ITEA Office
High Tech Campus 69 - 3
5656 AG Eindhoven
The Netherlands
T + 31 88 003 6136
E info@itea3.org
W www.itea3.org

ITEA 3 is a EUREKA strategic ICT cluster programme

State of the Art Document

15042_DANGUN Project

Editor:

Contributors:

History

Version	Date	Remarks
V1.0	01 July, 2019	A first version of SotA

1. Introduction

1.1. Overview of TJA

1.1.1. Problem statement and market value chain

Mobility is a basic human need and the independence that was brought due to the invention of the motor car into the 20th century. Its' invention has meant that people could have the freedom for land transport and has shaped the manner in which countries have evolved. Whilst the automobile has allowed there to be much progress across the world, this has resulted in the emergence of other problems, namely, extensive road networks, accidents, pollution, etc. Current environmental pressures and the evolution of Information & Communications Technologies (ICT) are changing our perspectives with regards to ground mobility. A major concern is traffic congestion on roads converging to major cities resulting in a high number of hours people spend in traffic jams. These traffic jams are a major source of driver discomfort and anxiety. Within this context, generalist vehicle OEMs are much interested in deploying Traffic Jam Assistants (TJA) within the next years leveraging on the use of close-to-production sensors that can be deployable by generalist manufacturers.

The DANGUN project proposes an Intelligent Perception System for Autonomous Vehicles that are to be deployed as part of a TJA system for testing and verification in Korea and France, this in order to leverage the France-Korea technological partnership and to take into account the specificities of each country. From a business perspective, the TJA function responds positively to the demands of the markets in both countries.

ICT and electric vehicles are changing the automotive industry; furthermore, the Google demonstration in October 2010 has changed the perspective on autonomous vehicles. Today, Google has operated over two million km in an autonomous driving. Moreover, technological giants such as Apple, Uber, and new automotive entrants like Tesla have also shown their interest. These companies' interests represent an opportunity to the automotive industry, which can benefit from the new technologies whilst leveraging our extensive knowledge on system validation and safety - passenger vehicles with autonomous capabilities need to be tested and validated in order to warrant their safety prior to their deployment.

Table 1 shows the classification of automation levels for passenger vehicles (NHTSA, US Government agency). Whilst the ultimate goal is to attain door-to-door automation (Level 4) at all times. Today, the ambition is to have a gradual deployment of systems that can operate autonomously under special conditions, Level 2 Function Automation. Mercedes Benz and BMW introduced the TJA (Traffic Jam Assist) system to the market in 2014. In that same year, BMW introduced the APS (Automatic Parking Systems). They also planned to have the ALC (Automatic Lane Change) and highway pilot to be market-ready by 2016. The automotive industries in Korea and France have their own roadmaps to develop this autonomy.

Table 1. Level of Automation defined by NHTSA

Level 0	No-Automation
Level 1	Function-Specific Automation

Level 2	Combined Function Automation
Level 3	Limited Self-Driving Automation
Level 4	Full Self-Driving Automation

In DANGUN, their approach is to centre on the use of a combination of passive perception sensors (front vision), active perception (the 77GHz-79 GHz dual radar) and advanced vehicle navigation algorithms in order to attain TJA capabilities that can be commercialized in vehicles from a generalist Vehicle OEM. For this purpose, two vehicles will be built in order to demonstrate the TJA system. These will then be tested following in-company development procedures. Figure 1 shows the envisaged configuration of such vehicle.

Figure 1. Sample vehicle with TJA autonomous capabilities

In the autonomous vehicle market, the estimated price of a TJA function would cost on average, $2,036USD, with common components as those shown in Figure 1. Within such systems, substantial software will be embedded, different algorithms will be used within the intelligent perception systems, and other algorithms will be used for decision-making, whilst others will be used for vehicle control and safety.

From a vehicle OEM perspective, the supply chain will be structured by tier 1 and tier 2 suppliers. Tier 2 manufacturers will provide with specialist sensors and advanced components such as intelligent cameras, GNSS receivers, etc. Due to this, Tier 1 suppliers will then be responsible for specific functions, for example, Lane Departure Warning (LDW), Adaptive Cruise Control (ACC), etc. Typical Tier 1 suppliers include Valeo, Bosch, to name a few. Tier 2 includes Mobileye, HERE, amongst other suppliers. A typical supply chain structure is shown below in Figure 2.

Consortium members are very much interested in technologies for autonomous vehicles. For example, Valeo produces 24GHz short and wide range radars, they have recently completed the initial development phase of a 77GHz/79GHz dual radar (first prototypes ready), which they would like to test as a part of a TJA system. Another example is LG. LG is working on passive sensors, namely on front-vision cameras for object classification and AVM (Around View Monitoring) technology, as well as techniques for the validation and verification of automotive systems. The autonomous vehicles roadmap for the group Renault/Renault Samsung includes a TJA as one of the first products, targeting both European and Korean markets.

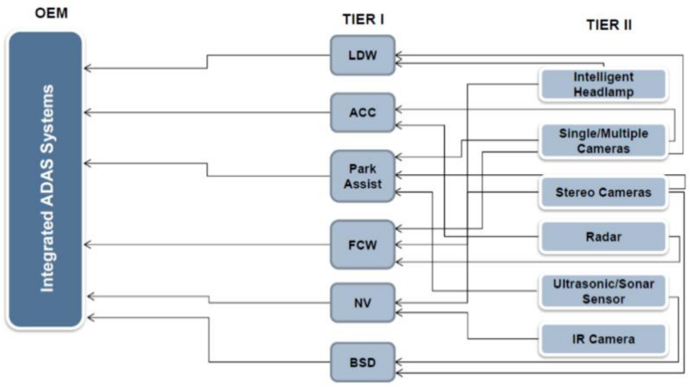


Figure 2. Supply chain of ADAS (Advanced Driver Assistance System)

Vehicle OEMs need to gain experience on the deployment of Autonomous Vehicles as a service, initial studies indicate that initial applications might be on last mile services or shuttle-like vehicles, operating in constrained environments. The rationale is that vehicles with limited autonomous capabilities and economically viable configurations can be deployed at Level 4, to reduce the dependency on drivers as emergency mechanisms[1]. Therefore, rather than deploying vehicles with highly automated capabilities and expensive sets of sensors, simpler vehicles could be made available at Level 4, under the monitoring of a command centre. The vehicles, when experiencing difficulty, shall stop and request external operator intervention. A remote operator will then immediately take over and move the vehicle so it can restart again its autonomous operation. The project will explore the use of different teleoperation techniques on DANGUN vehicles. That is to combine autonomous capabilities with distance guidance.

1.1.2. State-of-the-Art analysis

General Motors (GM) announced that vehicles with autonomous driving capabilities will be released by 2020. BMW also announced the commercialization of autonomous vehicles by 2020 with Continental Co. Volvo demonstrated platooning with a truck leading vehicle and sedan proceeding vehicles in the SARTRE project. Nissan has plans to develop autonomous vehicles in various models by 2020.

It is likely that four autonomous systems will be mass-produced within a few years or are already in commercial production, as listed in figure 4. These are TJA, APS (Automated Parking System), ALC and highway pilot. TJA and APS are already commercialised by BMW and Daimler, the other items shall be in the market in the next few years. Figure 4 shows the status of the basic autonomous driving capabilities as announced by several vehicle OEMs.

[1] Google Inc. Has publicly stated that after more than 2 million Km of their fleet of vehicles will be under full computer control, the weakest point appears the use of human drivers as the emergency stop. The emergence of the automation paradigm is becoming a major issue.

System	Automation Level	OEMs	Situation in the market	Discussion Points
Traffic Jam Assist	Level2	●Daimler, BMW, VW ○Other OEMs	Launched	➢ Use in only Highway
Automated Parking System	Level2	●BMW ○Other OEMs (JP,EU)	Launched	➢ Remote Parking included or not ➢ RE3 in R79
Automated Lane Change System	Level2 Level3	○Daimler, Audi, BMW, VW, Volvo ○Toyota, Nissan, Honda	R&D phase To be launched within 1~2 years	➢ Which Automation Level ➢ R79
Highway Pilot	Level3	○EU, JP, US OEMs	R&D phase To be launched within 1~2 years	➢ R79

Figure 3. Development status of four primary autonomous systems (Source: ISO TC204)

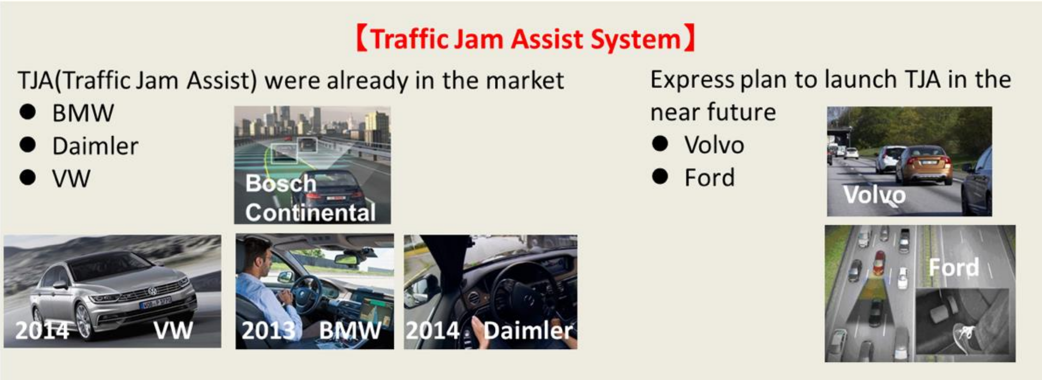


Figure 4. Production of TJA (Source: ISO TC204)

Delphi demonstrated the public road driving of an autonomous vehicle. The vehicle ran from Palo Alto to New York (Figure 5). Mercedes demonstrated the autonomous driving of public road for 103 km in more than 20 cities.

