Autonomous Vehicle: From a Cognitive Perspective

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ABSTRACT: To make an autonomous vehicle more cognitive, it needs the implementation of advanced cognition theories and AI theories. In this paper, we firstly make a brief overview of current advanced theories of cognition in Psychology and Computer Science. Then we mainly analyze and compare the architectures of the autonomous vehicles winning DARPA Challenges. The layout of sensors and the design of software system are critical to the winning autonomous vehicles. However, there's no paper published to compare the different architectures of autonomous vehicles recently. By comparing different autonomous vehicles, we find some common points shared among them and more differences due to the various sensors layouts and the difference among cognition architectures, which could give some valuable directions to the researchers in both computer science and cognition fields.

1 INTRODUCTION

An autonomous vehicle (AV) or self-driving car is a vehicle which mounts with sensors, such as cameras, LIDARs, ultrasonic sensors, microwave sensors, GPS, wheel odometers and magnetic compasses, etc., to sense their surroundings and get useful information about the road, and the position of the vehicle for autonomously safely driving (Shuming Tang 2010).The promotion of AVs will be a good potential solution to the traffic problems faced to the whole world currently, such as traffic jams, traffic accidents, energy consumption, and so on. In China, the famous event "Future Challenge"(FC) , which is supported by China NSFC, has been held for consecutive 5 years (2009~2013). The event is partly intended to promote the development of AV in China, and we can see a great progress in AV development over the past 5 years.

There are a lot of papers published on AVs, some of which show how to create an AV(Thrun, Sebastian, et al. 2006, Leonard, John, et al. 2008, Montemerlo, Michael, et al. 2008, Urmson, Chris, et al. 2009), while most of which focus on partial but detailed technologies in an AV (Chaturvedi, Pooja, et al.2001, Discant, Anca, et al. 2007, Enzweiler, Markus, et al.2009, Darms, Michael, et al. 2008, Mogelmose, Andres, et al. 2012a, Mogelmose,Andres, et al. 2012b, Mathias, Markus, et al. 2013). In other words, to our best knowledge, there is no paper published to compare the different architectures of autonomous vehicles recently and are few papers published on autonomous vehicle in cognition topics.

We try to solve the two problems presented above. In this paper, we for the first time combine autonomous vehicle architectures with cognition theories and compare different architectures of autonomous vehicles. (Fig.1 shows the cognition architecture of AVs discussed in the following sections.) In other words, our contributions are : (1) comparing different architectures of autonomous vehicles; (2) combining cognition theories with autonomous vehicle technology towards a more cognitive autonomous vehicle system; (3) giving some possible research directions to make a more intelligent autonomous vehicle.

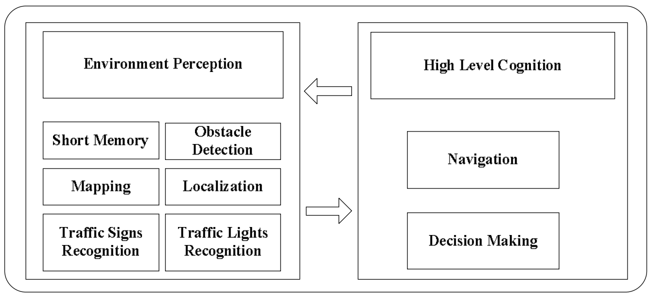

Figure 1. Cognition architecture of autonomous vehicle

In the following part of this paper, there are five sections. Chapter 2 is a brief on definitions and main research points of cognition in psychology and computer science. Chapter 3 ~ 5 mainly compare the different architectures of autonomous vehicles won the DARPA Challenges under the embodied cognition theory. Finally, in Chapter 6, we make a conclusion with giving some valuable research directions in both autonomous vehicle and cognition.

2 COGNITION

Cognition can be briefly defined as acquisition of knowledge (Reed, Stefen K. 2007). However, various disciplines hold different views about intrinsic definition of cognition.

