Online Driving Style Recognition using Fuzzy Logic

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Abstract— Nowadays more and more driver assistance systems are implemented in cars. By adapting the system to the driving style of the driver, the acceptance of the driver to such a system could be enhanced. In this paper a system for online driving style recognition is designed. It is implemented in *Matlab/Simulink* and uses fuzzy logic for identifying the current driving style. It is fully parameterisable via a central parameter file and could therefore be adapted to nearly every car. The recognition was tested by using a vehicle dynamics simulation with 68% correct classifications over time.

I. INTRODUCTION

A. Motivation

The driving style is important in many fields of application. It is used in accident research and road construction. The most relevant field for the use of a driving style recognition system is the individual adaptation of driver assistance systems. There are many reasons why the knowledge of the driving style is important. Firstly, for the energy consumption of a car, especially an electric car, the driving style is a very meaningful factor. A sporty driving style with higher velocities and higher accelerations results in an increasing energy consumption and a calm driving style with lower velocities and lower accelerations results in a decreasing energy consumption. The second application where the driving style is useful is the parametrization of driver assistance systems. When the driving style is known, the systems could be adapted to the driving style. For example, the accelerations set up by a cruise control system could be adapted to the desired accelerations. Thereby the acceptance of the driver for a specific system could be enhanced. With higher acceptance the driver uses the system in the long term. This could enhance the driving safety, too.

B. State-of-the-Art

As mentioned above, driving style recognition is used in different fields of application. Examples from different topics are briefly presented below. Friedrich and Ziegler present a method for automatic adaption of a driver assistance system to the driving style in [5]. While it is a patent the statements are very unspecific. That is why, this work describes most methods given in the literature regarding functionality and structure. The intent of the inventor was a targeted adaption of driver assistance systems to the driver for enhancing

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driving safety and comfort.

Deml et al. first try to capture the term driving style in [3]. It is stated that lateral and longitudinal acceleration behavior is suitable for classification of the driving style. But the authors also say that there are situational influences on the driving style. The acceleration values therefore may not be used isolated from the given driving situation. Based on the theoretical study, a field experiment with 26 subjects found significant parameters to distinguish between different driving styles. The conclusion was, that the acceleration behavior is a suitable parameter when the driving situation is taken into account.

Aljaafreh et al. differentiate between two driving styles in [1]. The authors distinguish between normal and aggressive driving. The readings of a 2-axis-accelerometer and the speed are used as inputs. The inputs are fed into a fuzzy inference system. The membership functions, which create sharp outputs from the inputs, are inferred from real recorded data.

Ly et al. use inertial sensors to identify the driver in [8]. The system distinguishes between two drivers on basis of parameters from inertial sensors, like accelerations, vehicle speed, gyrometer output, steering angle, throttle value and brake pedal value. They use an event based method with two different learning algorithms. Three types of events (Braking, Acceleration, and Turning) are defined and identified in the data. The experiments were done with a test car and two different drivers on different routes.

Johnson and Trivedi use a smartphone to identify the driving style in [6]. The driving style is divided into two categories in this paper: "typical" (non-aggressive) and "aggressive". All gathered data from different sensors inside the smartphone is fusioned and processed internally and no external processing is needed.

An example from the field of accident analysis and prevention is given in [2]. The authors did two studies in which they revealed factors for the driving style and the associations between them.

Plöchi and Edelmann give an overview of different driver models in [9]. They concentrate on the interest of engineers and they notice that there is a wide range of driver models, because the demands on the models are different for each application. Not only different driver models but rather different methical modeling approaches are discussed.

C. Contributions of this work

The system provided in this paper is an online system. That means it works while driving. It differentiates between different driving situations by using a signal from the naviga-

tion system called *road class*. It uses only data available on the CAN bus (controller area network) of the vehicle. That is why, the system could be used in nearly every car, no matter if it is a car with a combustion engine or an electric car. For full spectrum of functionality the car has to be equipped with an ACC[1] system. Until the now, the system only works in simulation.

