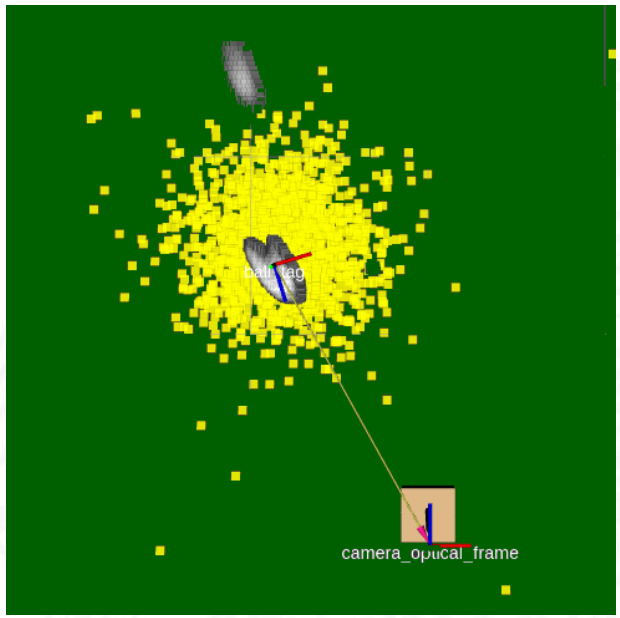
Outline

Goal

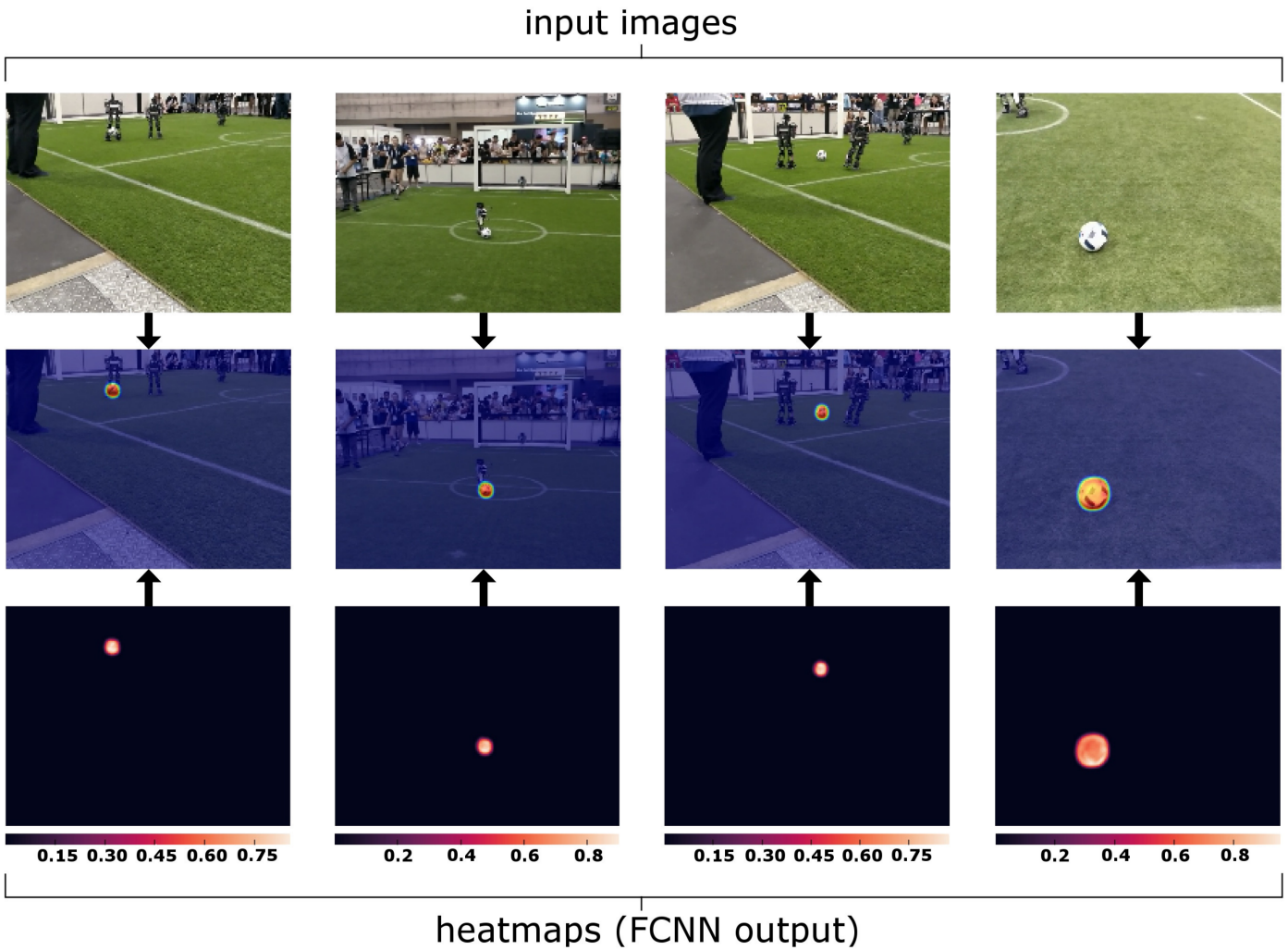




Motivation

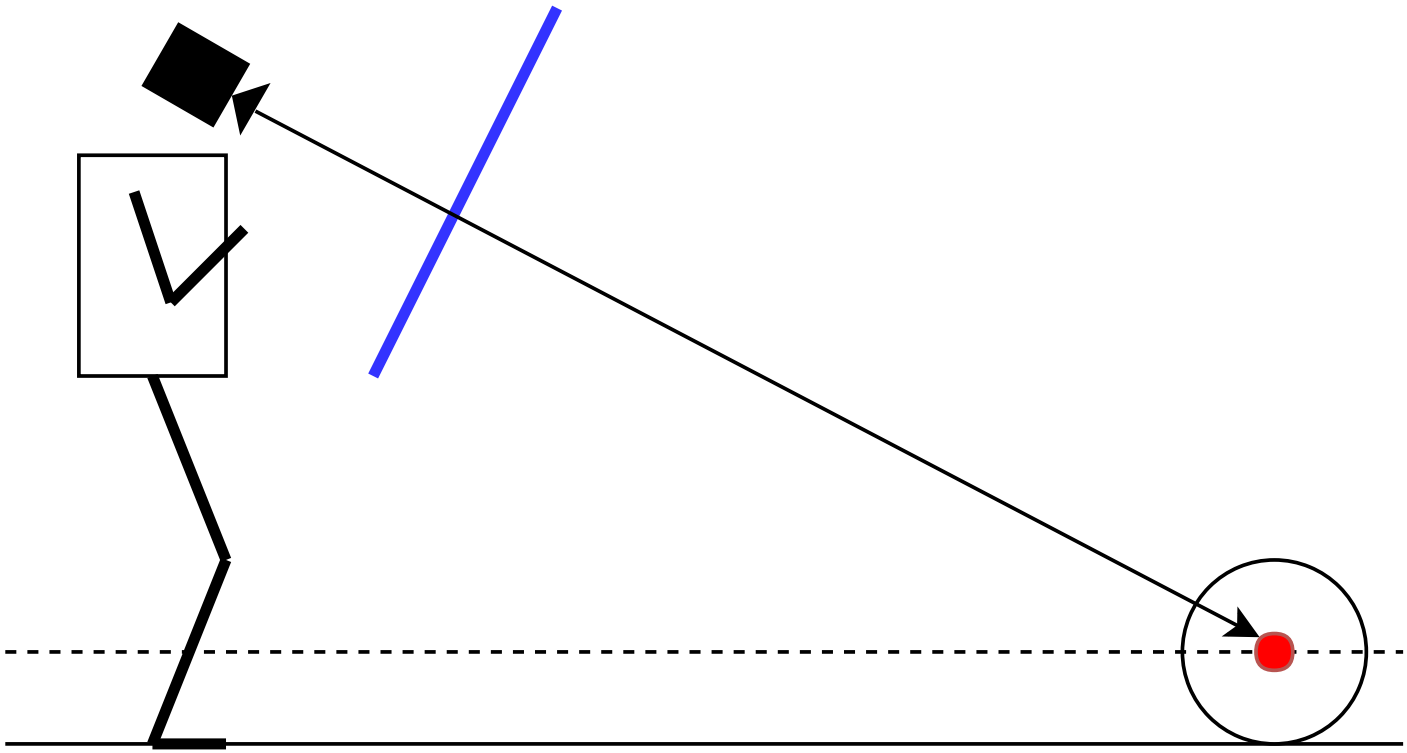
- Reduce the data loss between vision pipeline and world model
  - No cluster detection
  - Use the data available
- Increase filter robustness
- Accurate representation of estimation confidence

