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A Feasibility Study on a Traffic Management System for Autonomous Driving Services based on Dynamic Map*

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Abstract—**An autonomous driving service in urban areas is still a challenging problem. It is necessary to simultaneously solve tactical planning problems and operation planning problems, such as a scenario for passing through an intersection with oncoming vehicles. To realize the service by using a centralized management system, it is necessary to guide thousands of vehicles in real-time. Therefore, efficiency and robustness are required for the management system. In this study, we propose a centralized path planning system to make tactical level decisions to manage the path plans of multiple vehicles based on Dynamic Map. The proposed system selects an operational-level planner to generate a detailed motion plan for each vehicle based on a decision-making algorithm. Then, the conflicts of motion plans between vehicles are detected and resolved by using a spatio-temporal reservation map on Dynamic Map. We report the results of simulation tests of 10,000 hours to evaluate the efficiency and robustness of the proposed system using the map data of an existing city.**

I. Introduction

It is necessary for a sustainable society to provide “mobility” for people who are difficult to move, such as elderly, injured or sick persons. An autonomous driving service in urban areas is a key technology for those people. The authors are researching the services of mobility society using Dynamic Map (DM) [1]. DM is a digital map service which incorporates static and dynamic information related to the map, such as lane structures, travel information of vehicles and mobility service requests. This paper presents a tactical level path planning system to control autonomous vehicles in urban areas based on DM.

Path planning problems are classified into several hierarchies. Paden classified the planners into four components [2]: "Route Planning", "Decision-Making", "Motion Planning" and "Vehicle Control". Our planner has functions of "Decision Making" and "Motion Planning". To drive a vehicle in urban areas, both a function to make tactical decision, such as a right and left turn at intersection, and a function to generate a detailed motion plan, such as a lane keeping maneuver, are required. Many advanced driver assistance systems based on "Motion Planning" and "Vehicle Control" methods have been proposed for typical traffic scenarios. For example, a motion planner for passing unsignalized intersections has a feature that it is robust to a sudden situation change such as jumping out of pedestrians from a blind spot [3]. Since these methods are solutions of individual problems, it is necessary to develop a decision-making method to select an optimal motion plan with considering a traffic context. In recent years, methods for making decisions on complex traffic situations have been proposed. However, its implementation cost and robustness has not been deeply tested. Therefore, we propose a centralized path planning system and evaluate its computational efficiency and robustness in actual use case. To realize a real time traffic management system with realistic operation cost, the system resolves conflicts of motion plans of multiple vehicles by putting the tactical level traffic problem between vehicles in a specific motion planning problem of a vehicle based on a decision-making method.

In this paper, we first describe the data structures of a digital map and the framework of a path planning system in section III. Next, a decision tree that maps complex traffic problems into a simple one to one motion planning problem are described in section IV. In the section V, the details of the motion planner for individual traffic scenarios are described. Finally, for evaluating the robustness of the proposed method, a simulation test of 10,000 hours using real map data is shown in section VI.

II. Related works

Various path planners have been proposed for developing autonomous vehicles and advanced driver assistance systems. In recent years, a tactical level planner with decision making has been proposed for developing fully autonomous vehicles. In this section, the related works of path planners are described.

A. Decision-making methods

In the path planning method with decision-making, the methods of controlling the whole traffic flow by using a centralized system have been proposed [4]. As a typical example, there is a method of scheduling vehicles passing in an intersection to improve traffic efficiency [5][6]. A cooperative planning method at intersections which manages the reservation request to pass the intersections is also proposed [7]. In these methods, in an environment where there is no uncertainty, each vehicle can safely travel with planned motions. On the other hand, in environments with uncertain factors such urban areas, more detailed motion planning and more frequent updating of plans are required to keep safety. Therefore, the decision making part becomes more important and complicated. A decision making method based on a state machine with a hierarchical structure is a typical approach [8]. In this approach, the operational level

