DRIVER ACTIVITY RECOGNITION THROUGH HAND GESTURES

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Preface

This study is a product of a master's thesis project by two Software students at Aalborg University. Throughout the study appropriate terminology is used, this means that the readers must have some knowledge about computer science.

Joakim Iversen

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Contents

1 Introduction

Driver activity recognition and monitoring is an advancing research topic as vehicles are becoming more technological. As various assistance systems are implemented in cars [5], drivers have adopted a more relaxed driving style. This results in some drivers using suboptimal steering techniques, such as only having one hand on the steering wheel. The goal of the research is to find a way to encourage good driving behaviour. The research is further focused on preventing possible accidents caused by fatigue, sleepiness, reckless behaviour, or distractions [4]. Observational studies [11; 6] have further showed that very few drivers use the recommended steering techniques, thus resulting in them having less control over the vehicle.

Various technologies have been utilised in experiments in an attempt to solve these problems, a few examples being cameras [12; 10], pressure pads [8], and infrared sensors [8]. One of the most utilised methods throughout the research is eye and iris detection [1; 2], focusing on the driver's gaze and how much of the iris is covered by the eyelid. Few studies have also looked at limb recognition to determine the activity of the driver [12; 10; 13], however these setups include externally placed cameras making them unfit for regular driving.

In order to prevent the detected accidents from happening, a feedback method to alert the driver is required. Various experiments [9; 3; 7] have been made to determine which type of feedback is best for certain situations, however most of them utilise immediate feedback requiring the drivers to shift their attention when it happens.

Based on the problems regarding distractions and poor steering techniques, the goal of this study is to develop a system capable of accurately recognising a driver's activities using hand gestures. These recognised activities are used to warn the driver about suboptimal driving behaviour, which is presented at times where the driver can comprehend this feedback.

Research Contribution Summaries 2

2.1 Utilising The Leap Motion Technology To Classify Hand Gestures In Vehicles

The paper is found in Appendix A.

Driver activity recognition and monitoring is a widely researched topic. One of the primary reasons for this, is to reduce the number of accidents caused by distracted and fatigued drivers. Within the field, some of the most researched observations methods are eye and iris detection, which bases its prediction on the driver's gaze. However, fewer studies focus on driver's hand gestures to determine the activity. Different types of distractions are further analysed, to understand driver interactions in vehicles.

Throughout this paper, we research hand gestures and how these could be used to determine the current activity of a driver. The analysed hand gestures are the naturally occurring interactions that every driver is performing to control the vehicle, e.g. holding the steering wheel or using the gear stick. In order to do so, we are utilising a Leap Motion controller placed at the roof, just above the steering wheel. The data stream provided by this Leap Motion is extracted and classified using a SVM algorithm, which allows the system to determine the driver's current hand gesture.

The system averaged an accuracy of 85.60% based on 17 evaluations performed in 2 cars with 13 participants. From this we conclude that hand gesture recognition is a viable method to accurately determine a driver's activities and that it should be studied further.

2.2 Driving Performance Evaluation Through Timely Feedback: An Exploratory Study

The paper is found in Appendix B.

Current driver activity recognition systems are primarily focused on detecting certain states such as fatigue or sleepiness. These states are however only part of the problem that comes with the monotonous driving task and the accidents that follows. Statistics [4] shows that driving while distracted and reckless driving behaviour also causes accidents each year.

To prevent these suboptimal driving styles, feedback is required to alert the drivers of their reckless behaviour. Most research papers experiment with feedback systems that provide feedback immediately, regardless of the situation. In this article we develop a system utilising timely feedback, which provides feedback at appropriate times where the driver's cognitive resources can comprehend it, without compromising the driving performance. By utilising the Leap Motion technology and our previously built driver activity recognition system, we explore usages of this system in combination with timely feedback, by conducting a pilot study with a driving academy and a field test with regular drivers.

Our system showed good correlations between the actual situation and the system's predictions. The system's feedback, not just timeliness but also frequency and message, was well received by both the participants and the driving academy, and some participants were surprised about their own subconscious behaviour. The participants showed an interest in the system, and mentioned that implementing gamification principles would be a viable solution to help them stay focused on the road.

Conclusion 3

As cars have been implemented with more assistance systems, drivers have adopted a more relaxed driving style. In order to prevent accidents caused by this, we have developed two systems, DOS and DOSAF. DOS being capable of detecting the driver's current actions through hand gesture recognition, and DOSAF expanding DOS by providing timely feedback to inform the driver about their driving behaviour.

We conclude from DOS that hand gesture recognition is a viable method for detecting a driver's current activities, despite the Leap Motion technology having range limits and problems with light reflections. Based on the interviews from the DOSAF evaluation, we can further conclude that providing feedback during full stops is a viable solution, as the driver has more time to register the feedback and think about the provided message.

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A Utilising The Leap Motion Technology To Classify Hand Gestures In Vehicles

Utilising The Leap Motion Technology To Classify Hand Gestures In Vehicles

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ABSTRACT
Driver activity recognition and monitoring is a widely researched topic. One of the primary reasons for vehicle accidents is distracted drivers. The most researched observation method are eye and iris detection, where the prediction is based on the driver's gaze. Understanding what drivers are doing while driving could help develop systems to prevent further accidents. Throughout this article, we explore hand gestures and how these can be used to determine the activity of the driver, due to the natural occurring interaction inside the car include distinct hand gestures, e.g. holding the wheel or the gear stick. With an average accuracy of 85.60% based on 17 evaluations in two cars with 13 participants and six different gestures, we conclude that hand gestures provide enough insight to accurately classify driver activities.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; See http://acm.org/about/class/1998/ for the full list of ACM classifiers. This section is required. Experimentation

Author Keywords
Driver Activity Recognition; Leap Motion; Hand Gestures; Classification.

INTRODUCTION
The automobile evolution has expanded with newer and easier ways to use the car, including automatic assistance systems like the ABS brakes, automatic gear transmission, and autopilot features. In addition to the automobile evolution, so too has the evolution on everyday devices. As it has become safer to control a vehicle, the safety of drivers and passengers has increased [16]. At the same time, decreasing the difficulty of driving increases the comfort levels of drivers, enabling them to do other tasks, such as using their phones, while still feeling in control of the vehicle. The reason for most frequent road accidents are distracted drivers [11]. Consequently, driver activity recognition is a widely researched topic, where the goal is to understand what drivers are doing while driving, and prevent dangerous situations by preemptively detect instances of distracted driving and alerting the drivers.

As the secondary driving task controls have become more requiring and infotainment oriented [20], the cognitive resources spend on using them have increased. Phone usage have also increased significantly [11], despite being illegal to use while driving. Both [40] and [42] have shown that messaging and talking on the phone requires a lot of cognitive resources, to such a degree that it is considered a very dangerous activity to do while driving. Visual, kinetic, and cognitive resources are being used while using the infotainment controls or the phone, which decreases the focus on the road and increases the response time to react on events.

By utilising driver activity recognition it would be possible to determine the driver's actions while driving, and whether they are primary task related or not. Most researched systems use gaze and eye movements to determine the activity of drivers and hand gestures are mostly used for interaction purposes.

While driving, many distinguishable gestures take place, such as grabbing the gear shift, manipulating the secondary tasks by finger presses, resting the hand, and holding on to the steering wheel. This study explore hand gestures in cars, and more importantly if these could reliably distinguish and determine the activity performed by the driver. This study utilises the technology provided by the Leap Motion controller, a depth camera able to recognise arm, hand, and finger movements and supply a stream of output information in real time. The Leap Motion controller is small and allows for unique positioning inside the vehicle.

Based on the lack of research done within the topic of using hand gesture recognition for observation purposes within cars, we have decided to explore a system capable of recognising the driver's activities through the naturally occurring hand gestures. We develop a proof-of-concept system to determine two gestures for the left hand and four gestures for the right hand and evaluate the accuracy of this concept system.

RELATED WORK
According to [40], humans' have a set of cognitive resources which is used when performing e.g. visual perception, kinetic movements, and cognitive tasks. Driving and focusing on the road takes up a certain part of these resources. Multitasking

takes away some of the cognitive resources spend on the primary task in order to do the secondary task. In an automotive context, these tasks are what is known as a distraction. In a vehicle context, distractions comes in two kinds, internal and external distractions. Internal distractions are those happening inside the vehicle, e.g. secondary controls, handheld devices, and passengers. External are things occurring outside the vehicle, e.g. other drivers, the landscape, and billboards.

