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The automated driver as a new road user

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ABSTRACT

Although road infrastructure has been designed to accommodate human drivers' physiology and psychology for over a century, human error has always been the main cause of traffic accidents. Consequently, Advanced Driver Assistance Systems (ADAS) have been developed to mitigate human shortcomings. These automated functions are becoming more sophisticated allowing for Automated Driving Systems (ADS) to drive under an increasing number of road conditions. Due to this evolution, a new automated road user has become increasingly relevant for both road owners and the vehicle industry alike. While this automated driver is currently operating on roads designed for human drivers, in the future, infrastructure policies may be designed specifically to accommodate automated drivers. However, the current literature on ADSs does not cover all driving processes. A unified framework for human and automated driver, covering all driving processes, is therefore presented. The unified driving framework, based on theoretical models of human driving and robotics, highlights the importance of sensory input in all driving processes. How human and automated drivers sense their environment is therefore compared to uncover differences between the two road users relevant to adapt road design and maintenance to include the automated driver. The main differences identified between human and automated drivers are that (1) the automated driver has a much greater range of electromagnetic sensitivity and larger field of view, and (2) that the two road users interpret sensory input in different ways. Based on these findings, future research directions for road design and maintenance are suggested.

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1. Introduction

Although roads have been developed to accommodate human physiology and psychology for over a century, human errors have been the main cause of traffic accidents (National Highway Traffic Safety Administration, 2015; Transportavdelingen Trafikksikkerhet, 2018), with driving performance failures being the greatest contributing factor to

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these accidents. Other errors in human behaviour include falling asleep, intoxication and distraction. Consequently, Advanced Driver Assistance Systems (ADAS) have been developed to mitigate human shortcomings. From the introduction of ADAS to higher levels of automation, automated driving features have evolved rapidly and are now able to take over operating a vehicle under an increasing number of road conditions. Due to this evolution, a new road user has emerged, the *automated driver*.

The automated driver comes with promise and possibilities. For example, in the short term, lower levels of automation represented by ADAS can reduce the number of traffic-related accidents (Eckstein & Zlocki, 2013; Östling, Lubbe, Jeppsson, & Puthan, 2019). Furthermore, the sensors utilised by the ADAS features, e.g. cameras and lidars, provide a way to monitor the road infrastructure. As identified by Osichenko and Spielhofer (2018), this can eventually replace manual and time-consuming processes used for monitoring road infrastructure inventory. Currently, maintenance and design factors remain that hinder the detection of inventory elements, including occlusion of signs, fading or damage to road signs and markings as well as improper installation (Osichenko & Spielhofer, 2018; Wali et al., 2019). Some of these issues can be mitigated by improving the automated detection equipment's hardware and software. The other piece of the puzzle might lie in making certain changes to roadway elements, such as paint type or texture choice, while others could be related to maintenance issues, e.g. trimming vegetation, or repainting road markings.

In the long term, higher levels of automation are widely expected to produce automated drivers that are superior to human drivers. Despite this expectation, little effort has been put into ensuring that the road infrastructure will work for the new automated road user. Consider the example of roadside LED signs and message boards, which have been developed as an improvement over conventional signs for humans, both in terms of visibility and use of dynamic information. On the other hand, LED flicker can adversely affect an automated driver's performance. This occurs because camera-based detection of signage typically uses algorithms to manage exposure, and LED flicker causes oscillations in overall image brightness, leading to automated drivers incorrectly identifying LED traffic signs (IEEE P2020 Working Group, 2018). Automated driving has also been suggested to be a factor that lowers road construction costs (Khoury, Amine, & Saad, 2019). The reasoning behind this claim is the idea that an automated driver is assumed to have different characteristics than humans, including longer sight distances, which might allow for a more flexible road design that better suits the terrain, leading to less earthwork during road construction.

Road authorities and society in general therefore have incentives both in terms of increased safety and higher cost-efficiency to adapt current road design policies to accommodate automated driving. In order to include the automated driver in road design, road authorities need to establish characteristics of these automated drivers that will impact road design and maintenance. SAE International's established definition of an automated driving system (ADS) provides a good taxonomy for describing the role of humans and ADS in driving tasks at different levels of automation (SAE International, 2018). However, it does not include details about these systems' software and hardware that shed light on how the ADS differs from human drivers.

In the following, a unified framework of driving covering both human and automated driver is presented based on existing theoretical models of human driving and mobile robotics, respectively. The unified framework presents perception or sensing as a fundamental process in all phases of driving. Furthermore, perception/sensing represents the direct interaction between driver and road infrastructure and is therefore a natural starting point for understanding how road infrastructure design can facilitate automated driving. Using human senses (sight, hearing, smell, and sense of equilibrium) as references, the automated driver's sensors will be compared and contrasted with these human senses. Differences between the two road users are discussed, leading to suggestions for road infrastructure design adaptions that could facilitate automated drivers.

2. The driving processes

2.1. Human driving

In order to drive safely, humans need to observe their environment and correctly analyse it. Groeger (2000) and Underwood and Radach (1998) describe this process as an initial assessment made of the scene that is immediately followed by rapid analysis. The next step is establishing regions of potential interest and identifying which parts of the scene require more attention. The understanding of the driving environment created in the driver's mind is referred to as "internal representation" (Van der Molen & Bötticher, 1988). This representation of the environment, along with continued sensory input, forms the information needed for humans to make decisions while driving, such as choosing their driving trajectories, speed, and manoeuvers.

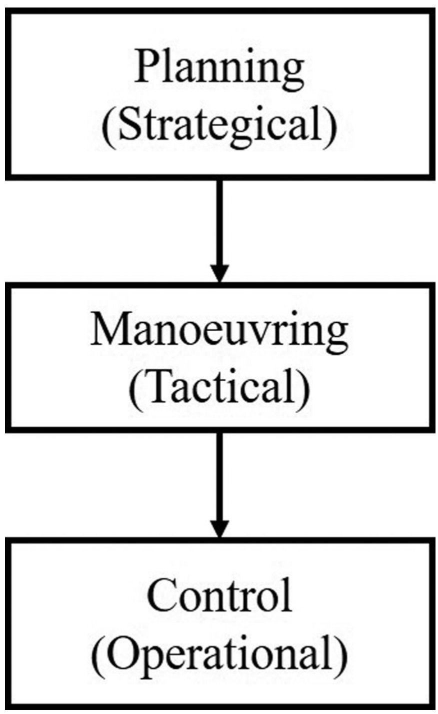

Figure 1. Human driving based on Michon (1985), Van der Molen and Bötticher (1988) and Näätänen and Summala (1974).

