Learning the Odometry on a Humanoid Robot

Bachelor's Thesis

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Outline

RoboCup

- annual robotics competition
- win against soccer world champions by 2050
- multiple leagues
  - Humanoid Soccer League

Robots in the RoboCup [bit]

Odometry

- integration of motion information
- proprioceptive and exteroceptive sensors
- base for more complex localization algorithms
- legged robots
  - zero velocity assumption
  - step integration

Standard Odometry's disadvantages

- robot's model is inaccurate
  - noisy sensors
  - mechanical deformations
  - actuator's backlash
- stable foot-to-ground-contact assumption often violated
  - slippage

Our approach

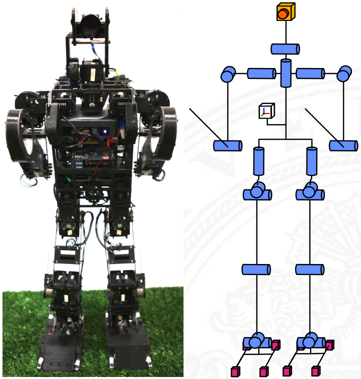
- estimate walking step size based on proprioceptive sensor data
- machine learning
  - systematic error
  - dynamic error
- data generated in simulation and real world

Outline

1. Introduction
2. Basics
3. Related Work
4. Approach
5. Evaluation
6. Conclusion
7. References

Wolfgang OP

- robot platform used in the RoboCup Humanoid League
- 3D printed parts and humanoid structure
- foot pressure sensors, IMU, joint encoders

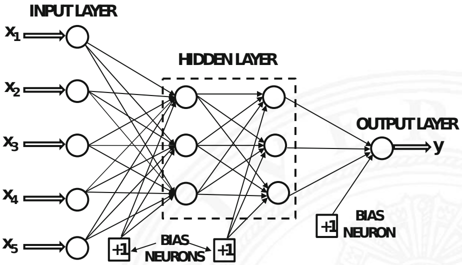


Wolfgang and a schematic representation of its kinematic chain.

Source: [BGVZ21]

Supervised Learning and Neural Networks

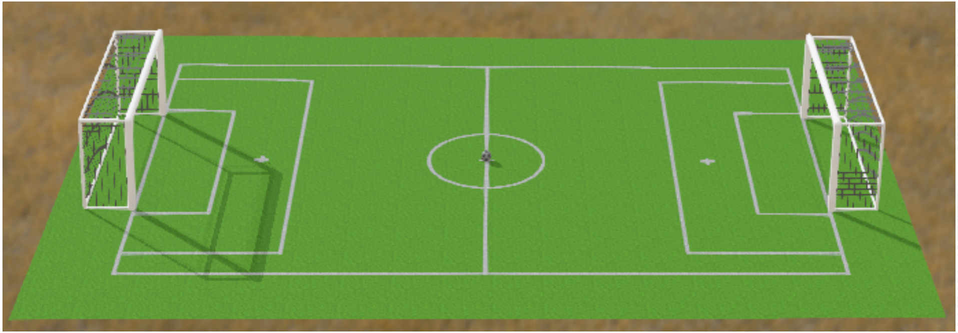
- usage of annotated data
- artificial neural networks
- Multi-Layer Perceptron
  - fully connected layers
- Recurrent Neural Networks
  - temporal context
- Long-short-term memory
- many hyperparameters



A multi-layer perceptron [Agg18]

Simulation in Webots

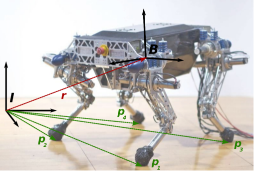
- rigid body simulation
- Humanoid League Virtual Season
- gap between soft- and hardware



Soccer field in Webots

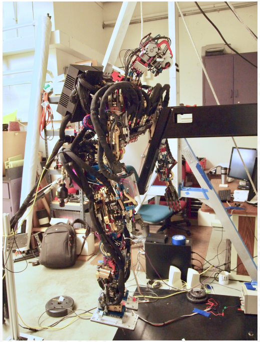
Outline

Kalman Filter-based Approaches



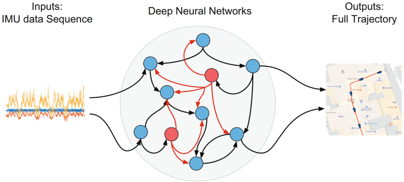
Bloesch et al. use IMU measurements and kinematics in EKF [BHH$^+$13]