Internal Distractions

Stutts et al. [43] observed 70 drivers with cameras installed in their cars over the course of a week. Here they observed distractions that occurred, hand positions, gaze direction, and irresponsible vehicle events such as crossing the lines and sudden braking. A larger number of distractions were reported; using the phone, eating and drinking, grooming, reading and writing, and fumbling around with objects in the vehicle. Each distraction was shown to have a significant impact on the number of hands on the steering wheel and eyes directed inside the vehicle instead of on the road. Preparing to eat or drink and reaching, leaning, or looking for objects inside the vehicle also had a significant impact on the number of irresponsible vehicle events.

Manipulating the secondary controls includes a wide range of tasks such as; changing the music settings or radio channel, adjusting the heating of the car, and setting up or following the GPS instructions [34, 23]. Each of these does not seem complicated, however they each force the driver to shift attention from the road and onto the task, both visually and cognitively [40]. According to NHTSA [32] phones are one of the primary offenders in regards to distracted drivers crashing. Interaction with passengers have both positive and negative effects on driving [21]. The driver is less likely to get sleepy while communicating with a passenger, and the passenger takes a responsibility and helps with observing the road. It is however an internal distraction as communicating requires cognitive resources [15, 40]. [48] researched the concept of mind wandering and how it increases a driver's response time. Results showed that while mind wandering the observed drivers' response time increased from 0.9 seconds to 1.1 seconds. It furthermore causes a form of inattentional blindness, where drivers are less likely to register critical situations on the road.

External Distractions

Statistics from the danish road directorate [45] shows that accidents occurs 15 times more often on city and rural roads, compared to on the highway. The reason for this is that the highway has less surprising elements; usually everything can be seen well in advance, everyone is heading in the same direction with similar speed, and entering and exiting the highway can be done so without braking in front of others [28]. Driving in different kinds of landscapes or with different road conditions impacts the driver's focus on the road. The driver's stress level is reduced if the road condition is considered simple, such as driving on a straight wide road in an open landscape with clear sight of incoming traffic and turns. Consequently, driving an easy road takes away some of the attention put into driving. This effect is reversed in stressful conditions [4, 3]. Landmarks and events happening externally makes the driver shift attention [3]. The behaviour of the cars surrounding the driver can also act as a distracting element [39], especially when they are driving differently than expected.

Driver Activity Recognition

From researching the topic, various approaches of driver activity recognition were observed. The most researched approach has been detecting the gaze of the drivers where both head direction, eye, and eyelid movements are used to determine their activity. With this approach, the goal is often not on the activity, but instead the emphasis is put on detecting sleepiness and drowsiness from the driver. One of the possible detection solutions to this is by tracking the driver's eye movement, gaze, and face orientation [6, 7, 33, 12]. Across all studies, the tracking was performed using a camera. Based on the images, a machine learning algorithm was taught to recognise heads and faces. Such research proves that the eyes and face reveals whether the driver is distracted or sleepy. Eye tracking is actually a combination of iris and eyelid detection. Based on how much of the eye is covered by the eyelid, the system can determine if a driver is sleepy or distracted [18, 14]. Gaze tracking have proven to be a reliable solution in regards to detecting if the driver is distracted or looking at the road [1].

Some of the more recent research has looked into predicting aspects on the driving not obviously related to the gaze. [13] use driver gaze to predict where the drivers attention is allocated, where previously only fatigue and sleepiness were detected. Based on data from the 100-Car Naturalistic Driving Study dataset [17], the authors associate glance patterns with information about the driving environment, driver behaviour, and driver demographics.

Gesture Recognition

Another approach is limb detection, where the determined activity is based on hand position and movements. Usually, hand gestures are only studied for interaction purposes, where natural user interaction can make the interaction more fluid and intuitive. The authors of [46, 44, 47] analysed drivers activities through limb recognition using depth camera. In most of these experiments, the camera is mounted on the side of the vehicle, viewing the driver from the side, and silhouette recognition is used to determine the driver's activities in these cases.

Others have experimented with applying sensors and pressure pads to the driver seat, allowing them to analyse the different movements between a regular and a distracted driver [37]. The authors further expanded their system, by making it able to differentiate between different drivers [38]. This makes it possible for the car to detect which driver is currently driving, allowing other systems to adjust based on the individual driver's preferences.

When driving, people are already making hand gestures, such as holding the steering wheel, grabbing the gear stick, or manipulating the secondary controls. Hand gesture recognition have shown potential in other fields such as medical [19], communication [25, 35, 41], and entertainment [22, 24]. In regards to driving, some of the larger car manufacturers such as BMW [10] have started exploring gesture interaction to control their interfaces. This feature requires less visual and/or touch precision, resulting in more time to look at the road.

Making hand gestures within a defined space opens up new ways to control and manipulate the vehicle. Researchers have found that using hand gestures for interacting with secondary tasks in a vehicle can have a positive effect on driving, as hand gestures require less cognitive resources. The most notable benefits are the reduced time spent looking away from the road and the reduced mental strain that comes along with it [5, 34, 9, 2].

This study examines hand gesture recognition in vehicles using the Leap Motion technology. The Leap Motion allows for unique positioning inside the vehicle, that can be focused around the driver's limited interaction area. Previous studies on hand gesture recognition in vehicles are suboptimal, as their setups would not be usable in a regular driving context. This study uses hand gestures for observatory purposes, to get an indication about the drivers hand activity.

MOTIVATION

Driving a vehicle is done by performing a set of gestures such as holding the steering wheel and grabbing the gear stick. By observing the features and movements of their hands and arms, it should be possible to get an adequate view into what the driver is currently doing. As the driver is bound to the driver seat, their area of interaction is limited, thus limiting the required observation to this area. If it could reliably be determined that the hands were positioned at the steering wheel, with some intervals of using the gear stick with the right hand, we could deduce that the driver is attentive of the road. Too much interaction with the secondary controls could further indicate that the driver is most likely focusing on those instead of the road, resulting in him being inattentive.

The overall concept of this study is to detect the naturally occurring gestures performed while driving. With knowledge of the driver's hand positions, we can deduct information about what the driver is currently doing.

SYSTEM OVERVIEW

The system is named Driver Observation System (DOS).

The detectable gestures are all related to operating the vehicle and internal distractions. For this study, we focus on detecting the following gestures:

1. Hands on the steering wheel
2. Resting the hand
3. Using the gear stick
4. Using secondary controls

Based on these actions, the level of attention can be measured through how much time not spent on having the hands on the steering wheel. In order to recognise the hand gestures detected by DOS, we intent to make a classifier. Seeing as this is a proof-of-concept, the classifier's initial training and base parameters are built using a two different subjects in two different cars. This is later evaluated with multiple participants.

Technology

Within the field of arm, hand, and finger recognition, Microsoft's Kinect [26] and the Leap Motion [30] were the most viable technologies. As Kinect acts as a full-body camera it is able to detect gestures between 40 and 400 centimetres [27]. Leap Motion has a shorter detection range, between 0.25 and 60 centimetres [31], due to it being focused on detecting arms, hands, and fingers. The 40 centimetre minimum on Kinect makes it hard to place within a car, making the Leap Motion the most suitable hardware for this study. In addition, the Leap Motion's short minimum range and wide angle allows us to experiment with unique positions that are not possible with normal cameras.

Implementation

The Leap Motion controller is able to provide a stream of data about the hands within its field of view. The data is extracted and calculated based on the frames captured by the infrared camera at a frame rate between 40 and 115 FPS, depending on the settings. Each frame contains data about the direction and position of each arm, hand, and finger within the field of view.

From the Leap Motion controller, we have identified and experimented with different data values, to understand which values distinguishes the most between different gestures. The values are observed while performing the required gestures to observe which can distinguish the gesture adequately. As an example we excluded hand velocity. We want to determine if the hands are on the steering wheel and not differentiate between turning and simply holding it. In this case, the gesture would have contradictory velocity values, making it ambiguous. The used values include both location and directional properties for both hands and fingers. The following information is used for the classifier:

- Hand centre and direction x, y, and z
- Hand pitch, roll, and yaw
- Palm normalised x, y, and z
- Grab and pinch strength
- Finger direction x, y, z and stabilised tip position

All of these values are represented as a double ranging from $-1.0 <= value <= 1.0$, where grab and pinch strength ranges from $0 <= value <= 1.0$. DOS is utilising a Support Vector Machine (SVM) algorithm for the classification of hand gestures. The SVM algorithm is a supervised learning algorithm that functions well in cases with a high number of variables and loads of training data [36]. In our case, the data stream supplied by the Leap Motion controller acts as variables. For the classifier implementation we utilise LIBSVM [8], a freely available library allowing us to utilise machine learning. The SVM type is a classifier.

The classifier takes a set of samples as input for the training phase of the classifier. A sample consists of all of the above mentioned values, along with an extra value used to describe what gesture the sample represents. When training the classifier, we use samples where the gesture is known beforehand, gathered by performing a controlled test in the vehicle.

