The Technical and Differential Impact Analysis of Autonomous Vehicles

Chenji Lu

Department of Aeronautics and Astronautics, University of Southampton, United Kingdom

Abstract

This paper discusses the development of autonomous vehicles (AVs) and their social and sustainability impact. The development is based on various modern structures and technologies, such as perception systems, decision systems and platform manipulation. Considering this, AVs will have different impacts on society, the economy and sustainability. With the high sensitivity of different distance and classification sensors, the response time of AVs is much faster than that of human drivers, which can help to develop a collision-free driving. Moreover, AV markets will stimulate technological and economic growth. The development of electrified AVs will dramatically decrease greenhouse gas emissions and a convenient autonomous transportation system will encourage more people to take public transportation, which should optimise the public route space.

Keywords

Intelligent vehicles; perception system; decision-making system; vehicle safety, vehicle market; vehicle sustainability.

1. INTRODUCTION

1.1. Innovation

According to Senator Gary Peters, in the Iraq War, the US military lost more soldiers in logistics operations than they did in combat. This is because driving an unarmed fuel truck across intricate terrain is extremely dangerous (Thibodeau, 2018). Therefore, in October 2000 the U.S. Department of Defense announced a national defence authorisation file and said that by 2015, one-third of operational ground combat vehicles would be unmanned (National Defense Department, 2000). This was the initial motivation for AV innovation.

1.2. Structure

Generally, AVs consist of a perception system, a control system and a platform. Perception system can detect and classify the external environment where the vehicle operates. The vehicle's control system makes decisions and controls the motion of the vehicle based on external environment inputs and vehicle platform manipulation, which deals mostly with sensing and AV actuation with the intention of achieving the desired motion (Behere, 2015).

1.3. Development Levels

According to Australian institute of traffic planning and management national conference, researchers have defined four levels of development. First is function-specific automation, which involves one or more control functions, such as auto-breaking and electronic stability control. Most recent vehicles have at least one of these functions. In 2019, the US National Highway Traffic Safety Administration announced that more than half of vehicles had installed an automatic emergency braking (AEB) system. Several high-volume automakers such as

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202012_6(12).0044

Mercedes-Benz and Volvo made 90% of their cars install AEB (Department of Transportation, 2019). The second level of development is called combined function automation, which involves automation of at least two primary control functions designed to work in unison to relieve the driver of control. An example of this is adaptive cruise control technology that combines speed control, radar detection and lane centring. Some luxury car companies, such as BMW, Lexus and Tesla, offer these functions in their cars. The first and second levels relate to the primary status. The third level is known as limited self-driving automation, in which vehicles have the ability to cede full control of all safety-critical functions under certain traffic environments. However, the vehicle requires a driver to monitor its behaviour and, in some circumstances, the vehicle needs the driver to take control. Only a few high-technology companies, such as Google, are in this stage. Finally, the fourth level is full self-driving automation in which the vehicle can handle any environments and has all safety-critical driving functions. At this stage, true AVs are achieved (Davidson, 2015).

2. TECHNOLOGY

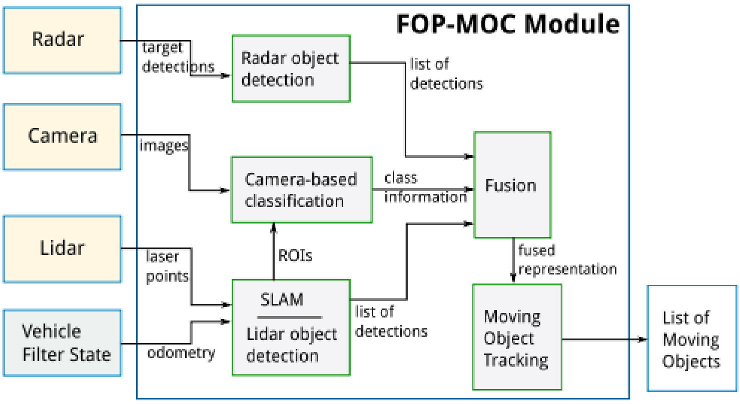

Fig 1. Schematic of a multiple sensor perception system (Chavez, 2016)

