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# Applicability of Neural Networks for Driving Style Classification and Maneuver Detection

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**Abstract:** Maneuver and driving style detection are of ongoing interest for the extension of vehicle's functionalities. Existing machine learning approaches require extensive sensor data and demand for high computational power. For vehicle onboard implementation, poorly generalizing rule-based approaches are currently state of the art. Not being restricted to neither comprehensive environmental sensors like camera or radar, nor high computing power (both of what is today only present in upper class' vehicles), our approach allows for cross-vehicle use: In this work, the applicability of small artificial neural networks (ANN) as efficient detectors is tested using a prototypal vehicle implementation. During test drives, overtaking maneuvers have been detected 1.2 s prior to the competing rule-based approach in average, also greatly improving the detection performance. Regarding driving style recognition, ANN-based results are closer to targets and more patient at driving style transitions. A recognition rate of over 75 % is achieved.

**Keywords:** Artificial neural networks, Driving style estimation, Overtaking maneuver detection.

## 1 Introduction

Recently, developing new vehicle functionalities has been a challenge between almost all major car manufacturers in order to match and exceed their competitors. Knowledge of the actual driving state and traffic scenario around a vehicle has become a key factor for many innovative features, enhancing safety, comfort, energy efficiency and driving experience. Traffic scenarios are derived from diverse factors, including the actual performed maneuver and driving style, the road type and its condition, visibility and weather conditions among others. With this information acquainted, the vehicle is able to adapt its components accordingly: Improved handling for parking procedures or winding roads, pre-crash preparation for safety critical scenarios or an adaptive energy management for stop-and-go traffic are just some examples of possible benefits.

In order to gain extensive scenario knowledge, various information sources need to be merged, including monitoring of the traffic environment using radar, camera and LiDAR sensors. Even

* Supported by Volkswagen Group Research.

though they are already available in well-equipped upper-class vehicles, they are not for the vast majority yet. Furthermore, vehicle2x communication is only about enter markets in the near term.

### 1.1 Motivation and Use Case

Drive modes have been introduced successfully to extend the application range of vehicles on the driver's desire. Looking at systems of different manufacturers — e.g. eDrive (BMW [1]), Dynamic Select (Mercedes [2]), FlexRide (Opel [3]) or Volkswagen's Driving Modes — settings like normal, dynamic, efficient and comfort are usually available [4].

Each mode contains a set of vehicle parameters adapting handling, engine and gear selection behavior beside others. For example, steering assistance and softer chassis suspension in *comfort* mode or stiffer steering and faster throttle response in *dynamic* mode are common tunings. Moreover, *individual* allows for (yet limited) mixed adjustments according the needs and preferences of the driver. [4]

Hence, in order to archive an optimal driving experience, the driver may change the mode during his trip, depending on the actual traffic scenario. Nonetheless, behavior monitorings show most drivers are not switching drive modes frequently, yet [5]. Thus, a way to significantly enhance the drive mode concept and the driving experience is the automated suggestion or selection of suitable modes according the actual scenario; Scenarios need to be interpreted in a timely manner.

Table 3 (appendix) lists possible drive mode suggestions as a function of road types, driving styles and maneuvers. Taking a closer look at the maneuver part, stopping, emergency maneuvers and reversing are easily and reliable detected using rule-based methods as they have explicit and constant signal patterns [6]. On the other hand, the detection of overtaking maneuvers and different driving styles is more complex, for which the development of lightweight detectors is required.

### 1.2 Content and Structure

Section 1 introduces basics about overtaking maneuvers and driving style. The actual state of the art for both topics are shown by a short comparison of related work in Section 2. As a result, scientific gaps are worked out in Section 3, giving details on the research questions and goals for this work. In Section 4, our approach is presented, after a brief overview upon our methodology and the utilized soft- and hardware is given. The conducted experiments are described in Section 5, including data recording, Model-in-the-Loop (MiL) tests and the prototypal implementation. At the end, the results are presented in the final Section 6, including a critical reflection of the outcome and an outlook for possible future work.

## 2 Related Work

In the fields of driving style, overtaking and lane-change detection, numerous studies provide a sound knowledge basis. Since both tasks have not yet been looked at together, each is considered in detail at their respective subsection.

### 2.1 Detection of Overtaking Maneuvers

Overtaking maneuvers are generally used to bypass slower vehicles (or obstacles) located ahead on the same lane. Typically, they are conducted through acceleration and a temporal usage of the adjacent lane, therefore, making them a dynamic and risky maneuver. Although they do also appear on multi-lane motorways (as common lane changes), these cases are not primary addressed for this work. Following Walker et al.'s [8] definition, this maneuver consists of a sequence of three phases, as shown in Figure 1. They are further grouped into preparation (1-2) and execution

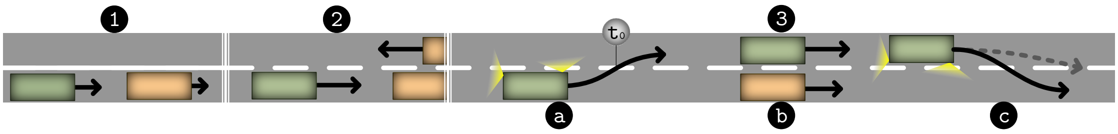


Figure 1: Phases of an overtaking maneuver.

