Extraction of Risk Knowledge from Time To Collision Variation in Roundabouts

Duncan Deveaux[†], Takamasa Higuchi[‡], Seyhan Uçar[‡], Chang-Heng Wang[‡], Jérôme Härri[†], Onur Altintas[‡]

[†]EURECOM, Campus SophiaTech, 450 route des Chappes, 06904 Sophia-Antipolis, France
E-mail: {deveaux,haerri}@eurecom.fr
[‡]InfoTech Labs, Toyota Motor North America R&D, Mountain View CA, USA
E-mail: {takamasa.higuchi,seyhan.ucar,chang-heng.wang,onur.altintas}@toyota.com

***Abstract*— Roundabouts are intersections which require understanding the intentions of other road users to be crossed safely. In this paper, we investigate on the nature and variation of driving risk in roundabouts, to allow connected vehicles to quickly assess a personalized and real-time level of risk associated with crossing a roundabout. First, Time To Collision (TTC) information is extracted from real roundabout vehicle tracks. Then, a supervised machine learning model to assess the probability for a given vehicle to exit the roundabout at the next available exit is trained. Finally, a risk metric is defined based on TTC thresholds and risk probability, which is found to show a strong correlation with the coefficient of variation of TTC values over a roundabout. Once integrated in knowledge-centric frameworks such as Vehicular Knowledge Networking, the obtained risk knowledge has a potential to support driver assistance systems in roundabouts.**

I. Introduction

Connected and Autonomous Vehicles (CAV) face a variety of challenging driving situations in ever more complex road infrastructures designed with human-driven vehicles in mind. Despite an increasing driving intelligence, complex road infrastructures or the proximity of vulnerable road users are expected to alter CAV driving strategies to avoid potential *risky* or complex driving situations. Specific driving contexts including low visibility, occlusion, yield type intersections requiring interacting with human-driven vehicles, as well as congested traffic conditions have been studied to be challenging to navigate autonomously for CAV, especially when more than one of the specific contexts mentioned are involved [1]. Such situations may cause CAVs to return control to a human supervising driver, cruise at a reduced speed, or stop completely [2].

Roundabouts are yield-type intersections which require understanding the intentions of other road users. Several works have focused on the impact of introducing CAV traffic in roundabouts through calibrated micro simulations [3, 4, 5]. While CAVs have been found to reduce the number of sequential, i.e., rear-end type conflicts for penetration rates above 50%, findings are mixed for lower penetration rates. [3] and [4] detected an increase in the number of conflicts in roundabouts for lower CAV penetration rates. While the overall amount of conflicts decreased for low penetration rates in [5], roundabouts have been subject to disproportionately more sequential conflicts caused by a human-driven rear vehicle following a CAV front vehicle than the reversed situation. As such, the definition of sequential conflicts-based risk metrics in roundabouts is a key to support the safe crossing of roundabouts by CAVs in mixed traffic scenarios featuring a majority of human-driven vehicles.

Given the ability to assess the level of risk in any roundabout, CAVs could dynamically adapt their driving behavior to human-driven vehicles to improve passenger safety. We refer to the ability of real time risk assessment as driving risk *knowledge*. We make a distinction between information and knowledge as introduced in [6], which gives a generic definition of knowledge applied to CAVs. Unlike information which is defined as static content, knowledge refers to a model able to produce abstract content from a set of input information. As an example, in a rear-end collision warning system, the distance between two vehicles as well as the speed of both vehicles is information. On the other hand, a process able to infer the minimal inter-vehicle distance after which the car following situation becomes risky is knowledge.

Works have considered the definition of driving risk knowledge in vehicular networks to improve passenger safety. For example, in [7], driving risk knowledge is created in a microscopic driving simulator considering crossing, merging, sequential, and diverging conflicts. Generally, estimating driving risk is a complex task. The perception of risk is subjective, and what is deemed safe by a given passenger might be considered risky by another [8]. What is more, risk perception varies among countries and differing driving laws. For example, overtaking on the inside is considered risky in most European countries, but permitted under certain conditions in California. As such, the definition of driving risk knowledge rather than static risk information is a promising approach as it has the potential to be personalized for each CAV based on passenger preferences and local context.

The Time To Collision (TTC) between two vehicles is a commonly used objective risk indicator, or Surrogate Safety Measure (SSM). It is an information defined as the remaining time to a collision between a following and a front vehicle, should both vehicles maintain a constant velocity. A standard approach to create TTC-based driving risk knowledge is to consider a TTC threshold under which a situation is flagged risky. Various TTC thresholds can be defined to adapt to different road users and contexts. Early research suggested critical TTC thresholds of 1 to 1.5 seconds, and considered values up to 5 seconds to enable collision avoidance systems on highways [9]. More recently, crash statistics-based research found the average pre-crash TTC value at time of braking to vary between 1.1 and 1.4 seconds [10]. As such, decreasing TTC thresholds can be used to represent increasing levels of risk.