In order to test and configure the algorithm, a data set of approximately 15000 samples was collected and split into two categories, training data and testing data. 75% of the data set was used for training the algorithm to recognise the different classifications. The remaining 25% was used for validating the algorithm's accuracy. These test results were used for further tweaking of the algorithm's values and kernel configurations. This process was repeated until the tweaking had no significant impact on the accuracy. During our tweaks, we found that a linear kernel provided the best results with cost set at 10, the remaining values are similar to the default values [8].

During the evaluations, we determine what action were performed 4 times pr. second, based on a single sample at the time of determination. In addition, we use a confidence threshold where we only accept the classifier's determination if it is more than 70% confident about the result. Besides the gestures focused on, drivers perform various other actions such as eating, drinking, smoking, communicating with their hands, and using phones [43]. The confidence threshold is implemented to catch these actions and the transitions between all actions.

Calibration

To achieve the most accurate readings of the driver, the system has to be calibrated to the individual vehicle. This is necessary as vehicles' interior design can differ greatly. The interaction can also vary due to different modalities utilised to interact with vehicles, e.g. buttons, rotary controller, etc.

To overcome this problem, a calibration program have been built. When executed, the program builds a new data set, in which it collects data about the driver's current hand position. This is done by the driver performing the first of the desired gestures, i.e. hand on the steering wheel, resting the hand, holding the gear stick, and interacting with the secondary controls with his right hand. Meanwhile the left hand is hidden from the Leap Motion's line of sight. The program collects a new data sample approximately 20 times pr. second. After mimicking the first gesture for approximately 600 measurements, he continues to the next gesture and repeats the process. After completing all the right handed gestures, he switches hands, and performs all of the left hand gestures.

The newly collected data set is used as training data for the classification algorithm. This particular set is then used when performing an evaluation in the respective vehicle.

Hardware Setup

To properly capture all the desired gestures, the Leap Motion controller had to be placed in close proximity to the driver. As such we experimented with placement around the gear stick, dashboard, door, and roof. Results showed that the most efficient placement for the Leap Motion controller is at the car's roof, just above the steering wheel, pointing downwards. This position is furthermore fitting due to the Leap Motion controller's short range. Figure 1 shows the position of the Leap Motion controller.

In order to power and acquire the data gathered by the Leap Motion, a laptop has to be connected by cable. To avoid additional distractions for the driver and remove the laptop operators hands from the Leap Motion's detection field of view, the laptop is placed on the backseat of the car.

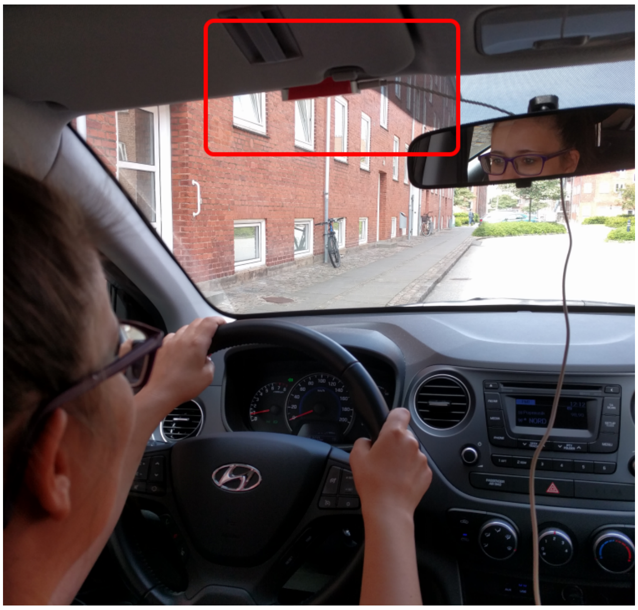

Figure 1. The leap motion placement. The leap motion can capture both hands and a large part of the area of interest.

EVALUATION

Participants

A total of 13 participants (4 female, 9 male) aged from 20 - 82 ($M = 37.1$, $SD = 19.0$) participated in the experiment. 4 Participants did the evaluation in both cars, for a total of 17 evaluations. The participants are all family, friends, or colleagues.

Setup

The system is evaluated based on its ability to correctly detect the hand gestures. Accuracy was measured during a performance test, performed in a stationary car. The car remained stationary throughout the experiment, as the experiment could be conducted without starting the car. In preparation for this evaluation, the car was equipped with a video camera pointing towards the driver seat, ensuring that all actions were recorded. The evaluation was performed in two different cars, a Hyundai i10 (car A) and a Volkswagen Passat (car B), with 8 evaluations performed in car A and 9 in car B.

Procedure

Before the evaluation started, the system was calibrated for that particular car. The evaluation consisted of the participants mimicking driving the car for five minutes, while being recorded by the system and the video camera. The drivers were told to drive as they normally would. The driver's hand gestures and when they were performed was then extracted from the video, allowing for comparison to the data gathered by the system. The results of this comparison resulted in the system's performance.

Gestures	*Participants* #1	#2	#3	#4	#5	#6	#7	#8
Left								
Wheel	45.89	63.11	99.83	100.00	96.47	68.69	77.74	71.60
Rest	100.00	100.00	-	100.00	100.00	100.00	94.74	0.00
Total	47.75	63.35	99.83	100.00	96.82	69.64	79.05	66.75
Right								
Wheel	85.16	88.58	98.32	99.75	99.64	97.10	86.87	86.87
Gear	73.07	89.78	87.05	99.50	100.00	72.86	96.95	88.30
Rest	100.00	1.09	100.00	54.48	22.00	-	-	-
Secondary	81.48	94.29	37.14	78.33	96.61	50.00	84.16	96.69
Total	85.07	82.36	88.82	89.20	96.09	87.30	88.26	88.15

Table 1. Accuracy of the 9 participants in car A.

Gestures	*Participants* #1	#2	#3	#4	#5	#6	#7	#8	#9
Left									
Wheel	98.69	87.76	86.50	84.05	99.02	96.94	97.11	96.30	71.50
Rest	89.87	-	-	12.09	-	98.41	25.71	93.33	-
Total	98.12	89.23	86.50	78.77	99.02	97.11	91.26	96.19	71.50
Right									
Wheel	95.67	98.69	86.54	97.37	88.22	94.93	99.72	94.37	95.93
Gear	63.79	99.39	98.61	68.97	53.03	89.01	64.74	99.09	78.44
Rest	-	4.04	98.57	83.90	100.00	21.50	97.69	83.33	59.26
Secondary	98.52	95.55	81.41	91.33	87.07	59.55	40.87	71.95	80.00
Total	88.12	90.47	90.89	86.15	82.80	82.65	84.62	89.24	87.08

Table 2. Accuracy of the 9 participants in car B.

Results

Table 1 and Table 2 shows the results of the 17 evaluations. As the participants were instructed to act as they normally would, some gestures were not performed by all participants. These are noted by a minus symbol (-), in the tables.

Car	*Instances*	*Left correct*	*Left %*	*Right correct*	*Right %*
A	9797	7627	77.90	8636	88.16
B	11084	9950	89.58	9630	86.75

Table 3. Recorded instances and their accuracies across the experiments.

Table 3 shows the total percentage from the entire evaluation, taking into consideration the samples spent on every task. The average percentage of the left hand accumulates to 83.74%, with the right hand at 87.46%. This gives an average percentage for both hands of 85.60%.

Holding the hand on the steering wheel reached a combined accuracy of 84.40% for the left hand and 93.70% for the right hand.

Resting the hands achieved the lowest accuracy throughout the entire evaluation. For the right hand resting gesture, the observed accuracy was at 56.47% in average between both cars. As there is not enough space to comfortably rest the left hand in as many different positions as the right hand, the left hand resting gesture achieved a higher accuracy of 74.42%.

The system is also reliable in determining if the user is manipulating the secondary controls. An average percentage of 77.91% were achieved in the two vehicles. The results showed that the system's primary problem with recognising the secondary controls task, was differentiating between using the gear stick and the secondary controls.

Detecting the right hand on the gear stick proved to be very accurate, 88.44% in car A and 79.45% in car B, despite the gear stick being positioned close to the secondary task and the hand gestures for both being similar.

DISCUSSION

The results from the evaluation shows that with the right hardware, it is possible to detect a driver's current activity through their hand gestures. While not perfectly accurate, it still provides a determination of what is happening within the car. However, with an overall accuracy of 85.60% for both hands, this determination is bound to have false positives and false negatives. For example, in a system responsible for warning drivers that they are driving dangerously, this can be dangerous. Too many false positives could end up annoying the driver, resulting in them disabling the system. Too many false negatives would cause the system to not warn the driver, resulting in the driver continuously driving dangerously.

