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OBSTACLE DETECTION BASED ON HISTORY INFORMATION IN SELF-DRIVING VEHICLES

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ABSTRACT. Self-driving is the budding technology gaining momentum in enhancing safety, accessibility, and comfort in the automated transport facility. With safety and comfort, the prime issues are resource utilization and power consumption of the components in the integrated system. This paper proposes a mechanism for obstacle detection in self-driving Intelligent Transport Systems and database information. The history-based obstacle detection reduces the power consumption while utilizing the resources to the maximum. The proposed mechanism of obstacle detection is evaluated in comparison with the existing and driver-based mechanisms.

Keywords: Self-driving, Energy consumption, Intelligent transport systems.

INTRODUCTION

A survey reveals that at least one person dies every minute, and annually, the auto crash rate hits ten million on an average. The injuries from auto crash are diverse, where the common phenomena is human error (Jones, 2001, 2002; Luk et al., 2016). To reduce such error, self-driving has come into existence. The main aim of self-driving is automated driving without human intervention in decision and control, except when choosing the target destination. Self-driving is gaining momentum with the advancement in technology.

Self-driving vehicles will use normal roads, which means there is no exclusive environment for the vehicle. Hence, it is a great challenge to design such a vehicle with automated decision and controlling capabilities. Self-driving visionises to reduce human errors, apart from rendering the comfort of humans. Furthermore, it provides increased mobility, enabling the physically challenged, non-driving, and elderly people to commute easily without driving manually. In the last few decades, research efforts from the academia and industries have been made to make self-driving completely autonomous on realistic roads (Bertozzi, Fascioli, Bianco, & Plazzi, 1999; Dickmanns, Mysliwetz, & Christians, 1990). Many projects on automatic driving vehicle research have been made and tested in diverse road environments (Furgale et al., 2013; Levinson et al., 2011; Junqing Wei et al., 2013).

The benefits and comforts of self-driving cars are very promising. However, there are different hidden challenges to achieve the successful self-driving. The design of the self-driving cars should posses anti-lock brakes, electronic stability control, adaptive cruise control, lane departure warning systems, lidar system, and infrared camera. These mentioned components need to be integrated into a single control system for context-aware decision making in a co-ordinated manner. This coordination involves the sensors and trajectory maps obtained from the GPS systems.

Self-driving is the context-aware decision by the coordination of computer vision, machine learning, electronics, artificial intelligence, and control theory. The decision is based on the three action co-ordinations, i.e. perception, planning, and control. Perception is the analysis of the context of decision making on the road considering all the aspects. Planning is the process of decision making and control as the actual decision to be made. The three modules should work and decide the control without human intervention. This needs the different components, such as sensors, cameras, and actuators. The sensors and control system will consume a lot of energy in decision making. The main focus of this article is to reduce the energy consumption during the decision making of the self-driving vehicle. The illustration of a single case in decision making is proposed, which substantiates the proposed obstacle detection system.

OVERVIEW OF OBSTACLE DETECTION RESEARCH WORK

A survey by Briane et al. (Paden, Cap, Yong, Yershov, & Frazzoli, 2016) presented the recent development in self-driving since the last three decades. The authors have also discussed the different aspects of research challenges, algorithms used in sensors, and actuators in obstacle detection. The trajectory-based autonomous system environment was proposed by Li et al. (Li, Sun, Cao, He, & Zhu, 2016) to avoid collision and have resulted in a safe drive.

The novel behaviour-based planning framework based on trajectories to detect static and dynamic obstacles claimed 90.3% reduction in computational time (J. Wei, Snider, Gu, Dolan, & Litkouhi, 2014). Joshi et al. (2016) proposed a Driver Assistance System in Intelligent Transport System (DASITS), which is a self-driving mechanism for vehicle and driver safety. All the mechanisms focus on collision, obstacle detection, or safety of the vehicle and passengers, but hardly the focus on the power consumption of the different integrated components. Hence, this paper introduces an obstacle detection mechanism that takes power consumption into consideration through sensors and lidars. The proposed mechanism utilizes trajectory, intelligent transport system (ITS), and history information in obstacle detection.