It is challenging to select a relevant TTC threshold to determine whether a situation is risky, given the subjectivity of driving risk definitions. As such, it is not trivial to define TTC-based driving risk knowledge which can adapt to the preferred risk thresholds of various CAVs. Thus, the contributions of this paper are threefold. First, TTC values are computed from real, drone-captured roundabout tracks. Then, a model is trained to assess the probability for a vehicle to exit the roundabout in a given situation. Based on the probability of roundabout exit, a risk metric is defined by weighting critical TTC values with the probability of occurrence of the risk, i.e., the following vehicle not exiting before a potential collision. Finally, this novel TTC-based risk metric in roundabouts, along with traditional TTC-based risk estimators, are found to follow a close linear relationship with the variation of TTC values in the roundabout. In turn, this linear relationship can be distributed as knowledge in vehicular networks following vehicular knowledge networking approaches [6]. As such, personalized risk knowledge can be distributed in vehicular networks, matching the preferred risk threshold definition of each vehicle and context.

The rest of the article is organized as follows: Section II describes the augmentation of the RounD dataset through the computation of TTC values for vehicles inside roundabouts. In Section III, a model is defined and trained to estimate the probability of exiting the roundabout for a vehicle in a given position. Using the knowledge of TTC values and roundabout exit probability, Section IV describes TTC-based risk metrics applicable for roundabouts. Section V documents a strong linear relationship between the coefficient of variation of TTC values in a roundabout and TTC-based risk metrics. It describes the research applicability of the findings of this paper, while Section VI summarizes the article.

II. RounD: Time to Collision Extraction

In this part, the RounD dataset is considered to obtain roundabout vehicle tracks. After introducing the considered roundabout, the process of augmenting the dataset by TTC values computation is described.

A. The RounD Dataset

The RounD dataset contains drone-captured vehicle tracks extracted from three German roundabouts. It is provided by Krajewski et al. [11]. It provides realistic vehicle tracks on roundabouts, which we use as a basis to evaluate TTC-based risk in real roundabout mobility. The measurement-related positioning error is typically less than 10cm. Track data is divided into 24 recordings, each containing 15 minutes of data. Out of the 24 provided recordings, 22 were extracted from a unique roundabout which we use in the study. Vehicle track data is available at a rate of 25 pictures per second and includes data on the position, heading angle, velocity, and acceleration of each vehicle. Figure 1 illustrates the roundabout featuring extensive track data which was used in this study. It is a two-lane roundabout featuring four entries and four single-lane exits.

Fig. 1: Layout of the Considered Roundabout [11]

To assess the evolution of risk in the considered roundabout, we augment the dataset by computing TTC values for pairs of vehicles driving in the circular lanes of the roundabout. The TTC is a metric for potential collisions involving a following and a front vehicle. As such, the first step to compute TTC values for vehicles in the circular lanes of the roundabout is the definition of a procedure $front(v)$ to detect the vehicle which is directly in front of a given vehicle v.

B. Front Vehicle Detection

To begin with, the considered roundabout is augmented with discrete cells to facilitate the detection of front vehicles. First, the circular part of the roundabout is divided into virtual lanes of W_L width each. Then, each virtual lane is itself split into N_{slices} slices of $\frac{2\pi}{N_{slices}}$ rad arc measure. In turn, this allows the definition of discrete position coordinates for vehicles in the roundabout of the form (L, S). L and S represent, respectively, the identifier of the virtual lane and the virtual lane slice where the centroid of a vehicle is located. This discrete coordinate system can then be used to facilitate the detection of front vehicles. To avoid artifacts during front vehicle computation, the width of each lane as well as the number of slices per lane should be chosen such that two vehicles cannot simultaneously have the same coordinates in the discrete coordinate system. Given the size of passenger vehicles featured in the RounD dataset, we set $W_L = 2.25m$ and $N_{slices} = 30$.

Figure 2 illustrates the definition of virtual lanes and slices over the considered roundabout through blue-colored lines. Vehicles are represented by red boxes and annotated with

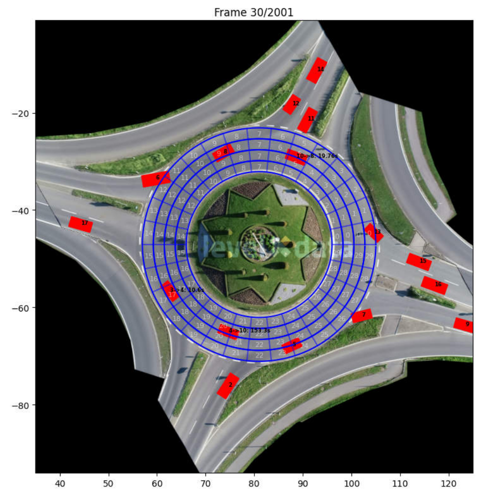


Fig. 2: Front Vehicle Detection and TTC Computation

Algorithm 1 Detection of a Front Vehicle in RounD Tracks

– Let $front\_slice(L, S)$ a function which returns the adjacent slice of S in lane L in anti-clockwise direction.

