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A THREE-LEVEL CONTROL ARCHITECTURE FOR AUTONOMOUS VEHICLE DRIVING IN A DYNAMIC AND UNCERTAIN TRAFFIC ENVIRONMENT

Jun Miura, Motokuni Ito, and Yoshiaki Shirai

Department of Computer-Controlled Mechanical Systems, Osaka University

Suita, Osaka 565, Japan

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ABSTRACT

This paper proposes a novel control architecture for autonomous vehicle driving in a dynamic and uncertain traffic environment. The architecture is composed of three levels: (1) the *operational level* deals with a reactive control of a vehicle in a short time cycle; (2) the *tactical level* decides proper maneuvers based on prediction of future states using probabilistic traffic models; (3) the *meta-tactical level*, which is the feature of the architecture, timely activates an appropriate tactical-level planning procedure according to both the history of maneuvers and the current traffic condition. A utility-based maneuver evaluation method is also described. The proposed architecture was tested on a highway driving simulator in various traffic scenarios; simulation results show the feasibility of the architecture.

INTRODUCTION

In recent years, there have been growing interests in ITS (intelligent transportation systems). Autonomous driving is one of the research areas of ITS. Tasks in driving can be divided into two levels: at the higher level, maneuvers such as lane changing and overtaking are determined to meet the objective of driving (e.g., a target arrival time) under the constraints imposed by an actual traffic condition; at the lower level, a selected maneuver is translated into actual control operations. These levels are called as the *tactical level* and the *operational level*, respectively [4, 7]. Although past research has been mainly focused on the operational level (e.g., [2, 6]), the tactical level should be investigated more actively for realizing intelligent vehicles that can maneuver safely and efficiently in a dynamic and uncertain traffic environment[7].

This paper is concerned with the tactical level planning of an autonomous vehicle. In real traffic, sensory information on which an autonomous vehicle makes decisions is *uncertain* (e.g., measurement error or occlusion). In addition, the situation is *dynamic*, i.e., the situation evolves as time elapses. Thus, the tactical level planning should be based on the prediction of the future traffic condition with consideration of uncertainty.

Niehaus and Stengel [5] modeled the movement of a nearby vehicle using a probabilistic distribution, which is continuously updated using the Kalman filtering, and generated a safe plan considering the probable worst-case scenarios. Only a local and short-time prediction is performed in planning. Forbes et al. [3] proposed to model all levels of planning for an automated vehicle using a fixed probabilistic network. Although they proposed an efficient computation method for the network, extending the approach to more complicated scenarios may still be difficult because of increasing computational cost. Sukthankar et al. [7] proposed a distributed reasoning scheme for the tactical level planning. Independently operating planning modules with different algorithms vote for the desirable action, and the high-scored action is selected and executed. The parameters and the relative weight of each planning module are tuned through an evolutionary learning method. The proposed scheme seems fitted to the tactical level planning that requires a relatively short-term prediction.

To make a plan with a long look-ahead tends to be computationally expensive if all alternatives are considered in every situation. Moreover, it may be inefficient to always carry out such a planning. Therefore, we propose to introduce a meta-level planning (called the *meta-tactical level*) to control the tactical level, i.e., to adaptively limit the search space of the tactical level and to activate the tactical level only when it is necessary, according to both the history of maneuvers and the current traffic condition. The resultant control architecture is composed of three levels: *meta-tactical level*, *tactical level*, and *operational level*.

We apply this architecture to automated highway driving of a vision-based vehicle. We tested the architecture on a highway driving simulator. In the simulator, the autonomous vehicle is assumed to have a vision system to measure the position and the velocity of other vehicles which are not completely occluded. The uncertainty in these measurements is calculated using a probabilistic model of vision uncertainty.

THREE-LEVEL CONTROL ARCHITECTURE

Figure 1 schematically depicts the proposed three-level control architecture. The meta-tactical level continuously watches predetermined events on traffic and, on occurrence of an event, activates an appropriate tactical-level maneuver selection procedure. Then the tactical level determines the best maneuver to perform and send it to the operational level.

The operational level translates the maneuver into the vehicle control primitives for execution. Example primitives are: keeping constant distance to the front vehicle and lane changing. In addition, the operational level occasionally handles emergency situations such as an abrupt deceleration of the front vehicle. This level is realized as a reactive system.

We suppose that two independent processes are running in parallel; one deals with the meta-tactical and tactical level; the other deals with the operational level. These two processes correspond to the control flows drawn by dotted arrows in Figure 1.