OBSTACLE DETECTION MECHANISM BASED ON HISTORY INFORMATION

This proposed mechanism changes the obstacle detection level according to the driving environment. In this system, safety is ensured by communication between the management server and ITS during the automatic driving operation (Chen, Jin, & Regan, 2010; Kolosz & Grant-Muller, 2015). In particular, after users set the destination, the selected route information is transmitted to an administrative server. When the server determines that the route is appropriate, it transmits the road traffic condition and the traffic accident history to the Automatic Driving Vehicle (ADV). Based on the distribution of the traffic accident history as shown in Figure 1, ADV changes the obstacle detection level. The history information reduces the workload of the vehicle to newly detect the environment. The obtained information will intimate the system priorly on the possible threats occurred earlier. The earlier caution information reduces the task while saving the power. In Figure 1, the red and yellow areas show the areas where a lot of accidents occurred in the year, while the green areas show that the traffic accident was minor in the past. This information helps the self-driving system to take the context-based decision.

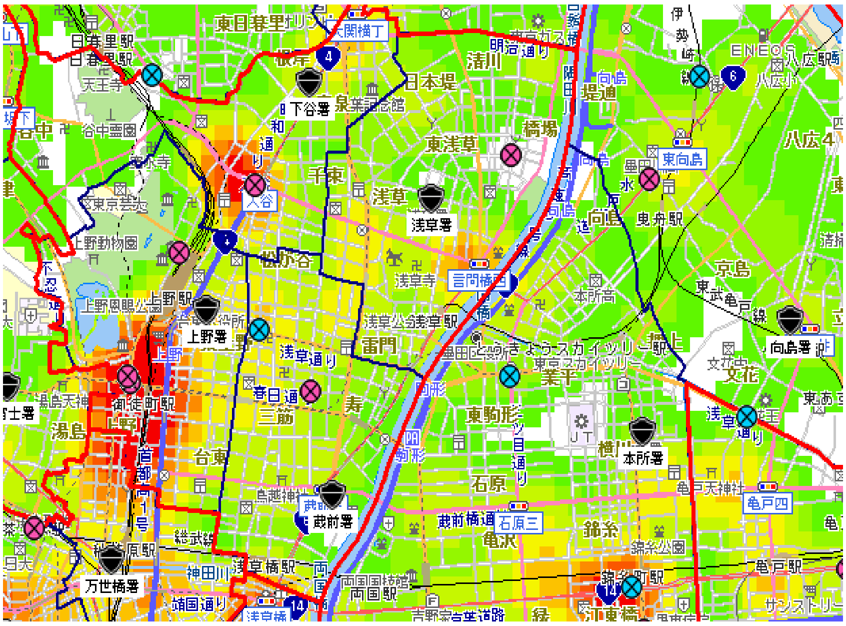


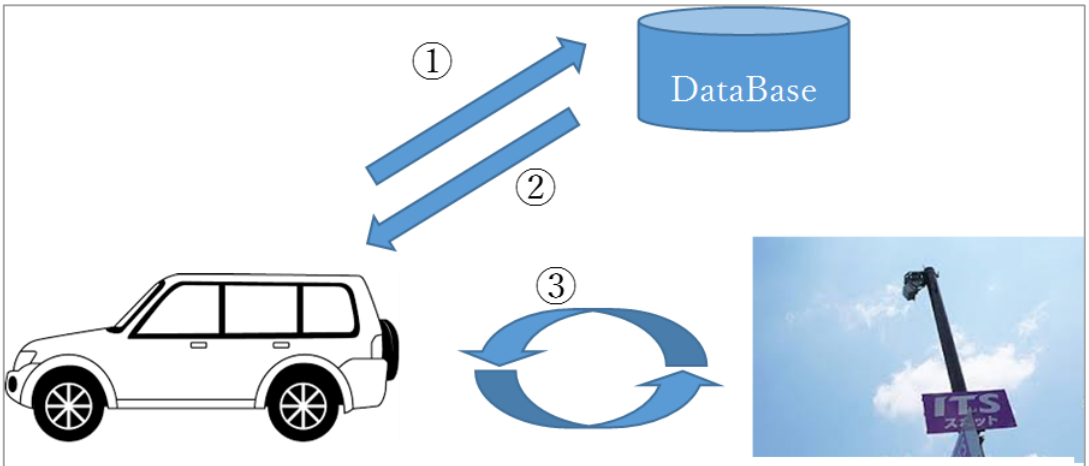
Figure 1. Distribution of traffic accident.

