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# Deep Learning Based Measurement Model for Monte Carlo Localization in the RoboCup Humanoid League

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**Technische Aspekte Multimodaler Systeme**

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# Outline

# Motivation

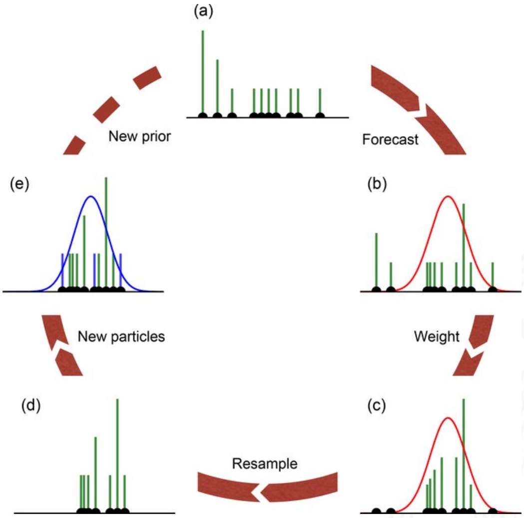

Source: `bit-bots.de`

# Particle Filter



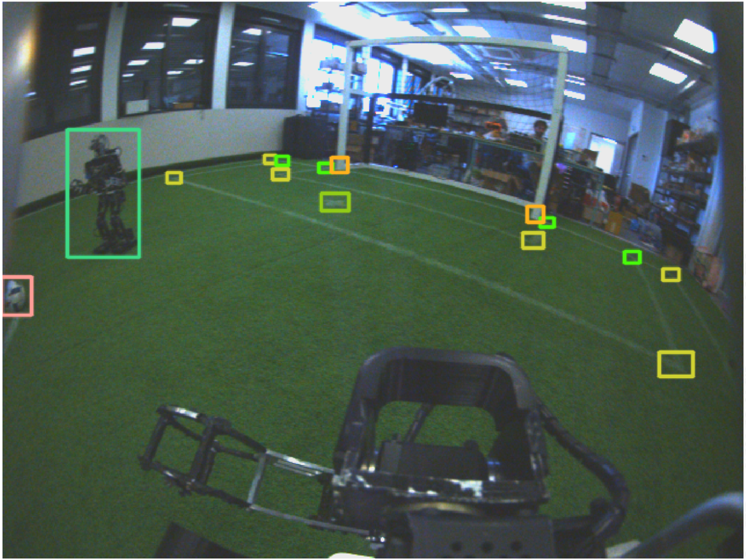
- approximate belief about state with particles
- update particles
  - prediction
  - measurement
  - resampling
- state here: $(x, y, \theta)$

# Particle Filter steps




Steps of the particle filter from [BBR19]

- Rhoban [ABB+24] - field features and goalposts

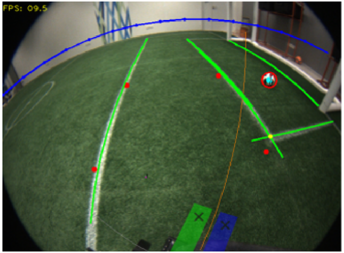


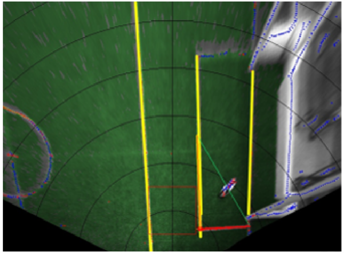
# Related Work - RoboCup

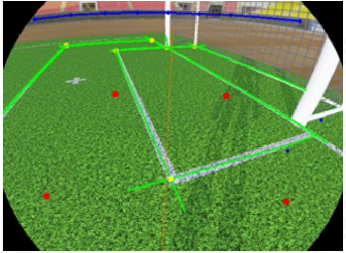
- CIT [HKK+23] - lines and goalposts

# Related Work - RoboCup

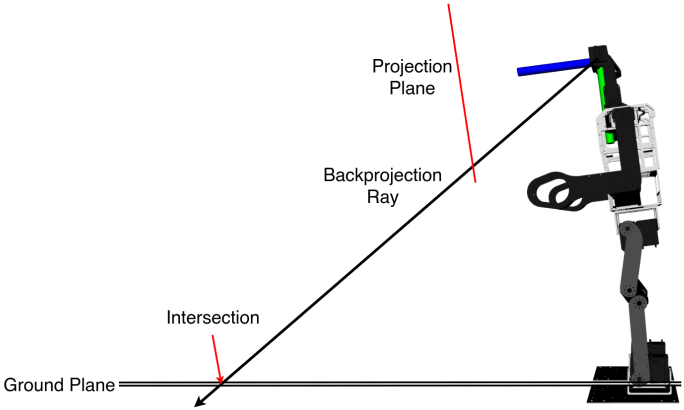
- StarKit [DKL$^+$22] - Hough Transformed Lines