As shown in Figure 1, human driving is often separated into three levels: the planning phase, the manoeuvring phase and the control phase (Michon, 1985; Näätänen & Summala, 1974; Van der Molen & Bötticher, 1988). In the planning phase, a human driver performs a strategical assessment of their choice of route, mode of transportation and intended cruising speed, weighing these against the aim of the trip and time available for it, e.g. getting to work on time.

In the manoeuvring phase, the overall plan from the planning phase is turned into tactical, long-term driving behaviour, for instance maintaining a preferred speed and following the intended route. Environmental input can change this process, for example, queues on the originally planned route can cause a change in route, or a slow-moving vehicle can introduce the need to overtake (Van der Molen & Bötticher, 1988).

Lying at the bottom of the hierarchy is the control level, which corresponds to the operations of the vehicle including steering, acceleration, and deceleration. This is also where emergency manoeuvring takes place.

2.2. Automated driving processes

The association SAE International has created a taxonomy for driving automation where the degree of automation is divided into six levels. Level 0 represents no automation, whereas levels 1 and 2 are driving automation levels that support the human driver and are typically ADAS functions. Levels 3–5 differentiate between three levels of ADSs, which are defined as "The hardware and software that are collectively capable of performing the entire DDT [Dynamic Driving Task] on a sustained basis, regardless of whether it is limited to a specific operational design domain (ODD)" (SAE International, 2018).

The dynamic driving task entails the real-time operational and tactical functions required to operate in on-road traffic following the hierarchical structure for human driving presented in Figure 1, yet excluding the strategic function, i.e. trip scheduling. The ODD is the set of conditions for which the automated features are expected to work. For instance, an ADS feature can be designed to operate only on access-controlled freeways with good lane markings in fair weather conditions. As the SAE definition of automated driving neither includes the strategic level nor goes into specifics on how the vehicle works in terms of hardware or software, the framework developed in this paper will introduce automated driving in terms of frameworks taken from the field of robotics. This will allow a more comprehensive definition of automated driving processes, and subsequently the creation of a unified framework for human and automated driving.

Developed half a century ago using Shakey, the first mobile robot, the field of robotics describes the way a machine moves by naming three distinct processes: sense, plan and act (known *as S-P-A architecture*) (Nilsson, 1984). A shortcoming of this architecture is that a robot has to stop and process information before moving, which creates a stop-and-go movement instead of a continuous trajectory (Gat, Bonnasso, & Murphy, 1998). In the mid-eighties, Brooks introduced a reactive alternative known as *subsumption architecture* which, unlike S-P-A architecture, did not have to execute movements sequentially. This ability provided more fluid motion as it reacted faster to its surroundings, but had the drawback of not being easily taskable, meaning that it needed to be reprogrammed for new tasks (Brooks, 1986). A third category of robotic architecture is the *hybrid system*, which incorporates the deliberative S-P-A architecture in order to obtain the best high-level control, for instance finding the optimal path, as well as the reactive architecture's superior capability for obstacle avoidance in unknown and dynamic environments (Davies & Jnifene, 2007; Sheikh, Jamil, & Ayaz, 2014). An example of hybrid architecture adapted from Davies and Jnifene (2007) can be seen in Figure 2.

The Defense Advanced Research Projects Agency (DARPA) Urban Challenge of 2007 serves as an example of how hybrid architecture works. In this challenge, self-driving vehicles had to navigate a mock urban setting, while adhering to traffic rules including passing slow-moving vehicles, handling intersections with other vehicles, and parking (Montemerlo et al., 2009). Contestants were given a road network description file containing geometric information on lanes, lane markings, signage, and points of interest, such as check points, as well as an aerial image of the site. These elements constituted the *Global world model* available at the start of the challenge, while data gathered during driving could be used to enhance this model.

In the *Task manager* function, a destination was entered, for instance, reaching a given check point in the Urban Challenge. The desired destination and world model would then be used to calculate a planned path. This path could be implemented in different ways, either by using the fastest route or implementing strategies such as added risk management, for instance, by avoiding left turns. The *Global world model*, *Task manager* and *Path planner* make up the deliberate layer in Figure 2.

The vehicle's trajectory planning and control are in the reactive part of the system, which can handle new events and is dependent on sensory input. Based on the planned path from the deliberate layer and live sensor data, the vehicle finds the free space available and calculates the optimal trajectory. This process involves how the vehicle understands its own location, detecting static and moving objects in addition

