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ÚSTAV JAZYKŮ

LITERATURE SEARCH ON FULLY-AUTOMATED VEHICLES

REŠERŠE NA AUTONOMNÍ AUTOMOBILY

BACHELOR'S THESIS
BAKALÁŘSKÁ PRÁCE

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VEDOUCÍ PRÁCE

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VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ
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Bakalářská práce

bakalářský studijní obor **Angličtina v elektrotechnice a informatice**
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NÁZEV TÉMATU:

Rešerše na autonomní automobily

POKYNY PRO VYPRACOVÁNÍ:

Svět automobilů se stále více mění a postupně se blíží doba, kdy se automobily změní z mechanických, řidičem ovládaných, na autonomní stroje. Vaším úkolem bude prozkoumat dostupné zdroje informací a prezentovat je v ucelené formě, jak stručně z hlediska technického, tak i potenciálních vlivů na společnost a případných negativ. Rovněž přidejte výhled do budoucna.

DOPORUČENÁ LITERATURA:

Lipson H., Kurman M.: Driverless Intelligent Cars and the Road Ahead, 2016, MIT Press, ASIN: B01K13FURS

Cheng H.: Autonomous Intelligent Vehicles: Theory, Algorithms, and Implementation (Advances in Computer Vision and Pattern Recognition), 2011 Springer, ISBN-13: 978-1447122791

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Vedoucí práce: Mgr. Pavel Sedláček
Konzultant:

doc. PhDr. Milena Krhutová, Ph.D.
předseda oborové rady

Abstrakt

Tato práce je zaměřena na autonomní automobily, obsahuje krátkou historii vývoje těchto automobilů, metody, které byly použity, zařízení i algoritmy používané v autonomních automobilech a možnou budoucnost autonomních aut. Práce také obsahuje soupis dostupné literatury na toto téma, obohacené o komentář či názor autora.

Klíčová slova

Rešerše na autonmní automobily, Autonomní automobily, Autonomní vozidla, Historie autonomních automobilů, Deep learning

Abstract

This thesis is focused on automated vehicles and contains a brief history of the development of automated vehicles, methods used, as well as devices and algorithms used in such vehicles, and a possible future of autonomous cars. It also lists the most beneficial literature on this topic, while providing additional information or author’s opinion on the matter discussed.

Keywords

Literature search on fully-automated vehicles, Automated vehicles, Autonomous automobiles, Autonomous vehicles, History of autonomous automobiles, Deep learning

Prohlášení

Prohlašuji, že svou bakalářskou práci na téma Rešerše na autonomní automobily jsem vypracoval samostatně pod vedením vedoucího bakalářské práce a s použitím odborné literatury a dalších informačních zdrojů, které jsou všechny citovány v práci a uvedeny v seznamu literatury na konci práce.

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V Brně dne ....

(podpis autora)

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1. Introduction

I have chosen the topic of automated vehicles, as it is a promising concept, which has lately been receiving increased attention from the automotive industry. Autonomous cars have many advantages over human-driven cars, several of these will be mentioned further on in the thesis. The technology used in automated vehicles is fascinating and complex, capable of correctly recognizing objects and organisms, and even making moral decisions by itself.

In this thesis, I present the concept of autonomous vehicles introduced by acknowledged authors, several definitions and different levels of automation are proposed. I also provide a brief history overview to display the progress made in the field of automated vehicles, several early civil prototypes are mentioned for the same reason. A research of available literature lists the main sources of information and the ideas presented by acknowledged authors. The hardware and software used in automated vehicles are described and its usage shown on several projects. Deep learning, a crucial and heavily utilized technology in automated vehicles, based on neural networks, is mentioned, unfortunately only on a limited scale due to length restrictions and purpose of this thesis. Further on, the concept of moral decisions which a vehicle is required to make is introduced. Moral Machine, a survey platform by MIT, is used as an example of such situation. In the last chapter, I provide a brief overview of possible future legal problems and changes related to automated vehicles.

2. Definition

The definition of an autonomous automobile can be found, amongst others, in the publication of Broggi et. al.:

> An intelligent vehicle is defined as a vehicle enhanced with perception, reasoning, and actuating devices that enable the automation of driving tasks such as safe lane following, obstacle avoidance, overtaking slower traffic, following the vehicle ahead, assessing and avoiding dangerous situations, and determining the route. (2008:1176)

A different approach to autonomous automobiles is presented by The National Highway Traffic Safety Administration. While Broggi et. al (2008) list only the necessary capabilities of an autonomous car, the NHTSA defines five levels of vehicle automation which are considering the gradual automation of vehicles. This approach is, therefore, more accurate to the current situation in which car manufacturers slowly transition their cars towards being fully automated. The reasoning behind the approach of Broggi et. al. might be that the slow transition from level 0 to level 4 is technically more demanding than the leap from the level 0 to the level 4.

Issued in the year 2013, NHTSA's "Preliminary Statement of Policy Concerning Automated Vehicles" states five levels of vehicle automation:

- No-Automation (Level 0): The driver is in complete and sole control of the primary vehicle controls – brakes, steering, throttle, and motive power – at all times.
- Function-specific Automation (Level 1): Automation at this level involves one or more specific control functions. Examples include electronic stability control or pre-charged brakes, where the vehicle automatically assists with braking to enable the driver to regain control of the vehicle or to stop faster than possible by acting alone.
- Combined Function Automation (Level 2): This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering.
- Limited Self-Driving Automation (Level 3): Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions, and to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control but with sufficiently comfortable transition time. The Google car is an example of limited self-driving automation.
- Full Self-Driving Automation (Level 4): The vehicle is designed to perform all safety-critical driving functions and to monitor roadway conditions for an entire trip. Such design anticipates that the driver will provide destination or navigation input but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles. (NHTSA, 2013)

Another possible approach is the J3016_201609 standard issued in September of 2016 by the SAE International, a global association of engineers and technical experts.

Level	Name	Narrative definition	DDT		DDT fallback	ODD
			Sustained lateral and longitudinal vehicle motion control	OEDR		
Driver* performs part or all of the *DDT						
0	**No Driving Automation**	The performance by the *driver* of the entire *DDT*, even when enhanced by *active safety systems*.	*Driver*	*Driver*	*Driver*	n/a
1	**Driver Assistance**	The *sustained* and *ODD*-specific execution by a *driving automation system* of either the *lateral* or the *longitudinal vehicle motion control* subtask of the DDT (but not both simultaneously) with the expectation that the *driver* performs the remainder of the *DDT*.	*Driver* and *System*	*Driver*	*Driver*	Limited
2	**Partial Driving Automation**	The *sustained* and *ODD*-specific execution by a *driving automation system* of both the *lateral* and *longitudinal vehicle motion control* subtasks of the *DDT* with the expectation that the *driver* completes the *OEDR* subtask and *supervises* the *driving automation system*.	***System***	*Driver*	*Driver*	Limited
***ADS* ("*System*") performs the entire *DDT* (while engaged)**						
3	**Conditional Driving Automation**	The *sustained* and *ODD*-specific performance by an *ADS* of the entire DDT with the expectation that the *DDT fallback-ready user* is *receptive* to *ADS*-issued *requests to intervene*, as well as to *DDT performance-relevant system failures* in other *vehicle* systems, and will respond appropriately.	*System*	***System***	*Fallback-ready user (becomes the driver during fallback)*	Limited
4	**High Driving Automation**	The *sustained* and *ODD*-specific performance by an *ADS* of the entire *DDT* and *DDT fallback* without any expectation that a *user* will respond to a *request to intervene*.	*System*	*System*	***System***	Limited
5	**Full Driving Automation**	The *sustained* and unconditional (i.e., not *ODD*-specific) performance by an *ADS* of the entire *DDT* and *DDT fallback* without any expectation that a *user* will respond to a *request to intervene*.	*System*	*System*	*System*	**Unlimited**

Figure 1 SEA International - Summary of levels of driving automation (Source: *SAE International. (2016). Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles.)*

According to the SEA International, there are several differences between the J3016_201609 standard and the NHTSA's list. One of them is that SEA's description provides functional definitions and is therefore rather descriptive, unlike the NTHSA's list which is normative. Another difference is the consistency with current industry practice and prior art, as J3016_201609 is based on currently used technologies. The J3016_201609 standard is advantageous in multiple disciplines, namely: engineering, law, media, public discourse, and others. The standard also avoids any ambiguity, as all terms are clearly defined (2016).

BASt (the Federal Highway Research Institute), a technical-scientific research institute of German Government, presented a definition of automation levels based on the allocation of tasks between the driver and the automation system, and the intended range of vehicle's speed.

According to the allocation of tasks, there are five levels of automation, namely: driver only, assisted, partial automation, high automation, and full automation. The description of each level along with the exemplary systems can be found in the figure bellow.

