IoT solutions for Sustainable Cities: An Online Adaptation for the Driver Intent Inference Algorithm

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***Abstract*—In this paper we introduce an adaptation to the "driver intent inference algorithm for urban intersections". This algorithm has been proven to detect potential right turns of vehicles by estimating the probability of a driver to turn right, and we propose to use it for reducing the number of cycling deaths at an intersection. We extend this algorithm following the IoT design principles and thus, with this approach, cyclists' safety no longer depends only on actions taken inside the vehicles, but also can use additional safety solutions based on standards and available information shared about the vehicles and drivers in vehicular networks. Our approach proposes to process the inference algorithm outside the vehicle, considering cloud and edge computing. We use predicting models for identifying driver's intention of turning right at intersections and the use of edge connected devices running our algorithm for alerting cyclists of possible collisions, thus preventing as many collisions as possible in intersections.**

***Index Terms*—Sustainable cities, Internet of Things application, Road safety, Vulnerable road users, Online processing, IoT data management aspects.**

I. Introduction

The newly adopted 2030 Agenda for Sustainable Development has set an ambitious target of halving the global number of deaths and injuries from road traffic crashes by 2020. Without sustained action, road traffic crashes are predicted to become the seventh leading cause of death by 2030. The security of Vulnerable Road Users is important to the World Health Organization, which in the Global Status report on road safety 2015 [1], states that *"the mortality of Vulnerable Road Users (VRUs), i.e., pedestrians, cyclists, and motorcyclists is intolerably high and needs to be addressed"*. The report includes information from 180 countries, informing that the worldwide total number of road traffic deaths has plateaued at 1.25 million per year, where 4% are cyclists. Making walking and cycling safer is critical for reducing the number of road traffic deaths and is essential for achieving the Decade of Action for Road Safety's aim to promote non-motorized forms of transport [2].

TABLE I
WORLD TRAFFIC DEATH BY REGION. SOURCE WHO REPORT [1]

		Death		
Region	**Population**	**Traffic**	**Cyclist %**	**Cyclists**
Western Pacific	1,700,000,000	294100	7%	20587
African	1,225,080,510	325871	4%	13034
Southeast Asia	1,941,775,797	330101	3%	9903
The Americas	1,001,559,000	159247	3%	4777
Eastern Med	651,529,000	129654	3%	3889
European	743,704,000	69164	4%	2766

Table I shows each world's region death cyclists percentage, where the Western Pacific region presents the higher number. The total cyclists' deaths by region are considerably high in the Western Pacific and African regions in contrast with European and Eastern Mediterranean regions. This information shows that compared to high-income countries where cycling infrastructure is more developed, low- and middle-income countries have the most cyclists' deaths. Nevertheless, the total number of death cyclists in every region deserves attention. For example, according to the *United States National Highway Traffic Safety Administration*[1] *(NHTSA)*, in its report "Traffic Safety Facts 2015" [3] states that 818 pedal-cyclists were killed. Among those, 27% of killed pedal-cyclist where killed at an intersection.

Vehicular networks are a particular domain area where the Internet of Things technologies (IoT) have an opportunity to improve the design and operation of safety applications. In this domain, it is also considered the use of edge and cloud computing, so that the use of vehicular data such as speed and positioning can be extended as part of novel solutions. IoT technologies will be part of the full stack [4], from new devices running the vehicular network protocols to standard exchangeable IoT data for vehicular networks. With this IoT Architectural new approach, the safety and security of cyclists

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[1]See https://www.nhtsa.gov/

and/or pedestrians do not rely only on vehicular manufacturers but also add the external element allowing more solutions to prevent deaths.

One particular point of interest where vehicles and cyclists interact is at street's intersections, where 27% of cyclists deaths occur. One way to address this problem is to predict driver's intention of turning right at intersections, to alert cyclists of possible collisions [5]. The intent inference algorithm proposed by Liebner et al. [6]–[8] has been proposed to infer, based on a velocity profile, a driver's intention to make a right turn at intersections. The algorithm uses local data generated by the vehicle and is designed to run inside the same vehicle. To extend the algorithm's use, it needs to be adapted to new conditions to be processed outside the vehicle, and thus enable the functionality to send alerts to VRUs that potentially might be involved in collisions with cars at intersections.

