Towards Intelligent Navigator That Can Provide Timely Advice on Safe and Efficient Driving*

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Abstract

This paper proposes a novel concept of intelligent navigator *that can give the driver timely advice on safe and efficient driving. From both the current traffic condition obtained from sensory data and the driver's goal and preference in driving, it autonomously generates advice and gives it to the driver. Not only* operational level *advice, such as emergency braking due to an abrupt deceleration of the front vehicle, but also* tactical level *advice, such as lane changing due to the congested situation ahead, can be generated. Two main components of the intelligent navigator, the advice generation system and the road scene recognition system, are explained. On-line experiments using the prototype system show the potential feasibility of the proposed concept.*

1 Introduction

In recent years, there have been growing interests in ITS (intelligent transportation systems). One ultimate goal of ITS research is to realize a fully autonomous vehicle [8, 9]. It is, however, still difficult to achieve this goal because a very high reliability and safety will be required for deployment. Thus, as a practical step towards the goal, we propose the *intelligent navigator*, that can, in place of a human navigator sitting on the next seat, give the driver appropriate advice on safe and efficient driving.

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 the actual traffic condition; at the lower level, the selected maneuver is translated into actual operations of steering, accelerating, and braking. These levels are called as the *tactical level* and the *operational level*, respectively [3, 7].

Operational level driving can be assisted relatively easily using various sensing capabilities such as vision for lane detection (e.g., [1]) and for detecting other vehicles (e.g., [6]); if some dangerous situation arises, the driver can be warned. Such an assistance capability using on direct sensory data is one of necessary functions of the intelligent navigator.

Sukthankar et al. [7] pointed out the importance of tactical level driving in realizing safe and efficient autonomous driving. This is also true for driver assistance systems. Since the quality of maneuver selection may have considerable effects on safety and efficiency, it is important to generate advice on appropriate maneuvers in a timely fashion.

In real traffic, sensory data based on which the intelligent navigator generates advice 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 advice generation should be based on the prediction of the future traffic condition with consideration of uncertainty [2, 5, 7].

Recently, we proposed an architecture for autonomous driving with three control levels [4]. This architecture enables an on-line maneuver selection with a long-term prediction under uncertainty. Based on the architecture, we are now developing an intelligent navigator prototype for the highway driving domain. This paper describes the architecture of the intelligent navigator and the results of on-line experiments.

2 Overview of the System

Fig. 1 schematically depicts the architecture of the intelligent navigator system. The driver gives the system the goal of driving (e.g., the target arrival time) and his/her preference to specific driving styles (e.g., the driver may want to avoid lane changing as much as possible). The road scene recognition subsystem recognizes the current traffic situation using vision. The advice generation subsystem generates appropriate advice and give it to the driver. The driver may control the vehicle according to the given advice.

Fig. 2 illustrates the internal architecture of the advice generation subsystem, which has three levels of reasoning to cope with a dynamic and uncertain traffic environment.

The meta-tactical level continuously watches predetermined events on traffic and, on occurrence of an event, activates an appropriate tactical-level maneuver selec-

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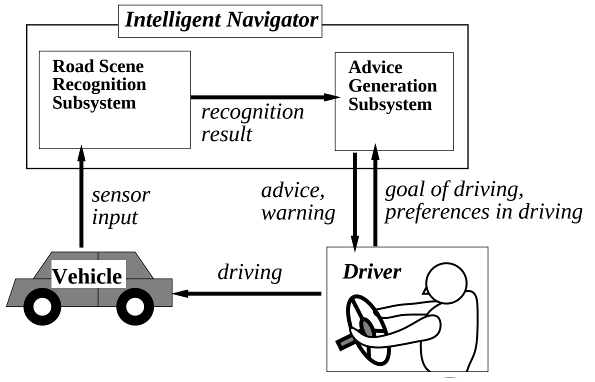


Figure 1. Overview of intelligent navigator system.