The experiments performed by [25, 35, 41], who all used the Leap Motion for sign language, resulted in an accuracy of 90%, 80%, and 65% respectively. [44] reached an accuracy of approximately 60% with their system mounted outside the vehicle and looking at the driver from the side. We determine between a total of 6 states, where the other projects range from

2 to 31 classes. Compared to previous studies, our work on a classification system reaches the accuracy of similar systems with high accuracies.

The setup within the car worked well. The position in which the Leap Motion is placed on the interior roof is accessible in almost every car. However, due to the Leap Motion's very wide detection area which sometimes picked up the hands of the person in the passenger seat, the laptop had to be placed on the back seat. Combined, these two problems forced the USB cable to be drawn directly from the Leap Motion and in between the driver and passenger seat, resulting in the cable being a slight distraction for the driver.

The Leap Motion controller proved to be a solid choice in regards to hardware. Once calibrated, the system was effective at distinguishing between the different hand gestures. During the evaluation we did however encounter certain limitations with the Leap Motion. The biggest issue came when driving on a sunny day. The sun's reflections within the car would be picked up by the Leap Motion, resulting in it having difficulties detecting the driver's hands. The Leap Motion is not capable of handling reflections from other light sources if it interferes with the frequency at which the Leap Motion's own LED pulses [29]. As such, the solution lies in preventing reflections or using other frequencies, both of which cannot be affected from our position. Secondly, the Leap Motion could have distance problems within some cars. With different cars comes different car interiors, resulting in varying distances between the Leap Motion and the driver's hands. This could cause the hands to sometimes being out of range for the Leap Motion, resulting in the Leap Motion either reading the hands wrong or not detecting them at all. A possible solution for this would be to implement multiple Leap Motions, preferably one for each hand. It is however currently not possible to connect two Leap Motions to the same laptop, resulting in a second laptop having to be implemented into the setup. While possible, the one Leap Motion worked sufficiently.

During the evaluation and based on the results, we learned that it was necessary to calibrate the system for the various car interiors we would encounter. As such we implemented an on-the-fly calibration feature, allowing dynamic alteration of the training set used for the classifier. This ensured optimised training data for the interior of the car which proved overall positive for the results. We learned that certain hand gestures are hard to calibrate accurately. As shortly introduced in the evaluations results, resting your hands while driving can be done in various ways. For the system to accurately predict the resting hand, the same position would have had to be used during the calibration. This revealed another problem with calibration.

With a total of 17 evaluations performed by a wide variety of participants in two cars, the classifier has been tested though many different driving styles and behaviours. The evaluations were performed while the vehicle was holding still, thus not reflecting real life driving entirely.

As introduced earlier, distractions can be both internal and external. The current iteration of our system only attempts to detect the internal distractions, leaving the driver vulnerable to external ones. Attempting to detect external distractions could be possible with information regarding the current environment, such as traffic, weather, landmarks, and road conditions. In combination with hand gestures we might detect certain changes in behaviour as the external conditions varies.

CONCLUSION

As cars have been equipped with automatic assistance systems, driving itself have become easier, safer, and more comfortable. This have caused drivers to believe that they have more time for other tasks, such as their phone or GPS. Statistics shows that phone usage is the most common reason for distracted drivers to crash. In this experimental study, we have explored the possibilities of using hand gesture recognition hardware to determine where the driver's hands are while driving.

Our research shows that hand gestures of a driver can be accurately recognised and classified. The chosen hardware did however have certain limits in form of range and reflection from other light sources, reducing its performance and accuracy. The evaluation was performed by 13 participants, resulting in a wide array of driving styles being tested by the system. Despite the varying styles, the system proved accurate with a combined accuracy for the left hand at 83.74% and 87.46% for the right hand across two vehicles. Based on these preliminary results, we believe the concept could be a viable solution for driver activity recognition, however further exploration is required.

FUTURE WORK

Based on the preliminary findings from this study, we will further investigate possible uses of the driver activity recognition system developed. The next step of the project is to further evaluate the concept in an application for real life problems. Further studies could focus on dynamic driver evaluation, after drive evaluation, emergency systems, driver classification for insurance calculation, or for accident assessment. Further features could include automatic vehicle calibration and multiple Leap Motion controllers.

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B Driving Performance Evaluation Through Timely Feedback: An Explorative Study

Driving Performance Evaluation Through Timely Feedback: An Exploratory Study

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ABSTRACT
The usages of driver activity recognition are primarily focused on detecting certain markers of e.g. fatigue or sleepiness. But fatigue and sleepiness are only parts of the problem with the monotonous driving task, where also distractions and reckless driving cause vehicle accidents. All of the researched papers' developed systems provide feedback immediately, regardless of the situation. We provide timely feedback at appropriate times, where the driver's cognitive resources can comprehend this without compromising driving performance. By utilising the Leap Motion technology and our activity recognition system DOS [11], we explore usages of the system by conducting a pilot study with a driving academy and a field test with 10 participants. Our system showed good correlation between the actual situation and the system predictions. The system's feedback was well received by both participants and the driving academy, and some participants were surprised about their subconscious behaviour.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; See `http://acm.org/about/class/1998/` for the full list of ACM classifiers. This section is required.

Author Keywords
Driver Activity Recognition; Leap Motion; Feedback; Field Evaluation.

INTRODUCTION
As the automobile industry has evolved, cars have become easier and safer to operate due to the amount of implemented technology [10], such as automatic assistance systems like the ABS brakes, automatic gear transmission, and autopilot features. This decrease in difficulty increases the overall comfort of driving. This new level of comfortability have changed the driver's perception of the focus required to safely control a vehicle, thus resulting in them performing other tasks such as operating the infotainment unit or using their phones. Similar behaviour is shown in semi-autonomous vehicles, where the semi-autonomous features makes the drivers trust the system. The semi-autonomous features are still early in development, and despite the system warning the drivers' about this, they still lose focus on the road and divert their attention elsewhere [30, 22]. This lack of focus and carelessness, is the reason that the most frequent reason for road accidents is due to distracted drivers [6]. Consequently, driver activity recognition is a widely researched topic, where the goal is to understand what drivers are doing while driving, and prevent dangerous situations.

Despite phone usage being illegal while driving and infotainment systems becoming more and more simplified, it have not stopped drivers from getting distracted. Apple has announced that in iOS 11, a *"Do Not Disturb While Driving"* feature will be implemented, as a way to remove potential distractions coming from the smartphone while driving [35]. Distractions are however inevitable as other factors can disturb the driver.

Observational studies [33, 12] further prove that very few drivers apply the recommended steering techniques, with two hands on the steering wheel at either 9 and 3 o'clock or 8 and 4 o'clock [19]. Using inferior hand positions on the steering wheel reduces the overall control of the vehicle, thus increasing ones reaction time. It has been suggested that drivers change their hand placement based on perceived risk [31] or changes in mental workload [5].

This lack of focus on the road combined with unavoidable distractions and improper steering techniques all contribute to decreased reaction times and control of the vehicle, exposing the driver, passengers, and the surrounding environment to unnecessary risks. A solution could be to provide feedback on drivers' dangerous behaviour and recommend changes to accommodate a safer driving style.

Different manufacturers utilise different feedback methods to alarm drivers of inattention in semi-autonomous vehicles [26]. Some favour visual and others audio. The activation is handled differently, as both static timers and dynamic detection is used. Various kinds of feedback methods are being utilised including visual, audio, and vibration. Each of these offer challenges in an automotive context; visual requires moving the eyes from the road, audio cues can be missed due to other sounds and noise, and vibration are hard to distinguish from the naturally occurring vibrations and road bumps.

This study explore a combination of visual and audio feedback and how this can affect drivers' driving behaviour. While driving, many factors have an impact on the driver's cognitive resources. As such, providing feedback on how to improve their driving style should be done in a timely manner. A feedback system dynamically activated based on the drivers behaviour could decrease the number of messages and the annoyance of the system, compared to a statically timed activation system [28].

This feedback system will expand upon DOS (Driver Observation System) [11], by utilising the driver recognition capabilities in a real world setting. The combined system and the feedback are evaluated in a field study by a driving instructor and regular drivers.

RELATED WORK

There are two aspects to consider; the understanding and behaviour of the drivers and findings from providing feedback in an automotive context. We need a better understanding of the strain of driving and the drivers behaviour, to which we explore the research in these fields. By exploring manual and semi-autonomous vehicles, it is seen that the different manufacturers use different methods of alarming the driver of dangerous situations [26]. Based on the many different systems, it appears that the optimal solution has not been found yet.