Nomenclature	**Description of automation degree according to drivers' expectations**	**Exemplary systems**
Driver Only	The driver continuously (throughout the complete trip) accomplishes longitudinal (accelerating/ braking) and lateral (steering) control.	No (driver assistance) system active that intervenes in longitudinal and lateral control.
Assisted	The driver continuously accomplishes <u>either</u> lateral <u>or</u> longitudinal control. The other/ remaining task is – within certain limits - performed by the system. • The driver must monitor the system <u>permanently</u>. • The driver must be prepared to take over complete control over the vehicle at any time.	Adaptive Cruise Control: - Longitudinal control with adaptive distance and speed control, Parking assistance system: - Lateral control is accomplished by the parking assistance (automatic steering into the parking space, the driver accomplishes longitudinal control).
Partial automation	The system takes over the lateral <u>and</u> longitudinal control (for a certain period of time and/ or in specific situations). • The driver must monitor the system <u>permanently</u>. • The driver must be prepared to take over the complete control of the vehicle at any time.	Motorway assistant: - Automatic longitudinal and lateral control - On motorways up to a certain top speed limit - Driver must monitor the actions constantly and respond immediately when prompted to take over
High automation	The system takes over lateral and longitudinal control for a certain period of time in specific situations. • Here, the driver <u>need</u> <u>not</u> monitor the system permanently. • If necessary, the driver will be prompted to take over control, allowing for a sufficient lead time. • All system limits are recognised by the system. The system is not capable of re-establishing the minimal risk condition from every initial state.	Motorway chauffeur: - Automatic longitudinal and lateral control - On motorways up to a certain top speed limit - Driver is not required to monitor the actions constantly. In case prompted to take over, the driver must respond within a certain lead time.
Full automation	The system takes over lateral and longitudinal control completely within the specification of the application. • The driver <u>need</u> <u>not</u> monitor the system. • Before specified limits of the application are reached, the system prompts the driver to take over control, with sufficient lead time. • In absence of driver takeover, the system will return to the minimal risk condition. • All system limits are recognised by the system. The system is capable of returning to the minimal risk condition out of every situation.	Motorway pilot: - Automatic lateral control - On motorways up to a certain top speed limit - Driver is not required to monitor the actions - In case the driver does not respond to a takeover request, the vehicle will brake down to a standstill.

Figure 2 BASt levels of automation – definition (Source: The Federal Highway Research Institute. (2012). Legal consequences of an increase in vehicle automation.)

The paper also deals with several legal questions concerning the liability of both the vehicle keeper and the driver, as well as product liability of the manufacturer, and motor vehicle liability insurance.

3. History

Even though current concept might differ from the concept of the very first self-driving car, an attempt made by the Tsukuba Mechanical Lab in 1977 (Fraichard, 2014), it is important to introduce the history of autonomous automobiles briefly. While one might argue that the idea of an autonomous vehicle is rather a new one, Broggi et. al. clearly state, that the first notion of autonomous automobiles is almost 50 years old:

> Although the first ideas were born in the 1960s, the level of maturity of the technology at that time did not allow pursuit of the original goal of implementing fully autonomous all-terrain all-weather vehicles. The first documented prototypes of automated vehicles were fielded by a few groups in the military arena in the mid 1980s. (2008:1176)

When one of the current models is compared with some of the early models the progress made in the field of autonomous vehicles can be clearly observed. Broggi et. al. refer to several early civil prototypes. One of them being the No Hands Across America experiment conducted by Carnegie Mellon Navlab group which in 1995 "[…] demonstrated automated steering, based solely on computer vision, over 98% of the time on a 2800 mile trip across the United States." (2008:1176)

Another, more current, prototype which was introduced later in 1995 by Bundeswehr Universität Munich (UBM), Germany, was "a vehicle that was demonstrated with a 1758 km trip from Munich to Copenhagen in Denmark and back. [This] vehicle was able to drive autonomously for 95% of the trip." (Broggi et. al., 2008:1176) While driving autonomously, the car was not able to localize its position, as it did not use a GPS module, and was only able to follow the present road until it was instructed differently, making it insufficient for current requirements.

The last vehicle mentioned in Broggi's Intelligent Vehicles is the Argo project conducted by VisLab at the University of Parma. A low-cost model equipped with a Pentium 200 MHz processor and several cameras inside the cabin of the car. Broggi et. al. describe the vehicle as follows:

> The vehicle was able to follow the lane, locate obstacles, and – when instructed – change lane and overtake slower vehicles. The main milestone of this project was the successful

test of the Argo vehicle in a tour of Italy of more than 2000 km called 'Millemiglia in Automatico' in which the vehicle drove itself for 94% of the total distance. (2008:1176)

To attract more attention towards autonomous vehicles the DARPA Grand Challenge was founded, marking a great milestone in the development of autonomous automobiles. In 2004, a race for autonomous vehicles was launched by The Defense Advanced Research Projects Agency (DARPA), a 200 kilometers long race in unstructured environments named "Grand Challenge". (Broggi et. al., 2008)

4. Research of available literature on the topic

Throughout this thesis, several papers describing the levels of automation were reviewed, as each differs in the approach to the topic. The National Highway Traffic Safety Administration and their “Preliminary Statement of Policy Concerning Automated Vehicles”, the J3016_201609 standard issued by the SAE International, and the German BASt-project. Each provides useful information on the topic and, to some extent, influenced its successors.

To further illustrate the usage of sensors several papers describing the hardware and software of DARPA’s Grand Challenge and Urban Challenge competitors were used. Among other resources, articles from the Journal of Field Robotics as well as the literature published by the groups behind every vehicle mentioned were researched.

There are many impacts of automated vehicles, several of them are mentioned in the final report by Pennsylvanian Department of Transportation. The paper deals with changes in infrastructure, workforce training needs, driver licensing, and others. These are very beneficial topics to this thesis as they present a broader perspective on the technology.

The Social Dilemma of Autonomous Vehicles, an article by Iyad Rahwan, et. al., presents crucial information on the topic of moral dilemma in automated vehicle technology. The main aim of the article is to point out the complexity of the algorithms used for moral decisioning in automated vehicles.

The research of available literature on the topic follows.

The book Driverless Intelligent Cars and the Road Ahead, written by Lipson H. and Kurman M., introduces the topic of autonomous automobiles while pointing out the benefits of such technology. It also raises potential problems and lists a brief history of autonomous car’s development.

Further information regarding the development of intelligent vehicles, as well as the usage of AI in current vehicles, can be found in Cheng’s Autonomous Intelligent Vehicles: Theory, Algorithms, and Implementation. Cheng also references several papers throughout his book. An example of such referencing can be seen in the following quotation.

Autonomous intelligent vehicles are now widely applied to Driver Assistance and Safety Warning Systems (DASWS), such as Forward Collision Warning, Adaptive Cruise Control, Lane Departure Warning. (2011:4)

In the chapter “Anatomy of a Driverless Car”, Lipson and Kurman list the hardware used in a driverless car, explaining the functions and drawbacks of each device. Both authors suggest that autonomous cars should be equipped with the following essential equipment (2016):

- Digital cameras
- Light detection and ranging (lidar)
- Radio detection and ranging (radar)
- Ultrasonic sensors (sonars)
- Global positioning systems (GPS)
- The inner ear (IMU)
- High bandwidth BUS

As presented in the book, these devices can be categorized as follows:

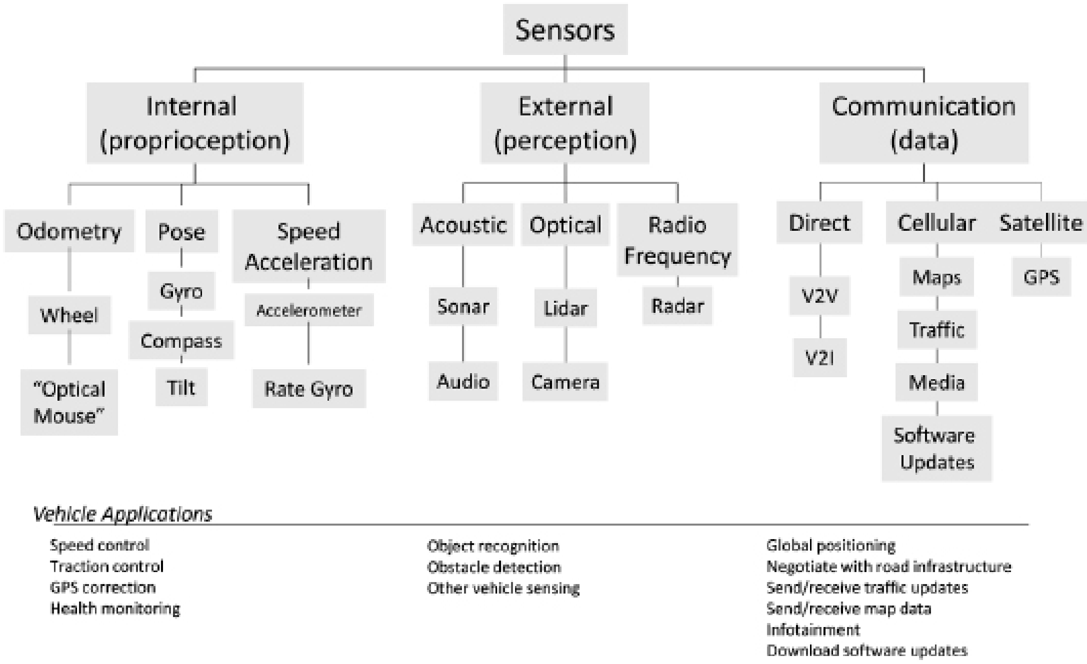

Figure 3 Key sensors (Source: Lipson H., and Kurman M. (2016). Driverless Intelligent Cars and the Road Ahead. MIT Press.)