The goal presented in this article is to adapt the existent driver intent inference algorithm for urban intersections to process said algorithm outside the vehicle and be able to alert the VRUs, thus preventing as many collisions as possible at intersections. In this paper, parameters such as delay and packet loss are the primary factors to consider, as the adapted version requires the data to travel through a network before making any prediction. With those parameters, we set a baseline for comparing different approaches, such as cloud and edge computing, and the necessity of having reliable communication networks to ensure an effective alarm system.

The remainder of this paper is organized as follows. In Section II we present the state of the art of algorithms for predicting driver behaviors as well as other road safety solutions designed to prevent cyclists in urban scenarios. In Section III we present the proposed adapted version of the intent inference algorithm, including an analysis of performance considering offline and online processing and taking into account the disadvantages of getting the input data through a vehicular network. Section IV presents the experimental results of our performance evaluation. Section V presents the concluding remarks and future work.

II. Related Work

A. *Algorithms for predicting driver behavior*

The intelligent driver model [6] and the parametric models [7] improved the prediction accuracy of driver behavior on streets and increased the ability to infer the path of drivers in different situations such as intersections. The difficulty that those algorithms present is that they do not consider cases where there is more than one vehicle on the road and the driver's behavior changes according to the preceding vehicles. That is why is hard for this algorithms to infer vehicle's trajectory in those cases.

Another approach is presented in [9] where the authors use Hidden Markov Models (HMM) to identify driver's behavior and the maneuvers made by them. For training and detecting maneuvers, the application needs to have access to the CAN bus and its information, making it harder the process of collecting this information since specialized access is required and may not be available in uncontrolled environments.

The usage of naturalistic data to infer driver's behavior has been proposed in [10], where the authors offer an interesting alternative. Using naturalistic data to infer driver's intentions at intersections is possible as has been previously proved in [11], but this approach requires collecting training data to generate the prediction models for each intersection and that increases the difficulty when a large-scale deployment is considered.

Another proposal of algorithm is presented in [12], as it offers a 90% success in predictions at generalized intersections, but uses specific driver's information such as wheel turning and force used at braking or accelerating. Even if we consider that we could share all that information through a network, their prediction times are around 1,6 seconds before the actual maneuver occurs, so it might not be enough time for predictions carried out outside the car itself. Considering the *Time to Collision (TTC)* parameter [15], we need more time to alert drivers and cyclists of possible collision so they can react in time.

Considering all that, the model we propose to adapt is the algorithm proposed in [8], where the information needed for predicting turning behavior is standard and is already been transmitted through vehicular networks. Besides that, the scenario that this algorithm considers is realistic as it adds preceding cars to the equation so it is more suited for an urban scenario. As well, this algorithm presents a prediction of 3 seconds on average before the threshold of *TTC*, so it may provide enough time for transmitting the information and alerting cyclists early enough for them to react and prevent (or mitigate) a collision. The algorithm and proposed adaptation will be presented in more detail in Section III.

B. *Road safety solution for cyclists*

A solution to increase road safety for cyclists is presented in [13], where the authors propose a vulnerable road user alert system that includes cyclists into the traffic awareness and aids to establish the presence of cyclists and vehicles. The context presented is in the framework of a smart city. This alert system does not consider predicting possible collisions but only rising awareness for road users.

Other solution for safety of VRUs is presented in [14], where the authors propose a smartphone-based beacon stuffed WiFi Car2X communication system. The solution uses the WiFi Hotspot/Direct of smarthpones, so they can entablish communications between the vehicles and the VRUs. They also include a method for alerting of possible collisions considering the estimated path of vehicles and VRUs. In particular, they consider the scenario where a pedestrian is walking and his/her path will collide ahead with the path of a vehicle coming from other road to the intersection. The study considers a smartphone inside the car and the pedestrians smartphone acting as a continuous beacon with the WiFiHonk application running.