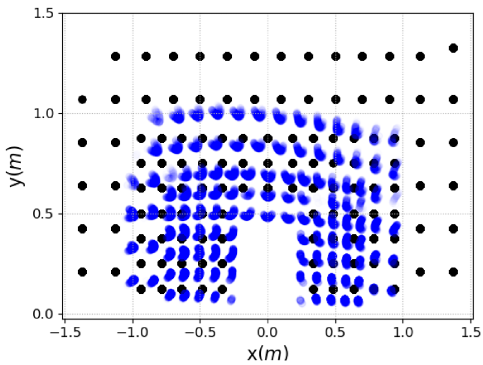
# Interlude - Inverse Perspective Mapping

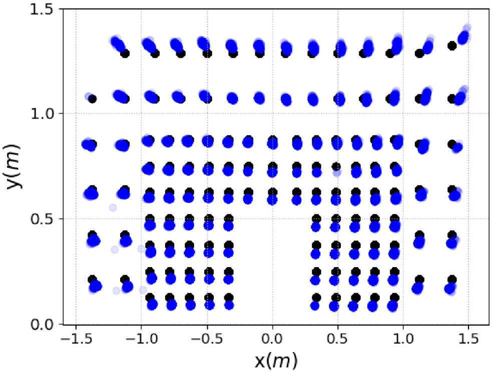



[Gül19]

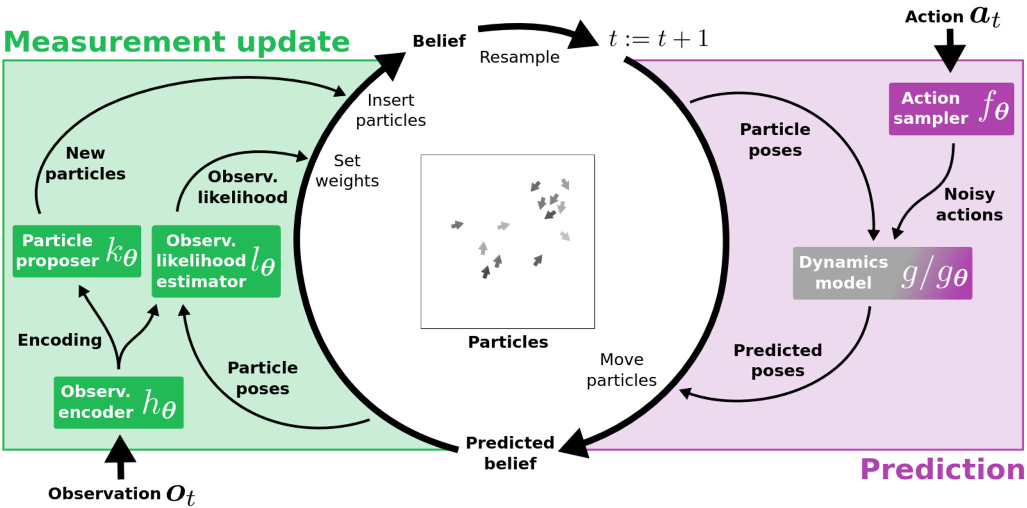
# Related Work - RoboCup

- Reprojection Problematic [dSdAMY+24]



