Aware and Intelligent Infrastructure for Action Intention Recognition of Cars and Bicycles

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Abstract: Action intention recognition is becoming increasingly important in the road vehicle automation domain. Autonomous vehicles must be aware of their surroundings if we are to build safe and efficient transport systems. This paper explores methods for predicting the action intentions of road users based on an aware and intelligent 3D camera-based sensor system. The collected data contains trajectories of two different scenarios. The first one includes bicyclists and the second cars that are driving in a road approaching an intersection where they are either turning or continuing straight. The data acquisition system is used to collect trajectories of the road users that are used as input for models trained to predict the action intention of the road users.

1 INTRODUCTION

Traffic accidents have become one of the most common causes of death among young people (World Health Organization (WHO), 2015). Although fatalities have decreased for motorists in most countries, this is not the case for vulnerable road users (VRUs), (Niska and Eriksson, 2013) including pedestrians, bicyclists and moped riders. With the trend towards increased vehicle automation, there is a large potential for reducing the effects of an accident, or, if possible, avoiding the accident completely. This can be done by building sensor-based safety systems that can detect vehicles and VRUs and give warnings or actively react on the information. The practical use of an aware and intelligent infrastructure system as proposed in this work is to enhance the performance of connected and automated vehicles in cooperative intelligent transportation systems (C-ITS). With support from wireless communication, the system allows future connected and automated vehicles to receive collision warnings about approaching vehicles or VRUs from the infrastructure-based sensor system well in advance to enable better planning and foremost, avoid accidents.

Enabling the development of such systems requires knowledge on how road users behave, and how that behavior can be described so that the automated vehicle functions can make correct interpretations and decisions. Another possible outcome of this research is insights on how vehicles should be programmed to be interpretable by other road users. This work focuses on data mining for action intention recognition of bicycles and cars using trajectories of road users captured with a 3D camera-based data acquisition system mounted in the infrastructure. Furthermore, the focus is also to find the input variables that enable high accuracy modeling performance.

2 RELATED WORK

Previous work on data driven methods for predicting future events of road users include (Lidström and Larsson, 2009) where the authors propose an artificial potential field approach to predict driver intentions based on vehicle speed and location along with traffic light status. Lidström and Larsson also elaborate on using particle filters (Lidstrom and Larsson, 2008) to predict the driver intentions. In both approaches they use Vehicle-to-Vehicle communication to collect data from cars maneuvering in an intersection, turning either left or right. In a recent study (Muhammad and Åstrand, 2018) bicycle and car trajectories indicating a vehicle driving straight or turning are used to train a binary classifier based on particle filters to separate

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the two different behaviors. In (Doshi and Trivedi, 2009) the authors explore the possibility of including features indicating the drivers visual search prior to maneuver i.e. head pose and eye gaze to predict driver behavior. The results indicate that these features improve driver attention and behavior estimation, as well as intent prediction. The research group further proposes to use a Bayesian extension to a support vector machine (SVM), known as a relevance vector machine (RVM) to detect lane following and lane change behavior (Morris et al., 2011). The classifier uses approximately 500 input signals from e.g. the vehicle CAN bus, tracked objects from the on-board radar and parameters from a driver monitoring system capable of tracking head motions. These methods however require detailed information from the vehicles (Doshi and Trivedi, 2009). In (Lidström and Larsson, 2009) advanced technologies from infrastructure are needed and in (Morris et al., 2011) information from the observed vehicles is needed. Our approach, however, only needs the positions of the observed road users.

Deep learning, as presented in (Alahi et al., 2016), show that using Long Short-Term Memory for predicting human-human interactions and their future trajectories is highly effective. Based on 3.2 s of video data of a pedestrian, this system provides a heat map of possible trajectories for the next 4.8 s. In (Dominguez-Sanchez et al., 2017), an end-to-end pedestrian intention prediction system is proposed based on a Convolutional Neural Network (CNN). This approach uses the video data alone to extract the current movement direction of the pedestrians. In a previous study, based on data from the Joint Attention in Autonomous Driving (JAAD) data set, extensive examination of data driven approaches was performed for feature extraction and classification to predict intentions of pedestrians (Varytimidis et al., 2018). The task was to predict whether the pedestrians were to cross a street or not. Combining a CNN as a feature extractor and a support vector machine as classifier yielded the best performance. In (Fang and López, 2019) a monocular camera is used as input to a CNN used for human pose estimation and intention recognition for VRUs. The JAAD data set was used for pedestrian intention recognition, and a new video data set was created for cyclists. The cyclists used their arm to indicate their intention and the CNN was trained to detect their intention. In a recent study (Mohammed et al., 2019) fixed cameras were used to capture bicyclist behavior with the purpose to improve traffic microsimulation models. The study focuses on following and overtaking behavior and the data used for the analysis come from bicycle trajectories including position coordinates of the bicycle, object size and speed.