Figure 5. A vehicle equipped by Delphi drove from Palo Alto to New York in Autonomous mode (Source: AVS 2015, Delphi)

1.2. Overview of Teleoperation

In recent years, the development of autonomous vehicles has received increasing attention. Researchers and engineers are devoted to developing and implementing intelligent unmanned vehicles that can replace human drivers in difficult and tiring scenarios, such as long-range transportation in high-way. Industrial players include various types of companies, such as High-Tech companies (Google/Waymo, Baidu, Uber, etc.), vehicle manufacturers (Ford, Renault, BMW, Mercedes-Benz, Nissan, etc.). A lot of start-up companies are funded in recent years, aimed to take one share of the huge potential market. Research institutes and universities across the world also play an important role in this domain. Their contributions are witnessed through the public competition (such as DARPA Urban Challenge), or via the collaboration with the industrial players.

Thought tremendous energies are dedicated to this domain, the realization of a fully autonomous vehicle remains an extraordinarily difficult challenge. It involves multiple fundamental aspects of artificial intelligence and robotics, such as perception, localization, mapping, planning, decision making, machine learning, and control, etc. The prototypes of autonomous vehicles that exist today are still far away compared to an ordinary driver in terms of environment understanding and decision making. A typical problem is that an autonomous vehicle stops and blocks the road when it can no longer understand the environment or fails to make a safe decision. Fig. 6 shows how the unexpected environment could make it hard for the autonomous vehicle to understand or make a safe decision.

Figure 6. Unexpected environment could make it hard to understand or carry out a safe decision for an autonomous vehicle.

Fig. 6 illustrates a situation where an autonomous vehicle could block itself because the unexpected environment does not correspond to the programmed structured environment. There is no doubt that the level of intelligence for an autonomous vehicle is still far from enough to handle complex environment scenarios like the one shown above. So, an immediate question arises: what do we do in such circumstances? What solution do we need so that the autonomous vehicle can overcome this situation and thus help the traffic restore to its normal order?

According to the literature, teleoperation is a promising solution to overcome this issue. It can be seen as an intermediate solution towards the fully autonomous solution. According to the American National Standards Institute in 2003, the autonomous vehicle can be classified by different levels. Level 0 is the direct teleoperation, where a remote operator completely controls the behavior of the vehicle and the vehicle does not embed any autonomous functions. Level 10 is a fully independent autonomous vehicle where no human intervention is required. In between this is so-called shared or supervisory teleoperation. This mode is a combination of human interaction from teleoperation and autonomous operation.

For the DANGUN project, we have surveyed the existing teleoperation solutions for autonomous vehicles. We have then proposed what would be the desired teleoperation use case for this project. Particularly, we strive for a solution based on shared/supervisory teleoperation principles.

2. Related projects

Teleoperation of ground vehicles has been studied for a long time in the domain of field robotics. One of the first application was for space exploration by lunar rovers by USA, Russia, amongst other countries. (Ruoff, 1994). Then the subject remained a research topic necessary for military applications, for exploration of high-risk sites like nuclear sites.

Telerobotics has remained an important research topic in academic laboratories, even if this type of research has been quite quiet compared to conventional robotics. For example, the Sandia National Laboratory had intensive research on teleoperation in the 80s and 90s, with several projects on cars (McGovern & Douglas E, 1989). Carnegie Mellon University worked on the Stripe project (Supervised TeleRobotics using Incremental Polyhedral Earth reprojection) at the end of the 90s (Kay, 1997). In that time, communication technologies were rather limited, and communication between the vehicle and the teleoperation console was done by radio. Another example of teleoperation comes from the Singapore Institute of Manufacturing Technology who worked on the teleoperation of military vehicles at the beginning of the 2000s (Jian, Ibanez-Guzman, & Teck Chew Ng, 2004).

More recently, the emergence of a new generation of communication technologies, namely the cellular communications like 3G and 4G, allowed for the exchange of a larger amount of information between the vehicle and the console to be processed. Also, applying this technology to the automobile became conceivable. Other laboratories started to work on teleoperation, like the Institute of Automotive technology in the Technical University of Munich (TUM) (Gnatzig, Chucholowski, Tang, & Lienkamp, 2013) in Germany, or Chalmers University (BODELL & GULLIKSSON, 2016) in Sweden.

In 2018, even if most of the autonomous driving players already worked on it, teleoperation became vital for the deployment of driverless vehicles when the Californian laws for autonomous driving tests request that the driverless vehicles operating must allow for remote control (Wired, 2019). Therefore, even if most of the companies working on autonomous driving do not communicate much about it, a review of patents allows to confirm that all of them work on teleoperation: Waymo (US Brevet n° 9465388, 2016), Apple (US Brevet n° 10,328,897, 2019), General Motors (US Brevet n° 6,449,472, 2002), Nutonomy (US Brevet n° 16,276,426, 2019), Nissan, Drive AI, Zoox, etc. Also, new companies like Phamtom Auto (Phantom, 2019) or Designated Drivers (Designated Drivers, 2019) concentrate all their activity and business on the remote control of automobiles. It is noticeable that a majority of the patents were released from 2016, i.e. after the beginning of the DANGUN project.

3. Related technologies

3.1. Lane detection with cameras (including front camera and AVM)

3.1.1. Front camera

The object detection algorithm in the Front-camera system is shown as Figure 7. When the Front camera captures an image frame, the object detection system extracts various features from the image. After that, object candidates are generated based on the extracted features and filtered by the pre-trained classifier. Object candidates that pass through the classifier are tracked by the tracker.

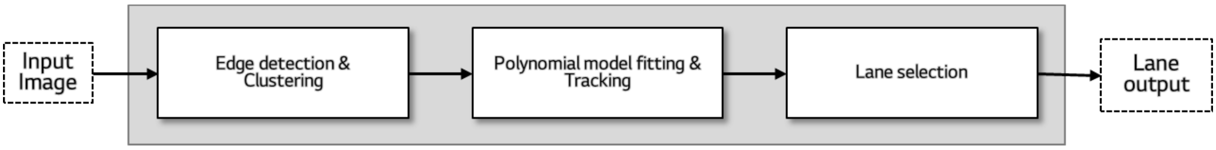


Figure 7. Object detection algorithm in the front camera system

3.1.2. Around View Monitoring (AVM) System

In a traffic jam situation, conventional lane detection in the front camera cannot work in bumper to bumper conditions and crawling situations because the vehicle speed is very low and front camera cannot detect the lane mark. Therefore, in a traffic jam situation, the AVM system is better than any other sensors for detecting the lane. AVM camera can detect the lane mark from a 360-degree image around the vehicle. The lane detections algorithm in AVM system is shown as Figure 8. In this 360-degree image around the vehicle, the lane algorithm performs feature extraction and grouping, finds the real lane position information from lane groupings through lane selection and curve fitting.

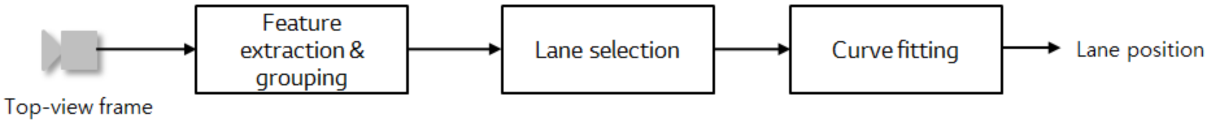


Figure 8. AVM System

3.2. Object detection with cameras (including front camera and AVM)

The object detection algorithm in the Front-camera system is shown as Figure 9. When the Front camera captures an image frame, the object detection system extracts various features from that image. After that, object candidates are generated based on extracted features and filtered by the pre-trained classifier. Object candidates that pass through the classifier are tracked by the tracker.