(3a-c). During the preparation phases, the wish for overtaking arises and suitable gaps for a safe execution are sought out by the driver. Both phases can be used for early prediction or detection sensitivity optimization [11]. Normally, the indicator is set at the end of the first two phases. In phase (3), the maneuver is finally conducted through changing lanes to the left (a), passing the slower vehicle (b) and reeving in front of it (c). The first lane change related action can be used to detect its beginning — either a noticeable vehicle acceleration or corresponding steering motion. This usually happens around 1–2 s before crossing the center marking, representing a universal measurable and comparable detection time ($t_0$). [11]

Given this, negative values represent a prediction of upcoming overtaking maneuvers and positive values a delayed detection, respectively. Beside timings, the detection rate is another important measurand, representing true and false positives. In literature, several approaches of machine learning techniques are described. This allows for a comparison as conducted by Li [7]. Table 1 summarizes the findings, taking both, overtaking maneuvers and lane changes into account.

Keeping in mind the different data sets used for each method, it is still notably that ANNs and support vector machines rank within similar high performances. Leonhardt et al. [9]-[11] got very good results combining the driver's steering behavior and eye movement track with the actual traffic scenario (position of other vehicles, road sign recognition), using a wide array of radar and six camera sensors. Compared to Bayesian Networks, ANNs receive a top performance of 98 % true positives and 2 % false positives, given an average detection time of roughly –3 s.

Mandalia and Salvucci [12] have used a support vector machine for detection while restricting their input to onboard sensor and lane position data only. For reaching the optimum true positive rate of 97,9 % (false positive rate of 5 %), they used a 1.2 s timeframe analysis, archiving an average timing of roughly –1 s. In conclusion, it should be stressed that the consideration of external sensor data greatly improves the detection timings and minimizes false positive rates.

### 2.2 Driving Style Detection

Looking at driving styles on the other hand, no general valid definition is available. This can be explained by the subjective differences in classification which depends on the point of view

Table 1: Performance of selected overtaking and lane changing detectors. [6].

| Method | True positive | Timing | False positive | Reference |
|---|---|---|---|---|
| Bayesian Network | 80 % | -1,5 s | n/s | Dagli [22] |
| | 92 % | n/s | 20 % | Hou [19] |
| | 80 % | n/s | 6 % | Hou [19] |
| | 90 % | -2 s | 9 % | Leonhardt [9] |
| | 70 % | -7,8 s | n/s | Leonhardt [9] |
| Fuzzy Logik | 88 % | n/s | 14 % | Hou [23] |
| HMM | 86 % | 0 s | 6 % | Jin [26] |
| | 72 % | -0,5 s | 33 % | Proff [24] |
| | 78 % | 0,5 s | 67 % | Tezuka [25] |
| ANN | 98 % | -3 s | 2 % | Leonhardt [11] |
| | 78 % | -0,5 s | 12 % | Proff [24] |
| SVM | 84 % | -1 s | 8 % | Bengtsson [28] |
| | 91 % | 0,4 s | 4 % | Kim [27] |
| | 98 % | -1 s | 5 % | Mandalia [12] |

Table 2: Performance of selected driving style recognition methods.

| Method | True Positive | Timing | False Positive | Reference |
|---|---|---|---|---|
| Rule-based | ca. 70 % | ca. 600 s | ca. 4,9 % | Colombo [15] |
| Fuzzy Logik | 68 % | ca. 100 s | 2 % | Dörr [16] |
| ANN | 65,5 % | k. A. | ca. 1,8 % | Brombacher [29] |
| | 60,4 % | k. A. | k. A. | Dong [30] |

(driver, passenger, external observer), the individual scenario (environmental influences) and personal properties (experience, habituation, etc.). Therefore, driving styles can be understood as an accumulation of single maneuver ratings over a variable time horizon, each having an individual impact on its perception. For a general classification, subjective ratings are usually objectified through averaging.

Depending on the desired application, different sets of driving styles are used for approximation. They often depend on one-dimensional ratings of a single, measurable feature, e.g. {calm, normal, aggressive} using distance keeping, {efficient, normal, inefficient} using energy consumption, {slow, normal, dynamic/sporty} in terms of vehicle dynamics or {unexperienced, average, experienced} in terms of general driving experience. Driving dynamics (lateral and longitudinal acceleration) are the most common features. [13], [14]

Following this scheme, Ebersbach [17] did extensive research trying to establish a statistical connection between driving styles and lateral acceleration. Meseguer et al. [18] chose a similar approach using fuel consumptions for driving style classification. In essence, an increase in the distribution is observable for more dynamic driving styles by both authors. Colombo et al. [15] developed a promising method to overcome parts of these flaws by determining an average across more than 20 maneuver ratings. In detail, the vectorial sum of the normalized lateral and longitudinal acceleration is used as input features. In their evaluation, driving style are correctly assigned with an accuracy of roughly 70 %. In practice, it takes up to ten minutes for driving style changes to be detected.