II. Fuzzy logic

Fuzzy logic is a method which uses fuzzy sets that allow to one model states which were not possible with classical binary logic. With fuzzy logic it is possible to implement rules from type `IF X AND Y THEN Z`, while the `X`, the `Y` and the `Z` could be described in natural language. Before these rules could be used, all input signals have to be converted into so called linguistic variables. This step is called *fuzzification*. Different membership functions are used to do this. Usually easy triangular or trapezoid functions are used to keep the computational cost low. After the transformation into linguistic variables, the inference rules could be applied and after that a so called *defuzzification* is needed to generate a sharp output value. A graphical representation of the basic fuzzy logic process can be found in Fig. 1. The most basic
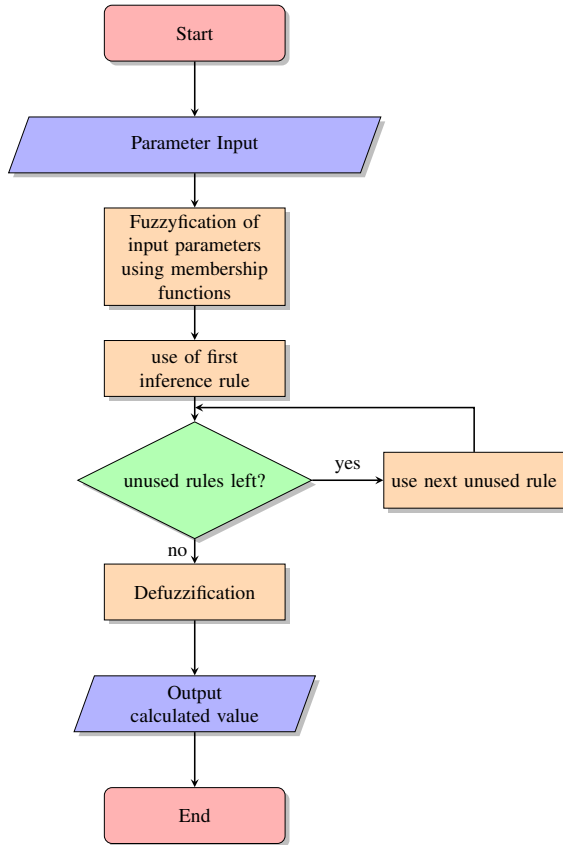
Fig. 1. The Fuzzy logic process

form of fuzzy logic is used to generate a characteristic value

[1]ACC stands for adaptive cruise control, a system which automatically controls the speed of a vehicle. With a radar sensor leading vehicle is tracked and the vehicle speed is controlled in order to maintain a safe distance.

for each parameter. More Information about Fuzzy Logic can be found in [11] or [10].

III. Driving style recognition system

A. Terms and definitions

In literature there are definitions for the terms driver type and driving style, but they are often used interchangeably and different literature uses different definitions. That is why there is no clear definition in general for these terms. In the context of this work it is assumed that the driver type is the physical constitution and the characteristics of the driver itself. There are implications from the driver type on the driving style but the two terms don't mean the same. The driving style is the way of executing the driving task. It is determined by the driver type, the driver condition, the driving situation and the purpose of the trip. The impacts on the driving style are given in Fig. 2.
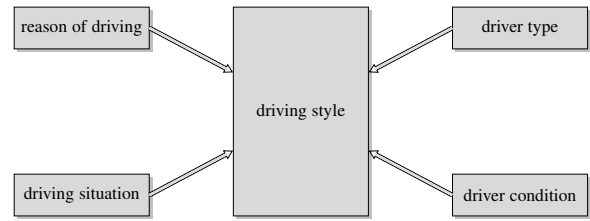
Fig. 2. Impacts on the driving style

There are different possibilities to distinguish between different driving styles. The scale could be continuous or discrete. In literature discrete scales vary between two and eight levels. In this work a discrete scale with three levels (sporty, normal, comfortable) is used to distinguish between different driving styles. This allows differentiation with high selectivity.

B. Structure of the System

As the driving style strongly depends on the driving situation it is necessary to distinguish between different driving situations. In this work this distinction is realized through a signal *road class* which is provided by the navigation system of the car. The navigation system sends a different value of the signal for dirt track, urban streets, rural roads and motorways. When driving on a dirt track, the system does not try to recognize a driving style, because it is not necessary. On dirt tracks the driver usually tries not to damage the car and take it back on paved roads. For urban streets, rural roads and motorways the system tries to recognize the driving style. The driving style is traced independently for each kind of street and the driving style recognized for the actual driven street is determined. For every road class there is a different subsystem for tracing the driving style. So different parameters can be incorporated for every road class. The time gap for example is a very important parameter on motorways or rural roads but on urban streets the time gap is often dictated by traffic and therefore it is not a suitable parameter for the driving style on urban streets. An overview of the

parameters that are used in different situations is given in TABLE I. The parameter selection is based on literature and the availability of the parameters on the CAN bus of cars.

