Predicting Bicyclist Maneuvers using Explicit and Implicit Communication

8th Road Safety and Simulation Conference

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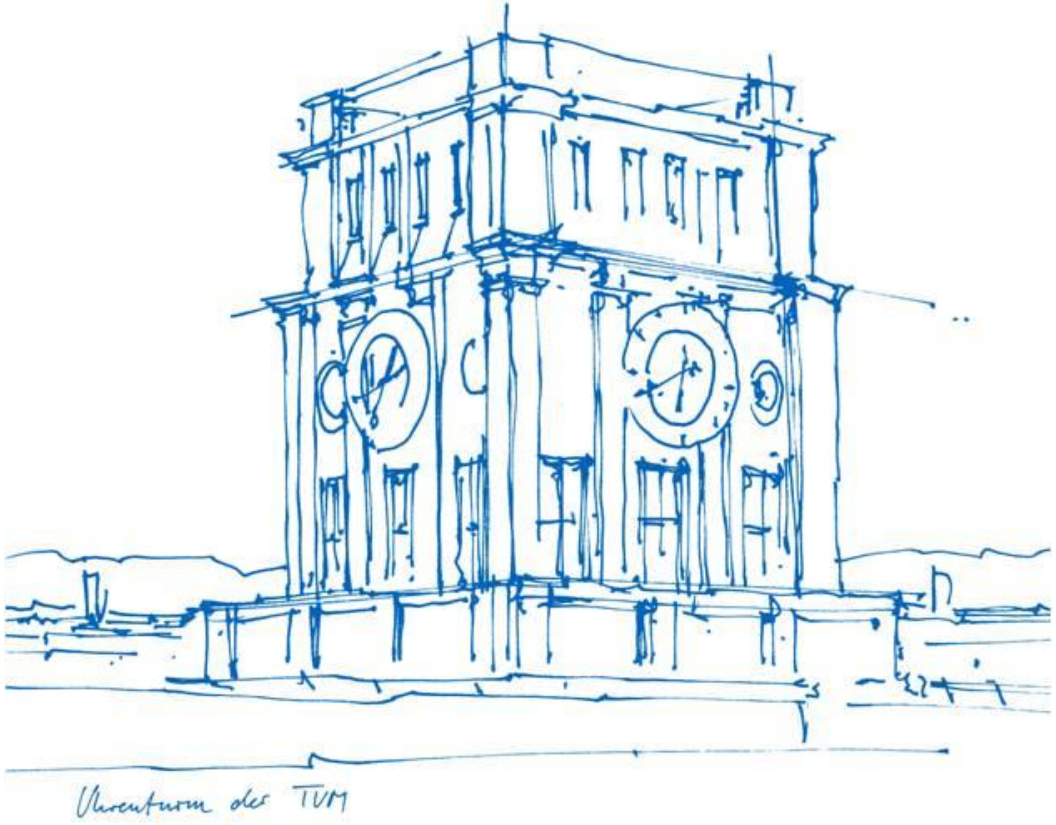
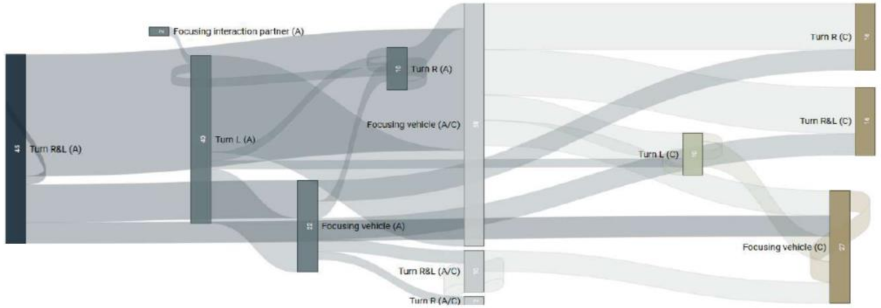


Motivation

1. Most approaches found in the literature for the road user behaviour prediction address either:
   1. The trajectory and sequence prediction problem or
   2. the action classification problem (overall ca 80% prediction accuracy e.g. Barbier M. et al. 2017)
2. Most recent scientific work on this topic relies on Ensemble Methods, Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) based models (e.g. Pool, Kooij, & Gavrila, (2019), Viktor Kress, Jung J, Zernetsch S, Doll K, Sick B. (2019), Saleh K, Hossny M, Nahavandi S. (2018))
   1. Proposed methods are tailored to specific data input types, perception methods and detector types.
   2. The deployment of deep learning models is a time consuming and complicated process heavily relying on the specific data input and the dimensionality of the prediction task.

