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Identification of Driver Lane Change Intent using Fuzzy Logic

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Summary

If operation of the Lane Departure Warning System (LDWS) fails to recognize the intention of the driver and malfunctions, it may cause a risk of accidents occurring. In this paper, driver's lane change intention is detected by determining which available lanes the driver can move into according to his/her acceleration/deceleration pattern. The acceleration/deceleration pattern of the driver is represented by throttle and brake pedal reflexes for acceleration/deceleration and this operation uses fuzzy logic to predict the driver's movement in traffic and calculates the cost. The cost is calculated for a plurality of available lanes in which lane change is possible and if the lane change intention of the driver is determined to be the most ideal moment for the driver to change lanes, LDWS is not warned. The algorithm is confirmed by conducting a Human-In-The-Loop (HITL) simulation.

Keywords: city traffic, safety, simulation, user behavior, V2V (vehicle to vehicle)

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1 Introduction

In recent years, with conversion to electronic technologies in the automobile industry, advanced driver assistance systems (ADAS) have been developed to detect and prevent accidents using sensors such as cameras and radar. ADAS is an active safety system that uses various cognitive sensors to detect accident and vehicle conditions so if a vehicle behaves unintendedly to the driver, or if the driver did not detect the accident risk, it detects and prevents this. Systems such as the Autonomous Emergency Brake (AEB) of these ADAS systems have been commercialized and by being included in the vehicle safety assessment of EuroNCAP (The European New Car Assessment Program) as well as in the NHTSA's safety assessment, its necessity has been validated. ADAS can be used more efficiently by detecting driver intention. For example, in case of LDWS (Lane Departure Warning System) that provides a warning sound if lane departure occurs and LKAS (Lane Keeping Assist System) that prevents lane departure automatically, if the driver intends to change lanes but does not use the turn signal, the driver's cognitive load will increase as a warning sound [1] or interfere with lane changes by intervening with vehicles. So rather, it can interfere with safe driving. Therefore, recognizing driver intention according to ADAS is a critical issue to improve the system, it is necessary to detect the driving intention of the driver in advance. In this study, we focused on changing of lanes which is one of the most frequent accidents relative to driver's lane changing decision.

McCall, et al. [2] applied the Sparse Bayesian Learning (SBL) method to predict the driver's intention to change lanes. Doshi, et al. [3] compared results of predicting driver's lane change intention with the combination of driver's head motion, driver's eye gaze line and vehicle data. Lisheng Jin, et al. [4], Mizushima, et al. [5] and Meyer-Delius, et al. [6] suggest the driver lane change intention using HMM (Hidden Markov Models), one of the machine learning methods. Lisheng Jin, et al. presented results of a driver intention detection experiment with an accuracy of 80 percent or more using HMM, steering and steering velocity data. Mizushima, et al. used HMM and steering data to determine the driver's lane change intention. Mandalia, et al. [7] and Aoude, et al. [8] used SVM (Support Vector Mechanism) as one of the other machine learning methods. Mandalia, et al. studied the intention of driver's lane change with the SVM, that considers distance from the preceding car, speed of the preceding car, and driver's eye gaze as variables. Aoude, et al. also studied SVM and HMM in comparison with driver intention. In this paper, by detecting the intention if the driver changes lane, if intention of the driver to change lane is determined, the warning of the LDWS is omitted to minimize the driver's cognitive load. In determining the driver's intent, the items related to the privacy of the user, such as camera in the vehicle, are rejected by the driver. Therefore, assuming that a radar sensor is used to recognize traffic flow around the driver and it is known and determined if current acceleration/deceleration pattern of the driver is appropriate for available lanes and the driver decides to change to another lane.