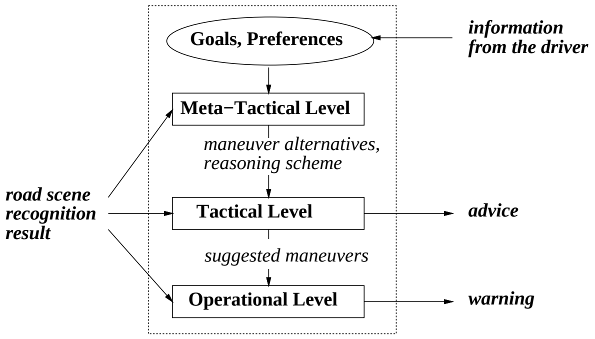


Figure 2. Architecture of advice generation subsystem.

tion procedure. Then the tactical level determines the best maneuver to suggest and give it to the driver.

The operational level mainly checks immediate dangers, such as an abrupt deceleration of the front vehicle, by watching near surrounding areas of the vehicle. This level also lets the driver know an appropriate timing for executing the determined action; for example, if the system has advised the driver to move to the next lane, this level watches the situation of that lane and tells a good timing for lane changing.

3 Generating Tactical Level Advice

3.1 Information from the Driver

The intelligent navigator receives the driver's goal and preference in driving to be used for advice generation. Such information is given in the forms of *loss function* and *cost assignment*, because a statistical decision theory is used for advice generation.

Loss function $L(t)$ is used to represent various requirements on the time of arrival at the destination exit. $L(t)$ is defined using the *target* arrival time t_{target} and the *estimated* arrival time t. Fig. 3 shows some examples of $L(t)$. The loss function could be changed during driving according to the change of the goal.

Cost C is used to represent the driver's degree of preference to each maneuver. For example, C_{change} is the

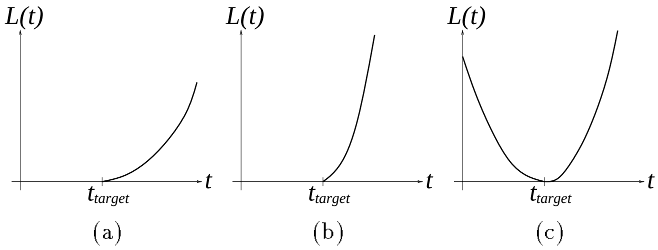
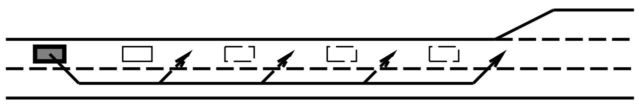
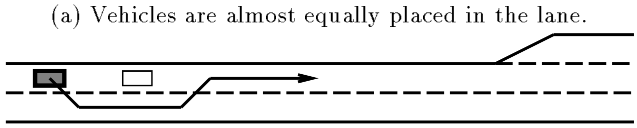


Figure 3. Examples of $L(t)$:
(a) loose requirement on the arrival time;
(b) tight requirement on the arrival time;
(c) both late and early arrivals are undesirable.



(a) Vehicles are almost equally placed in the lane.



(b) Only a few (slow) vehicles are in the lane.

Figure 4. Estimated traffic situations and overtaking scenario.

cost related to the lane changing maneuver; if the driver puts the largest importance on safety and very much wants to avoid possible risks related to lane changing, a high C_{change} is given to the system.

3.2 Tactical Level Reasoning

We here present one example of actual tactical level reasoning, which is for decision on overtaking with consideration of an approaching exit. The road scene recognition subsystem uses vision to estimate the position and the velocity of other visible vehicles, as explained in Section 4. For invisible (occluded) ones, it adopts a probabilistic traffic model of the placement of vehicles. Refer to [4] for the details of the probabilistic traffic modeling.

