Impact of Surrounding Cyclists on Car Driver Behavior Recognition at Roundabouts

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***Abstract*—Driving behavior prediction at roundabouts is an important challenge to improve driving safety by supporting drivers with intelligent assistance systems. To predict the driving behavior efficiently steering wheel status was proven to have robust predictability based on a Support Vector Machine algorithm. Previous research has not considered potential effects of surrounding traffic on driving behavior, but that consideration can certainly improve the prediction results. Therefore, this study investigated how different surrounding cyclists impact driving behavior of an ego car. A simulator study was conducted to collect driving behavior data of ego car drivers in the scenarios with different surrounding cyclist position settings. The impact of the surrounding cyclists on the ego driver behavior was found: When there were surrounding cyclists, the recognition rate of ego driver behavior patterns reached 100% later than when there was no surrounding traffic. In conclusion, driving behavior pattern recognition at roundabouts is impacted by surrounding cyclists, and the impact can be expressed in a quantitative way.**

I. INTRODUCTION

A. Motivation

Roundabouts are considered important road infrastructure because converting an intersection into a roundabout has caused fewer injury accidents for both, motor car drivers and pedestrians [1–3]. However, the effect on cyclists' safety is negative. According to a study in Belgium [4], roundabouts increased cyclist injury accidents by 27% and fatal accidents by 41-46%. The most dangerous situations are the ones in which (a) a car enters a roundabout when a cyclist is circulating and (b) in which they both circulate in parallel and the car driver exits the roundabout [5]. These accidents can be decreased when in-car warning systems issue warnings to their drivers in case they overlook a potential risk. Warning systems work efficiently if they can predict their drivers' oncoming behavior precisely and then implement an appropriate warning strategy [6]. To develop a driving behavior prediction model that works for all roundabouts with different traffic situations, it needs to be known how surrounding traffic effects the driving behavior at roundabouts.

B. State of the Art

Many studies have focused on driving behavior prediction in the scenarios on motor way and (urban) intersections. Pentland (1999), Kuge (2000), and Mizushima (2006) assumed that future human behavior was a sequence of internal mental states that could not be observed but predicted by abstracting the observable present behavior, so Hidden Markov Models (HMM) were used for predicting driver behavior [7–9]. In Tango and Botta's study (2009), three machine learning techniques were compared for predicting driver behavior on motor way: Neural Network (NN) and Support Vector Machine (SVM) had comparable performances on car-following/lane-changing classification; HMM performed better for three patterns: car following, lane changing, and lane keeping on free lane [10]. HMM and SVM algorithms were also used to develop prediction models for driving behavior at intersections in Aoude's (2012) study, and the both showed comparable performances [11]. For turning behavior at intersections, Naito (2010) proposed a prediction model that was adapted to the individual characteristics of each driver to acquire prediction accuracy of 95.6% at a position of five seconds driving distance to the intersections [12]. Liebner (2013) proposed a Bayesian network model to predict driving behavior at intersections in the presence of preceding vehicles [13]. Also considering other traffic at intersections, Gadepally (2014) developed a driving behavior model that was suitable for the scenarios that involved unknown decisions of other vehicles. In these studies, machine learning algorithms were proved to be suitable algorithms to predict the driving behavior on motor way and at intersections [14].

Other studies were in the focus of driving behavior at roundabouts. St-Aubin (2013) and Mudgal (2014) modeled speed profiles at roundabouts and concluded that speed profiles differed significantly across drivers and roundabouts [15] [16]. Zhao' study (2017) is the only one about driving behavior prediction at roundabouts. The study used naturalistic driving data at three specific roundabouts to recognize whether a driver would leave the roundabout based on an SVM algorithm. The recognition rate reached 90% at a distance of approximately 10 m before the exit of the roundabouts. The results showed that the data of steering wheel angle and steering wheel angle velocity were effective features to recognize two different driver behavior patterns at roundabouts (the pattern of staying at roundabouts and the pattern of leaving roundabouts) [17]. The study can be criticized because surrounding traffic was not controlled in a naturalistic driving condition, and thus, how the surrounding traffic impacts the driving behavior recognition at roundabouts was still an open question.

C. Research Questions

This study focused on the question of how the surrounding cyclists impact the driving behavior recognition at round-

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abouts. The recognition results of driving patterns in different simulation scenarios, in which there were cyclists with different tracks disturbing ego car driver behavior, were calculated. Then, the recognition results for the different scenarios were compared.

II. METHOD

A. Simulator Study

A simulator study was conducted to acquire driving behavior data of thirteen participants with a driving simulator. The simulator uses a projection system with a field of view forward and to the sides ($270° \times 40°$) and a complete vehicle. A within-subject design was applied in the study.