- Humanoid robots play soccer against each other
- Completely autonomous operation
- Four players per team
- Communication via WiFi is allowed



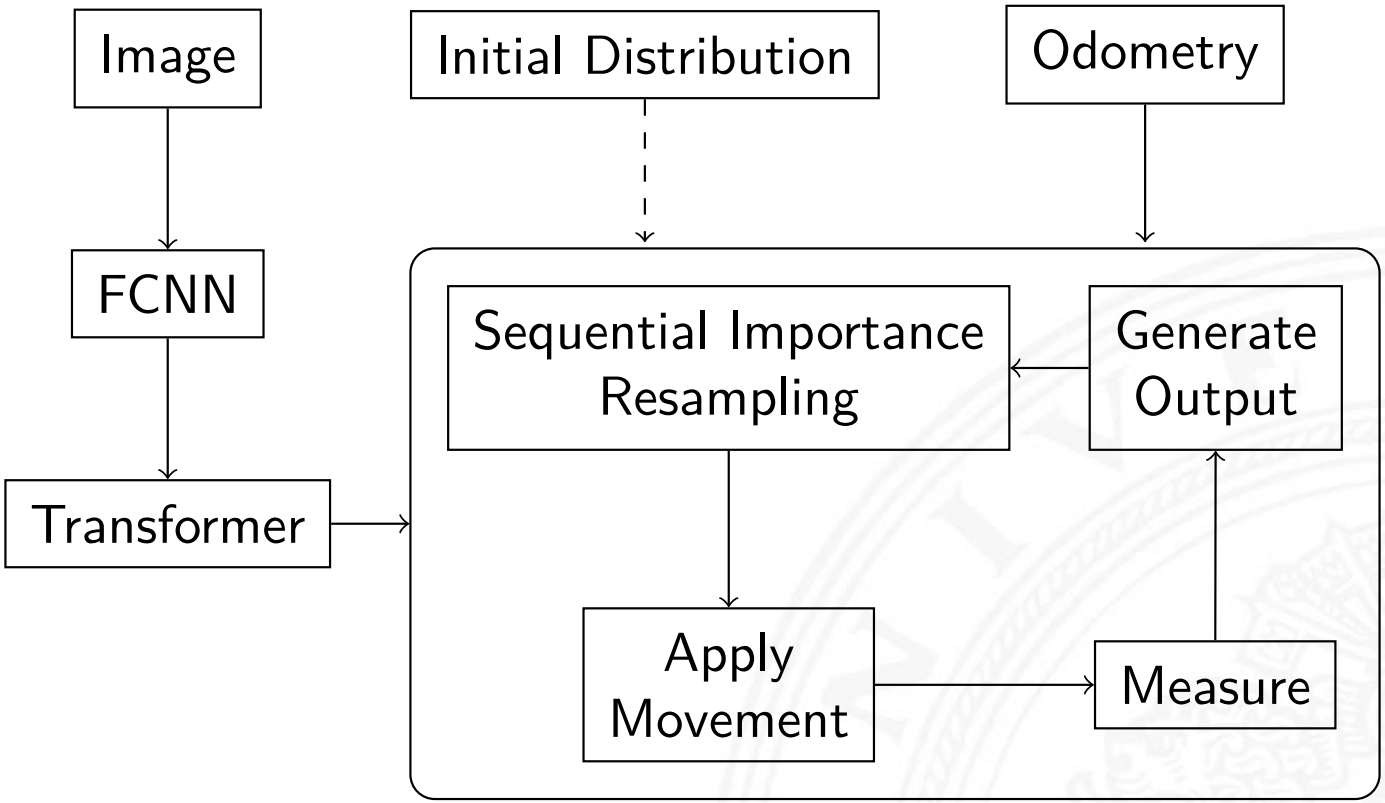
Exemplary results of FCNN application in RoboCup [SBB18]