Dörr et al. [16] assessed several dimensions of driving styles using fuzzy logic. In their simulation, they got a similar classification rate of 68 %. The thresholds and weighting values were implemented manually. Therefore, better adaptation using machine learning can be expected for their approach. In general, it can be stated that an objective interpretation of driving styles is difficult to archive as their transitions are smooth. Besides that, subjective perception depends on diverse, partly unmeasurable influences. And even during dynamic driving, slower maneuvers may appear due to limiting traffic conditions. As a consequence, the rating of a single maneuver is technically possible, but the probability of hitting the right classification is rather poor, therefore making changes more difficult to detect.

## 3 Scientific Gap and Research Question

Comparing the findings, it is obvious that the vehicle integration of existing machine learning-based approaches for our application is problematic due to their extensive computing demands and needs for external sensors. Furthermore, a reliable overtake maneuver detection has not been proven, yet. Rule-based algorithms are available but show only insufficient performance. Looking at driving styles, work conducted by Colombo et al. show a promising approach. Nevertheless, quicker recognition timings are required.

In order to overcome these flaws, the applicability of ANNs as efficient detectors needs to be further investigated. A simplification of the design process is expected looking at their adaptability to real-world data. Furthermore, by using their capabilities of detecting previously unknown correlation patterns, improved recognitions of borderline cases are expected to occur. Therefore, attention should be given to a comprehensive training data set, including high quality target data.

# 4 Simulation and Evaluation of the Concept

In this section, the main steps of the project are sketched. Section 4.1 lists the used hard- and software. Section 4.2 gives introduction into the data recording and labeling process. Then, the following Subsection describe how the detectors are designed inside a Model-in-the-Loop (MiL) simulation, allowing for quick adjustments. Section 4.3 explains the training procedure. Finally, Section 4.4 shows the results of a pilot ran and 4.5 gives details results.

## 4.1 Technical Preliminaries and General Concept

For this project, a MicroAutoBox II 1513 prototyping device is directly connected to a Volkswagen Golf R in order to participate in its CAN bus communication. It is giving restrictions on computing and storage capacity since both concepts need to be implemented onto the prototype device in order to compare their behavior in real-time.

Software-wise, MATLAB and MATLAB Simulink are used for implementation of the software model, simulation and data evaluation. The C-code compilation generated from our Simulink is loaded onto the MicroAutoBox. In order to fit in ANNs, a MATLAB Simulink toolbox has been set up in advance. It allows for both, online training and usage of a pre-defined nets. Furthermore, a devCUBE deep-learning workstation is available for ANN offline training.

## 4.2 Data Recording

At the outset, no suitable labeled dataset has been available for the designated vehicle. Therefore, data recording has been conducted at various roads around Wolfsburg. Both, recording and labeling of the data are operated via dSPACE's ControlDesk, while full CAN bus traces are recorded at 100 ms. Soon it had become apparent that common overtaking maneuvers on the road do not occur often enough in order to create a sound data set. Therefore, additional overtaking maneuvers have been recorded on a Volkswagen test ground, supported by an auxiliary vehicle. Among all possible speed and road course combinations {speed-categories of both vehicles, road curses, driving and steering behaviors}, 500 out of approx. 16.000 possible maneuver types have been chosen for readjustment.

In order to minimize input lag — especially for overtaking maneuvers — keyboard hotkeys have been defined with the help of ControlDesk's Python Script API. Nevertheless, a manual adaption is still necessary to correct timings within the remaining response time of around 1 s. Therefore, the first occurrence of acceleration pedal or steering wheel activity of the overtaking maneuver are defined as the earliest possible time $t_0'$ (regardless the indicator stalk's position). Lane detection data serves as an additional reference in order to determine $t_0$ for each maneuver (cf. Figure 3).

Then, each maneuver is categorized regarding its driving dynamics {low, normal, high} and its road course {straight, left or right corner, mixed course} for scenario-individual evaluation. In the end, 87 overtaking maneuvers and 13 possible false positives (fast turning, evasive maneuvers) resulted. For the driving styles {normal, efficient, dynamic}, recording took place on a track containing three different driving environments {rural, overland, motorway} and varying traffic densities. The training data set contains 73 min of driving data. Test runs were then executed on different tracks to prevent impacts of overfitting. Altogether, over 100 km of data have been recorded in 92 Minutes.