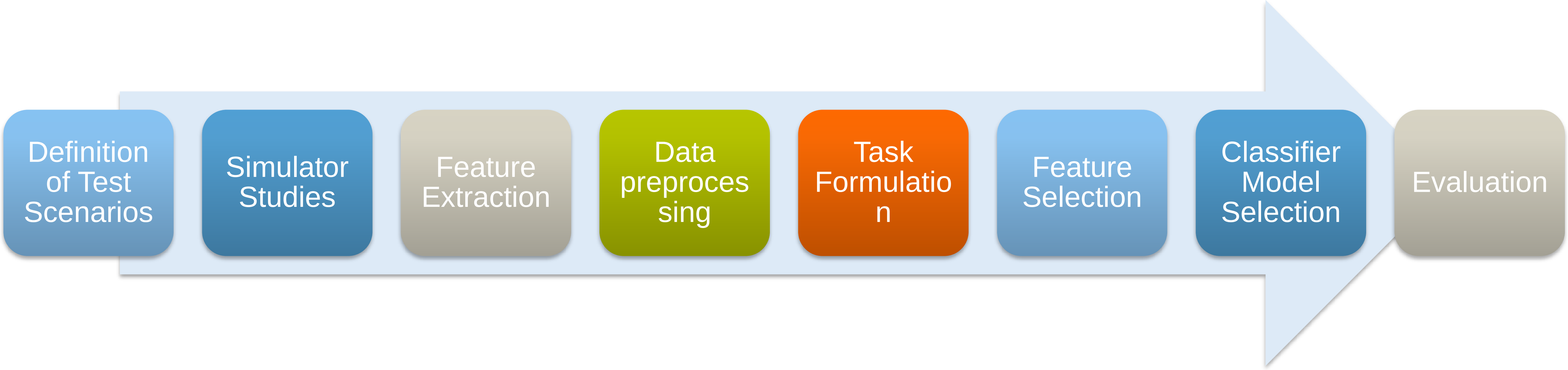
The development of a standalone method for introducing the benefits of the additional information gain originating from the bicyclist communication cues has the potential to expand and support existing models and functions in the field of automated driving.

Examples of bicyclist gestures in traffic scenarios

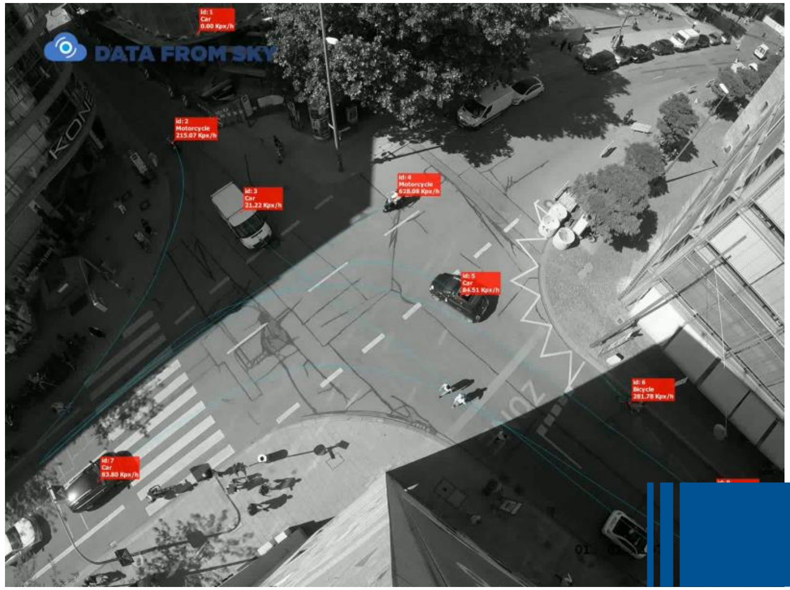


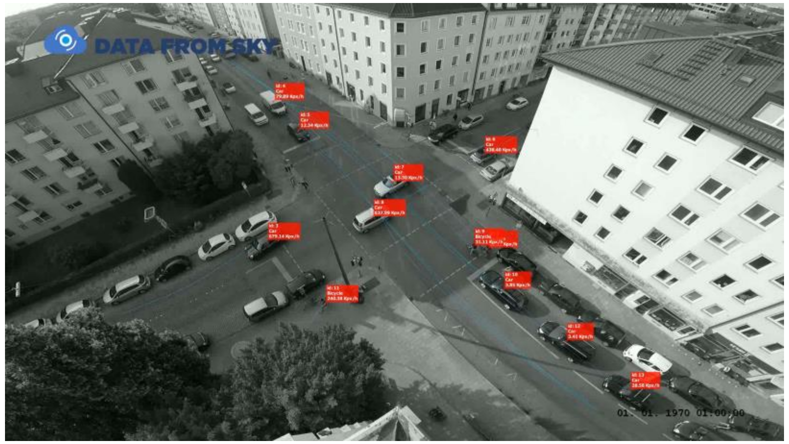
Example of a Sankey diagram for sequences and their frequencies of head movements of a pedestrian when crossing

