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A Classification Method for Driver Trajectories during Curve-Negotiation

Sarah Barendswaard[1], Daan M. Pool[2], Erwin R. Boer[1] and David A. Abbink[1]

Abstract— **When taking a curve, drivers follow their own unique trajectory. Most driver style classifiers in literature are based on inertial inputs, denoting whether a given driver is aggressive or calm. However, this does not give any indication of a drivers trajectory style, i.e. whether a driver is curve cutting. To fill this void, this paper introduces a novel rule based classifier that categorises seven different trajectory styles. The classifier is applied to data from a fixed-base driving simulator study in which 45 subjects drove on three roads, comprising three different velocities: 25, 50 and 80 km/h, with three corresponding radii: 20, 80 and 204 m. The results show that some classes are more prevalent than others, with biased outer curve negotiation performed by a majority of the subjects and with no drivers classified as centerline drivers. The proposed trajectory classifier is shown to exhibit high levels of consistency, with 93% of drivers exhibiting consistent trajectory classes for at least 66% of the right curves driven and 84% exhibits consistent trajectory classes for atleast 66% of the left curves driven. Where this consistency indicates a potential for generalising the classification results to other curves. Additionally, this classifier can be used to adapt trajectory-driven advanced driver assistance systems, thereby serving as an alternative to driver modelling.**

I. INTRODUCTION

Driver-style classification is emerging as a critical factor in driver assessment and profiling [1], road safety [2], human-centered advanced driver assistance (ADAS) systems [3], and even driver-modeling [4]. Driver assessment and profiling is important for power management [5] where calm drivers consume less fuel than aggressive drivers in the same scenarios [6]. Unsurprisingly, there is also a relationship between driving style and road safety [2], with 23% of deaths in traffic being related to 'aggressive' driving styles [7]. This has been a motivation for the development of a number of different ADAS, of which *personalised* implementations explicitly adapt their algorithm to a given driver style [8].

A number of different ways to classify human driver styles have been proposed ranging from classifying groups of people [9] to differentiating between individual people [10] and different genders [11]. Studies on supervised classification techniques have based the definition of their classes on the friction circle [12], or a subjective Driver-Style-Questionnaire (DSQ) [11], or a rule-based decision tree on throttle aggressiveness [13]. Whereas unsupervised techniques use feature extraction techniques such as Principle Component Analysis [14] in combination with hierarchical clustering [15].

Most data-mining efforts to classify human driver style have focused on *inertial* behaviour (i.e. gas pedal deflection, throttle, braking, acceleration) [11], [14], [16] [10], [12] [13] [15] [9]. Where sometimes thresholds are defined to indicate whether drivers show a particular level of agressiveness [9] [12], however a drivers level of inertial behaviour can change in a single manouvre. Studies find that a single driver exhibits multiple styles for a single manouvre (segmented into multiple time windows), sometimes showing three times more clusters than drivers [17] or that there are 5 segments where a single driver shows different inertial behaviour within a given curve [18]. Moreover, these inertial classifications do not directly distinguish between different trajectories nor can they categorise these i.e. curve-cutting style: an output that can directly be used with trajectory driven ADAS. Alternatively: trajectory classification is inherently consistent for a single manoeuvre, and can categorise different trajectories.

Trajectory classification has been attempted by [19], by using identified parameters of a driver model and the steering angle as the features for classification. The results have shown poor discriminative properties due to the use of steering wheel angle as an input feature, where steering wheel deflection is proven to be a bad metric to discriminate between drivers lateral position [4]. Conversely, a naturalistic driver study describes different drivers by indicating a driver trajectory typology in curves [20]. However, this typology is without any numerical quantification.