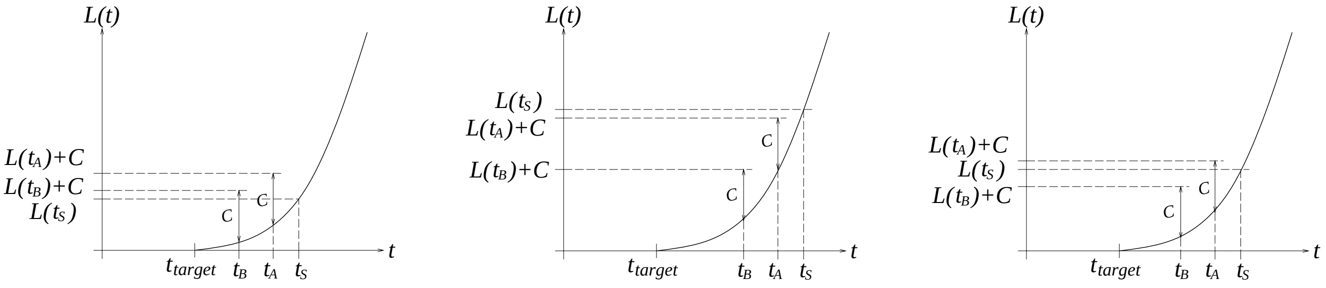
Consider the scenario shown in Fig. 4[1]. The vehicle with the intelligent navigator (called *MyVehicle*, drawn as a painted rectangle in the figure) on the left lane[2] is approaching the exit to take. Since the speed in the current lane is becoming a little bit slow, the driver starts thinking of overtaking vehicles ahead. The overtaking maneuver is generally faster, but there may be risks of lane changing itself and of missing the exit. Such a tradeoff is considered as follows.

The vehicle information in the current lane is usually obtained for the vehicles just before and behind *MyVehicle*, and other vehicles are not visible due to occlusion.

There are two possible situations of the invisible area:

- *Congested*: vehicles are almost equally placed in the lane (Fig. 4(a))

[1] This was originally presented by Sukthankar et al. [7].
[2] Note that the slower lane is the left one in Japan.



(a) "Go Straight" (b) "Overtake" (c) "Overtake If Not Congested"

Figure 5. Maneuver evaluation and given advice.

- *Not Congested*: just a few (slow) vehicles are blocking our lane (Fig. 4(b)).

Since the system is not be able to judge which situation is true, the maneuvers with and without overtaking in each traffic situation are evaluated and compared with each other.

Basically, if one maneuver is better than the others in any situations, the system simply provides the advice to take the maneuver. Otherwise, the system cannot decide which maneuver should be selected. In this case, the driver may be able to observe the invisible area; thus the system provides conditional advice that complementarily uses the driver's recognition ability.

Let T_A be the estimated arrival time of the maneuver with overtaking in the congested situation, T_B be that of the same maneuver in the other situation, and T_S be that of the maneuver without overtaking (the result of this maneuver is supposed to be equal in both situation).

In addition, the cost $C = C_{change}$ is considered for the overtaking maneuvers. The result of comparison and given advice is as follows:

- If $L(t_A) + C > L(t_B) + C > L(t_S)$, the maneuver without overtaking is always better than the other; the given advice is "Go Straight" (see Fig. 5(a)).
- If $L(t_S) > L(t_A) + C > L(t_B) + C$, the maneuver with overtaking is always better; the advice is "Overtake" (Fig. 5(b)).
- Otherwise ($L(t_A)+C > L(t_S) > L(t_B)+C$), the maneuver with overtaking just in *Not Congested* situation is advisable; the conditional advice "Overtake If Not Congested" is generated (Fig. 5(c)).

3.3 Traffic Situation Estimation Using Velocity Map

In some cases it is possible to estimate the situation of the invisible area by the velocity difference of the two lanes. For example, normally the velocity difference can be supposed to be small at the position far from any entrance or exit. If the velocity of our lane is slower than the other, it is estimated that just a few slow vehicles are blocking our lane and thus the traffic situation is *Not Congested*.