In Psychology, researches of cognition mainly focused on pattern recognition, attention, memory, vision image, language, problem solving and decision making. They consider vision, audition, tactile, olfaction and gustation as low level perception of cognition and categorize language understanding, problem solving and decision making into high level cognition. The views like how to bridge low level perception with high level cognition and how human intelligence forms lead to different research topics in Psychology. In this paper we classify the different research topics into three categories chronologically. They are: Cognitivism, Connectionism and Embodied Cognition (Anderson, Michael L. 2003). Cognitivism is a theoretical framework for understanding the mankind mind. It was a response to behaviorism .While the main research point in Behaviorism are focused on the corresponding external relationships between perception and action, cognitivists tries to disclose the internal relations between perception and action. Cognitivism believes that symbol computing is the core of intelligence. Connectionism believes that numerous connected units network is the basis of generating intelligence. It tries to use artificial neural network to interpret the intelligence of human. The network is formed by connecting weighted nodes hierarchically. The weights represent the mutual influences between synapses in the brain (Zhongzhi Shi 2008). Embodied cognition was developed when traditional symbol operation based cognition theories were questioned by phenomena such as Chinese room(Barsalou, Lawrence W. 2010). In Embodied cognition theory, cognition is not about intellectual demonstration but more related to the body and its surrounding physical environment (Anderson, Michael L. 2003, Mahon, Bradford Z. , et al. 2008). Intelligence then can be described as the sum of the physical experience the body obtains when it interact with the environment, that is, intelligence is related to the interaction between body and the environment. Embodied cognition gives a framework on bridging the low level perception and high level cognition (Mahon, Bradford Z., et al. 2008).

The research of cognition in Computer Science is mainly focused in the field of Artificial Intelligence (AI), where the researches on cognition are to improve the intelligence of machine. According to (Stuart Russell & Peter Norvig, 2009), we can classify the definitions of cognition in AI into four categories: (1) thinking like a human; (2) acting like a human; (3) thinking reasonably; and (4) acting reasonably. That computer programs may think like a human requires us understand how human thinks firstly. We should have a whole understanding of the inner progress of mind. Being acting like a human, the computer programs should be with the ability of automated reasoning, machine learning, computer vision, and so on. They also need to pass the Turing Test. To think reasonably requires computer programmers first find the "Law of Thought" proposed by the ancient Greek philosopher Aristotle and others. The law tries to find "the right way of thinking". Acting reasonably requires computer programs can operate automatically, percept environment, adapt to the change of environment, create and pursue goals, and make the best decision under uncertain situations. Currently, the major researches in Computer Science focus on the imitation of human mind by creating intelligent software and hardware, not just to understand it. For example, a hidden Markov model obtained good results in speech recognition, however, no scientific experiment can show human also recognize speech in this way (Stuart Russell & Peter Norvig, 2009). AI also combines the methods used in symbolism and connectionism, using big data to research and improve machine intelligence.

3 THE ARCHITECTURE OF AUTONOMOUS VEHICLE

Shuming Tang (2011) presented a view on the cognition system of an AV, where it divided the cognition of an AV into three stages: perception, cognition and decision, which was different from the view in this paper. According to Embodied Cognition theory, the cognition system of an autonomous vehicle can be divided into two parts: environment perception and driving decision. The two parts in the vehicle interact with each other to ensure the vehicle move to the destination safely. The two parts correspond to the low level perception and high level cognition separately, where environment perception via sensors belongs to the low level cognition, navigating and decision making belong to the high level cognition. In the following sections, we mainly survey the architecture of an AV body, which composes of hardware and software, and see how it interacts to the environment to drive smartly.

3.1 *Hardware*

Since the DARPA Challenges remain the largest demonstration of autonomous vehicle technology to date (Levinson, Jesse, et al. 2011), we mainly compare the hardware and software architecture of AVs attending the DARPA Challenges. The hardware specifications are similar among these cars. The basic requirements of an AV in hardware include: (1) enough space for the sensors and computers; (2) electronically actuated throttle, brake, shifter, and steering system (Levinson, Jesse, et al. 2011); (3) various sensors such as Velodyne, SICK, camera, etc. (4) Power unit(s) for the equipments and sensors. By surveying the teams won the DARPA Challenges, we find that the most generally used sensors were: GPS/INS and SICK. Other popular sensors were: Velodyne, radar and camera. Although they used the same kind of sensors, the layout of these sensors differed much among the teams (Montemerlo, Michael, et al. 2008, Urmson, Chris, et al. 2009, Bacha, Andrew, et al.2008). In Chapter 4, we can see the impacts of different layout to the algorithm when the same problems were tackled. The specification of computers in the vehicle is not a problem, because volume and price are lower and lower while their computing power are higher and higher year by year.

3.2 *Software*

The low-level software configuration involves operating system selection, communication methods between different processing modules, and so on . This paper mainly focuses on the cognitive modules in the vehicle. For a more in-depth low-level software configurations, please refer to (Thrun, Sebastian, et al. 2006, Leonard, John, et al. 2008, Montemerlo, Michael, et al. 2008).

