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How do Drivers Take a Curve? The Comfort Factor Model (CFM)

Julian Eggert[1], Karsten Kreutz[2], Lina Gaumann[2] and Jürgen Adamy[3]

***Abstract*— Human drivers are quite able to anticipate the dynamics that will occur in a curve and adjust their velocity accordingly. However, inappropriate speed estimation in curves is frequent in accidents, either by misjudgement of own speed or misestimation of the curve speed of others. In this paper, we investigate the major factors which contribute to human curve speed adaptation. By extracting undisturbed curve driving trajectories from real-world driving datasets, we empirically investigate and analyze the statistical relationship between between the maximal curvature $\kappa_{\max}$ along a curve and the minimal velocity $v_{\min}$ that an average driver takes when driving along that curve. We then propose the Comfort Factor Model (CFM), a minimalistic curve driving model explaining the observed data based on a constant comfort factor γ, which describes how a driver behaves when compared with the maximal but still safe curve.**

I. Motivation

How do drivers decide about the best velocity they should take throughout a curve? Such a question surely involves a broad set of cognitive, perceptual and sensorimotor considerations. In a first phase of anticipation, when the curve is still at some distance, visual estimation, memory or map data gives a first rough estimation of curve conditions and curve geometry. Experience with similar curves in the past allows a first guess about an appropriate approach velocity. Once the human driver starts entering the curve, proprioceptive and vestibular perception allows to refine the assessment by relying on our sense of our vehicle's position, movement, and spatial relationships with the world around us.

A great deal of these processes seem to be intrinsically driver specific, depending on a driver's subjective experience. On the other side, curve, vehicle and environment physics set clear constraints on the ways that a curve *can* be driven. Neglecting the modulation by personal driver preferences, we observe general regularities in the way that drivers take a curve, like e.g. a systematically stronger velocity reduction for sharper curves and vice-versa.

So the question is: **What would be a minimal model to capture the general rules of curve driving behavior?**

In this paper, we contribute to this question in two ways. First we inspect naturalistic driving data sets for trajectories of general undisturbed curve driving, and empirically analyze the systematic average dependencies between the key parameters maximal curvature $\kappa_{\max}$ along a curve and minimal velocity $v_{\min}$ that drivers take when driving along that curve. Second we introduce the **Comfort Factor Model (CFM)**, which explains these data-based findings. For this the CFM relates $\kappa_{\max}$ and $v_{\min}$ using two parameters, a comfort factor γ, which quantifies the speed propensity of the driver when taking curves and the friction coefficient μ_z, which describes the curve-relevant physical conditions between road and vehicle.

The relevance of such a model is given by the fact that a substantial percentage of accidents today occur by misjudgements related to curve driving [1]. Increasing safety in situations involving curve driving is therefore an important aspect of intelligent Advanced Driver Assistance Systems (iADAS) or fully Autonomous Driving vehicles (AD). In both cases, for risk assessment and behavior planning, the behavior of other vehicles has to be predicted. For example, to avoid accidents in curves, it has to be predicted how fast vehicles will drive, at which points of the curve they will brake and at which points they will accelerate. With the CFM we introduce a minimal model for describing the main curve driving characteristics of average drivers, which can be used for such purposes.

In the following, we first summarize previous work in section II. In section III we explain the data analysis which serves as the basis for the model, and in section IV, we present the Comfort Factor Model. Sections V and VI discuss and summarize the results.

II. Previous Work

Previous modeling work on curve driving can be classified into 3 domains: I) Vehicle properties and vehicle behavior in curves, concentrating mainly on vehicle models and their physical properties which are assumed to be known, II) Investigations about driver and driver types or driver styles during curve driving, and III) Driver models for other traffic participant's behavior prediction, with applications on risk assessment and optimal behavior planning in iADAS and AD. In this paper our focus is on type III applications.

The main problem of type III models is that the driver and vehicle parameters are only coarsely known, so that they have to rely mostly on "average" driver properties.

The main source of risk during curve driving is loss of control due to sideslip or rollover when the speed is too high. Since this is largely caused by the involved centrifugal and centripetal forces acting on the vehicle in the curve, it is straightforward that many models involve them in some way or another.