A similar scheme of sensors used in autonomous automobiles can be found in Cheng's Autonomous Intelligent Vehicles: Theory, Algorithms, and Implementation. In addition to the sensors used, the usage of created data is shown.

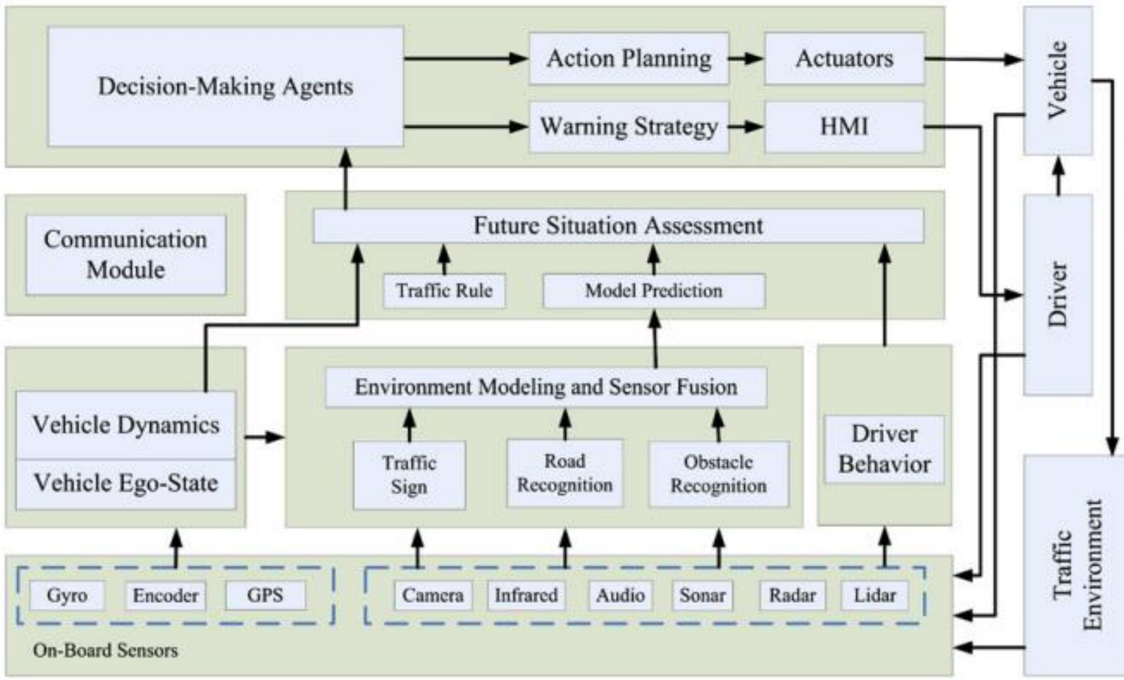

Figure 4 Sensors and data usage (Source: Cheng H. (2011). Autonomous Intelligent Vehicles: Theory, Algorithms, and Implementation (Advances in Computer Vision and Pattern Recognition). Springer.)

The automobile industry is slowly entering a new era in which cars no longer need a person to drive them. Construction of such cars is now possible due to the progress made in the fields of artificial intelligence and robotics technology which enabled development of technologies like computer vision, neural network, and others. "Nowadays brainless cars", as Lipson and Kurman (2016) refer to human-driven cars, will become obsolete, as autonomous automobiles can make commuting easier and safer than ever before.

Azmat, Schuhmayer, and Kummer suppose, that in the next decade (2020 onwards) the first wave of completely automated automobiles will be commercially available. Authors also mention advantages for people incapable or not permitted to use current human-driven cars. Level 4 automation is predicted to reduce the costs of mobility services for disabled. (2016:149)

Very similar opinion to the one voiced by Lipson and Kurman (2016), regarding the positive impact of autonomous vehicles on safety, is voiced by Broggi et. al.:

> An intelligent vehicle able to assess the driving scenario and react in case of danger would allow up to 90% of traffic accidents that are caused by human errors to be eliminated, saving human lives. (2008:1177)

According to the World Health Organization, car accidents are rated as the number one cause of death among young people (15 to 29 years old) and the number two for all age groups. Many of such accidents could have been prevented with the use of autonomous automobiles, as most of car accidents happen due to preventable human error, or the “4Ds” (drunk, drugged, drowsy, or distracted drivers). Only in the United States, self-driving cars would reduce the number of driving-related deaths approximately by 66%. (Eno Center for Transportation)

Sadly, even though the traffic-related death rate is high, vehicle safety seems to be an overlooked topic among present society. According to Lipson and Kurman, current society seems to overlook the enormous amount of deaths caused by car accidents. Roughly 1.2 million people die in car accidents every year. Lipson and Kurman compare this mortality rate to “having ten Hiroshima-scale atomic bombs go off each and every year.” (2016:14)

However, safety is not the only reason autonomous cars are receiving an increasing amount of attention these days. Another reason is the commercial aspect of such technology. While some may argue that driving is fun and people enjoy the time spent behind the wheel, research by Boston Consulting Group provides rather different perspective.

> […] A survey of more than 1,500 U.S. drivers revealed that 55 percent of respondents said they would likely, or very likely, buy a partially automated car within five years, and 44 percent said they would be very likely to buy a fully self-driving car within ten years should they become commercially available. The report predicted that the first autonomous vehicles would be available for purchase in the year 2025, and that by 2035, roughly 10 percent of new vehicles sold will be fully autonomous, representing a global market worth $38 billion. (Lipson & Kurman, 2016:12)

The demand for autonomous vehicles also varies depending on the age of drivers. While older people prefer human-driven cars, the younger generations would welcome the change. According to Lipson and Kurman, it is mainly due to the fact that younger people, also called Gen Y, regard driving simply as a mean of transport, not as an activity which they should be enjoying and cherishing. They would rather spend the time in their own way, not driving. (2016)

While there are many advantages to autonomous automobiles, such technology also has several drawbacks. Azmat mentions the reduction in taxes and insurance collection, and the liability of legislations and insurance. (2015)

Another drawback of autonomous automobiles is the self-driving carsickness. According to Diels and Bos, the likelihood of motion sickness is increased in autonomous vehicles. This is due to the lack of vehicle control which decreases the ability to anticipate the future motion of the vehicle. The likelihood of motion sickness can also be increased by rearward facing seats (2015).

Gruel W. and Stanford M. J. (2016) describe several scenarios of possible long-term effects which could arise with the usage of autonomous automobiles. One of the possible scenarios is that autonomous vehicles are not going to change the behavior of people which will result in a safer, cheaper, and less energy demanding traveling.

In another possible scenario, authors expect an increase in attractiveness of traveling by car, resulting in higher traffic volumes which might have devastating effects on land use.

The Pennsylvania Department of Transportation also mentions the need to change driver's license training to match the level of automation used, the focus of training would slowly transition from existing requirements to the interaction between drivers and vehicles, and basic familiarity with electronic assist features. Assuming that the vehicle will not require any human interaction, skill testing may become obsolete. Possible changes in age and medical condition restrictions are also mentioned. It is necessary to note that the paper assumes incorporation of automated vehicle technologies into all motor vehicles. The possibility of a new license class for drivers which choose to drive their vehicle manually is considered as well. (2014)

According to PennDOT (Pennsylvania Department of Transportation), the following factors will influence skills testing criteria while approaching fully connected and automated environment:

- Levels 2 and 3 (according to NHTSA 2013) automation will likely require a more comprehensive knowledge test. It is also proposed that the knowledge test should include basic familiarity with electronic assist packages and equipment, regulatory and liability issues, and guidance on interactions between human and vehicle.
- Standardization of electronic assist features is crucial as it would prove quite challenging to test drivers' knowledge on automated and electronic assist features if these features were to operate differently in different vehicles. The driver must be able to interact with car's features regardless of the make and model of the vehicle.
- Automated vehicles should be allowed to use all their features for the road (skills) testing purposes, as some of the features might not be easy to deactivate.

(2014)

Further on, the research is divided into two chapters according to the basic hardware/software division.

5. Technology used in autonomous automobiles

While the software of autonomous cars may differ in used algorithms, devices that provide data to the cars are very much the same. To feed the vehicle with visual data of its surroundings built-in sensors are used, namely: digital cameras, light detection and ranging (lidar), radio detection and ranging (radar), ultrasonic sensors (sonar), global positioning systems (GPS), inertial measurement unit (IMU) and high-definition digital maps. Junior (Stanford's autonomous research vehicle, a 2006 Volkswagen Passat wagon) is an example of the usage of such sensors.