#### 4.2.1 Overtaking Detector

Useful inputs for detectors include the vehicle's steering and movement sensors. In detail, the steering wheel movements {position, torque, turning speed and acceleration}, the acceleration behavior {accelerator and brake pedal usage}, turning rates and lateral acceleration as well as the indicator lights are of special interests. On a straight stretch, the steering wheel's position and torque as well as the lateral vehicle acceleration and yaw rate have a similar w-shape as shown in Figure 2. These redundant signals are left out in order to minimize the network input size.

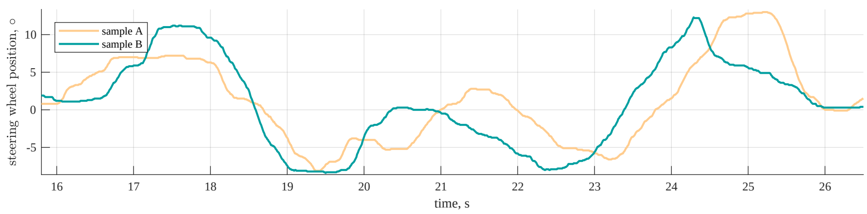


Figure 2: Signal path of the steering wheel's position during a overtaking maneuver.

The steering wheels movement marks the derivation of its position over time, making it inherent against bends' impacts. Nevertheless, varying courses of the road during a maneuver cannot be filtered out without position data [20]. Preliminary investigation showed that the near-start of a maneuver (A), the initial lane change (B) and merging (C) can be detected best using ANNs [11]. Figure 3 shows the relative position of the three labels (A, B, C) used at target data (dotted lines).

The indicators (dashed lines) and the relative position of the lane markings (solid lines) are also shown. Here, the vehicle is crossing the center markings at 24 s. We represent the maneuver using the state machine shown in Figure 4.

Thereby, the time sequences of the phases is modeled and the three ANN detectors (A, B, C) are responsible for the state transitions. Each state has a certain follow-up time $t_i$. Canceling of the maneuver is also detected by monitoring the brake pedal's position. The final reeve is undetectable more often due to lower driving dynamics towards the end of the maneuver (cf. Figure 1: optional trajectory at phase 3c), making an overall time limit of 15 s necessary.

#### 4.2.2 Driving Style Detector

Due to the limited research scope, we concentrate on a results-oriented approach, i.e., skipping the optimization of driving style classes. Three common classes are used — namely energy efficient (*eco*), normal (*nor*) and dynamic (*dyn*) driving [6].

In order to enhance the data basis on which the actual driving style is estimated, Colombo et

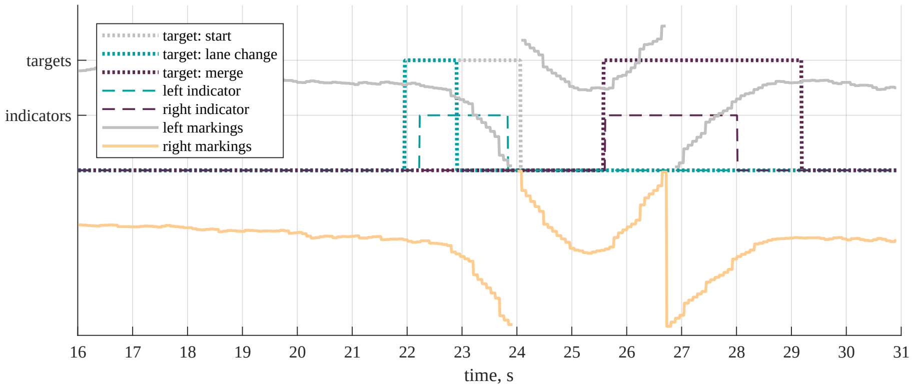


Figure 3: Overtaking maneuver represented by lane detection data and indicators showing the relative position of the data labels.

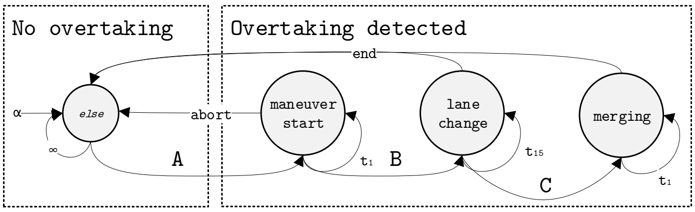


Figure 4: State machine representing overtaking maneuvers.

al.'s maneuver-based approach is extended by a multidimensional and continual rating process. Therefore, driving efficiency[1], longitudinal and lateral accelerations are considered separately. For the combination of different dimensions, knowledge of their relative position is necessary. Figure 5 shows the positions as a function of driving efficiency and dynamics. As both dimen-

