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Overall Reviews of Autonomous Vehicle A1 - System Architecture and Algorithms

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Abstract: This paper describes an autonomous vehicle A1 that won the Hyundai Motor Group 2012 Autonomous Vehicle Competition. The A1 was developed for autonomous on-road and off-road driving conditions without driver intervention. The autonomous driving system consists of four parts that are localization, perception, planning, and control. Localization which estimates the ego-vehicle position on the map should be first performed to autonomously drive the A1. A perception algorithm detects and recognizes the objects around the ego-vehicle are also important to prevent collisions with obstacles and road departure. A planning algorithm generates the drivable motion of the A1 based upon previous information from the localization and perception system. Subsequently, a vehicle control algorithm calculates the desired steering, acceleration and braking control commands based on the information from the planning algorithm. This paper also presents the entire system architecture that the A1 used to accomplish all the required missions in the 2012 Autonomous Vehicle Competition.

Keywords: Autonomous vehicles, System architecture, Perception, Localization, Planning, Control

1. INTRODUCTION

The realization of autonomous driving is the ultimate goal of intelligent vehicle technology. Autonomous vehicles can improve driver safety and comfort by reducing traffic accidents and driver workloads; in addition, optimal driving technology for the autonomous vehicles can reduce environmental pollution. The Defensive Advanced Research Projects Agency (DARPA) in USA holds the Grand Challenge and Urban Challenge competition to stimulate autonomous vehicle research (Urmson et al., 2008, Thrun et al., 2007). The goal of these challenges is to verify the feasibility of autonomous driving. In addition, capital investment by global automakers and IT companies (such as Volkswagen, BMW, and Google) has increased to commercialize autonomous vehicles. In South Korea, two Autonomous Vehicle Competitions (AVC) were organized in 2010 and 2012 by the Hyundai Motor Group to encourage autonomous driving technology research in Korea. More than ten South Korean universities participated in the competitions; our Hanyang University group successfully completed all AVCs missions and won in 2010 and 2012.

In this paper, we present the system architecture and autonomous driving algorithms of our autonomous vehicle A1. The vehicle was developed by the Automotive Control and Electronics Laboratory (ACE Lab) and the Machine Monitoring and Control Laboratory (MMC Lab) at Hanyang University. The autonomous driving system of A1 has a distributed architecture based on an in-vehicle network (IVN), which consists of FlexRay, CAN, and Ethernet. This architecture separates the entire system into subsystems that allows the independent development and testing of each subsystem.

Algorithms for autonomous driving of A1 are composed of four parts (Localization, Perception, Planning, and Vehicle Control). In localization, the information of the ego-vehicle on the map is calculated based on the GPS and on-board sensors. The driving environments around the A1 are inferred at perception through the integration of several types of information such as laser scanners, cameras, and roadmaps. The planning algorithm determines the behavior and motion of the A1 using information from the localization and perception algorithm. Finally, the vehicle control algorithm follows the planning motion by actuating the low-level control modules such as steering, acceleration, and braking.

2. OVERVIEW OF AVC 2012

The 2012 AVC took place with 14 teams who qualified and passed the document examination; the final 10 teams went into a final race through the preliminaries. On September 20 2012, the final race (with various missions) started on the 3.4 km on-road and off-road test track of Hyundai Motor Group. The final ranking was determined by the sum of the lap time and mission penalties. Fig. 1 and *Table 1* show the track of 2012 AVC and the mission penalties.