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In [2], driver intent at urban intersections is estimated. A maximal threshold curve target velocity is calculated from a desired maximal lateral acceleration, and this is fed into an Intelligent Driver Model [3] to regulate the velocity along the curve. In [4], driving risk assessment is extended by an additional curve-driving risk factor which increases risk when drivers get close to the maximal safe curve velocity gained from centrifugal forces. Safe curve driving behavior is then derived by minimizing risk while maximizing utility.

In an early analysis with 227 driven curves [1] could establish an inverse relationship between the maximal lateral acceleration and the minimal velocity. This and other papers served as the basis for curve driving models based on centrifugal resp. centripetal forces, by connecting maximal lateral acceleration with minimal curvature. In a recent papers like [5], the aspect of comfort in curves was added, in the sense that curve velocity is chosen based on maximal driving comfort. In their case, comfort was measured as the average quadratic deviation of the lateral acceleration. Other works such as [6] or [7] extend further on these ideas.

In this paper, we go a step further in the way that we try to validate statistical support about the relationship between the maximal curvature $\kappa_{\max}$ and the minimal velocity $v_{\min}$ during the curve. In addition, we look at their possible relative displacement. By this we want to find out if a simple relationship suffices to model curve-driving behavior for iADAS or AD.

III. Empirical Investigation

A. Scope and Assumptions

We assume that in "uninfluenced" curve driving conditions, human drivers behavior is mainly guided by the curve characteristics, or that the curve characteristics at least impose bounds on the velocity that the drivers can maintain. In this section, we investigate the statistical relationship between maximal curvature $\kappa_{\max}$ and the minimal velocity $v_{\min}$ during the curve.

B. Data Set Choice and Trajectory Preselection

To isolate the effect of curves on the driving behavior, we screened real-word driving data sets for "uninfluenced" curve driving behavior trajectories.

Naturalistic traffic situations usually exhibit curve driving behavior which can be affected by several internal and external factors. The internal factors are given by the drivers state and its assessment of the driving situation; these are largely unobservable or could only be inferred indirectly as e.g. by driver monitoring. In contrast, external factors are given by anything related to the driving situation and environment.

While the internal factors are not accessible, we can try to minimize the effect of the curve-unrelated external factors by data choice. We therefore screened several data sets with the following set of criteria for the trajectory selection:

- The drivers' curve-taking behavior should not be influenced by external factors like other traffic participants, traffic lights/signs or traffic rules (stopping or yielding).
- Variations in environmental conditions which modify the curve physics, as may occur for example for rainy conditions, snow or gravel vs. regular roads, should be avoided.
- Environmental conditions which change the drivers situation assessment, as e.g. given by poor visibility, should also be avoided.

The first criterion is the main one, while the remaining ones are rather technical requirements.

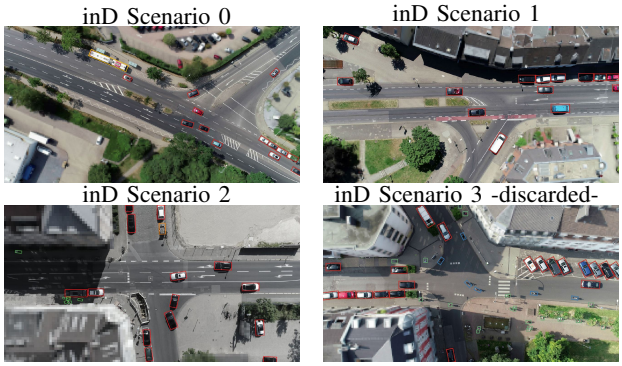


Fig. 1: The 4 scenarios from the inD trajectory dataset used in this paper (in addition to the KITTI dataset), adapted from [8]. Scenario 3 was discarded because it did not provide "uninfluenced" curve driving trajectories.

In addition, we filtered out trajectories subject to irregular driver behavior unrelated to curve driving. Specifically, we used only trajectories with a minimal curve radius $R \leq 50\,\mathrm{m}$ and skipped trajectories which were considered as incomplete (e.g. recordings that start in the middle of the curve) or with cars that stopped or drove backwards.