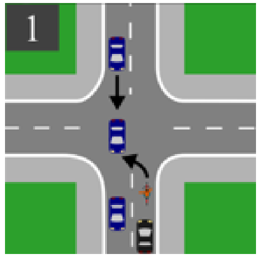
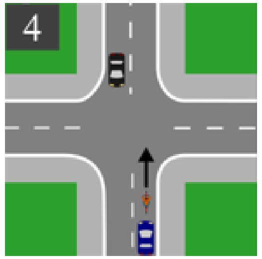
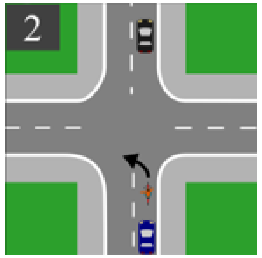
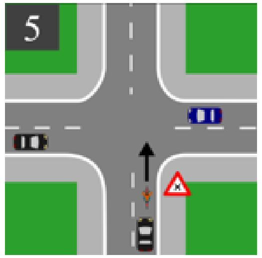
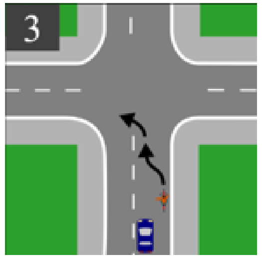
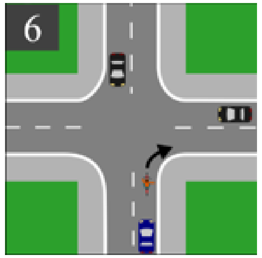
Overview of the Methodological Approach