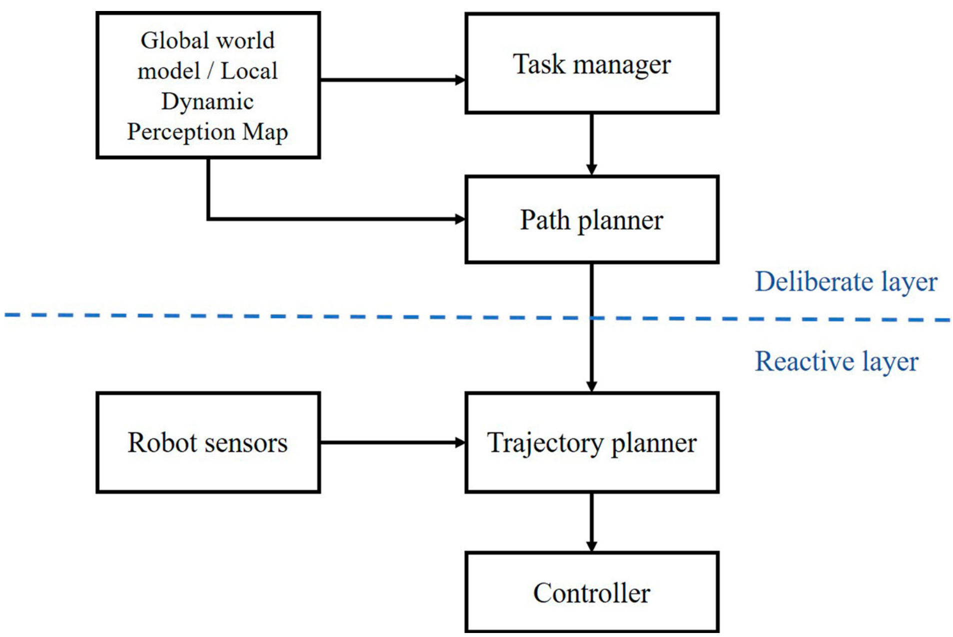

Figure 2. A hybrid robot control architecture adapted from Davies and Jnifene (2007).

to the expected movements of dynamic features, creating what Gruyer et al. (2017) refer to as a local dynamic perception map (LDPM). Trajectories can be altered by dynamic events like an object lying in the road, which imply that the vehicle needs to go around it. The chosen trajectory is translated into commands to control the vehicle's heading and speed and are therefore continually reassessed.

2.3. A unified framework for human and automated driving

As described previously, the processes by which human and automated drivers operate are similar. Thus, a unified framework for both human and automated driving is presented in Figure 3. Human and automated drivers alike use external sources of information to form a global world model based on maps and experience. Driving can be described for both human and automated drivers as starting with a deliberate planning stage where the goal of the trip is turned into a route. Next, the actual trajectories are chosen depending on the driver's local dynamic perception map, e.g. their knowledge of the route in question as well as their dynamic perception while driving. The drivers combine these factors into their actual control of the vehicle, always checking their planned action against their continual sensory input.

While human and automated driver operate in similar fashion on a general level, the way in which they solve their tasks is not the same. For example, in simple cases an automated system can find a suitable path faster than a human (McCourt, Mehta, Doucette, & Curtis, 2016). At the same time, dependent on conditions, path planning can be complex and computationally demanding for automated path planners, giving humans, with their ability to make intuitive decisions based on knowledge and experience, an advantage (Sun, Cai, & Shen, 2015). Due to their different strengths and weaknesses, human and

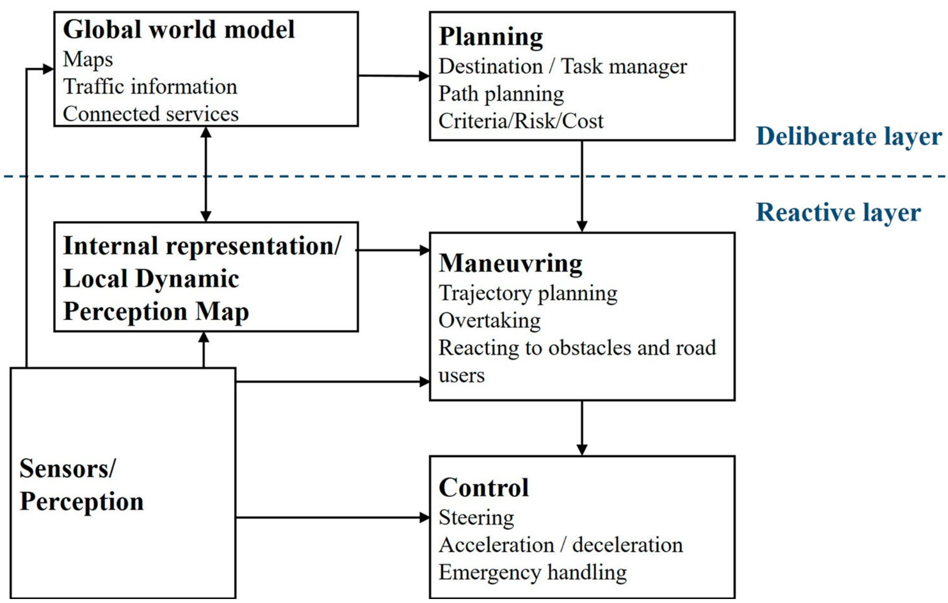

Figure 3. Framework for human and automated driving.

artificial intelligence is sometimes combined. This can be done by humans collaborating with a machine, for instance where they insert way points that are combined with automatic path planning. It may also take place as separate processes where human and machine choices comprised of separate confidence estimates are both inserted into a decision fusion algorithm. The benefit of a combined approach is that a man-machine solution can both realise dynamic threat avoidance and reflect personal preferences in chosen paths (McCourt et al., 2016; Sun et al., 2015).

In Figure 3, the global world model includes external information which can be provided by getting access to positioning services, the internet, or other connected services such as ITS-G5/DSRC. Connectivity is thought to dramatically change the process of driving for automated drivers. Vehicles can first be alerted about objects or incidents that lie outside their sensor ranges and then communicate amongst themselves, theoretically eliminating rear-ending other vehicles, crashing into obstacles and even front-to-front collisions (Shladover, 2018). There are currently three standardisation initiatives for ITS-G5/DSRC (ARIB in Japan, WAVE in USA and ITS-G5 in the EU) based on the IEEE 802.11p protocol. It has been suggested that these communication protocols are not fully developed (Coutinho, Boukerche, & Loureiro, 2018). Insufficient communication quality in terms of packet delivery rate and update delay have been identified in the case of vehicle platooning (Rashdan, Müller, & Sand, 2016), while Zhao, Jing, Hui, Liu, and Khattak (2019) tested a DSRC-based rear-end collision warning system which had an average correct warning rate of 90%. Line of sight remains an issue for ITS-G5/DSRC (Huang, Zhao, & Peng, 2017; Lu, Cheng, Zhang, Shen, & Mark, 2014) as well as privacy (Eckhoff & Sommer, 2014). The alternative, cellular services, would need an unprecedented coverage and level of service to provide reliable vehicle to vehicle communication. The combination of short-range and cellular communication is promising according to Bey & Tewolde (2019) and Yang & Hua (2019). If the issues relating to the quality of communication services are solved, the safety benefit suggested by Shladover (2018) also requires full penetration of communication devices in vehicles. Furthermore, in some situations, such as avoiding crashing into obstacles, it would not be applicable for the first driver to reach the object as it relies on a prior road user to report the obstacle being present. Communication to and between vehicles still provides an external source of information that can provide safety benefits in both the short- and long term but cannot, to date, be assumed to be present at all times or in all cases.