The focus is on curve driving with automobiles. From available data sets, some were discarded because they only contain very sparse curve data, as it is the case for NGSIM [9], [10]. Others concentrate more on involved pedestrians, like the Stanford drone [11] dataset, or the agents influence each other, like in the INTERACTION set [12]. In addition, a high sampling frequency and accuracy is desirable.

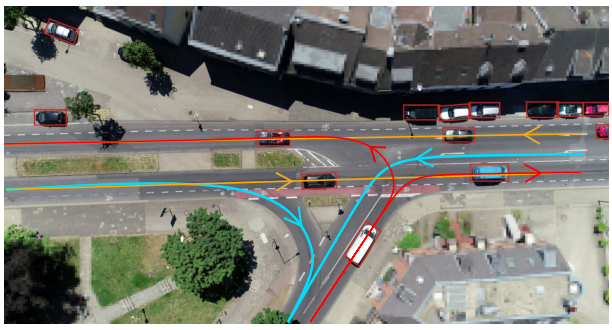


Fig. 2: Aerial view of the inD scenario 1, overlaid with the vehicle paths (adapted from [8]). Color blue indicates paths suited for the extraction of uninfluenced curve-driving trajectories, while orange and red paths are straight trajectories and influenced trajectories, which are not used for investigation.

C. Data Preprocessing

As a result of the considerations of the previous section, we concentrated on two data sets: The inD [8] data set, taken with drones hovering above the crossings, and the KITTI data set [13], recorded from a test vehicle equipped with four cameras and different sensors.

The inD (intersection Drone) data set provides trajectories from four unmanaged crossings with varying priority rules, see Fig. 1. The sampling rate is 25 Hz and trajectories are gained from 4K videos. The maximal admissible velocity by traffic rules is 50 km/h. The inD scenario 3 is rather exhibiting a high density traffic and in addition required high driver cognitive load, resulting in overly cautious driving behavior, so that it also was discarded.

The KITTI data set offers a broader set of situations with a variety of maximally allowed velocities and traffic rules. The measurement inaccuracy of positions is smaller than 0.3 m and of velocities smaller than 0.03 m/s.

The remaining trajectories from both data sets then were filtered for "uninfluenced" ´curve driving according to the set of criteria from section III-B. This led e.g. to the exclusion of some driving paths in which the observed car has to yield, see Fig. 2. A final visual inspection was applied as a quality check. Overall, by this we could extract 582 suitable trajectories, 44 from KITTI and the rest from the inD dataset.

From the trajectories we extracted the curvature. Since noise and discrete sampling has detrimental effects on the curvature calculation, we analyzed a series of interpolation and smoothing methods. We found that the best setting is a B-spline interpolation with degree 5, combined with subsequently by symmetrical first-order low-pass filtering.

D. Analysis

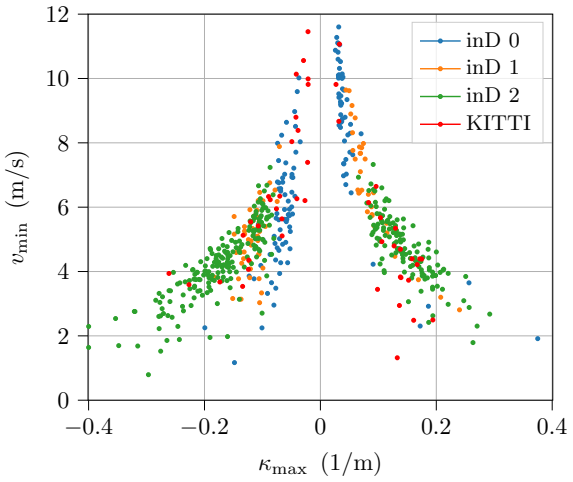


Fig. 3: Plot of $\kappa_{\max}$ vs. $v_{\min}$ for the 582 "uninfluenced" trajectories from the datasets. The different scenarios/datasets are indicated by color and cluster in different areas depending on the scenario properties. Overall, we get a quite good coverage of the different conditions.

Human drivers generally tend to take larger curves with higher velocities and to decrease velocity for curves with smaller radii. At some point of the trajectory we find a maximal curvature $\kappa_{\max}$ (i.e., minimal curve radius); and also at some point, the velocity reaches its minimal value $v_{\min}$. In this section we look at the relation between these two trajectory parameters.