road class	considered parameters
dirt track	• none
urban street	• longitudinal acceleration • deceleration • speed
rural roads	• longitudinal acceleration • lateral acceleration • deceleration • speed • time gap
motorways	• longitudinal acceleration • speed • time gap • ACC activation

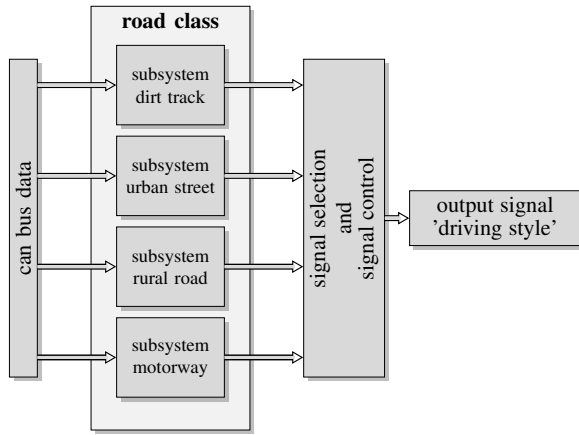The general structure of the system is given in Fig. 3 In

Fig. 3.   Top-level structure of system

fact there is a fifth subsystem which is not depicted in the picture. It is used if the driver drives on motorways with activated ACC. In this case the only evaluated parameter is the ACC speed setting. This subsystem differentiates between two situations. If there is no speed limit on the motorway (for german motorways, there is no general speed limit, only a so called *advisory speed limit*) it checks if the ACC speed setting is set between specified thresholds. It is only evaluated, if the actual speed is above a minimum speed for motorways. If the speed is below this minimum speed, it is considered that there is a special situation like a traffic jam for example and the driver is not able to determine the speed by himself. According to the speed and the thresholds the driving style coefficient (a value between one and three,

one for *comfortable* and three for *sporty*) is set to the suited value. The second situation is when a speed limit is present on motorways. When the desired ACC speed setting is set above the speed limit, the driver is directly classified as *sporty*. When the desired speed is below the minimum speed for motorways, the driver is classified as *normal*, because he does not determine the speed himself. If the ACC speed setting is between this minimum speed and a specified threshold, the driver is classified as *comfortable*. If the ACC speed setting is below the threshold but below the given speed limit for this road section the driver is classified as *normal*. The concept for the driving style classification could be seen in Fig. 4.
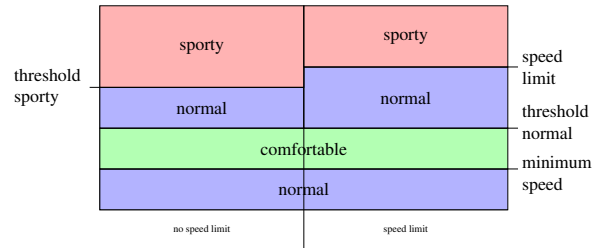

