

Accepted Manuscript

Collaborative approach for a safe driving distance using stereoscopic image processing

Cristina Olaverri-Monreal, Gerd Ch. Krizek, Florian Michaeler, Rene Lorenz, Matthias Pichler



PII: S0167-739X(17)30712-4
DOI: <https://doi.org/10.1016/j.future.2018.01.050>
Reference: FUTURE 3957

To appear in: *Future Generation Computer Systems*

Received date : 19 April 2017
Revised date : 2 January 2018
Accepted date : 25 January 2018

Please cite this article as: C. Olaverri-Monreal, G.C. Krizek, F. Michaeler, R. Lorenz, M. Pichler, Collaborative approach for a safe driving distance using stereoscopic image processing, *Future Generation Computer Systems* (2018), <https://doi.org/10.1016/j.future.2018.01.050>

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Collaborative Approach for a Safe Driving Distance Using Stereoscopic Image Processing

Cristina Olaverri-Monreal, Gerd Ch. Krizek, Florian Michaeler, Rene Lorenz,
Matthias Pichler

University of Applied Sciences Technikum Wien. Höchstädtplatz 6, 1200 Vienna, Austria.

Abstract

Disregard for the rules regarding the minimum safety distance can make the avoidance of a rear-end collision nearly impossible. In a joint effort to enhance safety and improve the decision making processes on an individual level, we contribute to the state of the art with an innovative and affordable system that identifies vehicles and provides a rear-end distance warning system capable of recognizing dangerous situations, and which can also inform other vehicles of the danger, independent of their communication capabilities or equipment. Vision sensors garner information through the stereoscopic capturing and processing of images by rear cameras to calculate the distance between the leading and following vehicles. Visual data related to the safety distance is provided to the following vehicle in real-time, relying on an asynchronous collaborative process. A detailed error analysis of the distance calculation is provided based on the measurement procedure and roadway geometry. Relying on the communication between the two vehicles, an in-vehicle system was compared to the rear-mounted distance warning system under lab-controlled conditions. Both human-machine interaction paradigms were evaluated in terms of their impact on driver response. Results showed that both systems influenced the driver in keeping a time gap of two seconds.

Email address: {olaverri, krizek}@technikum-wien.at, florian@michaeler.at, renelorenz@gmx.net, matthias-pichler@aon.at (Cristina Olaverri-Monreal, Gerd Ch. Krizek, Florian Michaeler, Rene Lorenz, Matthias Pichler)

Keywords: Cooperative Systems, Tailgating, Safety Distance, Image Capturing

2010 MSC: 00-01, 99-00

1. Introduction

A major field of research concerned with increasing road safety is the development of cooperative systems, or systems that allow vehicles or other road users to communicate with each other to solve or prevent dangerous situations. However, the production of vehicles equipped with such systems is still very limited and only expected to increase slightly in the coming years. Therefore, further use cases must be developed and tested in order to understand the impact that high penetration rates of Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) (together V2X) communication technology will have on road safety and road users.

In a scenario where the penetration rate of vehicles equipped with V2V and V2I technologies is not 100% co-operative, systems should not only communicate and share information between vehicles, but also address their drivers. Relying on this, Advanced Driver Assistance Systems (ADAS) support the driver in challenging driving situations, specifically in data collection and analysis from other vehicles. Visual awareness of the driver can therefore be increased after having processed information that stems from nearby driver behavior.

Disregard of the minimum safety distance makes it exceedingly difficult to stop in time to avoid a rear-end collision. Several findings have shown that the average driver will not have adequate headway time, the time that drivers need to adequately react to a specific event based on their distance to other vehicles [1].

Such a scenario might occur when unforeseen circumstances cause a leading vehicle to brake suddenly. In road traffic, there is a recommended minimum distance of 2 seconds to the vehicle in front [2]. In addition, aggressive tailgating behavior often forces the leading vehicle to increase speed and disregard speed



Figure 1: Cooperative driving in which visual data related to the safety distance is provided to the following vehicle in real-time.

limits, which jeopardizes everyone's safety. In an effort to reduce the major cause of rear-end crashes on our roads, road marks remind drivers to maintain the safety distance in many European countries (e.g. Spain, France, UK). In some of these countries, tailgating is punishable by law [3].

In order to encourage observance of the law for the sake of safety, we extend in this work the approach presented in [4], in which a system was introduced that warns the rear driver in an unobtrusive manner when the distance to the leading vehicle becomes dangerous with:

- a detailed error analysis of the influence of the road geometry on the distance calculation between the leading and trailing vehicle and the measurement procedure itself.
- A simulation-based system evaluation section, in which an additional VANET-based system was compared.

Our contribution consists of a novel visualization of messages that is independent of the communication capabilities of the following vehicle, being thus applicable for example in scenarios with low penetration rates of connected and autonomous vehicles. Visual data related to the safety distance is provided to the following vehicle in real-time, relying on an asynchronous collaborative process in which the partners involved in the collaboration are not necessarily working and communicating concurrently. Figure 1 illustrates the idea.

The following section considers related work in the field of video-based assistant systems. Sections 3, 4 and 5 present a detailed description of the collaborative principle and development process followed. Section 6 describes

50 an error analysis based on the measurement procedure and road geometry, and
section 7 describes the evaluation process of the presented approach. Section 8
summarizes important points in this study and concludes the paper.

2. Related work

The use of video-based data to increase driver awareness has been addressed
55 in several works. The goal of the works presented in [5, 6] was to enhance the
driver's visual perception of vehicles traveling in the opposite lane. To this end,
the authors developed a co-ADAS for the overtaking maneuver relying on Ve-
hicular Ad Hoc Network (VANET) technology. The system shared information
with vehicles traveling in the same direction, in the same lane, after the follow-
60 ing vehicle started the request for the transmission of a video-stream between
the leading and following vehicle.

The combination of images from several cameras to enhance the driver's
visual awareness is an extended approach used in object detection processes [7,
8]. The benefits of using synchronized cameras, such as smoother enhanced road
65 detection through the combination of visual fields, were elucidated when this
approach was compared with approaches based on a single camera to obtain 3D
information from a disparity map in [9].

Driver following behavior has also been recorded and evaluated using differ-
ent technologies based on vision, including cameras. For example, the authors
70 in [10] analyzed video-based data and found that the time headways and stand-
still distances were dependent upon vehicle type. The average headway was
around 2 seconds when a car was following and 3 seconds when a truck was
following.