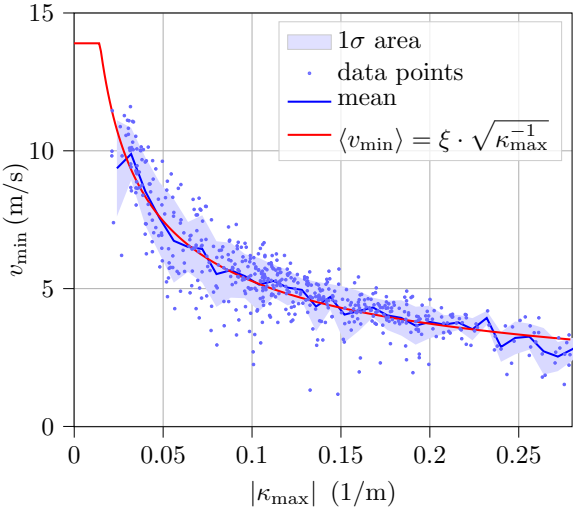


Fig. 4: All measured trajectory points $\kappa_{\max}$-$v_{\min}$ with mean and standard deviation. In red: Curve of least-squares fit of the mean minimal curve velocity $\langle v_{\min} \rangle = \xi \sqrt{\kappa_{\max}^{-1}}$ to the data.

For this purpose, we extracted $\kappa_{\max}$ and $v_{\min}$ from every valid curve-driving trajectory. The result is shown in Fig. 3, with the different scenarios as colored clusters. There is a gap for low curvatures, since curves with radii $R \leq 50\,m$ ($|\kappa_{\max}| < 0.02$) were excluded.

We observe 4 things: I) The different scenarios are reflected by their corresponding curvatures and II) we can observe a characteristic inverse relationship between $\kappa_{\max}$ and $v_{\min}$, III) the distribution is quite symmetric and IV) there seems to be an upper limit which the trajectory points do not exceed. We also see that the variety of trajectories considered covers the $\kappa_{\max}$-$v_{\min}$-range rather well.

Due to the symmetry, we will only look at the absolute curvature from now on. Fig. 4 shows the systematic decay of $v_{\min}$ with increasing $|\kappa_{\max}|$, together with its mean and standard deviation. Applying a least squares minimization fit of the measured $\kappa_{\max}$-$v_{\min}$-points with the curve of mean minimal velocity

$$\langle v_{\min} \rangle = \xi \; \kappa_{\max}^{-\beta} \tag{1}$$

leads to $\beta = 0.506$ and $\xi = 1.642$. This means that the points are arranged to a very good approximation according to

$$\langle v_{\min} \rangle = \xi \sqrt{\frac{1}{\kappa_{\max}}} \quad . \tag{2}$$

The result of this interpolation can also be seen in Fig. 4 (red curve).

It is also interesting whether the points of maximal curvature $\kappa_{\max}$ and minimal velocity $v_{\min}$ coincide. For this

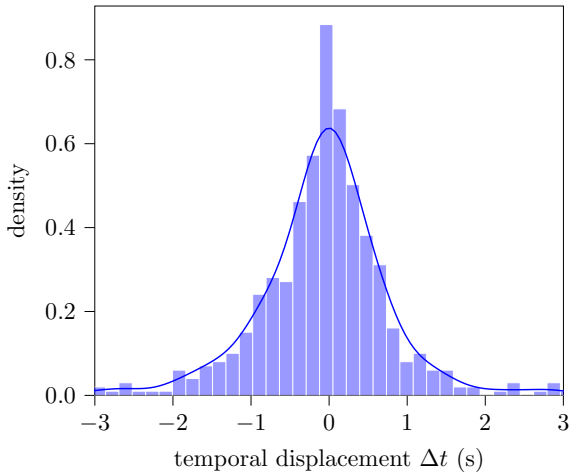


Fig. 5: Temporal displacements between the point of maxima curvature κ_{max} and the point of minimal velocity v_{min} of the trajectories, with a clear symmetry around 0.