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planners, such as an obstacle avoidance planner and a planner for passing through an intersection, are prepared to generate the detailed trajectory of a vehicle. And, the decision making method switches to use the optimal operational level planner with understanding the traffic context [9]. In these methods, since the decision making process is designed by manually, if there are many types of traffic rules, designing and testing the methods becomes difficult. Then, a method which can automatically construct a decision making structure based on a partially observable Markov decision process (POMDP) are proposed [10]. Cunningham et al. proposed a POMDP based method which generates the optimal motion plan by evaluating the various types of safety policies according to the traffic environment [11]. [12] is a state-of-art tactical level planner based on POMDP. The advantage of the POMDP based methods is that the safety behavior are effectively selected in a traffic environment with considering the uncertainty of objects. Because of the high calculation cost [12], it is suitable for onboard systems, however, it is not suitable for controlling a large number of cars by a centralized system.

B. *Motion planning methods*

As operation and control level planners, various methods have been proposed from a simple planner like adaptive cruise control to an advanced planner with a considering uncertainty of traffic environment. The physical model based control planner can be seen in [3] [13]. By assuming the uncertainty of the target motions, the safety trajectory and passing speed can be determined theoretically. These methods have advantage that if the traffic scenario is matched, the safety of the plan is guaranteed by the physical basis. Stochastic model based approaches are also proposed for control level planners. Eidehall et al. proposed a probabilistic prior for avoiding obstacles by analyzing the parameters of a driver model from human driving data [14].

III. PATH PLANNING SYSTEM BASED ON DYNAMIC MAP

In this section, the data structures of DM to represent a road network and motilities are explained first. Next, a framework of the path planning system for managing multiple vehicles on DM will be explained.

A. *Data structures of Dynamic Map*

DM is a data sharing platform for expanding conventional road map information to handle dynamic information such as vehicles and traffic environment. In this research, Nagoya COI format [1] is used for DM (Fig. 1). The road and mobility information necessary for explaining the proposed path planning system will be explained below.

1) *Geometric structures*

There are "Position" and "Area" information as the geometric structures of a map. There are two types of position information. The first one is P which denotes the global position according to the geodetic system on a map. The second type "Lane Position" X represents the relative coordinate system on the lane structure of a map. X denotes the longitudinal and lateral offset value in a lane and the index number of the lane.

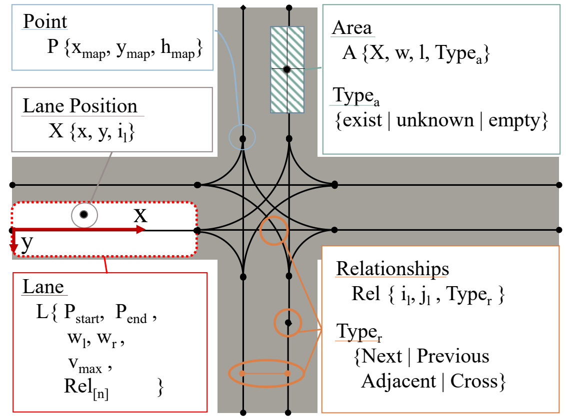

Figure 1. Static data structures of DM.

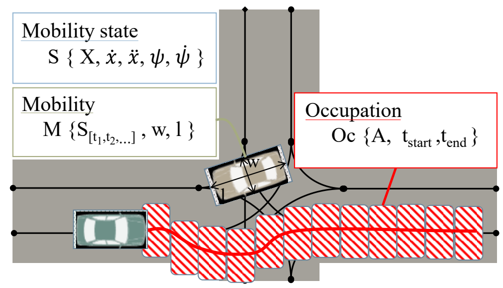

Figure 2. Dynamic data structures of DM.

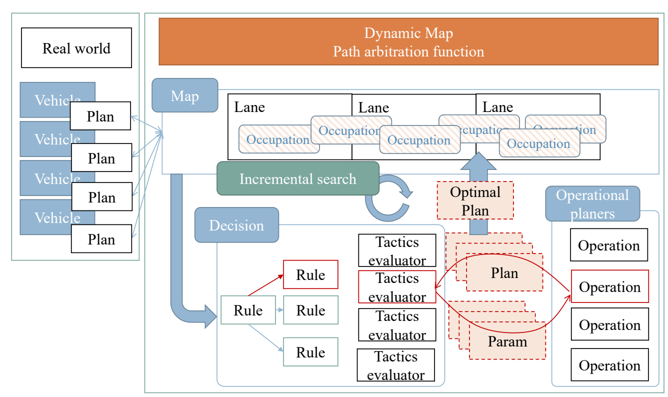

Figure 3. Schematic diagram of the path planning system on DM.