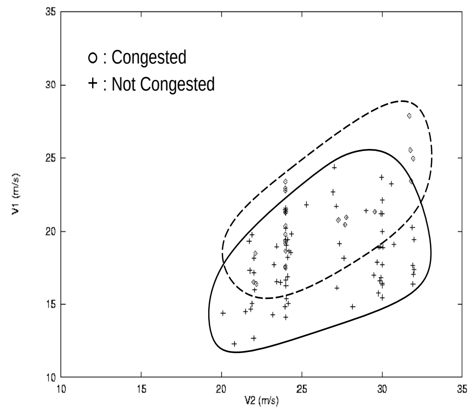


Figure 6. The result of simulation experiment for the velocity map.

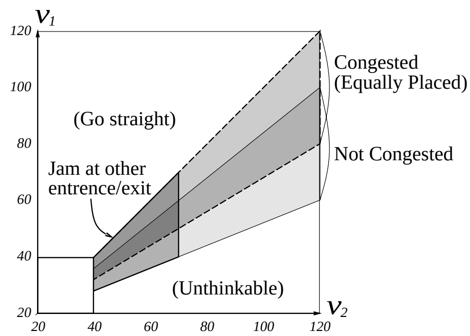


Figure 7. An example of the velocity map.

We verified that such an estimation is valid using a highway driving simulator. Fig. 6 shows the result of the experiment, where v_1 and v_2 axes respectively represent the mean velocities of the slower and the faster lane. In the velocity space each situation has own distribution. The result indicates the *Congested* situation occurs when the velocity difference is smaller (the area in the dotted line), and the *Not Congested* situation appears when the velocity difference is larger (the area in the solid line).

Then we constructed the velocity map (see Fig. 7) that supports the efficient evaluation at the tactical level. This map is referred to for selecting possible situations.

(a) Input image. (b) Detected white regions. (c) Detected boundaries. (d) Extracted shadow regions. (e) Detected vehicles and their relative position and velocity.

Figure 9. Lane and vehicle detection.

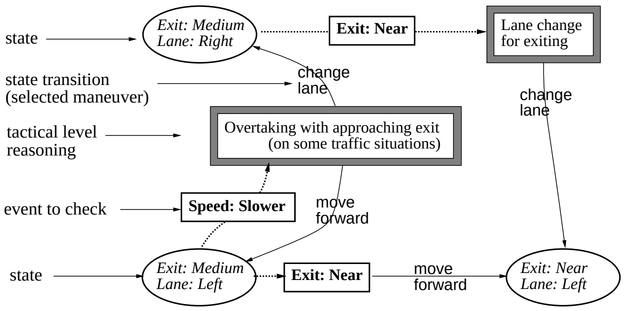


Figure 8. A part of state-transition graph for the meta-tactical level.

3.4 Meta-Tactical Level Reasoning

The meta-tactical level (see Fig. 2) continuously watches important events on traffic. Examples of possible events are: the average speed of the current lane slows down; the exit is approaching. It also periodically updates the estimation of the arrival time.

Since it is inefficient to always check all events, only selected events are monitored which are considered to be important in the current state. To realize such an adaptive focus of attention, we construct a state transition graph. Fig. 8 shows a part of the transition graph. For example, at state `[Exit: Medium, Lane: Left]` (which means that the distance to the exit is medium and the vehicle is on the left lane), possible events are: (1) the speed becomes slower (`Speed: Slower`); (2) the exit becomes near (`Exit: Near`).

4 Road Scene Recognition

This section describes the road scene recognition subsystem (see Fig. 1). The recognition process is composed of the following steps:

1. Detect lane boundaries and estimate the position of *MyVehicle*.
2. Detect other vehicles and estimates their relative position and velocity.
3. Make correspondence between frames and integrate data using Kalman filter.
4. Track vehicles based on template matching.

4.1 Lane Boundary Detection and Vehicle Position Estimation

First, the system extracts white regions corresponding to the two white boundaries of the current lane by thresholding the image and labeling. Then, a line is fitted to each set of white regions. The region between the two lines is considered as the current lane. Using the width of the lane, the image regions of other lanes can be extracted. Fig. 9(c) shows an example result.