2.1. Perception System

In the robotics community, there is a commonly heard phrase that 'Sensing is easy, perception is difficult'. (Chavez, 2016). Fig. 1 shows the schematic of the most used perception system (PS). The PS aims to detect, classify and track several sets of moving objects that may move in front of the vehicle. The moving object input is gathered by three sensors, namely lidar, radar and camera. Each object is then depicted by its position, size and class. Class information is gathered through shape, speed and visual detection. Lidar and radar data extract kinetic and appearance information and only appearance information is extracted from the camera (Fig. 2). These three data inputs are taken by using a fusion approach and the final output of the fusion method comprises a list of object detections that is used for the tracking module to classify the object and estimate the moving object states (Chavez, 2016).

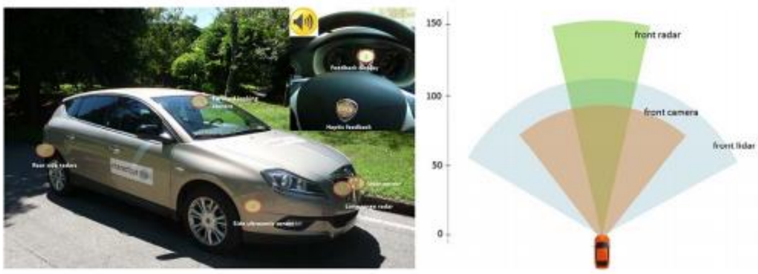

Fig 2. Left: Examples of AVs. Right: Field of view of the three frontal sensors (Chavez, 2016)

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202012_6(12).0044

According to Chavez (2016), there are four types of moving object in particular that may appear in front of a vehicle, which are a pedestrian (p), a bike (b), a car (c) and a truck (t). Equ. 1 shows the basic belief assignment $m_l(A)$, which provides a classification mass function of different objects. A is in {p,b,c,t}, and m describes the probability distribution for the class of the moving object. The performance factors, ($\alpha_p, \alpha_b, \alpha_c, and\ \alpha_t$), are used to represent the lidar result for detecting pedestrians (p), bikes (b), cars (c) and trucks (t). Respectively, the uncertainty factors, ($\gamma_b, and\ \gamma_c$), represent a wrong detection or uncertainty about bikes and cars. When a bike is detected, because of laser visibility, the object can still be a part of a car or a truck. For this reason, the classification could be bike, car and truck ({b,c,t}). For the same reason, when a car is detected, the object may be a part of a truck, so the classification can be car and truck ({c,t}). However, pedestrians are small enough to distinguish them from other objects and a truck is large enough to be distinguished from others. Finally, in all cases, the ignorance hypothesis Ω represents the lack of knowledge and general uncertainty about the class (Chavez, 2016).

$$m_l(A) = \begin{cases} m_l(\{\mathbf{p}\}) = \alpha_p & \text{if class} = \mathbf{p} \\ m_l(\Omega) = 1 - \alpha_p & \\ m_l(\{\mathbf{b}\}) = \gamma_b \alpha_b & \text{if class} = \mathbf{b} \\ m_l(\{\mathbf{b},\mathbf{c},\mathbf{t}\}) = \gamma_b(1-\alpha_b) & \\ m_l(\Omega) = 1 - \gamma_b & \\ m_l(\{\mathbf{c}\}) = \gamma_c \alpha_c & \text{if class} = \mathbf{c} \\ m_l(\{\mathbf{c},\mathbf{t}\}) = \gamma_c(1-\alpha_c) & \\ m_l(\Omega) = 1 - \gamma_c & \\ m_l(\{\mathbf{t}\}) = \alpha_t & \text{if class} = \mathbf{t} \\ m_l(\Omega) = 1 - \alpha_t. & \end{cases}$$

Equ 1. Lidar probability distribution for the class of moving objects (Chavez, 2016)

The camera classification is based on lidar detection and the technology is known as regions of interest (ROI). Lidar helps the camera focus on specific regions of an image. For each interest region, appearance properties are extracted and a classifier algorithm, which is based on logistic regression, combines all the features and forms a good result (Friedman, 2000). Equ. 2 shows the basic belief assignment $m_c(A)$. This equation is based on the previous lidar equation but is more complex because objects with relative similar size may appear in one region. Therefore, the equation should take account of set, such as {p,b}, {b,c} and {c,t} and add a new factor c_c to indicate camera sensor accuracy (Chavez, 2016).