To bridge this gap, this paper introduces a newly developed numerical trajectory classifier in curves. It is based on lateral position on a road, before and during a curve as features, defining a rule-based *curve-trajectory classifier* of driver behaviour. The rules depend on where the driver is before curve entry (i.e. above, on or below the centerline) and how many transitions the drivers trajectory makes across the centerline band during the curve. To show the effectiveness of the proposed trajectory-based classification, the classifier is applied to a large dataset collected from 45 subjects, that drove over three different curves at a constant lateral acceleration and constant speed in a dedicated driving simulator experiment.

This paper is structured as follows: details of the rule-based classifier are described in Section II-A. The details of the human-in-the-loop driving experiment performed for data collection is elaborated in Section II-B. Finally the results and conclusion are presented in Sections III and IV, respectively.

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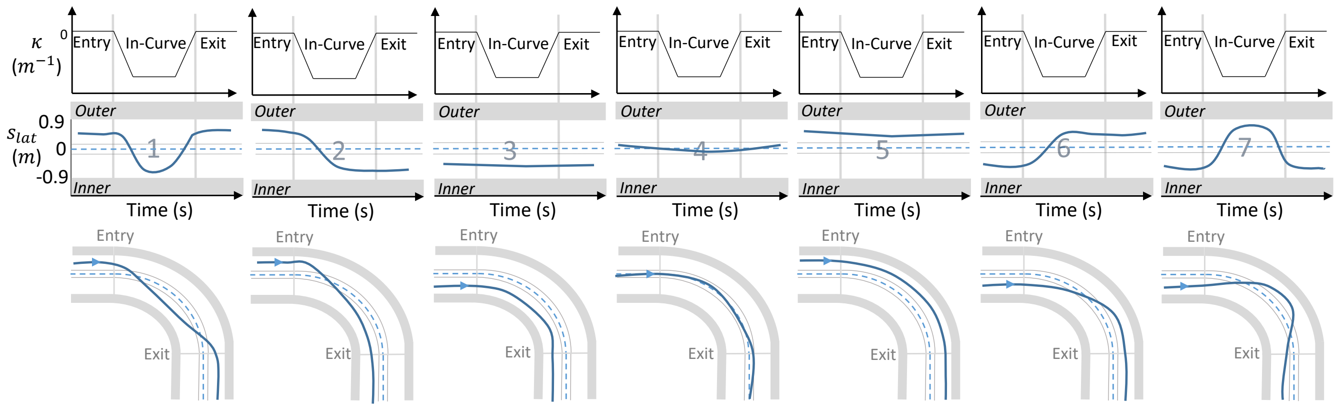

Fig. 1: The proposed rule-based classes in Figure 2 for a trajectory during curve negotiation.

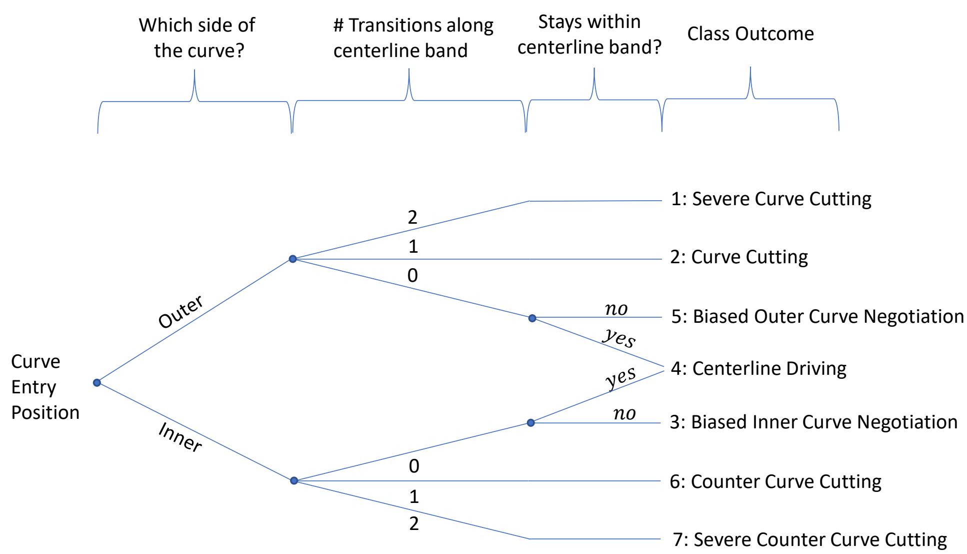

Fig. 2: A decision tree illustrating the rule-based classifier deduced from knowledge of the driver trajectories found in this paper. The centerline band is taken at ± 0.1m from centerline.