Rear-end collision prevention has been addressed in several works focusing
75 on the implementation of Advanced Driver Assistance Systems (ADAS). For
example a recent work presented a stereo-vision-based driving assistance system
utilizing a mobile device capable of detecting vehicles and lanes [11]. A further
study [12] proposed a new time-based Collision Warning System (CSW) which

alerted the driver in the leading vehicle of an imminent rear-end collision. The
80 system was based on the calculation of the following parameters: the time-
to-last-second-acceleration (T_{lsa}) for the leading vehicle and the time-to-last-
second-braking (T_{lsb}) [13] for the following vehicle. The values were compared
and a warning was then conveyed to the driver in the event that a certain
threshold was surpassed.

85 After the driver is warned, they can take action to prevent or mitigate the
consequences of a rear-end collision (press the throttle, honk the horn or flash
the brake lights to alert the following driver). After a series of experiments and
tests, the authors conclude that among the aforementioned three actions, the
scenario in which the leading vehicle accelerates shows significant improvement
90 of results in preventing rear-end collisions. However, in order for the driver to
fully accelerate there must be no obstacles ahead, rendering this method useless
in many urban traffic scenarios.

There are also works that focus on systems for detecting, monitoring and
alerting tailgating behavior. To discourage tailgating, a low-cost Tailgating
95 Warning Sensor (TWS) was presented in [14]. The device warned the driver if
they were engaged in tailgating or if a collision was imminent. It consisted of a
compact optical electronic sensor mounted on the front of the vehicle.

In [15] a model for rear-end collision was proposed that was based on vehicle
dynamics, perception reaction time, brake intensity, friction between tires and
100 road surface to calculate the stopping distance of the following vehicle. The
model was tested and validated in a field experiment.

An additional work was able to robustly track objects (from within a mov-
ing platform) in a complex environment [16] using the Infinite Gaussian Mixture
Model (IGMM). The method combined the Deterministic Non-model-based ap-
105 proach with Gaussian Mixture Shadow Model (GMSM) to remove shadows. The
tracking strategy was improved further by computing the similarity of color his-
tograms.

Binocular stereo images were used in another work to measure distance head-
way in real time. The high computational cost related to this method was

110 reduced by combining it with optical flow [17].

All the rear-end collision avoidance systems presented in this section collected information by using sensors or cameras mounted in the rear vehicle. In [18], however, a rear-end parking assist camera located in the leading vehicle was used to collect the relevant data, as rear-end parking assist cameras are
115 already standard in many new cars.

In line with this work, we contribute to research in the field by elaborating on the cooperative system to promote the observance of the safety distance (Tailigator) in an unobtrusive manner that was discussed in [4]. The system detects the distance to the following vehicle by means of object detection and
120 optical stereoscopy. In order to make it possible for the driver being tailgated to communicate with the following vehicle, our system components reside in the leading vehicle. If a certain threshold value regarding the distance between both vehicles is exceeded, the leading vehicle displays a message in the rear windshield reading that required safety distance has been violated. This message
125 is intended for the driver of the following vehicle. Figure 2 illustrates the idea. The novelty of this approach consists of the leading vehicle indicating to the tailgating vehicle that the distance is too close, relying upon a more common manner of human communication.

3. System setup

130 As described in [4] our system runs on a Raspberry Pi B+ or Linux-based microcomputer with 4 USB connectors and 40 general purpose input/output (GPIO) pins for hardware connection and two cameras connected through a USB port. To calculate the distance between two adjacent vehicles, the following steps are performed:

- 135 • Stereoscopic capture of images.
- Vehicle detection on both images by building a Cascade classifier using OpenCV, the comprehensive library developed for image processing.



Figure 2: Message displayed to the tailgating vehicle.

- Distance calculation relying on stereoscopic vision.
- Warning message display addressing tailgating vehicle.

140 Figure 3 depicts the location of the cameras in the rear part of a vehicle. In order to build a cost efficient system with a minimal power supply need, we used two USB LogitechHD270 web cameras with a focal length of 4 mm, which guaranteed a field of view of 60°. They were compatible with Raspberry Pi and ensured a smooth mounting in the rear windshield of a vehicle. The system
 145 was able to detect vehicles in the same lane at a maximum distance of 100m. To provide power to the Raspberry Pi and the connected cameras, we used a mobile battery pack that provided 30000 mAh capacity and up to 2A output current.

4. Image capturing and vehicle detection

150 Simultaneous image capturing was performed, as described in [4], to prevent potential errors that could occur due to modification of the vehicles' positions



Figure 3: Location of the cameras in the rear part of the vehicle.

during the distance calculation while the vehicles traveled at a speed of 130 km/h (80.78 mph).

In order to achieve a smooth process, we divided program capturing functions into two separate threads, thereby allowing for a triggering process via a common control signal from an independent source. Figure 4 illustrates the procedure.

The capturing itself was done relying on OpenCV library algorithms. By using two threads to capture the images, we reached a time difference of 0.2 seconds between the two cameras. The time frame we used to detect all the vehicles and calculate their distances was every 3 to 6 seconds with an image resolution of 640 x 480. Higher rates resulted in damaged or incomplete camera images. Additionally, a buffer clearance of the Linux camera driver was regularly required to prevent access errors and damaged images. The following subsections describe the process of building the Cascade classifier.

4.1. Collecting training material

For training the classifier we collected positive and negative images with the following characteristics:

- Positive images consisting of the target detection object. We captured over 600 positive images of front-views of cars by recording them from the rear windshield of a vehicle on a variety of roads. We ensured that captured images were made in a variety of light and weather conditions, and that they featured different types of vehicles. Figure 5 shows examples