Yang et al. place one IMU on each of the robot's calves [YZBM23]



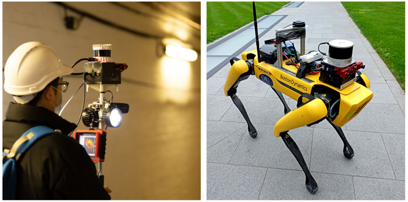
Rotella et al. make changes to fit a humanoid robot [RBRS14] [sar]

Neural Network-based Odometry



Chen et al. trained a recurrrent neural network on raw IMU data [CLMT18]

Rouxel et al. compute transformation of head pose of humanoid [RPH+16]



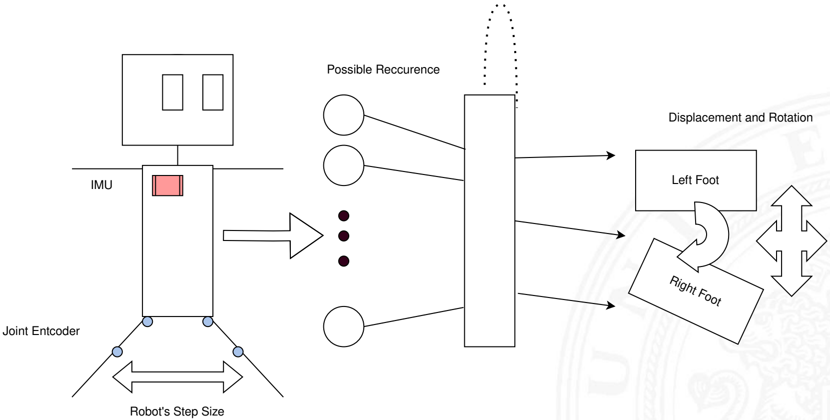
Buchanan et al. train an LSTM and a transformer to predict a device-specific IMU bias [BAC+2a]

Summary of Related Work

- many approaches for odometry regarding quadruped robots
- IMU data and kinematics frequently used
- supervised learning and recurrent models
- mostly used to estimate a velocity
  - higher computational resources
- few approaches use data gained in simulation

Outline

Our approach



Overview of approach.

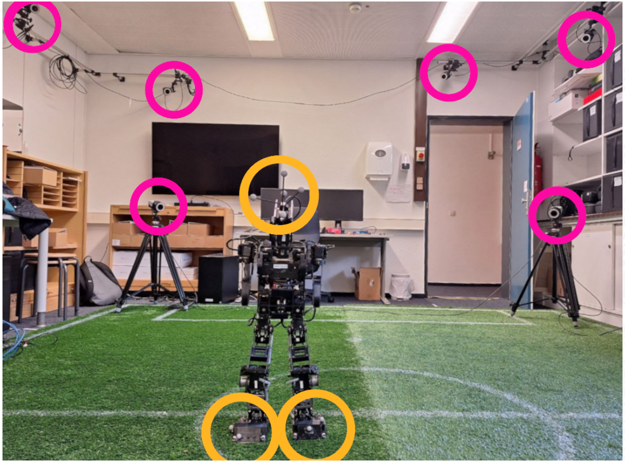
Data Collection in Webots

- collect large dataset quickly
- random velocity sampling
- record relevant data of robot
- label from simulation interface
- simulated 10.000 runs equalling 39 hours of walking

Webots Wolfgang model

Data Collection in the Real World

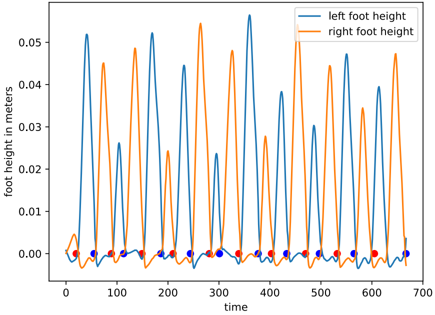
- motion capture system
- conservative sampling
- record robots' feet and head
- label from MoCap system
- 45 minutes of raw walk sequences



Motion Capture Setup

Data Processing

- remove invalid data
  - falls
  - oclusions
- align the data with foot step times
  - lower foot switches
- normalize via z-score



The height of the soles during walking.