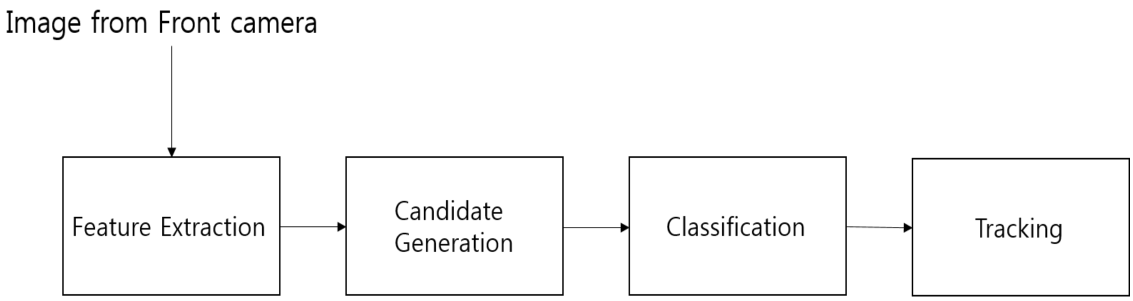


Figure 9. Process of object detection

The Front camera object detection system has Object Detection Area (ODA) as shown in Figure 10 to satisfy the requirements of customers with optimal calculation time.

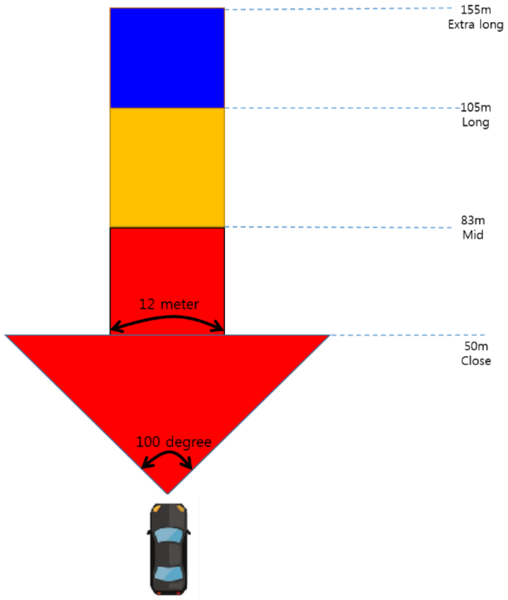


Figure 10. Object Detection Area (ODA)

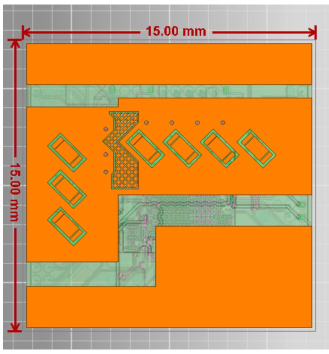
3.3. Object detection with Radars

3.3.1. Current technology trend of a corner Radar

- Transition from 24GHz to 77GHz Corner Radars are now more competitive
- Introduction of CMOS technology and System on Chip solutions (SoC)
- Compact sensors with 77GHz
- Priority to Low cost, High volume sensors with Worldwide frequency approvals for the Mainstream business

3.3.2. Future technology trend of a corner Radar

- More range for NCAP 2022
- More range for Automatic Lane Change (premium brands)
- More radars around the car (premium brands), including smaller sensors with Antenna on Package solutions
- High Definition radars for Robotaxis (i.e. Waymo Roof POD)



3.4. Multi-sensor data convergence for object detection

3.4.1. Sensor characteristics and evaluation

As mentioned in the previous section, the concept of object information fusion is compensating the uncertainty, due to the sensor's respective characteristics. It means that the object information fusion system does not always improve object detection and tracking performance. Advantages and disadvantages of object information fusion are as follows. Object information fusion through multi-sensor increases the systems' complexity. The type of data and its quality now depend on the combination of sensors detecting the objects. Different sensors produce distinct kinds of measurement misinterpretation. These are the disadvantages of using multi-sensor object information fusion [1]. Nevertheless, the advantage of object information fusion through heterogeneous sensors is that it can provide complete sensing coverage surrounding the vehicle. In addition, in the case of sensor failure, erroneous detection or misinterpretation, it provides redundancy. Therefore, understanding the sensor characteristics is crucial for reliable object information fusion performance [2], [3], [12]–[16], [4]–[11]. As shown in Table 1, in commercial ADAS, radar and camera (or stereo camera) are used to detect and track objects.

Table 1. Characteristic table of typical range sensors

		Radar	Camera	LIDAR
Range	Accuracy	+	-	++
	Resolution	+	-	++
Angle	Accuracy	--	+	O
	Resolution	--	+	O
Velocity	Accuracy	O	-	+
Night capability		+	--	+
Weather capability		+	--	-
Object classification		-	+	O
Cost		Cheap	Cheap	Expensive

++: Better / +: Good / O: Normal / -: Poor / --: Bad

3.4.2. The frameworks of object information fusion algorithm

The frameworks of object information fusion algorithm consist data association, tracking, track merging, and track management method [1], [17], [26]–[29], [18]–[25]. Terminologies for object tracking are as follows. Object means the measurement data from sensors. Track indicates the output of the tracking algorithm. Data association represents the determination of objects indicating the same obstacle among objects from other sensors. For data association, Nearest Neighbor (NN) or Probabilistic Data Association (PDA) are used most frequently. Figure 11 shows the concept of NN and the PDA method [30]–[37]. NN method finds the nearest Mahalanobis distance of the object and assumes it represents the obstacle. PDA method estimates the measurement information based on objects, which are located within a valid boundary that depend on Mahalanobis distance. Generally, the PDA method demonstrates better performance than the NN method with noisy object data from sensors.

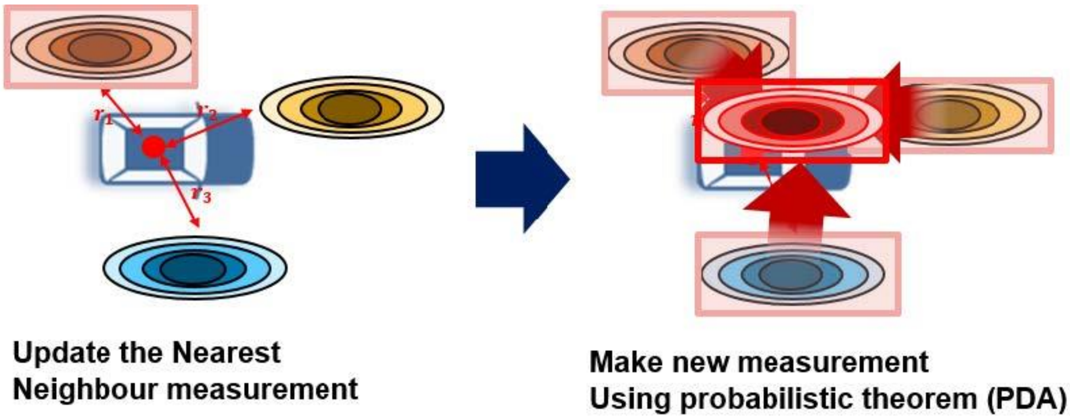


Figure 11. Description of Nearest Neighbour method and Probabilistic Data Association

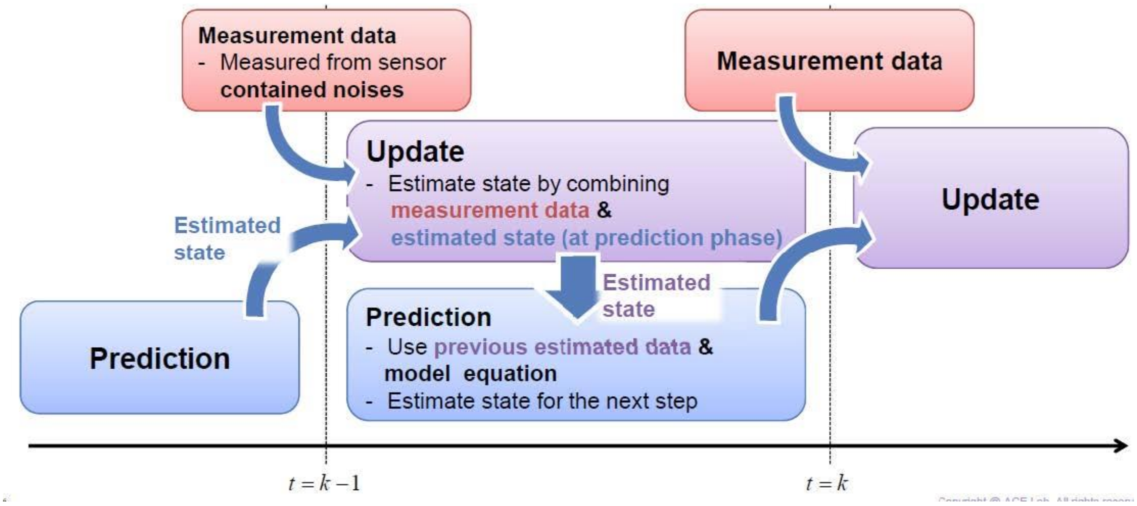


Figure 12. Concept of Kalman filter

The tracking algorithms have been developed as Kalman filter and particle filter [19], [20], [26], [27], [35], [38]–[42]. These tracking algorithms are applied in numerous ways to track objects. Figure 12 exhibits the concept of Kalman filter. Kalman filter is the optimal state estimation method, based on the covariance of states. The track merge algorithms have been developed as the cross-covariance method and probabilistic data association [43]. Cross-covariance method fuses objects information, in which the objects are located within the valid boundary, based on the covariance of object information. Object information fusion algorithm generates a lot of track information due to the usage of heterogeneous sensors. To manage track information efficiently, the track management method is necessary. Generally, track management is composed of three track statuses (tentative, confirmed, terminate). Then, it is utilized to judge the tracking status, based on the covariance of the track.