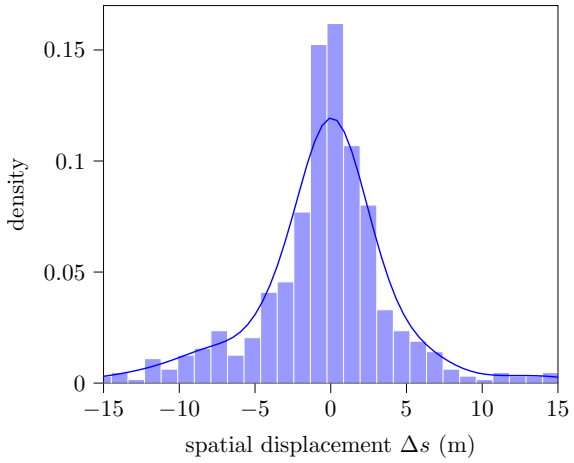


Fig. 6: Spatial displacements between the point of maxima curvature κ_{max} and the point of minimal velocity v_{min} of the trajectories. On average, drivers reduce speed to the minimal velocity at the point of maximal curvature, as can be seen from the symmetry of this and the previous figure.

purpose, we calculated the temporal and spatial difference

$$\begin{aligned} \Delta t &:= t_{v_{\text{min}}} - t_{\kappa_{\text{max}}} \\ \Delta s &:= s_{v_{\text{min}}} - s_{\kappa_{\text{max}}} \end{aligned} \tag{3}$$

of each trajectory. The results are shown by the histograms in Figs. 5 and 6. It can be seen that for the average of all trajectories no considerable displacement exists. So κ_{max} and v_{min} coincide in space and time *on average*. A more detailed analysis of the different scenarios one by one revealed, especially for the KITTI data, a small negative difference in Δt, indicating that the point of minimal velocity preceded the point of maximal curvature. This could eventually be explained by single driver variances or preferences, since the KITTI data has been recorded using one or a few drivers only.

IV. The Comfort Factor Model (CFM)

In this section, we relate the findings from data to a simple, minimal model of the "average" curve driver. Ideally, such a model is parameterized by a few constants and customizable to a specific, personalized situation if more information (e.g. about the driver and the environment) is known.

A. Main Influential Variables

The main influential factors that interact during curve driving are I) the driver, II) the curve and its geometry and III) the vehicle, respectively its behavior in the curve. This means that we expect to rely on at least 3 parameters for a model.

During the driving of a curve with radius R and velocity v, the centrifugal force

$$F_{\text{ZF}} = m\,\frac{v^2}{R} \tag{4}$$

acts on the vehicle by its inertia. On the other side the centripetal force, limited to

$$F_{\text{ZP,max}} = \mu\, mg \tag{5}$$

keeps the vehicle on track, composed by a friction coefficient μ times the weight force on the ground. This weight force is the product of the vehicles mass m and the gravity acceleration g. The friction coefficient μ in this case determines how strongly the tires and the street adhere together laterally and is largely determined by tire material, road constitution, longitudinal slip and slip angle [14], [15].

The forces act in a direction normal to the current curve direction, F_{ZF} to the outside and $F_{\text{ZP,max}}$ to the inside direction. If the centrifugal force exceeds the maximally possible centripetal force, the vehicle can not follow the curve any more. This means that

$$F_{\text{ZF}} \leq F_{\text{ZP,max}} \;\Rightarrow\; v \leq v_{\text{max}}(\kappa) = \sqrt{\mu g R} = \sqrt{\frac{\mu\, g}{\kappa}} \tag{6}$$

has to be always fulfilled to enable a safe passing through the curve. Assuming a typical longitudinal slip of 0.1 and a slip angle between 4° and 8°, we get for moderate velocities an approximately constant friction coefficient of around $\mu \approx 0.42 - 0.62$ [15].

B. Main Hypothesis

Based on Eq. 6, we can then calculate the maximally admissible lateral acceleration that a driver will experience during curve driving.