In (Walker et al., 2014) a framework for visual prediction on static scenes from video data is presented. The framework is based on representative and discriminative mid-level elements and combines a visual representation with a decision theoretic framework. The framework can predict how vehicles will move in a possible future given that all other objects in the scene remain stationary. In (Mínguez et al., 2018), balanced Gaussian process dynamical models are used to build action recognition models of pedestrian activities i.e. walking, stopping, starting, and standing. The model is capable of predicting actions 1 s in advance with high accuracy.

Equipping all vehicles with connected satellite navigation receivers, such as Global Positioning System (GPS) devices, could be used to capture the trajectories as suggested in (Herrera et al., 2010) (Carli et al., 2015). However, to obtain high accuracy positions an additional correction signal is required such as differential GPS or Real Time Kinematics (RTK) GPS. Relying on the self-reported GPS-positions, requires that all vehicles are equipped and connected. With an intelligent and aware Infrastructure-based data acquisition system, the behavior of all vehicles can be captured.

This paper explores different classifiers for building aware and intelligent infrastructure capable of recognizing actions and intentions of cars and bicycles. The proposed models take a few positions along with speed and heading samples to predict the road users' intention to go either straight or turn at an upcoming intersection. In addition, by using a data mining approach, the paper explores which input variables contribute the most to the correct classification. Certain subsets of variables, compared to using all available variables, are found that improve the performance of the two models.

The contribution of this paper is twofold, a comparison between four well known classification methods is made where the models make use of a limited number of historical samples to predict the road users' intention. Secondly, the paper extracts a subset of variables that improves the classification performance for the car and bicycle models.

The rest of the paper is organized as follows, Section 3 describes the data used. Section 4 describes the methodology used for the proposed approach and Section 5 presents the experimental investigations. Finally, Section 6 concludes the work and presents future research directions.

3 DATA

The data used in this study is collected with a commercial 3D camera data acquisition system with low visual light capabilities (OTUS3D[1]) with built-in object detection and trajectory estimation. The stereo base for the two cameras is 50 cm and the field of view is 95°. The system is mounted in the infrastructure at an elevated position in a streetlight post to give an overview of the observed areas. The two available data sets consist of trajectories of bicycles or cars captured in real traffic. The bicycle data is collected at a bicycle path with a turn off. The car data is collected at an urban road section with an intersection. The vehicles (bicycles and cars) are either going straight on the road or turning off the road. There are in total 134 trajectories with bicycles, whereof 70 are turning. There are in total 217 trajectories with cars, whereof 22 are turning. In all the scenes, there is only one road user present. Instead of pre-processing the data by, for example, calculating any modes of the signals, the input vectors in this paper consists of only the raw data, described in Table 1, forming n multivariate time series vectors $\mathbf{x} \in \Re^{\mathbf{m}}$, where m is the number of variables. The data is collected with a fixed sampling rate (4 Hz).

Table 1: Description of Variables Captured by the 3D Camera Data Acquisition System.

Variable	Description
p_x	Longitudinal position (m)
p_y	Lateral position (m)
t	Time (timestamp)
v	Speed from camera system (m/s)
$\widehat{v}$	Estimated speed from p_x, p_y, t (m/s)
h	Heading (degree)

Each vector is extracted from the trajectories in Fig. 1 and is a sliding window including the variables $p_x(t), p_x(t-1), p_x(t-2), ..., p_x(t-T), p_y(t), p_y(t-1), p_y(t-2), ..., p_y(t-T), v(t), v(t-1), v(t-2), ..., v(t-T), \widehat{v}(t), \widehat{v}(t-1), \widehat{v}(t-2), ..., \widehat{v}(t-T), h(t), h(t-1), h(t-2), ..., h(t-T)$. Where t is the time and T is the number of previous samples to use. In this work five different variables are used and for each variable the time stamps $t, t-1, t-2, t-3, t-4$ i.e. T=4 are used, which will result in m = 25. For each input vector $\mathbf{x_i}$ the associated output y_i indicates whether the vehicle is turning or not in the upcoming exit. Thus, all vectors that come from a trajectory that describe a turning vehicle have y=0, and vehicles that go straight have y=1.