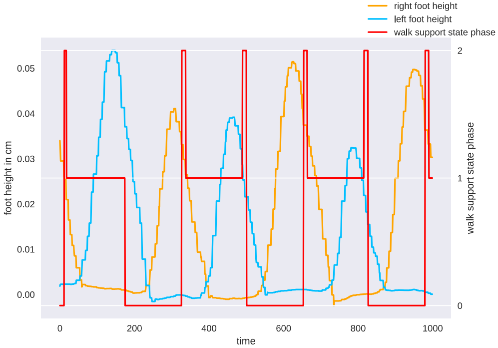
Hyperparameter Optimization

- Optuna study using Tree-structured Parzen Estimator [OTW+22]

Parameter	Values
Architecture	MLP, RNN, LSTM
Optimizer	Adam, SGD
Loss Function	MSE, MAE
Acitvaton Function	ReLU, tanh, sigmoid
Learning Rate	[0.0001, 0.1]
Dropout	[0.01, 0.15]
Epochs	[10, 50]
Number of Hidden Layers	[1, 5]
Layer Size	[4, 128]
Recurrent Size (LSTM/RNN only)	[4, 64]
Recurrent Depth (LSTM/RNN only)	[1, 16]
Batch Size	[128, 512]

The hyperparameters used for the neural network architectures. The values presented in [·] are intervals.

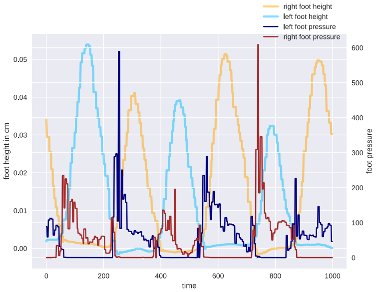
Current Step Detection



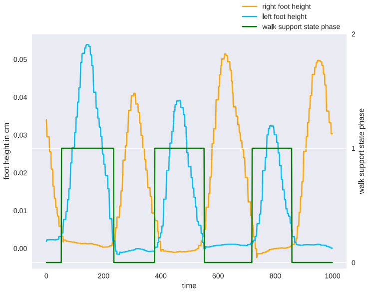
Walk support state and height of the soles.

- based on internal model
- independent of actual ground contact

Step Detection



Pressure detected by soles' cleats and sole heights.

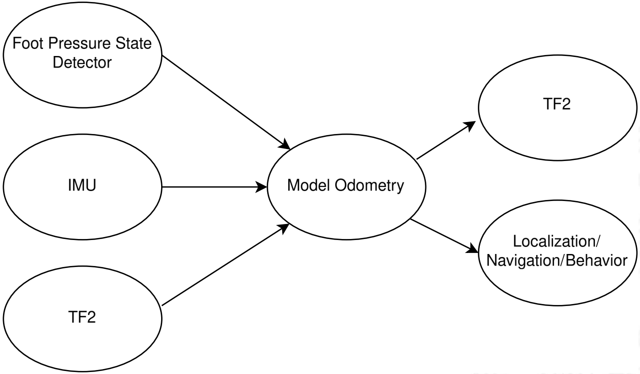


Foot pressure based walk support state and height of the soles.

- cleats measure pressure
- high pressure correlates with ground contact

- low-pass filtered sum of the cleats
- calculate derivatives and identify roots

Integration



The model odometry takes input from the foot pressure state detector, IMU and the kinematics from TF2.

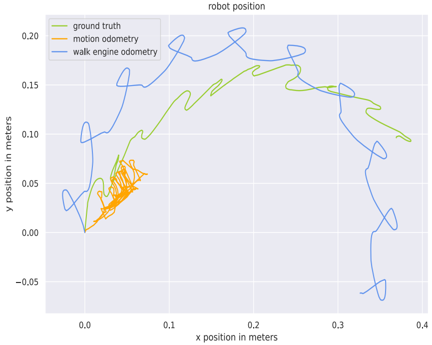
- special priority queue

Outline

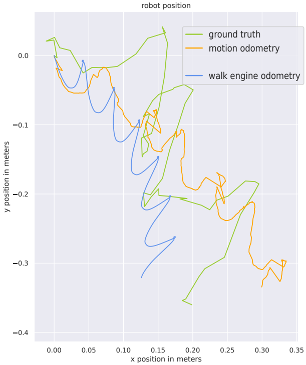
Baseline

- Walk Engine Odometry
  - based on splines generated by the walk engine
  - does not use external measurements
  - steps detected by internal model
- Motion Odometry
  - based on joint encoder measurements and IMU data
  - steps also detected by internal model

Baseline



Walk engine and motion odometry with ground truth in simulation.



