Predictive Braking With Brake Light Detection - Field Test

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ABSTRACT Driver assistance systems, such as adaptive cruise control, are an increasing commodity in modern vehicles. Our earlier experience of radar-based adaptive cruise control has indicated repeatable abrupt behavior when approaching a stopped vehicle at high speed, which is typical for extra-urban roads. Abrupt behavior in assisted driving not only decreases the passenger trust but also reduces the comfort levels of such systems. We present a design and proof-of-concept of a machine vision-enhanced adaptive cruise controller. A machine vision-based brake light detection system was implemented and tested in order to smoothen the transition from coasting to braking and ensure speed reduction early enough. The machine vision system detects the brake lights in front, then transmits a command to the cruise controller to reduce speed. The current paper reports the speed control system design and experiments carried out to validate the system. The experiments showed the system works as designed by reducing abrupt behavior. Measurements show that brake light-assisted cruise control was able to start deceleration about three seconds earlier than a cruise controller without brake light detection. Measurements also showed increased ride comfort with the maximum deceleration and minimum jerk levels improving from 5% to 31%.

INDEX TERMS Advanced driver assistance systems, Automotive applications, Intelligent vehicles, Machine vision

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION
The number of automated and partly automated systems has rapidly grown in passenger vehicles. Driver assistance systems (ADASs), such as adaptive cruise control (ACC) and collision avoidance, are currently considered to be a common feature or at least a common accessory. The development of these systems has drawn significant attention to passenger safety and aspects of comfort. In the US and EU, fatal traffic accidents in different kinds of junctions cover one fifth of reported cases. Especially when a junction is located in fast moving traffic, such as in highway situations, anticipation and overall situational awareness greatly impact passenger comfort and safety. By increasing understanding of the behavior of other vehicles with machine vision at junctions, the cruise controller can be designed to act more robustly and with more reaction time. Another aspect is ride comfort in situations in which an automation system starts controlling the vehicle. Our experience of adaptive cruise control and steering assistants is that control can feel abrupt, particularly, at the start period of braking. Even the overall control of the system could feel smoother. This is due to human sensitivity to twitches, namely, jerk (first-time derivative of acceleration). Moreover, reduced comfort and additional control commands can actually lead to motion sickness.

This paper presents a vision-based brake light detection control system that utilizes the already existing adaptive cruise control system via a controller area network (CAN) bus. Instead of safety, we focus on passenger comfort due to success in finding clear areas for improvement in terms of comfort. Improved comfort increases user acceptance of future ACC systems. Automatic emergency breaking and other safety features from another set of driving assistant functions are not within the scope of our current research.

A high-definition camera was installed in the ego vehicle windshield similar to the way in which manufacturers install windshield cameras. The camera was used to acquire machine vision data from the vehicle ahead and its braking light status. The machine vision and brake light status detection systems were developed and reported in [1]. The brake light status was then used to anticipate the braking need in the ego
vehicle. The ego vehicle cruise controller received additional braking commands when the algorithms detected brake lights in the vehicle ahead. The in-built cruise controller system handled all the speed variations but with specific CAN messages being used to externally command the actions.

The scope of our research was inspired by practical experience gained from driving cars with ACC. Regardless of the vehicle brand, using ACC on extra-urban roads during which vehicles may be stopped at various points, such as for traffic lights, seems to fairly often lead to inconvenient situations in certain conditions. Although ACC occasionally detects the stopped vehicle in sufficient time, the detection often occurs rather late. Then the deceleration is jarring, in some cases, close to emergency braking. This repeated abrupt braking, particularly in slippery conditions, does not encourage the use of ACC.

The rest of this paper is structured in the following way. Next, the main scientific contributions of the presented work are described, followed by a literature review of ADAS and ACC systems. Thereafter, the proposed machine vision system for predictive braking is described in detail and the conducted experiments designed to validate the applicability of the predictive braking system are introduced. Finally, results from experiments are presented, highlighting the benefits of the proposed system. The acquired results and their implications are comprehensively analyzed. Observations and remarks regarding the drawbacks and strengths of the proposed methodology are provided to motivate future research on the topic.