Transformer

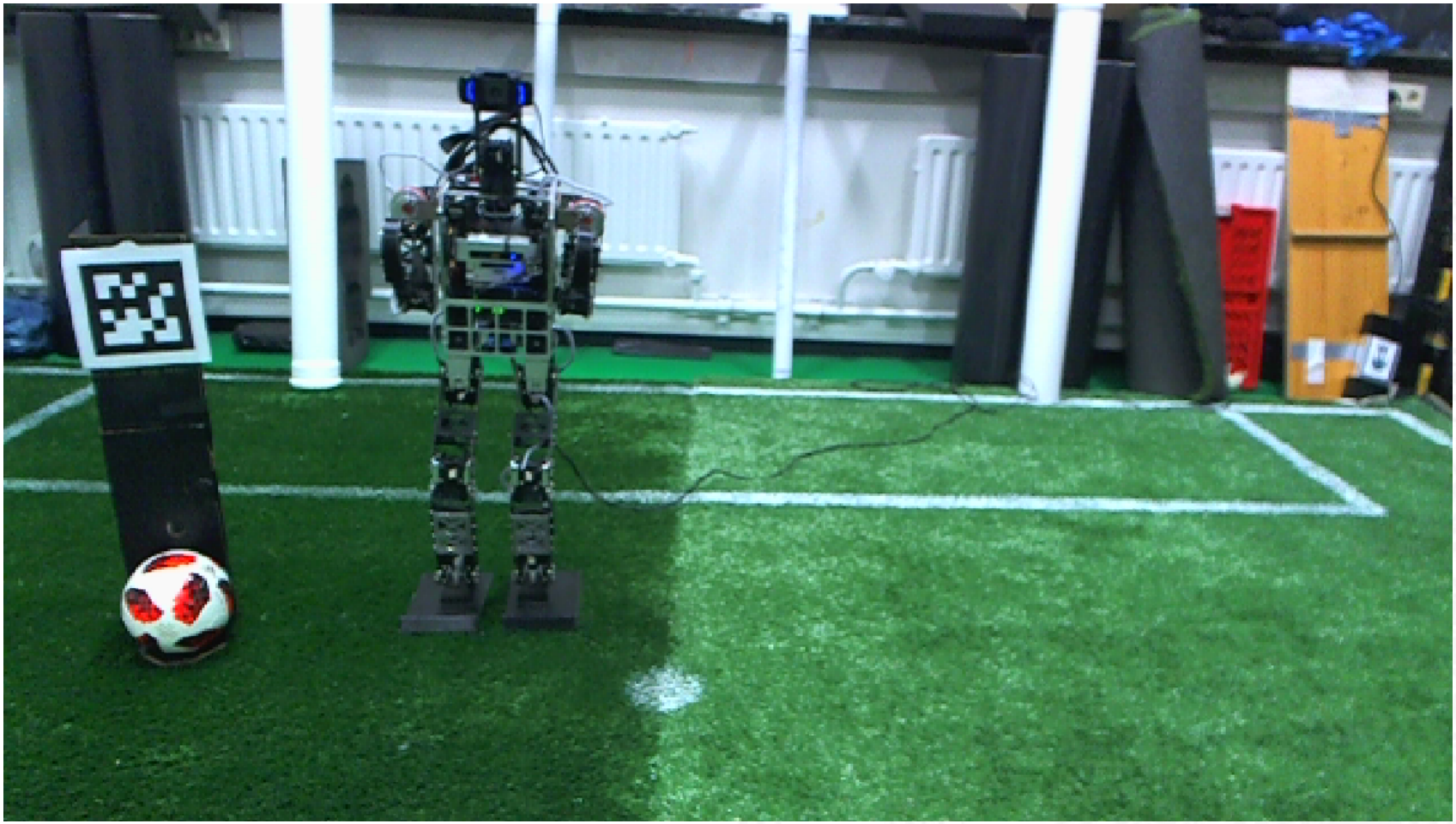


Graphic representation of the transform method.

Schematic Approach

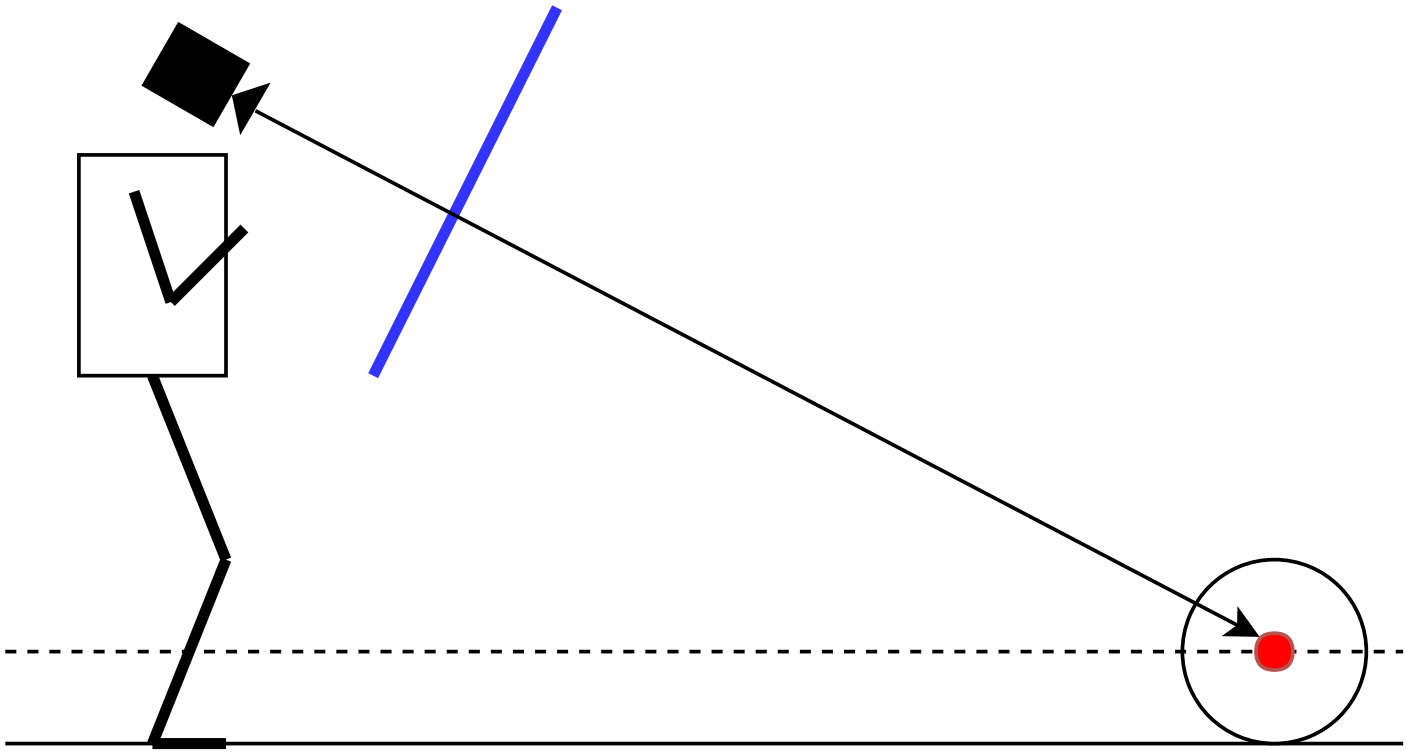


Schematic representation of the filtering process.