TACTICAL LEVEL

The tactical level selects the best maneuver among alternatives given by the meta-tactical level. Since the traffic condition includes various uncertainty factors, this level of planning is based on a statistical decision theory [1].

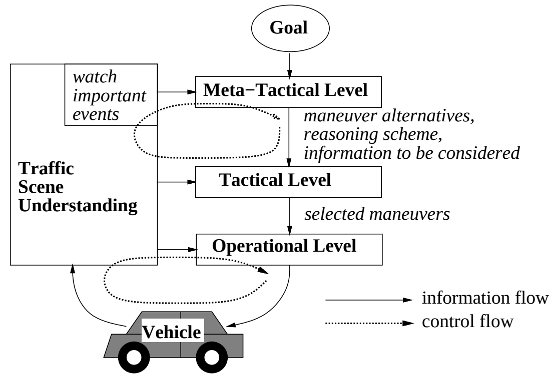


Figure 1: The three-level control architecture.

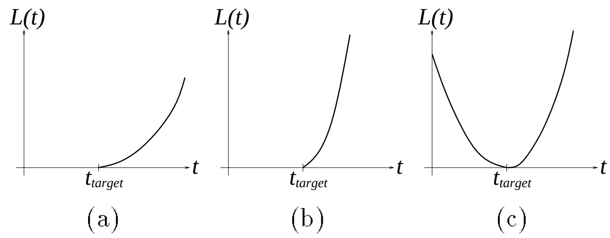


Figure 2: Examples of $L(t)$:
(a) loose requirement on the arrival time;
(b) tight requirement on the arrival time;
(c) both late and early arrivals are not desirable.

Utility-Based Evaluation of Maneuvers

The purpose of automated driving on a highway is to reach the planned exit safely and efficiently. There may be various requirements on safety and efficiency; for example:

- reach the exit as early as possible;
- reach the exit before the target arrival time;
- safety is the only concern.

In order to evaluate each maneuver based on such various requirements, we define (1) a loss function of the arrival time and (2) an extra cost required for each maneuver.

Let t be the *estimated* arrival time. The loss function $L(t)$ is defined according to the requirements on t with the *target* arrival time t_{target}. Figure 2 shows some examples of $L(t)$.

Using the loss function $L(t)$, the best maneuver is selected as follows. Let us consider the case that the planner compares two maneuvers A and B; A is a maneuver with lane changing; B is one without lane changing. Suppose the arrival times are estimated as t_A and t_B for maneuvers A and B, respectively. Also let C be the extra cost required for lane changing, which

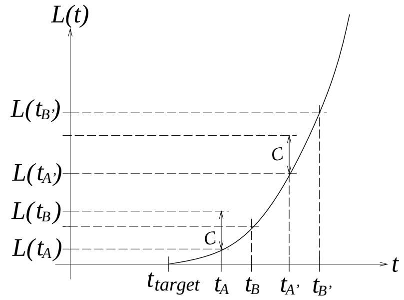


Figure 3: Maneuver selection.

represents the cost of possible risk. The condition that maneuver A is selected is given by

$$L(t_B) > L(t_A) + C. \tag{1}$$

With the loss function shown in Figure 3, since inequality (1) holds, maneuver B is selected. However, if the estimated arrival time becomes later (i.e., time pressure is higher) due to an unexpected traffic congestion (for example, $t_{A'}$ and $t_{B'}$ in Figure 3), maneuver A may be selected. Such an effect of time pressure on maneuver selection seems to coincide with our intuition on lane changing.

It can be viewed that cost C represents a kind of the vehicle's character; a low C means that the vehicle tends to change lane whenever possible; a high C means that the vehicle puts high priority on safety.

Example of Tactical Level Planning

We here present one example of actual planning procedure, which is for decision on overtaking with consideration of approaching exit.

Consider the scenario shown in Figure 4 [1]. The autonomous vehicle (called *MyVehicle*, drawn as a bold rectangle in the figure) on the right lane is approaching the exit to take. Since the speed in the current lane is becoming a little bit slow, *MyVehicle* starts thinking if it should overtake vehicles ahead. If *MyVehicle* moves to the left lane and successfully comes back to the original lane after overtaking, it will reach the exit earlier than keeping the current lane until reaching the exit. In overtaking, however, there may be risks of lane changing itself and of missing the exit. We model this situation and derive

[1] This scenario was originally presented by Sukthankar et al. [7].