3.5. Multi-sensor data convergence for lane detection

3.5.1. The necessity of multiple sensor-based lane detection

The front camera is a representative sensor used for lane detection. The lane detection algorithm using the front camera is quite a matured research area. Moreover, there already exists commercialized products widely used for ADAS systems.

However, there are some limitations to detect lanes with front cameras in congested traffic situations, as shown in Figure 12Figure 13. First, the front camera has an occlusion problem caused by the vehicles in front of it. In the traffic congestion situation where the distance from the front vehicle is close to the front vehicle, the lane does not enter the angle of view of the front camera. Second, the front camera cannot obtain lane information in a narrow area around the vehicle. In traffic congestion, which requires lane information in a narrow area near the ego vehicle, this limitation can cause a problem. Finally, the camera is highly influenced by external factors such as surrounding objects and illumination. In the case of traffic congestion with a lot of disturbance due to nearby vehicles and shadows, the camera performance can be hindered. Therefore, to overcome the limitations of the front camera, information convergence technology using various sensors is required.

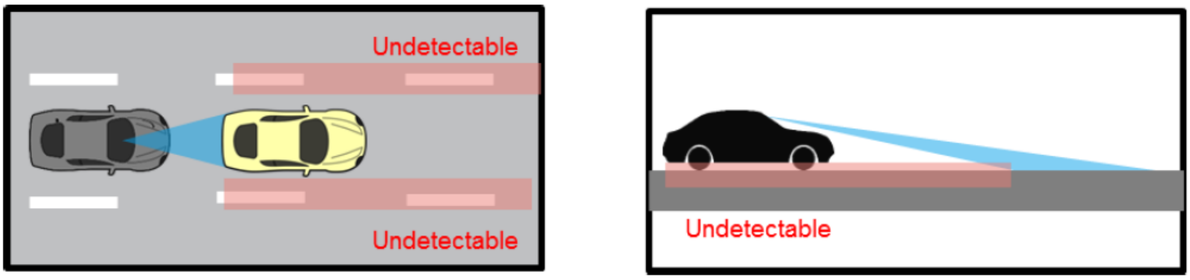


Figure 13. Limitation of front camera

3.5.2. Lane detection and information convergence algorithms

We investigated what kinds of sensors could be used to overcome the limitations of the front camera. According to [44], lane detection using information fusion of camera, LIDAR and GPS/Map has been widely researched. [45], [46], [47] and [48] introduced lane detection algorithm using lane information from the vision sensor and curb information from LIDARs as shown in Figure 14. [49] and [50] used Radar to detect on-road regions based on the reflectivity of the road. However surrounding vehicles would occlude the curb and the road when in heavy traffic situations. [20], [51] and [52] utilized the Global Positioning System and map to achieve lane information. But this approach requires a high precision map and high-quality GPS devices.

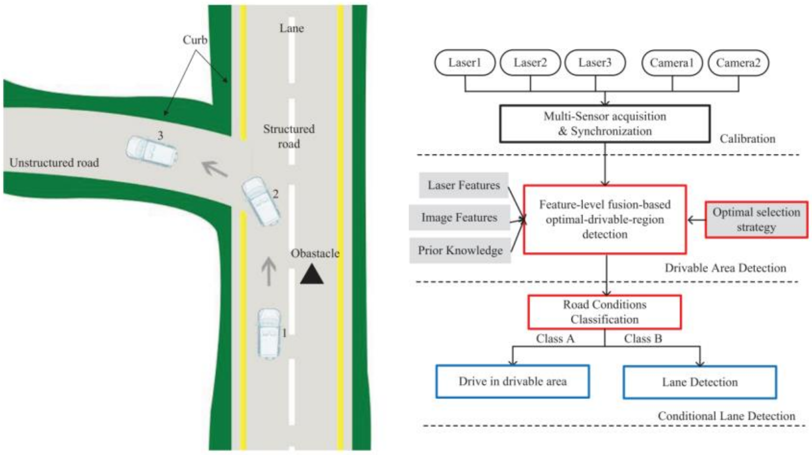


Figure 14. Lane detection algorithm using vision sensor and LIDAR

In addition, we investigated the method to fuse the information of each sensor. [45], [48] and [53] limits the ROI of the front camera using the curb information detected from other sensors. This approach can reduce the false detections, however, the approach cannot be a solution to solve fundamental limitations of the front camera. [54] converged information from multiple sensors with a weighted sum calculation. [55], [56] applied Kalman filtering as shown in Figure 15 and [57], [58] applied particle filtering which are the most used information convergence methods [44].

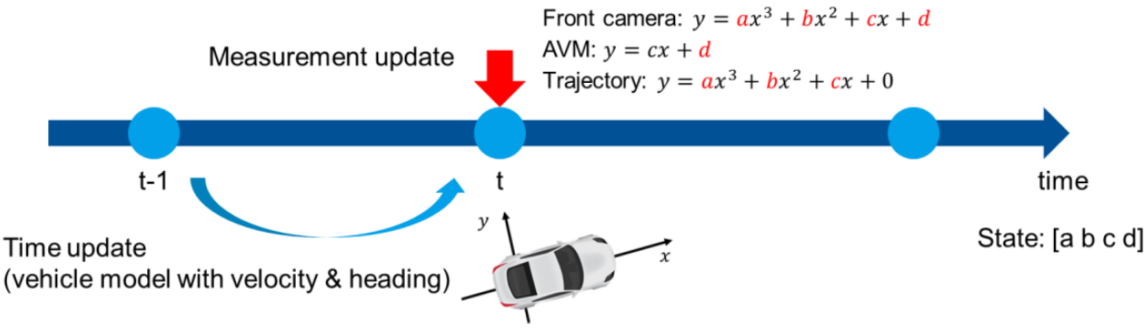


Figure 15. Lane fusion algorithm with Kalman filter

3.6. Vehicle control for TJA

During a traffic jam, the road becomes very complex as there are lots of surrounding vehicles. In addition to this, the surrounding vehicles stop and go repetitively whilst changing lanes, thus their movements alter suddenly and continuously. In such a complex environment, driving becomes more effortful for the driver. To facilitate driving, Traffic Jam Assist (TJA) system is proposed to help drivers during traffic congestion. This system makes the vehicle keep its own lane and maintain a proper distance to a preceding vehicle without a driver intervention by steering, accelerator and brake pedal. TJA is composed of three main parts. The first part is the detection of surrounding vehicles. The second part is the detection of the lane on the road. The third part is the control of ego vehicle's motion using the information of the surrounding environment which is provided by the first and the second parts. This part is often called the 'Vehicle control.' It is divided into longitudinal lateral control. Vehicle control gives direct influence on the vehicle's motion such as a lateral vehicle motion and a longitudinal vehicle motion, so it is directly related to the driver's safety. Furthermore, rapidly changing steering and acceleration reduces the ride comfort. Thus, vehicle control is very important since it can affect the driver's safety and comfort. However, there is often a trade-off relationship between safety and ride comfort. Thus, the various control modes are used to improve both safety and comfort [59]–[61]. The control mode is operated depending on driving situations. In a dangerous situation, the control mode that has a higher priority for the safety is operated. On the other hand, in normal driving, the control mode that has higher priority for comfort is operated. In some of the previous research, Model Predictive Control (MPC) framework is used to ensure safety and ride comfort [62], [63]. MPC generates a sequence of optimal control input using the prediction of future states. In Bageshwar's research [63], the control performance is improved when using MPC instead of a standard constant time gap algorithm. In addition to this, Li [62] suggested the longitudinal controller for multi-objective in order to not only consider the safety and ride comfort but also to consider fuel economy and tracking capability. Another strategy is a controller imitating human behavior [64], [65]. Fuzzy controller, which is based on the linguistic description of the driver's demand, is suggested.

3.6.1. Limits of previous vehicle control

There are some limits in the situation where the front car is cut-in or cut-out. The information of a preceding vehicle is changed non-consecutively. This discontinuous change makes discrete desired acceleration, so it reduces ride comfort. Furthermore, enough space to prevent collision with a cut-in car is needed. This transitional operation problem has been researched for the platoon. Li [66] suggested a safety region for the relative velocity between two platoons. Bageshwar [62] introduced Model Predictive Control(MPC) of transitional maneuvers for adaptive cruise control. When a surrounding vehicle moves into the ego lane, the control feasibility check is initiated.