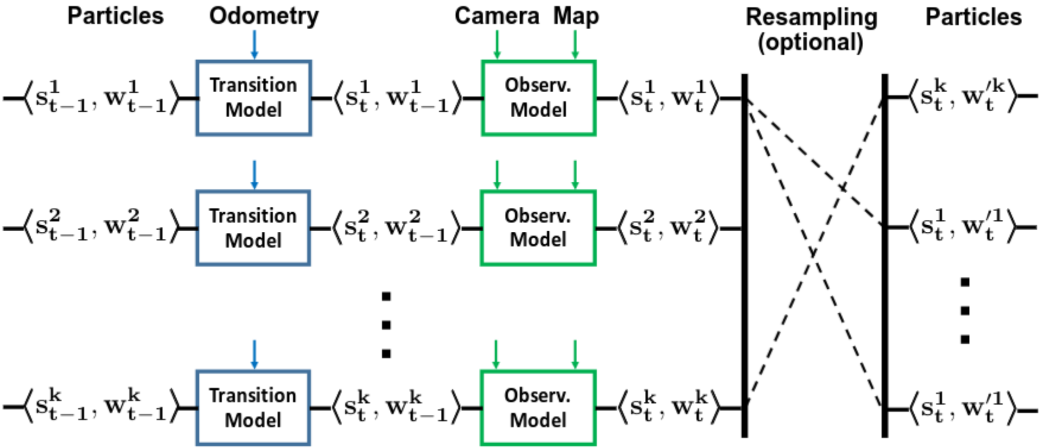



# Related Work



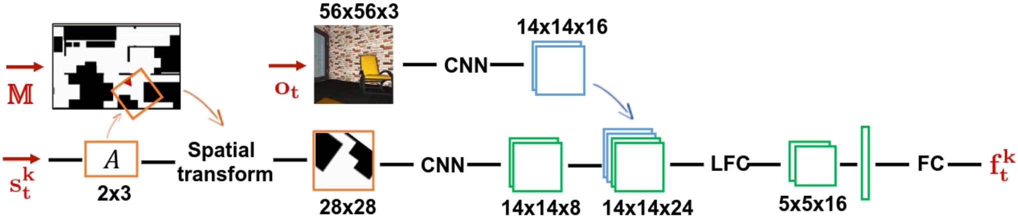

Jonschkowski et al.: Differentiable Particle Filters[JRB18]

# Related Work




Karkus et al.: Particle Filter Networks with Application to Visual Localization [KHL18]

# Related Work

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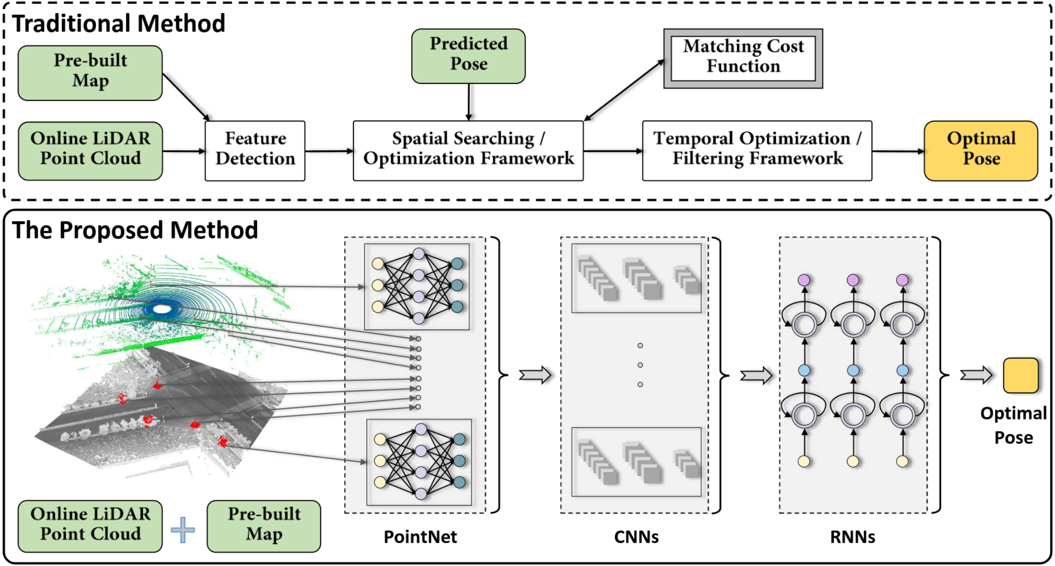
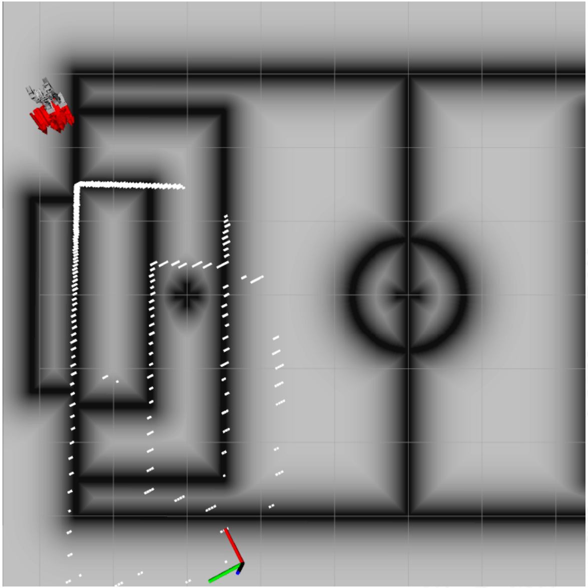