> The current suite of [Junior's] sensors includes a Velodyne HDL-64E S2 rotating 64-beam LIDAR and four cameras from Point Grey: a Ladybug3 spherical camera, two color Flea2's for forward stereo vision, and a Grasshopper for high resolution forward monocular vision. Also present are 6 Bosch automotive radars covering the front, rear, and side views, two SICK LD-LRS LIDAR scanners covering the blind spots, and an Applanix POS-LV 420 inertial GPS navigation system (Jesse Levinson et. al., 2011:163).

5.1 Digital Cameras

Much like human eyes, the cameras provide the vehicle with a stream of real-time data of its surroundings, enabling the vehicle to "see". Due to the amount of irrelevant information cameras can capture, specialized digital cameras are used, analyzing recorded data in real time inside the camera's hardware. This accelerates the process and eliminates any irrelevant information. Modern cameras can also further accelerate the process by listing all objects detected. Unfortunately, the car is still missing a crucial part of perception – the depth. The problem with missing depth can be solved with the usage of several techniques. One possibility is to use multiple cameras; with the usage of two slightly different viewing angles, a 3D model construction is possible. Another technique is to project a pattern onto a scene and measure the distortion; this can be achieved with the usage of a structured-light camera and a camera-projector. Due to the amount of reflected natural light and the short reach, this technique can be successfully applied only in closed spaces (Lipson & Kurman, 2016).

5.2 Lidar

Another essential sensor is the laser radar (lidar). A laser beam is used to "read" the environment by measuring the time delay of its reflection. As the laser beam is spinning, the lidar scans the area around the vehicle, creating a precise 3D model of car's surroundings. This data is used to create a digital model called "point cloud". Unlike cameras, lidars do not capture colors and are continuously updated as the laser spins. Lidars can precisely capture only slow moving objects as the speed at which they feed car's system is slow (Lipson & Kurman, 2016). Lidars are mostly "eye-safe", as they use very little energy in the laser, commonly of the order of one microjoule.

5.3 Radar

Currently heavily used in human-driven cars for adaptive cruise control and "blind spot" tracking, radars send electromagnetic waves and detect their echoes. While using different wavelengths, radars can be set to either scan small area or, with less precision, scan a larger area in a cone in front of the device. Due to its electromagnetic nature, radars, unlike cameras, can be used in low visibility situations, electromagnetic waves also travel through thin nonconductive materials. Another information, radars obtain, is the speed of the object, which can be computed using the Doppler effect. Some radars can omit information about stationary objects, therefore reducing the information car's system must processes. While highly effective, this method can be dangerous as it may possibly overlook some obstacles (Lipson & Kurman, 2016).

5.4 Sonar

Sonars work very similarly to radars. Sonars emit sound waves (pings) and detect their echoes. The distance and speed of the object are calculated from the echo's frequency, shape, and time delay. A 20kHz frequency is commonly used, making sonar inaudible to human's hearing. Sonars work best at close range, as the energy of sound wave decays rapidly with distance traveled (Lipson & Kurman, 2016).

5.5 GPS

GPS provides information about the location of the vehicle. With the usage of triangulation, a GPS receiver calculates precise position through signals received from atomic clock carrying satellites placed on Medium Earth Orbit. Atomic clocks are synchronized with each other as well as to ground clocks. The position of each satellite is precisely known. The precision of GPS depends on the signal strength and, therefore, can differ from several meters to a kilometer. Due to this inaccuracy, GPS cannot be used solely (Lipson & Kurman, 2016).

5.6 IMU

To help with the inaccuracy of GPS, an inertial measurement unit is used. Inside IMU is an odometer, accelerometer, gyroscope, and a compass. IMU feeds the car's computer with information about its position, acceleration, orientation, and tilt. IMU uses a technique called dead reckoning which calculates car's relative position without the need of GPS signal (Lipson & Kurman, 2016).

5.7 Buses

To transfer data between car's components buses are used. A CAN bus protocol is mainly used in current human-driven vehicles, enabling data transfer of approximately 1Mbps. Buses follow standards ISO 11898 and ISO 11519 to ensure connectivity with all the components used. Transferred data is encoded, reducing the amount of bandwidth used as well as saving time. Bandwidth and reliability are the most important values of a bus; bandwidth is the maximum rate at which data can be transferred (Lipson & Kurman, 2016).

Bandwidth can differ based on the microprocessors used to encode and decode the signal, and by the number of parallel channels which are used for transfer. To ensure quick reactions of autonomous automobiles, the bus must be able to transfer rather significant amounts of data in short time, making the 1Mbps speed insufficient. As Lipson and Kurman proposed, a new standard with higher bandwidth needs to be invented, either by increasing the number of wires/parallel channels or by using a compression algorithm. A reliable bus must be secure and able to correct errors caused by noise in its network (2016). To achieve the desired reliability, error detection and correction techniques are used.

6. Software

The most difficult part of constructing an automated vehicle is the software handling the vehicle's controls. It is necessary that the software be able to analyze all the data received from sensors correctly, and adapts car's movement accordingly. Such complexity cannot be achieved with the usage of simple if-then statements. According to Cheng (2011), car's software must be capable of: road detection and tracking, vehicle detection and tracking, and multiple-sensor based multiple-object tracking.

6.1 Road detection and tracking

The autonomous car must be able to locate road boundaries without any prior knowledge of the road and to calculate the position of the car with respect to the road. Video-based road detection and tracking are becoming increasingly popular, as it brings several advantages over the active sensors. The most significant advantage is that no modification of road infrastructure is necessary while using the vision sensors. While using vision-based road detection and tracking, it is necessary to acknowledge that:

- Vision sensors are ineffective in extreme illumination conditions.
- The large amount of data provided by cameras is slowing the real-time performance. Therefore, certain computer architectures and parallel processing techniques must be used.
- Shadows might cause incorrect data analysis, as it changes road's color and structure.
- Lane markings can appear discontinuous, as obstacles and vehicles can partly block the view of the road.

To further enhance road detection and to increase the speed of data processing, four assumptions are made:

- Lane boundaries and marking edges are assumed to be continuous. It is, therefore, possible to link them, even though some are dashed.
- Processing of the whole image is unnecessary, as lane detection and tracking can focus on specific regions of interest only. Results of previously processed frames are used to predict search regions for the current image frames.
- It is assumed that the lane widths are fixed or smoothly varying, allowing for enhanced search criterion. Searching is then limited to almost parallel lane markings.

- To simplify the reconstruction of road geometry, five commonly-used road models can be applied:
    - Straight road models
    - Curved road models (Clothoid lane models)
    - Parabola models
    - Quadratic models
    - 3D road models with horizontal and vertical curvature

(Cheng, 2011)

6.2 Vehicle detection and tracking

The automated vehicle must not only be able to detect the road, to successfully replace a human driver, it must also detect vehicles around, making vehicle detection and tracking a vital part of every automated vehicle's software. Vehicle detection and tracking are already powering driver assistance systems, automated visual traffic surveillances, and adaptive cruise controls, which are used in currently used human-driven cars.

There are several possible procedures for on-road vehicle detection. One possibility is the Cheng's multi-resolution hypothesis-validation structure inspired by A. Broggio - from a 640x480 image, three regions of interest (ROI) are extracted. A near, middle, and far ROI. To increase the efficiency and to simplify this hypothesis-validation structure, three steps are to be followed:

- ROI determination: ROI candidates are generated with the usage of vanishing points of the road.
- Vehicle hypothesis generation for each ROI using horizontal and vertical edge detection: A multi-resolution vehicle hypothesis based on the preceding candidate regions is created. Afterward, hypotheses for each ROI are generated from the analysis of edge histograms and combined into a single list.
- Hypothesis Validation using Gabor features and SVM (support vector machines) classifiers: A vehicle validation using the boosted Gabor features of 9 sub-windows and the SVM classifiers is conducted. According to the judging of the classifiers, it is determined whether hypotheses represent a vehicle or a non-vehicle.

(Cheng, 2011)

6.3 Multiple-sensor based multiple-object tracking

While vision sensors obtain a massive amount of data, they cannot be the only sensors used as they depend on the weather and lighting conditions. To ensure the proper function of a automated vehicle, combinations of radar/lidar based system and vision sensors are used, as they all have complementary properties. Cheng (2011) mentions several possible strategies and describes their fundamental concepts. One of them is a strategy proposed by Shimomura, N., Fujimoto, K., Oki, and T., Muro which is described below:

> […] a strategy that distinguishes between a static object and a moving object by estimating object speed has been proposed, where both the speed and the direction of the objects and the host vehicle are used to estimate the speed. (Cheng, 2011:81)

Another mentioned approach, proposed by Kaempchen, N., Buehler, M., and Dietmayer, K., offers a strategy where "[…] three different geometric object models are designed for small objects, the objects described by a rectangular shape like that of a car, and free-form objects, respectively." (Cheng, 2011:81)

"An approach that simplifies the fusion between range and vision sensors using corresponding sets of hypothesis […]" (Cheng, 2011:81), which was suggested by Alefs, B., Schreiber, D., and Clabian, M., is also mentioned.