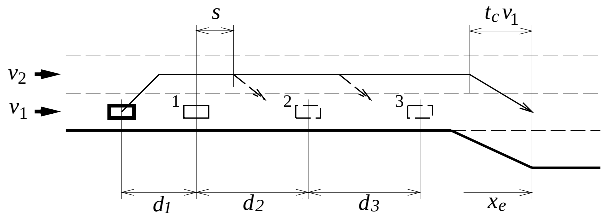


Figure 4: Overtaking with consideration of approaching exit.

an equation to calculate the *expectation* of the arrival time for the lane changing maneuver.

Suppose that the average vehicle speeds on the right and the left lanes are v_1 and v_2, respectively. Regarding the position and the velocity of other vehicles, *MyVehicle* uses vision information if it is available; if not, *MyVehicle* supposes that invisible (occluded) vehicles are almost equally placed within an occluded area. Here we consider the case that only the front vehicle is visible. For occluded vehicles, we model their placements such that the distance between vehicles is given by a normal distribution.

The mean μ and the variance σ^2 of the normal distribution are estimated from the relationship between their values and the average speed; this relationship has been empirically obtained [8]. Given μ and σ^2, the current position $x_k(0)$ of the kth car ahead at time $t = 0$ is specified by the following mean u_k and variance σ_k^2:

$$\mu_k = d_1 + (k-1)\mu, \tag{2}$$
$$\sigma_k^2 = (k-1)\sigma^2. \tag{3}$$

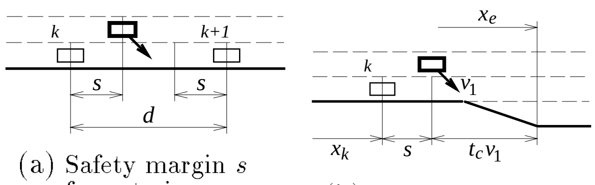
Let us consider the condition that *MyVehicle* can enter the space between the kth and the $k+1$th vehicles. The probability P_{i_k} that this condition holds is given by

$$P_{i_k} = P(2s \leq d), \tag{4}$$

where s is the safety margin for entering as shown in Figure 5(a).

Let us consider another condition that *MyVehicle* does not miss the exit after overtaking k vehicles. This condition is restated as the condition that the position of *MyVehicle* when it overtakes the kth vehicle is sufficiently before the exit (see Figure 5(b)). The probability P_{e_k} that this condition holds is calculated as

$$P_{e_k} = P(x_k(t_k) + s \leq x_e - t_c v_1), \tag{5}$$



(a) Safety margin s for entering between vehicles. (b) Condition for successful exit.

Figure 5: Conditions for overtaking.

where t_c is the necessary time for lane changing; x_e is the position of the exit; t_k is the time for overtaking k vehicles. Since t_k satisfies the following equation:

$$x_k(t_k) \;=\; x_k(0) + v_1 t_k = v_2 t_k - s, \tag{6}$$

t_k is given by

$$t_k = \frac{x_k(0)+s}{v_2 - v_1}. \tag{7}$$

From equations (5)(6)(7), we obtain

$$P_{e_k} = P\left(x_k(0) + s \le \frac{(x_e - t_c v_1)(v_2 - v_1)}{v_2} \right). \tag{8}$$

Assuming that above two conditions are mutually independent, the probability P_k of overtaking k vehicles and then successfully taking the exit is $P_k = P_{i_k} P_{e_k}$. In addition, the elapsed time t_{e_k} until *MyVehicle* reaches the exit after overtaking k vehicles is given by

$$t_{e_k} = (x_e - \mu_k - s)/v_1. \tag{9}$$

Using the above equations, the expectation of the arrival time t_e is given by

$$\begin{aligned} t_e &= T_n, \\ T_k &= P_k t_{e_k} + (1-P_k) T_{e_{k-1}}, \quad (k = 1, \cdots, n) \\ T_0 &= t_f, \end{aligned} \tag{10}$$

where n is the index of the farthest vehicle that *MyVehicle* possibly overtakes (i.e., $P_{i_n} > 0$ and $P_{i_{n+1}} = 0$); t_f is the expectation of the arrival time in case that *MyVehicle* cannot overtake any vehicles ahead, and can be calculated similarly to the case of t_e.

The expectation of the arrival time t'_e when *MyVehicle* keeps the current lane is given by

$$t'_e = x_e / v_1. \tag{11}$$

From t_e and t'_e, whether *MyVehicle* should change the lane for overtaking is decided by using equation (1).

