### Activity recognition and trajectory estimation using IMU and Lidar data

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# Activity recognition and trajectory estimation using IMU and Lidar data

#### Purpose

Propose a new pipeline for human activaty recognition and trajectory estimation with Inertial Measurement Unit (IMU) sensors.

#### Motivation

- Indoor trajectory estimation
- Measure activity level
- Human activity recognition

#### Approaches and methods

- Parametr
- Collect dataset human activity recognition and trajectory estimation (in process)
- Smooth ground truth to reduce noise
- Use augmentations for robustness
- Use conditional GANs for smart data augmentation (future)
- Combine Lidar data with gyroscope data to reduce bias (future)

### Problem statement

Find the superposition of functions  $F_{\rm tr}$ , which transforms sensors data to trajectory estimation and  $F_{\rm st}$  - to step labels.

#### Data

- $\mathbf{0} \ \mathcal{A} \in \mathbb{R}^{3 \times T}$  accelerometer readings
- **2**  $\mathcal{W} \in \mathbb{R}^{3 \times T}$  gyroscope readings

### Minimization of loss function

$$\underset{F_{\text{tr}}, F_{\text{st}}}{\operatorname{arg\,min}} \mathcal{L}\left(\left(F_{\text{tr}}\left(\mathcal{A}, \mathcal{W}\right), \mathcal{T}\right)\right) \tag{1}$$

### Metrics

#### RMSE

Absolute trajectory error (**RMSE**) defined as the root mean square error between predicted and ground truth trajectories:

$$\mathcal{L}_{tr}(\hat{\mathcal{T}}, \mathcal{T}) = \left(\frac{1}{N} \sum_{i=1}^{N} \left( (\hat{t}_{x_i} - t_{x_i})^2 + (\hat{t}_{y_i} - t_{y_i})^2 \right) \right)^{1/2}$$
 (2)

#### MHE

Mean Heading Angle Error: Average angle between velocities during whole experiment / (length /100 m).

### Metrics

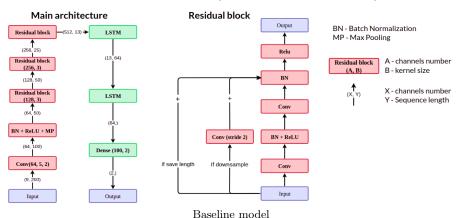
#### **GAP**

Distance between the first and the last points (GAP):

$$\mathcal{G}_{\text{tr}}\left(\hat{\mathcal{T}}\right) = \left(\left(\hat{t}_{x1} - \hat{t}_{xN}\right)^2 + \left(\hat{t}_{y1} - \hat{t}_{yN}\right)^2\right)^{1/2} \tag{3}$$

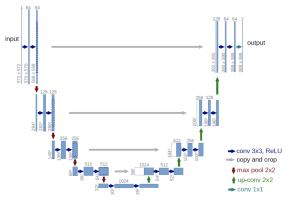
#### Baseline model

ResNet-18 without the last layer stacked with two LSTM layers



# Unet pipeline and results

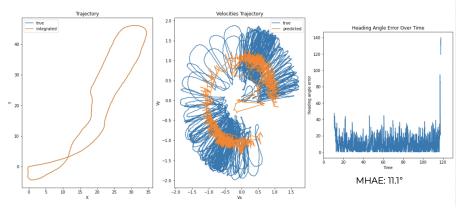
### **UNet: results**



#### 5 epochs training on RuDaCoP

	ResNet	UNet
MPE, %	10.5±0.5	8.0±0.6
MHAE,°	11.3±0.9	7.0±0.6
RMSE, m	11.2±1.4	10.0±1.5
Gap, m	18.6±3.0	15.5±3.2

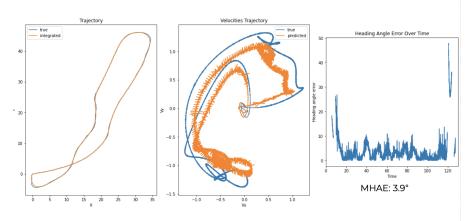
# MHAE metric: original data



Ground truth trajectory with out smoothing

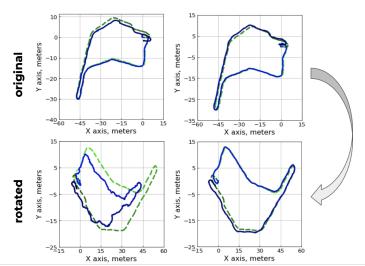
## Smoothing ground truth trajectory

# MHAE metric: smoothed data - fft



Smoothed ground truth trajectory

# **Augmentations: recall**



#### Future work

- Collecte dataset for activity recognition and trajectory prediction in 3D space for testing hypothesis.
- Use Lidar data (data from camera)
- 3 Use Generative neural network for data augmentation.
- Use open-source data for training as well as collected data.

### Список литературы

- Changhao Chen, Peijun Zhao, Chris Xiaoxuan Lu, Wei Wang, Andrew Markham, and Niki Trigoni. Oxiod: The dataset for deep inertial odometry. arXiv preprint arXiv:1809.07491, 2018
- Amani Jaafer, Gustav Nilsson, and Giacomo Como. Data augmentation of imu signals and evaluation via a semi-supervised classification of driving behavior. arXiv preprint arXiv:2006.09267, 2020
- Hiroki Ohashi, M Al-Nasser, Sheraz Ahmed, Takayuki Akiyama, Takuto Sato, Phong Nguyen, Katsuyuki Nakamura, and Andreas Dengel. Augmenting wearable sensor data with physical constraint for dnn-based human-action recognition.
  - In ICML 2017 Times Series Workshop, pages 6-11, 2017