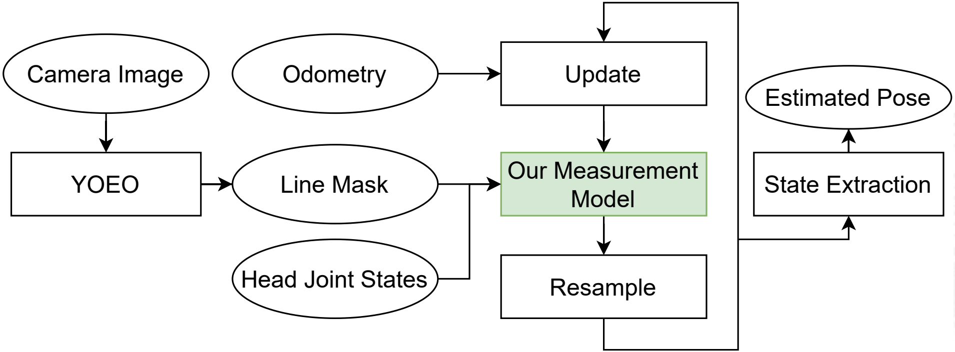

Lu et al.: L3-Net: Towards Learning based LiDAR Localization for Autonomous Driving [LZW+19]

# Baseline Example



Robot incorrectly localized using baseline approach.