According to Embodied Cognition theory and the definition of intelligence as acting reasonably in AI, an autonomous vehicle, moving in an urban environment or off-road environment should have the ability to sensor the environment and then make an optimal output for the motion system. Figure 2 describes the working flow of most advanced autonomous vehicles surveyed in this paper. Firstly, the low level environment perception modules output the information of environment and the vehicle's pose to high level navigation and decision making module. Then the high level cognition module generates the basic vehicle control information such as, speed, direction, acceleration speed, etc., utilizing the information of destination, map or routine and the outputs from low level perception processing modules. After the execution of the commands from high level cognition, the environment faced by the AV changes, the environment perception modules then output the latest information to navigation and decision making module, and a cognition loop forms.

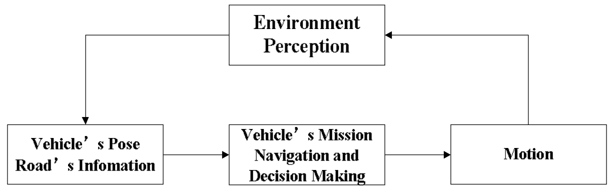

Figure2.Working flow of the autonomous vehicle

4 PERCEPTION MODULES

After surveying the basic architecture of an autonomous vehicle, now we discuss into more detailed environment perception modules by comparing the vehicles attending 2005 Grand Challenge and 2007 Urban Challenge. As pointed out above, the perception modules sense the surroundings and generate useful information for high level cognition. The perception modules include short memory systems, obstacle detection, localization and mapping, and some necessary but not discussed modules in the vehicles we surveyed, such as traffic lights detection, traffic sign detection and recognition.

4.1 *Short Memory Systems*

A Short Memory System of a vehicle can be analogical to the short memory system of a human brain. It helps the vehicle understand its surrounding environment and provides enough information for its decision making module. The remarkable characters of a short memory system include containing a wealth of information and approximately updating its real-time information. Almost every team had their own short memory system even they are in different names, Stanley and Boss called it Grid Map, Junior called it 2-D Map, Odin called it World Frame and Talos named it Local Frame. The main information contained in the short memory system includes position of static obstacles, trajectory and position of the moving obstacles and curbs position, etc.

4.2 *Obstacle Detection*

Detecting and avoiding collision to obstacles is a major mission when an autonomous vehicle moving on the road. There are two types of obstacles in the driving environment. One is static obstacles like trees and buildings and the other is dynamic obstacles like moving cars and pedestrians.

Before we survey the detailed methods used to detect obstacles, we have a brief overview of the sensors used in those methods. According to Discant, Anca, et al. (2007), the sensors used to detect obstacles can be divided into two categories: active sensors and passive sensors. While active sensors like LIDARs provide their own energy for illumination, passive sensors like cameras can only work when natural energy is available. Due to the intrinsic difference between active and passive sensors, the data processing steps differ much during the preprocessing period, see Figure 3. The general processing steps for the data acquired from passive sensors are: first segmenting an image into semantic parts, then extracting features from these parts, sending the features into a detection system to generate candidate interest regions, and in the last step sending the detection results into recognition system. The data processing module of active sensors processes the data they acquire in another way in the first several steps. They just collect the signals reflected from target objects then generate cloud points, some system would prefer to filter these points then send to recognition system. Generally, the computation intensity and time cost of active sensor data processing are much lower than passive sensor, yet with getting quite good results. While active sensors can be free from influence of illumination, they may suffer from an extreme weather like rain, snow, fog, etc. The main disadvantages of passive sensors are: (1).they may suffer from influence of illumination; (2). the processing of the images may cost a lot of time and get unreliable results. However, an image contains much more useful information than cloud points generated from active sensors. In practice, vehicles like Stanley and Odin used both types of sensors to work together to get a reliable result. Boss, Junior, Talos used active sensors only for the obstacle detection(Leonard, John, et al. 2008, Montemerlo, Michael, et al. 2008, Urmson, Chris, et al. 2009). No vehicle used passive sensors only for the obstacle detection.

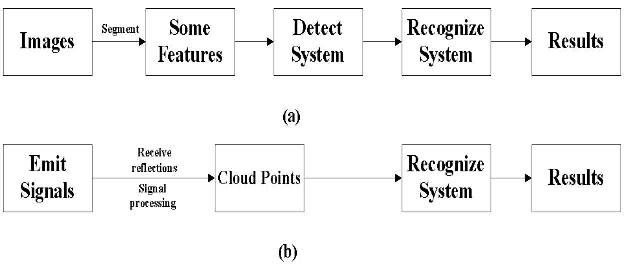

Figure 3. Data processing flow of different type of sensors: (a) Passive sensors' data processing flow; (b) Active sensors' data processing flow.