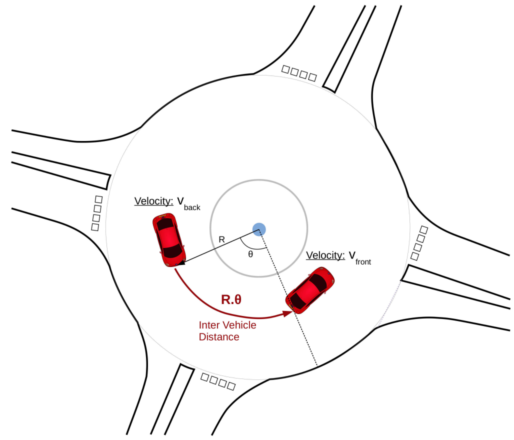
– Let $intersects(S, v)$ a function which returns whether v has a non-null intersection with slice S.

– Let V the set of vehicles currently in the roundabout area.

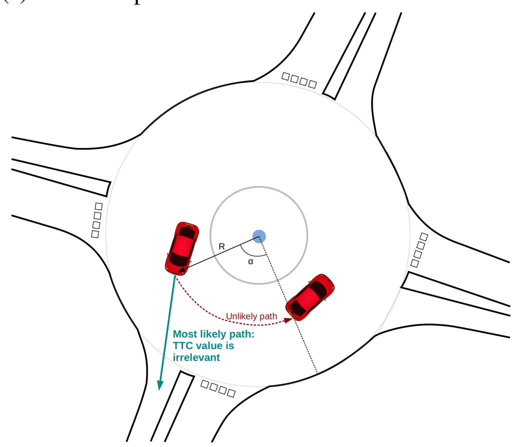
procedure front(v)

Let N_{slices} the number of slices of each lane.
Let c the centroid of vehicle v.
Let L the ID of the lane containing c.
Let S the slice of ID i of Lane L, where c is located.
Let $i \leftarrow 0$.
Let $S\_iterate \leftarrow S$.
Let $front\_v \leftarrow null$.
while $i < \frac{N_{slices}}{2}$ **and** $front\_v = null$ **do**
    $S\_iterate \leftarrow front\_slice(L, S\_iterate)$
    for all $w \in V \setminus \{v\}$ **do**
        if $intersects(S\_iterate, w)$ **then**
            $front\_v \leftarrow w$
            break
        end if
    end for
    $i \leftarrow i + 1$
end while
return $front\_v$

their unique identifier in the considered track file. Then, each vehicle v whose centroid is located in the circular part of the roundabout is considered for TTC computation, which starts with the detection of $front(v)$. The circular part of the roundabout is defined as the area covered by virtual lanes as illustrated in Figure 2. Finally, $front(v)$ is computed following the process described in pseudocode in Algorithm 1. The unique slice where the centroid of v is located is found. Then, the presence of any vehicle is iteratively checked in the $\frac{N_{slices}}{2}$ next front slices.



(a) TTC Computation in a Circular Roundabout Area



(b) Limits of TTC Computation in Roundabouts

Fig. 3: Roundabout TTC Computation and Challenges

C. TTC Computation

Once the front vehicle $front(v)$ of v has been identified, the TTC value for the [v, $front(v)$] pair of vehicles can be computed.

In straight road segments, the computation of the TTC for a pair of vehicles [v, $front(v)$] is expressed as the fraction of the Cartesian plane distance between v and $front(v)$ over their instantaneous velocity difference. In this context, both vehicles are assumed to drive in a straight line. On the other hand, vehicles crossing a roundabout are typically following its curve. As such, straight-line distance cannot be used to compute an accurate TTC value.

In a roundabout context, as illustrated by Figure 3a, we assume that vehicles follow a circular trajectory around the center of the roundabout when computing the distance between v and $front(v)$. It is computed as the length of the circle arc between the central front point of v and the central back point of $front(v)$. Then, the TTC is computed based on the instantaneous velocities of the two vehicles, as:

$$TTC = \frac{R \cdot \theta}{v_{back} - v_{front}}$$

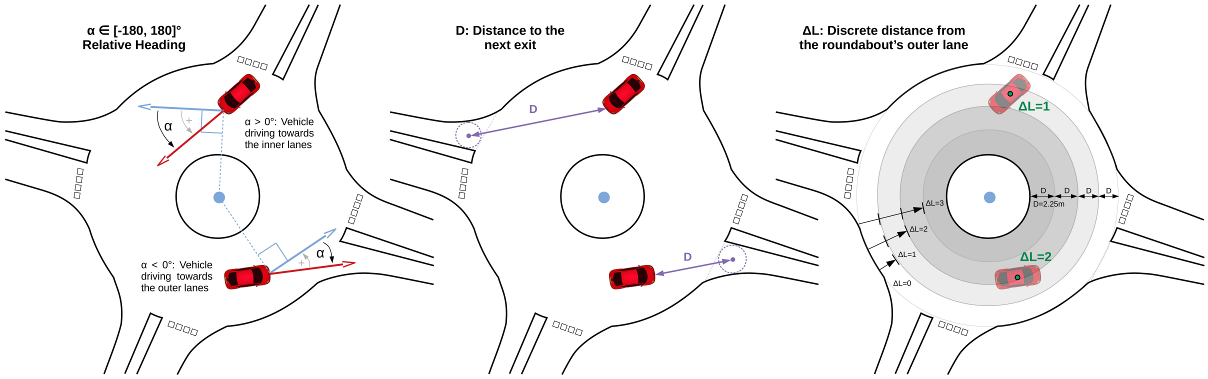


Fig. 4: Inputs for Roundabout Exit Probability Assessment

III. A Model for Exit Probability Estimation

The computation of TTC values in roundabouts as described in Section II can support the detection of risky situations. As introduced in [9, 10], TTC values under a threshold $TTC_{th} < 1.5s$ have been associated with a higher collision risk in highway traffic. This approach is well adapted in the case of highways, where vehicles mostly stay in the same lanes and have few opportunities to exit.