Figure 3 highlights how sensing/perception is essential to all driving processes. The way human and automated drivers alike sense their driving environment is also the most direct interaction between driver and roadway infrastructure: for both these reasons, the sensing processes of human and automated drivers are particularly focused on in the following section.

3. The sensing processes

Similar to humans, an automated driver is dependent on sensing its surroundings to be able to understand the traffic and the surrounding environment. To uncover significant differences between human and automated drivers that might impact road design, the following section compares the sensory system of the automated driver to that of the human.

As shown in Figure 3 sensory input provides necessary input for the global world model, the internal representation, manoeuvring and control processes. In the case of humans, it is easy to only consider vision as the accepted primary sense when it comes to driving (Macadam, 2003). However, Sivak (1996) evaluated on-road behaviours critical to driving and found that roughly 30% of these were dependent on more than one sense. This finding can be related to the fact that human senses are not used separately, but rather form an understanding of a situation in conjunction with one another (Guttman, Gilroy, & Blake, 2005; Walker, Stanton, & Young, 2006).

Humans have traditionally been said to have five senses (sight, hearing, taste, smell and touch), but this fails to recognise the kinesthetic system, which provides a human with an awareness of their position and movements (Farnell & Miller Jr, 2018). In the following, the definition by Rye et al. (2013) is used, where the five senses are defined as sight, hearing, smell, taste and equilibrium (balance and body position). The equilibrium sense includes the sense of touch, vestibular sensation (an organism's sense of spatial orientation and balance), proprioception (position of bones, joints, and muscles), and the sense of limb position that is used to track kinesthesia (limb movement).

Automated drivers have a range of sensors to generate the sensory input needed for driving. The selection and configuration of these vary between vehicles; however, the most commonly used sensors are laser, radar, lidar, ultrasonic and cameras (Gruyer et al., 2017; Hirz & Walzel, 2018; Steinbaeck, Steger, Holweg, & Druml, 2017). To some extent, these sensors are similar to human sensing as they function by processing the same physical effects and forces. For example, electromagnetic radiation is the basis for human vision and camera-based machine vision. The following section compares the sensory stimulus of human and automated drivers and summarises known differences. The human senses will all be covered with the exception of taste, which has limited use for driving purposes.

3.1. Vision

Human vision can be quantified by visual functions such as acuity, field, contrast, colour and night vision (Colenbrander & De Laey, 2005). Of these, visual acuity, i.e. the ability to resolve detail, is the only function that is regularly measured, while visual field and contrast sensitivity are only rarely considered (Colenbrander & De Laey, 2005). Despite its reliance on visual acuity, the relationship between visual acuity and safe driving is found to be weak at best (Colenbrander & De Laey, 2005; Hills, 1980; Owsley & McGwin, 2010). Rather, visual acuity is most commonly determined by drivers having relatively good vision, for instance, 20/40 (Colenbrander & De Laey, 2005), while sight distances for road signs in the US assume 20/30 binocular visual acuity (Owsley & McGwin, 2010).

Merely looking at visual functions does not fully describe human vision, on the contrary, training, experience and familiarity with the driving environment all affect how human drivers see their surroundings, referred to by Colenbrander and De Laey (2005) as functional vision.

Field of view (FOV) determines how much of the surrounding world a human driver can observe. Human binocular vision regarding subjects with no visual impairment is approximately 200° in the horizontal median, and 150° in the vertical (Wolfe, Dobres, Rosenholtz, & Reimer, 2017). The most widely accepted requirement for visual field is 120° in the horizontal median, although humans are able to rotate their heads to scan more of their surroundings. Although there is no equivalent vertical requirement, 40° has been suggested (Colenbrander & De Laey, 2005). Rear-view and side mirrors allow human drivers to see the road behind them to some extent; furthermore, ADAS functions, including parking aids, can help human vision. However, while humans are in their cars looking in mirrors or at screens, they lose their forward vision. Drivers having visual field defects, yet who are still deemed to be safe drivers, were found to engage in more scanning behaviour (head movement) compared to unsafe drivers having field defects (Owsley & McGwin, 2010). The area where humans can see clearly is called the Useful Field of View (UFOV), which is often defined in the region of only 20–30°; however, information from the peripheral vision is also important for driving (Wolfe et al., 2017).

The range of electromagnetic radiation that humans can detect is from 380 to 750 nanometer (nm) (Best and Textile Institute, 2012), although the range can be as great as 310 to 1100 nm depending on age and the brightness of the light source (Sliney, 2016).

3.1.1. The equivalent to sight for the automated driver

Vision for an automated driver is herein defined as the sensors that utilise electromagnetic radiation, i.e. cameras, radars and lidars. Automotive imaging consists of many different types of cameras where the optics are different for differing applications, e.g. the lens type can be close to either human vision or a wide-angle lens. The sensitivities of cameras also differ: some cameras utilise visible light, some in UV, while others operate in the infrared (IR) band. Moreover, there are hyperspectral cameras that cover several bands (Uzkent, Hoffman, & Vodacek, 2016). The main differences between human and automotive vision are that the vehicle has a greater FOV and is sensitive to a greater range of electromagnetic radiation depending on the sensor set-up. A vehicle can have sensors that cover up to a 360° FOV in the horizontal median, or sensor input can even form a spherical cap engulfing the vehicle.