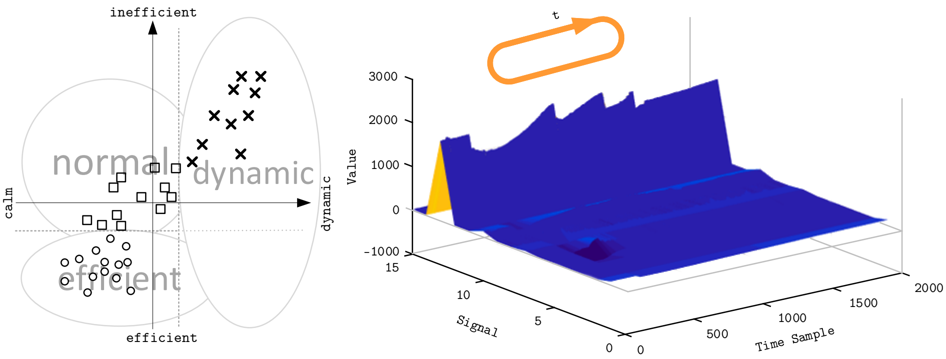


Figure 5: Left: Relative positions of driving styles {o, □, **x**} as a function of driving dynamics and energy efficiency. Right: Ring buffer containing 2000 samples of 15 different sensor signals.

sions usually correlate (high dynamics – low efficiency and vice versa), this might not always

[1] In regard to the flat topology around Wolfsburg, road gradients are not required in our approach.

be the case as demonstrated by Porsche InnoDrive [14]: In contrast to average human driving styles, a more efficient and more dynamic driving style is possible. Therefore, necessary priorities derived are $\{\text{dynamic}\} \succ \{\text{efficient, normal}\}$ to catch dynamic-efficient outliers.

Features like driving safety [21], steering behavior and social behavior are examples for criterions that are further increasing the availability of an evaluation basis. In our case, several ANN detectors undertake the task of driving style classification. First of all, the raw sensor data is preprocessed by a simple maneuver detector looking for acceleration, deceleration and turns. As soon as one of the listed basic maneuvers is observed, the sensor data are recorded and stored with all applying maneuver type labeled. Next up, the temporary stored sensor data are transferred into ring buffers according their received label(s).

In practice, a simple turn will only be assigned to the *turn* buffer, whereas braking right ahead to a turning maneuver lead to an allocation into *turn* and *deceleration* buffer. Figure 5 (right side) shows the content of a single ring buffer holding 2000 samples of 15 sensor signals. The visible ridge of signal 14 represent the engine speed. Its steps result from gear shifts and maneuver limits, as the oldest samples are overwritten when new maneuvers are buffered.

Additional to the three basic maneuver buffers, a moving time frame buffer stores the latest sensor data whenever the vehicle is above starting speed. All ring buffer serve as continuous input provider for the subsequent ANN detectors. Figure 6 shows several distributions of the accelerator pedal position for each of the three driving styles. The number of input features,

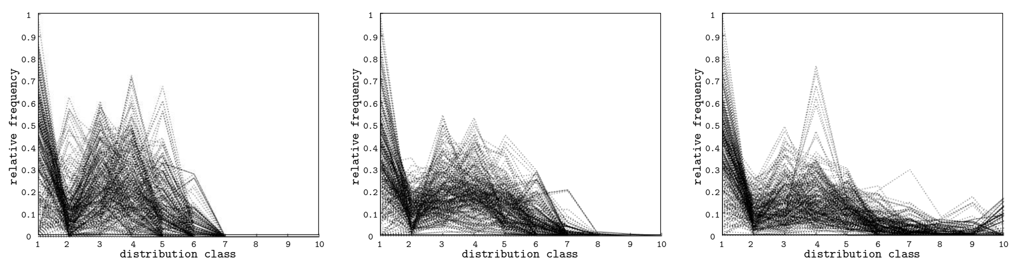

Figure 6: Distributions of the accelerator pedal positions for calm, normal and dynamic driving styles.

originating at 2000 time samples $\times$ 10-15 signals, is decreased using temporal reduction and quantization. This is archived with the help of discrete value distributions for each input signal. As a result, the input vector is reduced to 5-10 samples per signal. For Figure 6, class 1 reaches 100 % in the beginning, because all buffers are initialized with zero.

The number of samples varies, an equivalent size of 30 s is used for the three maneuvers and 200 s for the moving time frame. Again, since each buffer is initialized with zero, it takes two up to five minutes until they contain enough data for a sound detection. For dynamic driving detection, all of the above-mentioned features are used, including an additional fast acceleration (kick-down) detection for instant activation. For efficient driving, the turning ANN is left out as is mainly represents driving dynamics. Finally, majority vote is used to join the respective ANN ratings into a single output.

### 4.3 Neural Network Training

In search of an optimal ANN, several configurations are rated according their performances and complexities. Variations include different architectures (numbers of neurons, layers and connections) as well as input features, activation functions, training methods etc. Each network is first trained using MATLAB's own ANN toolbox. They are then converted into a Simulink compatible format for in-car use. In the end, the operational ANN-detector is transferred onto the prototype for demonstrating the functionality in real time.