The competition focused on urban environment challenges. To evaluate the urban driving technologies of participating teams, the competition was composed of nine missions (*Table 1*). In the **traffic light and crosswalk detection** mission, the vehicle detects traffic light status and crosswalk location and must stop within three meters from the crosswalk if the traffic light is red; however, it should pass the crosswalk when the light is green. The **school zone and sudden obstacle** mission evaluates two functions: compliance with the limit speed and emergency stops to avoid collision with unexpected obstacles. The vehicle should safely overtake a vehicle in the **overtaking** mission. The goal

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of the **passenger pickup** mission is to recognize a passenger and stop within five meters. In the **construction site** driving mission, a vehicle has to pass a construction site that was not shown on the map. In the **barrier** mission, a vehicle should detect a barrier that blocks the road and stop within five meters from the barrier. The objective of the **split road** mission is to recognize and follow the direction of the traffic light for a split road. The purpose of the **complex obstacle avoidance** mission is to validate the performance of path planning algorithm that finds a drivable path without a conflict with the complex **obstacles**. In the **parking** mission, a vehicle should detect the parking lot number and corresponding parking region using the vision system. Then, the autonomous vehicle parks itself at the detected parking position; an additional credit is awarded (*Table 1*) if the vehicle succeeds in reverse parking.

3. SYSTEM ARCHITECTURE OF A1

The architecture of A1 is represented in a hierarchical structure that consists of four layers (Fig. 2) and the entire autonomous systems of A1 are encapsulated into several subsystems based on the hierarchical architecture. Each subsystem was independently developed and tested by considering the functional and temporal characteristics.

Table 1 Mission information of 2012 AVC

Mission	**Penalty (credit)**
Traffic light and crosswalk detection	+2 min
School zone and sudden obstacle	+2 min
Overtaking	+2 min
Passenger pickup	+2 min
Construction site	+2 min
Barrier	+2 min
Split road	+2 min
Complex obstacle avoidance	+1 min
Parking (reverse)	+2 min (-2 min)

Fig. 1. The 2012 AVC track.

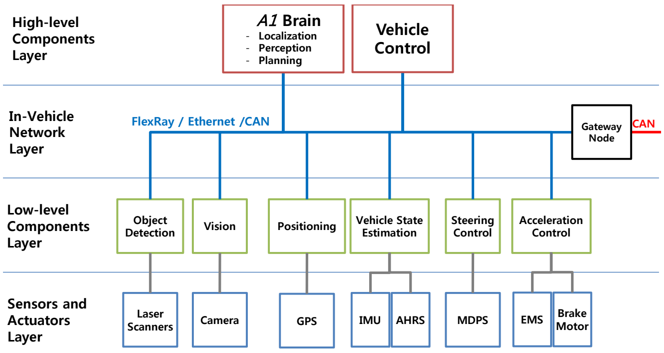


Fig. 2. A1 Distributed System Architecture.

3.1 High-level components layer

A high-level component layer integrates all other subsystem information to plan the behavior and motion of A1. There are two functional components in the layer that include an A1 Brain and a vehicle control. The A1 Brain consists of three parts (localization, perception, and planning). The **localization** function provides the information about where the ego-vehicle is located on the map. The **perception** function integrates the information about vehicle states, position, and driving environment offered from the low-level components layer through the IVN. The **planning** function determines the driving mode of the A1, and generates a drivable path and a target vehicle speed. The **vehicle control** node calculates the control commands for the steering, acceleration, and braking based on the path and target speed given by the A1 Brain. These commands are transmitted to the low-level components layer through the IVN.

3.2 In-vehicle network layer

The IVN layer defines communication among all nodes in the high and low level component layer. The IVN layer consists of FlexRay, CAN, Ethernet and Gateway. The FlexRay is used as the primary network for the A1 autonomous system. The FlexRay provides high bandwidth and a time-triggered scheme. By using the time-triggered scheme, the application SW of the distributed system is designed to be synchronized with minimum time delay (Park and Sunwoo, 2011). The CAN is a redundancy network of the FlexRay, and detects faults by using life signals from all the nodes. An Ethernet network is used to handle a large amount of laser scanner data. The gateway node is implemented to transmit the data from the automotive on-board sensors to the A1 network.