[1] https://viscando.com/

4 PROPOSED APPROACH

The proposed approach is motivated by the fast development of autonomous vehicular transport systems. To improve safety, vehicle awareness of their surroundings is of utmost importance. The vehicles themselves have perception sensors capable of detecting obstacles and other road users. Combined with the additional sensor systems in a connected infrastructure, as in this research, it may be possible to provide additional valuable information about complex traffic situations such as intersections.

In this work the data is collected using a fixed camera system mounted in the infrastructure. The aim is to understand what the most relevant variables are for predicting intentions, regardless of how the data is collected. Traffic behavior is highly dynamic and there is often only limited time available for detection, monitoring and decision making. Typically, it is difficult to obtain a clear line of sight for long time periods, particularly if the sensor is placed on a vehicle (instead of in the infrastructure). The models in this study use short time series, 5 samples that corresponds to 1.25 s, to predict if the bicycle or car will turn at the upcoming exit. The description of the method to extract which variables, and how many previous time stamps are needed to make accurate predictions, is presented in the next section.

This section describes the four classification methods that are compared while predicting the driver's intended actions. The tool used for classification is Matlab. The first model is a plain linear classification model (LM) (Hastie et al., 2009) $\mathbf{y} = \mathbf{X}\mathbf{w} + \varepsilon$, where $\mathbf{y}$ is the predicted output, $\mathbf{w}$ is the model weights found with least squares, and $\mathbf{X}$ is the input variables, see Section 3, and ε is the vector of random errors assumed to be identically distributed with zero mean and unknown variances. The second model is a multilayer perceptron neural network (NN) (Bishop, 1995), trained using the Bayesian regularization backpropagation training rule in Matlab. The third model is a support vector machine (SVM) (Vapnik, 1998), using a radial basis function (RBF) as a kernel. The fourth model is a random forest (RF) (Breiman, 2001) consisting of 100 trees trained to full depth and a majority vote is used to obtain the final output of the RF. Details of the classifiers are presented in the next Section.

It should be noted that the model is not predicting the next action as described in the literature reviewed in Section 2 but rather, what action the vehicle will take at the upcoming exit. Depending on where the sample is collected the distance to the intersection varies.

4.1 Classifier Configuration

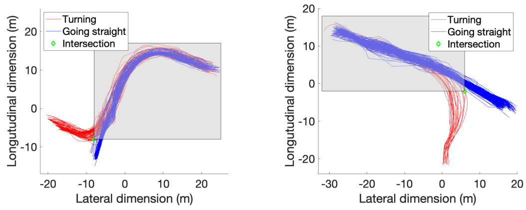
All hyper-parameters of the models are found experimentally. The network configuration for the NN that yielded the best performance was a one hidden layer perceptron with 3 hidden nodes, a Symmetric sigmoid transfer function was used in the hidden layer and a Logarithmic sigmoid transfer function in the output layer. The network is trained for 50 epochs. The SVM with the RBF function use σ=0.8 and the parameter C, which controls the trade-off between the training error and the rigid margins allowing some miss classifications, is set to 0.1. In a RF each tree is trained using data selected using random sampling with replacement (bootstrapping) resulting in that approximately one-third of the data is left out. For each tree k, the data that is not used for training, the out-of-bag (OOB) data, is used to estimate the generalization performance and variable importance (Breiman, 2001).

Initially 25 input signals are used for the modeling task. For the variables $p_x, p_y, v, \widehat{v}, h$ the time instances at $t, t-1$, $t-2$, $t-3$ and $t-4$ are used to predict if the vehicle will make a turn or go straight in the upcoming intersection. For the bike data set there are 5640 samples generated from the 135 trajectories; 2451 samples in the turning class and 3189 in the going straight class. For the car data there are 2593 samples generated from the 217 trajectories; 388 in the turning class and 2205 in the going straight class. A model trained with an unbalanced data set, however, may favor the majority class, which in this case is not desirable. Therefore the data is balanced resulting in 2451 samples in each of the bicycle classes and 388 samples in each of the car classes. Data from positions after the vehicles have turned at the turn off are not considered. The data used is visualized in Fig. 1. In this work, the models are built using five-fold cross validation and throughout this paper the result presented is the mean of the five models.