Assuming 6, it holds for a curve with maximal curvature κ_{max} the admissible maximal velocity during the entire curve will be

$$\bar{v}_{\text{max}} = v_{\text{max}}(\kappa_{\text{max}}) = \sqrt{\frac{\mu\, g}{\kappa_{\text{max}}}}. \tag{7}$$

With $a = v^2/R$ this results in the maximal feasible lateral acceleration

$$\bar{a}_{\text{max}} = \bar{v}_{\text{max}}^2\, \kappa_{\text{max}} = \mu\, g\ . \tag{8}$$

This constitutes an extreme upper bound. If drivers would take a curve at this velocity, it would not be safe even for

experienced drivers, since small driving jitter would already break the force equilibrium causing the vehicle to slip further or tilt.

The lateral acceleration is the main force that a driver feels. Corresponding relationships between lateral acceleration and velocity have been evaluated in [16] and [17]. High lateral accelerations are considered as uncomfortable by drivers [16].

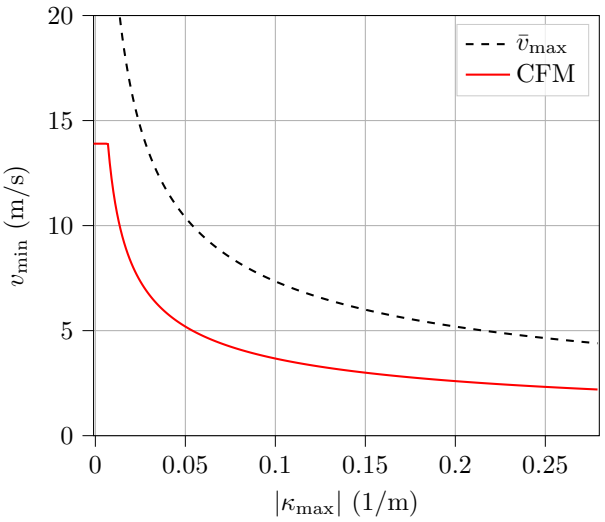


Fig. 7: The Comfort Factor Model distinguishes between the maximal feasible velocity $\bar{v}_{\max}$ with which the point of minimal curvature can be taken (the physical limit), and the actual minimal velocity $v_{\min}$ taken when driving through the curve. They are related by the comfort factor γ, and it is $\langle v_{\min} \rangle = \langle \gamma \rangle \, \bar{v}_{\max}$. Here we show $\bar{v}_{\max}$ together with $\langle v_{\min} \rangle$ for $\langle \gamma \rangle = 0.5$

This leads us to the following hypothesis: *Drivers take a curve in a way that they consider their behavior as "safe" and "comfortable" based on the experienced maximal lateral acceleration, which drivers regulate so that it is approximately constant across the curves. This means that they adjust their minimal velocity through the curve to the curvature in a way that approximately the same maximal lateral acceleration (or less) is experienced for all types of curves.*

Then it holds for the typical resp. realistic maximal acceleration and minimal velocity through a curve with maximal curvature that

$$\begin{aligned} a_{\max} &= \gamma^2 \, \bar{a}_{\max} = \gamma^2 \, \mu \, g, \\ v_{\min} &= \gamma \, \bar{v}_{\max} = \gamma \, \sqrt{\frac{\mu \, g}{\kappa_{\max}}} \end{aligned} \tag{9}$$

with a constant comfort factor $0 < \gamma < 1$. If we average over different trajectories each governed by Eq. 9, we get for the mean maximal acceleration and mean minimal velocity

$$\begin{aligned} \langle a_{\max} \rangle &= \langle \gamma \rangle^2 \, \bar{a}_{\max} = \langle \gamma \rangle^2 \, \mu \, g, \\ \langle v_{\min} \rangle &= \langle \gamma \rangle \, \bar{v}_{\max} = \langle \gamma \rangle \, \sqrt{\frac{\mu \, g}{\kappa_{\max}}} \end{aligned} \tag{10}$$

with the mean comfort factor $0 < \langle \gamma \rangle < 1$.