To date, there has not been a consistent approach to measuring image quality for the automotive industry (IEEE P2020 Working Group, 2018). Machine vision for automotive use is based on a charge-coupled device (CCD) or complementary metal–oxide semiconductor (CMOS) image sensors (Sliney, 2016; Stemmer Imaging, 2019). CMOS is most widely used due to its better performance at higher temperatures as well as its superior dynamic range (Hosticka et al., 2003). Cameras for automated driving applications have sensitivities ranging from the near ultraviolet (UV) through the visible spectrum and up to about 1000 nm depending on the sensor in question (Stemmer Imaging, 2019; Zhang & Niu, 2016). They can also have superior night vision to humans through their use of infrared (IR) imaging (Mahlke, Rösler, Seifert, Krems, & Thüring, 2007). Night vision enhancement systems (NVES) based on IR radiation come in two categories: near IR NVES uses active infrared headlights for 750–3000 nm, while far IR NVES are passive sensors for 6000–30,000 nm (Mahlke et al., 2007). Cameras are used for the ADAS function Lane Departure Warning, and there has been a fair amount of research completed on how varying light and weather conditions affect automated detections of road markings. In general, wet conditions are challenging for camera-based detection (A. Pike, Carlson, & Barrette, 2018). Successful detection of markings by LDW has been linked to contrast (A. M. Pike, Barrette, & Carlson, 2018; A. Pike, Carlson, et al., 2018; Hadi & Sinha, 2011; Pike & Songchitruksa, 2015) and edge smoothness has been suggested as being relevant to machine-vision detection (Lin, Wu, & Wang, 2016).

While the camera passively registers light, lidars emit laser light with wavelengths of typically 850, 905, 940 or 1550 nm (Hecht, 2018; Rablau, 2019); consequently, the camera detects its surrounding environment in terms of the time it takes for the light to return. Lidars can use rotating or stationary laser light, pulses, or continuous waves, but all lidars produce point clouds. Because laser emission at visible wavelengths, 400 nm to 780 nm, and near infrared wavelengths, 780–1400 nm, can cause eye damage (Douplik, Saiko, Schelkanova, & Tuchin, 2013), lidars can either use pulsing at 905 nm or wavelengths above 1400 nm for safe operation. The latter option, commonly 1550 nm (Hecht, 2018), produces a longer range, and with this range, a longer time for the signal to return. The slower response time can be mitigated by using multiple beams concurrently (Hecht, 2018). FOV differs for diverse lidars, and while a greater FOV provides coverage for a larger area, it is more susceptible to interference for instance from sunlight or headlights (Hecht, 2018). The angular resolution determines the lidar's ability to detect smaller objects, such as motorcycles or light poles. The resolution will depend on the lidar, i.e. the number of laser sources and how they are configured, as well as the distance to the object. The detection distance also depends on the characteristics of the object that reflect the light. The roughness, colour and reflectivity of the objects determine how much light is reflected back to the lidar rather than absorbed or transmitted (Yang & Wang, 2011). Lighter colours absorb less light than darker colours, and smooth surfaces reflect the light as a specular reflection, while rough surfaces create diffuse reflection. While higher levels of reflection generally produce longer detection rates (Hecht, 2018), highly reflective surfaces can also be difficult for lidars to register (Leonard et al., 2014). Some surfaces are particularly challenging, for instance glass where the light is transmitted through the glass and mirrors and where the light is refracted through the glass and hits the material behind the glass. Surface properties and the ability to detect objects in the road environment is worth noting for road infrastructure design, as surfaces of road elements could be optimised to be more prominent for automated drivers.

Radars operate similarly to lidars using radio waves at 24 GHz ($1.25*10^{-2}$ nm) for short-range and 76–80 GHz ($3.95*10^{-3}$ to $3.75*10^{-3}$ nm) for long-range (Hecht, 2018). This capability gives them longer range, lower angular resolution and better performance in poor weather compared to lidars (Van Brummelen, O'Brien, Gruyer, & Najjaran, 2018). Although not commonly used in automated vehicles at the present time, ground penetrating radars (GPR) are also worth noting. Traditional GPR technology used for infrastructure inspections, through mapping the subsurface profile of road- and railways, operate in the 1–3 GHz band; in general these provide excellent resolution but poor penetration depth (Cornick, Koechling, Stanley, & Zhang, 2016; Lalagüe, 2015). In recent years the use of GPR for localisation has become more common, with an operating range of 100–400 MHz, providing deeper penetration at the cost of resolution (Cornick et al., 2016; Kuutti et al., 2018) and making them suitable for navigation purposes.

The ranges of electromagnetic sensitivities and FOVs for automated driver and human driver is summarised in Figure 4.

3.2. Hearing

Auditory information has been found to improve human driving performance as it reinforces information received from the visual channel (Guttman et al., 2005; Macadam, 2003). Estimation of speed performed by humans becomes more accurate

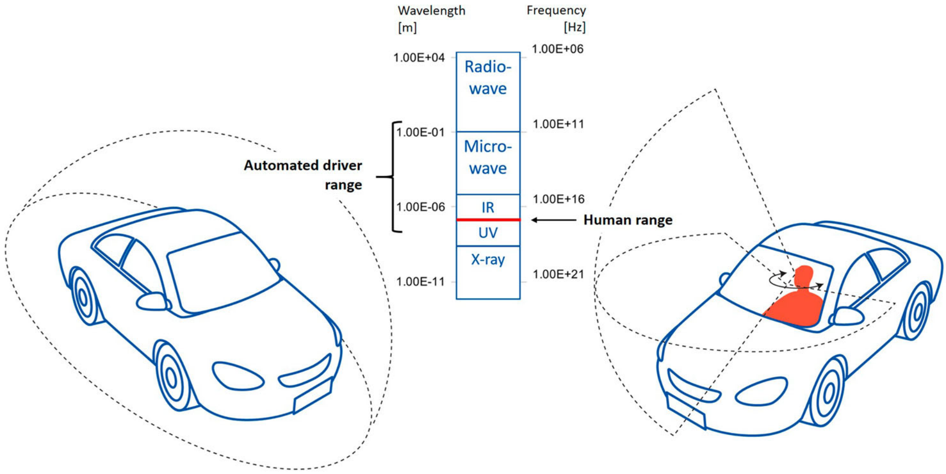

Figure 4. Automated driver vs human driver electromagnetic sensitivity and field of view.

with auditory information (Hellier, Naweed, Walker, Husband, & Edworthy, 2011; Macadam, 2003; Walker et al., 2006), and conversely, a lack of environmental noise can increase driving speed, reduce headways and induce more risky gap acceptance (Hellier et al., 2011; Walker et al., 2006). Recent research has found that when sensory input from two different senses is in conflict, the most reliable sense for a given task takes dominance. So although vision is the most trustworthy sense for spatial information, audition is dominant for temporal input (Guttman et al., 2005).