For model evaluation, four different metrics are used: (i) the mean classification error rate is used to find model parameters and for variable selection; (ii) distance to the intersection is used to benchmark the models and to understand how early the models can predict whether the bicycle or car is turning or not. For each sample, the distance is approximated with the Euclidean distance d_e to the intersection, as shown in Eq. 1

$$d_e = \sqrt{(p_x^o - p_x^i)^2 + (p_y^o - p_y^i)^2}, \qquad (1)$$

where o indicates the coordinate of the intersection and i is the coordinate of the current sample. In Fig. 1 the lower left corner of the gray box (-8,-8) is the point for the intersection used in the bicycle dataset and the



(a) Bicycle Trajectories. (b) Car Trajectories.

Figure 1: The Highlighted Area Limited by the Solid Line Indicate the Regions from Where Data Is Used for Training and Testing the Models.

lower right corner (-6,2) is the intersection point for the car data set. These points are from hereon called the intersection; (iii) true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) are used to illustrate the performance and; (iv) finally, to allow comparison between models, the precision $PR = \frac{TP}{TP+FP}$ and recall $RE = \frac{TP}{TP+FN}$ are used.

4.2 Variable Selection

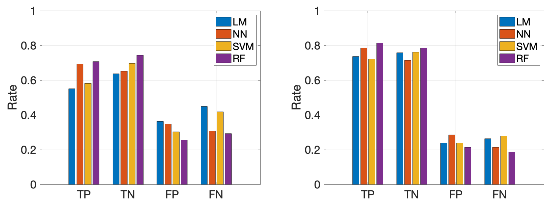
Initially the 25 input signals described above are used to build the classifiers, five variables with five samples $t, t-1, t-2, t-3$ and $t-4$ corresponds to time series of 1.25 s. The backward elimination method is used to find the most important input variables that influence the modeling of the behavior. The process uses the RF model as the classifier. The variable selection method is described below:

1. Build M models and for each model m, remove the m-th input variable.
2. Use the OOB data set to estimate the performance of each model m.
3. The model m with the lowest error indicates the signal m that influences the model the least and is removed.
4. The removed input variable is given a score indicating the order it was removed.
5. Remove the input variable and restart from 1 with M=M-1 input variables until M=1.
6. When M=1, the scores indicate the importance of each input variable.

5 EXPERIMENTAL INVESTIGATIONS

5.1 Classification

This section describes the initial classification results. In Fig. 2 a comparison of the classification accuracy



(a) Bicycle. (b) Car.

Figure 2: True Positives (TP), True Negatives (TN), False Positives (FN) and False Negatives (FN) for the Models Using All Available Variables.

Table 2: Mean, $\overline{m}$, Distance Error along with the Standard Deviation (σ) of the Mean, for the Bicycle and Car Action Intention Models.

Model	LM	NN	SVM	RF
Bicyle	8.5 (0.13)	7.6 (0.18)	6.8 (0.47)	5.9 (0.45)
Car	5.0 (0.21)	4.8 (0.33)	4.4 (0.43)	3.7 (0.40)

is found regarding true positives (TP — Samples correctly classified in trajectory going straight), true negatives (TN — Samples correctly classified in trajectory that is turning), false positives (FP — Samples erroneously classified as going straight) and false negatives (FN — Samples erroneously classified as turning). Generally, the RF model yields the best performance for both bicycle and car model whereas the performance of the NN, SVM is diversified. The LM yields overall poor performance.

Table 2 present mean distance from the samples to the intersection in meters for the samples that are miss classified. The standard deviation of the mean distance is also presented. As can be seen in both Fig. 2, Table 2 and Table 3 while using all available input variables, the RF model provides the best performance for both bicycle and car data sets. In addition, the performance of the car model is generally better than the bicycle model. In the next section, the search for the subset of the most important input variables is presented that can be used to model the action intention for both the bicyclists and the cars. Typically, one wants to find a few information-rich input variables that can be used to build a cost efficient (with few variables) model.