"Area" A is a structure representing a rectangular region on a lane. It consists of the values of a center position, width and length. "Lane structure L consists of a start and end position, right and left width, speed limit, curvature radius, stop line flag and "Relationship" information to other lanes. "Relationship" R represents the connection information "Next", "Previous", "Adjacent" and "Crossing" between two lanes.

2) *Data structures for motilities*

Figure 2 shows the data structures for motilities. The "Mobility State" S has values of position X, velocity $\dot{x}$, acceleration $\ddot{x}$, orientation angle ψ and angular velocity $\dot{\psi}$. The "Mobility" M consists of time series of mobility states as a motion plan, width and length of the mobility. The motion plans are registered by using regional occupation information "Occupation" on DM. The "Occupation" Oc consists of area A and the time span of the occupation.

B. Framework of the path planning system

Figure 3 shows the framework of the path planning system. The system first registers the current motion plan of each vehicle on DM by using the "Occupation" data structure. Next, as a decision process, the tactics of next time step are decided by a rule-based decision tree. Then, candidates of motion plans are generated with various parameter sets based on the decided tactics. To select an optimal motion plan, the safely of each motion plan are evaluated with the occupation data of other vehicles. Since this process updates the motion plans of all vehicles based on the occupation data on previous time, new conflicts of the motion plans will occur. To resolve the path conflicts, it is necessary to repeat the planning and decision process. In the proposed system, this resolving process is repeated for a certain period of time to sequentially resolve the path conflicts. In order to provide a Time-Constrained service, a quasi-optimal solution of this planning problem are determined without solving the global optimal solutions. Then, there is a possibility of remaining the conflicts of motion plans and it causes the operation switching to a human driver. The occurrence possibility of this problem should be sufficiently low to provide the planning service. A robustness of the proposed system are verified by an experiment described in section VI.

C. Sensing of traffic environment

To decide the tactics of a vehicle, the information of the surrounding traffic environment is collected. The sensing range starts from the current lane to 50m before and 25m behind. The collected information is lane occupation information (motion plans) of other traffic participants, area states, and lane information within the range.

D. Motion planners

To generate motion plans based on the decision process of the proposed system, we use five types of motion planners: "Following", "Passing each other", "To stop", "Obstacle avoidance" and "Intersection passing" (Fig. 4). In those motion planners, motion plan is generated by considering only one of the most important factors (without considering the movements of multiple traffic participants). For example, at the intersection passing planner, it only takes consideration into the velocity of a preceding vehicle or maximum yaw rate for comfortable driving. And the decision-making unit determines and resolves the conflicts of the motion plan of other crossing vehicles. The details of the motion planners are explained in section V.

IV. DECISION TREE FOR TRAFFIC MANAGEMENT

In this section, we explain a decision tree to select the motion planners with information on traffic participants and traffic regulations around a vehicle. The decision trees are also used in ontology-based decision-making methods for ADAS [15] and the autonomous driving system based on Markov decision process [11]. There is an advantage that system verification is easier than a machine learning based method for designing autonomous driving systems. The decision tree of the proposed method is shown in Fig.5.

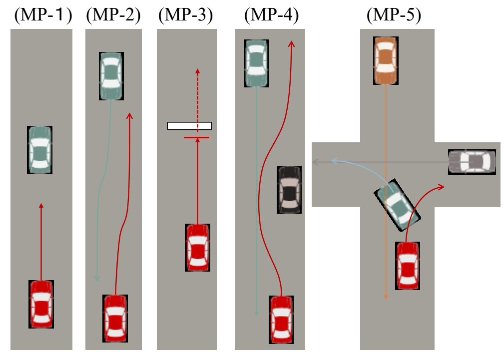

Figure 4. Motion planners: (MP-1)"Following", (MP-2)"Passing each other", (MP-3)"To stop", (MP-4)"Obstacle avoidance", (MP-5)"Intersection passing".