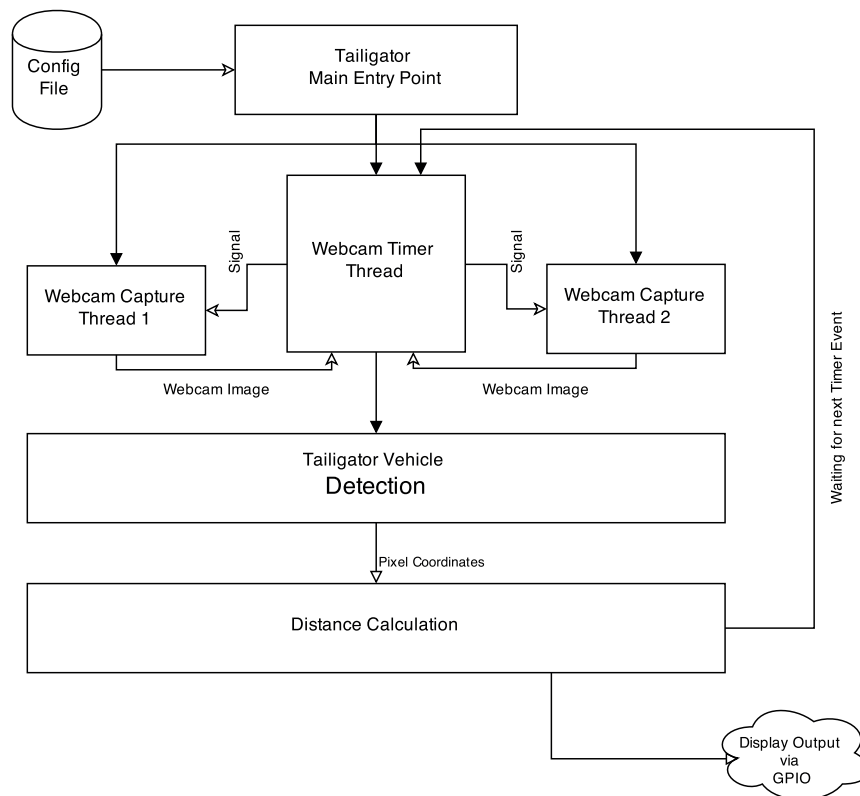


Figure 4: General structure of the software implementation of the Tailigator system.



Figure 5: Example of positive images.

of positive images acquired.

- Negative images consisted of different objects that were re-sized to fulfill the same conditions as the positive images. Our final sample consisted of around 2100 negative images.

We trained a Haar-like Cascade classifier in OpenCV [19] using the images we collected. The training was performed with a total of 30 stages and around 10 hours computation time. As a result, we obtained an xml-file as input for the OpenCV's detection-function.

4.2. Locate tailgating vehicle

As our application is only relevant for a scenario where two vehicles are following each other in the same lane, multiple vehicle detections in motorways or other multi-lane roads do not apply. We implemented a location algorithm that started to scan for information from the middlepoint of the image, and then from left to right. Afterwards, we used the object position from the Viola Jones Haar Cascade detector and compared the coordinates from the left-right images.

Algorithm 1 denotes the followed procedure. Figure 6 shows the vehicles detected. The vehicle in the same lane is tagged with a green circle. The

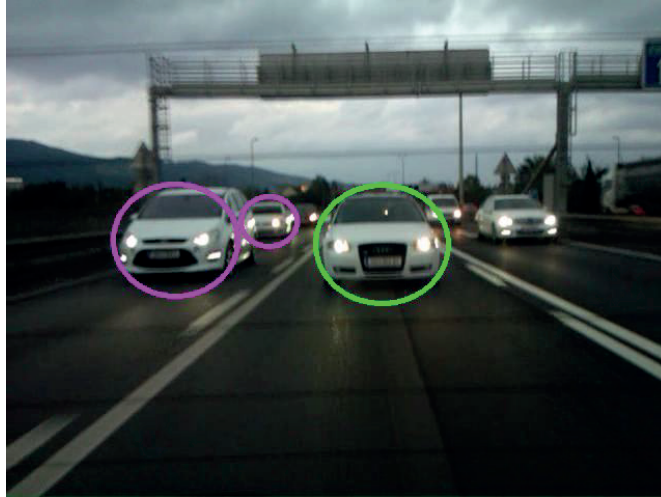


Figure 6: Vehicle detection and location of the vehicle in the same lane (green).

X-coordinate corresponding to this vehicle serves as input for the stereoscopic function.

195 5. Distance calculation

Stereoscopic vision sensors enable the calculation of the distance to a certain object using the relative pixel-position difference of the object on both pictures (shown in figure 7). To be able to calculate the distance to a certain object by stereoscopy the following conditions need to be fulfilled.

- 200 • Two cameras with the same specifications for sensor size, focal length and picture resolution.
- Perfect horizontal (and in certain cases vertical) alignment of the cameras to prevent miscalculations due to angular errors. These miscalculations could lead to an incorrect value for the pixel coordinates and therefore an incorrect distance. If proper alignment cannot be guaranteed, calculation
- 205 adjustments need to be made to compensate for the difference.

Algorithm 1: Tailgating vehicle location in the same lane as the leading vehicle.

Input: Processed image after detection

Input: Set of detected vehicles coordinates

Input: $middlepoint = \frac{imageWidth}{2}$

```

while !located do
  for currentStep=middlepoint;currentStep-- do
    if currentStep==xCoordinates then
      |           ▷ A hit as scanning left located=true;
    end
  else
    |   if (currentStep+addStep)==xCoordinates then
    |   |           ▷ A hit as scanning right located=true;
    |   end
  end
  else
    |   addStep++;
  end
end
end
return xCoordinates of tailgating vehicle

```

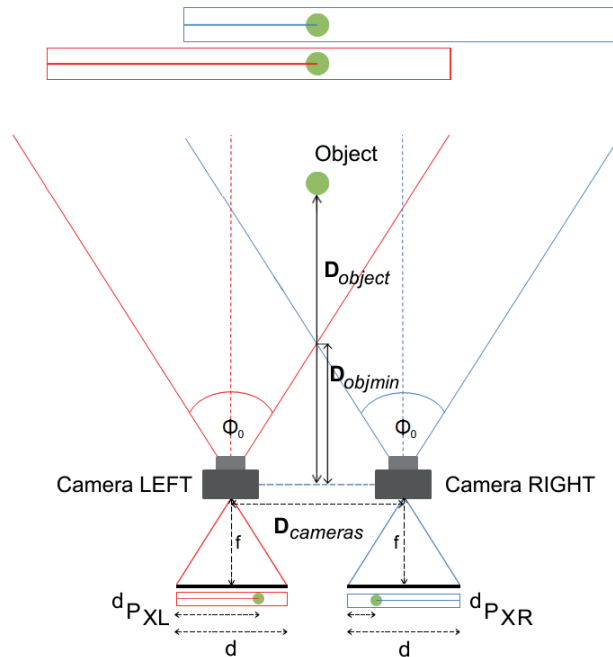


Figure 7: Camera setup for stereoscopic distance calculations. Adapted from [20]

- The distance between the two cameras must be properly set, as it influences the pixel offset between the two pictures. This could lead to inaccuracy if the offset is too small and the blind spot is located directly in front of the setup (generated by the camera distance and the field of view of both cameras).
- Synchronous capture of the images is essential to be able to prevent pixel shifts due to the movement in the calculation of distances between dynamic objects.