A four-arm roundabout with 40 m diameter was used to design the scenarios, in which, there were three possible driving patterns for the ego car driver, see Fig. 1: Pattern A was that the driver took exit A to leave roundabout, and pattern B and pattern C were that the driver took exit B and exit C respectively to leave roundabout. To predict the driving behavior of which exit the driver would take, recognition of two pairs of driving patterns had to be executed: 1) recognition of pattern A and pattern B, and then 2) recognition of pattern B and pattern C. Steering wheel status was proved to have the ability to recognize these patterns effectively when there was no surrounding traffic [17]. Here, to investigate the impact of surrounding cyclists on the recognition results, the cyclists were placed at the different position in following scenarios: in the scenario illustrated in Fig. 2 (a), when the ego driver entered the roundabout and intended to take exit A or exit B to leave the roundabout (see the yellow solid lines), cyclists entered the roundabout from left through exit C and left the roundabout through exit B (see the blue dashed line). With this setting, driving pattern A and pattern B with cyclist disturbance were observed and the recognition of these two patterns were executed. Similarly, in the scenarios illustrated in Fig. 2 (b) (c) (d), the cyclists with other three types of circulating tracks (see the dashed lines) were placed to cause effects on the different driving patterns (see the solid lines) and the recognition of patterns were also executed.

Fourteen roundabouts were connected in two tracks in random order. Eight of them contained the four types of cyclist circulating tracks crossed the two pairs of pattern recognition, see Fig. 3. At the other six roundabouts, no traffic and other cars were placed randomly as "distractors" for the participants to make the scenarios less predictable for the participants when they were driving on the two tracks. The participants were asked to drive through each track three times. When they were approaching the roundabouts, a text instruction appeared on the screen to inform them which exit they should take, see Fig. 4 (a), and the same information appeared again on a white sign when the participants were in front of the exit, see Fig. 4 (b). At the end of the tracks, the participants were informed to stop and take a break with text on the screen. In this duration, the driving behavior data of the participants (steering angle, steering angle velocity, acceleration, velocity, and position) were collected.

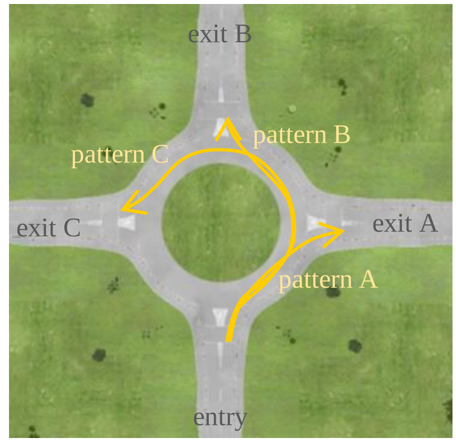


Fig. 1: Three typical driving patterns at roundabouts

B. Data Pre-processing

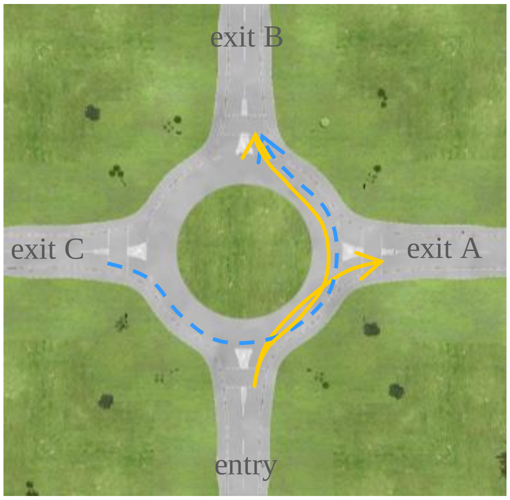
After data acquisition, the driving data at the roundabouts were selected for driving behavior analysis. The data were selected within a zone that was a circle with the diameter 30 m larger than the roundabout diameter, and the data outside of this boundary were removed. Then the car position data of all the drives were moved and rotated so that all drives had the same entry of the same roundabout, see Fig. 5. Thus, the data were ready for driving behavior recognition.