Driver

To properly design a system for drivers, two aspects have to be analysed; the cognitive resources required to drive and the norms and behaviour of drivers.

Cognitive Strain

Salvucci and Taatgen [24] explored the concept of multitasking, with a partial focus on driving and driver distractions. Through their experiments they explore how visual perception, kinetic movement, and cognitive tasks uses cognitive resources. In a regular driving scenario, a driver looks at the road while performing small kinetic tasks. If the driver have to control an infotainment unit, it requires spending cognitive resources that would otherwise have been spent on driving the car, reducing the driver's overall focus on watching the road and steering the car. The authors of [3] experimented with how much speaking compared to listening while driving affects the driver's cognitive resources. Through a reaction experiment performed within a high fidelity car simulator where the participant had to press a button whenever a vibrator vibrated, they concluded that speaking does indeed require more cognitive resources than listening while driving.

Hand Positioning

In regards to handling a steering wheel, the NHTSA have made a set of guidelines for proper steering [19]. They recommend a two handed symmetric positioning around either 9 and 3 o'clock or 8 and 4 o'clock, as this gives the most control over the vehicle and it allows for the airbag to deploy without injuring the driver's arms. Jonsson [12] observed drivers to find which hand positions drivers used while driving. The most commonly observed hand pattern is with one hand around the 10 o'clock or 2 o'clock position for left and right hand respectively. Symmetric steering techniques are very rare, with only 6 percent among males and 12 percent among females using them, despite being the recommendation from NHTSA [19].

Thomas and Walton [33, 31] have made several studies about drivers' hands' position on the steering wheel. They theorised that the driver's perception of risk can be measured based on how the driver is holding onto the steering wheel. Two hands on the upper half of the steering wheel suggests that the driver is focused due to being in a more intense situation, compared to using only one hand on the lower part of the steering wheel. Based on their work, De Waard et al. [5] further analysed that although hand position are related to risk perception, these are closer related to the mental workload the driver was experiencing. Fourie et al. [8] observed everyday drivers over a period of time, which further proved that drivers using two hands on the upper half of the steering wheel were driving slower than those having one or zero hands on the upper half. This further adds to the theory about hand positioning is depending on mental workload.

Feedback

The feedback provided to drivers can be of various forms. Feedback is provided to users based on their interactions, where a message is sent with information about the anomaly. In an automotive context, three primary types are explored by researchers; visual, audio, and vibration. Keeping in mind that Sundareswara et al. [28] found that feedback activated from static intervals tend to be ignored and deemed annoying by drivers, the success of a feedback system lies in the timeliness and immediate importance of feedback. Exploring a dynamically activated system would be in the best interest of drivers to avoid emergency states.

Visual Feedback

Visual feedback relies on the driver actively diverting their eyes from the road to where the feedback is provided. As visually demanding systems have started being incorporated into cars [13], the driver's visual resources are being diverted away from the road. Blissing et al. explored a system featuring a short latency after clicking buttons in the vehicle [1]. During this latency, an increase in driver glances on the road and course corrections were observed, such that the time waiting on the secondary system were spent on the driving task. Alternatively [25] explored the usage of augmented reality and gamification concepts to warn the driver of dangerous situations. They theorise that in regards to semi-autonomous or fully autonomous cars, the most dangerous situations arise when the driver is trusting the car to drive perfectly and no longer watches the road. They suggest a system where dangerous situations are recognised by the hardware and a visual overlay is placed on top of it, to increase awareness of the situation.

In regards to visual feedback, visually anthropomorphic designs are explored, as these had proven more trustworthy in previous studies [15]. These designs are focused on the impression of having a personal assistance in the car. Drivers would be able to relate and trust the messages from this system. [21] looked into attitudes and opinions towards assistive robots, where they explored different physical forms the robot could take. It was found that mechanical human-like and mechanical animal-like designs were favoured. [18] explored anthropomorphic user interfaces and how these are perceived. They conclude that these interfaces are more effective in 66% of the conducted tests and preferred by users in all.

Audio Feedback

Christiansen et al. [4] found that using audio as output compared to visual resulted in significantly fewer eye glances. However, task completion time took longer compared to the visual output, which is significantly faster to process. The need for visual information could explain the increase in the number of eye glances. They observed a decrease in primary driving task performance when using audio as output. Based on their findings using just visual feedback, they were able to categorise glance duration into three categories; less than 0.5 second, between 0.5 and 2 seconds, and above 2 seconds. The results showed that less than 3% of all glances were above 2 seconds, proving that the subjects' perception of risk reaches a threshold, where they are no longer comfortable ignoring the road. The results for audio were significantly lower with less than 1% of the glances being above 2 seconds.

A recent project made by Wang et al. [34] explore 3D sound cues to provide spatialised advisory information representing the state outside the vehicle during critical situations. These sound cues vary in intensity and movement based on the monitored traffic movements. If a car comes up from the rear and overtakes, the system provides sound from the back of the left side, and moving up past the driver as the vehicle moves past the driver. Their results show significant results for the understanding and response time for each of these situations in addition to reduced number of collisions.

Both Cao et al. [2] and Larsson [14] have explored the possibilities of audio feedback in combinations with other feedback methods for communicating while driving. Larsson [14] explored an audio feedback system for reading and sending text messages. This was performed in combination with a visual element in form of a tablet. The audio was initially performed through minor audio cues which proved insufficient and was instead replaced with a text-to-speech system. The final system required less and shorter glances than a purely visual system. Cao et al. [2] experimented with a feedback system where the intensity of the audio cue depended on the severity of the feedback. They further incorporated a vibration system into the car, allowing them to combine the audio feedback with vibrations. Throughout their evaluation they found that a pure vibration based system is a promising alternative to audio feedback, as it caused less interference while driving. In regards to response times and driver comfort, vibrations were however inferior compared to audio.

Vibratory Feedback

Riener et al. [23] explored a vibration feedback system and factors that can affect its results. Their vibration hardware is placed within the driver seat. Their experiments found that many factors impact the efficiency of a vibrations system. Meng et al. [16] used a vibration system to alert drivers of collisions. Directional tactile feedback is used to warn the driver of the direction of the danger. Ogawa et al. [20] have proven that ones heartbeat can be manipulated through the use of vibration. Based on these findings, Takahashi et al. [29] made a system that detects when the driver's heartbeat is slowing down, indicating sleepiness, which is then countered by the driver seat vibrating in a more up-beat rhythm. The idea is for the driver's heart to pick up this rhythm and therefore prevent the driver from falling asleep.

Author & Reference	*Feedback*
Blissing et al. [1]	Visual
Schroeter et al. [25]	Visual
Christiansen et al. [4]	Visual & audio
Larsson, Pontus [14]	Audio
Sundaresware et al. [28]	Audio
Cao et al. [2]	Audio & vibrations
Wang et al. [34]	Audio
Riener et al. [23]	Vibrations
Meng et al. [16]	Vibrations
Takahashi et al. [29]	Vibrations

Table 1. Overview of explored feedback studies.

Feedback Systems

Table 1 provides an overview of the feedback solutions presented in this article. The challenge for feedback systems is to get their message through to the driver in a quick and safe manner. The feedback should be timely and accurate, as they still consume cognitive resources and removes the attention from the road. This is important as the reason for the feedback system is to make the driver aware of the road. Dynamically providing this feedback seems like the best way, to ensure that only the minimum number of distractions are caused by the feedback Sundareswara et al. [28]. Keeping the number of feedback messages low, while still warning about important events on the road can however be an ambiguous goal.

Feedback can be provided at various occasions. There could be an upcoming accident that requires immediate breaking, it could be the road being prone to causing accidents, or to inform that bad weather is making the road slippery. With information about the driver's movement and physiological signals, feedback could be provided if the driver is behaving irresponsibly or showing signs of fatigue and sleepiness.

DESIGN

DOS is a system capable of detecting driver activity through hand gestures by utilising the Leap Motion technology. The goal of this study is to explore how DOS could be used in a real world setting. Based on the problems regarding distractions, fatigue, and poor steering techniques, we explore a system that can improve the driver's attention to the driving task, by informing about incidents of poor driving. The developed system is named DOSAF (Driver Observation System And Feedback), and is an extension on the previously developed DOS system. The extension includes providing feedback, collecting information while driving, and presenting this to the driver via an Android smartphone.

The exploratory nature of this study has inclined us to refer to it as a technology probe. The goal of this probe is to explore the usage and perception of a hand observatory system in a vehicular context. Technology probes are considered simple, flexible, and adaptable technologies with focus on three goals [9]. The first goal is to understand the needs and desires of the targeted users. The second is to field test the technology to evaluate the utility and value in the context. Lastly, technology probes allows inspiration for users to think and reflect upon the technology.