3.3 Low-level components layer

The low level component layer has sensor signal processing and low level actuator control roles. The object detection node extracts information about the static and dynamic object by using laser scanner data. The vision node detects and recognizes the static environment such as a crosswalk, traffic sign, or traffic light with multiple cameras. The positioning node and vehicle state estimation node are used for the precise estimation of the global position and attitude of the ego-vehicle. The steering node and acceleration node operate the individual actuator based on a command from the vehicle control node in the high level component layer to control the ego-vehicle.

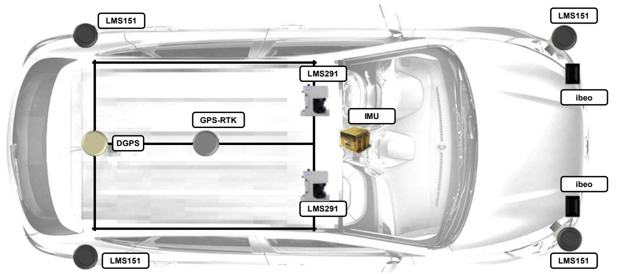


Fig. 3. A1 sensor installation (laser scanners, IMU, and GPS).

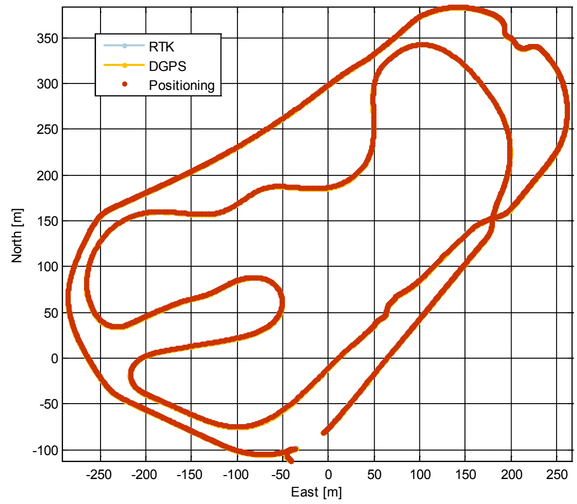


Fig. 4. Result of localization.

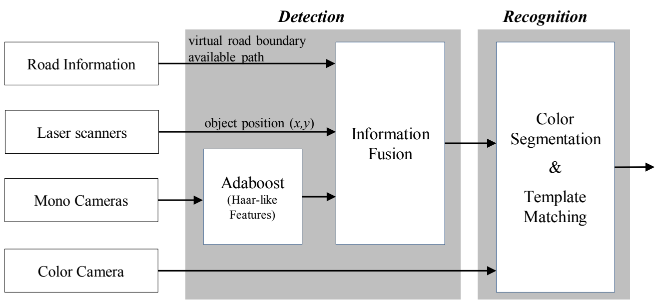


Fig. 5. *Architecture of the vision algorithm.*

3.4 Sensors and Actuators layer

The A1 is based on a Tucson ix platform manufactured by the Hyundai Motor Group. Mono and color CMOS cameras were installed in the back-side of the windshield to perceive visual objects such as passengers, crosswalks or traffic lights. For obstacle detection, a total of eight laser scanners are installed on the A1 as shown in Fig. 3. (Han et al., 2012).

The RTK-GPS and DGPS were installed to measure the global position of the ego-vehicle and is mainly used for localization since the RTK-GPS provides the ego-vehicle position with centimeter accuracy. However, the accuracy of the position drastically decreases and can cause autonomous driving failure if the RF connection between the RTK-GPS base and rover is broken. Therefore, DGPS is used for back-up GPS since it is not affected by the condition of the RF connection. An inertial measurement unit (IMU) was mounted on the center of the A1 to estimate the vehicle behavior. The IMU is also used to enhance the integrity and accuracy of the position estimates by integrating the IMU data with GPS measurements.