We have pointed out in section 3 that different vehicles chose and mounted sensors in different positions. The problems they met during processing data were different. We make a brief overview of them as follows. Junior used Velodyne mounted on the roof of the vehicle as a primary scanner. It estimated whether there's any the distance of two adjacent rings (generated by adjacent lasers) with the threshold value. However, this method may suffer from the pitching and rolling of the vehicle. By setting the distance to next laser as a function of range rather than a fixed value might address this problem (Montemerlo, Michael, et al. 2008).

Talos combined SICKs, Velodyne and radars for obstacle detection. When processing data clouds from Velodyne, it employed probabilistic method to build a nonparametric ground model. Here, we mainly discuss how it reliably differentiated between obstacles and non-flat terrain in its layout of sensors. By putting two SICK parallelly, it could measure the changes in vertical direction, so the ambiguity between obstacles and non-flat terrain was resolved, see Figure 4.

For dynamic obstacle detection, the winning teams used a short memory system surveyed above to record the past detected obstacles, then employed different methods such as point model, box model in Boss (Urmson, Chris, et al. 2009), and particle filter in Junior to detect and track dynamic obstacles (Montemerlo, Michael, et al. 2008).

4.3 *Localization and Mapping*

For the vehicles competed in DARPA Challenges, routines were generally predefined. Therefore, when AVs were driving on road, the first thing they should do was to localize themselves on the

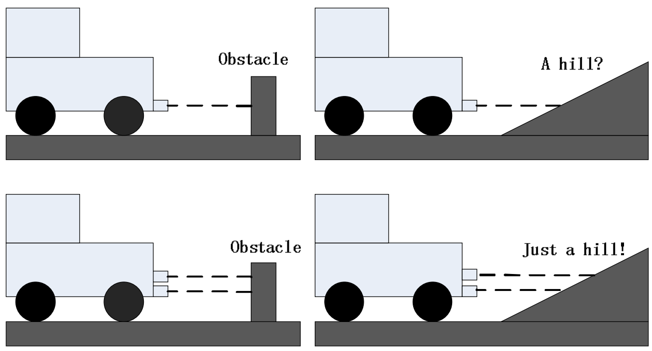

Figure 4. The position configuration of SICKs in Talos

routine with the help of various sensors. The most used sensors are GPS, IMU and wheel odometer. Junior also utilized RIGEL for curb detection. Stanley, Odin and Talos tried to make camera help them to detect the road and localize themselves. To safely navigate in dynamic urban environments, autonomous vehicles need higher localization accuracy than the one available from GPS-based inertial guidance systems (Levinson, Jesse, et al. 2011). In other words, the vehicles need to calculate the accurate positions of themselves with the help of established Short Memory Systems. The most used methods were using Kalman filter to estimate the position and using interpolation methods to smooth the routines, for detailed information please refer to (Thrun, Sebastian, et al. 2006, Leonard, John, et al. 2008, Monternerlo, Michael, et al. 2008, Urmson, Chris, et al. 2009). Levinson, Jesse, et al. (2011) tried to use

SLAM technology to help the localization achieve centimeter accuracy. However, the result was got under the given of pre-recorded laser map. It was not suitable for autonomous vehicle to drive in new environment for the first time.

4.4 *Other Modules*

We have reviewed the most important perception modules in the autonomous vehicles attended DARPA Challenges. While the DARPA Challenges remain the largest demonstration of autonomous vehicle technology to date, the traffic scenes were simplified in the competitions (Levinson, Jesse, et al. 2011). During the Urban Challenge, it was closed to pedestrians and bicyclists, had no traffic lights, and had few traffic signs.

In this subsection, we review some state-of-the-art methods for those critical problems of driving in cities and off-road environments. For simplicity, we choose the computing speed and accuracy as our main criteria.

Bicyclist & Pedestrian Detection: The most used sensors in these two topics are cameras. In recent years, someone combined LIDARs with cameras together, or using 3D laser data to get a good result (Premebida, Cristiano, et al. 2009, Szarvas, Mate, et al. 2006). Bicyclist and Pedestrian detection can be viewed as different topic in computer vision community, yet they share some common methods and algorithms, as Enzweiler, Markus, et al. (2009), Cho H, et al. (2010) showed that HOG/linSVM have a clear advantage in the accuracy and speed among other methods, such as wavelet-based AdaBoost cascade. Benenson, Rodrigo, et al. (2012) showed that by using stixels and without image resizing, their algorithm could achieve 20 times faster than previous methods while keeping the same accuracy.