2 Driver Behavior Recognition

The simulation revealed the experimenter's usual driving habits for lane change and traffic flow maintenance. Lane change is divided into four cases. Each case was divided into a left overtake lane change, a right overtake lane change, a left deceleration lane change, and a right deceleration lane change. The driver will reveal acceleration/deceleration pattern for his/her purpose and the driver's purpose is divided into five cases, from the four cases of lane change and the lane staying case. After it is determined that if there is no intention of the lane keeping by the driver, fuzzy logic based acceleration and deceleration patterns for lane change were extracted from four cases for lane change. After that, in comparison with the driving pattern of the driver, the most similar case was judged to be the lane changing intention of the driver. The outline of the overall algorithm is as follows.

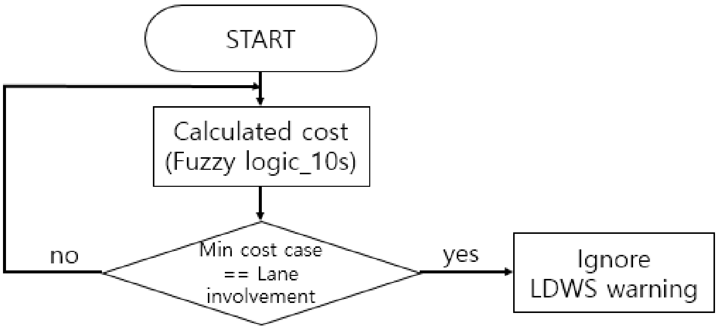


Figure 1 Disable lane departure warning system

2.1 Prediction of Acceleration/Deceleration Pattern

Generally, the driver performs acceleration/deceleration control according to distance to the target position and the relative speed. This control is suitable for using fuzzy logic because it can be expressed as an empirical rule. In this paper, a fuzzy logic algorithm controller is designed to output a pedal position for acceleration/deceleration by inputting the relative distance to the target position and relative velocity. Membership Function and Fuzzy Rule of fuzzy input and output variables are set as follows.

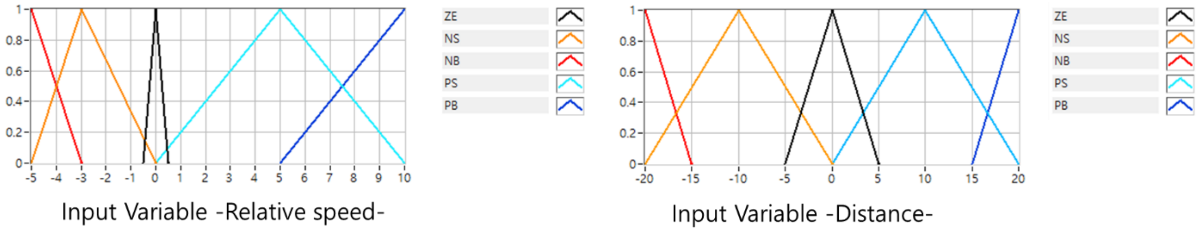
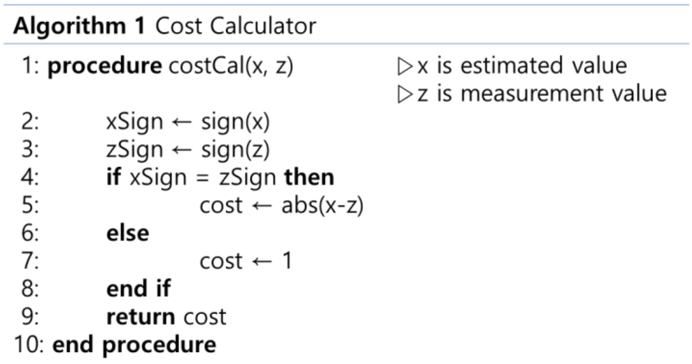


Figure 2 Membership Function of Fuzzy Controller(Input)

Figure 3 Membership Function of Fuzzy Controller(Output), Fuzzy Control Surface

2.2 Calculated Cost

The acceleration/deceleration pattern predicted from fuzzy logic is compared with the pattern to calculate the cost. The total cost accumulation time is 10 seconds and after the lane change was recommended to the driver, the cumulative time was determined based on an average time of 9.56 second. Cost calculation is performed every 10ms and is calculated as shown in Figure 4. The information required for the calculation is obtained through ‘Simulation Log program’ as shown in Figure 5.