4. AUTONOMOUS A1 DRIVING ALGORITHMS

4.1 Localization

The RTK-GPS receiver has centimeter level accuracy. The accuracy of the position for autonomous driving is satisfied using RTK-GPS; however, it is dangerous to use the standalone RTK-GPS due to the occasional temporary loss of satellite and RF connections. The positioning system should be augmented by additional sensors that provide more robust and continuous position data. The positioning and vehicle state estimation components in A1 integrate the GPS data with several on-board sensors that improve the accuracy, continuity, and integrity of the position and attitude estimates. The Bayesian filtering algorithm is applied for the vehicle state and position estimation; details are described in previous papers (Jo et al., 2011, Jo et al., 2010, Jo et al., 2012). Fig. 4 represents the4of the position estimation algorithm.

4.2 Perception - Static object detection and recognition

Multiple cameras were applied to meet the requirements of the vision-related missions. Two monochrome cameras were used to detect mission objects using a learning-based recognition method and a segmentation method. A color camera detected the particular color features of the mission objects (such as a passenger who wears orange clothing); in addition, an information fusion of cameras and laser scanners 4applied to overcome the limitations of camera based perception systems.

Fig. 5 shows the block diagram of the information fusion algorithm based vision system. The road information from the localization provides the road boundary and mission information. Laser scanners provide the size, direction, and position of the objects. Mono cameras based object detectors are applied for detection of passenger, traffic light, and parking location signs. A color camera achieves the color information of the mission objects. Based on the information, a vision algorithm performs the detection and recognition for the mission objects. The vision algorithms consist of learning based detection, information fusion, color segmentation, and template matching based recognition algorithms.

The edge based segmentation method detects the crosswalk. Horizontal edge detection is applied for zebra crossing detection. The zebra crossing consists of multiple horizontal patterns and can be effectively detected by the horizontal edge detection using a 1-D horizontal kernel. A vertical connectivity analysis is proposed to produce segments that are groups of edge connections. The rising and falling segment are paired by length since each segment includes clutters.

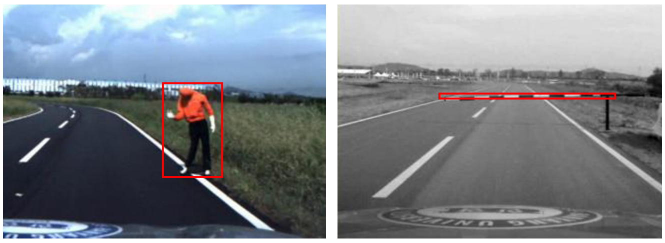
The region of interest (ROI) of a traffic light is predefined by the mission specification. Accordingly, the search regions of traffic 4are significantly decreased44crosswalk positions. Each search region is provided; however, the precise location of the traffic light should be detected to identify the traffic light status. For traffic light detection, two detection methods

(Adaboost based detection and color segmentation) are applied to increase the detection performance. For the traffic light detection on a split road, multi-scaled template matching is performed using object position information of the scanners. The object information of the laser scanners is used as the ROIs of the template matching; in addition, image scaling factors can be derived from the object positions. Typically, the object position information minimizes the resizing of the source image since template matching requires a source image that is resized to the identical size of the template. Fig. 6 shows that traffic light detection was successfully performed at far distances.

The structure of the passenger detection algorithm is similar to the traffic light detection algorithm. ROIs are determined to process the Adaboost based object detection and color segmentation using object positions given by laser scanners. The Adaboost classifier shows state-of-the-art performance in pedestrian detection; however, color segmentation is also applied to reduce false positives. The false positives of the passenger may cause undesirable vehicle stop conditions. Fig. 7 shows a successful detection result. The barrier is one of the most complicated missions due to its thickness. Cameras and laser scanners are used to detect the horizontal barrier. The precise distance from the detection algorithm is applied to stop the vehicle within a five meters stop area. Fig. 8 shows the detection results for parking. The approximate location for parking is provided by the organizer. The accurate parking space should be detected by using the camera since the GPS position roughly lies in a parking space.