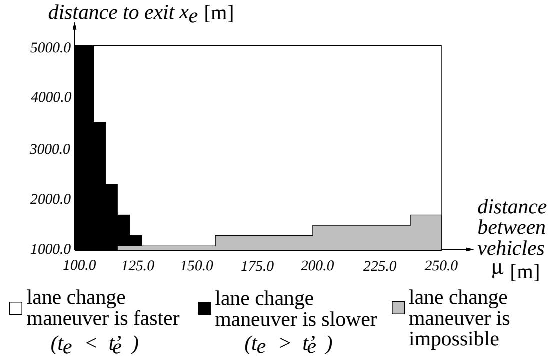


Figure 6: Comparison of expected arrival times for maneuvers with and without lane changing.

For the case that $v_1 = 80(km/h)$ and $v_2 = 100(km/h)$, we calculated and compared t_e and t'_e for several combination of μ's (the mean of distance between vehicles) and x_e's (the distance to the exit). The result is summarized in Figure 6. From the figure, we see that the larger μ is, or the larger x_e is, the more *MyVehicle* tends to change lanes.

META-TACTICAL LEVEL

The meta-tactical level planner continuously watches important events on traffic. Examples of possible events are: the average speed of the current lane slows down; the exit is approaching. The planner also runs with a periodical updating of the estimated arrival time.

Since it is inefficient to always check all events, the planner determines which events are important (or meaningful) according to the current situation. To realize such an adaptive focus of attention, we construct a state transition graph shown in Figure 7. For each state, possible events and their corresponding procedures at the tactical level can be retrieved from the graph. For example, at state `[Exit: Medium, Lane: Right]` (which means that the distance to the exit is medium and the vehicle is on the right lane), possible events are: (1) the speed becomes slower (`Speed: Slower`); (2) the estimate of the arrival time is updated (`Estimate arrival time`); and (3) the exit becomes near (`Exit: Near`). For the first two events, the tactical level planning `overtaking with approaching exit` is executed. For the last event, only the state is updated. The cur-

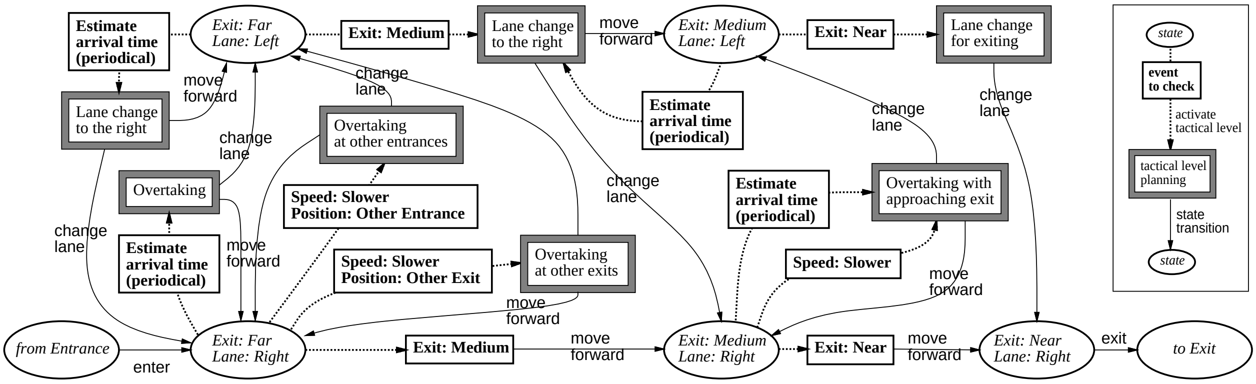


Figure 7: State transition graph for meta-tactical level planning. The meaning of each figure such as an ellipse is explained on the right.

rent transition graph is based on the following assumptions: there are only two lanes and no branches; the left lane is always faster than the right. It is, however, not difficult to extend the graph to remove such assumptions.

Currently the meta-tactical level only deals with selecting an appropriate tactical-level planning procedure. The meta-tactical level, however, can also be used for controlling the range of time and space of traffic condition to be considered in the tactical level. For example, in overtaking vehicles ahead, if *MyVehicle* has enough margin to the target arrival time, it may observe a broad area around it with prediction of a relatively far future state in order to select a sufficiently wide space to enter; if *MyVehicle* is in a hurry, it may search only a nearby area for the nearest space to enter. Such a usage of the meta-tactical level is now under investigation.

SIMULATION RESULTS

We tested the proposed control architecture on a highway driving simulator.