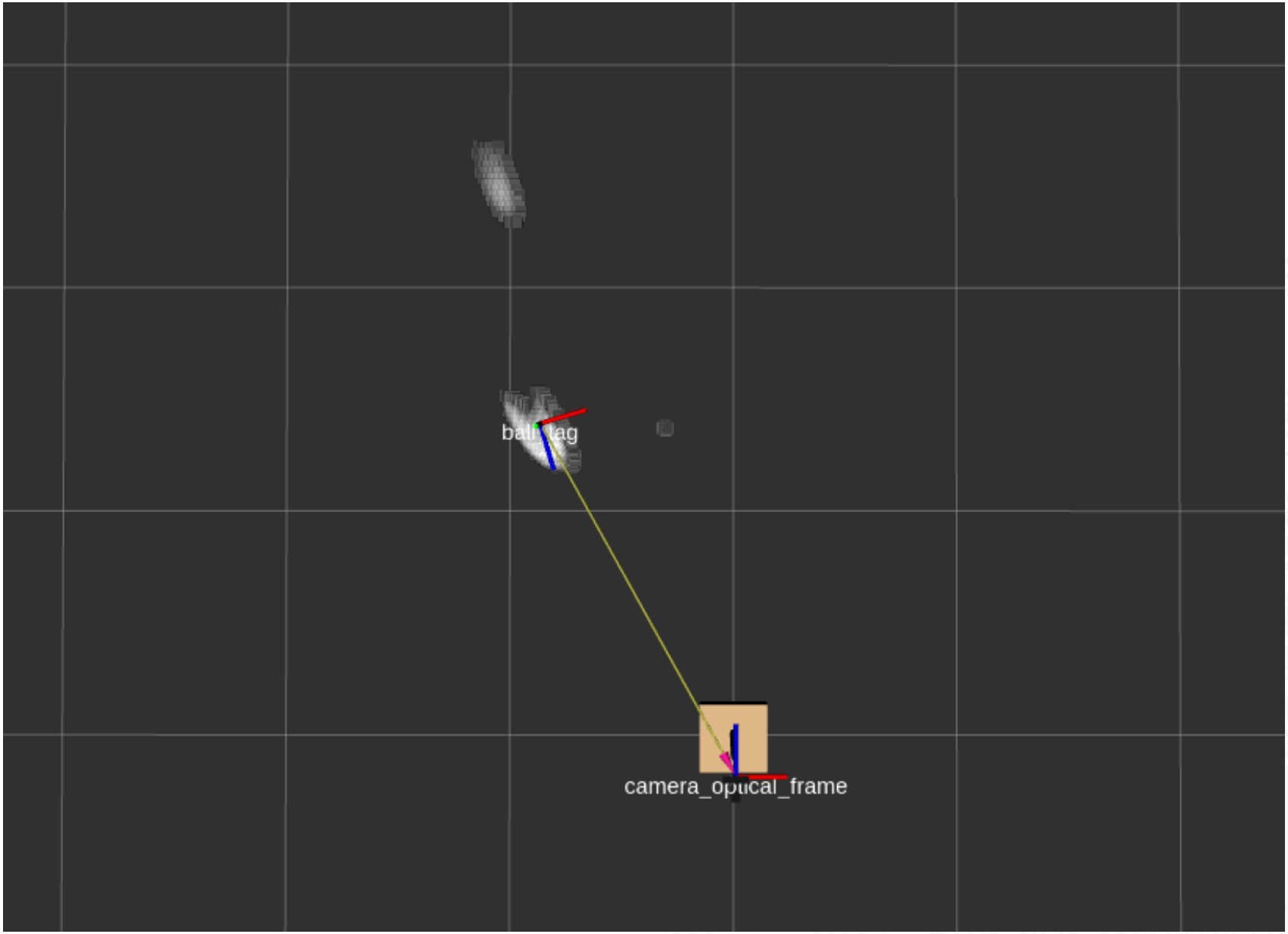


FCNN Output

Transformer



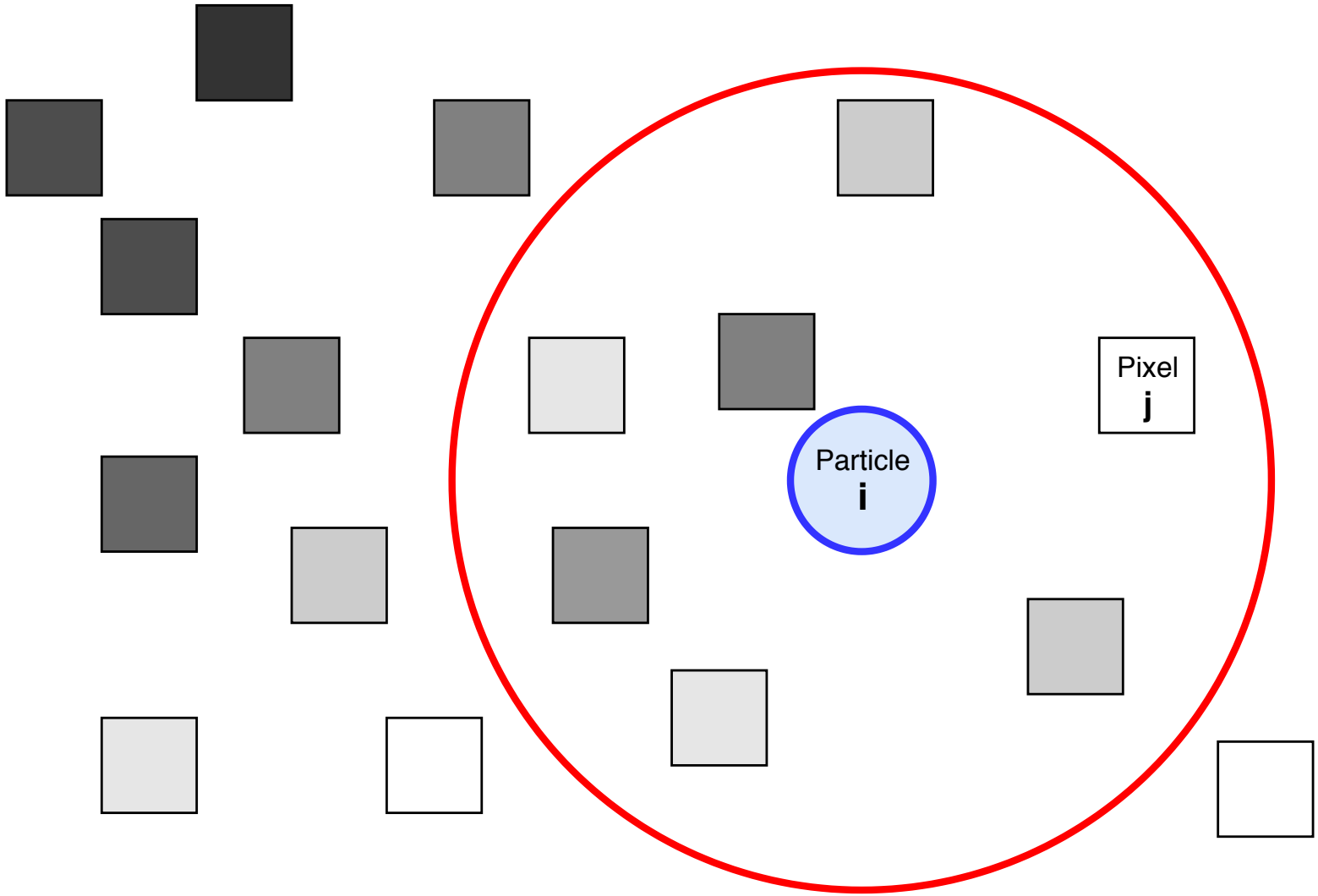
Position Estimation



Particle Weighting Requirements

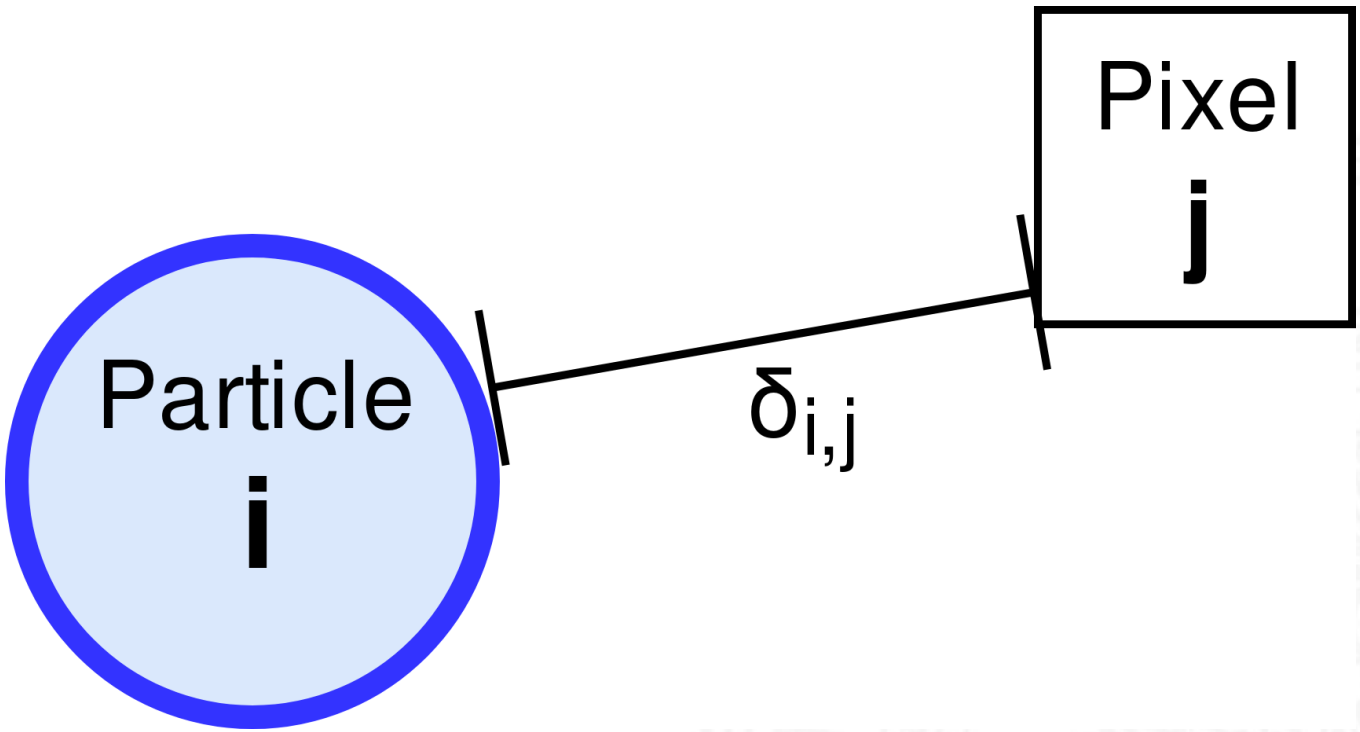
- Context aware