210

215

As depicted in figure 7, the distance calculation is only possible in the area

where the images of both cameras overlap. We measure the distance to an object D_{object} placed in front of the cameras using the parameters in the equation 1 by [20] such as the distance between the cameras $D_{cameras}$, the horizontal field of view φ_0 , the horizontal pixel resolution (pixel number) Px_h and the horizontal pixel difference to the same object in both pictures in pixels $Px_L - Px_R$.

$$D_{object} = \frac{D_{cameras} * Px_h}{2 * \tan(\frac{\varphi_0}{2}) * (Px_L - Px_R)} \quad (1)$$

6. Error calculation

6.1. Bounds for distance measurement

For the distance measurement there are two bounds that are the result of the systems geometrical arrangements and restrictions due to resolutions of the optical system. Equation 2, calculates the minimum measurable distance D_{objmin} , which is defined by the overlap of the fields of view of the system cameras.

$$D_{objmin} = D_{cameras} \tan\left(90^\circ - \frac{\varphi_0}{2}\right) \quad (2)$$

The maximum measurable distance is limited by the resolution of the system: if the horizontal pixel shift of the object is not observable by the system, the distance cannot be calculated (equation 3).

$$Px_L - Px_R > 1 \quad (3)$$

Applying equation 3 to the distance calculation in equation 1 results in the maximum measurable distance D_{objmax} in equation 4.

$$D_{objmax} = \frac{D_{cameras} Px_h}{2 \tan(\frac{\varphi_0}{2})} \quad (4)$$

For the system presented in [4], which we extend in this paper, the bounds are $D_{objmin} = 1.25m$ and $D_{objmax} = 401.8m \sim 400m$.

235 *6.2. Distance deviation due to delayed capture*

The two image capturing threads resulted in a time difference of 0.2 seconds. Due to this, an error in the distance calculation occurs that varies based on the differential speed between the tailgating vehicle and the leading vehicle, as denoted by equation 5.

$$DEV_{Dobj} = v_{Diff} \cdot t_{cap} \quad (5)$$

240 For example, for a speed limit of 130 km/h (80.78 mph) this results in an upper bound of the differential speed v_{Diff} and a resulting maximum distance deviation of $DEV_{Dobj} < 7.3\text{m}$. Figure 8 illustrates the deviation function.

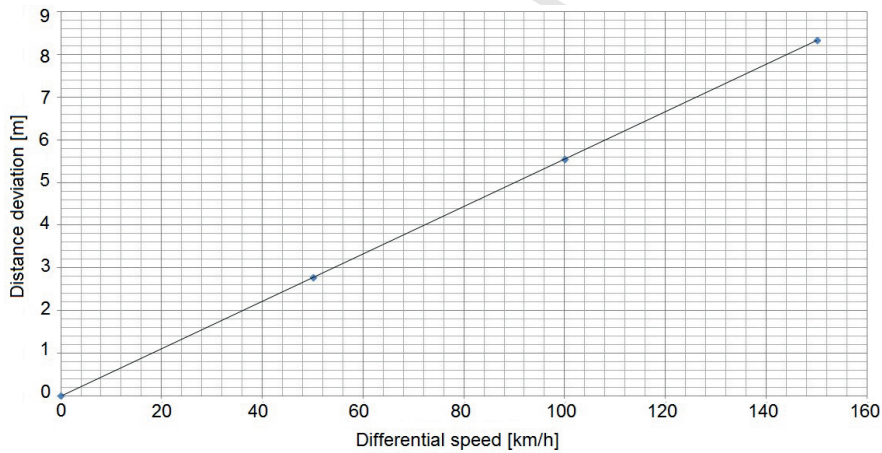


Figure 8: Distance deviation due to capturing delay.

6.3. Distance deviation on winding roads

245 Originally we calculated the distance between both vehicles for a straight road. In the case of curvy or winding roads, a deviation from the real distance will exist. If we assume a constant curved road with a curvature radius R we calculate the distance deviation as depicted in figure 9 assuming that the distance between the cameras D_{cam} is zero for the sake of simplicity.

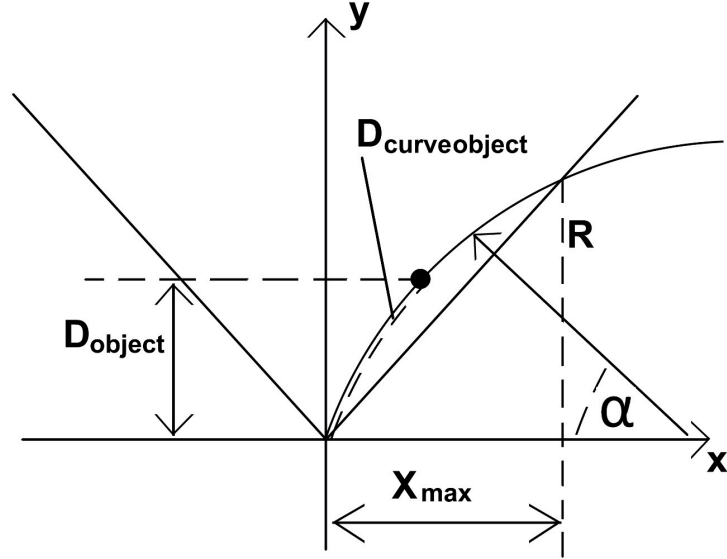


Figure 9: Distance deviation on winding roads.

Equation 6 denotes the maximal possible horizontal shift x_{max} of the measured object that is determined by the horizontal field of view of the cameras.

$$x_{max} = D_{object} \cdot \tan\left(\frac{\varphi_0}{2}\right) \quad (6)$$

The effective driving distance between the leading and following vehicles in circular curves of radius R is given by the properties of the circle [21] and particularly by the segment on the circle as denoted by equation 7, where the angle α is calculated as shown in equation 8 producing a negative value. The deviation between the distance of the circle's segment and the measured distance by the system is given by $Dev_D = D_{curveobject} - D_{object}$, where the deviation is denoted by the equation 9.

$$D_{curveobject} = R \cdot \alpha, \quad (7)$$

$$\alpha = \arctan\left(\frac{D_{object}}{\sqrt{R^2 - D_{object}}}\right) \quad (8)$$

$$DEV_D = R \left| \arctan\left(\frac{D_{object}}{\sqrt{R^2 - D_{object}}}\right) \right| - D_{object}. \quad (9)$$

260

The distance deviation is unsteady when the object is located at a distance that is equivalent to the curvature radius size, as this would mean that the object on the curved road is outside the horizontal field of view and therefore out of the range of measurement. Figure 10 depicts two different views of the distance deviation resulting from a winding road.