C. Driving Behavior Pattern Recognition in Different Scenarios

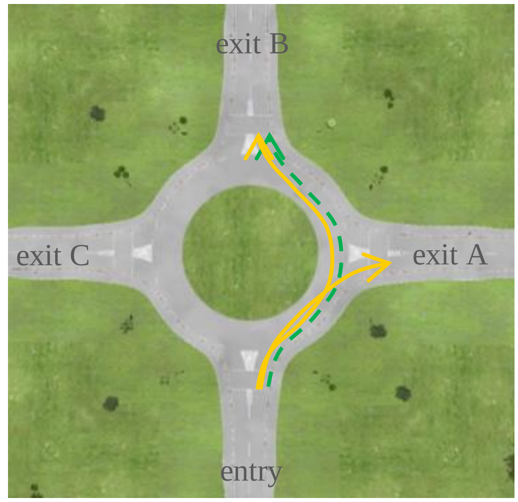
The recognition of following driving patterns was executed with the data from simulator study to investigate the impact of surrounding cyclists:

1) recognition of pattern A and pattern B without traffic,
2) recognition of pattern A and pattern B with the cyclists in the scenario illustrated in Fig. 2 (a),
3) recognition of pattern A and pattern B with the cyclists in the scenario illustrated in Fig. 2 (b),
4) recognition of pattern B and pattern C without traffic,
5) recognition of pattern B and pattern C with the cyclists in the scenario illustrated in Fig. 2 (c),
6) recognition of pattern B and pattern C with the cyclists in the scenario illustrated in Fig. 2 (d).

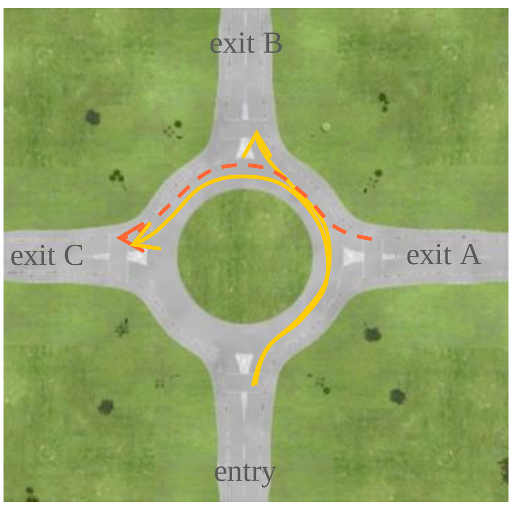
In this study SVM was adopted to make the pattern recognition because it has been proven to be effective and robust for the driving pattern recognition at roundabouts [17]. To make the recognition, the steering angle and the steering angle velocity were extracted as features firstly, and then these two features were standardized to avoid the variable in larger range dominating the one in smaller range. Then, to avoid biased recognition caused by imbalanced datasets of two classes (the class of leaving the roundabouts and the class of staying at the roundabouts), the two datasets were balanced with over-sampling [18]. Then, these datasets of two classes were merged together and split randomly into training



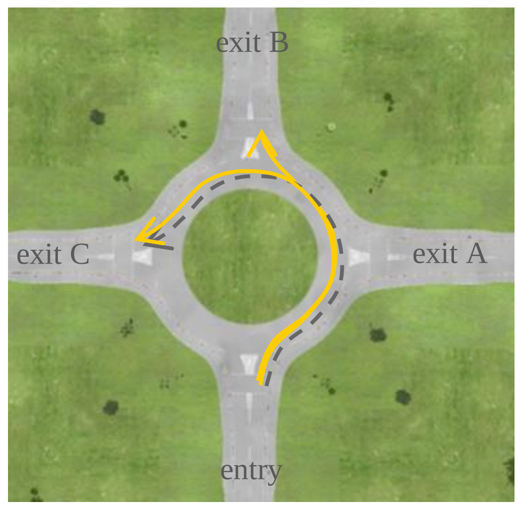
(a) Cyclist track 1



(b) Cyclist track 2

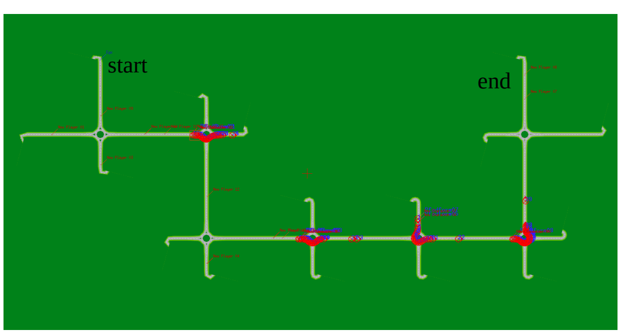


(c) Cyclist track 3

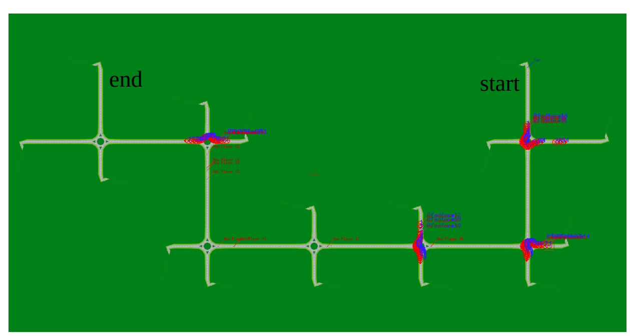


(d) Cyclist track 4

Fig. 2: Scenarios with different cyclist tracks



(a) Simulation track 1 for participants



(b) Simulation track 2 for participants

Fig. 3: Two simulation tracks for participants

(a) Information on the screen (Ausfahrt means exit in German)