A) The rule with the highest priority is "To Stop" when the preceding vehicle is stopped or when there is a traffic restriction such as a stop line or red signal.

B) Next, when an intersection or merging point is approaching within 20 seconds, 12 types of speed values for generating motion plans are prepared to find the optimal motion plan. The motion plan with the largest value of Time to Collision (TTC) is selected.

C) When there is an obstacle ahead, 6 types of side margin are prepared to find the optimal motion plan. Then, if an oncoming vehicle is running the side lane, the motion plan is generated to stop before 18m of the obstacle.

D) If the oncoming vehicle approaches within 3.5 seconds and the lateral margin is less than 2 m, narrow road passing planner is called to avoid the oncoming vehicle.

E) Finally, if neither of the above cases applies, the cruise planer is called.

The detailed motion plan is generated by the planner determined by the above rule. The generated plan is registered as lane occupation information on DM. Then, if a minimum value of TTC between the registered motion plans is less than 2 seconds, the motion plans are canceled and the motion plan "To stop" is selected. As a result, when another traffic participant has already registered the road usage plan in a scene such as passing through an intersection or avoiding obstacles, a waiting plan until the road is empty is generated. In each motion planner, since various parameters are required, the details of the motion planner and its parameters are described in the next section.

V. MOTION PLANNERS

In this section, the details of the motion planners will be described.

A. Common parameters for motion planners

Since a motion planner generates a motion plan according to a request from the path planning system, even if the decision of the system is changed, the motion plan should be seamlessly connected to the recent motion plan. Therefore, common parameters are used for the all motion planners to keep the continuity of the motion plans. Table I shows the list of the common parameters.

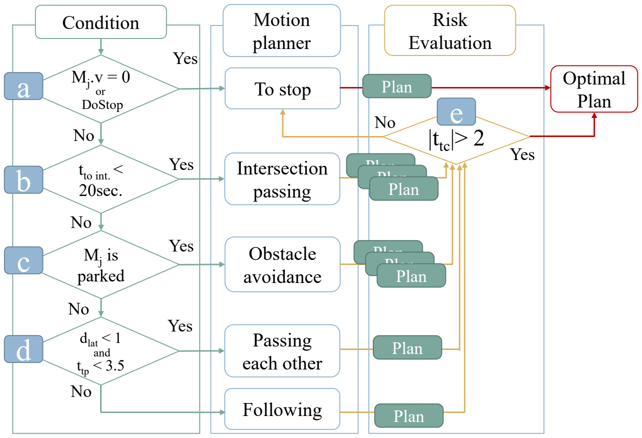

Figure 5. Decision making process.

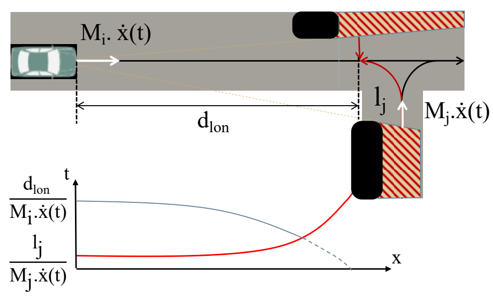

Figure 6. Relationship between a time to collision point of a passing vehicle and jumping out traffic participant.

TABLE I. COMMON PARAMETERS FOR MOTION PLANNERS

Parameter type	Symbol
Time delta	Δt
Planning horizon	t_{max}
Maximum longitudinal acceleration (>0)	$\ddot{x}_{max}$
Maximum longitudinal deceleration (<0)	$\ddot{x}_{min}$
Maximum lateral acceleration	$\ddot{y}_{max}$
Longitudinal distance to a target object	d_{lon}
Lateral distance to a target object	d_{lat}
States of the ego-vehicle	M_i
States of the related mobility j	M_j
Parameter X of the mobility i at the time t.	$M_i.X(t)$

B. Selection of maximum speed

For motion planning, traveling speed is the most important factor to keep safety. Therefore, the traveling speed determination method which is commonly used for the all motion planners are explained. The minimum value is selected from the following velocities ($\dot{x}_{max1}$ to $\dot{x}_{max4}$) as the traveling speed.