$$m_c(A) = \begin{cases} m_c(\{\mathbf{p}\}) = \alpha_p c_c & \text{if class} = \mathbf{p} \\ m_c(\{\mathbf{p},\mathbf{b}\}) = \alpha_p(1-c_c) & \\ m_c(\Omega) = 1 - \alpha_p & \\ m_c(\{\mathbf{b}\}) = \alpha_b c_c & \text{if class} = \mathbf{b} \\ m_c(\{\mathbf{p},\mathbf{b}\}) = \alpha_b(1-c_c) & \\ m_c(\Omega) = 1 - \alpha_b & \\ m_c(\{\mathbf{c}\}) = \alpha_c c_c & \text{if class} = \mathbf{c} \\ m_c(\{\mathbf{c},\mathbf{t}\}) = \alpha_c(1-c_c) & \\ m_c(\Omega) = 1 - \alpha_c & \\ m_c(\{\mathbf{t}\}) = \alpha_t c_c & \text{if class} = \mathbf{t} \\ m_c(\{\mathbf{c},\mathbf{t}\}) = \alpha_t(1-c_c) & \\ m_c(\Omega) = 1 - \alpha_t. & \end{cases}$$

Equ 2. Camera probability distribution for the class of moving objects (Chavez, 2016)

The radar sensor can only detect relative speed. The pedestrian (p) and bike (b) are slower than the car (c) and truck (t). Therefore, confidence factor α and β are defined with respect to set {p,b} and {c,t} and speed boundary Sp. The basic belief assignment $m_r(A)$ can be shown as Equ. 3 (Chavez, 2016).

$$m_r(A) = \begin{cases} m_r(\Omega) = \alpha & \text{if object}_{\text{speed}} < S_p \\ m_r(\{\mathbf{p},\mathbf{b}\}) = 1-\alpha & \\ m_r(\Omega) = 1-\beta & \text{if object}_{\text{speed}} >= S_p \\ m_r(\{\mathbf{c},\mathbf{t}\}) = \beta. & \end{cases}$$

Equ 3. Radar probability distribution for the class of moving objects (Chavez, 2016)

Table 1. PS results on highway, urban area, rural and test tracks (Chavez, 2016)

Scenario	Total objects				Detections					Classifications							
					Correct				False	Correct				False			
	p	b	c	t	p	b	c	t	all	p	b	c	t	p	b	c	t
Highway	0	0	702	281	n/a	n/a	687	271	22	n/a	n/a	669	251	0	0	4	0
					n/a	n/a	97.8%	96.4%	2.2%	n/a	n/a	95.2%	89.3%	0%	0%	0.5%	0%
Urban	65	7	619	97	57	6	580	88	17	57	6	570	78	9	1	6	5
					87.6%	85.7%	93.6%	90.7%	2.1%	87.6%	85.7%	92.0%	80.4%	13.8%	14.2%	0.9%	5.1%
Rural	9	0	68	6	9	n/a	62	5	9	9	n/a	60	5	3	0	5	2
					100%	n/a	91.1%	83.3%	10.8%	100%	n/a	88.2%	100%	33.3%	0%	7.3%	33.3%
Test track	248	0	301	0	247	n/a	300	n/a	1	240	n/a	300	n/a	0	0	0	0
					99.6%	n/a	100%	n/a	0.1%	96.7%	n/a	100%	n/a	0%	0%	0%	0%

The results for the PS system are shown in Table 1. In test track scenarios, the detection and classification are nearly perfect (96-100%). On highways, the accuracy is also good, with cars at 97.8% and trucks at 96.4%. In urban areas, vehicle detection and classification are still high, considering the increased number of moving obstacles and the busy environment. On rural roads, less traffic makes the accuracy for pedestrians and cars above 90% but trees confuse the system and decrease the correct rate for trucks (Chavez, 2016).