However, even when critical TTC values are computed in roundabouts, vehicles may potentially take an exit before being exposed to a collision risk. As illustrated by Figure 3b, TTC values are computed assuming the following vehicle will remain in the roundabout. As such, they may be under a risky threshold, yet not constitute a serious risk if the following vehicle exits the roundabout before having the opportunity to encounter the front vehicle. In turn, the fact that vehicles may exit the roundabout before encountering a risk, thus nullifying the risk for a subset of low TTC situations, should be accounted for.

In the context of car following situations in multilanes straight-line roads, [12] used a lane-change probability assessment model to weight the collision risk with the probability of lane changes by vehicles. Similarly, we train a supervised machine learning model aiming at computing the probability of a vehicle to exit a roundabout in a given situation. Provided the ability to accurately estimate that probability, false positives of risk detected for low TTC values where the following vehicle is likely to exit the roundabout can be eliminated.

A. Model Definition

We aim to train a model to output the probability of a vehicle v exiting at the next available exit of the roundabout, given the following input, as shown in Figure 4:

- The relative heading $\alpha \in [-180, 180]$ degrees of v. A value of $\alpha = 0$ means that v is strictly following the curve of the roundabout. A positive value indicates that v is driving towards the inner lanes of the roundabout. On the contrary, a negative value indicates that v is driving towards the outer lanes.
- The straight-line distance between the central front point of v and the next available exit of the roundabout.
- The discrete identifier L of the current virtual lane where v is located starting from $L = 0$ for the outermost lane of the roundabout.

We choose α as a key input feature of the model as it is anticipated to show a strong correlation with the intention of drivers to exit or not exit a roundabout at the next available exit. We also provide two additional features allowing to assess the distance of a given vehicle to the next available exit. Moreover, these three features can easily be sensed in real situations by a CAV, allowing to ease the potential application of the roundabout exit model in real situations.

Logistic regression is an adapted model implementation, as (i) the class to estimate is binary, i.e., exit or not exit at the next junction, and (ii) it can be used not only to classify whether a vehicle will exit but to estimate the exit probability of the vehicle, which is a key asset as it allows to weigh the collision risk. Moreover, in autonomous vehicle control scenarios, the behavior of vehicles can be finely adapted to the exit probability of potentially conflicting vehicles.

B. Training Data Collection

To train a supervised machine learning model to produce the probability of exit at the next available exit from the described input, training samples are extracted from the 22 recordings of the considered roundabout. For each frame of each vehicle whose centroid is present in the circular part of the roundabout, the described $[heading, distance, virtual\ lane]$ position input is extracted. Then, it is labeled by whether the vehicle exited the roundabout at the next available exit. In total, 2269561 labeled training samples were extracted from the available data.

Figure 5 illustrates a fraction of the obtained training samples as a scatter plot. It involves vehicles driving in the innermost virtual lane of the roundabout, as defined in Section II. The blue-colored points represent situations where the vehicle exits the roundabout at the next available exit after position input collection. The red-colored points represent situations where it stays in the roundabout. A clear

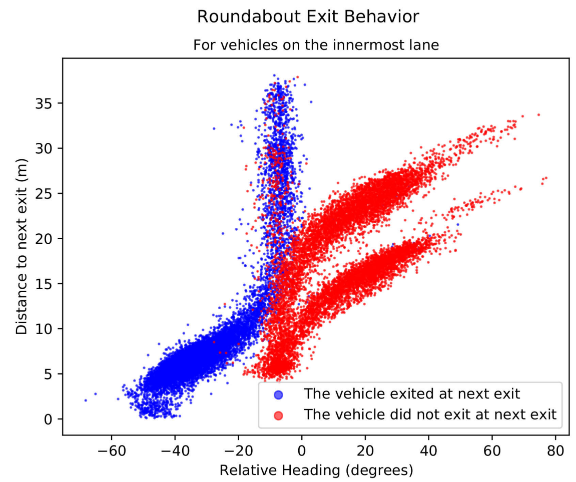


Fig. 5: Roundabout Exit Data for Vehicles in the Innermost Lane

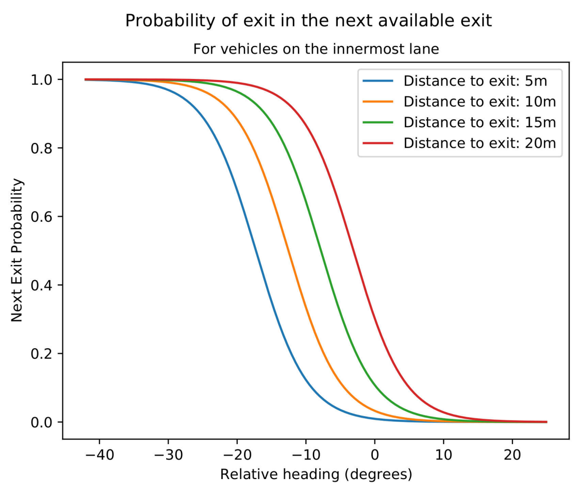


Fig. 6: Model Estimation of the Probability of Exiting the Roundabout for Vehicles in the Innermost Lane

pattern can be identified in the training samples. When a vehicle is close to the next exit, it is likely to exit only if it is clearly headed towards the outside of the roundabout. On the contrary, vehicles heading towards the inside of the roundabout are more likely not to exit.