In Table 3 the results from the recall and precision analysis are presented. These results also indicate that the RF model for both bicycle and car data provide the best performance. Generally, the non-linear models NN, SVM and RF yield better performance than the LM, in particular for the bicycle model.

Table 3: Average Precision and Recall for the Bicycle and Car Data Sets Using All Available Variables.

Model	Bicycle		Car	
	Recall %	Precision %	Recall %	Precision %
LM	55.1	60.3	74.0	75.5
NN	58.2	65.8	72.2	75.2
SVM	69.3	66.6	78.6	73.2
RF	70.8	73.5	81.4	79.3

5.2 Variable Selection

While applying the backward elimination variable selection method, the importance scores of the input variables are estimated and presented in Table 4 for both the bicycle and car models. The selection procedure is made on the five cross validation set, thus, the presented score along with the standard deviation is given in the table. The mean error of the RF classifier while performing the variable selection procedure can be found in Fig. 3 and Fig. 4 for the bicycle and car respectively. The graphs show how the performance of the model varies as variables are removed. The minimum error for the bicycle model is obtained by removing 20 of the 25 variables, see Fig. 3. In Table 4 the five variables with the highest score are highlighted (bold type): $v(t), v(t-4), p_x(t)$, $p_y(t)$ and $h(t)$. Consequently, these variables are the most important for deciding whether the bicyclist will turn or not. Beside the current position of the bicyclist, the model utilizes the speed variation of the bicyclist, thus the speed dynamics, $v(t)$ and $t-4$ are among the most important variables.

Fig. 4 illustrate the mean error for the car action intention prediction model and it is shown that by removing 19 of the 25 input variables the lowest mean prediction error is achieved. The six variables with the highest score from Table 4 are: $\widehat{v}(t), p_y(t), p_y(t-4), p_x(t), p_x(t-4)$ and $h(t)$. Whereas current position and the speed variation are important for the bicycle model, road position dynamics provide valuable information for the model predicting action intentions of the car i.e. time steps t and $t-4$ for both p_x and p_y are among the most important variables along with current estimated speed and car heading.

As can be seen in Table 4, the standard deviation of the score is low for the most important variables, indicating that the selection order is very similar between the cross-validation data sets, in particular for the variables with high score. The standard deviation is slightly higher for the variables that are less important.

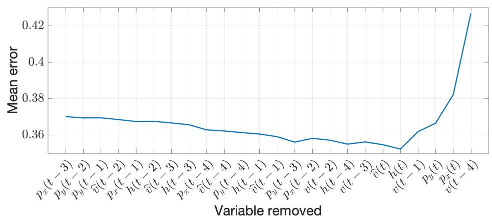


Figure 3: Mean Error as a Function of Variables Removed during the Variable Selection Process for the Bicycle Model.

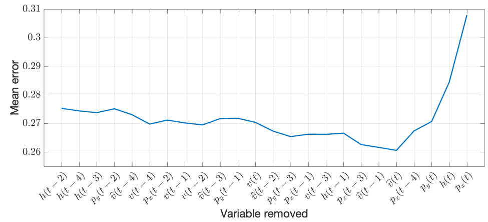


Figure 4: Mean Error as a Function of Variables Removed during the Variable Selection Process for the Car Model.

5.3 Classification with Best Set of Variables

By using a subset of the input variables, found using the backward variable selection method described in Section 5.2, the models are retrained. The results are found in Fig. 5 and Table 5. Both the bicycle and car models improved slightly with the reduced number of input variables, compared to using all available variables, leading to an observed lessening in distance error, see Table 5. This means that the model is capable of accurately predict the intention further away without using all variables. The standard deviation is also slightly lower for the models trained with the reduced number of variables. The best improvements are found for the car NN model, where the mean error decrease from 4.8 to 3.6, an improvement of 25%. While comparing the classification results in Fig. 2 and Fig. 5, for the bicycle RF model the performance is slightly improved. Notably only 5 out of the original 25 variables are used. In Fig. 5, for the RF car model, slight increase in TP and TN and a small decrease in FP and FN is observed, despite using only 6 out of the original 25 input variables. This indicates that, for the current traffic situations and the available data sets, an efficient subset of variables is found that the model can utilize to predict the action intention of both bicyclists and cars.