3.6.2. Difference between the electric and the internal combustion engine control

The propulsion component in an electric vehicle is the electric motor. By controlling the voltage and the electric current coming from the battery, the torque as well as the rotational speed of the motor are controlled and thus, the acceleration and velocity of the vehicle. The structure of an ICE engine is more complicated than that of one of the electric engines. As with an electric engine, the aim is to produce the desired torque at a certain rotational speed at the output shaft. However, the controls of the ICE engine are more sophisticated, since multiple variables such as air bypass command, fuel intake, spark timing and EGR command must be controlled.

3.7. Architecture of teleoperation

3.7.1. Direct Teleoperation

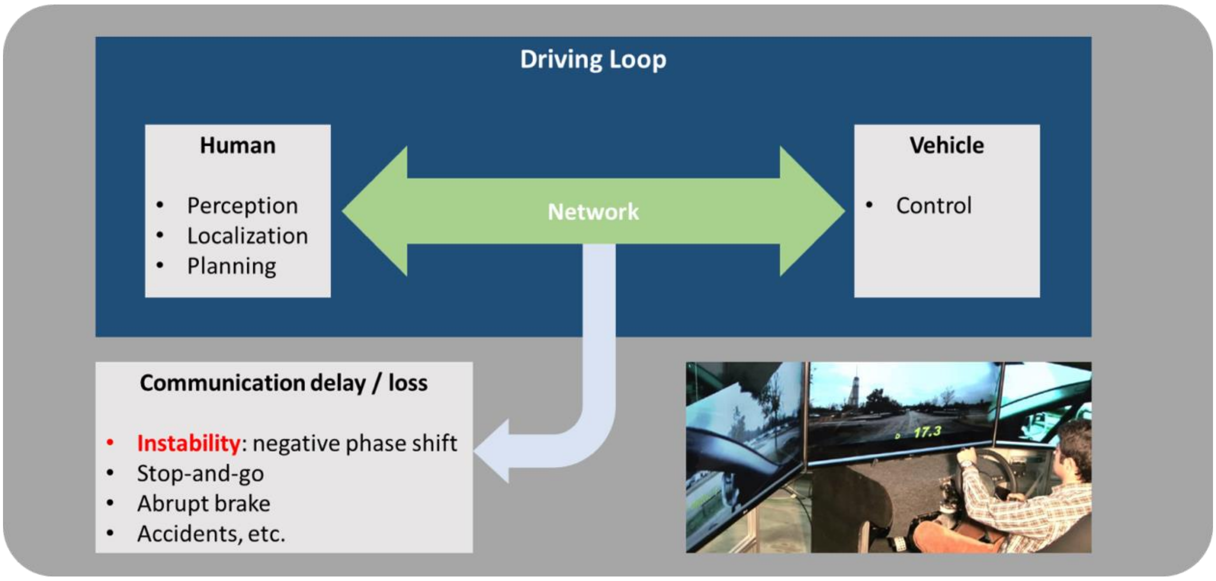


Figure 16. Direct teleoperation scheme.

Figure 16 illustrates the communication among components in direct teleoperation. In such a case, the vehicle is only responsible for conducting control commands sent from distant human operators. Through embedded cameras in the vehicle and communication network, the distant operator is able to visualize the remote environment, so that he/she is able to handle perception, localization and planning. Since the driving loop is a continuous procedure and the unavoidable delay from the network is directly involved, the instability issue is a direct consequence derived from control theory. As a result, it would give rise to stop-and-go behavior, abrupt brakes and other problems. This issue can only be mitigated by reducing driving speed and network delay but can never be eliminated completely.

For direct teleoperation, an example of industrial implementation is from Jaguar-Land-Rover group, see Figure 17 (a). In this application, the velocity speed is limited to 6.4 km/h. User must carry its key as detector within a certain range with respect to the car to enable the teleoperation. Either too close or too far would stop the car for safety reasons. On the other hand, the company Ericsson carried out a series of studies on the feasibility of using the state-of-the-art mobile network for teleoperation. They conducted preliminary tests in urban scenarios. The results show that for most cases, the network delay converges to some acceptable ranges. Figure 17 (b) shows one typical result. The redder the color is the more delay the network introduces. Orange spot characterizes the delay range from 70 milliseconds to 85 milliseconds, whilst the green spot characterizes the delay range from below 70 milliseconds.

On the research side, some researchers strive to rely on intuitiveness and predictive information to compensate for network delay. In the [Chucholowski 2013], [Orey 2016], [Hosseini 2016-1] work, the motion of obstacles in the street is estimated and projected on the screen so that distant operators can better understand the potential risk of a collision. See Figure 18(a).

Figure 17 (a) Direct teleoperation from Jaguar-Land-Rover group. (b) Feasibility of using cellular network for direct teleoperation from Ericsson.

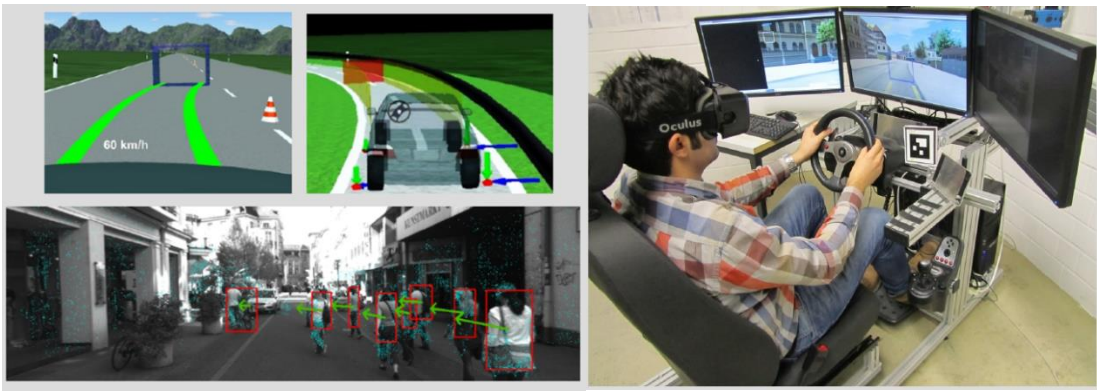


Figure 18 Research efforts to compensate network delay. (a) Freecorridor, predictive display. (b) virtual/augmented reality for remote driving.

The free corridor is another research concept. Depending on the current velocity of the vehicle, it predicts a look-ahead region where no obstacle should be involved inside. This logic is computed based on a full brake scenario. If there is any obstacle inside this corridor, the traversed distance during full brake will collide with it. Some other researchers take advantage of using virtual/augmented reality to enhance the intuitiveness of teleoperation driving, see Figure 18(b).

As a summary, it can be seen that both industrial and research players develop and deploy different methods in order to try to compensate for the unavoidable delay from the network.

3.7.2. Shared/Supervisory Teleoperation

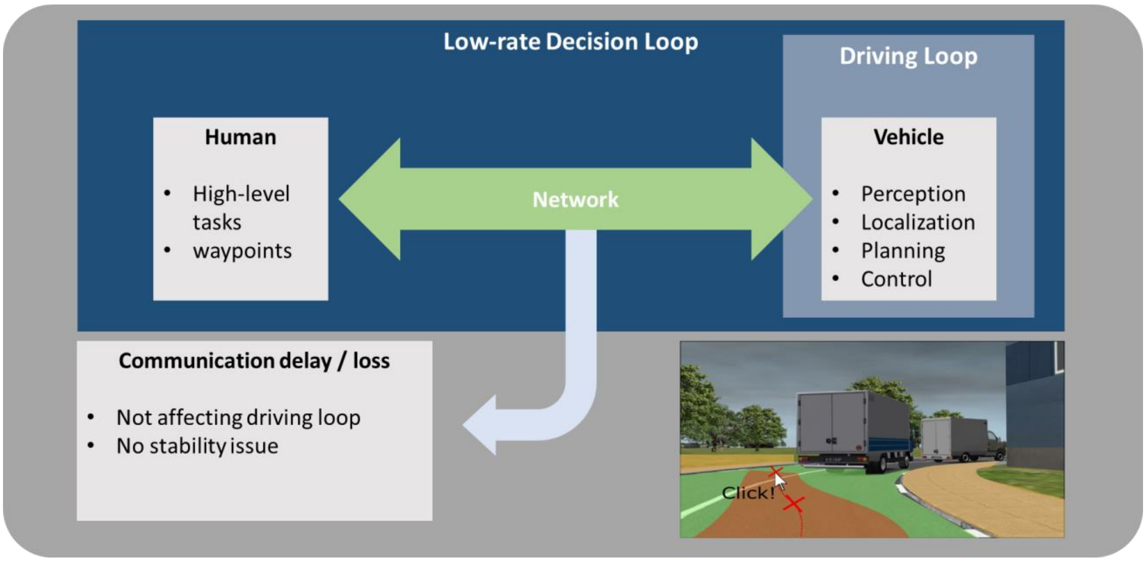


Figure 19. Shared/supervisory teleoperation scheme.