- Rating and distance of pixels in the environment need to be considered
- Weight should be maximal in an dense area with high-rated pixels
- Pixels are locally independent

Particle Weighting I

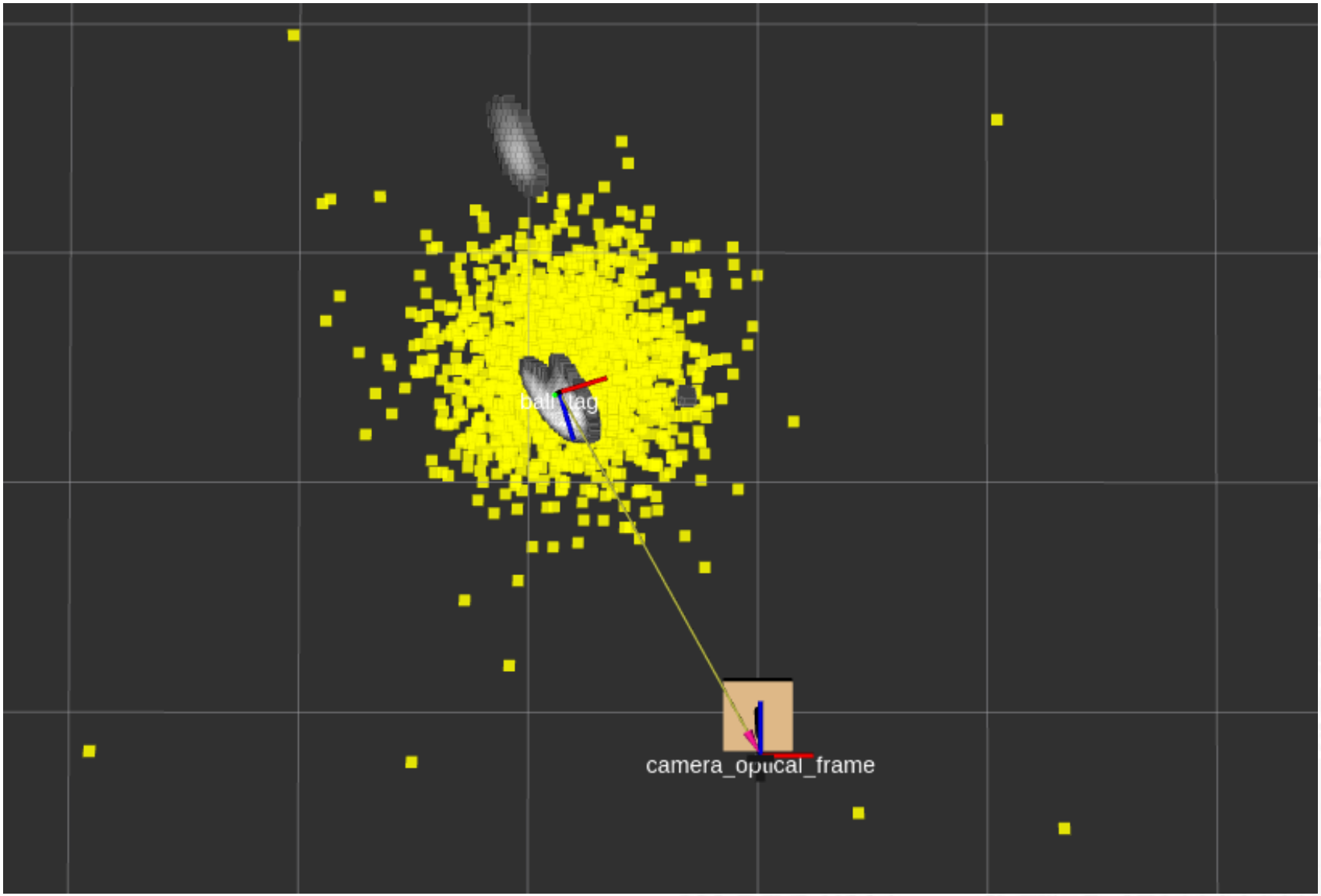


Selecting the closest k pixels with k=7 in this case.