Auditory feedback in vehicles provides information on the engine, transmission, tyres and aerodynamics (Walker et al., 2006) as well as warnings of disruptive events such as the proximity of emergency vehicles (Macadam, 2003). Whether a sound is audible to humans depends both on the power of the sound, measured in decibels (dB), and the frequency of the vibration (Hz). Humans hear above 0 dB and feel discomfort from 110 dB and up (Institute for Quality and Efficiency in Health, 2008). Normal hearing detects frequencies of sound between 20 and 20,000 Hz (Bagai, 2006). Humans are excellent at localising the sources of sounds, i.e. determining the range, elevation and azimuth angles of a sound's source (Duraiswami & Raykar, 2005). Hearing is also used to determine the movement of objects that are not immediately in view, and it is therefore vital for safe and effective orientation (Gatehouse & Noble, 2004). The distance range of hearing is dependent on the loudness of the sound (Pasnau, 1999) as well as environmental factors including temperature and humidity (Harris, 1966).

3.2.1. The equivalent to hearing for the automated driver

The most common sensor relying on sound waves for vehicles is the ultrasonic sensor (Gruyer et al., 2017; Hirz & Walzel, 2018). Commercial ultrasonic sensors for automotive parking applications typically operate in the region of 40–60 kHz, and have a range of 30–450 cm (Nordevall, 2015). They provide distance measurements to objects at low speeds, which is beneficial for parking aids (Alonso et al., 2011), preventing car crashes (Alonso, Oria, Fernández, & Rodríguez, 2009), measuring characteristics of road surfaces (Hirata, Sun, Ueda, & Hachiyay, 2016), detecting moving obstacles (Ohya, Kosaka, & Kak, 1998), and detection of ice by friction analyses based on noise produced by tyre–road interaction (Gailius & Jacenas, 2007).

Microphones can also be used to interpret acoustic sensory input. Fazenda, Atmoko, Gu, Guan, and Ball (2009) used these to warn human drivers of nearby emergency vehicles as modern cars can be highly insulated against external noise. Such a system could also be used for automated drivers to make use of external sound signals to help interpret the driving situation.

3.3. Smell

The car cabin is exposed to several toxic gases, some of which can cause drowsiness, headaches, nausea, and dizziness. Humans' natural breathing can also cause oxygen deficiencies (Galatsis & Wlodarski, 2006). Smell can provide drivers with an early warning of problems with their vehicle, e.g. the smell of rotten eggs from a failed catalytic converter (Allen, 2006) or the smell of car parts becoming overheated (Pisaturo & Senatore, 2016), which is similar to how humans rely on smell to detect general dangers and identify edible food (Bordegoni, Carulli, & Shi, 2016). In addition to harmful gases in the car acting as a safety factor for human operation, smell can also be used to support driving in a more direct manner by increasing drivers' attention or providing them with feedback about their driving behaviour. Bordegoni et al. (2016) performed experiments on the sense of smell (olfaction) and driver attention, arguing that the visual and auditory stimuli are already subject to high demands. Olfactory stimuli were found to be more effective at increasing the subjects' attention level than auditory stimuli. Furthermore, the subjects found smell to be a more pleasant type of feedback than sounds (Bordegoni et al., 2016). Dmitrenko, Maggioni, and Obrist (2018) reported that olfactory notifications telling drivers to slow down or change lanes was less distracting, more comfortable, and more helpful than visual feedback.

3.3.1. The equivalent to smell for the automated driver

Machine olfaction devices have been utilised for the past 30 years in a wide variety of commercial industries, and work similarly on humans by converting chemicals to electrical signals (Li et al., 2014). There are a number of different sensors available that cover various gases and pollutants (Galatsis & Wlodarski, 2006), but they are currently not being used in vehicles for other purposes than to assess the presence of hazardous fumes, or the pleasant smell of new cars (Li et al., 2014). However, the use of machine olfaction is being researched to provide indications of car problems. Similar to how a human can learn to associate the smell of rotten eggs with a failed catalytic converter (Allen, 2006), machines can be trained to detect unwanted odours. In higher levels of automation, a car would need to be able to self-diagnose errors and evaluate its own fitness for driving. Furthermore, olfaction is being researched as a valuable sensory input for automated driving due to potential customers' expectations. Humans prefer a clean ride; therefore, there might be a need to use artificial noses to detect spills or if the latest customer was a smoker (Walsworth, 2019).

3.4. Sense of equilibrium

Equilibrium senses provide input that human drivers rely on to understand the forces acting on the vehicle correlated to their own movements. They include temperature, pain, pressure and vibration, sense of spatial orientation and balance as well as the position of bones, joints, and muscles (Rye et al., 2013). Macadam (2003) discovered that humans rely on information obtained from the vestibular (inner ear) and kinesthetic (body distributed) channels for controlling vehicles. Direct contact with the vehicle through the seat, steering wheel, gear shift and foot pedals provide information on lateral forces, vehicular changes in stiffness and vibration, and feedback on roadway conditions, for example, changes in the friction level between tyres and road or wind gusts (Jensen, Tolbert, Wagner, Switzer, & Finn, 2011; Macadam, 2003).