Different from direct teleoperation logic, the shared/supervisory teleoperation does not include the network in the continuous driving loop. This is realized by embedding perception, localization, planning and control inside the vehicle. Compared to direct teleoperation, this is a significant step forward towards the fully autonomous vehicle. Since network delay is not involved inside the driving loop, there is no intrinsic stability issue. On the other hand, the distant operator only needs to deliver low-rate decision command to the remote vehicle, such as defining high-level tasks or assigning new waypoints.

The earliest concept comes from the PhD thesis of Fong at Carnegie Mellon University [Fong 2001] in Pennsylvania, USA, where they proposed a collaborative driving framework. In this concept, the human command is not always right but is seen as a noisy source of command information. The framework is characterized by two-way interaction so that computation and human experience are combined together to make a decision.

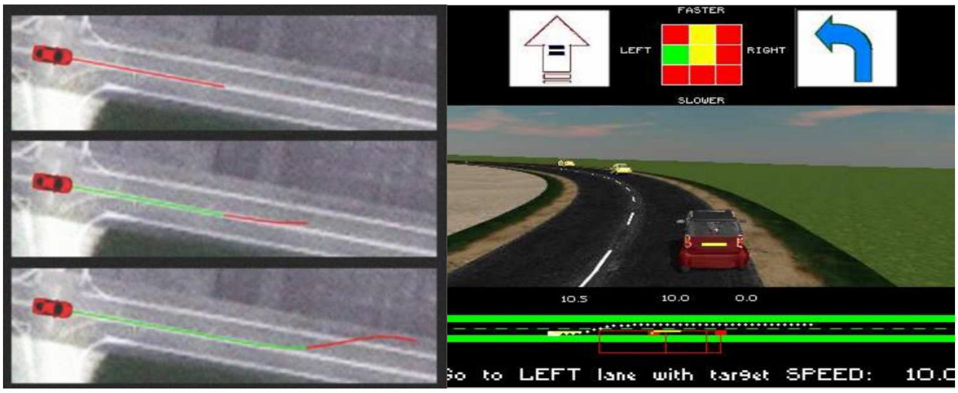


Figure 20. Examples of shared/supervisory teleoperation. (a) Trajectory based shared control. (b) Maneuver based trajectory planning.

In the research work [Gnatzig 2012], the distant operator can draw manually path segments through human-machine interface and command remote vehicle to follow these trajectories, see Figure 20(a). This method is easy and intuitive, but only adapts for a simple situation. In narrow corridors or U-turns, human drawn segments are probably not realizable. In the work [Glaser 2009], the system is designed for maneuver-based interaction in a structured environment. A distant operator can define high-level tasks such as, acceleration, deceleration, change lane etc. See Figure 20(b). This system is highly dependent on the well understanding of a structured environment.

Shared/supervisory teleoperation designed for the more general unstructured environment can be found in the research work [Hosseini 2014] [Lan 2015], see Figure 21. The former solution relies on the original sampling-based algorithm RRT for generating the rapid path. It then uses the optimization technique to smooth the generated path. Particularly k-mean clustering method is implemented to prune away similar or redundant paths, so as to simplify the decision process for distant operators. The latter research work employs a more sophisticated planning algorithm RRT* to generate an asymptotically optimal path. Another contribution is that the researchers developed a method to rapidly repair the RRT* results in case of un-modeled dynamic obstacle in the environment.

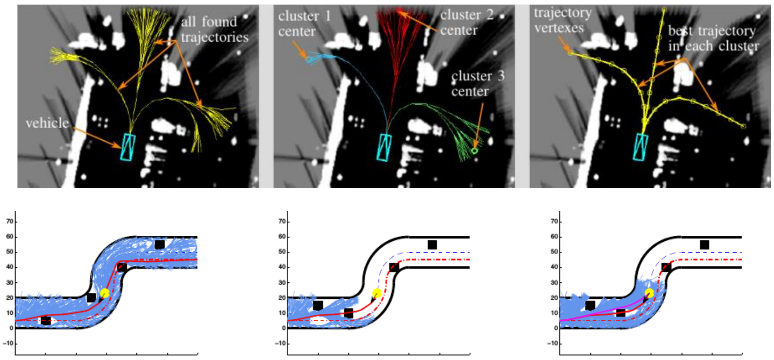


Figure 21. Examples of shared/supervisory teleoperation. (a) Interactive path planning in urban environment. (b) Enhancement is focused on using an optimal planning algorithm which can react efficiently to dynamic obstacles.

3.7.3. Comparison between the two methods

It can be seen from the previous description that direct teleoperation relaxes the requirements on autonomous algorithms implemented on the vehicle, but relies heavily on the attention, judgement and decision of the distant operator. Control instability is an intrinsic issue in such a method. It would be easy to prototype such a system, but hard to realize an efficient operation, especially in a congested environment. On the contrary, shared/supervisory teleoperation requires the implementation of perception, localization, planning algorithms, with an algorithmic level depending on a specific application. It is naturally immune to instability issues but relies on the quality of implemented algorithms. Most of the state-of-the-art development and implementation focus on using an efficient planning algorithm as described above. Fig. 18 illustrates briefly the comparison between these two methods.

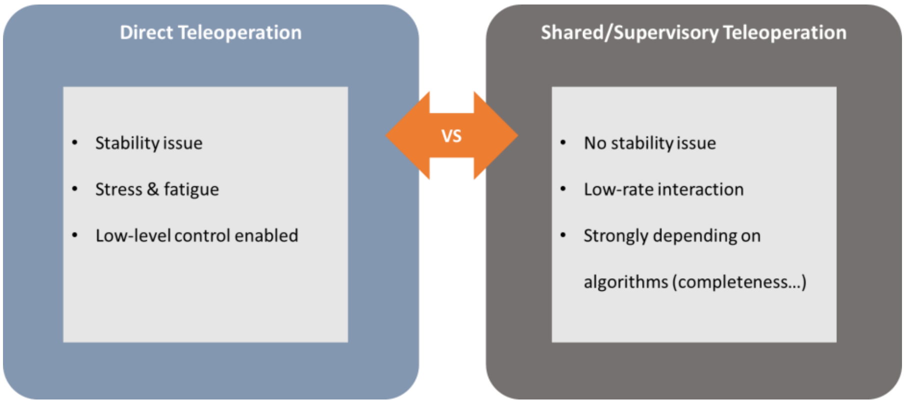


Figure 22. Comparison between direct teleoperation and shared/supervisory teleoperation.

After the surveys and investigation of the state-of-the-art about architecture for teleoperation, we have developed a shared/supervisory teleoperation system. It can be referred to as a semi-autonomous solution in another context. During the project, we worked a lot on the development and implementation of a planning algorithm is able to deal with the unexpected (labyrinth-like) unstructured environment due to an efficient planning algorithm, which is the key to our shared/supervisory teleoperation system.

3.8. Planning algorithm for shared/supervisory teleoperation

The planning algorithm is the key to the realization of an efficient shared/supervisory teleoperation system.

No planning algorithm is perfect, it is better to choose a specific planning algorithm for a specific application. When vehicle issues a teleoperation demand, it indicates that the onboard planning algorithm might no longer be able to handle the situation. The environment may be characterized by narrow corridors and U-turns. And it can be the unstructured or labyrinth-like environment. That probably means we must be equipped with a more powerful planning algorithm in our teleoperation system.

It must be complete: meaning that if there is a solution, the algorithm must be able to find it in a reasonable finite time period. It must also converge to the optimal solution so that the generated path is concise and direct to the maximum extent. It must also be able to react efficiently to the dynamic un-modelled environment so as to guarantee a fast response.

In the aspect of the human-machine interface, the planning algorithm must be suited to the interaction with the operator, for example, modify the environment; define the goal region, etc.

There are two main branches of planning algorithms: discrete algorithms and sampling-based algorithms.

The former is developed in line with Dijkstra's shortest path algorithm. Multiple extended versions exist such as A*, D*, D*-Lite, Anytime Repairing A*, Anytime Dynamic A*, Hybrid A*, etc. This branch of algorithms converts the planning problems to graph search problems. The performance strongly relies on discrete resolution. Thus, they bear a weaker notion of performance: resolution completeness, and resolution optimality. Some of them like D*, D*-Lite, or AD* can handle the dynamic environment in an elegant manner. However, the shortcoming of this type algorithm is that they do not suit very well with the non-holonomic robots. Furthermore, the computation burden would be a significant problem when the dimension of planning space is higher than two.