Walk engine and motion odometry with ground truth in real world.

SimNet and RealWorldNet

Parameter	SimNet	RealWorldNet
Architecture	LSTM	LSTM
Optimizer	Adam	Adam
Loss Function	MAE	MSE
Acitvaton Function	relu	tanh
Learning Rate	0.007	0.0261
Dropout	0.0688	0.1224
Number of Hidden Layers	1	1
Layer Size	87	125
Recurrent Size (LSTM/RNN only)	52	63
Recurrent Depth (LSTM/RNN only)	3	2
Epochs	81	85
Batch Size	512	497

Best performing hyperparameters.

- LSTM
  - importance of considering information from previous steps
- dropout of RealWorldNet is twice as high
  - real-world data is nosier

Experiments

- approaches vs. ground truth
  - five seconds
  - completly unseen data
  - sliding window
- SimNet on simulation data
- RealWorldNet on real world data
- SimNet on real world data

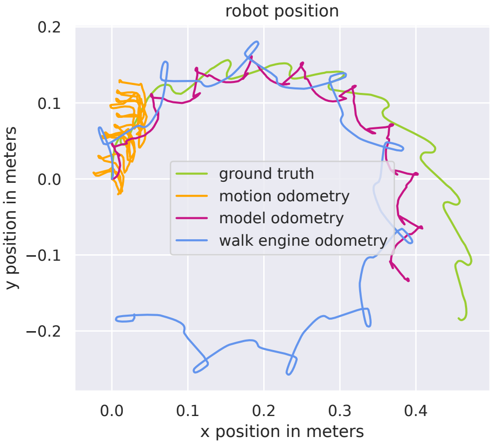
SimNet on Simulation Data

SimNet on sim data	Motion Odometry	Walk Engine Odometry	Model Odometry
total deviation in m after 5sec	0.4887	0.2761	**0.0506**
x deviation in m after 5sec	0.3428	0.1794	**0.0308**
y deviation in m after 5sec	0.2789	0.1716	**0.0334**
yaw deviation in rad after 5sec	1.1851	1.3609	**0.125**

Performance of the odometry approaches in simulation using the SimNet.

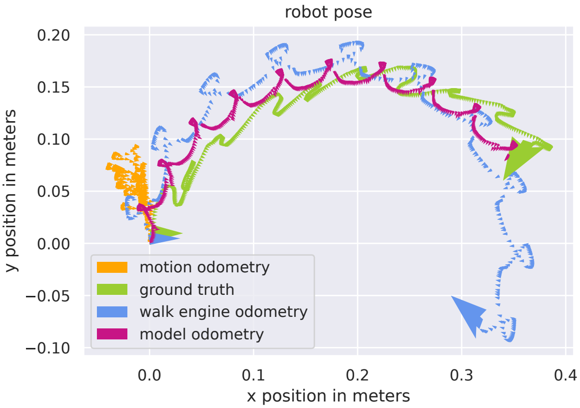
- model odometry outperforms both existing approaches
- big difference in rotational component

SimNet on Simulation Data



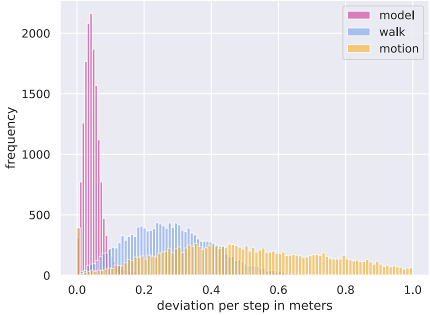
Walk engine and motion odometry with ground truth.

SimNet on Simulation Data Rotation

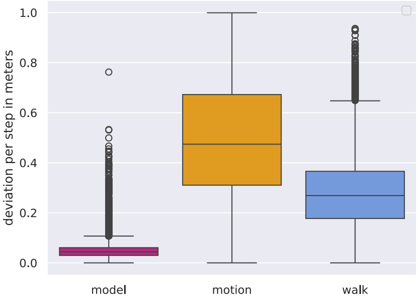


Quiver plot of the odometry approaches using SimNet on simulation data.

SimNet on Simulation Data Distribution and Boxplot



Histogram of the odometry approaches using the SimNet on simulation data.



Boxplots of the odometry approaches with the SimNet on simulation data.