For the determination of an optimal architecture, a large number of ANNs is trained and compared iteratively. In every iteration, properties like topology or input features vary. To ensure equal condition, their performances are evaluated using standardized training and evaluation sets. For signal preprocessing, a Simulink model is used assuring capability for subsequent real-time tests. Each network is trained with a maximum of 10.000 iterations or 30 min using Levenberg-Marquardt algorithm. Usually, ANNs are fully trained within 2.000 iterations.

Small networks with fewer inputs are always considered first as larger networks have a greater number of necessary mathematical operations. So, the ANN architecture grows until an optimal detection performance occurs and overfitting possibly sets in. In consequence, the driving style detectors remain quite shallow using a [x:2 2:1][2] topology. The overtaking detectors end up at the same depth using a [8:16 4:2] topology. Figure 7 shows the equal or poorer performance for deeper or larger ANNs.

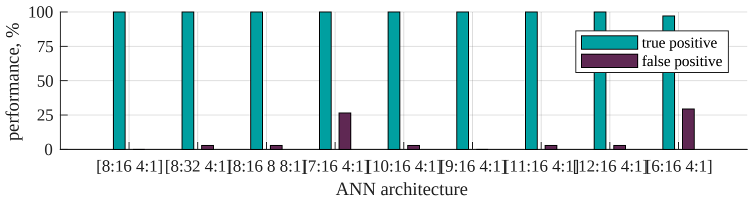


Figure 7: Performances of deep neural networks.

### 4.4 Prototyping and Pilot Run

In a last step, the identified ANNs are trained and tested again using all available data before compiling them for MicroAutoBox. In order to meet the resource limitations, the ring buffer hold 8-bit quantized signals matching the subsequent distribution classes of the signals. The overtake detectors are clocked at 100 ms, but they are only active if suitable preconditions are met (e.g. sufficient vehicle speed). Figure 8 shows the output of the overtaking detection ANNs during an overtaking maneuver (here, all three ANNs are active in order to compare their accuracy).

The driving style detecting ANNs are clocked on a 5000 ms cycle to reducing computational load. As a result, the detector quickly adapts for dynamic driving styles, e.g. in the event of a kick-down, but responds slower for inconclusive driving styles. Test runs show this behavior suiting subjective driver needs well. Figure 9 and 10 show the results of the respective majority votes (detector output, lower charts) as a sum of the three individual ANN outputs (uppermost charts). As expected, the ANNs for dynamic driving behave contrary to those for efficient

[2] Naming convention: ["inputs" : "neurons hidden layer 1" "hidden layer 2" ... : outputs] of a fully connected ANN.

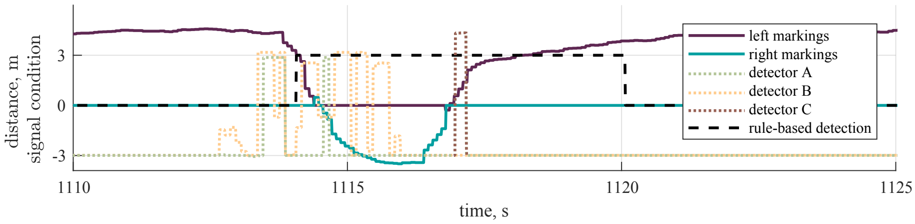


Figure 8: Output of the ANN-based and rule-based overtaking detectors.

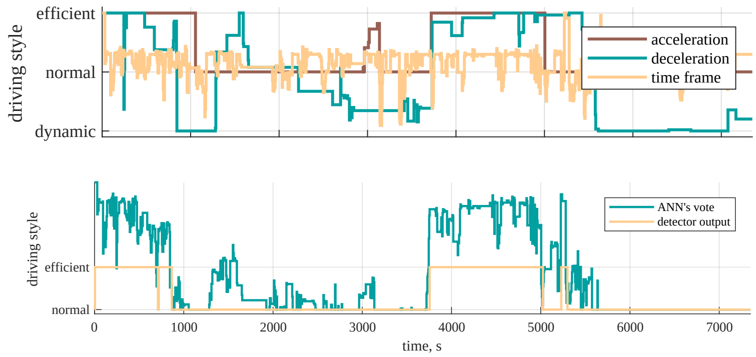


Figure 9: Output of the efficient driving style detector during a test drive.

driving. Nevertheless, isolated maneuvers conducted out of limits entail a temporary dynamic detection (cf. middle graph in Figure 10). Once in normal driving, the efficient detector can be enabled. However, as long as the dynamic detector is active, it overrides the efficient detector.