2.2. Decision System

After the PS, the object information passes through a decision system (DS). In Fig. 3, the prediction module (PM) can predict the different trajectories in which the surrounding vehicles may move. The future motion is represented by a probability distribution over multiple possible trajectories and each trajectory corresponds to different driver behaviours. The planning module can make a decision for the vehicle to execute based on the input from the PM and PS, and the decision are the control signals for the vehicle to execute. The planning module contains three parts. First is a decision-maker that provides high-level driving strategies. A local trajectory planner then plans the best solution for the given circumstance. Finally, a trajectory tracking controller can track if the vehicle has followed the planning module and give feedback to decision module (Chen, 2018).

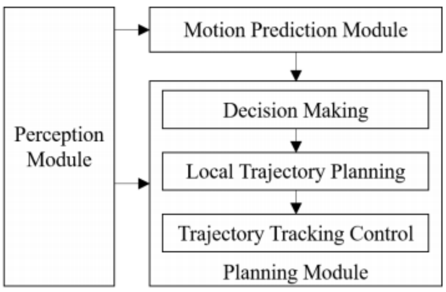

Fig 3. Decision system structure (Chen, 2018)

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202012_6(12).0044

There are many different circumstances that require the DS to make a decision. In this paper, the line change scenarios mainly focus on introducing how the DS operates. In the DS, speed data can fully represent the longitudinal motion because it can be integrated into a space position file or it can be differentiated into an acceleration profile. This speed data can be represented as $v(t) \in V \; with \; t \in [0, T]$, where V is a list of possible velocity and [0, T] represents a time period. The space position file can be written as x(t) and the acceleration data as a(t). The future decision can be denoted as $l(t) \in L, L = \{-1, 0, 1\}$ where l = 0 means no changing requirement, l = -1 means turning left and l = 1 means turning right. Therefore, the decision-making process can be formulated as an optimisation problem as Equ. 4 shows.

$$
\begin{aligned}
&\min_{f} \int_{t=0}^{T} \{J_v(v(t), l(t)) + J_a(a(t))\} \, dt \\
&s.t. \quad g_v(v(t), l(t), t) < 0, \quad t \in [0, T] \\
&\qquad\;\; g_x(x(t), l(t), t) < 0, \quad t \in [0, T] \\
&\qquad\;\; g_a(a(t), t) < 0, \quad t \in [0, T]
\end{aligned}
$$

Equ 4. Decision-making equation (Chen,2018)

J_v and J_a represent the costs of velocity and acceleration. g_a is a constraint for the acceleration profile, which sets the bounds for acceleration for passenger comfort. g_v is a constraint for velocity, which sets bounds for velocity due to speed limits. g_x is a constraint for events. These would mainly be caused by traffic signals, surrounding vehicles and merging. The result of the optimisation is sent to the control system and the vehicle then executes a decision (Chen, 2018).

Chen (2018) shows two scenarios in his paper (Fig. 4). (a) shows a merging situation where a red vehicle (AV) tries to merge into a lane in which a yellow vehicle is driving, where x_0 is the merge point. (c) shows the space location data of the red vehicle. The yellow bar shows the surrounding vehicle's movement and after point x_0, the host car cannot move into this area. In this scenario, the DS has made two class movements, where one is increasing the speed and passing the surrounding vehicle and the other is slowing down and letting the surrounding vehicle pass. The final outputs depend on the surrounding vehicle's movement and the safety features of each decision. (b) shows the host car trying to increase speed and changing to the left lane. (d) shows the local trajectory generated by the DS (Chen, 2018).

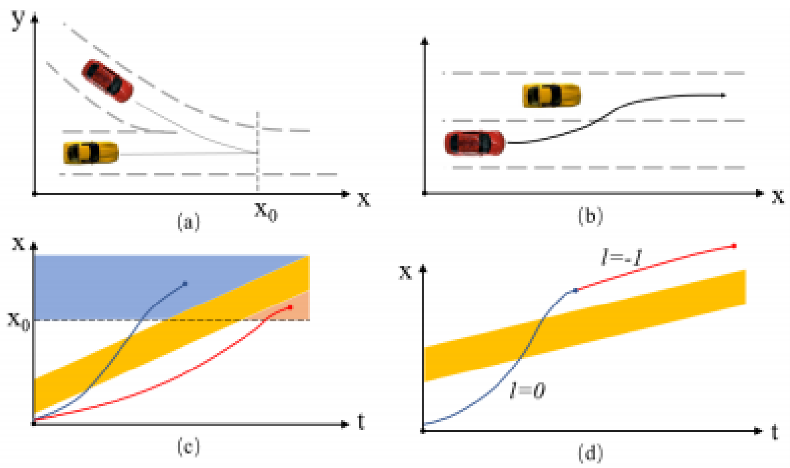

Fig 4. Example scenarios (Chen, 2018)