Traffic lights detection: In traffic lights detection, the most used sensor is camera. By extracting the color information then processed with the shape information, they could achieve good result. But the popular problem among the detection systems are the methods can't be popularized well, and being affected by the light condition very much(Yu, Chunhe, et al. 2010, Diaz-Cabrera, et al. 2012).

Traffic signs detection and recognition: After several decades of development in both computer vision community and intelligent transportation system community, the results of traffic signs detection and recognition tested in public datasets showed they were good enough(approximately above 95% in accuracy)(Mogelmose, Andreas, et al. 2012).However, some problems remain to be solved, such as how about the result when the systems work in adverse weather conditions?

5 NAVIGATION AND DECISION MAKING

We have surveyed the environment perception modules in AVs, now we step into another important modules in AVs-- navigation and decision making modules, which belong to the high level cognition in Embodied Cognition theory. Navigation and decision making modules are to generate the basic vehicle control information to make the vehicle drive safely and reasonably. Different vehicles had different separation of navigation periods, see Table I for detailed information. Generally, each vehicle would firstly use the information provided by Road Network Definition File(RNDF) to generate a series of sub-goals represented in points in the RNDF for the

Table 1. Compare of vehicles' high level cognition architectures

Vehicle	Mission Planning	Behavioral Planning	Error Recovery
Boss	● Generating graph to encode the dynamic environment and RNDF points; ● Generating paths with different costs; ● Detecting Blockages.	● Executing the policy generated by the mission planner; ● Making lane-change, precedence, and safety decisions, respectively, on roads, at intersections, and at yields.	Responding to and recovering from anomalous situations.
Junior	● Planning paths from every location in the map to the next checkpoint; ● Computing the costs of different paths.	● Generating different policies according to the situation; ● Generating smooth paths for vehicle to execute; ● Making lane-change, crossing the intersection and merging to the traffic, etc; ● Using FSM to switch between different driving states and tackle the exceptions.	
Talos	● Generating shortest route to the next MDF checkpoint; ● Making intersection precedence, crossing, and merging ● Passing; ● Blockage replanning ; ● Generating goals for the motion planner; ● Generating fail-safe timers; ● Turn signaling.		Using fail-safe timers to help error recovery.

vehicle to achieve. Then they set a cost function for the vehicle to choose a path which assumes to be optimal. Vehicle like Junior implemented global planning by using dynamic programming algorithm, which achieved good result. For free-form navigation in parking lots, it was different from the on-road navigation, because the movement of the vehicle was far less constrained (Montemerlo, Michael, et al. 2008).Junior used hybrid A* algorithm to search a near-cost optimal path to the goal and Boss used Anytime D* algorithm to get a suboptimal path(Urmson, Chris, et al. 2009).

Except for generating an optimal or sub-optimal path for the vehicle, during the running of the vehicle, the states of vehicles might change from one to another, such as from stopping to driving. There are also many exceptional states might occur. It's necessary for an autonomous vehicle to know which state it is in now, when to change to the next state and how to recover from exceptional states. Junior had a finite state machine to manage the vehicle's states and during the DARPA Challenge event, it almost never entered any of the exception states (Montemerlo, Michael, et al. 2008). However, other vehicle such as Talos was not so lucky and had an accident with the vehicle from Cornell due to stuck into exceptional states(Fletcher, Luke, et al. 2008).

6 CONCLUSION

We have mainly surveyed the advanced cognition theories and combined with them to analyze and compare the state-of-the-art autonomous vehicles won the DARPA Challenges. From the different layouts of sensors and software architectures, we have found that the advanced cognition theories such as embodied cognition theory can also be used as the system design guideline of an autonomous vehicle. And also, we have found that various autonomous vehicle, though may be different significantly in the sensors layouts and system designs, they share much basic knowledge with each other, such as using the short memory system for the short memory and probability theory and machine learning to tackle the uncertainty.

At last, from the survey, we still find some problems in the development of a more cognitive autonomous vehicle, which may be valuable directions for the related researches: (1) There's no systematic discussion of the robustness of the autonomous vehicle; (2) As 80% of information obtained by a human driver is from his/her vision, it's valuable for researches in computer vision field to improve reliability of computer vision methods; (3) Still there're not so much papers published in the evaluation of the reliability of the vehicle's cognition level; Lastly, we think there're a lot of work needed to be done in the cognition of pedestrians, bicyclists and vehicles' behaviors as the autonomous vehicle needs to interact with them properly.

In the future, we will research on vehicle detection, pedestrian detection and static obstacles detection to make the AV more cognitive in the following research works.

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