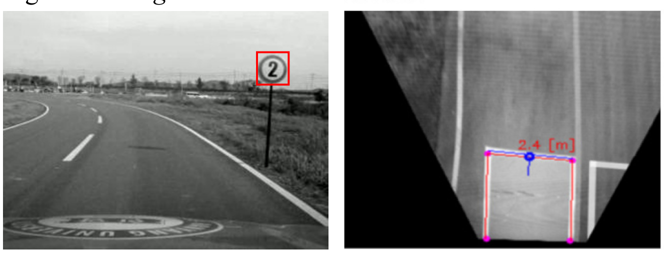
(a) (b)

Fig. 6. *Crosswalk and traffic light detection*



(a) (b)

Fig. 7. *Passenger and barrier detection*



(a) (b)

Fig. 8. *Parking location and parking space detection*

4.3 Perception - Dynamic object detection and tracking

For the overtaking mission, the moving vehicles around the ego-vehicle should be detected and tracked. Several types of laser scanners are applied to the detection and tracking of moving objects. The integrated probabilistic data association filter (IPDAF) based tracking algorithm is implemented for each laser scanner. The dynamic object lists from several types of laser scanners are integrated using the track to track the fusion algorithm to reduce conflict detection in the overlapped area. The associated tracks are merged using the covariance values of the position and velocity.

4.4 Path Planning

The A1 path planning algorithm focuses on local navigation since the road-map contains the global route of the track and mission information provided by the competition organizers. To find the local path, the planning algorithms are developed in consideration of the structured road navigation and the unstructured road navigation. The structured navigation algorithm is executed for typical road driving; however, the unstructured road navigation algorithm generates a complex path for abnormal situations such as construction sites and complex obstacles or parking.

The structured navigation strategy depends on road types. The off-road path planning algorithm focuses on high speed driving with collision avoidance since off-road environments are composed of various curves, straights, and static obstacles with wide road boundaries. For efficient driving, off-road path planning consists of two functions: generation of the path candidates and path selection (Chu et al., 2012). The generation of the path candidates provides a finite set of paths that satisfy the kinematic constraints of the vehicle motion. The path selection function searches for a smooth and safe path by an optimization technique. Fig. 9 describes the results of the off-road path planning. On-road driving environments contain multiple road lanes and are unlike off-road driving environments. The on-road path planner attempts to find a path that moves the vehicle toward the center of the driving lane; in addition, the on-road planner adjusts the goal location based on the perception information to fulfill several stop missions (such as crosswalks, passenger pickups, and barriers). It is also important to perform lane changing for on-road driving as well as lane keeping. The use of the moving obstacle information allows the planner to generate a lane change path for the A1 to overtake the front vehicle. Fig. 10 shows the on-road driving results in the overtaking mission.

For the unstructured road navigation algorithm, a path planning algorithm based on the hybrid A* is developed. This planning algorithm can generate an arbitrary path using goal configuration and obstacle map data. The hybrid A* algorithm is the modified version of the A* algorithm that is a graph-based search algorithm in 2D space. The conventional A* cannot handle the non-holonomic constraint for path generation because the graph of the A* algorithm has a lattice structure. In order to overcome this limitation, the hybrid A* generates a kinematic vehicle motion based graph which is given by

$$\frac{dx}{dt} = v\cos\psi, \quad \frac{dy}{dt} = v\sin\psi, \quad \frac{d\psi}{dt} = v\kappa,$$

where v is the vehicle speed, and κ is the curvature. In these equations, the vehicle position and heading angle (x, y, ψ) can be mapped to the node for the graph expansion. Based on the kinematic vehicle motion based graph data structure, hybrid A* iteratively expands graph and searches the obstacle map for finding a feasible path toward the goal position. The path in the construction site and complex obstacles mission are presented in Fig. 11 and Fig. 12, respectively.

