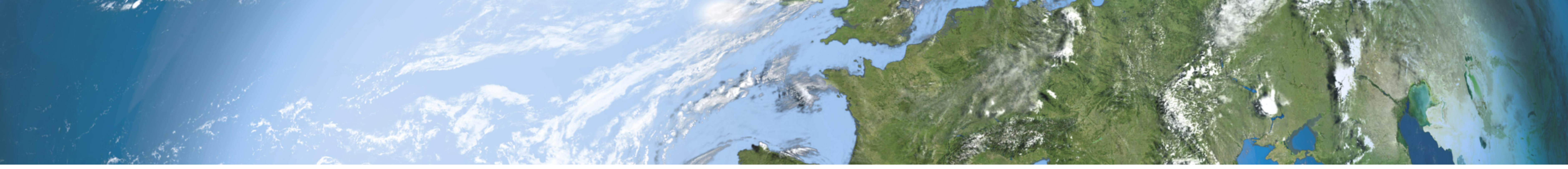

Detecting atypical motion for early awareness of potential safety-critical situations

Identify atypical motion by deviation of actual to predicted trajectory

Atypical behavior

- Real world data is complex, as are situations
- Find general approach, suitable to multiple situations
- Trajectory analyses: rare labeled data or protoypes, use semi-supervised approach

How do critical situations look like? How to identify black spots of infrastructure?

What are atypics?

- Atypical behavior can give hints to unknown safety issues: imagine potholes
- Atypical behavior can be part of a conflict (assuming conflicts are rare events)

Fig. 1: Example for trajectory prediction on ETH Zürich "BIWI Walking Pedestrians dataset". Gray: last 5 observsations, green: actual next 5 points, red: predicted.

Approach: Detect unexpected behavior

- Main idea: if future behavior (fig. 1) cannot be sufficiently predicted by a well-trained and generalizing neural net, the behavior is unexpected and thus seldom/atpyic
- **this is shown in severe discrepancies from observed and predicted trajectory**

Trajectory prediction

- Predict the next points from a number of (observational) points with a RNN which is autoencoder-like (fig. 2)
- Trained trajectory prediction on 4839 vehicle trajectories, observation length 10, prediction length 10 (@25 fps)
- Use Average Displacement Error (ADE) as metric

Detection of atypics

- Classify point as atypical, if prediction loss is greater than specific percentile of distribution of training losses
- Classify trajectory as atypical, if in a sliding window > 50% is atypical