II. Methodology

A. Rule-based Classifier

The proposed rule-based classifier uses the lateral position on the road s_{lat} at different instances on a known curvature profile κ, to define the classes, as illustrated in Fig. 1. These trajectory shapes are the result of the rules presented in the decision tree illustrated in Fig. 2. Where the rules are knowledge-based, i.e. are based on observation of the types of trajectories drivers take when driving a curve in the driving simulator. The possible lateral positions are defined relative to the road centerline at two different instances: before and during a curve. The root node looks at curve entry, where you can either be on the inner or outer part of the curve. The first decision node tackles the number of transitions along the centerline *band* that can be made during the curve. The second decision node determines whether you have stayed within the centerline band, where this is only of concern if you have made 0 transitions along this band.

Where you are during curve entry is important as it could indicate whether you have an intention to cut the curve [21]. How many transitions along the centerline is defining of how the curvature of the trajectory differs from that of the centerline [22]. The choice of having transitions across a band of $\pm$ 0.1 m rather than the centerline line is made such that drivers who significantly cross this region are distinguished. The value of $\pm$ 0.1 m is chosen as it was found to be the average standard deviation of straight lane driving in previous studies [3].

B. Dataset

The dataset used to test the proposed classification comes from 45 subjects driving three different curves in a fixed-based driver simulator experiment. The details of the road

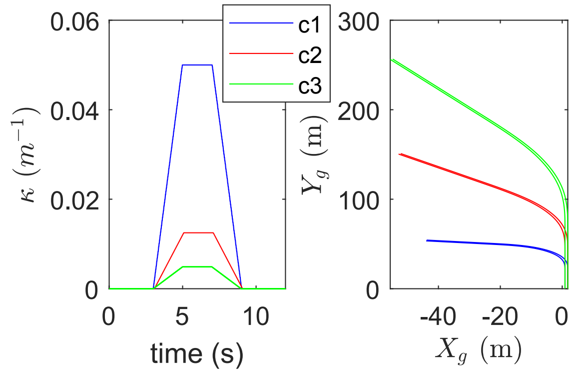

Fig. 3: The tested curves c1, c2 and c3, shown in birds eye-view as a function of global X_g and Y_g coordinates, and the corresponding curvature profiles κ.

TABLE I: The designed curve radii, car velocities and peak lateral acceleration of the three curves tested.

Condition	Radius	Velocity (km/h)	a_{lat} (ms^{-2})
c1	R= 20	25	2.41
c2	R= 80	50	2.41
c3	R= 204	80	2.41

design and experimental procedures are given next.

1) Road Design: A single-lane curve-driving study tested three different road profiles. The radii and respective velocities tested are listed in Table. I. The three different car velocities are chosen as limit velocities in Dutch traffic rules [23]. The corresponding radii are chosen such that all roads have a maximum centerline lateral acceleration of 2.41 ms^{-2}, which is the maximum lateral acceleration for road design [24].

The curves are designed to be clothoidal as illustrated in Fig. 3. 10-second straight section intervals were inserted inbetween curves and within each curve the clothoidal sections at curve entry and exit lasted 2 seconds. The maximum curvature section lasted chosen to last 2 seconds making the total time in the curve 6 seconds. Each curve was repeated 10 times, i.e. 5 right curves and 5 left curves, in alternating order.