Although there is evidence that humans are sensitive to these stresses, both in terms of assessing vehicular characteristics such as a car's size or weight, as well as aligning torque (i.e. how much force is needed to steer through a curve) (Walker et al., 2006), stimuli to the equilibrium sense remain relatively unexplored in literature compared to audio and visual feedback (Kammermeier, Kron, Hoogen, & Schmidt, 2004; Riener, Jeon, Alvarez, & Frison, 2017; Walker et al., 2006).

3.4.1. The equivalent of equilibrium for the automated driver

Accelerometers and gyroscopes are widely used in the automotive industry to obtain information about the vehicle's velocity, position and heading by measuring forces and rotations (Elkaim, Lie, & Gebre-Egziabher, 2015; Salychev, 2017). Often found as a set of three accelerometers and three gyroscopes, they produce a six degree of freedom sensor system used in the inertial measurement unit (IMU), the output of which is converted to navigation parameters by the inertial navigation system (INS) (Elkaim et al., 2015). INSs are self-contained non-jammable systems, but suffer errors that have an exponential growth over time and GPS-measurements are used to correct this issue (Spangenberg, Calmettes, & Tourneret, 2007). In the absence of GPS or other external sources of positioning, the vehicle relies on so-called dead-reckoning navigation. Dead-reckoning uses the initial position and calculates the following positions with the use of the IMU, the errors of which can be counteracted with the use of additional sensors such as odometers which alleviates drift, and magnetometers that provide heading and inclination data (Barbour, 2004). Another way to improve localisation performance is by using map-matching techniques (Spangenberg et al., 2007).

3.5. Cognition

The focus thus far has been on the sensors of the automated driver, compared to the human sensory system. The sensory inputs are turned into information and understanding through cognition. As Groeger (2002, p. 242) so eloquently puts it:

> "Statements to the effect that driving is a largely visual task … are as meaningless as the assertion that reading is a visual task. Both are obviously heavily dependent on visual perception. However, it is the further processing of that information which underpins our interpretation, comprehension, memory and non-reflex reactions to what we see"

Human drivers depend heavily on their ability to judge positions and movements of other road users, and to predict where these will be in the next few seconds (Hills, 1980). The driving skill has been found to increase with experience. Macadam (2003) linked this to the understanding of vehicle dynamics. Mourant and Rockwell (1972) found that responding to stimuli, especially beyond the visual channel, required experience. While Hills (1980) concluded that part of the art of driving may be "in developing the skill of looking in the right place at the right time. It may also involve the ability to predict accurately where the critical points in the scene will be in the next few seconds ahead".

Hollnagel, Nåbo, and Lau (2003) describe the study of driving as traditionally being viewed as either as a problem of guidance and control or as a human factors problem, neither of which is fully adequate to face the challenges of modern and future cars. They further emphasise that the introduction of ADAS, the human is no longer in direct control of the vehicle, but rather in co-operation with an automated driving system.

Cognition is connected to response time, a parameter widely used in road geometry design. Humans have response times as low as 180 milliseconds (ms) for visual stimuli, and about 140 ms for auditory and tactile stimuli when performing simple tasks (Macadam, 2003). The American Association of State Highway and Transportation Officials (2011) state that the reaction time of humans can be from almost negligible to over 1.64 s. Fuller (2005) found that experienced drivers showed anticipatory avoidance of hazard, while inexperienced drivers had a reactive mode of dealing with hazards, i.e. that response time is dependent on experience.

3.5.1. The equivalent of cognition for the automated driver

For the automated driver to outperform humans, they need to correctly understand a given driving situation, and anticipate the actions of other road users. The automated driver's capability to make fast decisions in complex situations, like humans are innately able to, can, per today's technological advances, be questioned (Pütz, Murphy, & Mullins, 2019).

Machines need to interpret sensory input, e.g. turning sensor data from the IMU into the position, heading and velocity in the INS. Although it is often assumed that vehicles will have shorter reaction times than humans (Farah, Erkens, Alkim, & van Arem, 2018) this depends on how much data needs to be analysed. The DARPA Urban Challenge in 2007 provides two examples of reaction times. Junior, the Stanford entry which placed second, had a time delay from entry of sensor data to action of approximately 300 ms (Montemerlo et al., 2009). Another participant, Little Ben from the Ben Franklin Racing Team, used 200 milliseconds as the worst-case scenario for its car's detection and reaction time (Benjamin, Leonard, Schmidt, & Newman, 2008). In the challenge, speed was limited to 30 mph or roughly 50 km/h, with lower speed limits in many places (Montemerlo et al., 2009), and there was no requirement for cars to detect traffic lights or signs (Berger & Rumpe, 2012). Although a technical feat, the challenge is still a long way from real-world driving. On the other hand, over a decade has passed since the DARPA 2007 challenge under which time hardware and software has been improved. Collin et al. (2020) published a study where all driving functions were defined by 24 tasks which were connected by 32 messages. They then simulated the latency of the system at different architectures with different safety levels, for instance with regard to redundancy. Their simulation suggested system latencies, or reaction times, of between 0.34 and 0.38 s.

Central to cognition is object recognition. There are several ways to detect objects such as vehicles and pedestrians through automated features. Vision-based detection can be made based on the recognition of objects directly from the pixels in images or by analysing subsequent frames (Sivaraman & Trivedi, 2013). Sensor fusion techniques allows for combining the strengths of different sensor types, e.g. cameras and radars (Wang, Xu, Sun, Xin, & Zheng, 2016) and machine learning techniques can be applied to teach the machine to discern different elements of the traffic scenario even in challenging lighting conditions and when the objects are partially occluded (Ohn-bar & Trivedi, 2015). Machines are generally found to be considerably worse than humans at broad categorisation, e.g. identifying an animal (Branson, Van Horn, Wah, Perona, & Belongie, 2014; Fleuret et al., 2011; Linsley, Eberhardt, Sharma, Gupta, & Serre, 2018), but superior in finding small distinctions, e.g. the species of bird in an image. Even when the human and machine reach the same conclusion, they do this based on different visual markers (Linsley et al., 2018). Differences in how humans and machines operate are worth noting, both to ensure safe co-existence on the road, but also to leverage the strengths of machine sensors and cognition.