4.2 Vehicle Detection

Once the lane regions are extracted, the system searches them for vehicles. Since there is a shadow area under a vehicle, we extract a dark region whose brightness is less than a threshold, which is determined by the mean and variance of the histogram derived from brightness on the lane region (see Fig. 10). Fig. 9(d) shows the extracted shadows for the image shown in Fig. 9(a), which are the candidates of the vehicle positions.

Fig. 11 is the projection of shadows and the detected vehicles (dotted rectangle) on the road surface. Since the size of each vehicle is assumed to be some constant value, the shadows of different sizes are determined not to be vehicles.

For each vehicles, we calculate the longitudinal position z_i and its uncertainty $\sigma^2_{z_i}$ (see Fig. 12) by:

$$\begin{aligned} z_i &= \frac{fh}{y_i}, \\ \sigma^2_{z_i} &= \left(\frac{fh}{y_i^2}\right)^2 \sigma_y^2 = \frac{z_i^4}{(fh)^2}\sigma_y^2, \end{aligned} \qquad (1)$$

where y_i is the averaged vertical position of a dark region and σ_y^2 is its variance.

4.3 Making Correspondence over Frames

We make correspondence of extracted vehicles over frames for reliable recognition. A newly obtained vehicles is matched with a previously detected vehicle if:

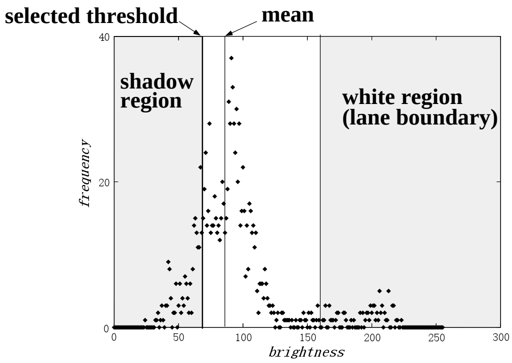


Figure 10. An example of histogram of the lane region and threshold.

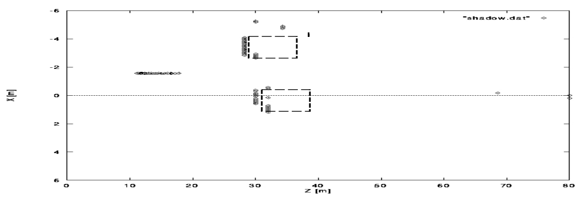


Figure 11. Projected vehicle position.

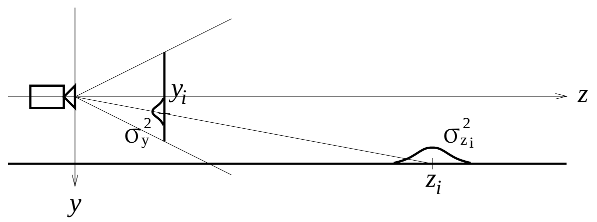


Figure 12. Calculation of vehicle position and uncertainty.

1. Both are on the same lane, *and*
2. The difference of positions is within a certain range computed from the previous uncertainty estimate.

The data of a matched vehicles is integrated with the previous data using Kalman filter.

4.4 Tracking using Template Matching

When a vehicle is detected, the corresponding image region of a certain size is registered as a template. Then the vehicle is tracked by template matching based on the normalized correlation, and the result of the tracking is used for the check of lane changing motion of other vehicles. The rectangles in Fig. 9(e) show the results of template matching.

5 Experimental Results

Fig. 13 shows the overview of the system. Two cameras are used to see the forward and the backward directions. Another camera will be used for observing

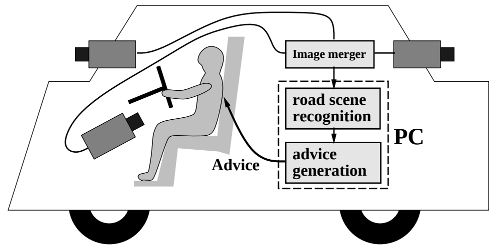


Figure 13. Design of experimental system.