B. SCIENTIFIC CONTRIBUTIONS

We present a novel methodology to improve advanced cruise control systems by smoothening the braking procedure. We propose utilizing machine vision algorithms to detect the brake lights of vehicles in front of the ego vehicle and then applying this information to predictive braking. A novel implementation of the system was developed utilizing the ACC CAN-bus messages of a research vehicle. Experimental results are reported which indicate the system is capable of smoothening the braking procedure by utilizing the brake light data acquired using machine vision. With the brake light data, the vehicle is shown to begin the braking procedure sooner compared to when solely relying on the factory-installed commercial radar. Acceleration and jerk measurements indicate that the braking procedure is smoother and more pleasant for the passengers. Our studies provide novel insights to improving ACC solutions with predictive braking. We believe our brake light assisted ACC renders cruise control more convenient to use and it also has implications on driving safety in some driving conditions.

II. STATE OF THE ART

The topic of passenger comfort has been of significant interest to researchers for decades. In 1976, Hoberock [2] found the highest acceptable peak accelerations in public transport vehicles to be in the range 0.11 to 0.15 g with 0.20 g being considered the critical limit. For jerk, the study found 0.30 g/s to be the critical threshold above which passengers would feel discomfort. The same discomfort limit for jerk was used by Hubbard and Youcef-Toumi [3]. More recent studies have found that the threshold for uncomfortable accelerations may be lower than previously thought. Du et al. [4] used the ISO standard for human exposure to whole-body vibration [5] to establish different levels of comfort for vehicle passengers, with accelerations only below 0.315 m/s² being considered entirely comfortable, and accelerations above 0.8 m/s² deemed uncomfortable. The importance of maintaining the lateral acceleration of the vehicle at a comfortable level has also been recognized in previous studies [6]–[8]. Moreover, heavy braking maneuvers trigger the anti-lock brake system (ABS), which further reduces the ride comfort due to the oscillations in the wheel speeds [9]. Therefore, it is highly important for predictive braking systems to recognize the need for braking as early as possible. It is an industry standard to The usage of radar in ADAS systems for distance measurement is an industry standard despite, however the shortcomings of radar have been noted in previous research [10], [11]. In addition, previous research has clearly demonstrated that even with an automated control system controlling the speed of the vehicle, the driver still adapts their visual behavior to the requirements of the system and anticipates impending collisions with the lead vehicle before the situation becomes critical [12]. By enabling automated deceleration maneuvers to start as early as possible, the trust of the driver and passengers in the automated control system would be enhanced, thus further improving the sense of safety.

Previous studies have examined passenger comfort in predictive braking systems. However, these studies have mainly been conducted using only simulations. Model predictive control (MPC) has been utilized in several studies. Luo et al. [13] designed a nonlinear model predictive controller (NMPC) for the adaptive cruise control of a hybrid electric vehicle. The controller was designed with fuel consumption, safety, and passenger comfort in mind. Limits for acceleration were included in the controller to account for passenger comfort. Similarly, Zhang et al. [14] developed an NMPC-based emergency braking system for passenger vehicles that would account for fuel economy, safety, and comfort. Matute et al. [8] designed a speed-planning MPC system that would also account for lateral acceleration, thus limiting the total acceleration of the vehicle and ensuring it would remain at a comfortable level. However, their system did not consider car-following. He et al. [15] developed an MPC-based predictive cruise control system which limited the degree to which the control commands can change between the prediction steps, which effectively low-pass filters the acceleration of the vehicle. The system was shown to successfully improve the comfort of the passengers by reducing peak acceleration and jerk values. MPC has also been suggested for use in coordinating the braking of multiple vehicles that are communicating with each other to avoid collisions and enhance
passenger comfort [16], [17].