7. Examples of the most used sensors in automated vehicles

In this chapter, several advanced intelligent vehicle projects are presented, and their sensors are listed. From this overview, it can be clearly seen that there are several sensors which appear to be used more commonly than others. Every project attended either the Grand Challenge or the Urban Challenge held by DARPA. These projects were, at the time, some of the most advanced automated vehicles created.

7.1 Carnegie Mellon University—Boss

The winner of the 2007 Grand Challenge, Boss, was a 2007 Chevrolet Tahoe equipped with active sensors including both lidars and radars, and passive sensors, such as Point Grey high-dynamic-range camera. The computation was done by ten 2.16-GHz Core2Duo processors in a CompactPCI chassis. Each processor had a 2 GB memory and a pair of Gigabit Ethernet ports. Detailed list of the sensors used can be found in the Journal of Field Robotics (25(8), 2008):

- Applanix POS-LV 220/420 GPS/IMU (APLX)
- SICK LMS 291-S05/S14 LIDAR (LMS)
- Velodyne HDL-64 LIDAR (HDL)
- Continental ISF 172 LIDAR (ISF)
- IBEO Alasca XT LIDAR (XT)
- Continental ARS 300 Radar (ARS)
- Point Grey Firefly (PGF)

Further, a model depicting locations of sensors is presented.

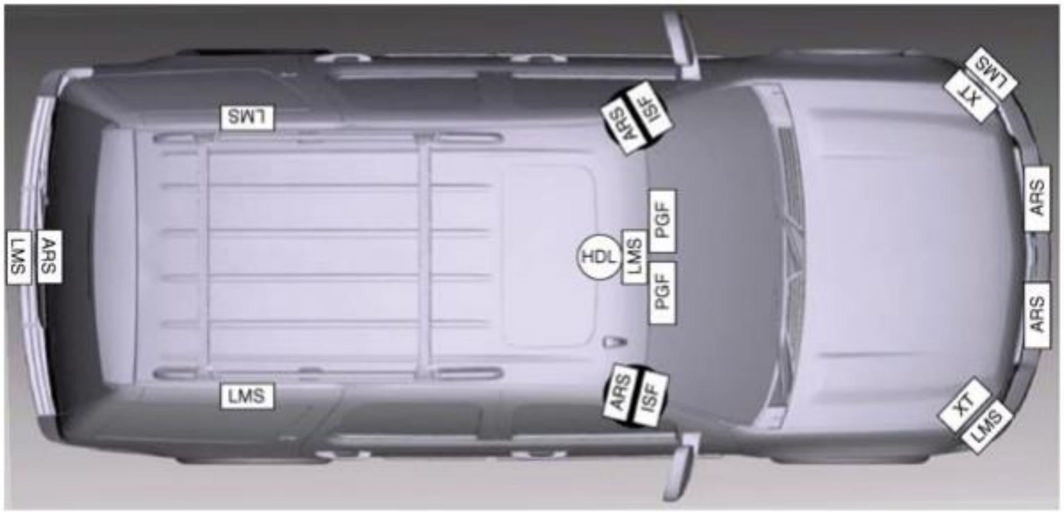

Figure 5 Boss- mounting locations of sensors (Source: Urmson Ch., et.al. (2008). Autonomous Driving in Urban Environments: Boss and the Urban Challenge. in Journal of Field Robotics 25(8), 425–466 (2008).)

7.2 Stanford University—Junior

Junior, the 2007 Urban Challenge participant, was a modified 2006 Volkswagen Passat wagon which used five laser range finders, five radars, a GPS/INS, two Intel quad core computer systems, and a custom drive-by-wire interface. Such equipment enabled the vehicle to detect an obstacle which is up to 120 m away (Cheng, 2011).

Montemerlo M., et.al. (2008) provides a list of sensors used:

- Applanix POS-LV 420 GPS/IMU
- Two SICK LMS 291-S14 LIDAR
- RIEGL LMS-Q120 Laser sensor
- Velodyne HDL-64E LIDAR
- Two SICK LDLRS
- Two IBEO Alasca XT LIDAR
- Five BOSCH LRR2 Long Range Radar

The paper also provides a picture of the vehicle depicting placement of sensors.

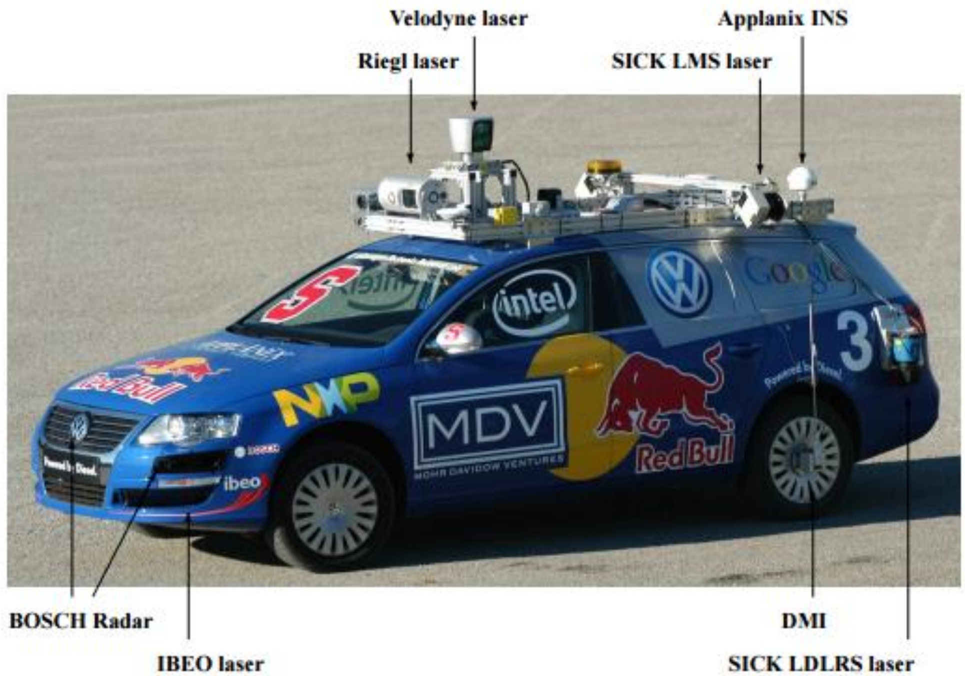

Figure 6 Junior- mounting locations of sensors (Source: Montemerlo M., et.al. (2008). Junior: The Stanford Entry in the Urban Challenge. in Journal of Field Robotics - Special Issue on the 2007 DARPA Urban Challenge, Part II 25(9), 569–597 (2008).)

7.3 Virginia Polytechnic Institute and State University—Odin

The 2004 DARPA Grand Challenge participant, Odin, was a modified 2005 Hybrid Ford Escape equipped with two, two quad-core processors, HP servers (Cheng, 2011). Due to the modular system used, the project took only 14 months to complete. The car was equipped with:

- Two IBEO Alasca XT Fusion LIDAR
- IBEO Alasca A0
- Four SICK LMS 291 LIDAR
- NovAtel GPS/INS

(Bacha A., et.al., 2008)

Once again, positions of sensors are depicted in the following figure.

Figure 7 Odin- mounting locations of sensors (Source: Bacha A., et.al. (2008). Odin: Team VictorTango's Entry in the DARPA Urban Challenge. in Journal of Field Robotics 25(8), 467–492 (2008).)

7.4 Cornell University—Skynet

Skynet was an autonomous 2007 Chevrolet Tahoe which competed in the 2007 DARPA Urban Challenge. The reason behind choosing a full-size SUV was the amount of room available, and, the fact, that the chassis was more likely to endure any low-speed collisions. The 2007 Chevrolet Tahoe was also equipped with many sensors which were easy to access, making the model even a better choice. Computing was done by 17 computers, each with dual-core Pentium Mobile laptop processor with frequencies from 1.66 to 2.13 GHz. Obstacle detection system used these sensors:

- Three IBEO Alasca XT Fusion LIDAR
- Two SICK LMS 291 LIDAR
- SICK LMS 290 LIDAR
- Velodyne HDL-64E LIDAR
- Eight Delphi FLR RADAR
- Unibrain Fire-I 520 b

(Miller I., et.al., 2008)

To better understand the car's system its architecture can be found bellow.