(b) Information on the sign (Ausfahrt means exit in German)

Fig. 4: Information for the exit that the participants should take

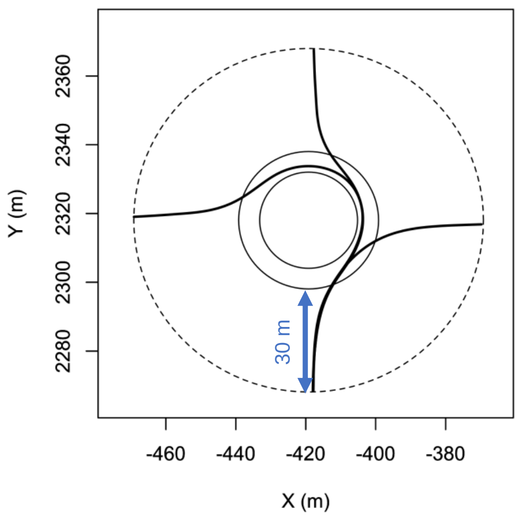


Fig. 5: Data selection with dashed circle

dataset (70%) and testing dataset (30%). After that, a five-fold cross-validation was used to the training dataset to identify the best parameters for the SVM model. At last, the model was validated with the testing dataset and the recognition rate of the model was calculated.

The recognitions were executed along the drives every two meters. The distances from the start points to the points where the recognition rates reached 100% were calculated. Then, the distances for the driving pattern recognitions in different scenarios shown in Fig. 2 were compared to investigate how the surrounding cyclists impact driving pattern recognition at roundabouts.

III. RESULTS

Fig. 6 and Fig. 7 depict the results of driving behavior pattern recognition in the different scenarios. The x-axis is the distance from the point where the recognition was executed to start point. The y-axis is the recognition rate that was calculated as the ratio between the number of instances correctly recognized and the number of instances presented in the test dataset. The details of the results are as follows:

In Fig. 6, the yellow dotted line shows the recognition results for the pattern A/B in the scenario without traffic. The recognition rate reaches an accuracy of 100% at the position with a distance of 34 m to the start point, see Fig. 8. The blue dotted line and the green dotted line depict the recognition results for the scenarios with cyclists left of the ego car and cyclists from back of the ego car that are illustrated in Fig. 2 (a) and (b) respectively. In the scenario with the cyclists left of the ego car, the recognition rate reaches 100% at the position with a distance of 38 m to the start point, see Fig. 8; in the scenario with the cyclists approaching the ego car from the back, the recognition rate reaches 100% at the position with a distance of 42 m to the start point, see Fig. 8. For patterns A/B in both of two scenarios with cyclists, the recognition rates reach 100% later than in the scenario without traffic.

In Fig. 7, the yellow dotted line shows the recognition results for the pattern B/C in the scenario without traffic. The recognition rate reaches an accuracy of 100% at the position with a distance of 60 m to the start point, see Fig. 9. The red dotted line and the dark grey dotted line are the recognition results for the scenarios illustrated in Fig. 2 (c) and (d). In the scenario with the cyclists right of the ego car, the recognition rate reaches 100% at the position with a distance of 68 m to the start point, see Fig. 9; in the scenario with the cyclists approaching the ego car from the back, the recognition rate reaches 100% at the position with a distance of 66 m to the start point, see Fig. 9. For patterns B/C in both of two scenarios with cyclists, the recognition rates reach 100% also later than in the scenario without traffic.