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202012_6(12).0044

2.3. Vehicle Platform Manipulation

Vehicle platform manipulation mainly contains platform stabilisation components (SC) and trajectory execution (TE) components. The task for the platform SCs is to keep the vehicle in a controllable state. Unreasonable motion requests from the previous DS will be rejected or adapted to maintain the safety and capabilities of the vehicle. For example, in Section 3.2, Fig.4a, the DS shows two possible trajectories. If acceleration goes over the speed limit or damages the engine, then SC will reject the acceleration command and execute a deceleration plan. TE components take input from the previous DS and then execute them. This is achieved through a combination of propulsion, steering and braking systems (Behere, 2015). This technology has already been installed in some AV platforms, such as Tesla's auto-park and auto-lane-change systems (Tesla, 2019).

3. IMPACT ON SOCIETY, THE ECONOMY AND SUSTAINABILITY

3.1. Social and Economic Impact

The autonomous technology will likely dramatically decrease the occurrence of vehicle collisions and fatal crashes. The natural reaction time is 1.44 seconds (Lotz, 2019). Meanwhile, tired drivers have a much longer reaction time. (Corfitsen,1994). However, for autonomous cars, the refresh frequency of the lidar sensor is 10Hz (0.1s) or more (Behere, 2015). The processing speed in recent microprocessors is in gigahertz (nanoseconds). Therefore, through sample mathematics, AVs will be at least ten times faster than humans. According to the National Highway Traffic Safety Administration (2016), drowsy driving was responsible for 72,000 crashes, 44,000 injuries and 800 deaths in 2013 (Green, 2018). Based on the available data, almost 33% of collisions, especially those involving fatalities, are avoidable if all vehicles were equipped with some autonomous technology such as an auto-braking system or a lane-departure warning (Gao, 2016; Fagnant, 2015). This means that at least 24,000 crashes, 14,666 injuries and 267 deaths could be prevented through autonomous technology.

In addition to this, AVs can benefit all of society. AVs are expected to advance mobility for groups who are too physically challenged to operate vehicles. Potentially, this could increase their social interaction and job opportunities, among many other impactss. (Zhao, 2017). AVs also have the potential to improve the driver's experience. Once drivers can take their hands off the wheel, they can spend their time on their computer or phone, meaning that the experience of driving would be much less onerous (Davidson, 2015).

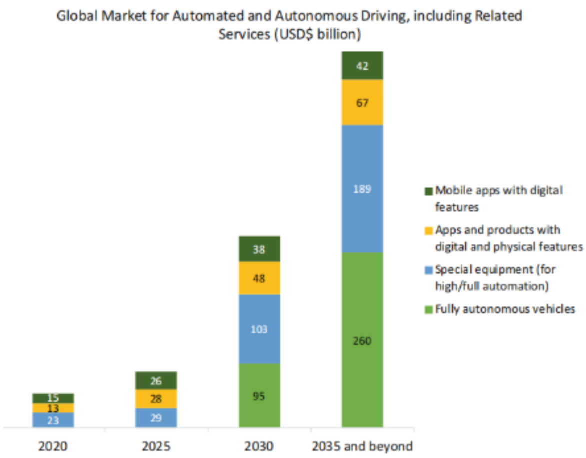

Fig 5. Global market for automated and autonomous driving, including related services (Adnan, 2019)

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202012_6(12).0044

The AV market share is expected to grow exponentially in the next 20-30 years. (Adnan, 2019). As Fig. 5 shows, the growth pace will be slower initially as improvements are made to the technology and they need to be built to accommodate these changes. Government incentives are expected to further accelerate the integration of AVs into the consumer market. In 2030, it is expected that the AV market share will be 7% of the total auto market. In 2035, the percentage will increase to 17% (Adnan, 2019).