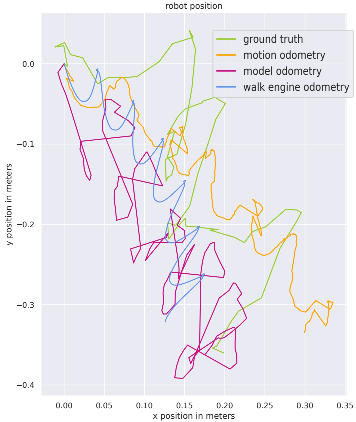
RealWorldNet on Real-World Data

RealNet on real data	Motion Odometry	Walk Engine Odometry	Model Odometry
total deviation in m after 5sec	0.2269	0.2107	**0.1795**
x deviation in m after 5sec	0.16	0.1328	**0.097**
y deviation in m after 5sec	0.1258	0.1321	**0.1285**
yaw deviation in rad after 5sec	0.29	0.4961	**0.287**

Performance of the odometry approaches in the real world using the RealWorldNet.

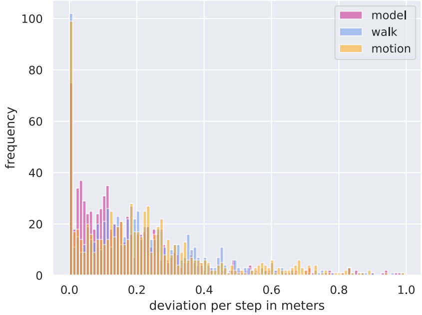
- model odometry still outperforms the other two approaches
- baseline approaches perform better in the real world compared to simulation

RealWorldNet on Real-World Data

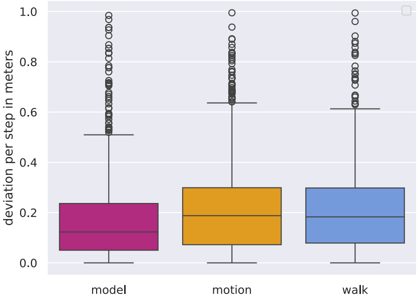


Walk trajectory of the odometry approaches in the real world using the RealWorldNet.

RealWorldNet on Real-World Data Distribution and Boxplot



Histogram of the odometry approaches using the RealWorldNet on real-world data.



Boxplots of the odometry approaches using the RealWorldNet.

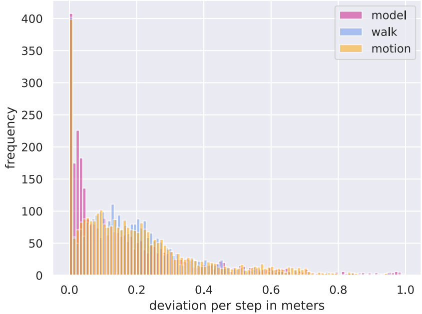
SimNet on Real-World Data

SimNet on real data	Motion Odometry	Walk Engine Odometry	Model Odometry
total deviation in m after 5sec	0.2041	0.1849	**0.1794**
x deviation in m after 5sec	0.1433	**0.1214**	0.1276
y deviation in m after 5sec	0.1144	0.1142	**0.0989**
yaw deviation in rad after 5sec	**0.3067**	0.4921	0.3427

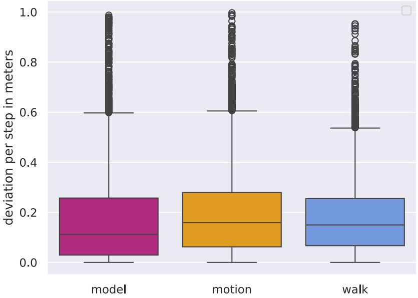
Performance of the odometry approaches in the real world using the SimNet.

- model odometry still outperforms other two approaches in terms of total deviation

SimNet on Real-World Data Distribution and Boxplot



Histogram of the odometry approaches using the SimNet on real-world data.



Boxplot of the odometry approaches using the SimNet on real-world data.

Outline

Conclusion

- lightweight odometry based on a neural network
- generated data in simulation and real world
- model odometry can be trained on simulation data and transferred to the real world without adjustment
- integrated the neural network into the existing software stack of the Hamburg Bit-Bots

Future Work

- calculate velocity factors to estimate directional velocity for bipedal robots
- incorporate IMU data over larger time frames to better estimate slippages
- pre-train model on data from simulation before training on data from real world
- use step detector for label generation

References

[Agg18] Charu C Aggarwal, *Neural networks and deep learning*, 2018.