In addition, simulation-based studies have utilized other methods, such as fuzzy logic and a sliding mode controller [18], an observer-based controller [19], and a PI controller [20], to optimize braking maneuvers with respect to passenger comfort. The PI controller-based system developed by Lee and Choi [20] limited both acceleration and jerk, providing a smoother experience for the passengers. Furthermore, they emphasized the importance of reducing the brake input just before the vehicle stops to prevent an unpleasant jerk that can easily happen when the speed falls to zero. Zhang et al. [19] noted that passenger comfort not only depends on the accelerations of the vehicle but also on the ride comfort. Thus, they designed a system controlling both the anti-lock brake system (ABS) and the active suspension system (ASS) to enhance passenger comfort.

Although a number of studies proposing new techniques for comfortably controlling the acceleration of a passenger vehicle have included car-following, it has been assumed that the distance to the car in front is known. Therefore, a clear research gap can be seen in a lack of combining vehicle detection and comfortable predictive braking. Moreover, while promising results have been achieved in previous predictive braking studies, they have tended to focus on testing the systems in simulated or limited hardware-in-the-loop (HIL) environments. In this article, we present our real-world tests with a novel system combining vehicle brake light detection with predictive braking aiming to optimize passenger comfort.

Brake light detection has been investigated in various studies. The previous works on the topic can be broadly categorized into daytime and night-time studies. The high contrast caused by the brake lights in dark environments enables even relatively simple color-space-filtering to work effectively [21], [22]. However, such methods are not effective in daytime lighting conditions due to the lower contrast. Thus, more sophisticated methods are required. Typically, a bounding box area is first identified for the vehicle using, for example, the histogram of oriented gradients (HOG) [23], [24] or deep-learning-based methods [25]–[27], and then the brake light status is identified within the box. Different methods utilized for the brake light status identification have included detecting high red chromaticity difference in the tail light region [24], CNN [28], and dictionary learning [29]. However, most brake light detection algorithms have typically been developed and tested with the lead vehicle being at a standstill in close proximity. Pirhonen et al. [1] devised a novel daytime brake light detection algorithm capable of also detecting the brake light status from moving vehicles, even at further distances. The novel braking control system presented in this article applies the aforementioned brake light detection algorithm.

### III. METHODS

#### A. CONTROL STEPS OVERVIEW

This paper presents a proof-of-concept of a predictive braking methodology for ACC systems based on machine vision. The approach utilizes machine vision to predict impending stops, decelerating the vehicle before the radar acquires sufficient confidence of the situation. A summary of the steps adopted in the predictive braking procedure are presented in Fig. 1.

![FIGURE 1. Overview of the braking procedure.](image)

To acquire information on the brake lights ahead, a previously developed brake light detection algorithm is applied [1]. Previous studies indicate the algorithm as being capable of detecting brake lights at long ranges, leaving the predictive braking system sufficient time to operate. Once brake lights are detected ahead, the goal of the system is to preemptively decrease the vehicle speed, as the possibility of a stop seems probable. Further analysis of the situation is carried out with an automotive radar, as the high accuracy distance measurements allow detailed control of the required braking procedure. Essentially, the radar eventually makes the final decision to notably decelerate and possibly stop the vehicle. The machine vision addition to the ACC system allows preparation for abrupt stops, thus enabling a notably smoother braking procedure. This in turn renders the ride more comfortable for the driver and passengers.

#### B. MACHINE VISION

In order to analyze the brake lights of the vehicle ahead, the brake light detection algorithm presented in a previous study of ours is adopted [1]. Full details of the algorithm are available in the original paper, nevertheless, the basic principles of the detection algorithm are summarized here and shown in Fig. 2. The detection algorithm consists of three stages (i-iii), object detection, image preprocessing and random forest classification respectively.

In Stage (i), the windshield camera feed resized to 800x600 is fed to YOLOv3 [25] object detector. With YOLOv3, the bounding box area of the vehicle ahead is captured. The bounding box of the vehicle ahead is then extracted from the original image for further processing.