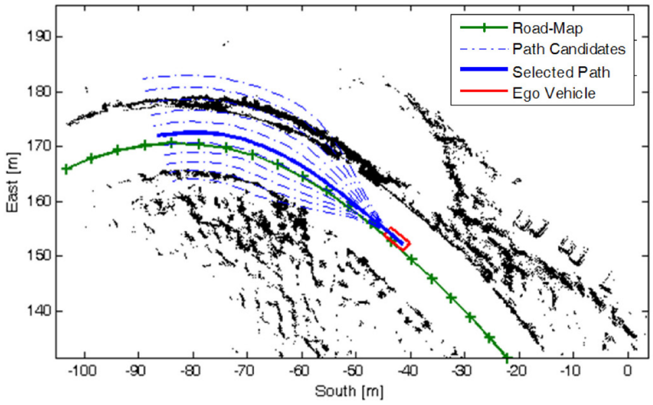


Fig. 9. *Off-road path planning results*

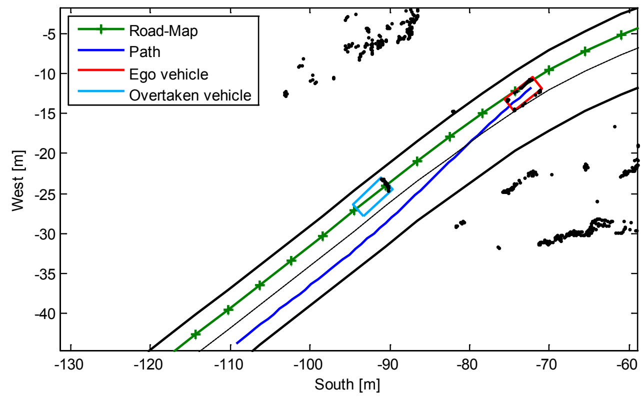


Fig. 10. *Overtaking results*

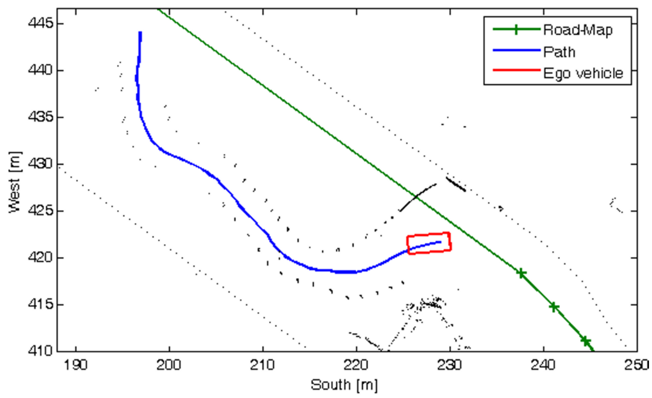


Fig. 11. *Construction site mission*

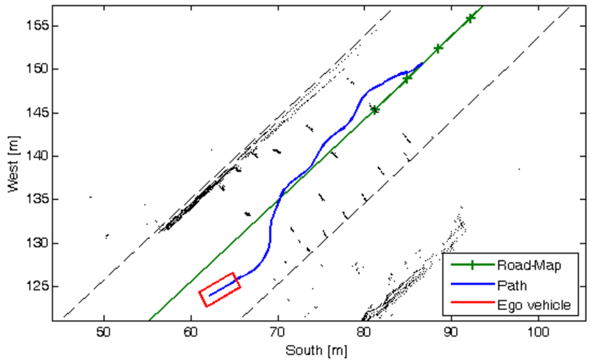


Fig. 12. *Complex obstacles mission*

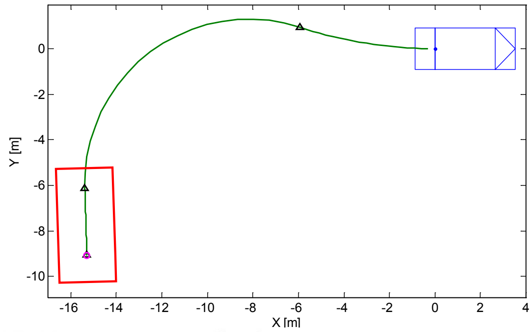


Fig. 13. *Experiment result of autonomous reverse parking*

The parking path is generated based on a circular arc connecting the car position to the center point of the parking area. Fig. 13 shows the experimental result of the autonomous parking system. The red box represents the parking area and the blue box is the shape of the vehicle. The green signal is the trajectory of the vehicle following the generated parking path. This result shows that the autonomous parking system has good performance for reverse parking. The vehicle accomplished parking at low speeds (about 7 km/h).