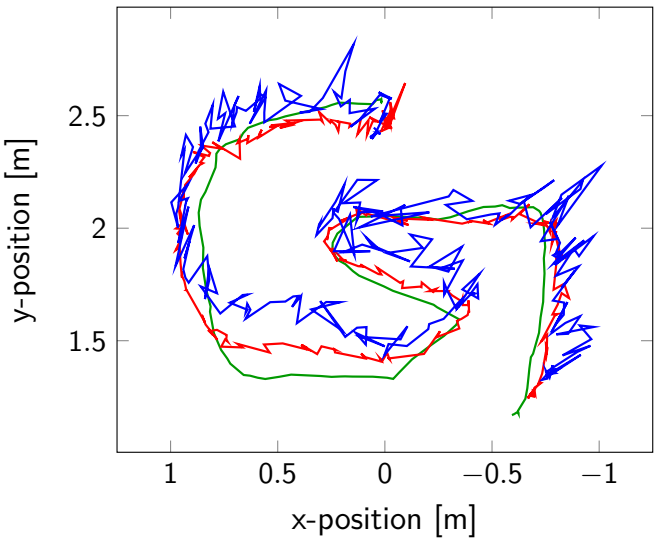
Particle Weighting II



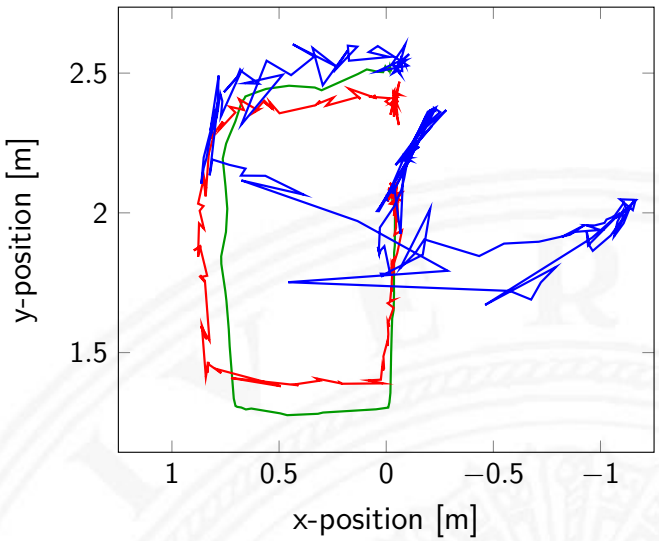
Position Estimation



Video.

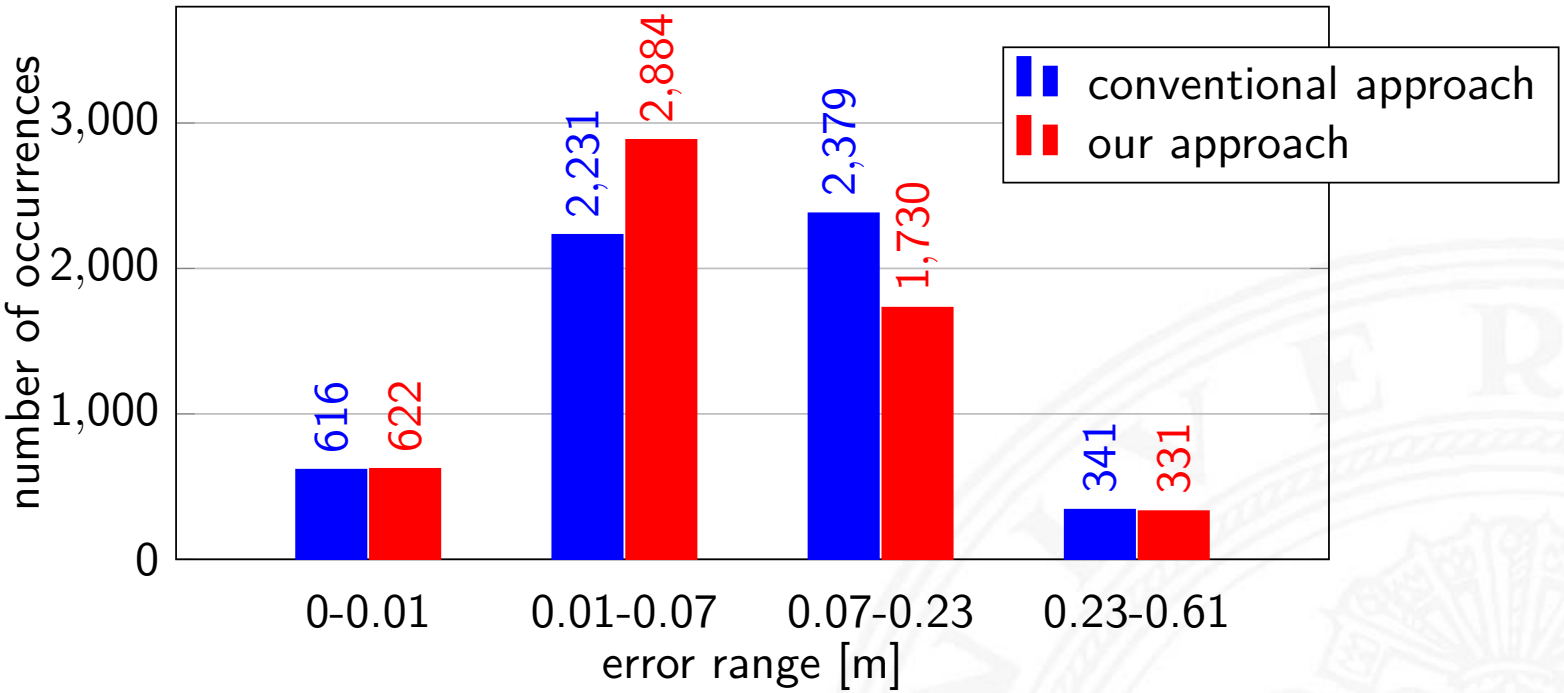


(a) Without false-positive detections in the FCNN



(b) With false-positive detections in the FCNN

The traces depicted are the estimate of the ball pose estimated in Cartesian space relative to the robot.