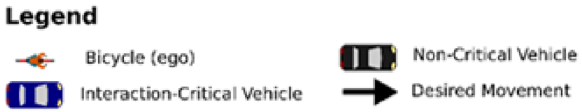


Definition of Test Scenarios



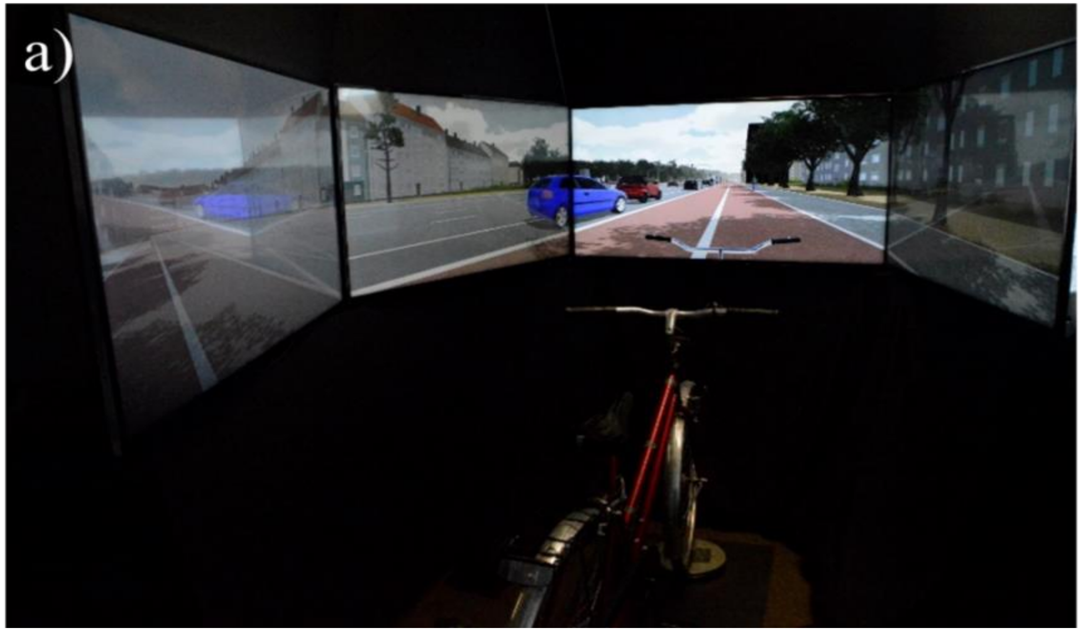


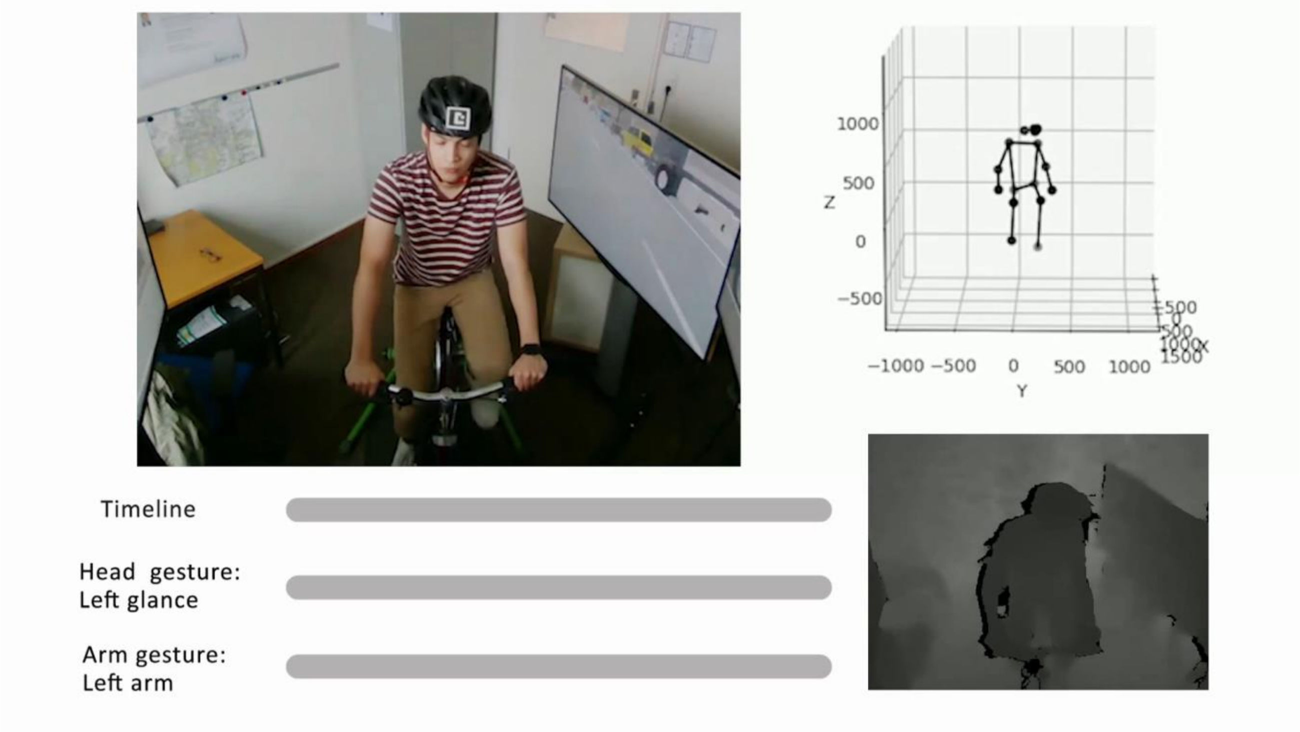
Description	Scenario	Description	Scenario
Left turn: Test subject is impeded by several vehicles driving straight in the opposite direction and therefore must yield to them and wait to proceed		Crossing: Test subject is not impeded by any other vehicles	
Left turn: Test subject is not impeded by any other vehicles		Crossing: Test subject is impeded by a vehicle approaching from the right with the right-of-way and therefore must yield to them	
Left turn: Test subject must perform a left turn preceded by lane change from right side of approach lane to left side, with a vehicle following behind		Right turn: Test subject is not impeded by any other vehicles	