265

6.4. Distance measurement error propagation

By using the method of error propagation, we additionally estimated the magnitude of distance calculation (leading to trailing vehicle) errors that originated from an erroneous position of the camera or its alignment, as well as from pixel-shift-related errors of the optical system. We assume that errors of the quantities $D_{cameras}$, φ_0 , and $Px_L - Px_R$ follow a Gaussian distribution, and we therefore calculate the variance for the measured distance by applying the Gaussian error propagation on equation 1. This leads to equation 10.

270

$$\begin{aligned} \sigma_{D_{object}}^2 &= \frac{Px_h}{2 \tan(\frac{\varphi_0}{2}) (Px_L - Px_R)} \cdot \sigma_{D_{cameras}}^2 \\ &\quad + \frac{D_{cameras} Px_h}{4 \tan^2(\frac{\varphi_0}{2}) \cdot \cos^2(\frac{\varphi_0}{2})} \cdot \sigma_{\varphi_0}^2 \\ &\quad + \frac{D_{cameras} Px_h}{2 \tan(\frac{\varphi_0}{2}) \cdot (Px_L - Px_R)^2} \cdot \sigma_{(Px_L - Px_R)}^2 \end{aligned} \quad (10)$$

275

To illustrate our approach, we apply the system setup of the original Tailigator system and estimate standard deviations for the $D_{cameras}$, φ_0 , and $Px_L - Px_R$.

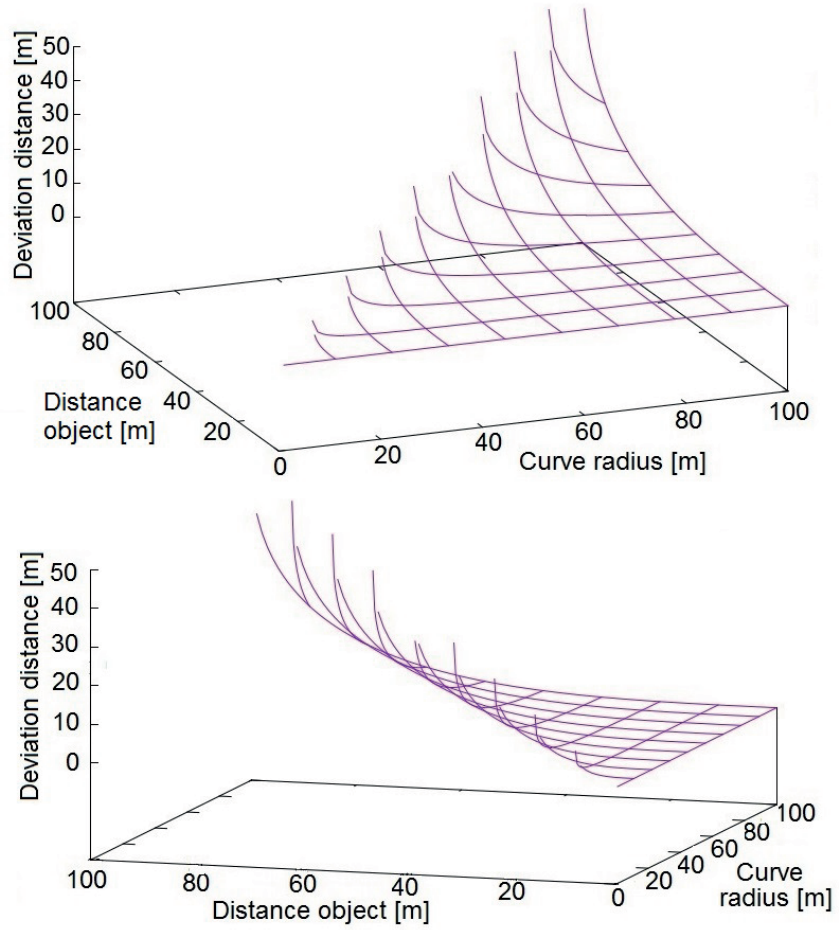


Figure 10: Plot DEV_D Distance deviation due to winding road.

- $D_{cameras} = 0.725m$
- $\varphi_0 = 60^\circ$
- $f = 4 \cdot 10^{-3}m$
- $Px_h = 640$
- $\sigma_{\varphi_0} \approx 2^\circ = 3.49 \cdot 10^{-2}$

280

- $\sigma_{(Px_L - Px_R)} = 2$

- $\sigma_{D_{cameras}} = 1 \cdot 10^{-2}m$

Based on the given setup, the assumed standard deviations and the regime of distance measurement in a 20m range, only the term relating to the pixel difference $\sigma_{(Px_L - Px_R)}^2$ contributes to a relevant error propagation.

$$\sigma_{D_{object}}^2 = \frac{556,52}{(Px_L - Px_R)} \cdot \sigma_{D_{cameras}}^2 + 91,27 \cdot \sigma_{\varphi_0}^2 + \frac{403,5}{(Px_L - Px_R)^2} \cdot \sigma_{(Px_L - Px_R)}^2 \quad (11)$$

$$\sigma_{D_{object}} = \sqrt{2.78 \cdot 10^{-3} + 0.111 + 4} \approx \sqrt{4.1} \approx 2.02m \quad (12)$$

Applying equations 11 and 12 we obtain the following results for the errors in a regime of pixel differences of $Px_L - Px_R = 20$, which corresponds to a distance of the measured object of 20.1m. Figure 11 shows the distance and its standard deviation depending on the pixel difference over the whole regime of pixel differences.

6.5. Distance error due to the lateral position deviation of the following vehicle

The approach presented in this paper targets tailgating scenarios that imply a deliberate act of driving too closely behind the leading vehicle, intending to overtake or force the leading vehicle to drive faster. As previously mentioned the location algorithm applies when two vehicles are following each other in the same lane. In the event of such a scenario we focus in this section on the obtained distance error due to the vehicle lateral deviation under time difference. As we had a time difference of 0.2 seconds between the two cameras, such a calculation is required in order to estimate the distance error that the vehicle's lateral movement, in case of a lane change or obstacle avoidance, might produce.