In Stage (ii), the resulting image from Stage (i) is thresholded with a predefined LAB colorspace parameter range. The main idea for this preprocessing stage is to put more emphasis on brake light candidate regions by filtering pixels that do not contain colors present in brake lights. The preprocessing creates a binary image indicating which pixels contain colors common in brake lights.

In Stage (iii), this binary image is resized to 30x30 and transformed into an input vector with a length of 2700 elements. The input vector is then fed into a random forest clas-
sifier [30], which outputs a confidence value representing whether the brake lights are on or off.

![Brake light detection algorithm workflow](image)

**FIGURE 2.** Brake light detection algorithm workflow.

### C. RESEARCH VEHICLE DESIGN

In order to demonstrate the feasibility of the described ACC system, a functional prototype was built on our Ford Focus 2019 research vehicle. The vehicle was equipped with an additional windshield camera, a computer, and a CAN communication interface device, as shown in Fig. 4. The installed components and their respective interactions are depicted in Fig. 3.

The installed windshield camera was utilized to capture images of the view ahead of the vehicle. Captured images were transmitted to the on-board computer, where they were processed with the previously described brake light detection algorithm. In case brake lights were detected ahead of the research vehicle, the computer adjusted the target speed of the vehicle ACC system via the CAN interface. Communication from the computer to the CAN interface was handled via TCP, and the interface transmitted the communication to the CAN bus. Detailed specifications for the components are provided in Tables 1, 2, and 3.

### D. DETAILED CONTROL

For a concept demonstration, a straightforward control logic was devised to show that the machine vision solution improves the braking procedure. The control logic utilizes CAN messages to adjust the speed while cruise control is on. The system builds on four different threads running simultaneously, Main thread, Thread I, Thread II and Thread III. The main topology and threads are presented in Fig. 5.

On system launch, all the threads are declared and initialized, with three out of four threads being started. The Main thread is responsible for running the brake light prediction algorithm, relaying the information to other threads, starting Thread III on demand, and storing a log file. Thread I includes frame capture functions; a separate thread was constructed to ensure that the prediction stage always receives the latest video frame. Threads II and III include the necessary functions for CAN communication.

CAN bus communication threads are solely responsible for communicating to the research vehicle networks. Two separate threads were used to ensure that the communication can be simultaneously read and written. The main purpose of Thread II is to read the current vehicle speed as well as the

| Camera (Flir Blackfly S) |
|--------------------------|
| Resolution               | 2,448 x 2,048 px |
| Frame Rate               | 35 fps          |
| Chroma                   | Color           |
| Shutter                  | Global          |
| Pixel Depth              | 12 bit          |

**TABLE 1.** Specifications for the windshield camera.

| CAN Interface (PEAK PCAN-Ethernet Gateway DR) |
|----------------------------------------------|
| Connections                               | CAN-to-Ethernet |
| Transmission Protocol                      | TCP             |
| CAN transceiver                            | NXP PCA82C251   |

**TABLE 2.** Specifications for the CAN interface.

| Computer |
|----------|
| CPU      | Intel Core i7-9700k |
| GPU      | Nvidia RTX 2080Ti  |
| RAM      | 32 GB DDR4         |

**TABLE 3.** Specifications for the computer.
Thread II continuously runs while the system is on, parsing the correct information from the CAN data frames on the research vehicle side. The correct information is then passed onto the Main thread for log purposes. The message formats used in the study are presented in Table 4 in hexadecimal format. The table includes both received and sent messages. The captured data from the vehicles network is in hexadecimal, which is then converted into decimal format for logging purposes. Vehicle speed data consists of two 8-bit sections that are converted into 16-bits, the speed data also includes an offset of 100. The cruise controller speed demand is sent in one 8-bit configuration. In Thread III, a CAN message imitating ACC speed adjustment message is sent in order to reduce the speed by 10 km/h. Once the detection algorithm running in Main thread recognizes a lit brake lights, Thread III is started.