AVs decrease operating costs and stimulate tourism. Nowadays, most AVs, like those by Tesla, are electrically powered. Electric vehicles should have a smaller vehicle operating cost than standard internal combustion engine vehicles. Currently, there are more companies and universities studying electric power engines than traditional engines. Therefore, the operating cost is likely to reduce over time as technology improves and economies of scale expand (Davidson, 2015). Guterres (2014) assumes a reduction of 50% in vehicle costs for AVs. Furthermore, there is evidence that shows that people take into account travel expenses when they make their travel decisions. With lower vehicle costs and a much more comfortable travelling experience, travelling spending looks to increase by 10% in 2021 and 20% in 2031 (Davidson, 2015). Considering this, AVs will likely stimulate the tourism industry over the next 20 years.

This will, however, also have some negative effects on society and the economy. AVs all communicate with a network that shares a large volume of data, such as data on locations, and this will lead to privacy concern. Highly intelligent systems may also lead to failure via malicious hacking (Adnan, 2019). In terms of the economic side, AVs may eliminate the traditional vehicle field. There are many jobs associated with transportation, including truck drivers, taxi drivers and bus drivers. It is likely that, at some stage, all of these jobs could be eliminated due to AVs (Davidson, 2015). Furthermore, once AVs are safe enough, this will reduce insurance costs but also largely eliminate insurance companies and car repair shops altogether. PricewaterhouseCoopers estimate that when AVs become widespread, the total size of the vehicle industry will drop by 90% (PWC, 2015).

3.2. Sustainability Impact

AVs will likely offer a window of opportunity to improve negative environmental phenomena. Vehicle operations are the prime sustainability target because they count for three-quarters of greenhouse gas emissions in vehicle life cycles. (Martin, 2019). The development of electrified AVs will likely dramatically decrease greenhouse gas emissions.

AVs will also likely play a significant role in future smart cities. AVs will likely also create a socially mobile transportation system, especially for people who are inconvenienced by the current system. As mentioned previously, this mobile transportation system will likely make much more human resources such as physically challenged individuals and people who are afraid to drive. Moreover, AVs will encourage people to take shared autonomous transportation system. (Amini, 2018). Autonomous technology is expected to increase the number of cars on the road. Therefore, having a shared and convenient autonomous transportation system will encourage more people to take public transportation, which should optimise the urban transportation systems. In the end, AVs will likely change perspectives regarding sustainability, while also increasing mobility and accessibility, as illustrated previously (Davidson, 2015).

4. CONCLUSION

AVs are an area of future development for the auto industry because their advantages significantly outweigh their disadvantages. Although their use has some negative impacts on the traditional auto industry and many jobs will be affected, their use also requires more engineers and research involvement, which makes more high technology job positions available.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202012_6(12).0044

Further to this, the huge AV markets will attract capital and human resources, which will dramatically stimulate economic development. In addition to this, accurate sensor detection and a fast response time can prevent most of the collisions, saving many lives and preventing financial loss. AVs will also play a significant role in future sustainability development. The development of electrified AVs will dramatically decrease greenhouse gas emissions and convenient autonomous transportation systems will likely encourage more people to use public transportation, which should optimise the urban transportation system.

The advancement of technology in AVs should be more human-centric and consider more ethical aspects, such as safety, accountability, economic prosperity and individual rights. Highly intelligent control systems will not only take the place of human drivers, but the technology will also revolutionise society. When technology goes wrong, critical thinking regarding the ethical design and policies can help lead the development of AVs towards a direction that brings the largest benefit to all (Adnan, 2019).

REFERENCE LIST

[1] Amini, M. H., Boroojeni, K. G., Iyengar, S. S., Blaabjerg, F., Pardalos, P. M., & Madni, A.M. (2018). A panorama of future interdependent networks: from intelligent infrastructures tosmart cities. In Sustainable interdependent networks (pp. 1–10). Berlin: Springer.

[2] Adnan, N., Nordin, S.M. and bin Bahruddin, M.A., 2019. Sustainable Interdependent Networks from Smart Autonomous Vehicle to Intelligent Transportation Networks. In Sustainable Interdependent Networks II (pp. 121-134). Springer, Cham.

[3] Behere, S. & Torngren, M., 2015. A functional architecture for autonomous driving. 2015 First International Workshop on Automotive Software Architecture (WASA), pp.3–10.