# Approach - Overview

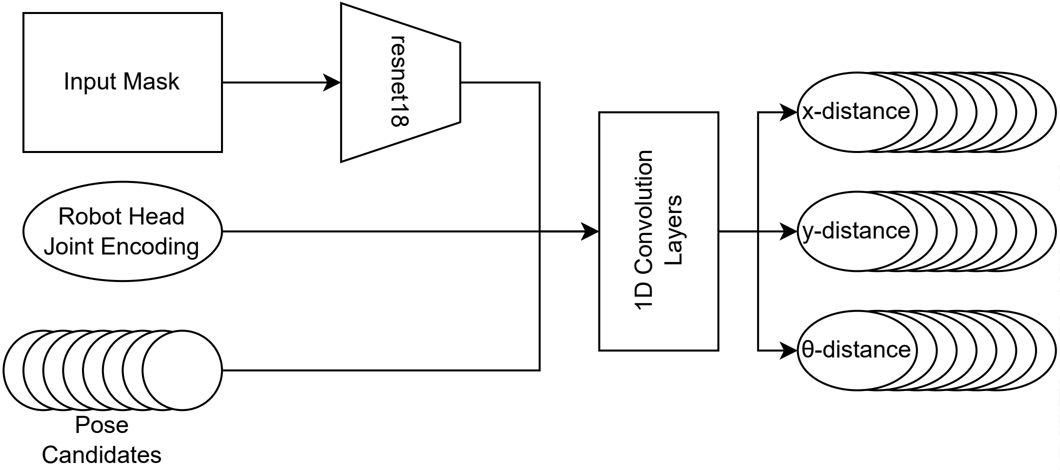



System Overview

# Approach - Example Input

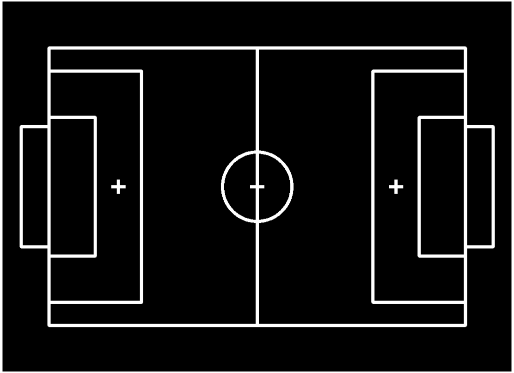
Example YOEO [VGBZ21] output image

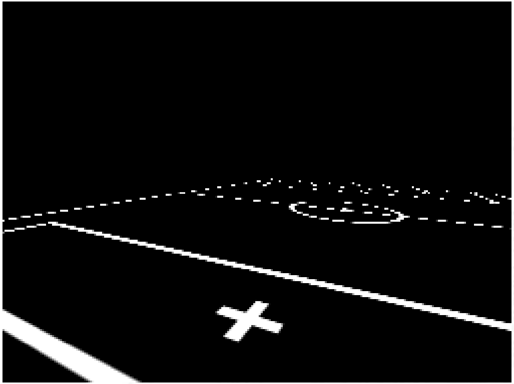
# Approach - Network Architecture




CNN architecture

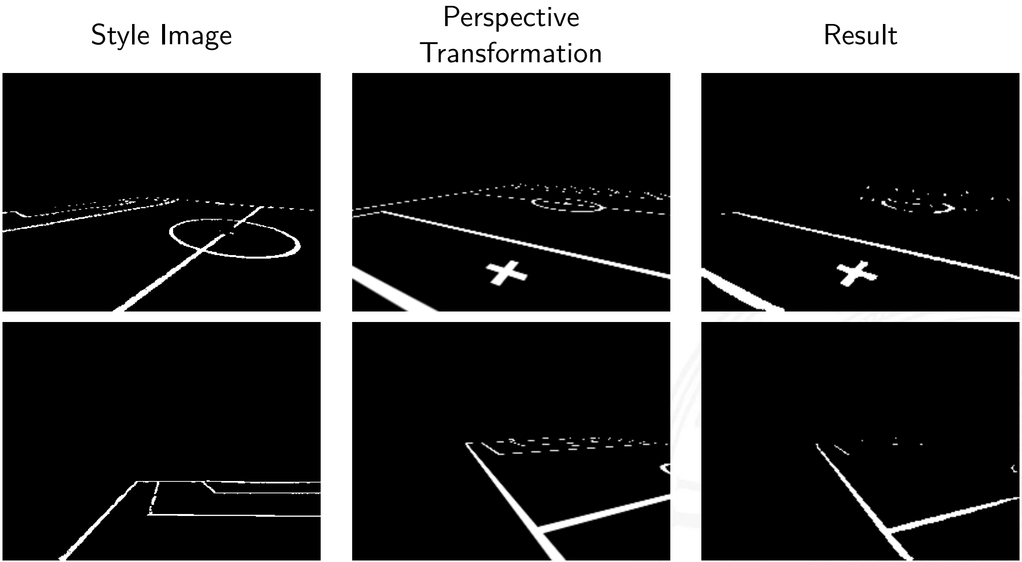
# Approach - Data Generation





Data Generation

# Approach - Style Transfer




Style transfer using CAST [ZTD+23]

# Approach - Data Generation

- draw 128 poses from normal distribution around generation pose
- calculate distances $\Delta x$, $\Delta y$, $\Delta yaw$ as labels

# Approach - Training



- $\sim$8 hours on perspective transformation
- $\sim$12 hours fine tuning on style transfer (mostly caused by inefficient programming)
- on RTX4090

# Approach - Integration



- Serialize PyTorch model using TorchScript
- C++ Torch bindings
- more painful than you think

# Approach - Weighing Function



$$\omega_p = \frac{1}{|\Delta x_p| + |\Delta y_p| + |\Delta yaw_p|}$$

- $\omega_p$ weight of particle $p$
- $\Delta x_p$ estimated linear distance in x direction between particle and robot pose
- $\Delta y_p$ estimated linear distance in y direction between particle and robot pose
- $\Delta yaw_p$ estimated angular distance around z axis between particle and robot pose