2) Control Task: Subjects performed a curve negotiation (lateral control) driving task in a fixed-base simulator at a fixed speed. A heavy sedan of 1.8 m wide was used to visually simulate the vehicle on a single lane road. A vehicle dynamics identical to previous investigations [3] approximated by a bicycle model, was controlled, in a simulation environment with apparatus identical to previous investigations [3].

3) Experimental-setup and Procedure: Before participating in the experiment, participants signed a consent form. The conditions outlined in Table I were presented in randomised order to each subject. During each round the participants were given a familiarization run of 160 s before collecting data for each condition.

4) Subjects and Instructions: The experiment was performed by 45 subjects between the age of 18 and 31 years (average of 22 years and standard deviation of 3.1 years). The range of driver experience was between 0 (no years of driving with drivers license) and 10 years, with an average of 3.3 years and a standard deviation of 2.7 years. All participants were all instructed to drive as they normally would and to hold their hands on the steering wheel at a "ten to two" position.

III. Results

A. Class Outcomes

The outcome of the classifier on a dataset of 45 drivers on 3 different curves is illustrated in Fig. 4. Showing the lateral position s_{lat} starting 3 seconds before curve entry and ending 3 seconds after curve exit, for all 7 classes. Curve entry and exit are indicated by a vertical grey line, the centerline is indicated at position $s_{lat} = 0$ and the effective road boundaries are illustrated by the grey bars, also indicating whether it is on inner or outer side of the curve. This graph shows that within the dataset collected, a rich variety in driver trajectory styles exists even in a rather homogeneous test group. Nevertheless, not all classes are are found to occur, no instances of the center-line driving (4) class are found for both right and left curves. Moreover, some classes are more prevalent than others as is shown with the percentage occurence in Fig. 5. For left curves, class 5 (biased outer curve negotiation) occurs 60% for c1, 48% for c2 and 44% for c3. On the other hand class 7 (severe counter curve cutting) occurs 7% for only c3. For right curves class 2 (curve cutting) and 3 (biased inner curve negotiation) are the most frequently occurring, contributing up to 96% together for c3. Some classes seem to correlate with curvature, for example: class 1 (severe curve cutting) occurs more frequently for larger curvature, whereas class 2 (curve cutting) occurs more frequently for smaller curvature. Seeming that some class 2 (curve cutting) drivers switch to class 1 (severe curve cutting) for increasing curvature.

B. Effect of Curve Direction

A clear difference between right and left curves can be seen in Fig 5. For right curves class 2 (curve cutting) and 3 (biased inner curve negotiation) are most prevalent (86% occurence together on average), whereas for left curves class 5 (biased outer curve negotiation) and 2 (curve cutting) are most prevalent (69% occurence together on average). Seeming that class 3 and 5 switch places for right and left curves. On observing these two classes, it can be seen that both trajectories lie on the negative side of the road as seen in Fig. 4 (which is on the right side of the road). This prevalence of a driver driving on the right (negative) side of the road stems from the drivers straight road bias found to be on average -0.1 m [3]. Drivers' lateral position is biased to the right side of the road, which makes the inner part of a right curve and the outer part of a left curve. This causes left curves to naturally often be biased outer curve