C. *Model Evaluation*

The obtained training samples are shuffled and divided into a training set and a validation set of, respectively, 80% and 20% of the overall training samples. They are used to train an exit probability estimation logistic regression model. The model reaches an exit prediction accuracy of 91% on the validation set, and is able to output a probability of roundabout exit. Figure 6 illustrates the probability for vehicles in the innermost lane of the roundabout to exit at the next available exit, based on their current relative heading and distance to next exit.

IV. TTC-Based Risk Metrics for Roundabouts

Based on the computation of TTC values and of the probability for vehicles to exit a roundabout, we define roundabout-wide risk metrics to evaluate a real-time understanding of the risk level in a roundabout.

For each of the 22 recordings of the considered roundabout, a roundabout exit probability model is trained based on training samples extracted from the 21 other recordings. Each of the 22 accordingly trained models features a prediction accuracy above 90%. Then, each recording is replayed frame by frame. For each frame, TTC values for each pair of vehicles located in the circular lanes of the roundabout are computed. Based on the exit probability model and the TTC values for each recording, roundabout-wide driving risk indicators are computed for various thresholds of risk.

As introduced in Section I, different critical TTC Thresholds should be used for different contexts to accurately represent risk. Moreover, TTC thresholds may be personalized for each CAV. In [13], human drivers have been allowed to tweak TTC threshold values to adapt them to their preferred driving behavior, while dynamic threshold update schemes have been studied which adapt to a learned human driver behavior in [14]. As such, the risk indicators defined in this section can be computed for various TTC thresholds, matching the preferences of different CAVs and road contexts.

We consider the TTC threshold values $TTC_{th} \in [1, 2, 3, 4, 5, 6]$ seconds. While values up to 5 seconds have been used as conservative thresholds to trigger collision avoidance systems in [9], values between 1 and 2 seconds have been associated with a critical risk of rear-end collision [9, 10]. As such, we consider $TTC_{th} \in [1, 2]$ to be associated with strong risk, $TTC_{th} \in [3, 4]$ with medium risk, and $TTC_{th} \in [5, 6]$ with more conservative values of low risk of rear-end collision.

In turn, for each threshold $TTC_{th} \in [1, 2, 3, 4, 5, 6]$ seconds, the following risk indicators are computed:

1. The number of risky events in a subset of the recording, i.e., the amount of situations where a pair of vehicles (v_1, v_2) featured a TTC value under the TTC_{th} threshold. A timeout of 1 second is enforced before counting another risk situation for a same pair of vehicles.
2. The accumulated time spent under TTC_{th} by vehicles over the course of a subset of the recording, i.e., the accumulated Time-Exposed TTC (TET) of vehicles of the recording. It measures the time of exposition to critical TTC values, as introduced by [15].
3. The *exit probability-weighted* accumulated TET of vehicles of a subset of the recording.

The second indicator, i.e., the accumulated TET over a subset of a recording, is computed as follows:

- Before the start of the computation, the risk indicator R_{TET} is initialized, $R_{TET} \leftarrow 0$.
- For each frame, and for each pair of vehicles (v_1, v_2), if the computed TTC value is below TTC_{th}, update R_{TET} as,

$R_{TET} \leftarrow R_{TET} + \frac{1}{F}$, with $F = 25Hz$ the frame rate.

R_{TET} does not handle the case where a roundabout exit is located between v_1 and v_2, and v_1 the rear vehicle exits the roundabout before having a chance to encounter the risk. As such, R_{TET} includes false positives of driving risk, where a low TTC value should not have been considered risky, as the following vehicle exited before potentially encountering the danger. To address this consideration, the third indicator is defined, i.e., the *exit probability-weighted* accumulated TET R^p_{TET}, which is defined as follows:

- Before the start of the computation, $R^p_{TET} \leftarrow 0$.
- For each frame, and for each pair of vehicles (v_1, v_2), if the computed TTC value is below TTC_{th}, update R^p_{TET} as,

  $R^p_{TET} \leftarrow R^p_{TET} + \frac{risk\_probability(v_1,v_2)}{F}$.
- $risk\_probability(v_1, v_2) =$
  $\begin{cases} 1 & \text{if no exit between } v_1 \text{ and } v_2. \\ P_{exit}(v_1) & \text{the probability of } v_1 \text{ exiting, otherwise.} \end{cases}$

At the end of each recording subset, the obtained risk metrics are normalized by the exact recording time in seconds and the number of vehicles having crossed the circular part of the roundabout in that time. This allows for an understanding of the real-time risk level in a roundabout, for various $TTC_{th} \in [1, 2, 3, 4, 5, 6]$ thresholds. In turn, road users may obtain real-time knowledge about the level of risk in a roundabout, personalized to match their preferred conception of the risk threshold.