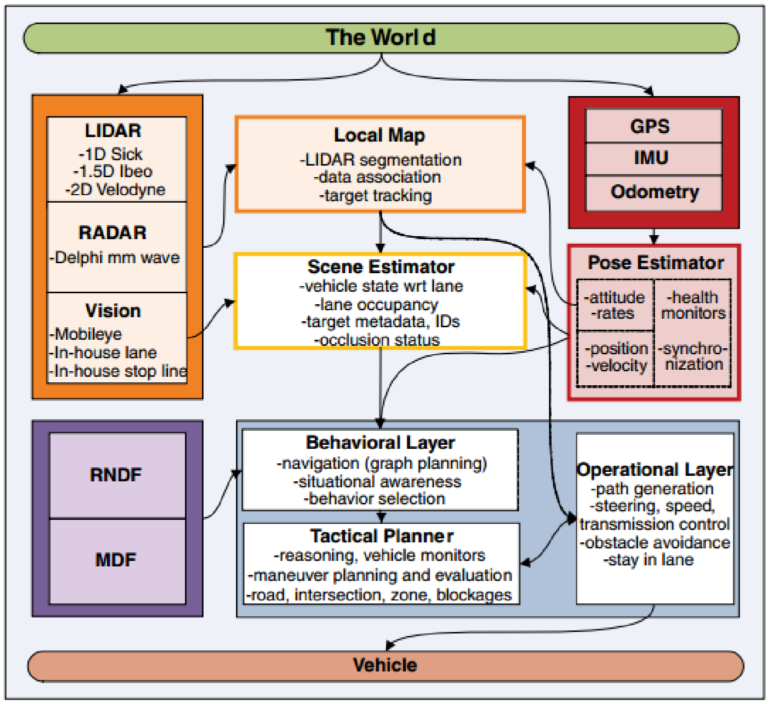

Figure 8 Skynet-System architecture (Source: Miller I., et.al. (2008). Team Cornell's Skynet: Robust Perception and Planning in an Urban Environment. in Journal of Field Robotics 25(8), 493–527 (2008).)

As can be seen from the figure, the vehicle used two groups of sensors to perceive the world. One group dealt with the vehicle itself and involved GPS receivers, IMU unit, and vehicle odometry. Data from these sensors was being fused in real time in the Pose estimator, providing information regarding the location of the vehicle. The second group dealt with detection of external objects and the road, using a combination of lidars, radars, and vision.

The "local map" used information provided by the lidar, radar, and vision data, accompanied with the data provided by "pose estimator" to initialize, locate, and track both static and dynamic obstacles. This provided the vehicle with a rather simplified map of obstacles relative to Skynet. This data, along with some additional information from vision sensors and the "pose estimator", is was further used in the "scene estimator" to develop key statistics about the vehicle and obstacles for the intelligent planner.

RNDF (route network definition file) and MDF (mission data file) were crucial files for the successful operation of the vehicle, these files contained, among other information, GPS waypoints and speed limits. This data was further used in the intelligent planning of three layers: behavioral, tactical, and operational.

7.5 University of Pennsylvania and Lehigh University—Little Ben

Little Ben, the vehicle of the Ben Franklin Racing Team, was a modified 2006 hybrid Toyota Prius which competed in the 2007 DARPA Urban Challenge. Unlike the Skynet, Little Ben was not an SUV, the reason behind choosing a smaller vehicle is that the compact size of the vehicle made many driving maneuvers easier. Seven Mac Minis with Core 2 Duo were used. The car was equipped with several sensors, namely:

- Three SICK LMS 291 LIDAR
- Two SICK LDLRS
- Velodyne HDL-64E LIDAR
- Three Hokuyo URG-04LX LIDAR
- OxTS Pose System

(Bohren J., et.al., 2008)

7.6 Oshkosh Truck Corporation—TerraMax

Unlike projects mentioned before, TerraMax, a 1999 MK23 Standard Cargo Truck which participated in the 2005 DARPA Grand Challenge, was based on a Medium Tactical Vehicle Replacement defense truck platform designed to match the needs of US Marine Corps. According to Cheng (2011), dimensions of the vehicle were the most important features of this project. The TerraMax weighted around 30000 pounds, was 27 feet long, and 8 feet high. Sensors used by the vehicle were:

- Three SICK LMS 291 LIDAR
- Trimble AgGPS132 GPS
- Two OxTS RT3100 GPS/IMU

- Three IBEO Alasca LIDAR
- Parma Vision System

(Team TerraMax, 2005)

Figure 9 TerraMax (Source: Team TerraMax. (2005). DARPA Grand Challenge 2005.)

8. Deep learning

Deep learning is an essential part of artificial intelligence (AI), enabling human-like recognition abilities which are crucial for the function of automated vehicles. The biggest problem of older AIs was the inability to recognize objects captured in an unusual context or differing levels of light. Deep learning can be used to automatize artificial perception and response as well as to improve the language comprehension of speech-recognition software. Because deep learning network is data driven, digital cameras and modern computers help significantly with its development, as they create a massive amount of data which can be used for training.

Deep learning, unlike logic-driven software, is based on neural networks, which simulate human brain functions. The brain is composed of cells called neurons which, when activated by a certain stimulus, pass signals to one another. Neurons activate only to the appropriate stimulus while ignoring all irrelevant stimuli. This process repeats itself until a neuron at the highest executive level is activated. Connections between neurons either strengthens or weakens (based on positive or negative experiences), this process is called synaptic plasticity and presents a fundamental concept of all neural networks.

When building an artificial neural network, it is necessary that:

- Neurons are connected in a decentralized network.
- Strengthening and weakening of connections between individual neurons is increasing the amount of data learned.
- Particular threshold must be reached before the neuron passes a signal along.

(Lipson & Kurman, 2016)

In 1957, one of the first artificial neural networks was built. Consisting of six racks of electronic equipment with a few hundred connections, creating a single layer of eight neurons. This network "learned" how to recognize several simple shapes without any hard-coded information. Making it "the great, great grandparent of modern deep learning neural networks" (Lipson & Kurman, 2016:202). At present, deep-learning networks incorporate over 150 layers of artificial neurons with about billion connections.

Currently, deep learning is used not only in the automotive industry; object detection, localization, and classification, speech recognition, transcription, as well as natural language understanding, are all areas where deep learning plays a crucial part. In automated vehicles, an AI is for example used in pedestrian detection, traffic sight recognition, vehicle recognition, and similar tasks.

To create a working AI capable of object recognition, the AI must be first fed training data - images with objects along with the information on the object. The training data is processed by the AI, and the results are then compared with the information supplied in the training data. If the results do not match the information (labels), the image recognition is repeated, this way, the AI can "learn" all the features necessary for successful recognition, and the model is refined. The amount of training data is commonly between ten to a hundred million images. To train the AI, graphics processing units (GPUs) are used, as they achieve higher efficiency than central processing units (CPUs) due to their highly effective parallel data processing (Dettmers T., 2015).

NVIDIA, a leading company in the field of graphics processing units, released several computing platforms capable of computer vision and end-to-end HD mapping. These platforms are developed specially to suit the needs of companies involved in the development of automated vehicles, as they use convolutional neural networks to "learn" how to operate the vehicle.

While this is a complex and fascinating technology worthy of more than few pages, only a brief introduction of deep learning and artificial neural networks was possible due to the nature of this thesis and its restrictions in length.

9. Moral decisions

In a case of malfunction, the AI must be able to choose a lesser evil in life-threatening situations. Many types of research are being conducted on this topic, as it is quite a controversial one. Moral decisions are the most intriguing part of the topic of automated vehicles as they combine software engineering and social sciences. Questions concerning the safety of the driver, passengers, and people, which could potentially be hurt, need to be addressed before autonomous cars will be able to cruise the road. This presents a complex problem, as there are many opinions on the matter. Perhaps, the car should have a self-preservative behavior.

This problem can be presented as a modified version of “The Trolley Problem” conceived by Philippa Foot in 1967. “A driver of a runaway tram can steer only from one narrow track on to another; five men are working on one track and one man on the other; anyone on the track he enters is bound be killed.” (Lipson & Kurman, 2016:250)

While dealing with this problem, it is also important to keep in mind that there are three potentially incompatible objectives which must be accomplished. The AI must be consistent in its decisions; the decisions must not cause public outrage, and not discourage the possible buyers (Rahwan I., Shariff A., & Bonnefon J., 2016).

Moral Machine, a platform created by MIT Media Lab, deals with “The Trolley Problem” further. It is a survey which enables the public to express their opinion on what the automated vehicle should do in a case of moral dilemma. The platform provides randomly generated scenarios in which the user must choose between two possible outcomes resulting in tradeoffs. As the user selects one of the possibilities, the outcome is archived and available for further analysis. The data collected is of high value to manufacturers of automated vehicles.

An example of such randomly generated scenario can be found in the figure bellow.