In addition, the performance is visualized as a function of the distance to the intersection for each trajectory. Fig. 6 visualizes the time series mapped to its trajectory ID along with a bar graph showing the percentages of samples in each trajectory that are miss classified. The miss classified time series are indicated by black markers. As can be seen, in the vast majority of the trajectories >50% of the time series are correctly classified.

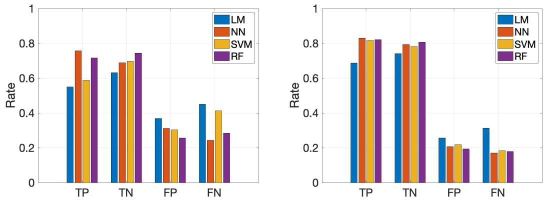
Table 4: Scores from Backward Elimination Variable Selection for Both Bicycle and Car Action Intention Models. The Mean of the Selection Scores Obtained over the Five Cross Validation Data Sets Is Presented along with the Standard Deviation inside Parenthesis.

Variable	Bicycle	Car
$p_x(t)$	**23.0 (0.0)**	**25.0 (0.0)**
$p_x(t-1)$	5.8 (0.8)	16.6 (0.5)
$p_x(t-2)$	14.6 (0.9)	6.6 (1.3)
$p_x(t-3)$	1.6 (0.9)	14.0 (0.0)
$p_x(t-4)$	4.4 (2.4)	**21.6 (0.9)**
$p_y(t)$	**21.2 (0.4)**	**20.2 (0.4)**
$p_y(t-1)$	7.2 (1.9)	11.8 (2.7)
$p_y(t-2)$	4.2 (2.8)	5.6 (3.0)
$p_y(t-3)$	4.4 (5.9)	18.6 (0.5)
$p_y(t-4)$	15.8 (2.7)	**23.2 (1.8)**
$v(t)$	**25.0 (0.0)**	18.4 (0.5)
$v(t-1)$	18.8 (0.8)	10.6 (0.9)
$v(t-2)$	16.2 (0.4)	6.8 (1.3)
$v(t-3)$	21.2 (1.8)	6.0 (3.5)
$v(t-4)$	**24.0 (0.0)**	8.4 (3.0)
$\hat{v}(t)$	18.6 (0.5)	**21.8 (0.4)**
$\hat{v}(t-1)$	11.0 (1.4)	15.6 (1.7)
$\hat{v}(t-2)$	6.2 (0.8)	15.4 (0.5)
$\hat{v}(t-3)$	12.0 (1.4)	6.0 (1.7)
$\hat{v}(t-4)$	10.4 (1.5)	12.4 (0.5)
$h(t)$	**20.2 (0.4)**	**23.2 (0.4)**
$h(t-1)$	7.6 (2.7)	10.2 (0.8)
$h(t-2)$	5.0 (1.7)	1.0 (0.0)
$h(t-3)$	12.4 (0.9)	2.6 (0.9)
$h(t-4)$	14.2 (1.3)	3.4 (0.9)

Table 5: Mean, $\overline{m}$, Distance to the Intersection for the Miss Classified Samples along with the Standard Deviation (σ) of the Mean, for the Bicycle and Car Action Intention Models While Using the Variables That Yield the Best Performance According to the Backward Elimination Variable Selection Method.

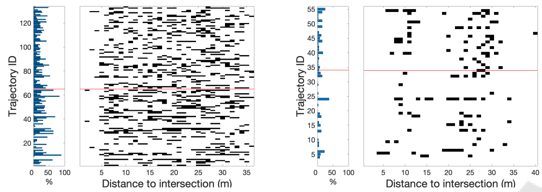
Model	LM	NN	SVM	RF
Bike	8.5 (0.12)	7.6 (0.18)	6.0 (0.45)	5.7 (0.44)
Car	4.7 (0.20)	3.6 (0.27)	3.6 (0.39)	3.7 (0.41)

Fig. 7 shows the mean error rate of all trajectories as a function of the distance to the intersection. While approaching the intersection the error rate is decreasing, this is in particular evident for the car model. As can be seen, already at 20 m from the intersec-



(a) Bicycle. (b) Car.

