Lane-Change Detection Based on Vehicle-Trajectory Prediction

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Introduction

- In this paper, it was determined that there was a problem with a false alarm when a vehicle changed lanes.
- It also proposes a method to predict the trajectory of the vehicle and use it to detect lane changes because this can lead to distrust of the driver's driving support system.
- Predict the trajectory that a person moves unconsciously.



- used a real-world traffic dataset published by the Federal Highway Administration.
- collected from eastbound I-80 in the San Francisco Bay Area.
- The measurement area was 500 m long and consisted of six highway lanes.
- measured three times per 0.1 second over a 15-minute period and collected data from 5678 vehicles.
- used 300 lane change data for training and 523 lane change data for testing.

Model Used

• SVM Model



Decision Boundary







Model Used

• SVM Model



Distance between Decision boundaries and support vectors



Proposed method

DRIVING-INTENTION ESTIMATION

A. Feature Extraction

B. Driving-Intention Estimation



The proposed method defines three types of features. Features of distance from the center line, lateral velocity, and potential.

To consider the curvature of the road, use the distance from the center line instead of the lateral position instead of the distance from the center line

A. Feature Extraction

converted into feature vectors used as inputs to the driving intention estimation model

Carry out a crash check assuming that another vehicle is moving at a constant speed.



$U_C =$	$\omega_P U_P +$	$\omega_F U_F$	(0	$< U_C$	≤ 1)	(10)

$$U_N = \omega_L U_L + \omega_R U_R \ (0 < U_N \le 1) \tag{11}$$

the red vehicle represents the target vehicle

the blue vehicles represent the selected adjacent vehicles

the yellow vehicles are not considered.

The transparent blue vehicle represents the virtual vehicle that is set by the proposed method.

B. Driving-Intention Estimation



(a) the distribution of the potential field when vehicle i is faster than the target

(b) the distribution of potential field when vehicle i is slower than the target

The red vehicle is the target, and the blue one is vehicle i.



(a) a case in which the driving intention is keeping

(b) a case in which the driving intention is changing and arrival



The red vehicle is the target

blue ones are adjacent vehicles

Transparent color denotes the predicted position

If a collision occurs during a lane change, the predicted trajectory is re-planned.

(c) a case in which the driving intention is adjustment.

The red vehicle represents the target

The blue one generates repulsive potential energy

The yellow one does not generate repulsive potential energy

Experimnets / Conclusion

The green rectangle represents the predicted position at each time step

The red line shows the ground truth



(a) when the target keeps the lane

(b) when the target changes the lane

The red vehicle is the target

The blue ones are adjacent vehicles

The yellow ones are other vehicles that are not considered



The black rectangle represents the initially predicted trajectory Re-planning was conducted because of the collision The green rectangle shows the re-planned trajectory The red line shows the ground truth

Experimnets / Conclusion

Two evaluation criteria were used: detection time τd and detection accuracy F1 score

 $\tau_d = \tau_c - \tau_j,$ (23) $F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}.$ (24)

First, the detection time : $\theta d = \theta c - \theta j$

where θc is the moment the target crosses the centerline

 θ j is the moment the proposed method determines that the target will change lanes

A large value of θd means a high initial detection performance, defined as follows

Based on detection time τd : 1) Success: $0 < \tau d < 5.0$ (judged within the time limit). 2) Failed: $\tau d \le 0$ (judged too late). 3) False alarm: $\tau d \ge 5.0$ (judged too early).

Experimnets / Conclusion

Two evaluation criteria were used: detection time τd and detection accuracy F1 score

 $\tau_d = \tau_c - \tau_j,$ (23) $F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}.$ (24)

Including precision in the F1 score allows you to evaluate the false alarm rate when determining that the proposed method does not change lanes as an incorrect lane change.

Lane change estimation method must satisfy recall with 100% accuracy

Conclusion

Without trajectory prediction				Proposed method		
		Detect	ion result	Detection result		
		LC	LK	LC	LK	
Ground	LC	523	0	523	0	
Truth	LK	36	487	17	506	

TABLE I RESULT OF LANE CHANGE DETECTION

LC	(lane	changing)	and	LΚ	(lane	keeping))
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TABLE II PERFORMANCE COMPARISON WITH PREVIOUS METHODS						
Method	Precision	Recall	F_1	τ_d		
Mandalia [8]	80.0 %	81.1 %	80.5 %	1.33 s		
Schlechtriemen [7]	93.6 %	99.3 %	96.4 %	1.65 s		
Proposed method	96.3 %	100 %	98.1 %	1.74 s		

Mandalia : Only use SVM

Schlechtriemen : Detect lane changes using feature extraction

Proposed method : Apply vehicle trajectory prediction methodology

Conclusion



(a) record of all features that are normalized

(b) driving intention estimated by the method

(c) the driving intention estimated by the proposed method

How I can use it in my model





There is a way to use V2X technology

Used V2V, V2I, V2N