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Algorithm 1 Cost Calculator
procedure costCal(x, z)          ▷x is estimated value
                                 ▷z is measurement value
    xSign ← sign(x)
    zSign ← sign(z)
    if xSign = zSign then
        cost ← abs(x-z)
    else
        cost ← 1
    end if
    return cost
end procedure
```

Figure 4 Calculator Cost Algorithm

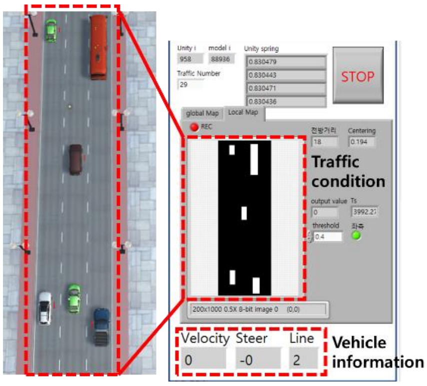

Figure 5 Simulation Log program

Prediction results are revealed in Figure 6 and it shows an average accuracy of 82.7 percent over the cumulative time of 10 seconds until the moment of lane change when comparing only the sign. The output indicates the accelerator pedal input for positive and the deceleration pedal input for negative. The predicted value is compared with the input value of the driver, and the cost is calculated using the pseudocode shown in Figure 4. If the signs are different, the cost is equal to 1 and the error value is calculated as the cost and to remove noise from the input device, a value between -0.05 and 0.05 of -1 (full brake) to 1 (full throttle) was calculated as 0.

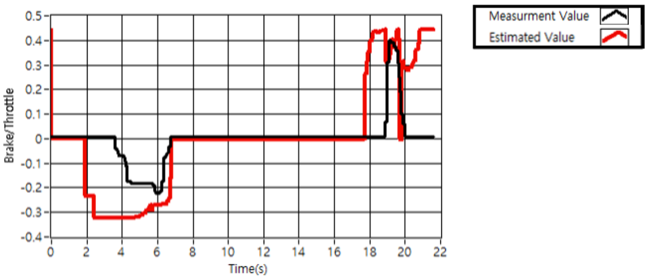

Figure 6 Estimate Result

3 Simulation Evaluation

The lane change experiment is at risk for collecting data using real vehicles so it was performed by constructing Human-In-The-Loop (HITL) using a virtual vehicle simulator. The driver inputs the vehicle's behavior through the vehicle model, visualizes the behavior of the vehicle, and constructs the HITL in which the driver performs the input by looking at the visualization result.

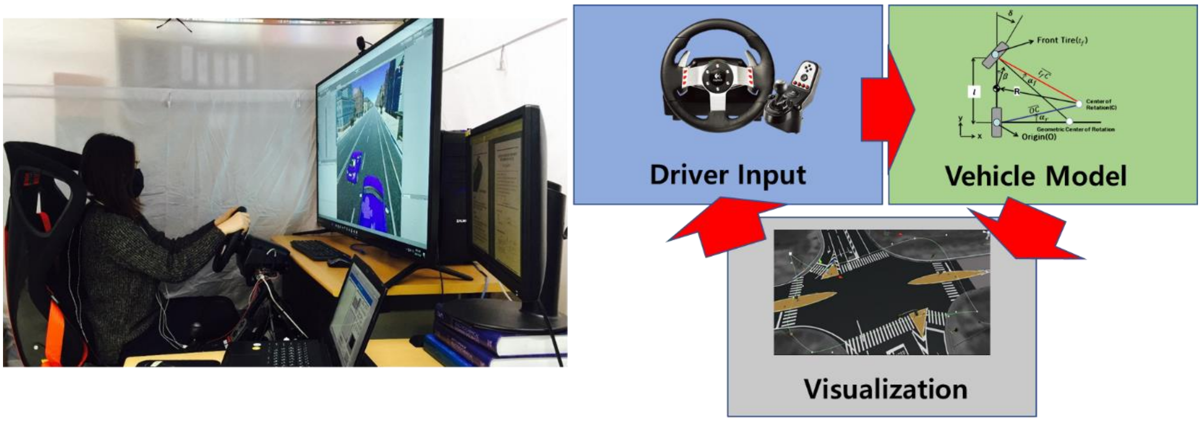

Figure 7 HITL Schematic

The field of view of the real driver is composed as follows. The side view mirrors and the rear-view mirrors used in real time lane change are implemented in the simulator so that they can be utilized.

Figure 8 HITL Driver View

3.1 Vehicle Model

In constructing the simulation, the vehicle model was constructed using the following model. [9]

$$\frac{d\beta}{dt} = -\frac{2(K_f+K_r)}{mV}\beta - \left\{1 + \frac{2}{mV^2}\left(l_f K_f - l_r K_r\right)\right\} r + \frac{2K_f}{mV}\delta \tag{1}$$

$$\frac{\mathrm{dr}}{\mathrm{dt}} = -\frac{2(l_f K_f - l_r K_r)}{I}\beta - \frac{2\left(l_f^2 K_f + l_r^2 K_r\right)}{IV} r + \frac{2 l_f K_f}{I}\delta \tag{2}$$