We first compare *MyVehicle* with other types of automated vehicles (called *Aggressive* and *Defensive*); *Aggressive* always changes lanes if the front car is slower than it and an adjacent lane is faster than the current lane; *Defensive* keeps the rightmost lane even if the front car slows down. For *MyVehicle*, we used the following loss function:

$$L(t) = \begin{cases} 0 & t \leq t_{target} \\ (t - t_{target})^2 & t > t_{target} \end{cases} \qquad (12)$$

where t_{target} is the target arrival time. Other vehicles for composing an experimental traffic scene, which are not necessarily considered to be automated, are randomly generated under the following conditions: (1) the target speed is within $70 \sim 100$ (km/h); (2) the distance to the front vehicle is within $40 \sim 65$ (m); (3) the behavior is like *Aggressive* .

Figure 8 shows the configuration of the highway used for comparison. In this comparison, *MyVehicle* performs two types of tactical-level planning, *overtaking with consideration of approaching exit*, which was explained before, and *lane change for exiting*. The target arrival time was set to $t_{target} = 135$ (s) and the cost for lane change was set to $C = 225.0$.

We performed 20 runs for each type of automated vehicle, and recorded the number of lane changes and the elapsed time from the entrance to the exit. The averaged values are summarized in Table 1. With appropriate decision-making on the lane change, *MyVehicle* behaved best in terms of given $L(t)$ and C.

Next, we show in Figure 9 a simulation result when *MyVehicle* traveled a little long distance. The configuration of the highway, traffic conditions during driving, perceived events for the meta-tactical level, tactical level procedures actually performed and selected maneuvers, ex-

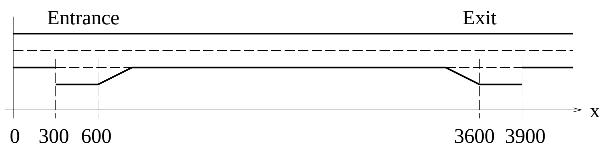


Figure 8: A highway configuration.

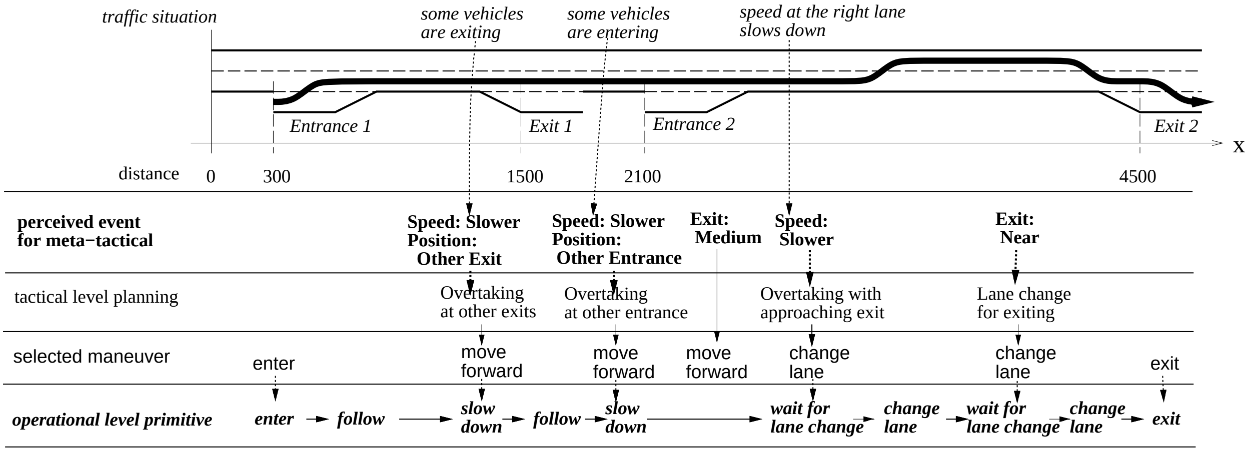


Figure 9: Simulation result of a long distance travel.

Table 1: Comparison results.

	elapsed time (s)	number of lane changes	loss
MyVehicle	130.5	1.6	240.0
Aggressive	121.9	2.6	293.8
Defensive	158.0	0	522.1

ecuted vehicle control primitives, and the trace of *MyVehicle* are indicated in the figure. *MyVehicle* succeeded in adaptively changing the lane and the speed in a dynamic and uncertain traffic environment.

CONCLUSION

This paper has proposed a novel control architecture for autonomous vehicle driving. The architecture is composed of three levels of planning: the operational level for executing primitives for vehicle position/velocity control, the tactical level for selecting appropriate maneuvers, and the meta-tactical level for timely activating an appropriate tactical-level planning procedure according to the current state. The proposed architecture has a potential applicability to an assistance system for human drivers.

A future work is to extend the repertoire of planning procedures in order to cope with more complex situations including urban traffic. Another future work is to verify the proposed architecture using real images taken from an actual vehicle on a highway.

Acknowledgment

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