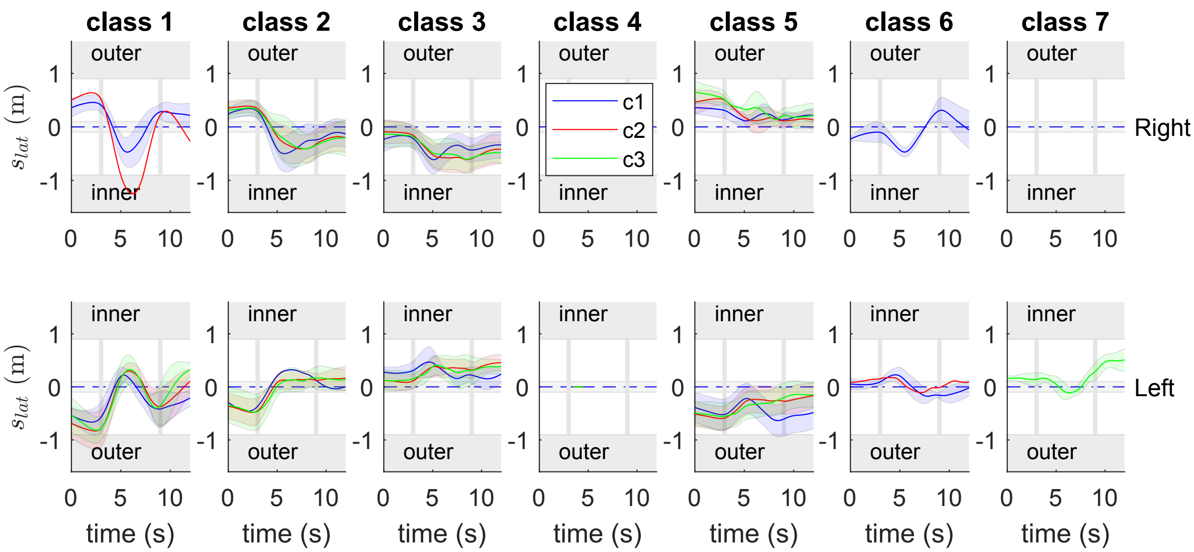

Fig. 4: The average and standard deviation of the outcomes of the classification for each class in the lateral position (s_{lat}) domain, respectively. The outcome of the classifications is shown for each curve respectively.

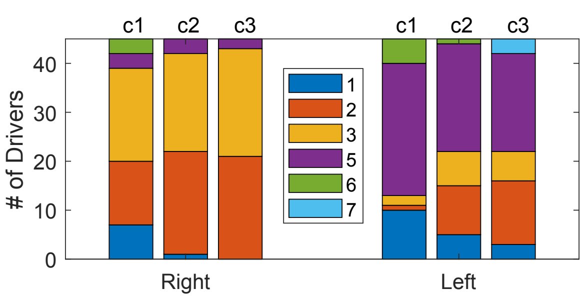

Fig. 5: The percentage occurrence of each class

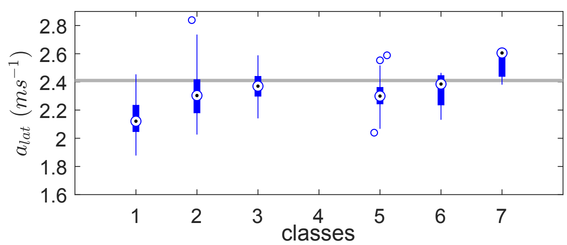

Fig. 7: The differences in average a_{lat} in the curve, given for all curves driven. A line at 2.41 ms^{-2} is outlined to represent a_{lat} when the centerline of the curve would be followed.

negotiation, whereas for right curves often be biased inner curve negotiation.

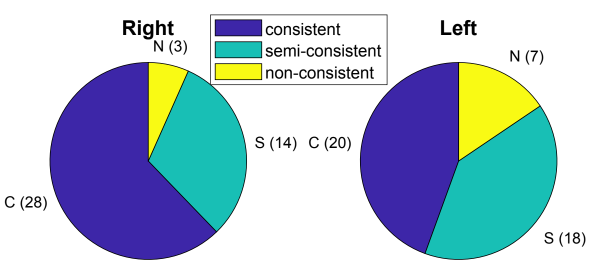

Fig. 6: Pie chart illustrating the number of drivers who are consistent, semi consistent or inconsistent in their driver trajectory style. *Consistent*: all three curves are driven with the same trajectory class, *semi consistent*: two curves are driven with the same trajectory class, and *inconsistent*: all three curves are driven in different trajectory classes.