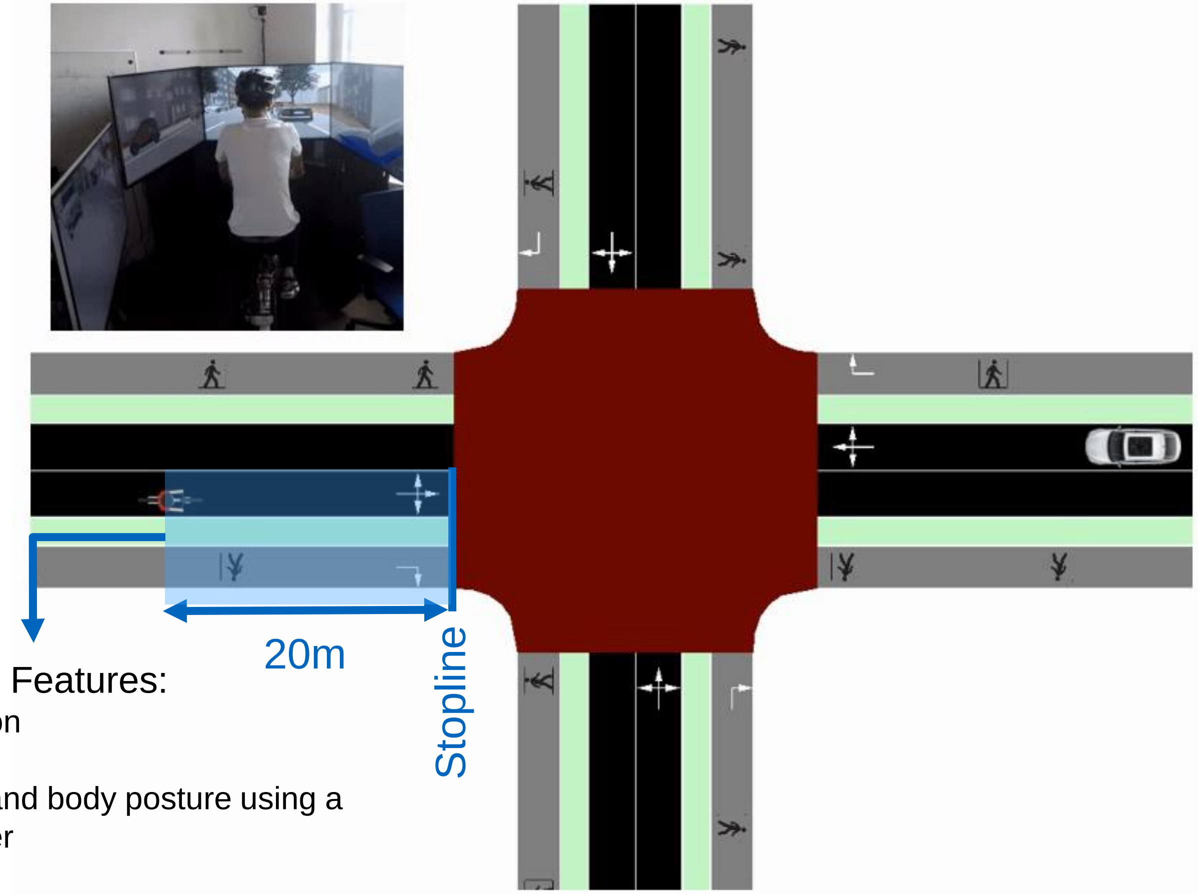
Test scenarios

Bicycle Simulator Studies





Feature Extraction and Data Preprocessing

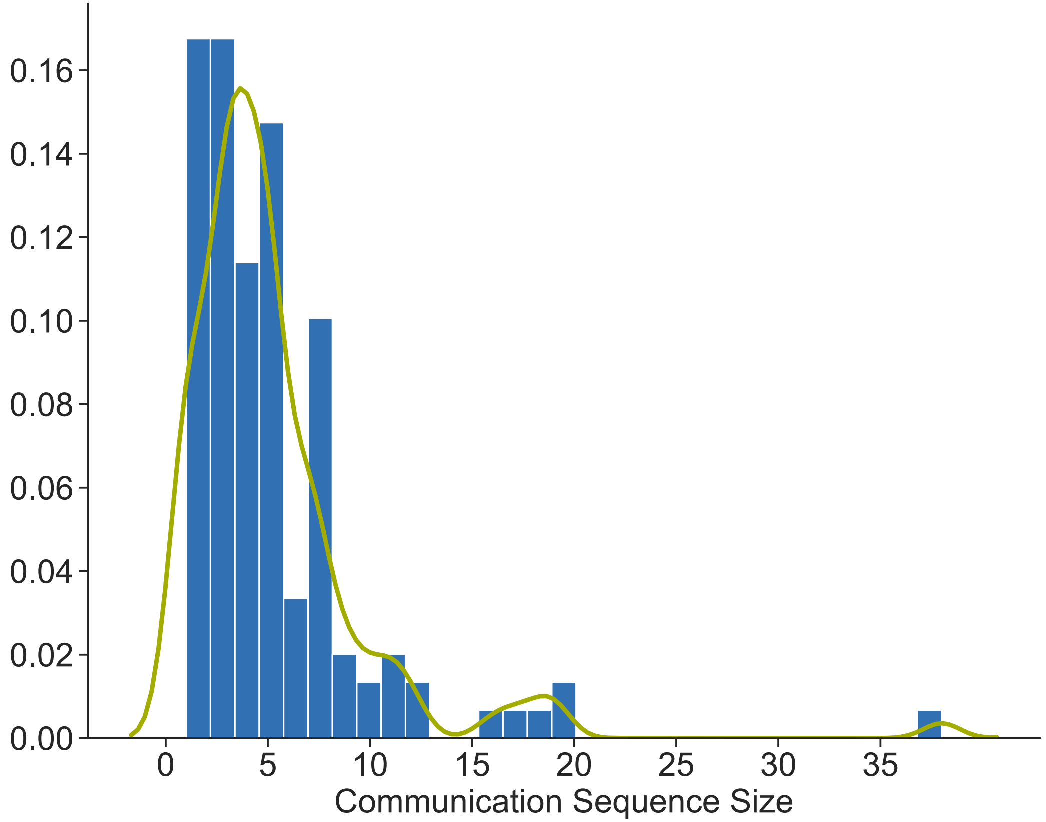


Extracted Bicyclist Features:

- Skeleton detection
- Head movement
- Gestures, head and body posture using a k-means classifier

Feature Extraction and Data Preprocessing

- Thirty-one test subjects participated in the simulator study (M = 21, F = 10)
- A total of 357 implicit (n = 357, 86.9%) and explicit (n = 54, 13.1%) gestures were recorded
- An average number of 5.2 implicit and/or explicit communication cues are performed by the test subjects in every scenario
- A timestamp value that corresponds to the estimated arrival time to the start of the intersection approach is associated with the communication cues
- In total 125 sequences of explicit and implicit communication cues were extracted for all different maneuver types



Distribution of communication sequence sizes of implicit and explicit communication cues in the bicycle simulator scenarios.

Task Formulation, Features Selection, Classifier Model Selection and Deployment

1. The prediction of the bicyclist maneuver type intention at an intersection approach can be formulated as typical multiclass classification problem. **The three predefined maneuver classes are 1) left-turn, 2) right-turn, 3) crossing**
2. The following classifiers will be deployed and tested:
    1. k-nearest neighbors’ *(kNN-C)*
    2. Extra trees classifier *(ET-C)*
    3. Decision trees classifier *(DT-C)*
    4. Random forest *(RF-C)*
    5. Logistic regression *(LR-C)*
    6. Linear support vector machine *(SVM)* coupled with SGD training *(SVM-SGDC)*
    7. SVM coupled with an appropriate C-support value and linear kernel for vector classification *(SVM-C)*
    8. Gaussian naive-bayes classifier *(GNB-C)*