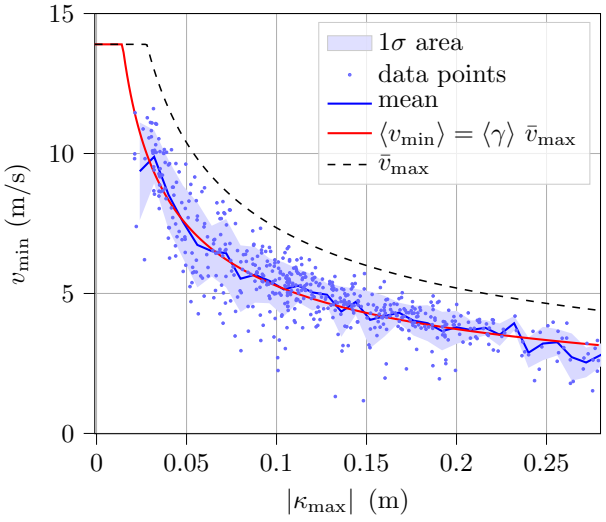


Fig. 8: The Comfort Factor Model (CFM) fits to the measured trajectory data. The physical limit velocity $\bar{v}_{\max}$ has been adjusted to provide a real upper bound to the data. The comfort factor was then calculated from the fit $\langle v_{\min} \rangle = \langle \gamma \rangle \, \bar{v}_{\max}$, resulting in $\langle \gamma \rangle = 0.7177$. This means that on average, drivers adjust their velocity in curves in a way that they experience a lateral acceleration which is approximately $2/3$ of the maximal lateral acceleration. See text for details.

The typical minimal velocity reached during the curve as a function of the maximal curvature is shown in Fig. 7 for a comfort factor of $\langle \gamma \rangle = 0.5$.

Comparing this curve with our findings from section III, we see that this matches with Eq. III-D if $\xi = \langle \gamma \rangle \sqrt{\mu \, g}$. Adjusting the coefficient μ for $\langle \gamma \rangle = 1$, so that it represents an upper bound for the set of trajectories, we find a realistic friction coefficient of $\mu = 0.55$. Finally, we perform a least-squares optimization to arrive at $\langle \gamma \rangle = 0.7177$ for the data. The plot can be seen in Fig. 8.

The parameter γ determines how close the driver steers near to the maximally admissible velocity $\bar{v}_{\max}$. It is therefore dependent on the driver's personal curve driving style. Plotting the factors γ for each trajectory, we gain a distribution of the typical comfort factors. We see in Fig. 9 that they remain approximately constant over the curvature, albeit distributed around the population average of $\langle \gamma \rangle = 0.7177$.

V. Discussion

The conclusions drawn so far for the CFM are valid for an average driver on an average road with average vehicle conditions[1]. Nevertheless, we see that the comfort factor γ exhibits a considerable variance. To which extent this is an inter- or an intra-driver variance remains to be investigated. It would also be interesting to analyze the deceleration and acceleration behavior before and after the point of maximal curvature. Here we expect that other considerations, like the minimization of overall jerk, might also play a role.

[1]However trajectories were chosen from inner city roads in good conditions only, so that the variability of μ due to road conditions is expected to be small.

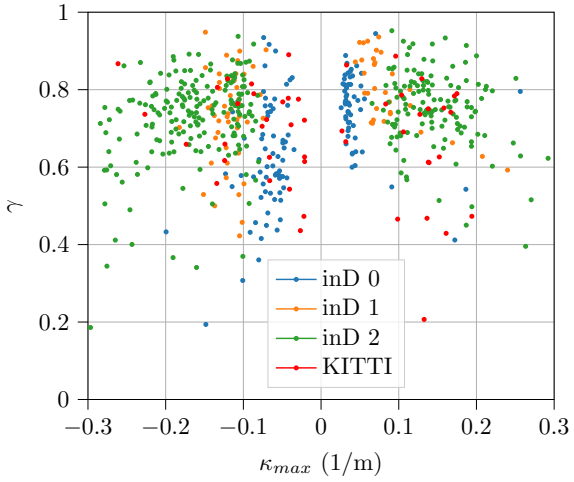


Fig. 9: Plot of the maximal curvature κ_{max} vs. the comfort factor γ for each trajectory. A $\gamma \approx 1$ indicates that drivers drive through the curve with a velocity that is close to the physical limit given by centrifugal vs. centripetal forces.