Providing Feedback

When to provide feedback is based on the driver's actions and state. For this probe, the actions are limited to distinguishable gestures that appear in all vehicles. These gestures include; driving related interactions such as holding the steering wheel or using the gear stick, hand resting from either fatigue or habit, and secondary tasks such as manipulating the radio or heating options. These gestures are arguably the most common while driving. The gestures are narrowed down from other activities such as interacting with mobile devices and using hands for social interaction purposes.

After consulting with the driving academy, *Trend Driving* [7], the feedback is supplied only at times where the driver would have time to comprehend this. [28] reported that the success of a feedback system is related to the timeliness, such that it is not annoying, ignored, and comes at times where the driver can comprehend it. This include times when the vehicle is holding still, e.g. while holding still at an intersection, roundabout, or after the drive has ended. In total, two types of driver evaluations are implemented:

- **While driving** - Timely feedback provided at appropriate times, describing the driver's most recent performance.
- **After drive** - A map containing the driven route and observed performance, allowing drivers to self evaluate.

We have explored the field of feedback within cars, and concluded that for our system, the most appropriate form of feedback is a combination of audio and visual. Vibration feedback is hard to distinguish with all the naturally occurring road bumps and vibrations caused by the car [23]. Visual feedback is reliant on the visual resources which are heavily utilised while driving. However, visual feedback are perceived and processed quickly, and can be clear in purpose [4]. Audio feedback is slower to process and interferes more with the driving performance than visual do. Audio does however not require eye glances, which allows for keeping the eyes on the road. Lone visual cues are prone to be overlooked, should the driver's gaze be focused elsewhere, and the content of the audio feedback can be overheard due to it appearing out of nowhere or being mixed with sounds from the environment. As such we want to utilise the reliability of noticing audio messages with visual feedback being available for further explanation. Despite the combination of audio and visual feedback being fairly requiring, we deem it fitting as feedback is only given in low pressure situations.

The feedback while driving is presented as an anthropomorphically voice reading a message out loud and visual text showing the driver a score and a message. This score is an indicator of the driver's performance, and is calculated based on their hand positions. The score ranges from 0 - 100, where a score of 100 is the best. Three different messages exist, and the provided message depend on the calculated score.

1. **Good -** $Score >= 80$: *"Good job on that last section".*
2. **Neutral -** $60 <= Score < 80$: *"Remember to hold the steering wheel properly".*
3. **Negative -** $Score < 60$: *"Your driving should be improved".*

The feedback is presented near the car's dashboard, granting the driver quick access to this information. Christiansen et al. [4] found that 97% of eye glances are below 2 seconds in duration. In less than 2 seconds, the driver should be able to locate the feedback and understand the message and score to complement their finding.

The after drive feedback can be accessed from the Android application, where a map is drawn of the driven route, see Figure 3. The route is divided into segments that each hold information about the driver's performance on that particular segment. Each segment consists of a line and a marker. In addition, segments are colourised to distinguish between good, neutral, and negative segments. This is represented with green, yellow, or red, depending on the driver's score. A final marker is shown at the end that contains the information from the entire trip.

Architecture

Hardware

DOS utilises the Leap Motion technology, a depth-camera specialised in arm, hand, and finger detection. The Leap Motion controller is placed right above the steering wheel, which the technology allows with the small minimum range it offers, see Figure 1. Due to the Leap Motion's requirements [17], the system has to be run on a laptop. The laptop is further connected to an Android device through Bluetooth, which is used for sending the Leap Motion results to the Android application.

Software

DOS provides a data stream of the current location of the driver's hand, calculated through machine intelligence based on the data stream provided by the Leap Motion. DOSAF expands DOS by calculating a driver state based on the observed hand locations and recognitions made. This driver state is based on behaviour, and can either be attentive or inattentive. In addition to the driver state, the determined hand gestures are saved. Recognitions are made approximately 4 timer pr. second.

The determined driver state and hand gestures are sent via Bluetooth to the Android application, on which it is associated with a driven segment. Besides the driver states and determined hand gestures, a segment includes the segment's start and end locations, distance between these, average speed, and the score of the segment. A new segment is created approximately every 60 meters driven, and the obtained information is associated with this segment. The presented message and related score are calculated based on the information gathered

Figure 1. Leap Motion placement within the car.

from the location of the last provided feedback up till the current location. The score is a percentage, calculated by dividing the number of attentive driver states with the total number of driver states. The screen presented when showing feedback is seen in Figure 2.

The user interface is simplistically designed, to keep the visual content concise. As such, the visual feedback is only visible for 8 seconds to avoid the feedback distracting the driver longer than necessary. By giving the driver 8 seconds to react to the message, they have time to check their surroundings before turning their head towards the screen to read the score and message.

When the car reaches its destination, all of the segments are saved. This prepares the application for its second purpose, the after drive evaluation. Here the driven route is loaded into a map, as seen in Figure 3. Each segment is represented by a red marker, which when clicked shows the information about the segment. At the destination, a blue marker is placed, with information about the entire trip, see Figure 4. An additional feature is developed for viewing information from multiple markers at once. By pressing the desired start and end markers, the information from all the markers inbetween is combined and presented. Another feature furthermore allows for hiding the red markers. As a red marker is placed every 60 meter, viewing the entire route with markers enabled is quite extensive.

DRIVING ACADEMY PILOT STUDY

Trend Driving, a driving academy located in Aalborg, helped us evaluate the rules for which we determine attentiveness. Their critique is used to improve the classification to better reflect what the driving instructors are looking after when they are teaching students. The focus of this evaluation is to evaluate the rules that we have implemented and to evaluate the use for their context as driving instructors.

Rules

We believe that the conditions to which we determine inattentiveness should be considered closely by other authorities with more knowledge of the area. With this in mind, we still need to evaluate the developed system, to which these numbers and conditions can be tweaked at a later time. For this study, we determine that the driver is inattentive during the following cases:

1. No hands on the steering wheel
2. No hands on the upper part of the steering wheel
3. One hand on the steering wheel and the other manipulating secondary controls

These rules are evaluated by a driving instructor, to ensure that they represent an adequate view of the drivers' steering technique and provide a proper review of their performance.

Procedure

One of us sat in the back of the car, with the driving instructor in the passenger seat, and the student at the wheel. During the course of two hours, the driving instructor evaluated DOSAF with two different students, both almost ready for their driving exam. We installed the system and calibrated the classifier to the interior before starting the drive. The driving instructor were in charge of the route, and the small talk from our part was kept to a minimum, however this did not affect the evaluation. After the driving sessions we had an interview with the instructor, divided into the performance of the individual student, DOSAF, and the concept of observing hand gestures to evaluate driving. During the drive, the feedback was limited to the audio part, to avoid distracting the student too much. Information about their hand positions, score, and route information was saved and used for the interview with the instructor.

Results

The results are based on an interview with the driving instructor, where the experience with DOSAF and the collected data are used as basis for the interview. The instructor thought that both students performed well during their respective driving sessions. The instructor was told to rate the students hand positioning performance based on his own observations. The range of the rate are from 0 to 100. The first student was rated 100 by the instructor based on her hand positioning, where DOSAF rated her 99. The driving instructor said that she performed as taught during their classes, keeping both hands at the top- and middle part of the wheel and performed gear switches quickly. The second student was rated 95 by the instructor and 96 by our system. There was a segment where her hands were positioned very low on the steering wheel during the drive, to which the instructor told her that she should keep these higher on the wheel. This exact segment was marked in our observations and the instructor agreed with the timing and reasoning as to why we gave a lower score. Both students were not affected by the equipment according to the instructor.

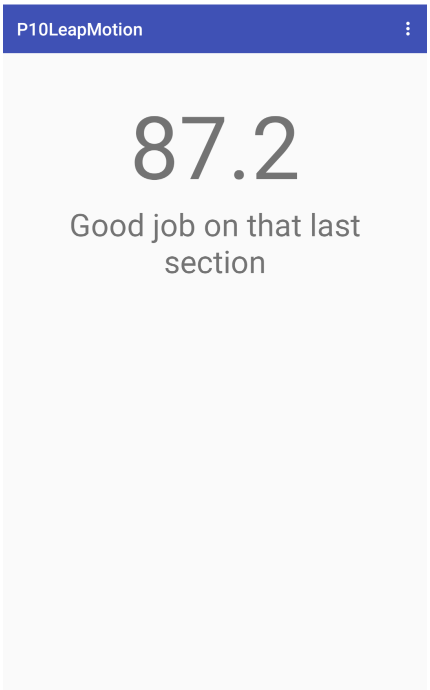

Figure 2. The feedback shown to the driver when driving.