Task Formulation, Features Selection, Classifier Model Selection and Deployment

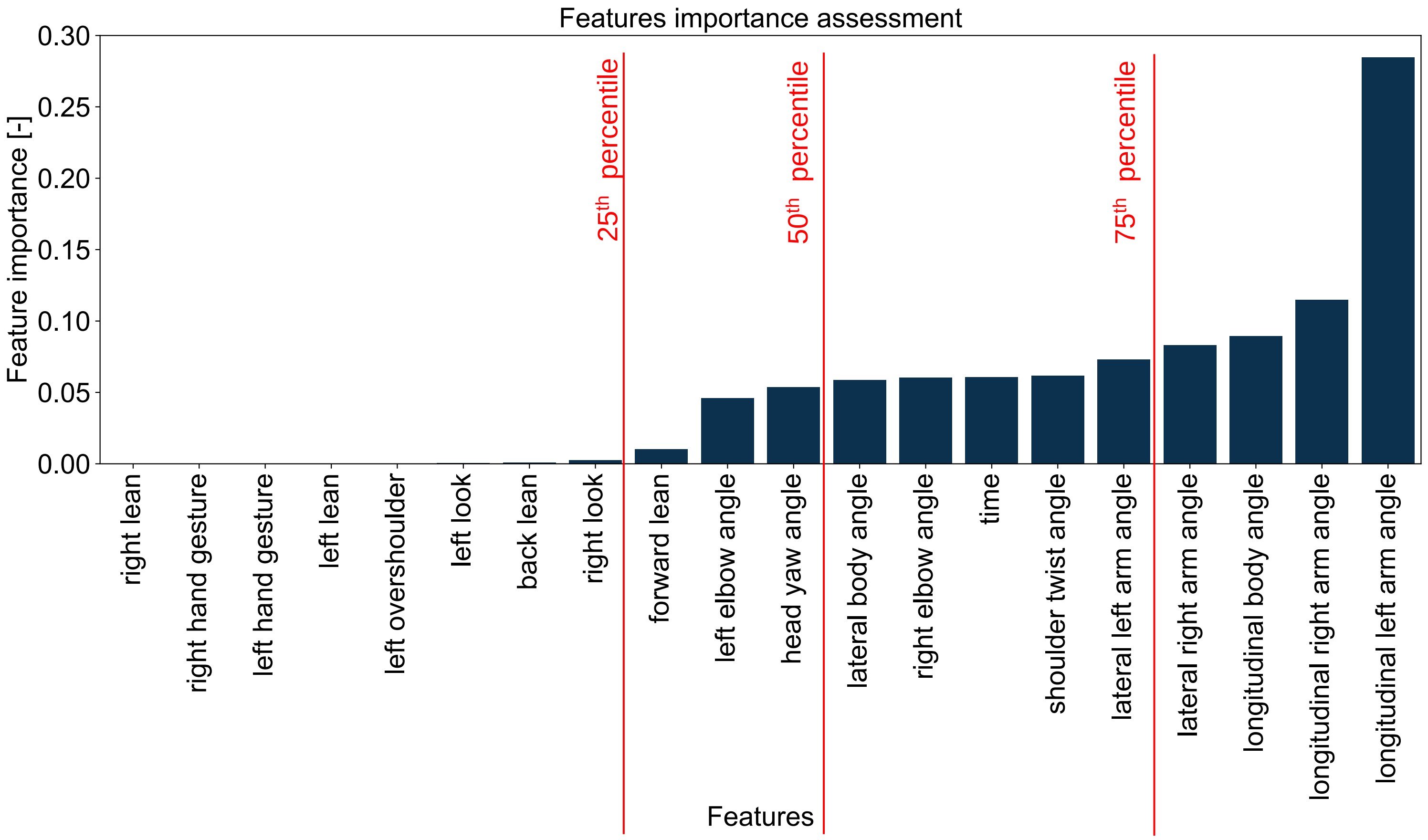
1. 20 independent variables are used for classification
2. Prior to training the classifiers, we use random forests for feature selection
3. The dataset is split into k = 10 equal subsets using stratified 10-fold cross validation. We then proceed on training and testing our model using the k-fold samples
4. The model evaluation will be performed using the averaged cross validation accuracy scores over all k-folds

Input variable	Type
lateral body angle (°)	Continuous
longitudinal body angle (°)	Continuous
left hand gesture (-)	Boolean
right hand gesture (-)	Boolean
left look (-)	Boolean
left overshoulder (-)	Boolean
right look (-)	Boolean
head yaw angle (°)	Boolean
back lean (-)	Boolean
forward lean (-)	Boolean
left lean (-)	Boolean
right lean (-)	Boolean
lateral left arm angle (°)	Continuous
longitudinal left arm angle (°)	Continuous
left elbow angle (°)	Continuous
time (s)	Continuous
lateral right arm angle (°)	Continuous
longitudinal right arm angle (°)	Continuous
right elbow angle (°)	Continuous
shoulder twist angle (°)	Continuous
Output variable	**Type**
Maneuver Type (left, right, crossing)	Discrete