IV. CONCLUSION

The results showed that, when there were surrounding cyclists that might have the risk of crashing with an ego car, the driving pattern recognition rate reached 100% later than in the scenario without traffic, no matter which direction the cyclists came from. It can be assumed that the results depend on the used classifier and the input features, and the selection of classifier and features is missing in this study. Therefore, future work should focus on other features and algorithms

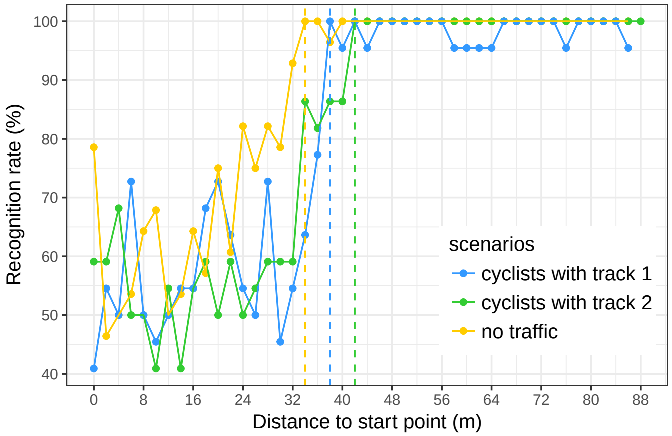


Fig. 6: Results of pattern A/B recognition for scenarios with/without cyclists

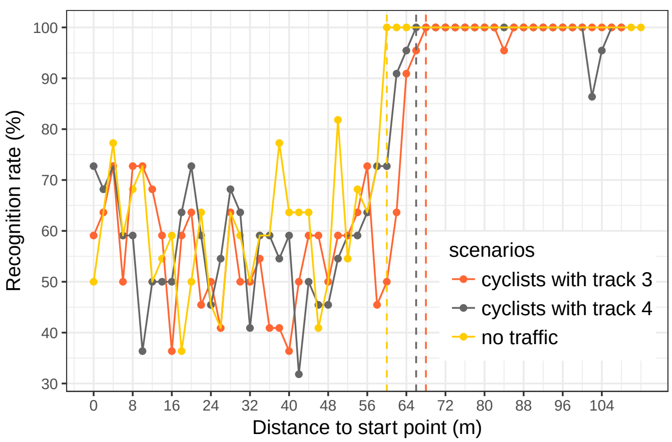


Fig. 7: Results of pattern B/C recognition for scenarios with/without cyclists

to improve the pattern recognition rate in the scenario with surrounding traffic.

In conclusion, the impact of surrounding cyclists on driving behavior recognition at roundabouts can be expressed in a quantitative way. The reason of this impact and its use in behavior prediction can be focus of future work.

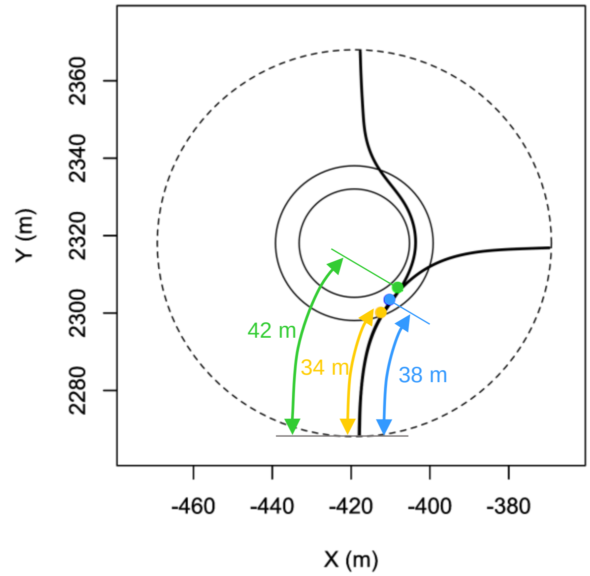


Fig. 8: Distances from the points with 100% recognition rates for pattern A/B to the start point

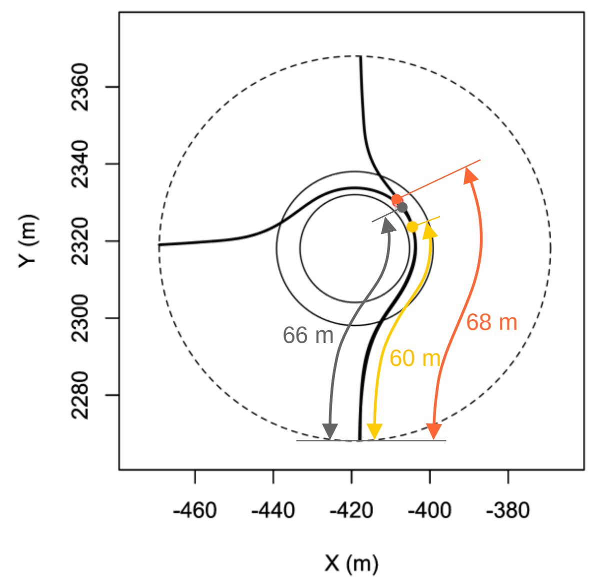


Fig. 9: Distances from the points with 100% recognition rates for pattern B/C to the start point

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