C. Driver Consistency Across Curves

Overall consistency of drivers gives an indication of how generalisable the classification results are when applied to different curves. Fig. 6 illustrates pie charts that give the number of drivers who are *consistent* in their trajectory class across 3 curves, *semi-consistent*: consistent across 2 curves and *non-consistent*: not consistent across all three curves. It can be seen that drivers are more consistent in their trajectory class for right curves, with 62% being consistent, 31% being semi-consistent and 7% inconsistent. For left curves 44% are consistent, 40% semi-consistent and 16% inconsistent. Where the most inconsistent curve negotiation styles are found for the sharpest curve (c1), as can be seen in the class occurrence distribution in Fig. 5. This difference from c1 could be a result of having a curvature much larger than c2 and c3 as shown in Fig. 3. Where c2 has a curvature 2.5 times larger than c3, c1 has a curvature that is 10 times larger than c3. With c1 being the most demanding curve, demanding the largest steering inputs, a difference in skill due to the elevated demand may be a factor that influences this inconsistency. Therefore the classification results can be more reliably generalisable between curves with similar curvature, or steering demands. Hence in a real-world application such as a trajectory driven ADAS, reclassification of driver trajectories on curves with similar curvature may not be necessary.

D. Discussion

The fact that class 4 (centerline driving) is not found to occur is interesting given that most driver models assume drivers enter the curve at the centerline [25] [26] [27]. Interestingly, if we were to classify trajectories coming from a driver model, with a zero curve entry bias, it would not classify using the proposed classifier in this paper. The knowledge based on empirical-drivers did not result in a root node including centerline, rather lateral position should either be positive or negative. This shows a mismatch between empirical and modelled driver trajectories. Moreover, the philosophy of control-theoretic driver models always aiming to reduce lateral deviation from the centerline seems to have no ground from naturalistic data, suggesting that designing the control reference to be a 'driver trajectory' makes more sense [28], for efficient modelling.

In terms of trajectory shape, it can be argued that classes 2 (curve cutting) and 3 (inner curve negotiation) are not very different from each other, especially in right curves. In fact, what seems to distinguish between them is a consistent lateral displacement. This is also reflected in the corresponding average lateral acceleration in Fig. 7, where class 1 (severe curve cutting) and 7 (severe counter curve cutting) are clearly distinguished (medians 0.5 ms^{-2} apart), classes 2 (curve cutting), 3 (inner curve negotiation), 5 (outer curve negotiation) and 6 (counter curve cutting) have medians with only 0.08 ms^{-2} apart. This can be explained by the fact that a_{lat} does not vary with any consistent bias on a trajectory. Moreover, the difference between class 1 and 7 stems from drivers taking larger-than-centerline radii trajectories for class 1 and smaller-than-centerline radii trajectories for class 7. However, when curves become longer, the maximum and minimum radii achievable tend towards that of the centerline value, meaning that the longer the curve, the difference in lateral acceleration achievable between class 1 and 7 will tend to zero [22]. This means that trajectory-based classification provides better discriminative abilities for this dataset, whereas a classifier based on lateral acceleration could obscure such refined differences in driver trajectory, as acceleration is not only 'blind' to consistent bias but also becomes increasingly indifferent between trajectories in longer curves.

IV. Conclusion

A novel rule-based classifier that categorises 7 different trajectory styles is introduced. The classification is applied to a dataset of 45 drivers negotiating three different curves, each with a different curvature and velocity. The classification results show that curve cutting and biased inner curve negotiation are the most prevalent classes for right curves, making up for 86% of class occurence on average. Biased outer curve negotiation and curve cutting are the most prevalent classes for left curves, making up 69 % of class occurence on average. Across different curves drivers show high levels of consistency: 93% are consistent for at least 2/3rd of the right curves driven, whereas 84% are consistent for at least 2/3rd of the left curves driven. This consistency gives an indication of how generalisable the classification results are when applied to different curves. Additionally, the new trajectory classifier can directly be used in any personalised ADAS, especailly trajectory driven ADAS, thereby providing an alternative to driver modelling.

V. Acknowledgements

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