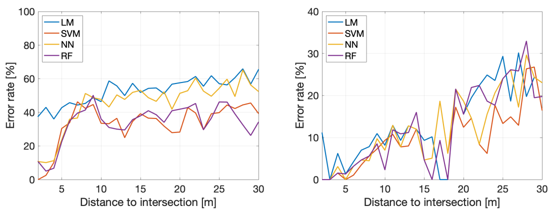
Figure 5: True Positives (TP), True Negatives (TN), False Positives (FN) and False Negatives (FN) of the Models Trained Using the Variables That Yield the Best Performance According to the Backward Elimination Variable Selection Method.



(a) RF Bicycle. (b) RF Car.

Figure 6: Percent of Time Series in Each Trajectory That Is Being Miss Classified (Left) along with a Visualization of, at What Distance the Model Make Errors (Right) for the Bicycle and Car RF Models. The Trajectories above the Red Line Are the Ones That Make the Turn, 70 Traces for the Bike and 22 for the Car.

tion the error rate is around 25% for the bike and for the car the performance is even more impressive, at 20 m from the intersection the error rate is <10%. The performance increase at 17 m for the car model depends on the very few data points available at that distance. In Table 6 the results from the recall and precision analysis are shown. For the bicycle data set, the SVM and RF clearly outperform the other two methods for both recall and precision performance. For the car data, the SVM model yields the best recall performance and the NN and the RF have similar precision performance. Another observation is that the difference between the models while using all variables is quite limited, however, while using a limited



(a) Bicycle. (b) Car.

Figure 7: Error Rate as a Function of the Distance to the Intersection for the Bicycle and Car Model Trained Using the Subset of Variables Found Using Backward Elimination Variable Selection Method.

Table 6: Average Precision and Recall for the Bicycle and Car Data Sets Using the Subset of Variables Found Using Backward Elimination Variable Selection Method.

Model	Bicycle		Car	
	Recall %	Precision %	Recall %	Precision %
LM	54.9	59.9	72.6	75.7
NN	58.8	66.1	82.8	79.5
SVM	75.7	70.9	83.7	78.5
RF	71.6	73.7	80.2	79.5

number of variables the LM model is outperformed by the non-linear models (NN, SVM and RF), which may indicate that the modeled traffic behavior is non-linear. Finally a comparison is made between the performance of the models presented here and previous findings from (Muhammad and Åstrand, 2018). In their work only heading was used as input for a particle filter-based model and performance of around 80% correct classifications of the intentions for both bicycle and car models is reported. While using three variables, heading, speed and the shortest distance from the border of the path are used for predicting the intention in the intersection, the performance is slightly lower, however the variance of the predictions also become lower. In this work, it was found that heading receives high scores for both bicycle and car models. This corresponds well with the findings in (Muhammad and Åstrand, 2018), where heading is found to be the most significant variable. Another comparison can be made to the findings in (Phillips et al., 2017) where the authors use a rich data set comprising 104 featured such as base features describing dynamics and position from the ego vehicle, history features from past states, traffic features based on surrounding vehicles, and rule features indicating legal actions at the next intersection. The data set consists of historical base features extracted from frames 0.5 s, 1 s, 2 s and 3 s in the past. The results from an LSTM indicate 80-85% accuracy on predicting the intention in upcoming intersections. The results obtained in this work, the car intention prediction model is within this range i.e. for distances above 20 m the accuracy is around 80%, and for distances below 20 m the accuracy is around 90%.

From a computational effort point of view, the models have low complexity and could execute fast on any modern vehicle ECU or C-ITS road side unit.

6 CONCLUSION

A method for predicting action intentions, i.e. whether to turn or go straight in an upcoming intersection, of road users is presented. Trajectory data sets from both bicyclists and cars are used to demonstrate the proposed approach. From the trajectories a sliding window is applied creating short time series used for building models that predicts the action intention. The no free lunch theorem is put to use as it was found that the RF yields the best performance for the bicycle data and the NN for the car data. The search for the most important variables for the classification task resulted in slightly improved performance while using only five variables for the bicycle model and six for the car model. For the bicycle model longitudinal and lateral position along with speed dynamics $v(t)$, $v(t-4)$ and $h(t)$ are needed. With the car model, estimated speed, heading and position dynamics (t) and $(t-4)$ for both longitudinal and lateral position are among the most important input variables.

Future work includes incorporating data describing relations between different road-users to enable modelling of how the behavior of different road users interplay in decision making. Moreover, while modeling interplay, time to decision becomes a natural model output instead of only the actual action intention, as used in this work.

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