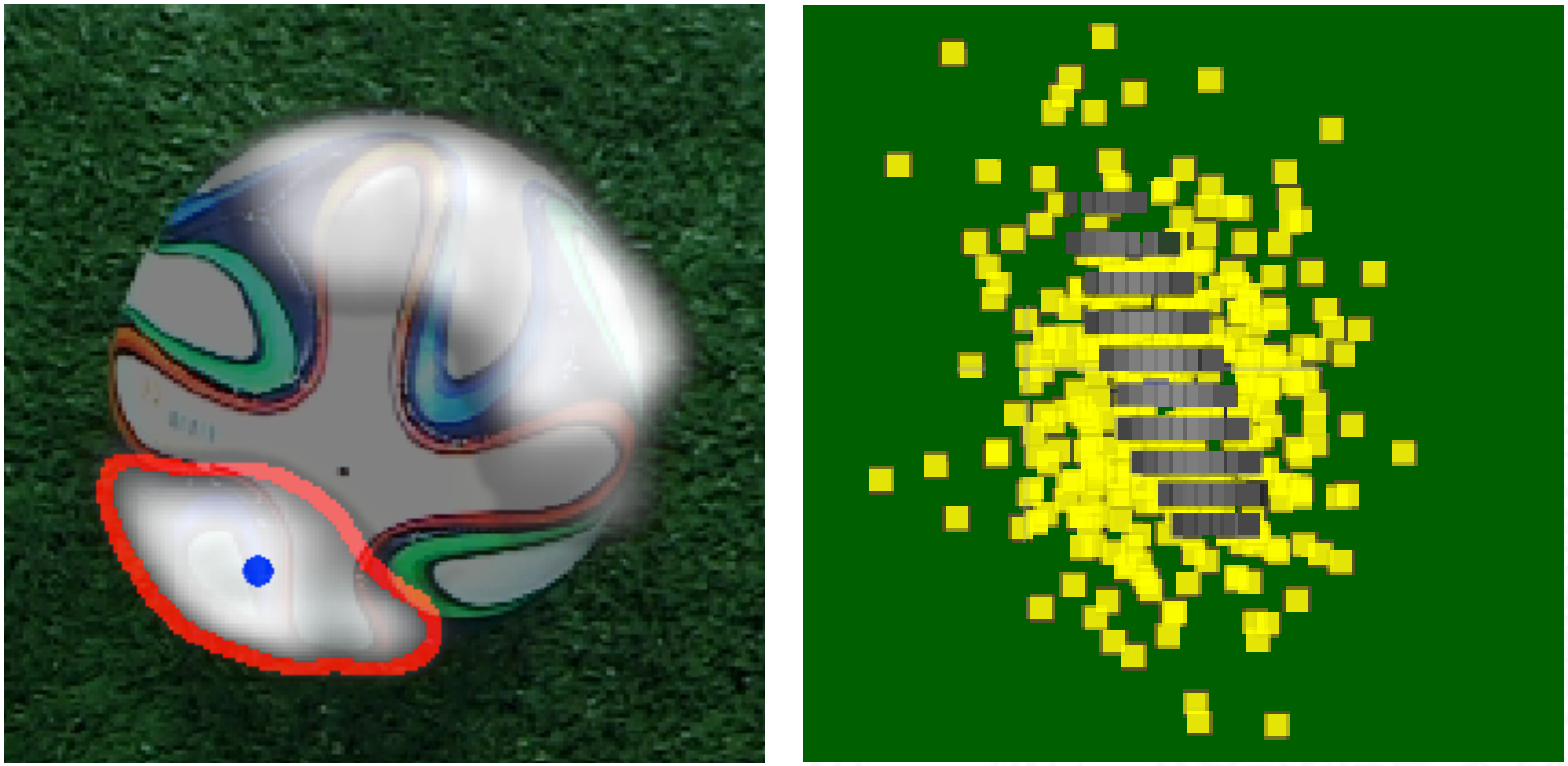


Bar chart depicting the distribution of the measurement error of our approach (**red**) compared to the error produced by the conventional method (**blue**).

Overview of the errors measured.

	mean error [m]	max error [m]	standard deviation of the errors [m]
conventional approach	0.0879	0.61	0.08142
our approach	0.0771	0.54	0.07714

Edge Cases



Examples of edge cases in the FCNN output

Conclusion

- \- Significant increase in required computing power
- \- Number of transformed measurements increases
- \+ No cluster detection necessary in the FCNN post-processing
- \+ Robust with erroneous input
- \+ More accurate representation of current state

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Outlook

- Use pixels with depth-information (Kinect)
- Evaluate the filter with a moving robot
- Integration into a complete system

[SBB18] Daniel Speck, Marc Bestmann, and Pablo Barros, *Towards real-time ball localization using cnns*, Robot World Cup XXII, Springer, 2018.

Particle Weighting

$$w(p_i^t) = \sum_{j=1}^{k} \frac{w(m_j^t)}{\delta_{i,j}^t} \text{ with } m_j^t \in C_i^t \tag{1}$$

Runtime Complexity I

Particle weighting function: $w(p_i^t) = \sum_{j=1}^{k} \frac{w(m_j^t)}{\delta_{i,j}^t}$ with $m_j^t \in C_i^t$ (2)

$\Downarrow$

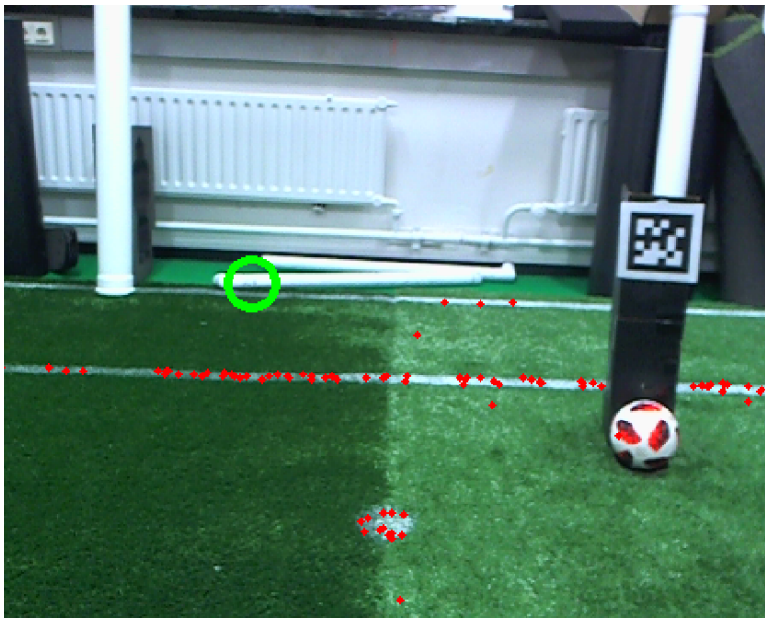
Runtime complexity: $\Theta(|P|(|M| + |M|log(|M|) + k))$ (3)

Runtime Complexity II

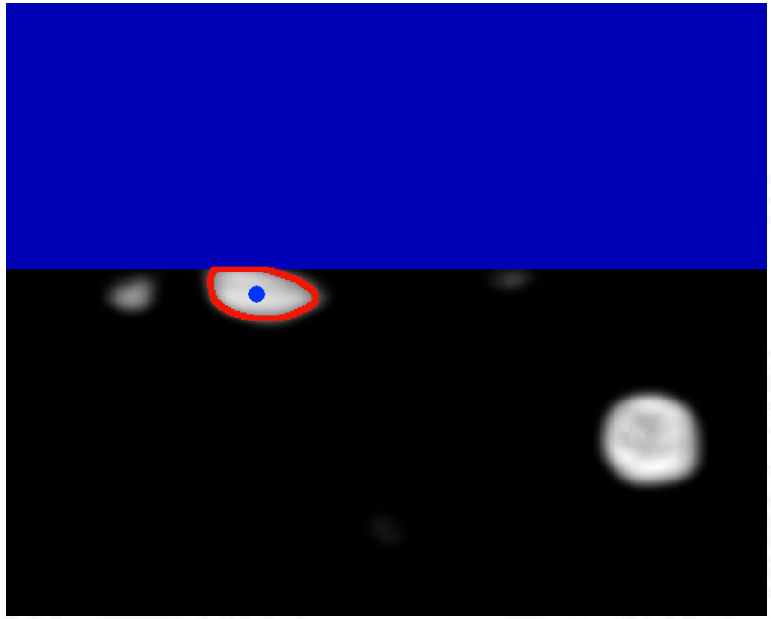
$$\text{Our method: } \Theta(|P|(|M| + |M|log(|M|) + k)) \tag{4}$$