Fig. 4.   driving style classification with ACC speed setting

The different subsystems are triggered with the respective value of the signal *'road class'*. When a subsystem is not active the output holds the last value. Inside a subsystem some parameters are classified as events, which are triggered when certain values are reached. For events like a *longitudinal acceleration event*, a memory block is used to save the maximum value of the acceleration from an event for the last ten events. The second biggest value from the memory is then fed into the fuzzy logic process to generate a characteristic value for the driving style. The second biggest value is used because the biggest value could easily be an outlier. In order to determine parameters like the *speed difference* a kalman filter (more information in [7]) is used, which generates a weighted average for a given number of samples. The weight of the older values is decreased exponentially. This average is then also fed into the fuzzy logic. All values from the different fuzzy logic blocks are then fed into the block *calculation driving style coefficient*, which calculates the *driving style coefficient* for the respective subsystem. The coefficient consists of two parts. The maximum value of all outputs of the fuzzy logic blocks and a weighted average from all outputs of the fuzzy logic blocks. These weights could be modified in a parameter file, so that every parameter could be weighted as needed. The two parts can also be weighted arbitrarily. The system could thus be adjusted to the user's needs very easily in order to achieve high performance. The structure for the subsystem 'rural road' is given in Fig. 5 as an example for all subsystems. Generating the output *driving style coefficient* is then executed. The two parameters for weighting the maximum value, the weighted average and the abbreviations used in the formulas are given in TABLE II. Using the values and parameters from TABLE II the calculation of the *driving style coefficient* works as shown
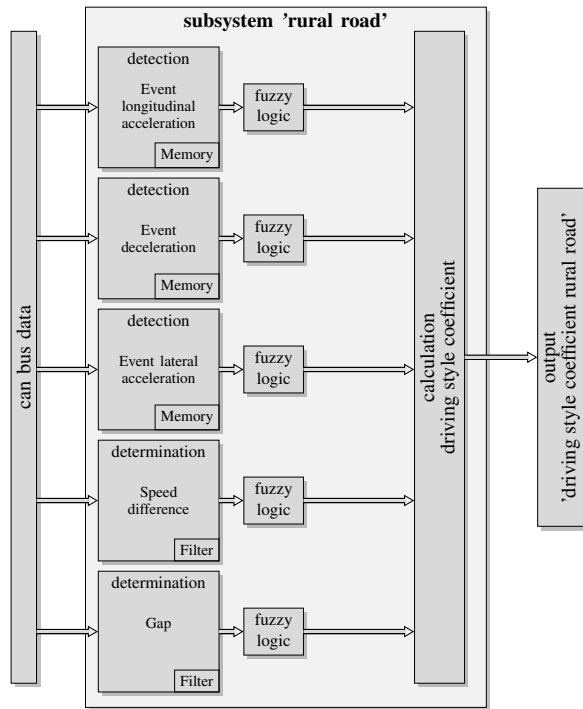
Fig. 5.   structure of subsystem 'rural road'

in formula 1.

$$dr_{style} = w_{max} \cdot max(p_1, p_2, \ldots, p_n)$$
$$+ w_{avg} \cdot \frac{\sum\limits_{i=1}^{n} w_{pi} \cdot p_i}{\sum\limits_{i=1}^{n} w_{pi}} \quad (1)$$

TABLE II
WEIGHTING PARAMETERS

name of parameter	abbr.	meaning and values
parameter values\inputs	p_i	outputs of the fuzzy logic block for each parameter. Numerical values between 1 and 3.
number of_ parameters	n	numbers of parameters used to classify the driver in the according subsystem.
parameter weights	w_{pi}	weights for each parameter to generate the weighted average.
weight_max	w_{max}	weighting for the maximum value for driving style coefficient in subsystem.
weight_avg	w_{avg}	weighting for the weighted average value for driving style coefficient in subsystem.
driving style coefficient	dr_{style}	Output of the block. A numerical value between 1 and 3.

In the block *'signal selection and signal control'* the correct signal is chosen regarding the actual road class. Also, some checks are made to assure that the outputs won't change with every calculation step or that the output signal is not switching from for example *sporty* to *comfortable* in a single step. After generating the last signal, threshold values are used to determine the final output *driving style signal*.

The signal is defined as '1' for *comfortable*, '2' for *normal* and '3' for *sporty*.

C. Implementation

The system is implemented in Matlab/Simulink. The fuzzy logic is realized using the *fuzzy logic toolbox*. The different subsystems are implemented as *enabled subsystems*. They are only active, if the road class signal has the corresponding value for the respective subsystem. Otherwise they hold their old value of the output until they are activated again. This allows the subsystems to go on with the old value on reactivation.

IV. SIMULATION RESULTS

To verify the system, simulations were conducted using the platform *CarMaker* from *IPG*. It is a simulation tool for global vehicle dynamics. It is customizable with our own models which could be integrated via Matlab/Simulink or directly over a C interface. In case of this work, the driving style recognition is integrated via a simulink model as a so called *vehicle control model*.

A. Setup and parameters

For the tests a course with a length of about 23 kilometers is used. It consists only of rural roads and urban streets. So only the subsystems for these two kind of roads can be tested. While there is no traffic implemented yet, the output for time gap[2] on rural roads was not used in the calculation for the *driving style coefficient* in the subsystem for rural roads. This is done by setting the respective weighting factor to zero.

A model of a battery electric sport car is used for the simulations. It is an accurate model with real values for the suspension and axle kinematics. This is important especially for the lateral dynamics. To imitate a real driver with high reproducibility and configurable parameters the *IPG-Driver* is used for the simulations in *CarMaker*. It's a parameterisable driver model, which operates the car during simulation. The changeable parameters are the maximum lateral and longitudinal acceleration, the maximum deceleration, the cruising speed, the pedal changing times and a coefficient how the driver cuts the curves. The used parameters for the simulations in this work can be found in TABLE III.