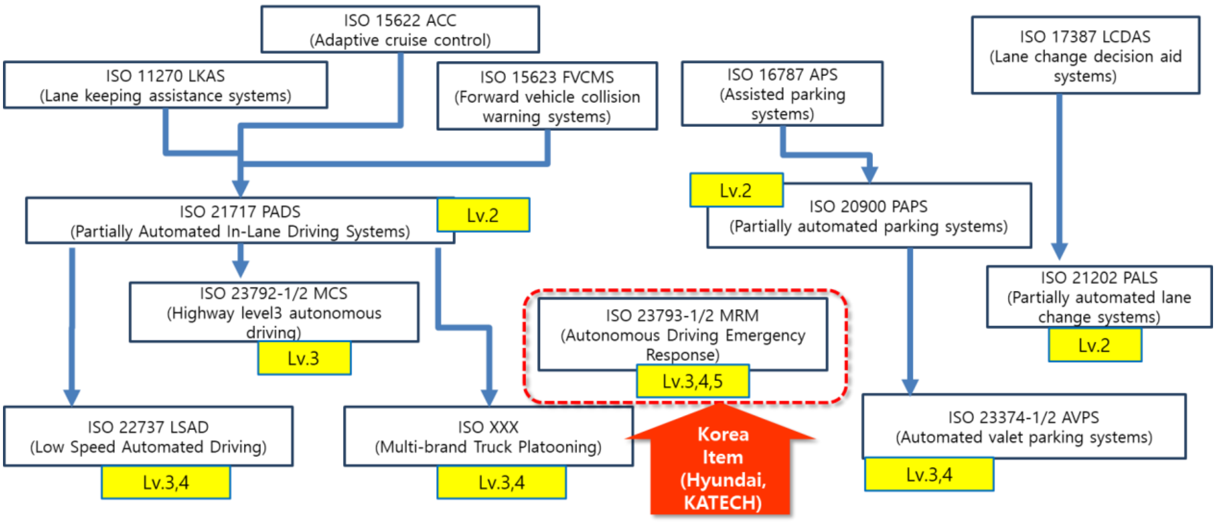
The earliest sampling-based algorithm is the famous RRT. It relies on random sampling in the planning space and quickly builds a connection tree to explore the space. It is simple and efficient. It can incredibly find a feasible solution in a high dimension complex problem. However, the problem is that the algorithm is focused on feasibility and not optimality. To resolve this issue, later research results proposed RRT* and RRT#. The key enhancement is that when adding a new node into the tree, it activates a reconnection process near such node to achieve asymptotical optimality. The sampling-based algorithm is naturally suited for non-holonomic robots and can resolve efficiently when planning space is high dimensional. In general, collision avoidance, the tree expanding, and neighbor search process are more complicated than those in the discrete planning algorithms. One other major constraint is that there was not yet a sampling-based planning algorithm which can handle the efficiently dynamic environment.

A recent new research result on planning named RRTX from MIT is a convergence between replanning method from artificial intelligence and optimal sampling-based planning from control theory. It means that this new algorithm is a probabilistically complete and asymptotically optimal re-planner. It borrows the mechanism of re-planning from D* and D*-Lite and also bears the optimality from RRT*.

We decided to build our planning algorithm based on this RRTX framework.

4. Related standards

4.1. Standards related to TJA



4.2. Standards related to teleoperation

A review of standards related to teleoperation gave poor results.

The ISO 15817:2012 norm deals with the safety requirements for remote operator control systems in the field of earthmoving machinery (15817:2012, 2012).

ASTM international published several standards related to robots including telerobots. ASTM E2521 is related to the Standard Terminology for Evaluating Response Robot Capabilities. Moreover, ASTM E2853 deals with Standard Test Method for Evaluating Emergency Response Robot Capabilities.

However, no standards directly related to the teleoperation of automobiles have been found.

5. Reference

[1] M. Darms, P. Rybski, and C. Urmson, “Classification and tracking of dynamic objects with multiple sensors for autonomous driving in urban environments,” in *2008 IEEE Intelligent Vehicles Symposium*, 2008, pp. 1197–1202.

[2] J. Fischer, A. Menon, A. Gorjestani, C. Shankwitz, and M. Donath, “Range sensor evaluation for use in Cooperative Intersection Collision Avoidance Systems,” in *2009 IEEE Vehicular Networking Conference (VNC)*, 2009, pp. 1–8.

[3] T. Stoyanov, A. Louloudi, H. Andreasson, and A. J. Lilienthal, “Comparative evaluation of range sensor accuracy in indoor environments,” pp. 19–24, 2011.

[4] Serdal Ayhan ; Mario Pauli ; Thorsten Kayser ; Steffen Scherr ; Thomas Zwick, *FMCW radar system with additional phase evaluation for high accuracy range detection*. 2011 8th European Radar Conference, 2011.

[5] J. Salvi, X. Armangué, and J. Batlle, “A comparative review of camera calibrating methods with accuracy evaluation,” *Pattern Recognit.*, vol. 35, no. 7, pp. 1617–1635, Jul. 2002.

[6] C. T.-S. on geospatial theory, P. and, and undefined 2002, “Testing and verification of the accuracy of 3D laser scanning data,” *isprs.org*.

[7] G. Caroti and A. Piemonte, “Measurement of cross-slope of roads: evaluations, algorithms and accuracy analysis,” *Surv. Rev.*, vol. 42, no. 315, pp. 92–104, Jan. 2010.

[8] W. Boehler, M. Vicent, A. M.-T. I. A. of, and undefined 2003, “Investigating laser scanner accuracy,” *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.*, vol. 34, pp. 696–701, 2003.

[9] K. Bakuła, A. Salach, D. Zelaya Wziątek, W. Ostrowski, K. Górski, and Z. Kurczyński, “Evaluation of the accuracy of lidar data acquired using a UAS for levee monitoring: preliminary results,” *Int. J. Remote Sens.*, vol. 38, no. 8–10, pp. 2921–2937, May 2017.

[10] S. Huang, J. Yang, and F. Eklund, “Evaluation of remote pedestrian sensor system based on the analysis of car-pedestrian accident scenarios,” *Saf. Sci.*, vol. 46, no. 9, pp. 1345–1355, Nov. 2008.

[11] R. Grewe, M. Komar, A. Hohm, S. Lueke, and H. Winner, “Evaluation method and results for the accuracy of an automotive occupancy grid,” in *2012 IEEE International Conference on Vehicular Electronics and Safety (ICVES 2012)*, 2012, pp. 19–24.

[12] M. Golparvar-Fard, J. Bohn, J. Teizer, S. Savarese, and F. Peña-Mora, “Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques,” *Autom. Constr.*, vol. 20, no. 8, pp. 1143–1155, Dec. 2011.

[13] T. Hermosilla *et al.*, “Evaluation of Automatic Building Detection Approaches Combining High Resolution Images and LiDAR Data,” *Remote Sens.*, vol. 3, no. 6, pp. 1188–1210, Jun. 2011.

[14] J. Kilian, N. Haala, M. E.-I. A. of Photogrammetry, and undefined 1996, “Capture and evaluation of airborne laser scanner data,” *Int. Arch. Photogramm. Remote Sens.*, vol. 31, pp. 383–388, 1996.

[15] J. Weng, P. Cohen, and M. Herniou, “Camera calibration with distortion models and accuracy evaluation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 14, no. 10, pp. 965–980, 1992.

[16] D. Veneziano, S. Hallmark, and R. S. and, “Accuracy evaluation of LIDAR-derived terrain data for highway location,” *Comput. Civ. Infrastruct. Eng.*, 2002.

[17] H. Cho, Y.-W. Seo, B. V. K. V. Kumar, and R. R. Rajkumar, “A multi-sensor fusion system for moving object detection and tracking in urban driving environments,” in *2014 IEEE International Conference on Robotics and Automation (ICRA)*, 2014, pp. 1836–1843.

[18] G. Reina, J. Underwood, G. Brooker, and H. Durrant-Whyte, “Radar-based perception for autonomous outdoor vehicles,” *J. F. Robot.*, vol. 28, no. 6, pp. 894–913, Nov. 2011.

[19] S. Thrun *et al.*, “Stanley: The robot that won the DARPA Grand Challenge,” *J. F. Robot.*, vol. 23, no. 9, pp. 661–692, Sep. 2006.

[20] C. Urmson *et al.*, “Autonomous driving in urban environments: Boss and the Urban Challenge,” *J. F. Robot.*, vol. 25, no. 8, pp. 425–466, Aug. 2008.