V. TTC Variation and Risk Knowledge

After having defined roundabout-wide risk metrics based on TTC values and the probability of vehicles to exit from the circular lanes of the roundabout, we investigate on the evolution of roundabout risk through time. In particular, we aim to study whether any correlation can be found between the variation of TTC values in a roundabout and the average level of driving risk in that roundabout. In order to assess the variation of TTC values over a roundabout without introducing a scale-related bias, we consider a normalized metric, which is the coefficient of variation or Relative Standard Deviation (RSD) of TTC values.

A. General Setup

To perform the evaluation, each of the 22 available 15 minutes-long recordings were sliced into a set of subrecordings, each of a duration of $T = 450$ seconds. For each subrecording, the risk metrics as detailed in Section IV are computed for TTC thresholds of $TTC_{th} \in [1, 2, 3, 4, 5, 6]$. What is more, we investigate on the link between the defined risk metrics and the seasonality or variation of TTC values over the course of the subrecording. For each frame of the subrecording, the set of available TTC values which fall in the range $[0, TTC_{max}]$ seconds are averaged. Thus, a single average TTC value is computed for each frame of the subrecording, i.e., at a rate of $F = 25Hz$. Finally, the coefficient of variation, i.e., RSD of the obtained averaged TTC values over the course of the subrecording is computed.

B. Impact of Positioning Error

In realistic driving environments, CAVs are subject to errors when estimating their relative and absolute position. Global Navigation Satellite Systems based positioning error is typically mitigated by sensor fusion and Real time Kinematic (RTK) algorithms on-board CAVS. In [16], accuracy in the order of magnitude of a centimeter for both absolute and relative positioning is achieved through cooperative sensing.

To evaluate the realistic applicability of the results of this work, we introduce various levels of positioning-related noise when computing TTC values. Uncorrelated positioning errors are introduced in the computation of TTC values:

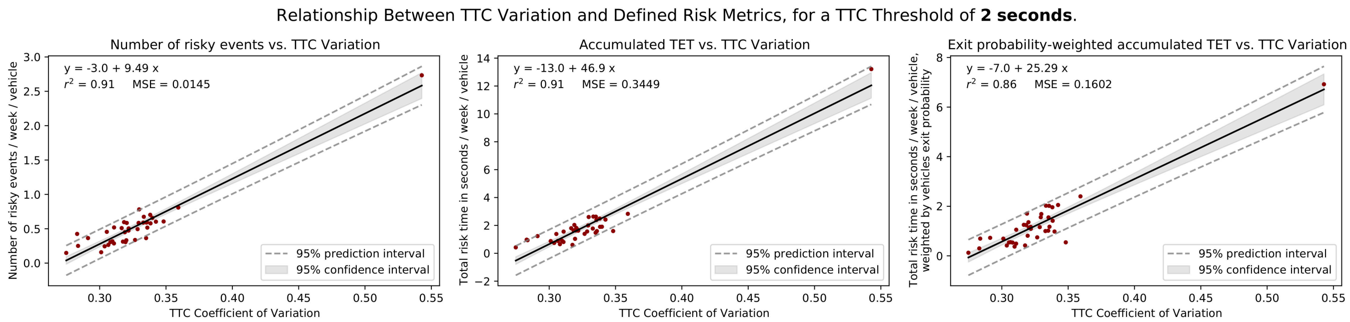
- Positioning errors are sampled from a normal distribution $\mathcal{N}(0, \sigma^2)$ of mean 0.0m, and whose standard deviation σ defines the spread of the error.
- When computing a TTC value between a pair of vehicles $[v,\ front(v)]$, a value of positioning error is sampled independently for both vehicles and temporarily added to their respective positions. Then, the computation of the TTC is performed as described in Section II-C using the altered positions.
- The process described in Section V-A is performed for: (i) No positioning error, (ii) $\sigma = 0.3m$, (iii) $\sigma = 0.5m$, (iv) $\sigma = 1m$ and (v) $\sigma = 5m$.

C. Results

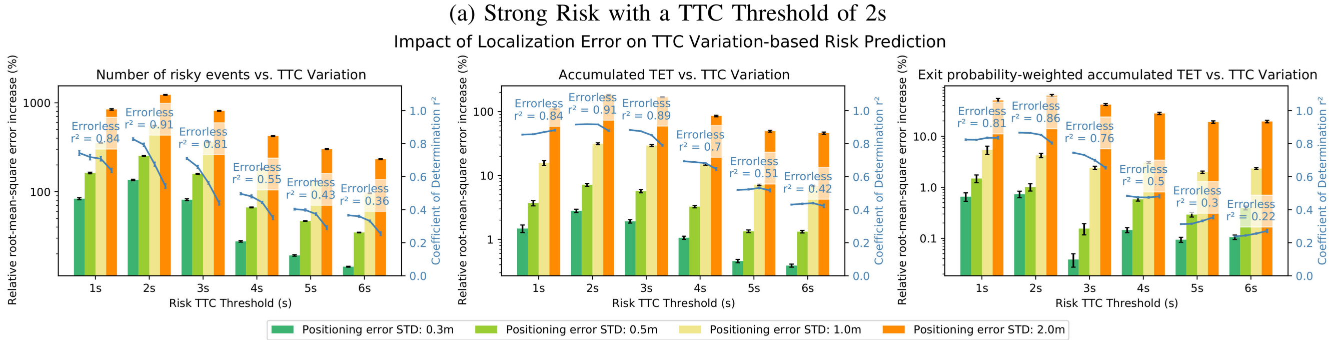
We observe a linear relationship between the RSD of TTC values and each roundabout-wide risk metric. The correlation is further strengthened after tuning the computation parameters to $T = 450s$ and $TTC_{max} = 7.5s$.