Infrastructure design could also impact how fast and successful the processing of sensor input is. Road marking detection can again serve as an example. Beyond the problems of capturing the lane markings on camera, lie the problems of correctly analysing them. Issues have been identified with relation to old markings, worn markings and asphalt cracks (Chen, Seff, Kornhauser, & Xiao, 2015; A. Pike, Carlson, et al., 2018), but also problems were other parts of the infrastructure are mistaken for lane markings such as road marking arrows or guardrails (Borkar, Hayes, Smith, & Pankanti, 2009; Chen et al., 2015).

4. Discussion

In order for the automated driver to be considered in future road design and maintenance, its characteristics must first be established. Understanding the differences between human and automated drivers can provide insight into how to ensure the safety benefits expected by automated driving. The current definitions of automated drivers, including the SAE International's ADS, do not provide insight into the unique characteristics of the automated driver. Therefore, a unified framework for driving has been established encompassing all parts of the driving processes. In this framework, how the driver senses their environment was shown to impact all the driving processes. Sensing of the environment also represents the most direct interaction between driver and the road environment. Thus, it is necessary to focus on the sensing processes of both human and automated road users as well how this sensory input is processed (cognition).

As presented in the previous section, there is a significant amount of research on both the different sensors used in driving automation, and the automated driving functions that they make possible. However, these seldom shed light on what changes are needed to make the road infrastructure easier to interpret for automated drivers. The unified framework and analysis of differences between human and automated drivers presented in this paper provide guidance on how to close this research gap.

The main differences identified between humans and automated drivers are that the automated driver has a much greater range of electromagnetic sensitivity and field of view (related to sight), and that the two road users interpret and act on sensory input in different ways (related to cognition).

Given the increased electromagnetic sensitivities, there is potential to use colours and contrasts to aid sensors that depend on available light, e.g. cameras, and use surface textures (roughness, transparency and reflective properties) to improve detection by sensors that actively emit radiation, e.g. radars and lidars.

Road design and road maintenance strategies both play a role in the success of automated driving features. Longitudinal road elements can be hard to distinguish in image processing, e.g. lane markings, cracks in the road and safety rails. Research on how different materials and finishes can help automated drivers correctly classify road infrastructure elements is encouraged. Regarding road maintenance, strategies will need to be updated to ensure the success of automated drivers, e.g. in relation to road damage repairs and maintenance of road markings.

Characteristics of the automated driver also have implications for existing road infrastructure. As mentioned previously, LED signs are hard to read for cameras due to flicker; for this reason, they might not be a cost-effective investment for the future. Glass and mirrors can cause lidars to misinterpret distances to objects. The way objects reflect laser light also impacts lidars' accuracy of object detection. These mechanisms should be considered both in the design of the road infrastructure and for the vehicles themselves. For example, using car paints that are easily detectable by an automated driver, and, if possible, distinguishable from static parts of the road environment, could also increase safety and lower reaction times.

Although it depends on the sensors' set-up on the vehicle, the automated driver usually has some sort of perception in all directions. The greater FOV of automated drivers has the potential to increase safety in traffic but depends on the correct interpretation of sensor data. Placement of sensors will have a specific impact on the eye height parameter which determines sight distance in geometric road design. To include the automated driver in road design, the current design parameters will need to be reevaluated. Definitions used for human drivers might not be directly transferrable to the automated driver. For instance, sensor placements are likely to be both higher and lower than the design criteria of eye height used in current design standards. Sensor fusion, which involves combining sensor input from different sensors, further complicates this definition.

Safe driving is dependent not only on what data is collected by sensors, but also how it is analysed. The amount of sensory data being processed, as well as the processing algorithms themselves, impacts the reaction time of the automated driver. Lower reaction times are expected to be a notable benefit from automated driving; however, in the current stages of development, it will be beneficial to process more sensory data for greater safety and redundancy. An understanding of trade-offs such as this one is important as road authorities will find themselves in a position where they need to develop policies to certify the automated driver for different uses. To better understand how the automated driver operates, one approach is to require programming that explains how automated drivers interpret their surroundings and how they reach their decisions, often referred to as *explainable AI*. The analyses of sensor data, or cognition of the automated driver, is also related to object detection. The differences in cognition for human and automated drivers suggest revising parameters (such as object height and reaction time) that are used to determine stopping sight distance in road design.

Despite the uncertainty surrounding what sensors the automated driver can be expected to have, and how the data from these will be interpreted, the findings of this study suggest areas for future research efforts. The following steps are suggested to identify concrete measures for including the automated driver in the design and maintenance of road infrastructure:

1. Parameters for geometric road design needs reevaluating based on the automated driver's development. Eye height and object height are examples of parameters that require a new definition. Reaction time will likewise need to be defined for automated drivers and monitored as vehicles and systems evolve.
2. The suite of sensors used by the automated driver detects a range of electromagnetic radiation considerably larger than the range visible to human drivers. This should be explored to optimise the design of road infrastructure elements. For example, research can uncover how colours, textures and materials can be used to help machine drivers separate roadway from safety railings or curbs.
3. Maintenance policies need revision as more knowledge about how wear and damages to the road infrastructure affect automated driving is generated.
4. Successful automated driving will require co-operation between road authorities, researchers, and vehicle manufacturers. Transparency with respect to how the infrastructure is sensed and interpreted should be encouraged, including trade-offs of latency versus redundancy and classification of objects.

5. Conclusion

As automated driving features continue to develop, a new road user, *the automated driver*, has emerged. To build infrastructure suited for this automated driver, more knowledge about the automated driver combined with a solid understanding of how the roadway is sensed and interpreted by the automated driver is needed. Current literature lacks a framework for automated driving that covers all driving processes. This paper has established a unified framework for human and automated driving based on theoretical models of human driving and robotics. The unified framework of driving provides an approach to relate the sensor technology used in automated driving to existing human senses to which the roadway infrastructure is currently adapted. The sensing processes of automated and human drivers have been reviewed to identify differences between the two road users. The understanding of these differences provides research directions that can enable inclution the new automated driver as a road user in road design and maintenance policies.

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