### E. FIELD TESTS

The field tests were performed at the Helsinki-Malmi airport. The tests were run on an empty airstrip. The airstrip was approximately 500m long, on which a 300m long test lane was constructed. The test lane was measured using a laser distance sensor, and traffic cones were placed at 50m intervals. At the start of the test lane, a 0 point was marked from which the test vehicle started the measurements. At the end of the lane, another vehicle with its brake lights on was placed at a standstill to imitate a traffic jam or a vehicle standing at traffic lights. Measurements were then driven at the following speeds: 50, 60, 65, 70 km/h. Each test included a drive with the research vehicle from the start of the test lane...
towards the stopped vehicle and ending at the point at which the radar based ACC fully stopped the research vehicle. The main difference can be seen at the point from which the radar based system and our system start the deceleration. Each test consisted of two types of drives, one with our system in place and another with the vehicle’s original system. Data was collected from all the drives, the vehicle’s original system behavior being the reference for our system.

F. FILTERING METHODOLOGY
The speed signals recorded via CAN interface were analysed off-line to assess the performance of the standard adaptive cruise controller versus the cruise controller with brake light detection. The speed signals were originally sampled at about 10 Hz sample rate. The speed signals were up-sampled to 25 Hz and low-pass filtered by fourth order low-pass filter with the cut-off frequency at 1 Hz. The speed signals were then derived to first achieve deceleration and then jerk (the time derivative of deceleration). The deceleration times, highest deceleration values and minimum jerk achieved are reported in Results section.

IV. RESULTS
Table 5 reports the deceleration times, highest occurring deceleration, and minimum jerk when running with the standard cruise control and machine vision aided cruise control. When approaching a stopped vehicle at 50 km/h speed, the brake light detection was able to lower the highest deceleration by 21%. The minimum jerk was improved by 31% at the same speed. At 60 km/h speed, the improvement in deceleration values was 24% and in the jerk values 19%. At 65 km/h, the respective improvements were 7% in deceleration and 18% in jerk. At the speed of 70 km/h, the results were dualistic. The brake light detection improved the situation on one run, but not on the other run.

Fig. 8 shows all the test runs in four different speed ranges, including only the actual braking event. In the figure, zero marks the time at which the vehicle has been stopped to a standstill. All four different speed ranges include a comparison of the machine vision aided cruise control and the original radar-based system.

The speed curves include a roughly 3 km/h offset from the ACC demand speed due to the ACC controller having an accepted steady state error. This small difference can be seen in the figures since the data is extracted from the CAN data. For example, when speed demand is set to 50 km/h the curve shows roughly 47 km/h, being the point at which the cruise control is deemed to be suitable.

The results show brake light detection-assisted cruise control enabled sufficiently early deceleration of the vehicle, consequently maintaining better ride comfort. Roughly speaking, the brake light detection allowed deceleration to start about 2.8 seconds earlier than braking with vehicle cruise control alone. The deceleration time was increased roughly by 23 per cent.

In distance, deceleration with activated brake light detection started about 30 meters earlier than without brake light detection. This roughly equaled to a 30 per cent longer deceleration distance and smoother deceleration than with the original cruise control alone. Fig. 9 reports the distances at which each system started the braking procedure. It can be clearly seen that the machine vision aided system consistently improves the distance. The results also indicated a gentler deceleration ramp with the brake light detection on. However, the ramp was not reduced as much as could be expected based on the time and distance increase, because the deceleration ramps were relatively gentle in the beginning.

V. DISCUSSION
The results indicate that the developed system was capable of detecting the brake lights of a stopped vehicle ahead, and began slowing down in advance. The deceleration of the vehicle began earlier in contrast to using the standalone original radar system of the vehicle. Earlier initiation of the deceleration led to lower peak acceleration as well as jerk values. The lower peak acceleration and jerk values in turn can improve the quality of the ride for the driver and passengers on board while ACC is activated. The results highlight that the addition of brake light detection-based predictive braking is possible and could be an attractive addition to current radar-based ACC system control.