- Legal speed ($\dot{x}_{max1}$)
- Accident risk predictive velocity ($\dot{x}_{max2}$)
- Operation error consideration velocity ($\dot{x}_{max3}$)
- Maximum lateral acceleration constraint ($\dot{x}_{max4}$)

Since the lane information of DM has the value of legal speed, we refer the value as $\dot{x}_{max1}$.

Next, as shown in Fig. 6, the accident risk predictive velocity is calculated when the "unknown" regions, such as the occluded area at an intersection and the behind region of a parked vehicle, are existed. Basically, since there is a possibility that traffic participants appear suddenly from the unknown-empty region boundary, a passing vehicle should be possible to stop before the crossing point. When the distance from the ego-vehicle to the crossing point is d_{lon}, the velocity satisfying this condition is obtained by Eq. (1).

$$\dot{x}_{max2} = \sqrt{-\frac{2}{3}\ddot{x}_{min} d_{lon}} \qquad \frac{d_{lon}}{M_i.\dot{x}(t)} < \frac{l_j}{M_j.\dot{x}(t)} \tag{1}$$

Then, as shown in the bottom graph in Fig6, since the occluded area is decreased with approaching the ego-vehicle to the crossing point, the distance from the unknown region to the crossing point is increased. At a certain time, the required time of the ego-vehicle to pass the crossing point with the current speed becomes shorter than the arrival time of a crossing traffic participant. Then, the ego-vehicle no longer needs to decelerate. Therefore, $\dot{x}_{max2}$ is used while the condition in Eq. (1). is satisfied.

Next, there are risks that a vehicle cannot follow a motion plan correctly due to various disturbances. Then, a driver needs to slow down to pass an obstacle when the lateral margin is narrow. The relational equation of the lateral margin and the passing speed have been proposed in previous work [16]. We apply this equation to calculate $\dot{x}_{max3}$ with parameters {α=1.73, β=0.42}.

$$\dot{x}_{max3} = 1/\{1+\mathrm{EXP}(-\alpha(d_{lat} - \beta))\} \tag{2}$$

Finally, $\dot{x}_{max4}$ is calculated to satisfy the parameter value of the maximum lateral acceleration as follows:

$$\dot{x}_{max4} = \sqrt{L_i.r\ \ddot{y}_{max}} \tag{3}$$

where $L_i.r$ is the curvature radius of the lane L. The motion planning is always performed by referring to these velocity values.

C. Following

From this section, we will explain the details of the five types of motion planners. The first planner is "following" that is used for following a preceding vehicle. In this planner, the speed of a vehicle $M_i.\dot{x}(t)$ is corrected to the speed of the target vehicle $M_j.\dot{x}(t)$ with the acceleration value $\ddot{x}_{max}$ or $\ddot{x}_{min}$ designated by the parameter. The time required to change to the target speed is given by Eq. (4), when the speed of the ego-vehicle is faster than the preceding vehicle.

$$t_{tf} = -|M_j.\dot{x}(t) - M_i.\dot{x}(t)| / \ddot{x}_{min} \tag{4}$$

Then, the relative distance between the vehicles is changed during the time t_{tf} as follows:

$$d_{tf} = |M_j.\dot{x}(t) - M_i.\dot{x}(t)|\, t_{tf} + \ddot{x}_{min} t_{tf}^2/2 \tag{5}$$

Therefore, the acceleration value of a vehicle is given according to the distance to the preceding vehicle as follows:

$$M_i.\ddot{x}(t) = \begin{cases} \ddot{x}_{min} & d_{lon}(t) < d_{tf} + 2M_j.\dot{x}(t) \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

As a result of the model above, the ego-vehicle follows the preceding vehicle at the position $2M_j.\dot{x}(t)$ behind as a time headway equals two seconds.

D. To stop

The second planner "To stop" is a planner to respond to traffic laws such as stop lines and traffic signals. The motion plan until stopping before a stop line is the same as the following planner. After that, it shifts to the standby mode to monitor the stop time or the state of the signal, and it will return to the other state after releasing the regulation.