Dependent and independent variables

Features Selection Results

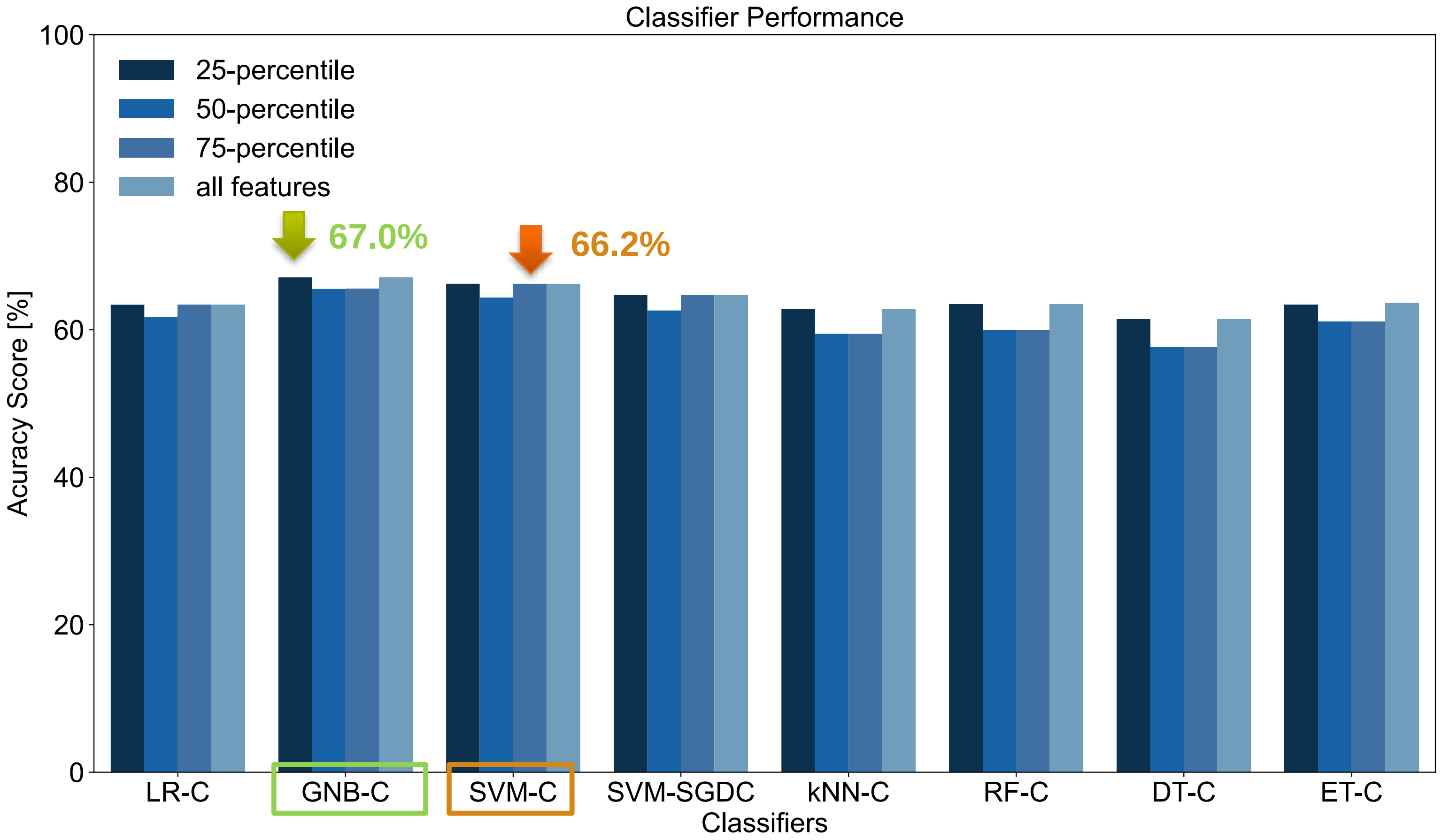
- The skeletal joint features achieve a higher importance compared to pre-classified gesture archetypes
- The longitudinal body right arm and left arm angles achieve the highest importance ranking compared to all other introduced features
- The skeletal joint metrics already incorporate gesture relevant information
- To assess the effect of the feature selection on the performance of individual classifiers, all classifiers will be trained using different feature group percentiles (100%, 75%, 50%, 25%) as minimum thresholds



Feature importance assessment using random forests

Model Results

- All classifiers achieve scores higher than 50% during training and testing, indicating that predictions are not generated randomly
- The **Gaussian Naive-Bayes Classifier (GNB-C)** achieves the highest accuracy score 67.0%
- The best accuracy scores for all classifiers are reached either using the 25th percentile or all features
- The **SVM classifier (SVM-C)** is the most robust classifier for the minimum number of available features (66.2% during testing)



10-fold cross validation accuracy score results during testing

Conclusions and Outlook

1. All assessed classifiers managed to address the classification task with relatively good performance using the 25th percentile as threshold for the feature selection.
2. A maximum prediction accuracy score in the test set of 67.0% is reached using the gaussian naive-bayes classifier (GNB-C)
3. The SVM classifier coupled with C-support for vector classification (SVM-C) achieves the best performance using the smallest number of input features
4. For the evaluated methods, the pre-classification of the vast majority of gesture classes is not a required step towards the model implementation. The bicyclists' skeletal joint metrics can provide information sequences with sufficiently high prediction performance
5. The proposed methodology has the potential to support motion planning approaches for predicting the trajectory of a bicyclist in traffic for automated vehicle applications, increasing traffic safety and the acceptance of automated vehicles
6. The association of the communication patterns with the bicyclist operational behavior in an integrated approach has the potential to further improve the prediction accuracy
7. The presented methodology may be adapted to study and predict the behavior of other types of vulnerable road users in mixed traffic such as e-scooter riders or pedestrians

Thank you for your attention!

ACKNOWLEDGMENT
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