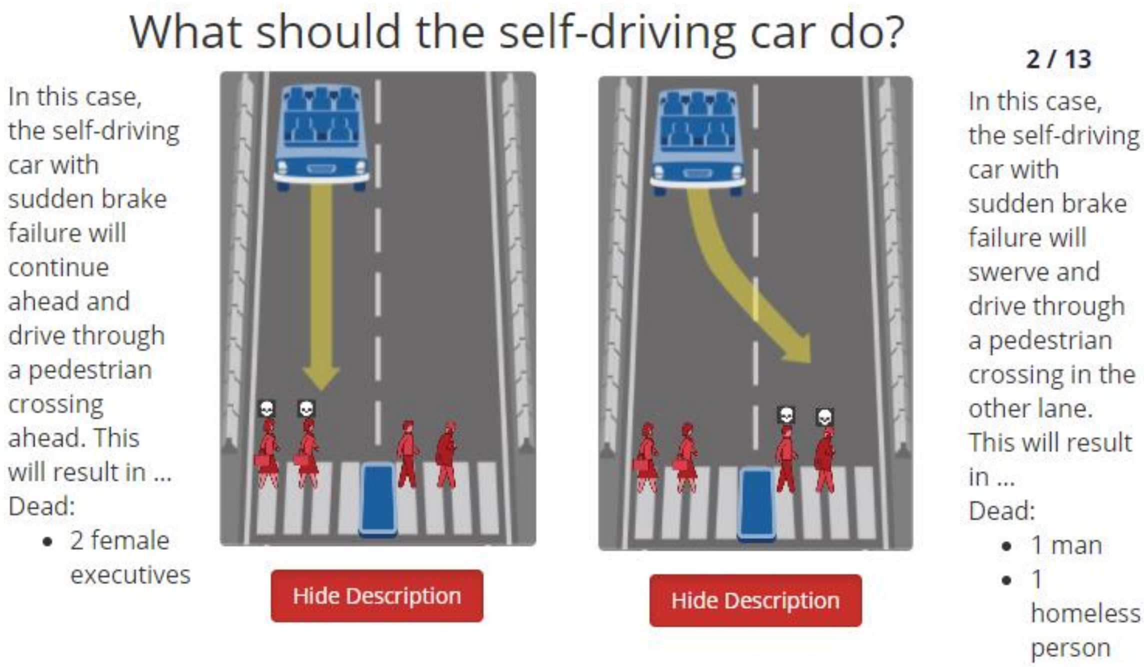

Figure 10 Moral Machine (Source: http://moralmachine.mit.edu/)

One of the possible attitudes towards the moral dilemma of automated vehicles is the utilitarian moral doctrine, an ethical theory which states that the best action is the one maximizing utility. In our case, it is an action resulting in a smaller number of harmed people. Such attitude raises several problems, as there are cases where the automated vehicle would be forced to harm its crew, discouraging buyers which prefer the safety of the vehicle. One of the important factors is also whether some of the crew of the car is family members, as it significantly changes people's attitude towards this dilemma. Another factor is the age of the possible victims. Parents prefer to reduce the risk of harm to their children while increasing risks to others (Rahwan I., Shariff A., & Bonnefon J., 2016).

While results of the Moral Machine show that people prefer the utilitarian approach, a paradox is also created, people are less likely to buy automated vehicles following this ethical theory. This type of situation is called a "social dilemma", in this particular case it is a modification of "tragedy of the commons", which first appeared in a 1833 pamphlet by English economist William Forster Lloyd and states as follows:

> If a person puts more cattle into his own field, the amount of the subsistence which they consume is all deducted from that which was at the command, of his original stock; and if, before, there was no more than a sufficiency of pasture, he reaps no benefit from the additional cattle, what is gained in one way being lost in another. But if he puts more cattle on a common, the food which they consume forms a deduction which is shared between all the cattle, as well that of others as his own, in proportion to their number, and only a small part of it is taken from his own cattle (Lloyd F. W., 1833).

According to Iyad Rahwan: "[…] Car manufacturers may simply program cars that will maximize safety for their clients, and those cars may learn, automatically, on their own, that doing so requires slightly increasing risk for pedestrians." Rahwan refers to this as the "Tragedy of the algorithmic Commons" (2016).

10. The future

While some might say, that the arrival of autonomous automobiles will be a significant step forward in the motor industry, it is also necessary to consider the risks that might arise.

Autonomous automobiles will store a massive amount of personal data, which could compromise personal privacy. The information about the whereabouts of the driver will always be recorded, so will the information about the car's surrounding, raising the possibility of selling such personal information to marketing companies, resulting in a targeted advertising based on locations visited.

Another field which would be altered by autonomous vehicles is the high-definition digital maps market; new business opportunities would be created. According to Lipson and Kurman (2016), creation and renewal of such maps are a costly matter, for these reasons, the digital map marketplace is in the future likely to be controlled by private sector companies. However, the need for high-definition digital maps will not last long.

> […] as digital cameras and deep-learning software continue to improve, the balance of reliance on a car's operating system will shift from stored map data to real-time scene recognition. Driverless cars' maps will become a less crucial component of a car's visual intelligence (Lipson & Kurman, 2016:239).

To reduce risks which might arise with the usage of automated vehicles, PennDOT (Pennsylvanian Department of Transportation) proposed in the year 2014 a timeline of recommended future actions. The timeframe is divided into three main parts, first part begins in the year 2014 and ends 2020, the second part deals with 2021 to 2030, and the third part concerns 2031 to 2040. The timeframe itself can be found bellow.

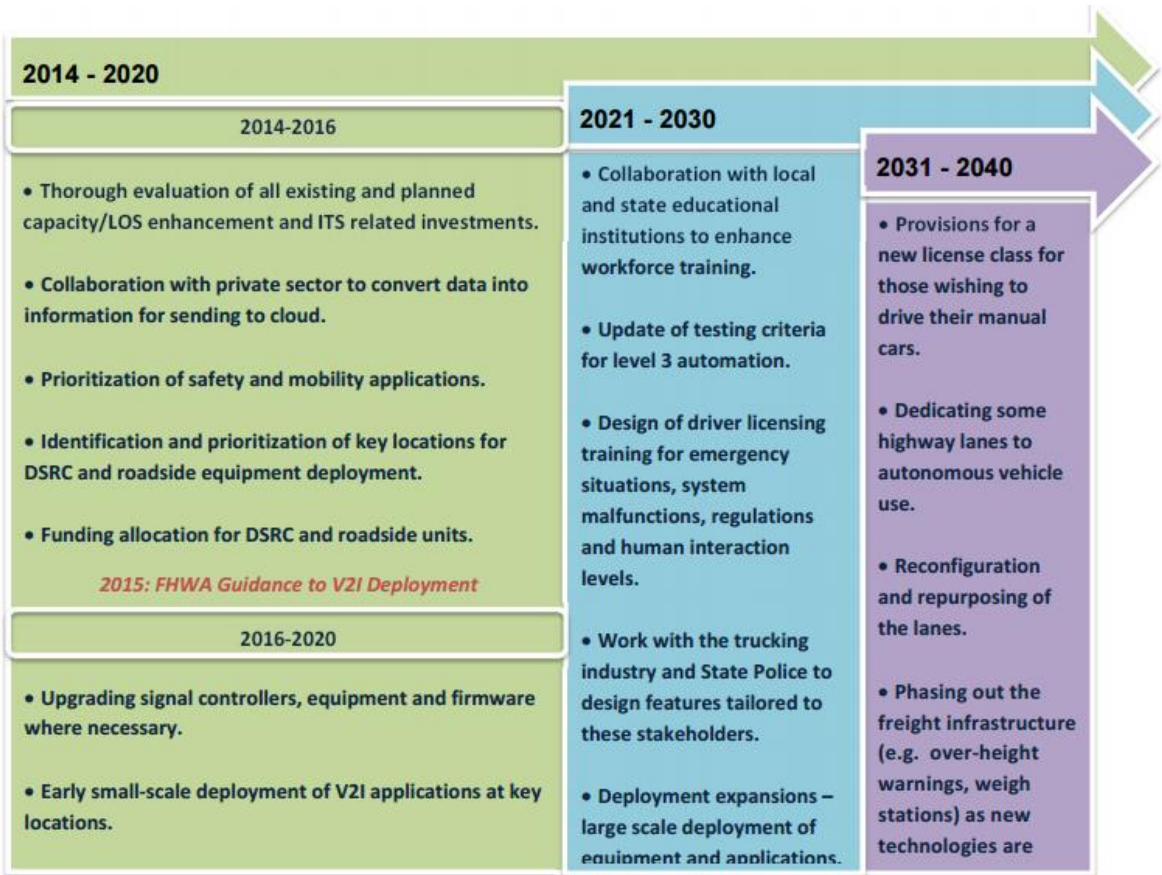

Figure 11 PennDOT recommended timeframe (Source: Hendrickson Ch., et.al. (2014). Connected and Autonomous Vehicles 2040 Vision.)