# Approach - Video

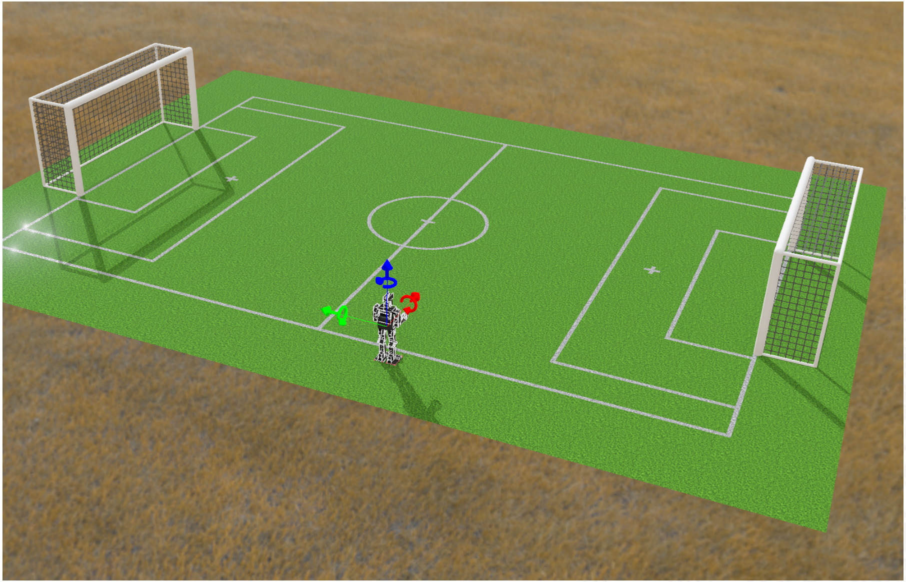
Video Time

# Evaluation

Three experiments

- Global Localization
- Pose Tracking
- Angular Error

# Evaluation



Evaluation Environment

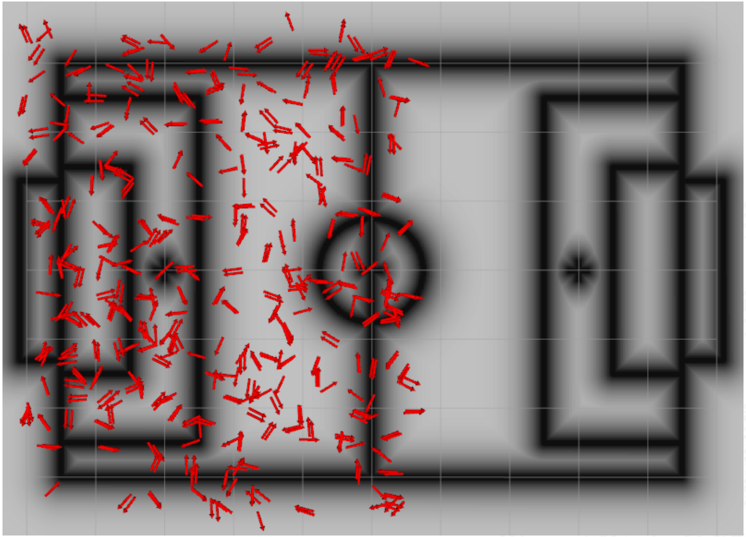
# Global Localization - Experiment Setup



1. Robot is placed at random pose
2. Particle filter is initialized
3. 10 seconds is allowed for convergence
4. Distance between particle filter estimate and ground truth is measured

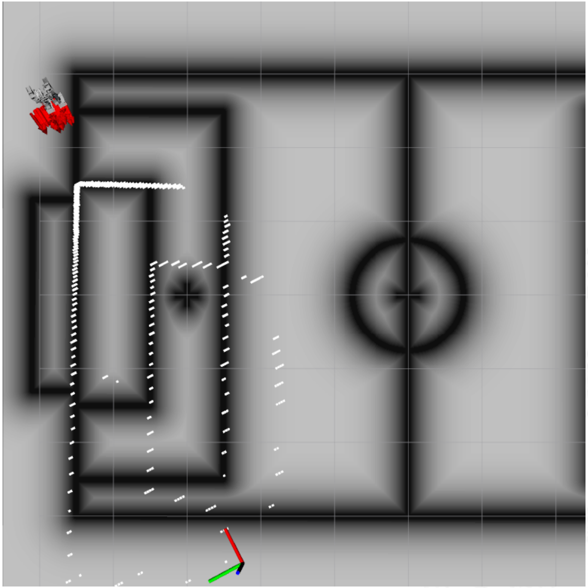
# Global Localization - Initialization





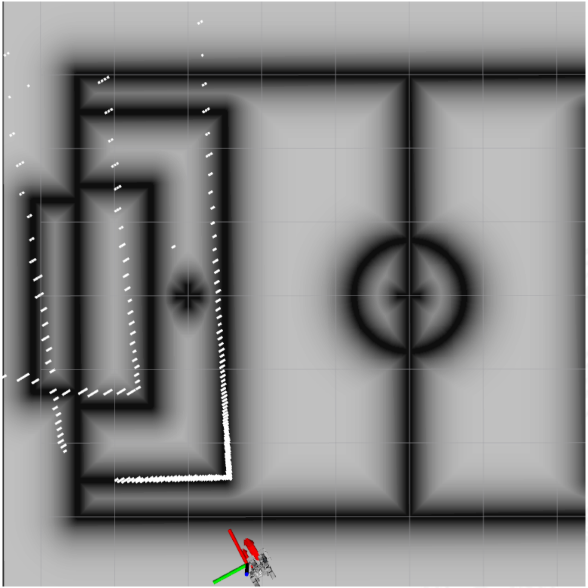
Particles after initialization on one field half.