## 4.5 Results

### 4.5.1 Overtaking Maneuver

Due to the few overtaking maneuvers during test drives, a deep evaluation of the maneuver detector is only possible using recordings at the test site. Therefore, different scenarios can be compared individually emphasizing differences in the performance. During dynamic driving, it is possible to trigger the overtake detection on purpose, e.g. by a sudden yank on the steering wheel. Nevertheless, in regard to the application, a positive driving style and overtake detection is not contrary. Figure 11 compares the output of the ANN- and rule-based detector next to the target. Two very slow maneuvers can be identified around 150 and 575 s that are not recognizes at all. But for usual and dynamic overtaking maneuvers, performed on a nearly straight road section, both detection methods archive a 100 % detection rate. For left-handed bends and straight road sections while driving normal, the ANN-based detector remains at 100 % true positive rate, while the rule-based reference method drops to ca. 66.7 % and 54.2 % respectively. For calm maneuvers, as much as 92.3 % are recognized using ANNs, while only 11.5 % are recognized using the rule-based detector (cf. Figure 12).

Figure 13 shows two results comparing the initial detection time. In the upper part, all detected

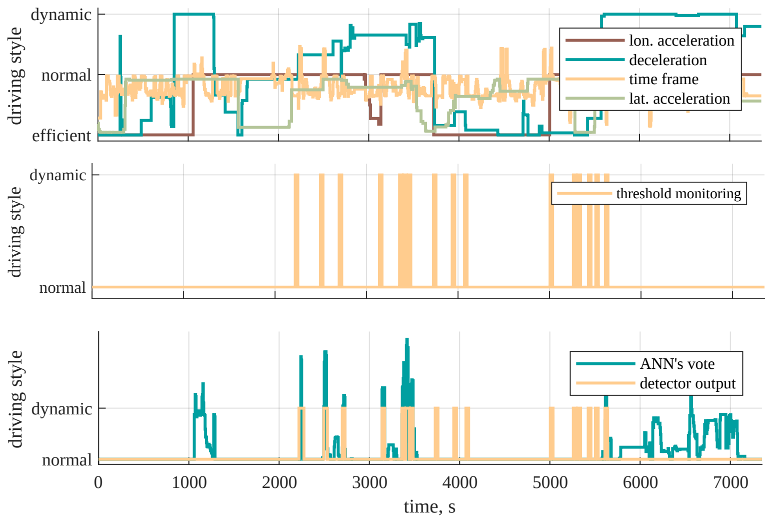


Figure 10: Output of the dynamic driving style detector during a test drive.

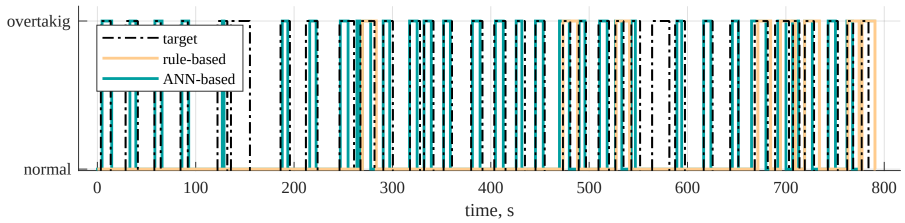


Figure 11: Direct comparison of the ANN- and rule-based overtake detectors.

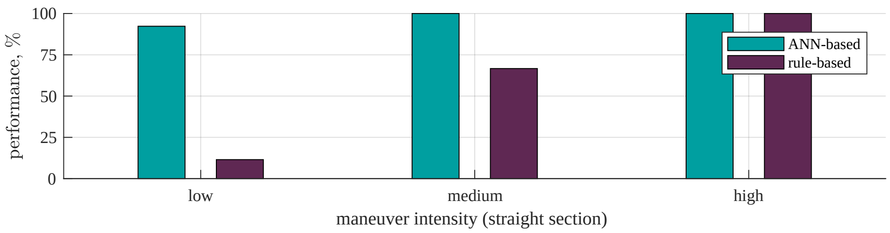


Figure 12: Results of ANN and rule-based detectors on straight roads.

maneuvers are compared. The ANN-based detector is approximately 1.3 s quicker, while the average lies within 0.4 s after the car crossed the lane markings. The lower bars compare all maneuvers detected by both methods. Here, the ANN-based detector is 1.8 s faster, detecting maneuvers 0.4 s prior to lane crossing in average. Overall, huge improvements by ANN-based detection are bought by a minor rise in false positives during dynamic driving maneuvers. A false positive rate of 3 % occurred whereas the rule-based detector does not give any.

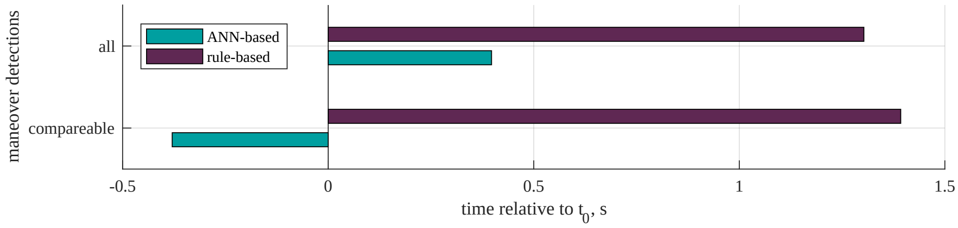


Figure 13: Compared detection timings of both methods.