Figure 7a illustrates the linear relationship between the RSD of TTC values in the roundabout and metrics of risk defined following a TTC threshold of $TTC_{th} = 2$ seconds. The leftmost, center, and rightmost graphs, respectively plot the (i) number of risky situations, (ii) accumulated TET, and (iii) roundabout exit probability-weighted accumulated TET metrics as defined in Section IV. The 95% prediction and confidence intervals of the linear regression are shown by, respectively, the gray-dashed and gray-filled areas. The outlier at a RSD value of 0.55 has been obtained from a recording where three vehicles were parked in the innermost lane of the roundabout, thus increasing the amount of rear-end conflicts and RSD of TTC values.

Figure 7b illustrates the impact of positioning error for all considered values of TTC_{th}. As in Figure 7a, the leftmost, center, and rightmost graphs, respectively consider the three risk metrics as defined in Section IV. For each TTC_{th} risk threshold value, the r^2 coefficient of determination of the linear relationship between the RSD of TTC values and the considered risk metric is showed under different positioning errors in blue-colored curves. The *errorless* r^2 refers to the r^2 value obtained when no positioning error was added to the TTC computations.



(a) Strong Risk with a TTC Threshold of 2s



(b) Impact of Positioning Error for Considered TTC Thresholds

Fig. 7: Linear Relationship between TTC Variation and Defined Risk Metrics

In turn, strong linear relationships between the RSD of TTC values and risk metrics can be observed for TTC threshold values up to $TTC_{th} = 3.0$ seconds. A weaker correlation can be observed for higher threshold values, which correspond to situations of less risk.

Moreover, for each value of TTC_{th}, an estimation of the impact of different levels of positioning error on risk metrics assessment is shown as a bar chart. For each value of positioning error σ, the fit error of the obtained linear regression line on ground truth errorless $(RSD, risk)$ data points is compared with that of the original errorless regression line. First, the original root-mean-square error (RMSE) of the fit of the errorless regression line on the ground truth data points is computed. Then, for each positioning error σ, the RMSE of the obtained regression line is computed from the same ground truth data points. Each bar illustrates the relative increase of RMSE in percents between the errorless and the error-featuring case. 95% confidence intervals are attached to each RMSE and r^2 values, which were obtained after running 20 distinct computations for each value of σ.

It can be observed that the exit probability-weighted risk metric as defined in Section IV is more robust to positioning errors than both other metrics. Positioning errors up to 1.0 meter feature an increase in RMSE of less than 10%. Such positioning error can be considered conservative considering existing RTK approaches, e.g., as in [16].

D. Discussion

Through the findings described in this paper, real-time knowledge on the level of risk in a roundabout can be computed from the RSD of TTC values in a roundabout. What is more, the obtained risk knowledge can be personalized to various thresholds of TTC. Knowledge can be created from 450 seconds of TTC data history in the roundabout to determine the average exposure to a personalized level of risk as defined by each CAV.

Through vehicular knowledge networking techniques as introduced in [6], the RSD of TTC values can be disseminated in vehicular networks so that each vehicle can independently obtain a level of risk which matches its preferred TTC threshold, i.e., understanding of risk. In turn, the roundabout driving risk knowledge can be used as a support to the automated driving features of CAVs, so that they can adapt their driving behavior to the expected level of risk.

The obtained results complete and relate to other works in the field of the impact of TTC variation on risk. [17] demonstrated a relationship between the volatility, i.e., micro variations of TTC values and the severity of crashes in highway environments. What is more, [18] investigated on the derivative of TTC values for pairs of vehicles and identified patterns in TTC variation which relate to a transition from a normal situation to a situation of risk.

As future work, the ability to transfer knowledge created from one roundabout to another will be further studied. We aim to investigate the applicability of knowledge created from RounD roundabouts to new and unknown cases. Moreover, we considered risk as defined by rear-end conflicts, measured through TTC. As future work, other types of conflicts could be considered, including lane changes or merging conflicts at entrance and exit junctions, to refine the computation of TTC or compute complementary SSMs.