# Global Localization - Example



Robot incorrectly localized using baseline approach.

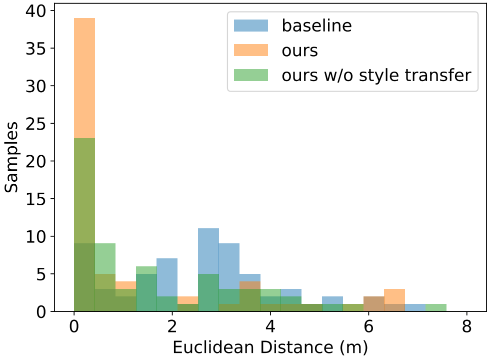
# Global Localization - Example

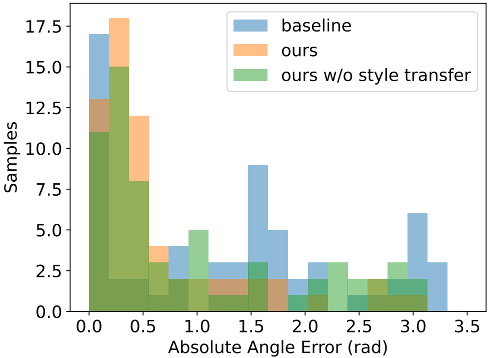


Robot correctly localized

# Global Localization - Results






Quantitative results for global localization.

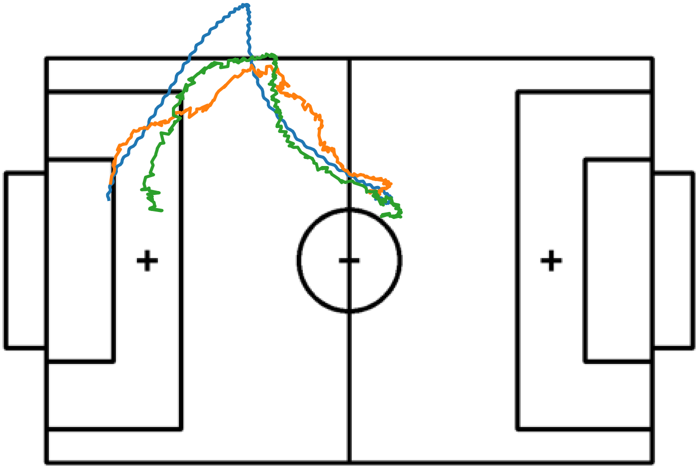
# Global Localization - Results



Performance of the global localization experiment for Euclidean distance error $d$ and absolute angle error $\alpha$.

| Approach | median $d$ | mean $d$ | $\sigma$ $d$ | median $\alpha$ | mean $\alpha$ | $\sigma$ $d$ |
|---|---|---|---|---|---|---|
| Baseline | 2.711 | 2.605 | **1.672** | 1.475 | 1.347 | 1.078 |
| Ours w/o style transfer | 0.793 | 1.660 | 1.723 | 0.467 | 0.961 | 0.948 |
| Ours | **0.263** | **1.332** | 1.982 | **0.383** | **0.669** | **0.737** |

# Pose Tracking - Example

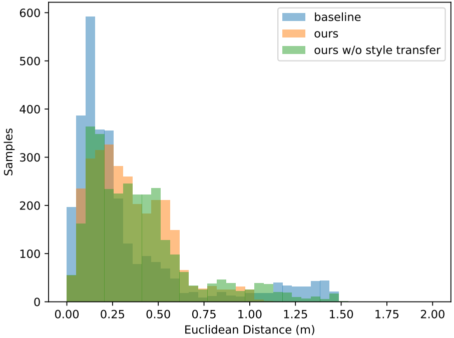


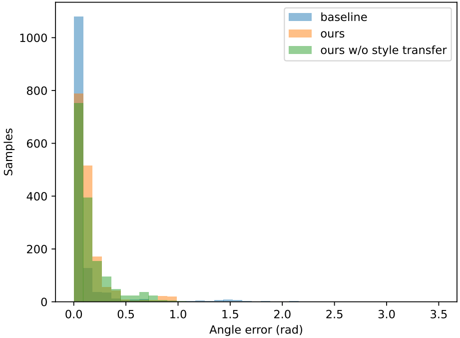
Example trajectory of the Pose Tracking experiment

# Pose Tracking - Experiment Setup

1. Robot is placed at random pose
2. Localization is initialized and allowed to settle
3. Sequence of generated velocities is commanded to walking engine
4. Pose produced by localization and ground truth is measured each step

# Pose Tracking - Results




Quantitative pose tracking localization.