III. Proposed approach

Our proposed approach for the online adaptation of the prediction algorithm consists in collecting the vehicle's information that comes from a wireless network, then processing the information outside the vehicle. When the prediction indicates that a right turn is highly probable, the system sends a warning message to the cyclist in danger. To test the proposed algorithm, several scenarios are considered, where we take into account delay and packet loss from the incoming network. With these testing scenarios, we evaluate the algorithm's performance considering *TTC* and probability of successful detection. The input and output data needs to travel through a network to be processed as presented in Figure 1, so testing the endpoints is crucial to validate the effectiveness of the alarm system.

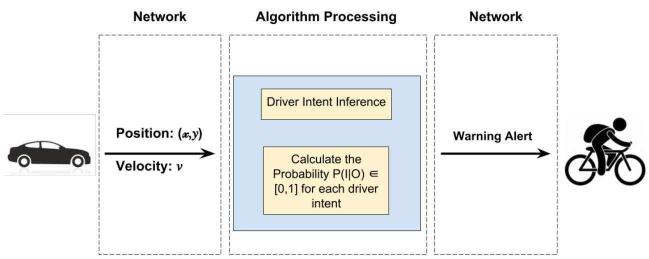

Fig. 1. Alert system's diagram: input from vehicle and output warning to cyclist.

Using the algorithm provided in [8], we proceed to adapt the *Intelligent Driver Model (IDM)* to define the driver behavior models. We use the simulation approach in [8] to determine the driver's intent and to raise a warning in case of the right turn causing a potential collision. In the following, we explain our adaptation in more detail.

The goal of the proposed algorithm is to infer driver's intent at urban intersections. The general idea behind this work consists in creating a simulated trajectory of each vehicle, using previously defined models and parameters. The simulated trajectory is compared with the real trajectory of the vehicle of a few seconds before to estimate the probability of each possible predefined trajectory hypothesis. The obtained probability distribution is then used to predict driver intention and the future trajectory of the car. The possible intentions of the driver are defined as follows:

I_1 : Keep straight
I_2 : Stop at red light
I_3 : Turn right
I_4 : Turn right and stop at the pedestrian crossing

For each intent one would expect a different set of desired velocity profiles, and for each type of desired velocity profile a different probability distribution for the maximum acceleration parameter a. The combination of profiles and maximum acceleration are presented in Table II.

Considering this, the first step is to model the car's acceleration $\dot{v}$ using the *Intelligent Driver Model (IDM) [8]* :

$$\dot{v} = a\left[1 - \left(\frac{v}{u}\right)^{\delta} - \left(\frac{d^*(v,\Delta v)}{d}\right)^2\right] \tag{1}$$

$$d^*(v,\Delta v) = d_0 + Tv + \frac{v\Delta v}{2\sqrt{ab}} \tag{2}$$

TABLE II
Hypotheses for driver intent inference

Intention I	H: Model X a(m/s^2)
I_1: Go straight	{1, 2, 3} X {1.5, 2.0, 2.5}
I_2: Stop at stop line	{1, 2, 3} X {1.5, 2.0, 2.5}
I_3: Turn right	{1, 2, 3} X {1.5, 2.0, 2.5}
I_4: Turn right but stop	{1, 2, 3} X {1.5, 2.0, 2.5}

The corresponding parameter values are given in Table III. With no preceding vehicle is present, the calculated acceleration $\dot{v}$ is determined only by the maximum acceleration parameter a, the current velocity v, the desired velocity u, and a fixed acceleration exponent δ.

TABLE III
Parameters of the Intelligent Driver Model According to [8]

Parameter	**Value**
Max. acceleration a	0..5 m/s^2
Acceleration exponent δ	4
Desired velocity u	0..60 km/h
Comf. deceleration b	3 m/s^2
Min. gap to leading vehicle d_0	2.0 m
Time gap to leading vehicle T	0.8 s

Parameters as minimum distance d_0 or time gap T come from calculated transit variables. In [8], the IDM is used in conjunction with three different driver's profiles going from defensive to sporty driving styles. For each driving style, the model considers three different maximum accelerations a: 1.5 m/s^2 for defensive, 2.0 m/s^2 for regular, and 2.5 m/s^2 for sporty driving styles. The probability distribution in [8] is calculated for each model and acceleration parameter a. Resulting values of these calculations are used later for inferring the driver's intent.