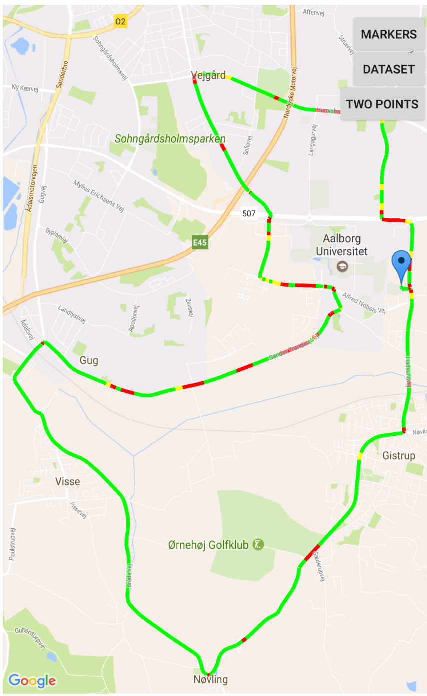

Figure 3. The driven route in the Android application. Red markers are currently hidden as the route contained 375 markers.

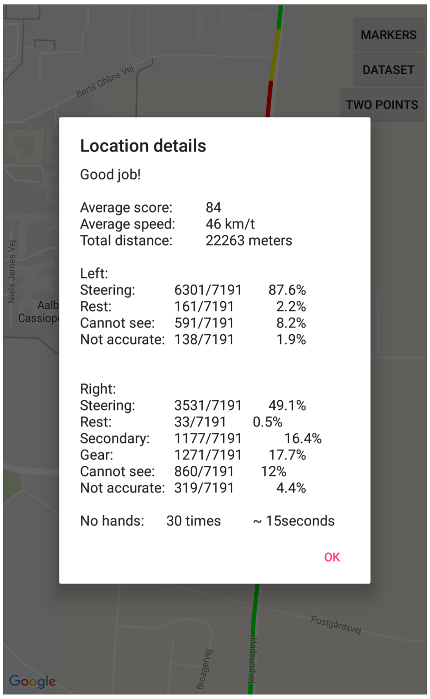

Figure 4. Combined information about the entire route.

Regarding the feedback feature, the instructor praised the timeliness and precision of the message. He felt that the feedback came at appropriate times, where the driver would have time to hear the message and not be distracted by it. Shorter and more precise instructions to keep the distractions at a minimum and to avoid complicated feedback were preferred. Dynamic messages suitable to the context were preferred over the score part. However, he agreed that the score had potential in combination with gamification principles.

Concerning the evaluation of the rules, the currently implemented rules reflect the reality nicely. He emphasises that relaxation is the reason why drivers perform badly, and that a more strict hands-on-the-wheel policy would be better, as two hands on the steering wheel improves the steering and reaction capacity of the driver.

The driving instructor liked the after drive map, where they had the ability to show their students what they were doing and evaluate certain areas. He believe that the system could help increase traffic safety. Using the system as an *"additional driving instructor"* for when they had passed their exam could be nice, however he believed that it would probably be turned off quickly.

REAL DRIVING EVALUATION

To evaluate DOSAF, a field experiment was conducted. Here a number of participants participated by driving a predetermined route with the system implemented.

Participants

As the effect of the system differentiates between users, 10 participants were evaluated in the experiment. The group consisted of 8 males and 2 females. Table 2 contains additional information about the participants. The experience stated in the table is the participants own evaluation of their driving experience on a scale from 1 to 10. The participants are all family, friends, or colleagues, all of which either studies or works.

	Range	*Mean*	*SD*
Age	23-25	24.1	0.74
Years with driving license	2-7	5.45	1.38
Experience	6-9	7.1	1.10

Table 2. Statistics information about the participants. Driving license is measured in years and experience was evaluated by the individual participants on a scale from 1 to 10.

Setup

The experiment was performed as a field experiment, with the participants being responsible for driving the car. They were given a predetermined route of approximately 20 kilometres, resulting in a 30 minute drive. The predetermined route was designed based on the statistics about rural driving being calmer than city driving [32]. To let the participant become familiar with the system, the first half of experiment therefore started in a rural area while the latter part took place in the city. Car-wise, it was preferred if the participants had their own car, as they would drive more naturally compared to using a borrowed car. As such, 5 participants drove their own car, while the remaining participants borrowed our car. Besides the participant, there were a test leader and an analyst within the car. The test leader was responsible for guiding the participant and answering questions. The analyst's task was to ensure that the system was working as intended, by validating the predictions. This was done by watching the live data stream running through the laptop. The laptop was placed on the backseat to avoid distracting the driver and to avoid the laptop analyst's hands being picked up by the Leap Motion camera. The only task given to the participants was to drive as they normally would.

Procedure

Before engaging the experiment, the participants were briefed about the system, the score it provides, and how often it gives feedback. The participants were furthermore instructed to drive as they were used to, while still obeying danish road laws. Lastly the planned route was shortly explained to the participants.

Throughout the drive, the test leader observed and noted how each participant reacted to the feedback provided by the system. This and the collected information are used for the interviews to assist the participants in remembering what happened and later show what DOSAF determined. After completing the route, the participants were immediately interviewed. The first part of the interview was based around questions regarding their driving behaviour, opinions about the feedback, and the system in general. During the second part, the participants were shown the route again, this time with markers containing score for each segment of the route, see Figure 3. If a score was low, the participant would be asked why they thought it was low, giving them a chance to recall the scenario by also showing the location. Perhaps they used the radio without thinking about it or lowered their hand positions due to fatigue. Their answers are both recorded and written down at the interview.

Results

The results of this evaluation are based on the answers the participants gave during the interviews and observations about their driving. The information gathered during the drives were used as a basis for the latter part of the interview. Some questions are asked regarding concrete usages of DOSAF and some questions leads the participants to reflect further. We collected all their answers and divided these into categories. The finding are reported here.

The structure of the results follows the goals of the technology probe, as described in the Design section. First we will go though the general observations made, followed by the evaluation of DOSAF, which leads to the participants reflections of the system and technology.

General Observations

Almost all of the participants mentioned feeling "watched" by the system while driving, thus affecting their driving behaviour. Participant #3 felt that *"the lady was breathing down his neck"* and participant #4 mentioned that the feeling of being watched would *"cling to him for days"*. The participants who borrowed a car for the experiment required a few minutes to become comfortable with the car, and they subconsciously drove more careful as it was not their own car. Participant #1 drove our car, and mentioned *"Well it's a new car, and I drive more safely and carefully when in a new car"*.

As observed, if the participants rated themselves high in regards to driving experience, they tend to relax more while driving. This is shown by lower hand positions and only using one hand on the wheel most of the time. When confronted with this, they generally agreed that they had enough control over the vehicle to only use one hand. The route included a small segment of cobblestone road, where all participants used both hands. The road conditions might have created a need for more control as the participants responded the way they did. It became clear through the experiment that the more familiar the participant was to the car, the more relaxed their driving style became. This resulted in more participants using the radio, falling back into their seat, and relaxing their hand positions. The participants stated that when they drive recklessly, they are well aware of this, however they still feel that they have the adequate control over the car.

Feedback

Throughout the evaluation, the participants average score ranged from 77 to 96 ($M = 85.4$, $SD = 6.6$). Compared to the message, the score gave a more precise evaluation of the driver's performance. Participant #7 felt that the score was better, as the message was the same all the time, due to his performance. In addition, participant #3 mentioned that the score provided a better understanding on how to improve as he could experiment with different styles. Participant #5, #7, and #10 liked that the system confirmed that they performed well enough. Participant #7 mentioned that *"When I got the confirmation that I was doing something good, then I tried to do the same and keep that rhythm going."* and also mentioned that he tried to relax more at this point.

While the message felt assuring when the performance was good, the more negative stages of the message lacked information about how to improve the performance. Participant #3 felt that the voice provided an objective view on his performance, and would rather listen to this feedback than a passenger telling him to improve. In addition, he mentioned that it might be humiliating if he got negative feedback while driving with friends.

Feedback Frequency

During the drives, the participants received the feedback between 5 and 11 times ($M = 7.4$, $SD = 2.2$). The feedback frequency of only providing feedback at full stops was well received by all the participants. Concerns were however shown about the calculations after a long distance motorway drive. Participant #1, #2, and #3 preferred more feedback, however the other consensus was that it should come more often in the start and decrease in number as the drive went on. Participant #6 commented that *"I had to drive for a while before getting a message."*, while he was driving in a rural area without any stops. Participant #8 expressed that the feedback should come as the driver did something irresponsibly. Participant #9 mentioned that the feedback an *"appropriate amount of times, not annoying like GPS that spams you. It was alright."*.