$$\text{Conventional method: } \Theta(|P|(|M|)) \tag{5}$$

Edge Cases II



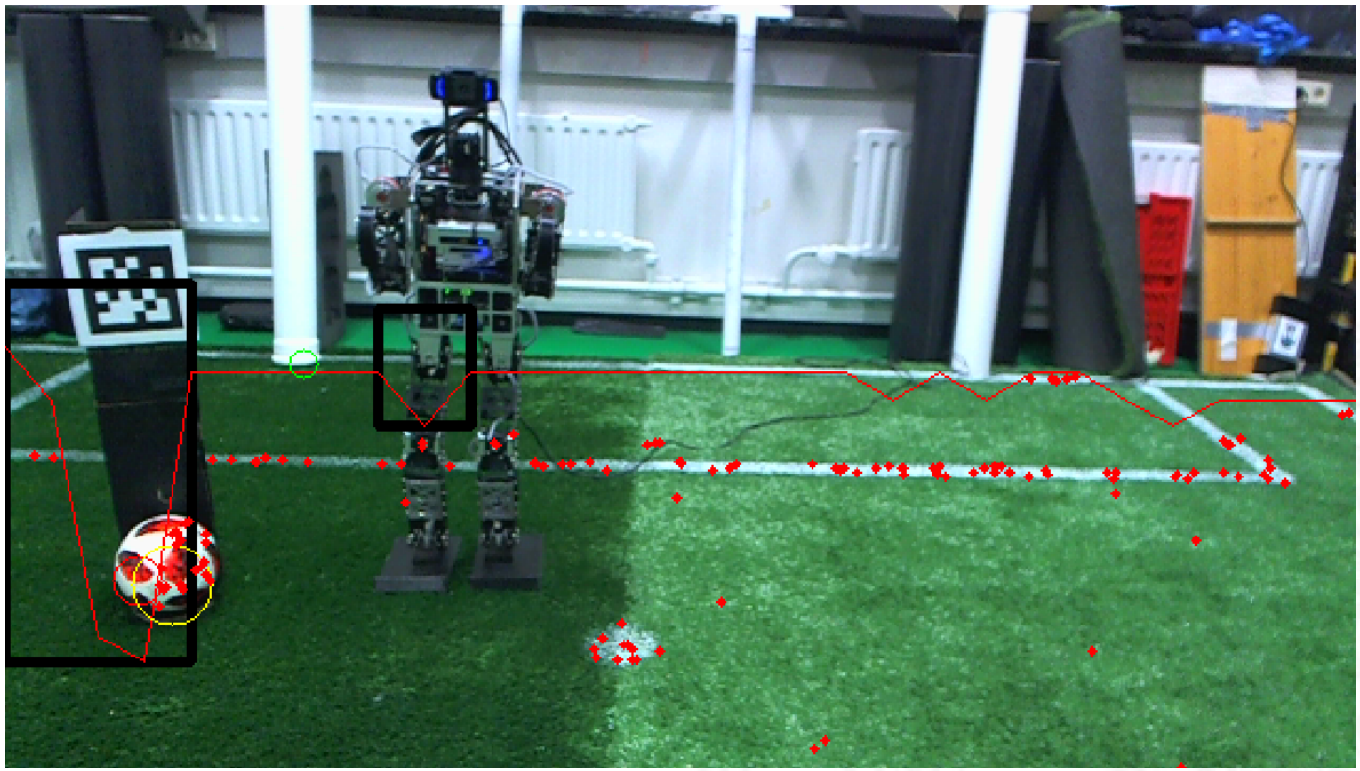
(a)



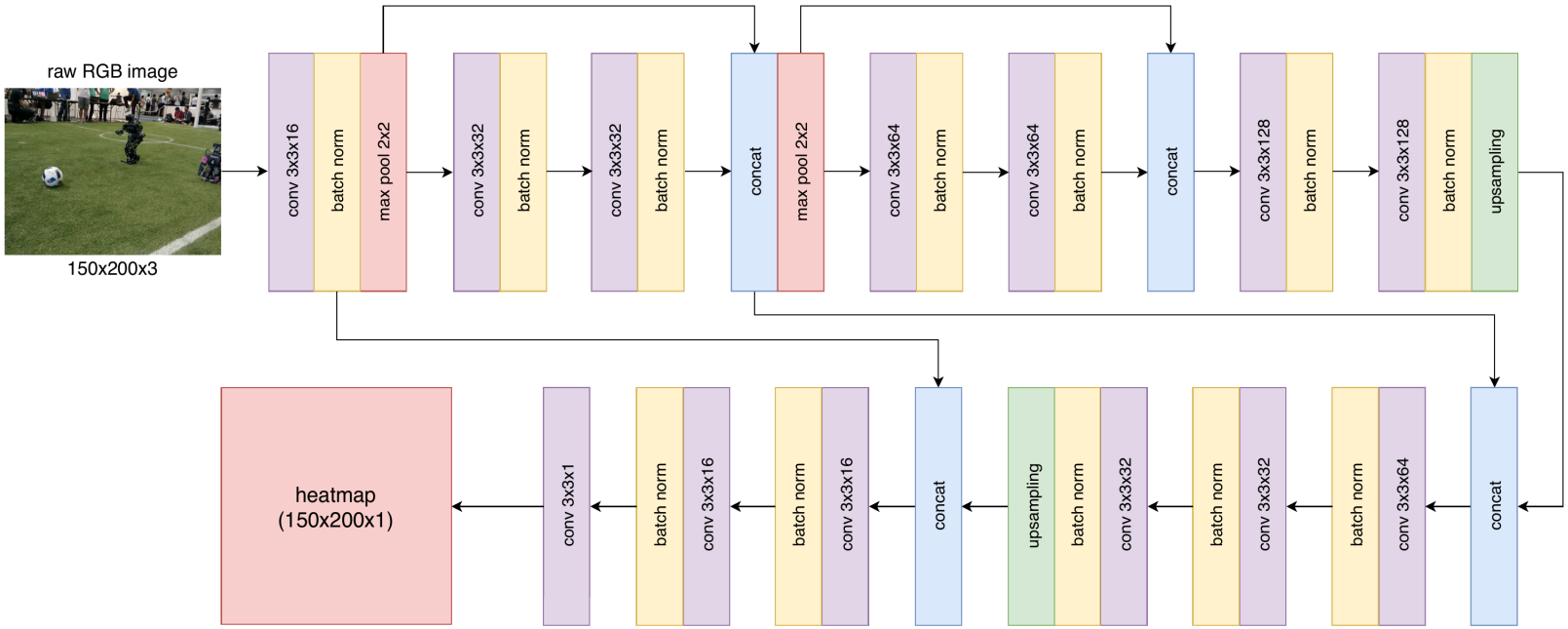
(b)

False positive activations in the FCNN output and the resulting error in the post-processing.

Vision Pipeline



FCNN



FCNN model used in this work [SBB18]