As there is no possibility to change the parameters during a simulation run, three simulations where run, one for each driver parameter set. The results from these simulations where split at distinctive points (points with velocity of $0 \frac{m}{s}$). The parts of the logs are combined in different constellations to generate test runs where the driver parameters change at these distinctive points. These combined results are then fed into the system, which generates the respective *driving style coefficient*. This allows to check if the system can identify a change in the driving style during a test run.

The system was parameterised using a base configuration. The most important parameters are shown in TABLE IV. All parameters are configurable via a central parameter file.

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[2]The time gap, also called headway is a measurement of the distance or time between vehicles in a transit system.

TABLE III
DRIVER PARAMETERS USED IN SIMULATIONS

name of parameter	used value	unit
comfortable		
longitudinal acceleration	2	$\frac{m}{s^2}$
deceleration	-3	$\frac{m}{s^2}$
lateral acceleration	3	$\frac{m}{s^2}$
cruise speed	70	$\frac{km}{h}$
speed deviation at speed limits	-15	$\frac{km}{h}$
normal		
longitudinal acceleration	3	$\frac{m}{s^2}$
deceleration	-4.5	$\frac{m}{s^2}$
lateral acceleration	4.2	$\frac{m}{s^2}$
cruise speed	100	$\frac{km}{h}$
speed deviation at speed limits	0	$\frac{km}{h}$
sporty		
longitudinal acceleration	5	$\frac{m}{s^2}$
deceleration	-7	$\frac{m}{s^2}$
lateral acceleration	6.5	$\frac{m}{s^2}$
cruise speed	115	$\frac{km}{h}$
speed deviation at speed limits	+15	$\frac{km}{h}$

TABLE IV
SYSTEM PARAMETERS USED IN SIMULATIONS

name of parameter	used value	unit
rural road		
threshold acceleration event	0.3	$\frac{m}{s^2}$
threshold deceleration event	-0.4	$\frac{m}{s^2}$
threshold lateral acceleration event	0.4	$\frac{m}{s^2}$
minimum duration acceleration event	1	s
minimum duration deceleration event	0.5	s
minimum duration lateral acceleration event	0.5	s
weighting factor for the maximum value	0.2	-
weighting factor for the weighted average	0.8	-
urban streets		
threshold acceleration event	0.4	$\frac{m}{s^2}$
threshold deceleration event	-0.4	$\frac{m}{s^2}$
minimum duration acceleration event	0.5	s
minimum duration deceleration event	0.5	s
weighting factor for the maximum value	0.2	-
weighting factor for the weighted average	0.8	-

This makes it easier for an engineer to apply the system for different vehicles.

B. Results

In the following part, the results for the simulations are found. Three different mixes of the simulations for the three driver parameter sets were created. The dashed blue line in the plots is the specified driving style in the simulations. The red line is the driving style which is identified by the system. For evaluation, three cases are distinguished. If the identified classification is the same as the driving style specified in the simulation it is called a `correct classification`. If the identified classification is next to the specified driving style (e.g. *normal* specified and *comfortable* identified) it is called a `differing classification`. A `wrong classification` is when the specified driving style is *sporty* and the identified classification is *comfortable* or vice versa.

In the first test drive shown in Fig. 6 the driver parameters were set to *normal* at the beginning, *sporty* afterwards, then *normal* again and *comfortable* in the end. In the second test drive shown in Fig. 7 the driver parameters were set to *comfortable* at the beginning, *sporty* afterwards, then *normal* and *sporty* again in the end. In the third test drive shown in Fig. 8 the driver parameters were set to *normal* at the beginning, *comfortable* afterwards, then *sporty* and *normal* again in the end.

In all figures the driving style coefficient follows the driving style defined in the simulation, except some small sections. There are nearly no `wrong classifications`, especially in mix 2 where there is no wrong classification at all. Also, it can be seen that the driving style coefficient
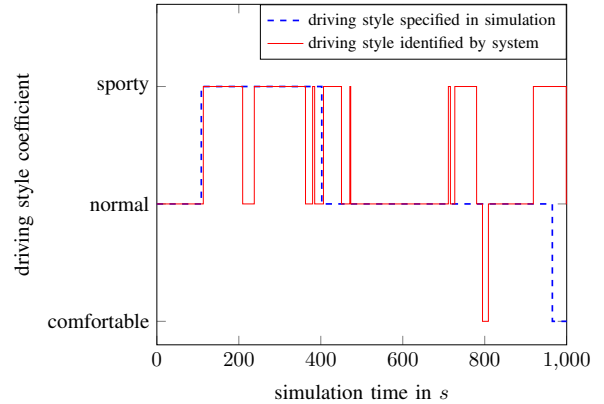