VI. Conclusion

Certain road infrastructures and driving situations are difficult to negotiate autonomously for CAV. In some cases, a slow down, a complete stop of the vehicle, or a take-over of driving features by a human supervising driver may be triggered. To reduce the likelihood of such events and improve CAV passenger comfort, the development of risk metrics and risk-reasoning is a key to let CAVs better understand their environment and adapt their driving behavior accordingly. In this study, we investigated on driving risk in roundabouts using real tracks extracted from the RounD dataset. Roundabout-wide driving risk metrics were defined which take into account both the occurrence of critical TTC values and the probability of occurrence of the risk, i.e., the probability of the following vehicle not exiting the roundabout beforehand. What is more, a strong linear relationship between the variation of TTC values and the defined roundabout-wide risk metrics allows CAVs to extract personalized driving risk knowledge from roundabouts. In turn, the driving behavior of CAVs in roundabouts can be adapted in real time according to their personalized risk thresholds.

References

[1] Oliver Pink, Jan Becker, and Sören Kammel. "Automated driving on public roads: Experiences in real traffic". In: *it - Information Technology* 57 (July 2015), pp. 223–230.

[2] Xin Xin et al. "A Literature Review of the Research on Take-Over Situation in Autonomous Driving". In: *International Conference on Human-Computer Interaction*. July 2019, pp. 160–169.

[3] Mark Morando et al. "Studying the Safety Impact of Autonomous Vehicles Using Simulation-Based Surrogate Safety Measures". In: *Journal of advanced transportation* (2018). DOI: 10.1155/2018/6135183.

[4] Aleksandra Deluka Tibljaš et al. "Introduction of Autonomous Vehicles: Roundabouts Design and Safety Performance Evaluation". In: *Sustainability* 10.4 (2018). DOI: 10.3390/su10041060.

[5] Navreet Virdi et al. "A safety assessment of mixed fleets with Connected and Autonomous Vehicles using the Surrogate Safety Assessment Module". In: *Accident Analysis & Prevention* 131 (2019), pp. 95–111. DOI: 10.1016/j.aap.2019.06.001.

[6] Duncan Deveaux et al. "A Definition and Framework for Vehicular Knowledge Networking: An Application of Knowledge-Centric Networking". In: *IEEE Vehicular Technology Magazine* (2021), pp. 2–12. DOI: 10.1109/MVT.2021.3066376.

[7] Seyhan Ucar et al. "Vehicular Knowledge Networking and Application to Risk Reasoning". In: *Proceedings of the Twenty-First International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing*. Mobihoc '20. 2020, pp. 351–356. DOI: 10.1145/3397166.3413467.

[8] Jade Montgomery, Kristofer D. Kusano, and Hampton C. Gabler. "Age and Gender Differences in Time to Collision at Braking From the 100-Car Naturalistic Driving Study". In: *Traffic Injury Prevention* 15.sup1 (2014), S15–S20. DOI: 10.1080/15389588.2014.928703.

[9] Richard Van Der Horst and Jeroen Hogema. "Time-to-collision and collision avoidance systems". In: 6th ICTCT workshop. Salzburg, Austria, Jan. 1994.

[10] Kristofer Kusano and Hampton Gabler. "Method for Estimating Time to Collision at Braking in Real-World, Lead Vehicle Stopped Rear-End Crashes for Use in Pre-Crash System Design". In: *SAE Int J Passeng Cars - Mech Syst* 4 (June 2011), pp. 435–443. DOI: 10.4271/2011-01-0576.

[11] R. Krajewski et al. "The rounD Dataset: A Drone Dataset of Road User Trajectories at Roundabouts in Germany". In: *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*. 2020, pp. 1–6. DOI: 10.1109/ITSC45102.2020.9294728.

[12] J. Kim and D. Kum. "Collision Risk Assessment Algorithm via Lane-Based Probabilistic Motion Prediction of Surrounding Vehicles". In: *IEEE Transactions on Intelligent Transportation Systems* 19.9 (2018), pp. 2965–2976. DOI: 10.1109/TITS.2017.2768318.

[13] Assaf Botzer and Oren Musicant. "Driver Choices of Time-to-Collision Thresholds for a Collision Warning System". In: 2016. DOI: 10.1145/2970930.2970958.

[14] J. Wang et al. "A Forward Collision Warning Algorithm With Adaptation to Driver Behaviors". In: *IEEE Transactions on Intelligent Transportation Systems* 17.4 (2016), pp. 1157–1167. DOI: 10.1109/TITS.2015.2499838.

[15] Michiel M. Minderhoud and Piet H.L. Bovy. "Extended time-to-collision measures for road traffic safety assessment". In: *Accident Analysis & Prevention* 33.1 (2001), pp. 89–97. DOI: 10.1016/S0001-4575(00)00019-1.

[16] Chuang Qian et al. "Cooperative GNSS-RTK Ambiguity Resolution with GNSS, INS, and LiDAR Data for Connected Vehicles". In: *Remote Sensing* 12.6 (2020). DOI: 10.3390/rs12060949.

[17] Behram Wali, Asad J. Khattak, and Thomas Karnowski. "The relationship between driving volatility in time to collision and crash-injury severity in a naturalistic driving environment". In: *Analytic Methods in Accident Research* 28 (2020), p. 100136. DOI: 10.1016/j.amar.2020.100136.

[18] Ye Li et al. "Analysis of the transition condition of rear-end collisions using time-to-collision index and vehicle trajectory data". In: *Accident Analysis & Prevention* 144 (2020), p. 105676. DOI: 10.1016/j.aap.2020.105676.