[BAC+2a] Russell Buchanan, Varun Agrawal, Marco Camurri, Frank Dellaert, and Maurice Fallon, *Deep imu bias inference for robust visual-inertial odometry with factor graphs*, IEEE Robotics and Automation Letters **8** (2022a), no. 1, 41–48.

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[CLMT18] Changhao Chen, Xiaoxuan Lu, Andrew Markham, and Niki Trigoni, *Ionet: Learning to cure the curse of drift in inertial odometry*, Proceedings of the AAAI Conference on Artificial Intelligence, vol. 32, 2018.

[OTW+22] Yoshihiko Ozaki, Yuki Tanigaki, Shuhei Watanabe, Masahiro Nomura, and Masaki Onishi, *Multiobjective tree-structured parzen estimator*, Journal of Artificial Intelligence Research **73** (2022), 1209–1250.

[RBRS14] Nicholas Rotella, Michael Bloesch, Ludovic Righetti, and Stefan Schaal, *State estimation for a humanoid robot*, 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, 2014, pp. 952–958.

[RPH+16] Quentin Rouxel, Gregoire Passault, Ludovic Hofer, Steve N'Guyen, and Olivier Ly, *Learning the odometry on a small humanoid robot*, 2016 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2016, pp. 1810–1816.

[sar]

References (cont.)

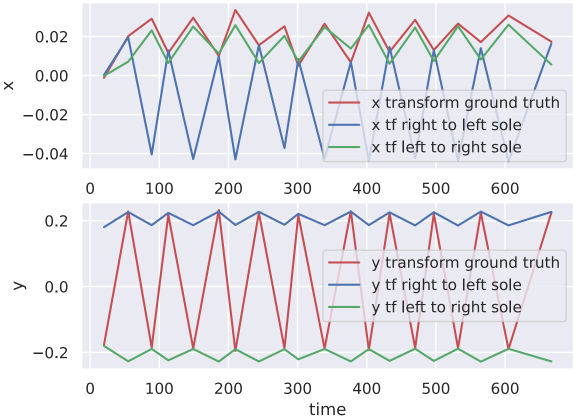
[YZBM23] Shuo Yang, Zixin Zhang, Benjamin Bokser, and Zachary Manchester, *Multi-imu proprioceptive odometry for legged robots*, 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2023, pp. 774–779.

SimNet and RealWorldNet Direct Comparison

SimNet and RealWorldNet on real data	Motion Odometry	Walk Engine Odometry	[SimNet] Odometry	[RealWorld-Net] Odometry
total deviation in m after 5sec	0.2269	0.2107	0.2062	**0.1795**
x deviation in m after 5sec	0.16	0.1328	0.1369	**0.097**
y deviation in m after 5sec	0.1258	0.1321	**0.1221**	0.1285
yaw deviation in rad after 5sec	0.29	0.4961	0.4524	**0.287**

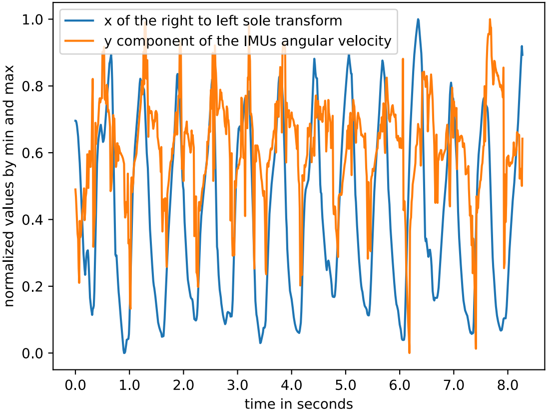
Performance of the odometry approaches in the real world using the SimNet and RealWorldNet.

Correlation TF and Step Size



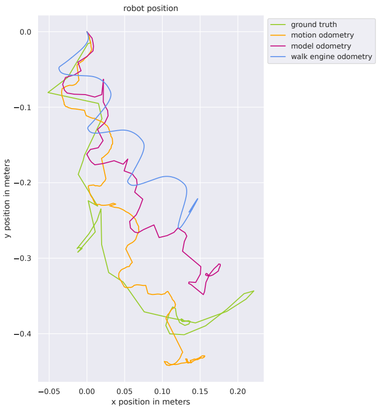
Similarity between tfs and ground truth.

Correlation IMU and Step Size



Similar patterns in the data for IMU and transform.

SimNet on Real-World Data



SimNet on real-world data trajectory.