E. Lane keep

The function of adjusting the lateral position in a lane is a basic operation that has been proposed as lane keep assistance systems. In this section, we explain a motion model to change the lateral position in a lane used in this research. The constraints of this planner are as follows:

- the headway angle of a vehicle equals zero in the start and end point.
- a vehicle shifts d_{lat} in the lateral coordinate of a lane during it travels d_{lon} in the longitudinal coordinate.

In order to satisfy these constraints, the angular velocity and the headway angle are given by Eq. (7) and Eq. (8).

$$\dot{\psi}(x) = K_s \sin(2\pi x/d_{lon}) \tag{7}$$

$$\psi(x) = \frac{d_{lon}K_s}{2\pi}(1-\cos(2\pi x/d_{lon})) \tag{8}$$

This operation is used with the speed control operations mentioned in Section V.C and V.D at the same time. In this case, the speed control affects to the lateral position of the vehicle at the end point. Therefore, the adjustment parameter K_s is obtained by Eq. (9) with the target shift value d_{lat} of the lateral coordinate.

$$\arg\min_{K_s}\left\{d_{lat} - \sum_{x=0}^{d_{lon}} M_i.v(x)\sin\big(\psi(x)\big)\right\} = 0 \tag{9}$$

F. Passing each other

The next planner "Passing each other" generates the motion plan that takes into consideration the road width for passing by an oncoming vehicle. In this planner, if the lateral margin between the ego-vehicle M_i and the oncoming vehicle M_j falls below 2m when both are running on the lane L_i and L_j, the planner gives lateral running position of the lane to make safety margin. The running position of the ego-vehicle is calculated by Eq. (10).

$$d_{lat} = (L_i.w_r - (M_i.w + M_j.w)/2)/2 \tag{10}$$

By using the lateral position d_{lat}, the specific motion plan is generated by the planner mentioned in section V.E.

G. Obstacle avoidance

When there is an obstacle such as a parked vehicle ahead, a motion plan for avoiding it is generated. Although the traffic scenario is similar to the scenario "Passing each other", there are two differences with it. One is that the generated motion plan will fully block the traffic of the opposite lane. Second is that since there is an unknown region behind the parked vehicle, the speed of the ego-vehicle is given by the accident risk predictive velocity mentioned in V.B. Therefore, when the lateral margin of avoidance is set to be large, the passing time becomes shorter but the distance traveled in the opposite lane becomes larger. On the other hand, when the lateral margin is small, the traveling speed becomes slow and the passing time becomes longer. In order to solve this trade-off problem, a multiple candidates of lateral margins are generated. The candidates of the lateral margin are given every 0.2m from 1.0m to 3.0m. Then, a plan that maximizes TTC to an oncoming vehicle is selected as the optimal motion plan. The specific motion plan is generated by the planner mentioned in section V.C and V.E.

H. Intersection passing

In the motion planner to pass through an intersection, six kinds of plans with different cruising speeds (entry time) are generated to evaluate the conflicts with other vehicles. Then, the maximum speed of the six is $\dot{x}_{max4}$ which is decided according to the turning radius of the lane based on Eq. 3. The velocity of the n-th candidate is given by $0.9^n \dot{x}_{max4}$. As shown in section IV.B, when TTC values of all the plans are less than 2, the vehicle shifts to the "To stop" plan.

VI. Experiments and Discussions

The proposed path planning system finds quasi-optimal solution of motion plans for vehicles. In complex traffic situations, there is a possibility to remain the conflicts of the motion plans between vehicles. Then, the autonomous driving mode is canceled and human needs to operate the vehicle. When this handover occurs frequently, it is difficult to provide an autonomous driving service. Therefore, we measure the occurrence probability of the plan conflicts by long-term simulation experiment and evaluate the robustness of the proposed system. Moreover, in order to operate the huge numbers of vehicles by a centralized traffic system in a real world, it is necessary to manage the vehicles with realistic equipment cost. Therefore, in this experiment, the number of vehicles that can be managed per computer is also evaluated.