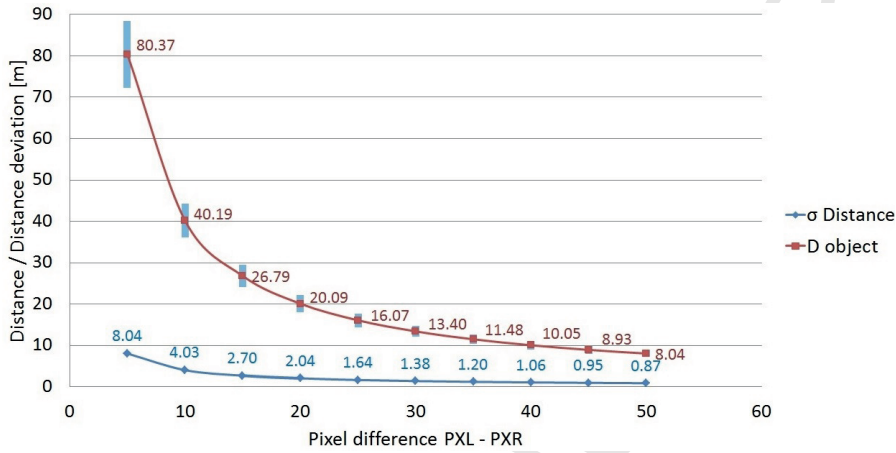


Figure 11: Distance and standard deviation depending on the pixel difference ($Px_L - Px_R$).

305 Figure 12 depicts the magnitude of the error due to lateral deviation in case of a lane change. The error depends on the lateral speed of the following vehicle during the lane change. We assume the lane change as a lateral uniform motion. In the worst case scenario of 1m/s the rate of error would be 31%. Under normal circumstances (speed ranging between 0.3 and 0.5m/s) the rate of error would
 310 be 10-15%, the same order as the distance error calculated in the section above.

7. Simulation-based evaluation

In [4] we presented the method and results from a qualitative interview conducted to obtain first cues regarding the usability of the Tailigator system. We showed that information regarding an unsafe headway displayed on the leading
 315 vehicle, as opposed to a method where the driver in the following vehicle received in-vehicle warnings, was evaluated as positive and useful. The participants considered the message directly transmitted from the leading vehicle to be clear and argued that it reflected better the potential intimidation which the leading driver might feel because of the aggressive driving behavior of the
 320 tailgating vehicle. However, these results relied on data collected after the system was explained through a video showing its functioning rather than after the

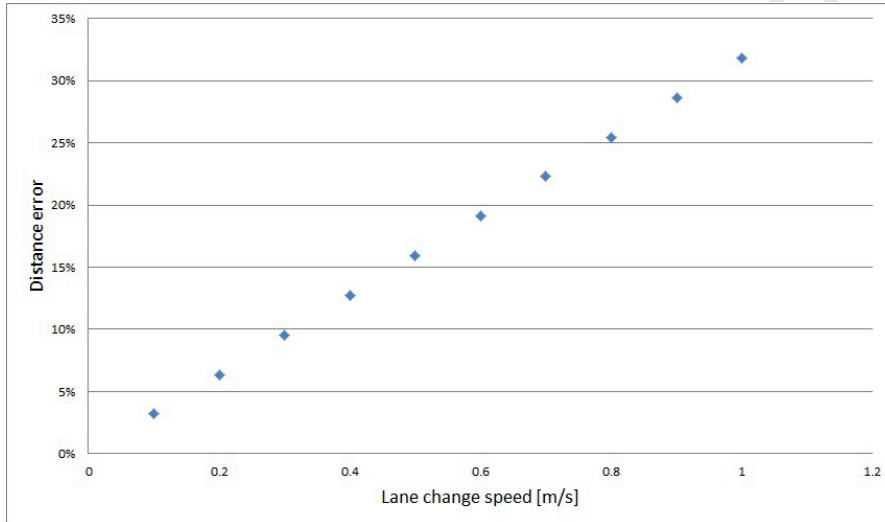


Figure 12: Error due to lateral deviation.

participants were directly involved in a real test.

To elaborate on these results we appraised the system from a user perspective, using the flexible and adjustable 3-dimensional driving simulator based on Open-StreetMap (OSM) data that integrates VANET communication capabilities to assess different information paradigms as presented in [22]. The simulation platform extended the microscopic driver-centric simulator based on the Unity 3D game engine [23] and Simulation of Urban MObility (SUMO) software [24] described in [25]. We asked 4 persons (2 males, 2 females, age=35, SD=1.7) to evaluate the performance of the two rear-end collision systems described as follows (figure 13):

1. Tailigator rear-end-collision system, which displays a headway warning on the rear part of a leading vehicle based on the functioning presented in this paper.
2. VANET system, which shows the warning on the in-vehicle display of the following vehicle and broadcasts the information related to the headway to the leading vehicle as time gap between vehicles.



Figure 13: Evaluated systems in the simulation platform. Left: Tailigator rear-end-collision system; Right: VANET system showing the warning on the in-vehicle display and which broadcasts the information related to the headway to the leading vehicle as time gap between vehicles.

7.1. Experimental setup

Both rear-end collision systems were activated when 2 vehicles were driving
 340 in the same direction in the same lane within a time gap of less than 2 seconds.
 The messages were continuously displayed to the driver until they adjusted their
 driving to the recommended two-second gap. Each of these tests followed the
 same structure to create comparable results in terms of driving performance.
 The order of the tested systems was alternated to avoid biased results. After
 345 a short introduction, the experiment was conducted among participants who
 navigated a driving scenario consisting of sections with different speed limits,
 in order to observe their effect on the headway. Furthermore, the traffic lights
 along the route provided data related to driving behavior and distances at slow
 speeds and stops.

350 The subjects were encouraged to adapt their speed to a leading vehicle whose
 speed was 10 km below the speed limit. When the distance between the two
 vehicles became larger than 300m, the simulation created a new leading vehicle.
 The length of the experiment was 15 minutes, divided as follows:

- 5 minutes acclimatization with the driving simulator, used as baseline data
 355 and during which time there was not always a leading vehicle.
- 5 minutes driving with the Tailigator rear-end collision system.