Fig. 6. Results for mix 1

follows the specification mostly with a small time gap. This is the case, because the system has to determine the new driving style before it could output it. In mix 2 the wrong classification at the beginning exists, because the system has a timer which sets the driving style coefficient to *normal* for the first 60 seconds. This time is used to prefill the filters and memory in order to provide consistent values. Without this timer, the classification in mix 2 would be even better.

The final complete results for the tests of the system can be found in Fig. 9. About two thirds of the time, the system identifies the right driving style according to the settings in the simulation.
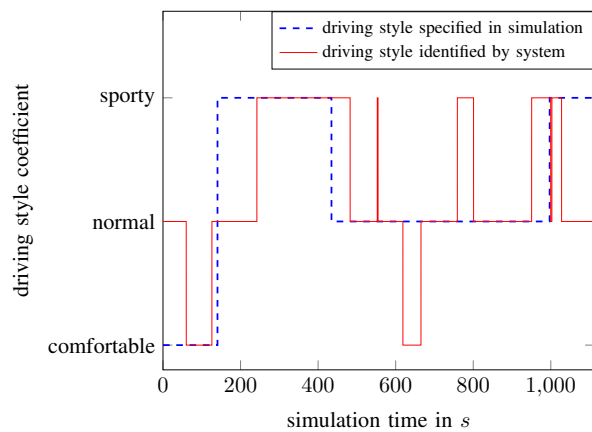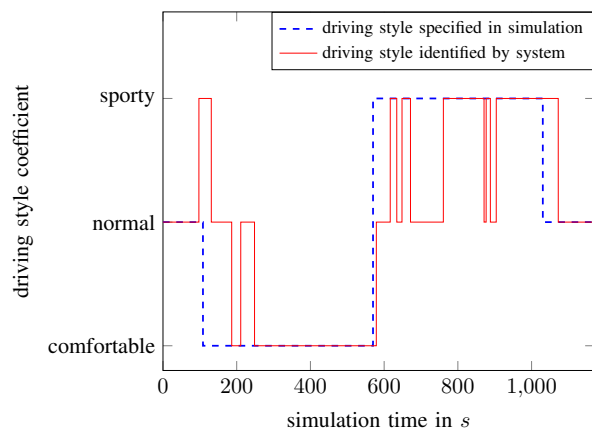
Fig. 7. Results for mix 2

Fig. 9. Results

Fig. 8. Results for mix 3

V. CONCLUSIONS AND OUTLINE

A. Conclusions

A system for identifying the driving style while driving was implemented and tested via simulations. Though the system was used in a basic configuration without any adaptions to specific car parameters, the results were quite good with a correct classification percentage of about 68% and a wrong classification percentage of only 2%. This is a satisfying result for the first test of the new implemented system. Since the output should not be used for safety-critical systems this is sufficient to test the system in a real vehicle.

B. Outline

In the future, the system has to be verified with traffic to check if the parts for the time gap work fine and to figure out if this could help in making the results better, especially to create less differing classifications. Also, a test run for motorways has to be implemented to verify the respective subsystem.

If a vehicle with a prototyping control unit is available the system could be flashed onto the control unit to verify the system under real ambient conditions in real traffic. The system could then be adapted to the used car to improve the percentage of `correct classifications`.
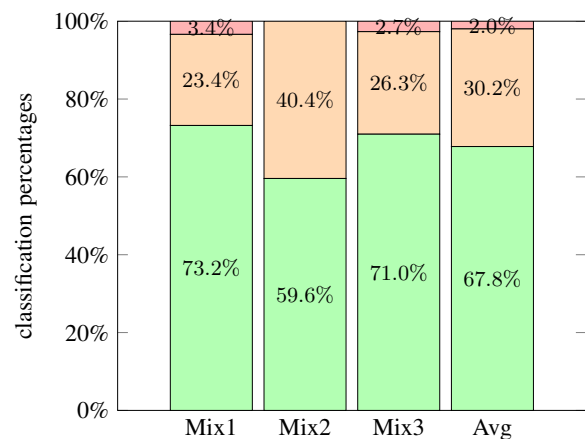
VI. ACKNOLEDGMENT

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