A. Experiment environment

The traffic scenario and experiment environment are as follows. We use a real road network of urban areas (35.7038, 139.5122)-(139.5222, 35.7012) as an experimental course. This course has four intersections shown in the figure, and the total length is about 4 km. 40 vehicles which are operated by the proposed system and 2 parked vehicles are randomly placed in this course. As shown in the figure, there is a narrow road to make the path conflicts in avoiding the parked vehicles. The computational environment to run the traffic simulator is as shown in Table II.

B. Measurement data and parameters

Data to be measured by the experiment are as follows: the total amount of traveling distance of vehicles, the number of path conflict events and the number of motion plan generation. In order to find the conflict of the motion plans between vehicles, an observer which independently checks the overlapping of the bounding box of vehicles are used. If a conflict event is occurred, the vehicle will be in a stopped state. Then, traffic events will not occur anymore and the conflict event rate cannot be evaluated correctly. Therefore, when a conflict event occurs, all of the positions of the vehicles are replaced randomly to resume the simulation. The parameters of this experiment are shown in Table III.

C. Results

The results of the experiment are shown in Table IV. The occurrence frequency of the plan conflicts is once every 77 hours on average. This frequency means that how often a driver needs to operate the vehicle. Since the frequency is sufficiently low, it is possible to realize a service in which a specialized operator can remotely monitor the system and help drivers. We discuss the main causes of the conflict problems. In many cases, the two vehicles gave way to each other in a junction during the repetitive processing of the proposed system. Finally, it arrives at the junction at the same time. In order to solve such a problem, an observer is needed to determine the order of priority of the junction like a signal. Next, the traffic efficiency is discussed. The average travel speed is shown in Table 3. Since the speed limit is 40 km/h in the half of the experimental course and the rest are 30 km/h, the average travel speed is efficient enough.

Next, the operation speed of the system is evaluated. The figure shows the number of motion plan generation times in each simulation hours. These results mean that the proposed system can generate about 16,000 motion plans per second by using the single computer shown in Table V. Since 10 million vehicles can be controlled by 625 computers based on the proposed system, it is concluded that it is sufficiently practical.

TABLE II. COMPUTATIONAL ENVIRONMENT FOR THE EXPERIMENTS

CPU	Core i7 6850k
Memory	32 GByte
OS	Ubuntu14.04 + ROS Indigo
Language	C++

TABLE III. EXPERIMENT PARAMETERS

Symbol	Value	Symbol	Value
Δt	0.03	$\ddot{x}_{max}$	1.2
t_{max}	18.0	$\ddot{x}_{min}$	-1.75
		$\ddot{y}_{max}$	0.25

TABLE IV. OCCURRENCE FREQUENCY OF PATH PLAN CONFLICTIONS

Time (hours)	Total trip (km)	Trip speed (km/h)	Sum of conflicts	Hours par conflicts
200	4,917	24.6	0	-
1000	24,100	24.1	14	71.4
5000	122,576	24.5	61	82.0
10000	268,383	26.8	129	77.5

TABLE V. NUMBER OF PATH GENERATION

	Total count of path generation (million events)				
Time (hours)	Following	Intersection Passing	Passing each other	To stop	Obstacle avoidance
200	3.55	1.9	0.3	1.4	2.2
1000	19.8	8.6	1.6	7.4	11.8
5000	96.9	47.8	8.2	36.3	62.1
10000	211.8	105.4	17. 6	80.1	133.4

VII. CONCLUSION

We present the path planning system to control autonomous vehicles in urban areas based on Dynamic Map. The propose system enables to generate 16,000 path plans in one second by combining the decision tree and the five types of the motion planners. As a result of the evolution experiment through 10,000 hours, the autonomous vehicle operated by the proposed system requires human assistance once every 77 hours on average. In the experiment, the first management failure of the path planning occurs at 200 hours after the start. This result shows that to evaluate robustness of the path planning system requires a long term test. In the future works, we will extend the system to support unmanaged traffic participants such as pedestrians and cyclists. We also aim to improve the robustness by partially using the solver of the globally optimal solution to avoid all path conflicts.

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