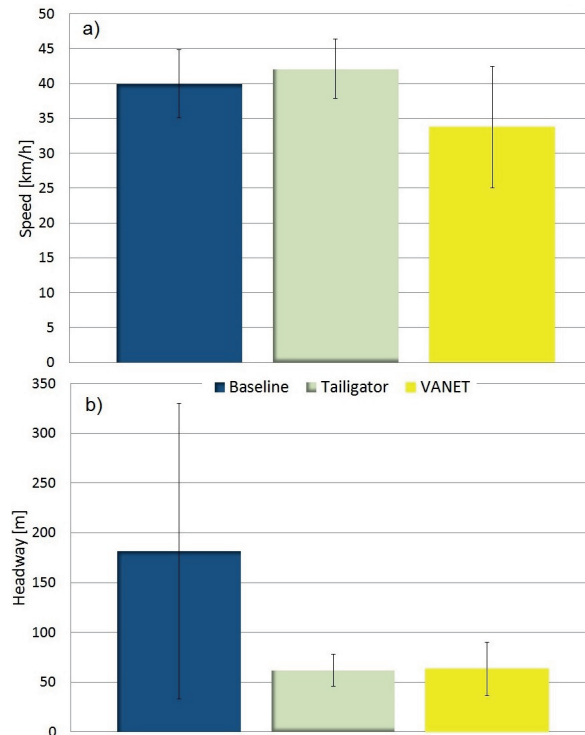


Figure 14: Comparative results of the effect of the evaluated systems on driving performance metrics: speed (a) and headway (b).

- 5 minutes driving while using the system VANET-based distance warning system.

7.2. Results

Both systems prompted the driver to maintain a time gap of about two seconds. However, in situations in which the vehicles approached a traffic-light and deceleration was required, the message was visible in the in-vehicle VANET system earlier than with the Tailigator system. Results showed some differences regarding driver performance depending on the system used. Braking patterns from drivers interacting with the rear-mounted distance warning Tailigator system were more abrupt and irregular than with the in-vehicle VANET-based

system. The comparison of the mean values of speed and headway did not show any statistically significant differences (figure 14).

370 However, the speed when using the VANET system was slightly lower than under the baseline condition or when using the Tailigator system, suggesting that this is a potential distraction that causes the driver to take their eyes off the road. The higher headway under the baseline condition was due to the fact that there were no leading vehicles during the whole driving phase, in order to familiarize the participants with the simulator.

375

8. Conclusion and future work

A cooperative approach imitating human communication in a situation in which a vehicle is tailgating another was proposed in this paper. This collaborative nature of driving for system safety improvement is helpful in situations 380 where tailgating is intentional, as it might remind some tailgaters to be rational. It is applicable in scenarios with low penetration rates of connected and autonomous vehicles and in vehicles that are not equipped with advanced brake assistance systems.

Relying on communication between the two vehicles, an in-vehicle system 385 based on VANET communication was compared to the Tailigator rear-mounted distance warning system under lab-controlled conditions. Both human-machine interaction paradigms were evaluated in terms of their impact on driver response, the rear-mounted distance warning system affecting the braking patterns more than the in-vehicle VANET-based system. Further research will 390 focus on the driving response to the received message with a bigger sample of participants.

The connectivity capabilities offered by the VANET system promotes the maintenance of a perfect time gap, however, in cases of intentional tailgating, the Tailigator rear-end collision system might be more effective in terms of 395 inciting behavioral change.

Some challenges related to the proposed technology stem from the 0.2 second time difference between the two cameras. This difference is due to the limitation of the proposed approach that relies on the implementation in the Raspberry Pi with OpenCV. In our comparison with the VANET system we did not include
400 the stereo error calculations, since the goal of the evaluation was to compare the performance of the two rear-end collision systems to see if differences regarding driver performance depended on the system used. We will elaborate on the obtained results in future work, which will include experiments that highlight the effect of these errors. The integration of real-time capabilities is planned as
405 a next step. We intend to extend the work by implementing a new software-architecture (including multithreading via 3rd party libs as QT or Boost) to investigate if the time difference can be improved, as well as using 320x240 to improve RPi capture speed. In future work we will also examine the empirical bounds of the system considering the localization noise that comes from the
410 Viola Jones detector to study the pixel difference.

Acknowledgments

This work was supported by the “KiTSmart Project - City of Vienna Competence Team for Intelligent Technologies in Smart Cities”, funded by national funds through the MA 23, Urban Administration for Economy, Work and Statistics,
415 tics, Vienna, Austria and the “Photonics Project: Foundations and industrial applications”.

References

- [1] M. Taieb-Maimon, D. Shinar, Minimum and comfortable driving headways: Reality versus perception, *Human Factors: The Journal of the Human
420 Factors and Ergonomics Society* 43 (1) (2001) 159–172.
- [2] SWOV Factsheet, Headway times and road safety,
https://www.swov.nl/rapport/Factsheets/UK/FS_Headway.pdf.

- [3] Abstand und Abstandsvergehen, <http://www.bussgeldkatalog.org/>.
- [4] C. Olaverri-Monreal, R. Lorenz, F. Michaeler, G. C. Krizek, M. Pichler, Tailigator: Cooperative system for safety distance observance, in: Collaboration Technologies and Systems (CTS), 2016 International Conference on, IEEE, 2016, pp. 392–397.
- [5] C. Olaverri-Monreal, P. Gomes, R. Fernandes, F. Vieira, M. Ferreira, The See-Through System: A VANET-enabled assistant for overtaking maneuvers, in: Intelligent Vehicles Symposium (IV), IEEE, 2010, pp. 123–128.
- [6] P. Gomes, C. Olaverri-Monreal, M. Ferreira, Making vehicles transparent through V2V video streaming, Intelligent Transportation Systems, IEEE Transactions on 13 (2) (2012) 930–938.
- [7] P. Barnum, Y. Sheikh, A. Datta, T. Kanade, Dynamic seethroughs: Synthesizing hidden views of moving objects, in: Mixed and Augmented Reality. ISMAR. 8th International Symposium on, IEEE, 2009, pp. 111–114.
- [8] X. Zheng, Y. Zhang, An image-based object detection method using two cameras, in: Logistics Engineering and Intelligent Transportation Systems (LEITS), International Conference on, IEEE, 2010, pp. 1–5.
- [9] G. Pelaez, D. Bacara, A. de la Escalera, F. Garcia, C. Olaverri-Monreal, Road detection with thermal cameras through 3d information, in: Intelligent Vehicles Symposium (IV), IEEE, 2015, pp. 255–260.
- [10] A. Houchin, J. Dong, N. Hawkins, S. Knickerbocker, Measurement and Analysis of Heterogenous Vehicle Following Behavior on Urban Freeways: Time Headways and Standstill Distances, in: Intelligent Transportation Systems (ITSC), 18th International Conference on, IEEE, 2015, pp. 888–893.
- [11] A. Petrovai, R. Danescu, S. Nedevschi, A stereovision based approach for detecting and tracking lane and forward obstacles on mobile devices, in: Intelligent Vehicles Symposium (IV), IEEE, 2015, pp. 634–641.