Using the brake light detection system led to an average improvement of minimum jerk values of 18%. Jerk is one of the most important factors in ride comfort. The acquired jerk values are mostly in line with the comfort limits stated in the literature [2], whereas the jerk values measured with the original ACC system surpass the given limits. Effectively, the presented system seemed capable of notably improving ride comfort, as passengers were not subjected to harsh decelerations. While conducting the test runs at the test site, similar improvements could be felt by all the researchers on

| Test runs       | Brake time (sec) | Acceleration min (m/s²) | Jerk min (m/s³) |
|-----------------|------------------|-------------------------|-----------------|
| ACC 50 km/h     | 15.51            | -2.02                   | -2.48           |
| ACC 60 km/h     | 13.84            | -2.57                   | -2.75           |
| ACC 65 km/h     | 13.38            | -2.67                   | -2.51           |
| ACC 70 km/h     | 7.53             | -3.77                   | -3.80           |
| BRAKE 50 km/h   | 10.87            | -2.93                   | -3.34           |
| BRAKE 60 km/h   | 11.87            | -2.70                   | -3.20           |
| BRAKE 65 km/h   | 11.11            | -2.98                   | -3.44           |
| BRAKE 70 km/h   | 11.67            | -2.85                   | -3.50           |
| BRAKE 70 km/h   | 11.30            | -2.94                   | -3.06           |


table 5. Individual test run deceleration times, acceleration minimums and jerk minimums.
The results also show two clear outlier measurement runs with speeds of 60 km/h and 70 km/h. In both cases the braking starts too late causing harsh deceleration and jerk values. One test occurred while the original ACC system was tested and the other with our system active. In both cases, it is clear that the radar-based detection did not work as intended, detecting too late the stopped vehicle in front. The second test run with 70 km/h shows that the camera-based detection started a bit too late but still drastically earlier than the radar-based one. These cases are apparent outliers since they notably differ from all the other braking curves. On the other hand, these two tests show the necessity of our system, proving that the radar-based system performs extremely poorly at times. Our system is built on the existing radar-based solution; thus, theoretically, it should never perform worse than the standalone radar-based solution. Deeper fusion of the systems would allow further improvement of the braking procedure.

The presented tests were carried out without access to the vehicle’s original camera or radar data, or direct access to control the brakes or the braking procedure of the vehicle. The machine vision system was effectively used to decrease the speed of the vehicle before the radar-based adaptive cruise control braking began. When the machine vision system detected brake lights ahead, the cruise control speed request was dropped by 10 km/h via the CAN bus. Shortly after, the radar-based braking was then carried out as the OEM system of the vehicle intended to. This was naturally not an optimal fusion of the systems, as the two sensors are not aware of each other, neither are their readings fused. A complete fusion of the systems was not implemented, as accessing the readings from the automotive radar or camera is practically impossible without working with the OEM. Control of the braking procedure is likewise extremely difficult without detailed knowledge of the OEM vehicle system. Nevertheless, the current implementation has the advantage of using the established OEM radar-based braking system as is, highlighting that the acquired results demonstrate the state-of-the-art in production vehicles. The machine vision system is implemented as a separate add-on to the system, without interfering with the original operation. The brake light detection only allows the vehicle to predictively decelerate to a more appropriate speed before starting the full braking procedure.

To more comprehensively benchmark the system, more tests in varying conditions could be carried out. The presented results only report the operation based on tests carried on a single day, with sunny weather and dry asphalt. Due to the availability of the test field, the resulting individuals runs do not match in number. In future studies of the system, more
FIGURE 8. Speed curves of the individual test runs.