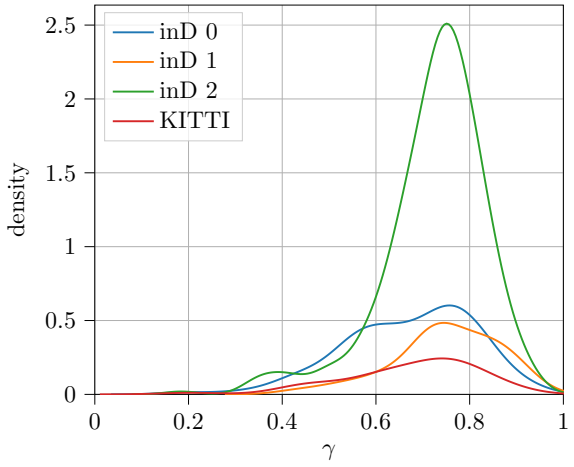


Fig. 10: A detailed plot of the distribution of γ for the different scenarios/datasets. Although the variance is considerable, the different scenarios settle at similar average γ's.

In the investigated datasets, information about the vehicle type is also annotated, mainly differentiating between passenger cars, trucks and buses, motorcycles and vulnerable road users (pedestrians and cyclists). For the analysis, we have used only the car trajectories, since they provided the broadest statistical basis. It is expected that other vehicle types result in different CFM parameters, with the vehicle type influencing mainly the vehicle properties as expressed by μ.

Although in principle the model would apply to any curve driving, roundabouts have been left out of the analysis. This is because they often do not exhibit what we call undisturbed curve driving, because the velocity is largely constrained by priority rules, various traffic signs or other traffic participants.

How does the proposed "comfort factor" relate to the subjective feeling of human drivers? Without further information about the driving scene, human perceived comfort is determined by acceleration and jerk. In the CFM proposed in this paper, the comfort factor γ rather provides a comfort in the sense of "feeling safe", since it is relative to the maximally admissible speed in the curve by curve geometry and vehicle properties via κ_{max} and μ. The model could thus be compared to human driving experience by asking "How comfortable did you feel when driving through this curve at that velocity"?

For situation-adjusted parameters γ, κ_{max} and μ, a driver model for single driver behavior planning in curves could be based on the CFM output.

For example, the targeted longitudinal velocity would be controlled in a way that it reaches v_{min} at the point of maximal curvature. The IDM [3] has a "desired velocity" parameter that could be used for exactly this purpose. For continuous behavior, the desired velocity would have to be ramped down until it reaches v_{min}.

In a more detailed setting, a curve driving model would not only consider the curvature κ at the point of maximal curvature but instead at each point of a trajectory and regulate the velocity at each point according to the corresponding $v_{\text{min}}(\kappa)$.

VI. Summary

In this paper, based on the analysis of 582 trajectories of "undisturbed" curve driving gained from an extensive screening of various naturalistic driving datasets, we have presented I) a statistical and II) a minimal analytical model that describes the relation between the maximal curvature and the minimal velocity that drivers choose to drive through a curve.

The model is minimalistic in a way that it captures the involved factors *driver*, *curve geometry* and *vehicle properties* by only 3 scalar variables γ, κ_{max} and μ. The factor $0 < \gamma < 1$ (average $\gamma = 0.7177$, variance $\sigma = 0.124$ for our data) serves to quantify the personal curve driving style. Here, γ-values closer to 1 describe a more dynamic, more aggressive and less safe curve driving style, since it is closer to side-slipping and exhibits higher lateral acceleration / centrifugal forces. The curve geometry is represented by its maximal curvature κ_{max}. The factor $0 < \mu < 1$ describes the curve friction coefficient ($\mu = 0.55$ for our data) . It depends strongly on vehicle and environmental factors; vehicle factors like tire condition, longitudinal slip and velocity and environmental factors like temperature, weather conditions and road constitutions. It can easily fall below $\mu < 0.3$ for wet roads or $\mu < 0.1$ for icy conditions.

In this paper, we have confirmed the hypothesis that drivers tend to adjust their curve driving dynamics in a way that results in safe and comfortable lateral acceleration. We could show that the lateral acceleration is approximately constant with respect to different curves, i.e., drivers adjust their longitudinal velocity in a way that, regardless of the curvature, they experience a similar lateral acceleration. This acceleration respectively the speed at the point of maximal curvature is related to the maximally possible speed at that point by a comfort factor γ, which enables safe driving.

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