- [12] A. Cabrera, S. Goyal, A. Martinoli, A new collision warning system for lead vehicles in rear-end collisions, in: Intelligent Vehicles Symposium (IV), IEEE, 2012, pp. 674–679.
- [13] Y. Zhang, E. K. Antonsson, K. Grote, A new threat assessment measure for collision avoidance systems, in: Intelligent Transportation Systems Conference, ITSC, IEEE, 2006, pp. 968–975.
- [14] N. Stone, J. Billingsley, Development of low cost range sensing instrumentation for collision avoidance applications, *Mechatron. Mach. Vision. Robot. Mechatron* 3 (2000) 127–133.
- [15] D. Shrestha, G.-L. Chang, A monitoring and alert system for tailgating behavior of drivers, in: Vehicular Technology Conference, 2005. VTC-2005-Fall., Vol. 2, IEEE, 2005, pp. 1308–1312.
- [16] Y. Zhang, Q. Chen, Y. Liu, A real-time tracking system for tailgating behavior detection, in: Proceedings of the Fourth International Conference on Computer Vision Theory and Applications (VISIGRAPP 2009), 2009, pp. 398–402. doi:10.5220/0001665703980402.
- [17] T. Ito, T. Sakagami, S. Kawakatsu, A real time distance headway measurement method using stereo and optical flow, in: Intelligent Vehicles' 92 Symposium., Proceedings of the, IEEE, 1992, pp. 230–235.
- [18] T.-H. Chang, C.-J. Chou, Rear-end collision warning system on account of a rear-end monitoring camera, in: Intelligent Vehicles Symposium, IEEE, 2009, pp. 913–917.
- [19] P. Viola, M. Jones, Rapid object detection using a boosted cascade of simple features, in: Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on, Vol. 1, IEEE, 2001, pp. I–I.

- [20] J. Mrovlje, D. Vrancic, Distance measuring based on stereoscopic pictures, in: 9th International PhD Workshop on Systems and Control, Young Generation Viewpoint. Izola, Slovenia, 2008.
- 480 [21] SDDOT, Road Design Plan Preparation Guide - Chapter 5 Horizontal Alignment, sddot.com/business/design/docs/rd/rdmch05.pdf, (accessed on: 15.04.2017).
- [22] F. Michaeler, C. Olaverri-Monreal, 3D Driving Simulator with VANET Capabilities to Assess Cooperative Systems: 3DSimVanet, in: Proceedings Intelligent Vehicles Symposium IV2017, Los Angeles, CA, USA, IEEE, 2017.
- 485 [23] Unity Technologies, Unity - fast facts, <https://unity3d.com/public-relations>, (accessed on: 20.06.2016) (2016).
- [24] DLR, Institute of Transportation Systems - SUMO – Simulation of Urban Mobility, sumo.dlr.de, (accessed on: 20.07.2016).
- 495 [25] C. Biurun-Quel, L. Serrano-Arriezu, C. Olaverri-Monreal, Microscopic Driver-Centric Simulator: Linking Unity3D and SUMO, in: Recent Advances in Information Systems and Technologies. Proceedings 5th World Conference on Information Systems and Technologies (WorldCist'17), Porto Santo Island, Madeira, Portugal, Springer, 2017, pp. 851–860.



Cristina Olaverri Monreal graduated with a Master's degree in Computational Linguistics, Computer Science and Phonetics from the Ludwig-Maximilians University (LMU) in Munich in 2002 and received her PhD in 2006 in cooperation with BMW. After working several years in different European countries and in the US, both within the industry and academia, she currently leads the Competence Team Intelligent Technologies in Smart Cities at the University of Applied Sciences Technikum Wien, Austria. Her research aims to minimize the barrier between users and systems in complex, dynamic scenarios that are critical to decision-making processes, such as driving a vehicle and innovative forms of mobile and ubiquitous interaction approaches to human mobility. Dr. Olaverri is a member of the IEEE Intelligent Transportation Systems (ITS) Council Executive Committee, Vice-president of Educational Activities, and a member of the IEEE ITS Board of Governors (BoG). In addition, she serves as chair of the Technical Activities Committee on Human Factors in ITS and associate editor of the IEEE Transactions on ITS and ITS Magazine.



Gerd Christian Krizek graduated in Theoretical Physics at the University of Vienna in the group of Caslav Brukner. He has been working since 1999 in the industry as engineer in the field of embedded systems and mechatronics. Since 2010 he is deputy program director of the Master degree program "Intelligent Transport Systems" and lecturer at the University of Applied Sciences Technikum Wien.



Matthias Pichler graduated with a Master's degree in Intelligent Transport Systems from the University of Applied Sciences Technikum Wien in Vienna 2015 in cooperation with the Austrian Institute of Technology. Currently he works for EBE Solutions GmbH in the field of developing railway systems.



Rene Lorenz graduated with a Master's degree in Intelligent Transport Systems from the University of Applied Sciences Technikum Wien in Vienna 2015 in cooperation with Rosenbauer International AG. Currently he works for Siemens AG Austria as Software Engineer in the field of SCADA-Systems for automotive industry.



Florian Michaeler graduated with a Master's degree in Intelligent Transport Systems from the University of Applied Sciences Technikum Wien in Vienna 2016. Currently he works for EBE Solutions GmbH as developer in the field of road based traffic telematics and traffic surveillance systems.

Highlights

- A cooperative approach imitating human communication in a situation in which a vehicle is tailgating another was proposed
- It based on a rear-mounted distance warning system that garners information through the stereoscopic capturing and processing of images by rear cameras
- Visual data related to the safety distance is provided to the rear vehicle in real-time
- This approach relies upon a more common manner of human communication.
- Field and lab tests **delivered good results in terms of simultaneous image processing** as well as impact on driver response