In our approach, we propose to simplify the options by reducing the driver intentions only to I_1 and I_3, which are keeping straight and turning right, respectively. Then, we proceed to calculate the probability distribution that can be modeled as a Bayesian network, based on the actual driver intent I, the applicable hypothesis H, and a not yet defined observation O:

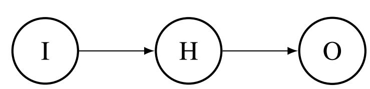

Fig. 2. Bayesian network

The probability for a particular intention I_j given the observation O can be written as:

$$P(I_j|O) = \sum_i P(I_j|H_i)P(H_i|O), \quad (3)$$

where $P(I_j|H_i)$ is either 0 or 1 depending on Hi. The probabilities for the individual hypotheses are calculated as follows:

$$P(H_i|O) = \frac{P(O|H_i)P(H_i)}{\sum_j P(O|H_j)P(H_j)} \quad (4)$$

The prior probabilities $P(H_i)$ can be obtained from:

$$P(H_i) = P(I_j)P(M_k)P(a_l|M_k), \quad (5)$$

where I_j is the intent, M_k is the desired velocity model, and a_l is the maximum longitudinal acceleration parameter associated with hypothesis H_i. This way, $P(M_k)$ and $P(a_l|M_k)$ can be obtained by the probability distribution graph. The distribution of the intent I is considered uniform so $P(I_j) = 0.5\,\forall j$.

Now, the simulation based approach proposed in [8] is chosen. Considering $\hat{s}$ and $\hat{v}$ as the simulated position and velocity of a vehicle, one can compare these values with the real values observed from drivers to obtain the probability distribution. The probability density function f_{AS} for hypothesis H_i is defined in [8] as:

$$f_{AS}(a(t), s(t)|H_i) = \frac{1}{2\pi\sigma_s\sigma_v} exp\left(-\frac{1}{2}e^2\right), \quad (6)$$

where

$$e = \sqrt{\left(\frac{s(t)-\hat{s}(t)}{\sigma_s}\right)^2 + \left(\frac{v(t)-\hat{v}(t)}{\sigma_v}\right)^2}. \quad (7)$$

Using the Bayes Theorem for probability density functions, the probability $P(H_i|a(t), s(t))$ is then determined as:

$$P(H_i|a(t), s(t)) = \frac{f_{AS}(a(t), s(t)|H_i)P(H_i)}{\sum_j f_{AS}(a(t), s(t)|H_j)O(H_j)} \quad (8)$$

The authors define $\sigma_s = 1.2m$ and $\sigma_v = 1.2m/s$ as values obtained from empirical evidence [8], . Using appropriate values for σ_s and σ_v is important as they have a major influence on how easily a hypothesis will be favored above others.

IV. Experimental Results

The data set employed to test the adapted algorithm corresponds to real traces provided by SUMO in the scenario of Tapas Cologne[2]. To obtain the relevant information, an initial simulation was carried out to obtain route traces. These route traces contain the edges that the vehicles traveled through. With this information, one intersection was selected from the map. For the selected intersection we obtained 268 vehicular routes that included right turns and going straight maneuvers. The routes were parsed to extract the *GPS* traces from vehicles with a frequency of 10 Hz. Each row data consists of the position (x, y) and speed v of a given vehicle.

The experiments consist in comparing the *TTC* and effectiveness of the algorithm in its online and offline versions, being the offline version the processing of the adapted algorithm inside the vehicle and raising the alarm in the same vehicle. The online version corresponds to the schema shown in Figure 1, for which we test the algorithm with an added delay and probabilities of packet losses.

When considering an offline processing scheme, the inference algorithm took 120ms in processing the data and notifying of a possible right turn event. As shown in Figures 3 and 4, there is a spike in the right turn probability at around 2.5 seconds before a vehicle reaches the intersection.