Table 1. Measured values and estimated time and losses.

triggered time t		126.5 (sec.)
distance from the entrance		2783 (m)
average speed	left	21.9 (m/sec.)
	right	25.3 (m/sec.)
estimated arrival time	keep lane	421.0 (sec.)
	change lane	364.3 (sec.)
estimated loss	keep lane	7638.8
	change lane	3448.6

the driver's behavior (e.g., response to the advice); at present, the system detects just the direction of the face, and the information is not used for the assistance. Two subsystem are working on one PC (Pentium-II 400MHz), and the processing ability reaches 10 frames/sec.

We show the result of an on-road experiment. The vehicle ran from Toyonaka entrance to Ibaraki exit of the Meishin expressway; the travel distance is about 12 km. We gave the system the loss function indicated by eq. (2), target arrival time $t_{target} = 460(sec)$, and the cost of lane changing $C_{change} = 2500$[3]. The actual arrival time was 527 (sec.).

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

5.1 Tactical Level Advice

Fig. 14 shows the situation where tactical level advice "Change to Right Later" was issued due to a reduction of the speed of the current lane. The upper-left and the upper-right part of each image are respectively the forward and the backward view. The lower-left part is the observation of the driver, and the advice is displayed on the lower-right part of the image.

In this case, by referring to the velocity map, only the situation *Congested* was selected. Table 1 summarizes the measured values of the road scene and the estimated time of arrival at the goal and its losses. The maneuver "Change Lane" was selected at the tactical reasoning module, but on the faster lane there was a passing vehicle. The vehicle, which had been detected by the backward camera (see Fig. 14 (a)), was tracked by filtering although it was not detected by two cameras at

[3] it means that 50 seconds' loss is allowed in exchange for lane changing

(a) The traffic becomes slow ($t = 121.7$)

(b) The driver is advised to change lane later ($t = 127.3$)

(c) The driver checks the faster lane ($t = 131.9$)

(d) Changing maneuver is executed ($t = 135.3$)

Figure 14. The driver is advised to change lane later.

(a) Front vehicle is approaching ($t = 48.9$)

(b) Brake advice is issued ($t = 50.2$)

Figure 15. The driver is advised (warned) to brake.

the moment (Fig. 14 (b)). Then the operational reasoning module advised the driver to "Change Lane Later" (Fig. 14 (b)). (Note that the bracketed advice means that the action should be executed later.) Following the advice, the driver checked the faster lane (Fig. 14 (c)), and changed to the lane after the vehicle had passed (Fig. 14 (d)).

5.2 Local Level Advice

Fig. 15 shows the situation where a local level advice "Brake" was issued due to the deceleration of the front vehicle. At present, this advice is issued if the following condition is satisfied:

$$d_{curr} + v_{curr} T_f < d_{thresh},$$

where d_{curr} (v_{curr}) is the current relative position (velocity) of the front vehicle with respect to *MyVehicle*; T_f is a constant time duration (currently 3 (sec.)); d_{thresh} is a threshold (currently 20 (m)). In the case of Fig. 15, d_{curr} and v_{curr} were estimated as 24.5 (m) and -2.0 (m/sec.); thus, the relative position after T_f (sec.) was estimated as 18.5 (m), which is less than d_{thresh}.

6 Conclusions and Discussion

This paper has proposed the concept of intelligent navigator that can give the driver timely advice on driving in a dynamic and uncertain traffic environment. The intelligent navigator system is composed of the road scene recognition and the advice generation subsystems. We constructed a prototype system and conducted experiments on the actual highway. The experimental results show the potential feasibility of the proposed system.

One important future work is to connect the system with traffic information systems (many examples are described in [10]). This will enhance the reliability of the intelligent navigator's advice.

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