[4] Chavez-Garcia, R.O. & Aycard, O., 2016. Multiple Sensor Fusion and Classification for Moving Object Detection and Tracking. IEEE Transactions on Intelligent Transportation Systems, 17(2), pp.525–534.

[5] Chen, J. et al., 2018. Continuous Decision Making for On-road Autonomous Driving under Uncertain and Interactive Environments. 2018 IEEE Intelligent Vehicles Symposium (IV), 2018, pp.1651–1658.

[6] Corfitsen, M.T., 1994. Tiredness and visual reaction time among young male nighttime drivers: A roadside survey. Accident Analysis and Prevention, 26(5), pp.617–624.

[7] Davidson, P. and Spinoulas, A., 2015, July. Autonomous vehicles: what could this mean for the future of transport. In Australian Institute of Traffic Planning and Management (AITPM) National Conference, Brisbane, Queensland.

[8] Department of Transportation. (2019). 10 automakers equipped most of their 2018 vehicles with automatic emergency braking. Available at: https://www.nhtsa.gov/press-releases/10-automakers-equipped-most-their-2018-vehicles-automatic-emergency-braking. [Accessed 19 Nov. 2019].

[9] Fagnant, D., & Kockelman, K. M. (2015). Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transportation Research Part A, 77,167–181.

[10] Green, F.N., López, I.A. and Simmons, M., 2018. Obstructive Sleep Apnea Disparity among Truck Drivers: Danger on American Roads. Florida Public Health Review, 15(1), p.8.

[11] Gao, P., Kaas, H.-W., Mohr, D., & Wee, D. (2016). Automotive revolution–perspective towards 2030: How the convergence of disruptive technology-driven trends could transform the auto industry. New York: Advanced Industries, McKinsey.

[12] Guterres, J (2014), Vehicle fuel cost per litre - Electricity vs. Petrol, Nenergy at http://negergy.com.au/blogs/news-reviews/11530353-vehicle-fuel-cost-per-litre-electricity-vs-petrol

[13] J. Friedman, T. Hastie, and R. Tibshirani, "Additive logistic regression: A statistical view of boosting," Ann. Statist., vol. 28, no. 2, pp. 337–655, 2000.

[14] Lotz, A., Russwinkel, N. and Wohlfarth, E., 2019. Response times and gaze behavior of truck drivers in time critical conditional automated driving take-overs. Transportation research part F: traffic psychology and behaviour, 64, pp.532-551

[15] Martin, G.T. & Ebc, 2019. Sustainability prospects for autonomous vehicles : environmental, social, and urban,

[16] NATIONAL DEFENSE AUTHORIZATION, FISCAL YEAR 2001. (2000). [ebook] Washington, D.C.: U.S Defense department, pp.40,41. Available at: https://www.govinfo.gov/content/pkg/PLAW-106publ398/pdf/PLAW-106publ398.pdf [Accessed 14 Nov. 2019].

[17] PricewaterhouseCoopers (PWC) (2015), The Insurance Industry in 2015: Potential impacts of automated driver assistance systems (ADAS) and autonomous car technologies on the insurance industry, Vol 7, at http://www.pwc.com/en_US/us/insurance/assets/pwc-top-insurance-industry issues-potential-impacts-of-automated-driver-assistance-systems.pdf

[18] R. Chavez-Garcia, T.-D. Vu, O. Aycard, and F. Tango, "Fusion framework for moving-object classification," in Proc. IEEE 16th Int. Conf. Inf. Fusion, 2013, pp. 1159–1166.

[19] Thibodeau, I. (2018). Driverless vehicles may reshape future of warfare. [online] Detroitnews.com. Available at: https://www.detroitnews.com/story/business/autos/2018/05/14/army-transforming-warfare-self-driving-vehicles-tanks-tardec/34880891/ [Accessed 14 Nov. 2019].

[20] Tesla. (2019). Autopilot and Full self-driving Capability. Available at: https://www.tesla.com/support/autopilot. [Accessed 19 Nov. 2019]

[21] Zhao, W., Gong, M., Chen, Y., Jiang, B., & Chen, H. (2017). Research on navigation method of substation inspection car based on image recognition. In Chinese Automation Congress (CAC), 2017, (pp. 3236–3240).