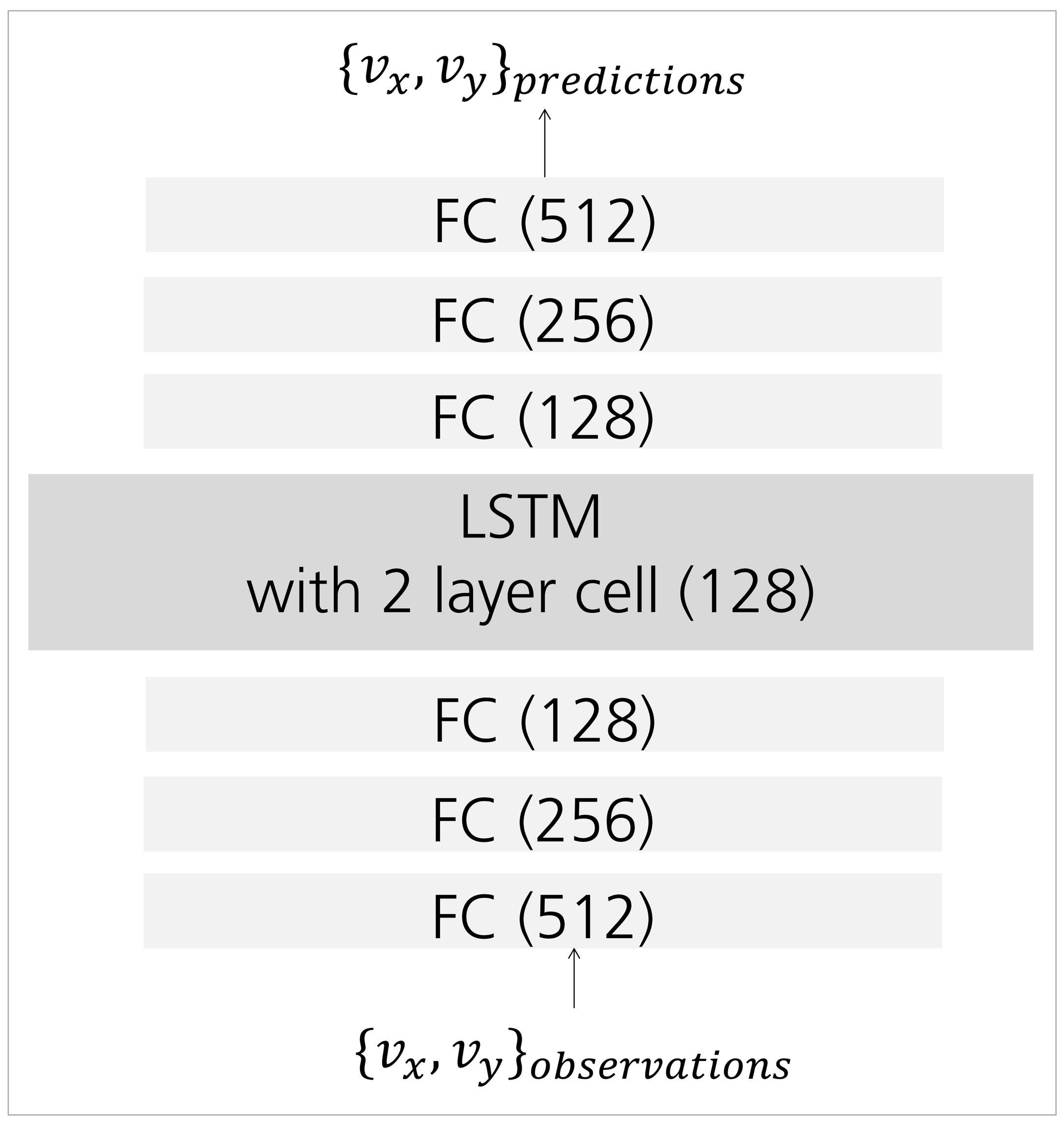

Fig. 2: The structure of the Recurrent Neural Network (RNN) for predicting trajectories.

Evaluation: Find abrupt and strong brakings of right-turning cars

- Field test (fig. 3):
  - driving of encounters of right-turning vehicle and crossing cyclist
  - Results in test set for atypics of 60 normal / 15 atypical traj.
  - 90th percentile of training loss as point classificator and sliding window size of 7 points yields highest f1 score (imbalanced data set)

Conclusion & Outlook

Single events like strong brakings can be found (feature: velocity) in a data-driven manner

- Apply to all modalities (cars, pedestrians and cyclists)
- Extend feature vector by taking position, heading, acceleration into account
- Compare to [Gap Time + Time To Conflictpoint] in this use case
- Early: awareness:
  - Use methods to find further atypical or critical incidents
  - Examine incidents and describe early trigger

(how can these situations be forecasted or detected early?)

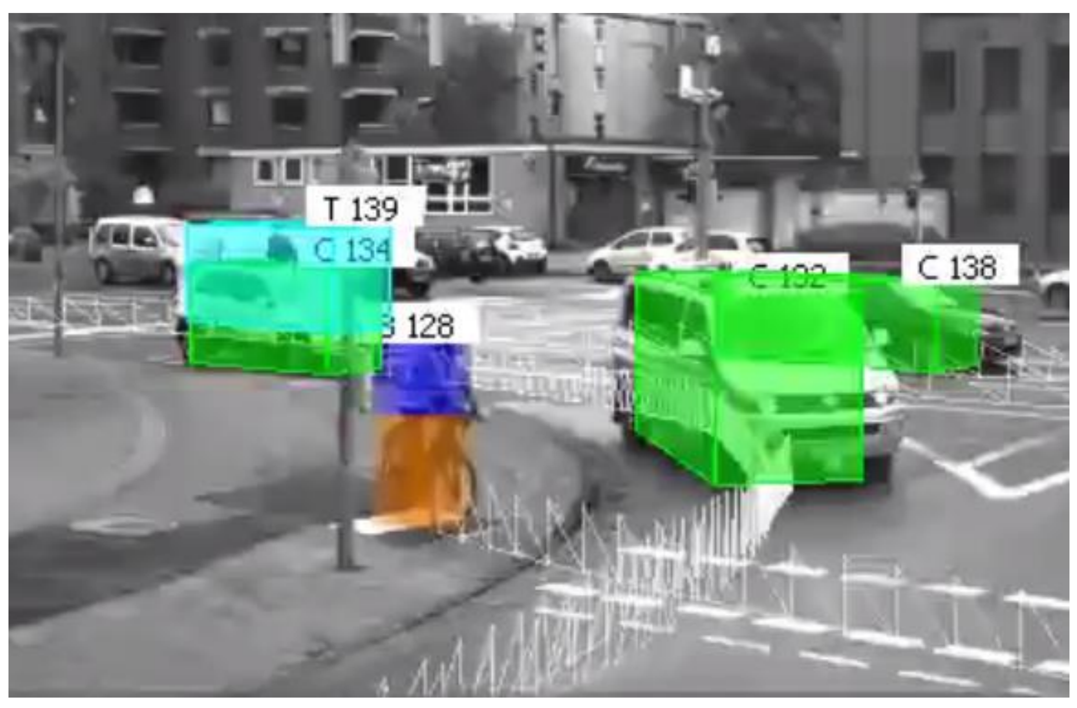

Fig. 3: Exemplary encounter during field test.

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