FIGURE 9. Comparison of the distances at which the systems started the braking procedure.

accurate test plan with an equal number of test runs should be advised. For transparency, a decision was made to report all the test runs that were possible to do in the given day at the test field. The distance from which the machine vision system could detect the brake lights in different weather conditions remains unclear. Moreover, the sunny conditions of the tests were not optimal for the machine vision system, due to the high overall brightness and reflected glares from...
the vehicle in front hindering the detection capabilities of the system. This was already reported in the original paper describing the brake light detection system [1]. With a lower brightness, as in cloudy weather conditions, the operation of the brake light detection would have possibly detected the brake lights from even farther away. Regarding condition of the asphalt, braking profile could be affected by slippery road or other hindrance to the estimated braking distance. In these scenarios predictively decelerating with the aid of machine vision could prove even more useful, as the radar-based braking may have trouble stopping the vehicle in time.

The presented method could not be utilized in every situation, as in for example steep uphills or downhill, or sharp turns. Based on our practical experience the current ACC system is not that capable in mentioned situations either. All sensors, such as radar and camera, faced forward suffer from similar inclinations and turns. While developing the system it was noteworthy that the camera-based solution seemed to be more robust towards small inclinations on the road. Deeper system-level fusion to the vehicle original radar-based cruise control would definitely solve many control challenges and could offer a solution to the perception side as well.

While driving the research vehicle, it could be clearly seen that slight bends on the roads significantly affect the cruise control; similarly, the operation was hazy on road inclinations.

Future research topics could include camera feed region of interest optimization, as well as more complex control logic. However, our future research focuses on the vehicle rear recognition stage and how to extract the vehicle directly in front. Currently, the system does not only account for the vehicle directly in front of the ego vehicle, but instead includes all vehicles ahead. In addition, future studies could focus on building a system that could utilize the radar data by fusing it with the camera data. In order to use radar data in fusion with camera a separate radar sensor should be installed. Future testing could also utilize camera data for distance estimation to the vehicle directly in front.

Driving assistance systems have their influence on the traffic flow and driver behavior. Also our improvement for ACC is likely to make the ego car to drive in a slower and more precautious manner. This in turn may have an influence on the traffic dynamics. It is also noteworthy that the predictive braking operates utilizing the original ACC system and will disengage if the driver presses gas or brake pedal.

Why the state-of-the-art ACC systems failed to recognize a stopped vehicle early enough to avoid abrupt braking? We believe there are several reasons. Non-moving objects are known to be more difficult to detect by radars than moving objects. Moving objects can be tracked using various algorithms whereas stationary objects are harder to track since there are no trajectory estimation involved. Radar sensitivity may also be limited for good reasons, for instance, in order to avoid false alarms. Furthermore, according to our test drives with the state-of-the-art vehicles, detection and classification of another vehicle takes some time before ACC activation. The activation time is away from vehicle deceleration time. We also expect fusion with camera data is becoming faster and more seamless in the future as vehicles approach higher levels of autonomy.

Before implementation to production grade vehicles the system should be tested for various different environments, road conditions and driver behavior. The first step could be to fuse the camera data with the radar data for more accurate perception and implement the already existing adaptive cruise control logic, instead of lowering the speed directly by 10 km/h. Also, the implementation of the system could be integrated to already available multi purpose camera control unit, which already include notable computing power and high-grade cameras.

VI. CONCLUSION

This paper presented experimental results highlighting the advantages of utilizing machine vision for predictive braking in ACC systems. The system builds on previous research on brake light detection. The brake light detection utilises established machine vision methods, such as object detection, color thresholding and classification. Previously acquired results are enhanced with the capability of controlling the vehicle braking via CAN messages, thus proving the performance in real life. Our solution was developed to improve abrupt behavior of commercial ACC systems. Regardless of the vehicle brand, current ACC solutions often brake harshly in situations where a vehicle approaches a stopped vehicle at a suburban speed (50-70 km/h). The improvement proposed here is a mean to increase user trust, comfort, and acceptance of ACC systems.

The research presented proves that such machine vision system could improve the existing ACC. Additional improvements could likely be reached if the machine vision system was fully integrated to the manufacturer vehicle systems, especially with the data acquired from the radar. The presented method could also possibly be used to improve other driver assistance systems, such as collision avoidance and brake assist systems.

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