[21] J. Ziegler *et al.*, “Making Bertha Drive—An Autonomous Journey on a Historic Route,” *IEEE Intell. Transp. Syst. Mag.*, vol. 6, no. 2, pp. 8–20, 2014.
[22] F. Kunz *et al.*, “Autonomous driving at Ulm University: A modular, robust, and sensor-independent fusion approach,” in *2015 IEEE Intelligent Vehicles Symposium (IV)*, 2015, pp. 666–673.
[23] J. K. Hackett and M. Shah, “Multi-sensor fusion: a perspective,” in *Proceedings., IEEE International Conference on Robotics and Automation*, pp. 1324–1330.
[24] A. Yilmaz, O. Javed, and M. Shah, “Object tracking,” *ACM Comput. Surv.*, vol. 38, no. 4, p. 13–es, Dec. 2006.
[25] J. Llinas and D. L. Hall, “An introduction to multi-sensor data fusion,” in *ISCAS ’98. Proceedings of the 1998 IEEE International Symposium on Circuits and Systems (Cat. No.98CH36187)*, vol. 6, pp. 537–540.
[26] G. Rigatos and S. Tzafestas, “Extended Kalman filtering for fuzzy modelling and multi-sensor fusion,” *Math. Comput. Model. Dyn. Syst.*, vol. 13, no. 3, pp. 251–266, Jun. 2007.
[27] S. Sun, “Multi-sensor optimal information fusion Kalman filters with applications,” *Aerosp. Sci. Technol.*, vol. 8, no. 1, pp. 57–62, Jan. 2004.
[28] K. Jo, M. Lee, J. Kim, and M. Sunwoo, “Tracking and Behavior Reasoning of Moving Vehicles Based on Roadway Geometry Constraints,” *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 2, pp. 460–476, Feb. 2017.
[29] C. Mertz *et al.*, “Moving object detection with laser scanners,” *J. F. Robot.*, vol. 30, no. 1, pp. 17–43, Jan. 2013.
[30] J. Areta, Y. Bar-Shalom, and M. Levedhal, “A hierarchical benchmark association problem in missile defense,” 2005, vol. 5913, p. 591315.
[31] Y. Bar-Shalom and Huimin Chen, “Multisensor track-to-track association for tracks with dependent errors,” in *2004 43rd IEEE Conference on Decision and Control (CDC) (IEEE Cat. No.04CH37601)*, 2004, p. 2674–2679 Vol.3.
[32] “The probabilistic data association filter,” *IEEE Control Syst.*, vol. 29, no. 6, pp. 82–100, Dec. 2009.
[33] T. Fortmann, Y. Bar-Shalom, and M. Scheffe, “Sonar tracking of multiple targets using joint probabilistic data association,” *IEEE J. Ocean. Eng.*, vol. 8, no. 3, pp. 173–184, Jul. 1983.
[34] J. Neira and J. D. Tardos, “Data association in stochastic mapping using the joint compatibility test,” *IEEE Trans. Robot. Autom.*, vol. 17, no. 6, pp. 890–897, 2001.
[35] D. Schulz, W. Burgard, D. Fox, and A. B. Cremers, “Tracking multiple moving targets with a mobile robot using particle filters and statistical data association,” in *Proceedings 2001 ICRA. IEEE International Conference on Robotics and Automation (Cat. No.01CH37164)*, vol. 2, pp. 1665–1670.
[36] P. P. A. Storms and F. C. R. Spieksma, “An LP-based algorithm for the data association problem in multitarget tracking,” *Comput. Oper. Res.*, vol. 30, no. 7, pp. 1067–1085, Jun. 2003.
[37] Li Zhang, Yuan Li, and R. Nevatia, “Global data association for multi-object tracking using network flows,” in *2008 IEEE Conference on Computer Vision and Pattern Recognition*, 2008, pp. 1–8.
[38] S.-L. Sun and Z.-L. Deng, “Multi-sensor optimal information fusion Kalman filter,” *Automatica*, vol. 40, no. 6, pp. 1017–1023, Jun. 2004.
[39] D. Simon, *Optimal state estimation: Kalman, H infinity, and nonlinear approaches*. John Wiley & Sons, 2006.
[40] Y. Wu, J. Lim, and M.-H. Yang, “Online Object Tracking: A Benchmark.” pp. 2411–2418, 2013.
[41] N. Kaempchen, K. Weiss, M. Schaefer, and K. C. J. Dietmayer, “IMM object tracking for high dynamic driving maneuvers,” in *Intelligent Vehicles Symposium, 2004 IEEE*, 2004, pp. 825–830.
[42] Feng Liu, J. Sparbert, and C. Stiller, “IMMPDA vehicle tracking system using asynchronous sensor fusion of radar and vision,” in *2008 IEEE Intelligent Vehicles Symposium*, 2008, pp. 168–173.

[43] B. La Scala and A. Farina, “Effects of cross-covariance and resolution on track association,” in *Proceedings of the Third International Conference on Information Fusion*, 2000, p. WED1/10-WED1/16 vol.2.
[44] A. Bar, H. Ronen, L. Dan, and L. Guy, “Recent progress in road and lane detection a survey.pdf,” *Mach. Vis. Appl.*, vol. 25, no. 3, pp. 727–745, 2014.
[45] A. S. Huang, D. Moore, M. Antone, E. Olson, and S. Teller, “Finding multiple lanes in urban road networks with vision and lidar,” *Auton. Robots*, vol. 26, no. 2–3, pp. 103–122, 2009.
[46] J. Hernandez, B. Marcotegui, and J. Hernández, “Filtering of Artifacts and Pavement Segmentation from Mobile LiDAR Data,” *ISPRS Work. Laserscanning*, pp. 1–6, 2009.
[47] J. Han, “Information Fusion-based Road Boundary and Obstacle Detection for Autonomous Vehicles,” 2011.
[48] Q. Li, L. Chen, M. Li, S. L. Shaw, and A. Nüchter, “A sensor-fusion drivable-region and lane-detection system for autonomous vehicle navigation in challenging road scenarios,” *IEEE Trans. Veh. Technol.*, vol. 63, no. 2, pp. 540–555, 2014.
[49] S. Lakshmanan and A. O. Hero, “Simultaneous detection of lane and pavement boundaries using model-based multisensor fusion - Intelligent Transportation Systems, IEEE Transacti ons on,” vol. 1, no. 3, pp. 135–147, 2000.
[50] S. Lakshmanan, Kk. Kaliyaperumal, and K. Kluge, “Lexluther: an algorithm for detecting roads and obstacles in radar images,” *Conf. Intell. Transp. Syst.*, vol. 1491, no. 1, pp. 415–420, 1997.
[51] G. Caprari, R. Siegwart, M. Bosse, and R. Moser, “ˆ Fabien T ache, Franc ¸ ois Pomerleau, Gilles Caprari, and Roland Siegwart,” vol. 28, no. 2009, pp. 180–203, 2011.
[52] M. Montemerlo *et al.*, “Junior: The Stanford Entry in the Urban Challenge,” *J. F. Robot.*, vol. 25, no. 9, pp. 569–597, 2008.
[53] X. Hu, F. S. A. Rodriguez, and A. Gepperth, “A multi-modal system for road detection and segmentation,” *IEEE Intell. Veh. Symp. Proc.*, no. Iv, pp. 1365–1370, 2014.
[54] C. Chun *et al.*, “Sensor fusion-based line detection for unmanned navigation,” *IEEE Intell. Veh. Symp. Proc.*, pp. 191–196, 2010.
[55] A. Borkar, M. Hayes, and M. T. Smith, “Robust lane detection and tracking with Ransac and Kalman filter,” *Proc. - Int. Conf. Image Process. ICIP*, pp. 3261–3264, 2009.
[56] Z. W. Kim, “Robust lane detection and tracking in challenging scenarios,” *IEEE Trans. Intell. Transp. Syst.*, vol. 9, no. 1, pp. 16–26, 2008.
[57] R. Danescu and S. Nedevschi, “Probabilistic lane tracking in difficult road scenarios using stereovision,” *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 2, pp. 272–282, 2009.
[58] P. Real, “Computer Analysis of Images and Patterns,” *J. Math. Imaging Vis.*, vol. 47, no. 1–2, pp. 1–2, 2013.
[59] S. Moon, I. Moon, and K. Yi, “Design, tuning, and evaluation of a full-range adaptive cruise control system with collision avoidance,” *Control Eng. Pract.*, vol. 17, no. 4, pp. 442–455, Apr. 2009.
[60] J.-J. Martinez and C. Canudas-de-Wit, “A Safe Longitudinal Control for Adaptive Cruise Control and Stop-and-Go Scenarios,” *IEEE Trans. Control Syst. Technol.*, vol. 15, no. 2, pp. 246–258, Mar. 2007.
[61] “Vehicle following control design for automated highway systems,” *IEEE Control Syst.*, vol. 16, no. 6, pp. 43–60, Dec. 1996.
[62] V. L. Bageshwar, W. L. Garrard, and R. Rajamani, “Model Predictive Control of Transitional Maneuvers for Adaptive Cruise Control Vehicles,” *IEEE Trans. Veh. Technol.*, vol. 53, no. 5, pp. 1573–1585, Sep. 2004.
[63] S. Li, K. Li, R. Rajamani, and J. Wang, “Model Predictive Multi-Objective Vehicular Adaptive Cruise Control,” *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 3, pp. 556–566, May 2011.
[64] H. Holzmann, C. Halfmann, S. Germann, M. Würtenberger, and R. Isermann, “Longitudinal and lateral control and supervision of autonomous intelligent vehicles,” *Control Eng. Pract.*, vol. 5, no. 11, pp. 1599–1605, Nov. 1997.
[65] S. Germann and R. Isermann, “Nonlinear distance and cruise control for passenger cars,” *Adv. Automot. Control 1995*, pp. 209–214, Jan. 1995.

[66] P. Li, L. Alvarez, and R. Horowitz, “AHS safe control laws for platoon leaders,” *IEEE Trans. Control Syst. Technol.*, vol. 5, no. 6, pp. 614–628, 1997.