The specifications of the vehicle used are as follows.

Table 1: Vehicle parameters

$symbol$	$parameters$	$Value/unit$	$symbol$	$parameters$	$Value/unit$
m	Mass	1500 kg	l_r	*CG to rear axle*	1.6m
I	Moment of inertia	2500 kgm^2	K_f	*Front cornering stiffness*	55000 N/rad
l_f	CG to front axle	1.1 m	K_r	Rear cornering stiffness	60000 N/rad

3.2 Simulation Procedure

The simulation procedure is as follows. While driving in second lane, participants were ordered to change lanes forward or backward in the preceding or following vehicle in the left/right lane and it is assumed that the lane change intention has been successfully determined if the cost of the position is the lowest immediately before the vehicle crosses the lane. The lane change can be expressed in four cases as shown in the following Figure 9.

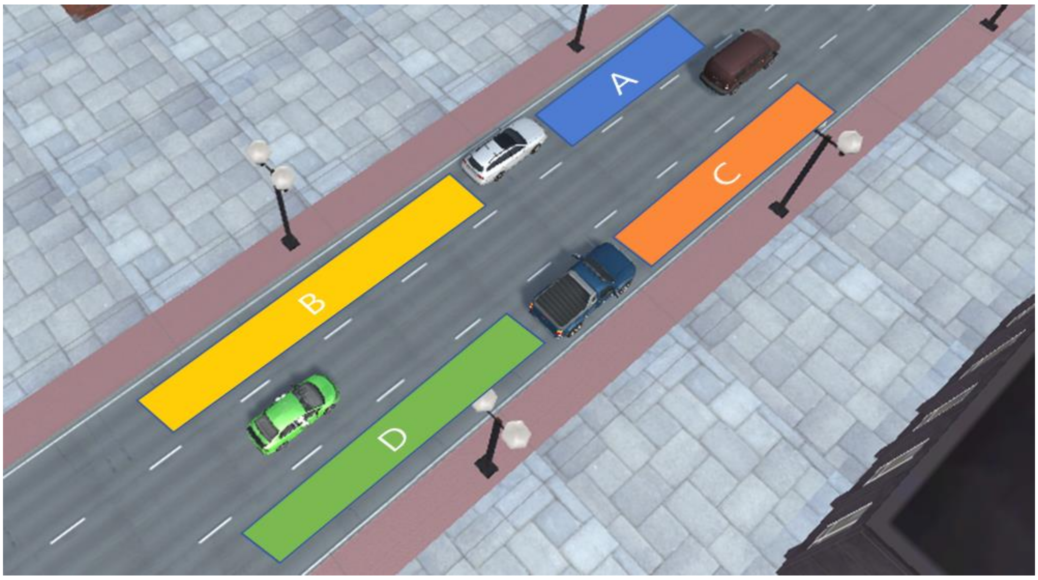

Figure 9 Lane Changeable Space

During the experiment, the participant (green sedan) is instructed to change the lane to the front (A) or back (B) of the left white hatchback or to the front (C) or back (D) of the blue pick-up truck. The speed of each lane is 30 m/s for the first lane, 25 m/s for the second lane, 20 m/s for the third lane and each vehicle may maintain some distance from the preceding vehicle, so there may be some speed changes.

4 Conclusion

According to the simulation, the cost for each position of the lane change intention judgment immediately before the lane change is as follows. Each experiment was performed three times for each location and excluded from the experimental results if an accident occurred or the lane change failed during the simulation.

Table 2 Simulation results

Simulation case A				**Simulation case B**			
A	B	C	D	A	**B**	C	D
676.3	962.1	678.4	966.4	999	**268.4**	999	295.7
546.2	823.4	**542,3**	932.9	999	**233.3**	999	287.6
770	919.8	774.2	925.4	999	303.6	999	**300.7**
Simulation case C				**Simulation case D**			
A	B	**C**	D	A	B	C	**D**
668	932.2	**654.9**	914.6	999	379.5	988	**349.8**
610.6	951.7	**600.6**	950.5	704	286.6	704	**201.6**
493.5	814.4	**490.9**	820.7	968.7	325.4	968.8	**161.8**

In checking each cost graph, it can be validated that each case in case A and case B is misunderstood once, and the accuracy of 83 percent is confirmed.

5 Future Work