In areas where accidents frequently occurred, in order to reduce the risk of accidents, it is not only vital to detect obstacles, but also to predicting their behaviour. Conversely, in areas where few traffic accidents occurred, this system reduces energy consumption by only detecting obstacle places. When passing through a route where information is not available, the risk of accidents is reduced by frequently detecting obstacles. In this mechanism, the obstacle detection mechanism is split into three levels based on the accident information data of the road as shown in Table 1.

Table 1. Levels of obstacle detection

Level 1	Maintain driving condition by performing lane detection and other vehicle detection.
Level 2	Try to detect obstacles near the car and distinguish which to avoid.
Level 3	Perform obstacle detection more frequently than Level 1 and Level 2 and try to avoid danger by predicting the motion of each obstacle.

For the case of Level 1 shown in Table 1, the risk of safety is decreased by not extremely reducing the detection frequency. Additionally in this system, even when the obstacle detection level is low, the road information during driving is also captured by ITS and the traffic situation is considered in real time to maintain safe driving. For example, when the ITS data reflects road congestion, the obstacle detection level is kept at a high state even in the case of safe roads from the accident distribution. Level 2 will detect the obstacles near the car and will decide which obstacle to avoid. For example, if the road has four lanes, the vehicle should only be concerned with the obstacles in the closest lanes. The two mentioned levels are concerned more on the static obstacles. Level 3 is more concerned on the obstacles in motion. The history database gives the past information and ITS provides the current road information. Figure 2 shows a configuration of the proposed mechanism working system model.



①Send the destination information to the administrative server

②Receive route suggestions and accident history from database

③Change the level of obstacle detection based on data obtained from ITS and information obtained from the database

System Evaluation

The proposed system is evaluated by comparing the driver and the existing system. When driving by the proposed system is set to Level 1 or 2, there is a high risk in irregular cases such as a person suddenly jumping on the road. Therefore, the discussion on this system will assume that such situation will not occur. Thus, driving is assumed to be a safe and secure ride. When driving on such a road, the obstacle detection level is set to a low state if the traffic condition is also good. In the case of driving by a driver on such a road, accidents due to human error such as dozing while driving and miserable driving are conceivable. However, in this system, the car is fully operated automatically, and hence, accidents caused by human error can be prevented.

This paper also considers energy consumption in this system. Here, power consumption is considered only when obstacle detection is performed without the obstacle motion prediction by the proposed system for five minutes. At the Automotive World 2015 held on January 15, 2015, Renesas Electronics reported that with self-driving, 50 W for lane detection, 1,000 W for discrimination of obstacles, and 10,000 W for predicting the motion of obstacles are required. When power consumption is calculated based on this value, a car requires 3,000,000 J of energy if you always keep on predicting the behaviour of obstacles for 5 minutes with the existing method. On the other hand, when driving with the obstacle detection level set to Level 1 and Level 2 by the proposed method, the energy consumption will be 1,500 J and 300,000 J, respectively. In either cases, the electric power is suppressed by more than 2,000, 0000 J. Therefore, it can be said that by using this system, a sufficiently low power consumption can be achieved even when considering the amount of power for acquiring information from ITS. Table 2 shows the advantages and disadvantages of the proposed mechanism, existing mechanism, and driving by the driver (manually).

Table 2. Levels of obstacle detection

	Reduce burden of driver	Avoid Human error	No exceptions accident	Obstacle detection	Energy Consumption
Proposed	○	○	△	△	○
Existing	○	○	△	○	×
Human	×	×	○	○	○

○ good, △ excellent and × bad

In this mechanism, there is a disadvantage that it involves a risk when accidents caused by other peoples' irregular driving (such as dozing while driving or forward driving) that occured on a road are assumed to be safe. This issue will be addressed in a future enhancement of the mechanism. However, it is thought that this risk will be reduced by improving infrastructure such as ITS, development of intervehicle communication technology, and automatic operation spread. This proposed model is the qualitative evaluation of the system whose infrastructure is yet to be known. The actual system can be modelled once the standards of the infrastructure are available for simulating. The results in simulation modelling can be drawn close to the real system. Currently, the results are for the conceptual model with the assumptions of the forecasted system.

CONCLUSION

The paper introduced self-driving, its benefits, and the components of the self-driving vehicles. An overview of obstacle detection by various researchers was presented. The proposed ITS and history-based integrated mechanism was introduced along with the system evaluation. The system evaluation of the conceptual model illustrated the reduction in power consumption when compared with the existing and manual human driving systems in different metrics. In future, the proposed system will be tested in a simulated environment for quantitative results and enhanced to be implemented and tested in real time.

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