Misconceptions

Despite most participants driving very carefully, either due to driving a new car or the feeling of being watched, some of them had noteworthy segments on their after drive map. They were either clueless about the segment or thought that they had rested for too long on the gear stick. These segments were often caused by subconscious secondary task usage. When shown the map and thinking back they remembered the segment and were surprised as to how much they subconsciously used these controls. Participant #8 referred to the system as *"creepy"* due to how precise it was at detecting his radio usage. Also participant #7 and #10 were surprised regarding their secondary task behaviour, where participant #7 mentioned that *"Apparently I touched the radio more than I realised."*. There were however deviations as participant #5 and #7 used their hands for communication purposes.

Gamification

The concept of gamifying the system was suggested by multiple participants. Getting a low score felt like a challenge, thus encouraging better driving behaviour in an attempt to increase the score. It was further suggested that these scores were saved on a high score, allowing it to be compared among friends, for each city, and for the entire country. The opposite effect was also observed, as some tried to lower their scores as well to understand the boundaries of the system. The system observed this behaviour and scored them accordingly, and the participants agreed on the systems predictions.

Participant #1, #2, #3, #6, and #7 said that it felt like a game, where the score motivated them to improve. Curiosity created an interest in finding out how to improve, by experimenting with different hand positions and styles. Participant #2 got a score of 91 on a segment and said *"Only 91? I can do better than that!"*, which sparked an interest to improve. Participant #3 mentioned that he *"Wanted to get to 100, and see how I am supposed to drive, to learn what the best way of driving is."*. Participant #6 showed explorative behaviour by stating that *"then I got the score of 97. After that I wanted to see if I could get a lower scores to test the system."*. Participant #5 mentioned that she did not try anything to improve the score, however she was still affected, as she tried to keep up with her previous score.

Alternative Implementations

There were several suggestions for future uses of the system, with the most common being assistance to newly educated drivers. The system could help reinforce a good hand position, even after leaving the driving school. The after drive map could further be used as parental monitoring, helping parents guide their children despite not being in the car. Participant #2, #4, #5, #7, #8, and #9 all suggested implementing the system into newly educated drivers' cars. Participant #5 had personal experience with being reckless as a newly educated driver, saying that *"At this point, I was a very irresponsible driver, but didn't really know it."*.

DOSAF could also be implemented in commercial vehicles as a safety measure. These vehicles transports passengers or large loads, and are therefore, arguably, more dangerous in case of emergencies. Participant #1 and #10 both saw potential in commercial vehicles e.g. trucks and busses. Participant #10 expressed that *"Depending on their scores you can have an evaluation discussion with their boss, if they drive irresponsibly."*.

DISCUSSION

The results showed that despite the participants were focusing on the road, most of them had segments in which they were deemed inattentive due to secondary task usage and didn't understand why. Subconsciously the participants were manipulating the secondary tasks. When shown these segments, the participants recalled their interactions and agreed on the systems predictions. This shows that the system is able to detect their actions and notify the driver about their inattentiveness, thus increasing the overall driving safety.

One of the suggested concepts among our results, was the concept of gamification. Numerous participants mentioned this as a way to engage them further into the driving task. Progress tracking, achievements, and high score comparison were suggested by the participants to increase their engagement. Schroeter et. al. [25] utilised gamification principles and augmented reality to increase engagement and warn drivers of dangerous situations. In addition, Steinberger et al. [27] looked into using gamification principles to increase engagement of drivers, to reduce boredom and exposure to potential distractions such as phone usage. All of these can result in speeding and reckless driving. Their evaluation showed that gamification principles can increase driver engagement, by providing progress and a sense of accomplishment in addition to making the task more enjoyable. In accordance with their results and findings, similar results were found for this study. By providing a score of their performance, some of the participants intuitively wanted to improve on this score. The way to improve the score is to drive more carefully and be more attentive on the road, which in term increases road safety.

In the related work section we analysed various researched methods of providing feedback in an automotive context. Visual, audio, and vibration were the most popular choices, due to the speed of perception and the low cognitive strain these causes. DOSAF uses a combination of visual and audio to ensure that the feedback is perceived by the drivers. Despite the feedback content being delivered through multiple channels that can distract the driver, the feedback is only presented at appropriate times. This complies with the findings of Salvucci and Taatgen [24] that the cognitive requirements should be kept at a minimum, to avoid affecting the overall driving performance. As such DOSAF only provides feedback when the car is holding still, and have driven at least 600 meters since the last given feedback. This accommodates Sundareswara et al. [28] finding that dynamically activated feedback is preferred, and keeping the annoyance low with fewer messages. In addition, the driving instructors at *Trend Driving* also recommended that the feedback is kept at a minimum. Consequently both the participants and the driving instructor expressed that the evaluated system provided an "appropriate amount" of feedback, that did not interfere negatively on their driving performance. In regards to the provided score, both the participants and driving instructor agreed with the scores calculated by the system.

NHTSA's [19] guidelines about hand positions on the steering wheel matches the ones provided by the driving instructor in the pilot study. These are however rarely used, as reported by [12]. The research as to why the steering wheel is not held properly is not clear, however there are two theories as to why. Thomas and Walton [33, 31] conclude that the drivers perception of risk, along with habits, comfort, and fatigue determine their positioning. Secondly De Waard et al. [5] found that it might be closer related to mental workload rather than perceived risk that determine hand positioning. Based on their research, we observed certain patterns during the evaluation. If the participant rated themselves more experienced and comfortable in a car, they were more prone to holding the steering wheel lower or only use one hand while driving. This behaviour could be explained by both of these theories.

The system could be implemented as a safety feature in semi-autonomous cars. Previous studies proved that despite the semi-autonomous car warning people about being aware when using the automatic driving feature, people still have tendencies to check their phones, user their computers, and generally turn their head away from the road. In these situations, the system would be able to detect their activities and warn them about it.

While the current system provides both visual and audio feedback, there are several ways of improving it. The current iteration of feedback could be improved by making more dynamic and instructive feedback, by giving concrete feedback on how to improve their driving. An example could be *"You should avoid using the radio too much"*. This was suggested by both the driving instructor and some of the participants.

During the interview, the driving instructor evaluated our rules on which the score is calculated. Although he found them appropriate, he mentioned that a more strict hands-on-the-wheel policy could be beneficial. A stricter policy could more accurately reflect the driving situation to better match the decrease in control. This is a valid point, and based on the comments from the participants, it would be a viable option for newly educated drivers. The feature could be implemented by lowering the score, whenever the driver's hands are on the lower part of the steering wheel or when driving with one hand. This would reinforce the driving behaviour learnt by the driving academy.

As statistics have shown, car accidents are more prone to happen in the city than on the motorway or in rural areas [32]. The knowledge of the car's current location could be utilised to affect the strictness of the system. This would allow the driver a more relaxed driving style during the less straining environments, while remaining strict during the more demanding conditions.

With its simplistic visual design, DOSAF can be expanded into an overlay feature for a GPS application. This would allow the driver to receive concise feedback about their performance, while still being able to follow the planned route.

DOSAF current iteration only handles distractions coming from the vehicle's dashboard. The recognition algorithm could be further trained to recognise phone usage. Unlike controlling a vehicle, using a phone always results in the driver's hand facing upwards towards their face. This makes phone usage a distinct hand gestures, easily recognisable by the algorithm, as it already considers palm and finger directions when making its predictions.

CONCLUSION

As cars have evolved and become easier and more comfortable to use through the implementation of various assistive systems, some drivers have adopted a more relaxed driving style. Steering with just one hand results in less control over the car, which can be dangerous should sudden situations occur. In this experimental study, we have explored feedback with the purpose of improving the drivers safety. A system capable of observing, recognising, and rating a driver's hand positions in accordance to rules formulated by us and validated by a driving instructor has been developed. Based on the system's observations, a calculated score reflecting the driver's performance and an associated message is provided.

Our design of combining a visual score with an audio description of the score and only displaying feedback when the car is at a stop, was well-received by the participants and the driving instructor. The participants liked the idea and found the feedback assuring, however concrete feedback on how to improve their driving was sought-after. The after-drive feedback is further able to inform the driver of any subconscious secondary task usage. Despite the feedback being appreciated by the participants, we believe that further research is required within the field of feedback while driving.

FUTURE WORK

The results from the driving academy evaluation indicate an educative aspect behind the system, in which safer behaviour and habits could arise. Gamification principles to increase engagement in the driving task could avoid interaction with other devices. A combination with multiple sources of information within the car, e.g. eye detection and posture, could improve the recognition precision and allow for a wide variety of additional actions to detect, such as proper mirror checking before turning and phone usage.

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