4.4 Vehicle Control

The appropriate acceleration, brake, and steering commands must be generated to follow the desired path determined by the path planner. The high level control system generates the control inputs (acceleration pedal position, brake pedal position, and desired steering) for the low level control, and the low level control system controls each of the actuators using the vehicle sensors. The high level system consists of two parts: the speed controller and the steering controller. The speed controller and the steering controller are responsible for the longitudinal and lateral vehicle motions, respectively.

The steering controller accepts as input the trajectory generated by the path planner. This system uses only the lateral offset of the preview point not to consider lateral offset of the vehicle C.G. The basic idea is that the vehicle always moves along the Ackerman geometry except for straight movement (Fig. 14).

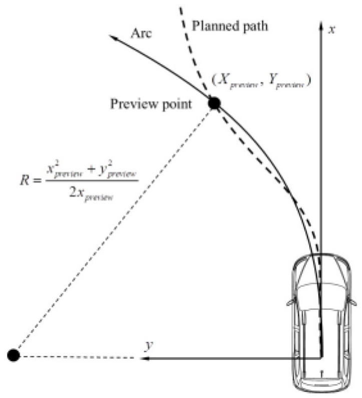


Fig. 14. *Concept of Lateral control*

The speed controller generates two control inputs calculated by the error between the target speed and the measured speed using the feedback / feed-forward control for the acceleration and the brake low-level control, respectively. The desired speed is calculated from the maximum lateral acceleration, $a_{y,max}$, with a tuning parameter dependent on tire and road conditions and road curvature calculated from the path planner.

$$V_{ref} = \begin{cases} V_{min} & (V_{ref} < V_{\min}) \\ \sqrt{a_{y,\max} / \kappa} & (V_{\min} \le V_{ref} \le V_{\max}) \\ V_{max} & (V_{ref} > V_{\max}) \end{cases}$$

where the lower and upper bound of the speed limit, V_{min} and V_{max}, are calculated depending on the road missions, range of perception, and total length of the planned path.

The speed controller also has transition logic to determine which one of acceleration and brake. In the acceleration mode, the acceleration controller consists of the P controller with feed forward.

$$\begin{cases} u_a = k_{ap}\left(V_{ref} - V\right) \\ u_b = 0 \end{cases}$$

where u_a and u_b are the control input for the acceleration and brake pedal and k_{ap} is the feedback gain. In deceleration mode, the controller consists of the PI controller.

$$\begin{cases} u_a = 0 \\ u_b = k_{bp}\left(V - V_{ref}\right) - k_{bi}\int V - V_{ref}\,dt \end{cases}$$

5. CONCLUSIONS

This paper describes the entire system architecture and algorithms for the autonomous vehicle A1. The vehicle was developed by ACE Lab and MMC Lab of Hanyang University for the Hyundai Motor Group Autonomous Vehicle Competitions. The algorithms for autonomous driving of A1 can be classified into four parts.

1) The localization algorithm estimates the position and attitude of the ego-vehicle on the map using GPS and on-board sensor data.

2) The perception system integrates the information from the laser scanners and cameras using an information fusion algorithm. This integrated information is offered to the entire autonomous driving system through the IVN.

3) The planning algorithm determines the behavior and motion of the A1 using the information from the localization and perception algorithm.

4) The vehicle control algorithm tracks the planning path by actuating low-level control modules that include the steering, acceleration, and braking systems.

Based on the proposed architecture and algorithms, the autonomous Vehicle A1 successfully completed all missions of the AVC competition and won in 2010 and 2012.

ACKNOWLEDGEMENT

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