11. Conclusion

In this Bachelor's thesis, I have described what constitutes an automated vehicle, while providing comparisons between the several approaches cited, and introduced possible levels of vehicle automation by The National Highway Traffic Safety Administration, the SAE International, and the German BASt-project, three acknowledged organizations in the field of automated vehicles. A brief history of the development of automated vehicles and several historical examples are provided. The main part of this thesis is a literature search on fully-automated vehicles which introduces the sources used and presents the most relevant ideas in a clear and structured manner. I have also described the hardware used in autonomous vehicles, namely: digital cameras, lidar, radar, sonar, GPS, IMU, and buses. The usage of such hardware is further depicted on several vehicles which competed either in the Grand Challenge or the Urban Challenge held by DARPA. In the chapter "Software" three essential capabilities of the automated vehicle's software are described, these essential capabilities are road detection and tracking, vehicle detection and tracking, and multiple-sensor based multiple-object tracking. Deep learning, a crucial technology used in automated vehicles, is also briefly mentioned in this thesis. Later on, moral decisions related to the topic of automated vehicles and the Moral Machine, a survey platform by MIT, are introduced. In the last chapter, I have selected several examples of possible risks and a brief overview of possible legal changes related to automated vehicles.

Due to the lately increased attention towards the topic of automated vehicles, there is no shortage of literature describing this fascinating technology. Sadly, one must be cautious when searching for relevant publications, as there are many approaches of rather experimental nature which might not be suited for practical use. Another challenge while selecting a relevant publication is the lack of unified laws and other legal aspects. While there are some pioneers in the field, like the Pennsylvania Department of Transportation, it is not yet clear, whether such laws will be accepted on a larger scale.

Automated vehicles combine some of the most advanced software with several, both "new" and "old", hardware sensors. Examples of "old" sensors are lidars, radars, and sonars. These devices use relatively simple in principle, some known for more than half a century. To process the information acquired by sensors, modern computational systems are used. While the examples provided above use mostly CPUs, it is possible, and perhaps even preferable, to use GPUs as they achieve higher efficiencies at parallel data processing. NVIDIA, a leading company in the field of GPUs, provides several platforms to aid the companies interested in the development of automated vehicles. These platforms are capable of computer vision and end-to-end HD mapping - technologies which use the deep learning.

Perhaps the most intriguing part of the topic of automated vehicles are the moral decisions as they combine software engineering and social sciences. The vehicle must be capable of “human-like reasoning” in case of an accident. While there are several possible approaches to this problem, the applied one must be perceived by the public as the “morally correct” one, which, at times, may prove to be very challenging. This makes the development of such software a difficult and time-consuming process. To aid developers, several surveys were conducted. The Moral Machine, introduced in chapter 9, is one of such surveys.

Overall, automated vehicles could be perceived as “the next big thing” because of the many industry fields influenced by the arrival of such technology. From changes in transportation, both private and public, to advances in infrastructure, the possible reach of such technology is enormous. Sadly, there are still many unsolved legal questions which might hinder the arrival of automated vehicles.

12. List of figures

13. List of references

- Azmat M. (2015). Future Scenario: Self Driving Cars - The future has already begun. Conference: iinovationsfördernder öffentlicher Beschaffung – 4.0 Platform innovation to e-mobility, Vienna, Volume: I. Retrieved November 1, 2016 from https://www.researchgate.net/publication/278329250_Future_Scenario_Self_Driving_Cars_-_The_future_has_already_begun

- Azmat M., Schuhmayer C., & Kummer S. (2016). Innovation in mobility: Austrian Expert's Perspective on the future of urban mobility with self-driving cars. Conference: Innovation Arabia: Quality and Business Management Conference (Business Innovation – Imperative for knowledge Economy), At Dubai, UAE, Volume: 9. Retrieved November 1, 2016 from https://www.researchgate.net/publication/303190703_Innovation_in_mobility_Austrian_Expert%27s_Perspective_on_the_future_of_urban_mobility_with_self-driving_cars

- Bacha A., et.al. (2008). Odin: Team VictorTango's Entry in the DARPA Urban Challenge. in Journal of Field Robotics 25(8), 467–492 (2008). Retrieved March 1, 2017 from https://ai2-s2-pdfs.s3.amazonaws.com/aaea/a58bedf6fa9b42878bf5914f55f48cf26209.pdf

- Bohren J., et.al. (2008). Little Ben: The Ben Franklin Racing Team's Entry in the 2007 DARPA Urban Challenge. in Journal of Field Robotics 25(9), 598–614 (2008). Retrieved March 1, 2017 from http://www.willowgarage.com/sites/default/files/J.%20Field%20Robot%202008%20-%20Little%20Ben.pdf

- Broggi A., et. al. (2008). Intelligent Vehicles. Springer Handbook of Robotics. pp.1175-1198. Retrieved November 1, 2016 from https://www.researchgate.net/publication/225898443_Intelligent_Vehicles

- Cheng H. (2011). Autonomous Intelligent Vehicles: Theory, Algorithms, and Implementation (Advances in Computer Vision and Pattern Recognition). Springer.

- Dettmers T. (2015). Deep Learning in a Nutshell: Core Concepts. Retrieved March 1, 2017 from https://devblogs.nvidia.com/parallelforall/deep-learning-nutshell-core-concepts/

- Diels C., and Bos E. J. (2015). Design guidelines to minimise self-driving carsickness. Conference: Automated Vehicles Symposium 2015, At Ann Arbor, Michigan. Retrieved November 1, 2016 from https://www.researchgate.net/publication/280307548_Design_guidelines_to_minimise_self-driving_carsickness

- Fraichard T. (2014). Will the Driver Seat Ever Be Empty? Retrieved November 1, 2016 from https://www.researchgate.net/publication/261213842_Will_the_Driver_Seat_Ever_Be_Empty

- Gruel W., and Stanford M. J. (2016). Assessing the Long-term Effects of Autonomous Vehicles: A Speculative Approach. Transportation Research Procedia, December 2016 (13:18-29). Retrieved December 10, 2016 from https://www.researchgate.net/publication/304001967_Assessing_the_Long-term_Effects_of_Autonomous_Vehicles_A_Speculative_Approach

- Hendrickson Ch., et.al. (2014). Connected and Autonomous Vehicles 2040 Vision. Retrieved March 1, 2017 from http://www.dot7.state.pa.us/BPR_PDF_FILES/Documents/Research/Complete%20

Projects/Planning/CMU%20WO%20001%20-%20Connected%20and%20Autonomous%20Vehicles%202040%20Vision%20-%20Final%20Report.pdf

- Lee D. D. (2007). 2007 DARPA Urban Challenge The Ben Franklin Racing Team Team B156 Technical Paper. Retrieved March 1, 2017 from http://archive.darpa.mil/grandchallenge/TechPapers/Ben_Franklin_Driving.pdf
- Levinson J., et.al. (2011). Towards fully autonomous driving: Systems and algorithms. Conference: Intelligent Vehicles Symposium (IV). Retrieved November 1, 2016 from https://www.researchgate.net/publication/224244859_Towards_fully_autonomous_driving_Systems_and_algorithms

- Lipson H., and Kurman M. (2016). Driverless Intelligent Cars and the Road Ahead. MIT Press.

- Lloyd F. W. (1833). Two Lectures on the Checks to Population. in Population and Development Review 6(3), 473-496 (1980). Retrieved March 1, 2017 from https://www.jstor.org/stable/1972412?seq=1#page_scan_tab_contents

- Miller I., et.al. (2008). Team Cornell's Skynet: Robust Perception and Planning in an Urban Environment. in Journal of Field Robotics 25(8), 493–527 (2008). Retrieved March 1, 2017 from https://pdfs.semanticscholar.org/c975/6eb2f948d05f5a28105b76d376b6c25c4a48.pdf

- Montemerlo M., et.al. (2008). Junior: The Stanford Entry in the Urban Challenge. in Journal of Field Robotics - Special Issue on the 2007 DARPA Urban Challenge, Part II 25(9), 569–597 (2008). Retrieved March 1, 2017 from http://robots.stanford.edu/papers/junior08.pdf

- National Highway Traffic Safety Administration. (2013). Preliminary Statement of Policy Concerning Automated Vehicles. Retrieved November 1, 2016 from http://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf

- Rahwan I., Shariff A., & Bonnefon J. (2016). The Social Dilemma of Autonomous Vehicles. Retrieved March 1, 2017 from https://www.researchgate.net/publication/301293464_The_Social_Dilemma_of_Autonomous_Vehicles
- SAE International. (2014). Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems. Retrieved March 1, 2017 from http://standards.sae.org/j3016_201401/

- SAE International. (2016). Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. Retrieved March 1, 2017 from http://standards.sae.org/j3016_201609/

- Team TerraMax. (2005). DARPA Grand Challenge 2005. Retrieved March 1, 2017 from http://archive.darpa.mil/grandchallenge05/TechPapers/TeamTerraMax.pdf

- The Federal Highway Research Institute. (2012). Legal consequences of an increase in vehicle automation. Retrieved March 1, 2017 from http://bast.opus.hbz-nrw.de/volltexte/2013/723/pdf/Legal_consequences_of_an_increase_in_vehicle_automation.pdf

- Urmson Ch., et.al. (2008). Autonomous Driving in Urban Environments: Boss and the Urban Challenge. in Journal of Field Robotics 25(8), 425–466 (2008). Retrieved March 1, 2017 from http://www.fieldrobotics.org/users/alonzo/pubs/papers/JFR_08_Boss.pdf