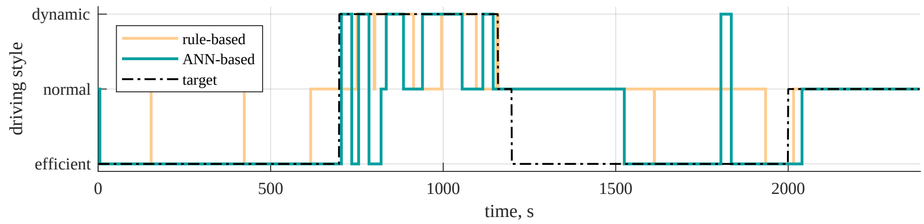


Figure 14: Direct comparison of the second evaluation run.

### 4.5.2 Driving Style

Two test runs have been conducted for comparison of the driving style detectors' performances. The congruency of label and detector output is measured — both need to match. Figure 14 shows the output of both detectors on the second, more challenging evaluation run. On the first run, ca. 82 % have been archived; on the second run, over 75 % have been archived by the ANN-based detector. Compared to Colombo et al.'s approach, the overall performance is approx. 30 % better.

## 5 Conclusion and Outlook for Future Work

Within this research project, suitable sensor signals for distinguishing driving styles and detecting overtaking maneuvers have been successfully identified. Furthermore, ANNs trained with manageable set of real-world data emphasize their advantages for the desired purpose. In comparison to existing rule-based approaches for vehicle controller systems, the ANN-based detec-

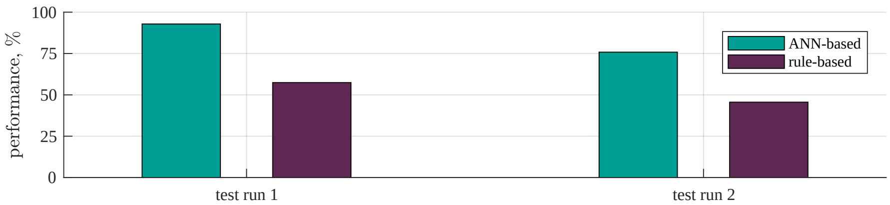


Figure 15: Results of two evaluation runs.

tors show a better performance in both, detection rate and timing. While greatly improving the reliability of borderline cases, it must be mentioned that one is possible to provoke false positives, e. g. by accelerating on a left-hand turn at higher vehicle speeds or other similar behaviors.

Anyhow, false positives due to dynamic driving are not contrary for the intended purpose of automated switching driving modes. Also, in order to assess the results of this approach to the results of related work (Table 1), our vast data set must be kept in mind.

For the automated and adaptive drive mode selection, important parameters like user-accepted points of changeovers, switching frequencies and fully individual driving modes are identified as further research topics. The latter may lead to smooth transitions of single driving modes.

A valid classification of driving styles, considering a wide spectrum of different behaviors, is difficult to obtain. Either way, due to the subjective perception of driving styles, studies using different types of drivers will be required in order to meet the individual customers' requirements. Unsupervised classification methods may help to overcome this flaw, allowing for driver-individual classifications. Forecasts of upcoming traffic scenarios in order to realize an optimized predictive vehicle setup become possible. In particular, slow switching systems like air condition going on towards energy management units.

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Table 3: Suggestions for adaptive driving modes [6].

| | Still standing | Stop & Go | Overtaking | Emergency maneuver | Backing up | Parking, shuting | Else |
|---|---|---|---|---|---|---|---|
| City | Eco | Eco | — | Dyn | Com | — | — |
| Driveway | Eco | Eco | — | Dyn | Com | — | — |
| Motorway | Eco | Eco | — | Dyn | — | — | — |
| Overland | Eco | Eco | Dyn | Dyn | — | — | — |
| Serpentines | Eco | Eco | Dyn | Dyn | Com | Com | — |

| | Still standing | Stop & Go | Overtaking | Emergency maneuver | Backing up | Parking, shuting | Else |
|---|---|---|---|---|---|---|---|
| Efficient | Eco | Eco | Nor | Dyn | Com | Com | Eco |
| Normal | Eco | Eco | Dyn | Dyn | Com | Com | Nor |
| Dynamic | Dyn | Dyn | Dyn | Dyn | Dyn | Com | Dyn |

| | City | Driveway | Motorway | Overland | Serpentines |
|---|---|---|---|---|---|
| Efficient | Eco | Nor | Eco | Eco | Eco |
| Normal | Eco | Dyn | Com | Nor | Dyn |
| Dynamic | Dyn | Dyn | Dyn | Dyn | Dyn |