# Pose Tracking - Results

Performance of the pose tracking experiment for Euclidean distance $d$ and absolute angle error $\alpha$.

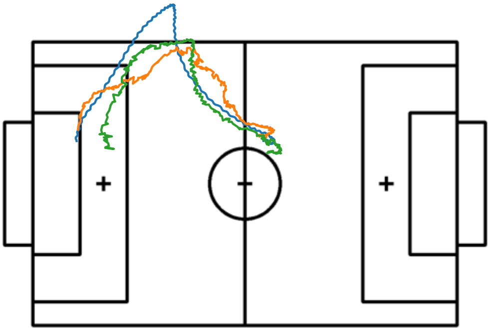
| Approach | median $d$ | mean $d$ | $\sigma$ $d$ | median $\alpha$ | mean $\alpha$ | $\sigma$ $d$ |
|---|---|---|---|---|---|---|
| Baseline | **0.201** | **0.331** | 0.353 | **0.043** | **0.100** | 0.228 |
| Ours w/o style transfer | 0.329 | 0.393 | 0.286 | 0.088 | 0.140 | 0.209 |
| Ours | 0.307 | 0.346 | **0.211** | 0.077 | 0.110 | **0.167** |

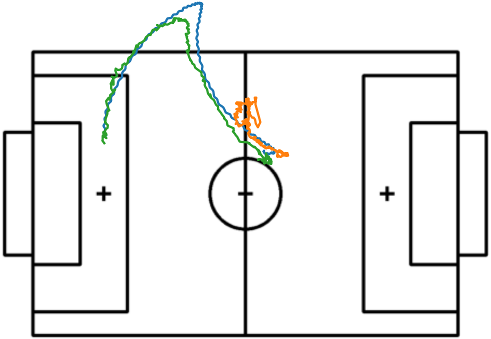
# Angular Error - Motivation



- Baseline approach relies on good calibration
- Many falls $\rightarrow$ bad calibration
- Especially problematic for long distance measurements

# Angular Error - Example Pose Tracking





Ground truth blue, ours green, baseline orange

# Angular Error - Results

| Head Tilt Error | Approach | median $d$ | mean $d$ | $\sigma$ $d$ | median $\alpha$ | mean $\alpha$ | $\sigma$ $d$ |
|---|---|---|---|---|---|---|---|
| $0^\circ$ | Baseline | **0.201** | **0.331** | 0.353 | **0.043** | **0.100** | 0.228 |
| | Ours | 0.307 | 0.346 | **0.211** | 0.077 | 0.110 | **0.167** |
| $3^\circ$ | Baseline | **0.229** | 0.402 | 0.416 | **0.047** | 0.166 | 0.505 |
| | Ours | 0.334 | **0.393** | **0.254** | 0.075 | **0.122** | **0.208** |
| $-3^\circ$ | Baseline | **0.245** | **0.393** | **0.461** | **0.045** | **0.116** | 0.240 |
| | Ours | 0.316 | 0.440 | 0.920 | 0.080 | **0.115** | **0.164** |
| $5^\circ$ | Baseline | 0.530 | 0.826 | 0.756 | 0.179 | 0.404 | 0.706 |
| | Ours | **0.364** | **0.436** | **0.334** | **0.085** | **0.148** | **0.227** |
| $-5^\circ$ | Baseline | 0.384 | 0.702 | 0.738 | 0.105 | 0.186 | 0.266 |
| | Ours | **0.369** | **0.413** | **0.270** | **0.092** | **0.135** | **0.189** |

# Conclusion

- better global localization
- worse performance in pose tracking in idealized conditions
- better robustness to significant angular error
- (better computational performance)

# Future Work

- introduce IMU measurement to better take orientation into account in network
- vision transformers
- style transfer and deploy on real robot

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[VGBZ21] Florian Vahl, Jan Gutsche, Marc Bestmann, and Jianwei Zhang, *Yoeo–you only encode once: A cnn for embedded object detection and semantic segmentation*, IEEE International Conference on Robotics and Biomimetics (ROBIO), 12 2021.

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