It is possible to judge the driver’s intention to change lanes only by the surrounding situation in simulation and the acceleration/deceleration pedal operation. However, it is difficult to detect the driver’s lane change intention if real time driving is difficult such as A case, even though the driver has intention. The algorithm needs to be modified to allow stable cost calculations in more diverse environments and based on various experimenters, research will be developed to improve the accuracy by learning the fuzzy rule in real time driving.

Acknowledgments

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References

[1] *Traffic Safety Facts Research Note*, National Center for Statistics and Analysis, Report No. DOT HS 812 381, 2017.

[2] McCall, Joel C., et al. *Lane change intent analysis using robust operators and sparse bayesian learning*, IEEE Transactions on Intelligent Transportation Systems, ISSN 1558-0016, 8(2007), 431-440.

[3] Doshi, Anup, and Mohan Trivedi., *A comparative exploration of eye gaze and head motion cues for lane change intent prediction,* IEEE Intelligent Vehicles Symposium, ISSN 1931-0587, 2008, 49-54.

[4] L. Jin, H. Hou, and Y. Jiang., *Driver intention recognition based on continuous hidden Markov model*, International Conference of Transportation, Mechanical, and Electrical Engineering, ISBN 978-1-4577-1700-0, 2011, 739-742.

[5] Mizushima, Takuya, Pongsathorn Raksincharoensak, and Masao Nagai., *Direct yaw-moment control adapted to driver behavior recognition,* SICE-ICASE, ISBN 89-950038-4-7, 2006, 534-539.

[6] Meyer-Delius, Daniel, Christian Plagemann, and Wolfram Burgard., *Probabilistic situation recognition for vehicular traffic scenarios*, IEEE International Conference of Robotics and Automation, ISSN 1050-4729, 2009, 459-464.

[7] H. M. Mandalia and D. D. Salvucci, *Using support vector machines for lane-change detection*, Proceedings of the Human Factors and Ergonomics Society Annual Meeting, ISSN 1541-9312, 49(2005),1965- 1969.

[8] Aoude, Georges S., et al. *Driver behavior classification at intersections and validation on large naturalistic data set*, IEEE Transactions on Intelligent Transportation Systems, ISSN 1524-9050, 13(2012) ,724-736.

[9] Abe, M., Manning, W., *Vehicle Handling Dynamics First Edition*, ISBN 978-1-8561-7749-8, Butterworth-Heinemann, 2009.

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