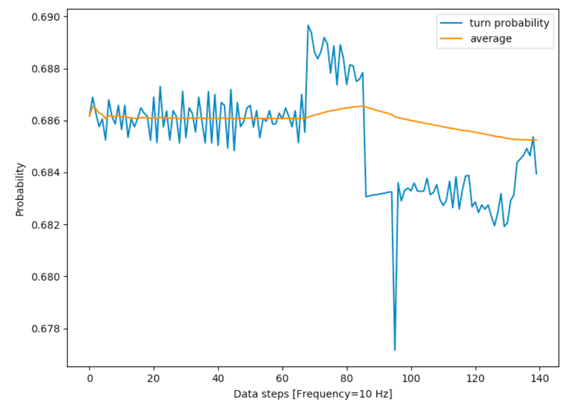

Fig. 3. Probability of right turn in each step of the data sent by the vehicle

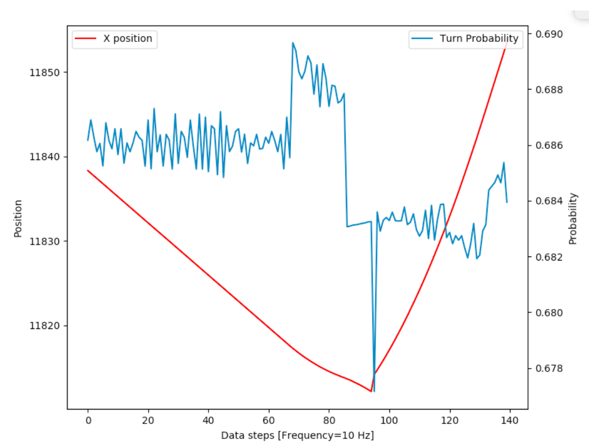

Fig. 4. Probability of right turn vs the X position of the vehicle

In the case of the online version, we consider a delay of each package as D_i, where i indicates the number of a sent packet. Therefore, the total delay is defined as:

$$D_T = \sum_i D_i. \quad (9)$$

[2]TAPAS Cologne: http://sumo.dlr.de/wiki/Data/Scenarios/TAPASCologne

In addition, other delays correspond to the processing time of the algorithm P_T, and the delay for the alert message to reach the cyclist D_C. The final notification time delay N_D is then defined as:

$$N_D = D_T + P_T + D_C. \tag{10}$$

The minimum inference time required by the adapted algorithm is:

$$Inf_T = N_D + TTC, \tag{11}$$

which means the vehicular motion data and the alert message need at least Inf_T to be transmitted, processed, and transmitted again to finally warn the cyclist of a possible collision. To be effective, the alert needs to arrive to the cyclist before the *TTC*; otherwise, the collision may happen anyway. It should be noted that we are considering the option of the alert message traveling further from the processing device. If we consider that the processing device raises the alert directly to the cyclist (e.g., when the algorithm is running on the cyclist's mobile device), then $D_C = 0$.

TABLE IV
CONFUSION MATRIX FOR RIGHT TURN INTENTS

n=268	**Actual: Right Turn**	**Actual: Keep Straight**
Predicted: Right Turn	149	97
Predicted: Keep Straight	15	7

Furthermore, for calculating the accuracy of the inference algorithm, we define the metric as:

$$Accuracy = \frac{TruePositives \dotplus FalseNegatives}{TotalSamples}, \tag{12}$$

where

- TruePositives: maneuvers correctly detected as right turn behavior
- FalseNegatives: maneuvers correctly detected as keeping straight behavior
- TotalSamples: The total amount of routes tested

With the Accuracy metric and the results in Table IV, we can test the algorithm in the presence of packet losses, with the aim to see how reliable the algorithm is when the network quality decreases. As can be seen in Table V, the accuracy rate decreases when the packet loss decreases. This should be interpreted as the need of having a highly reliable network to achieve a good rate of correct inferences in the alert system.

In general, the results showed that even in the offline version of the adapted algorithm, the accuracy is below 60% for the selected intersection. The reason for this behavior is that the data set considered an intersection with a yield sing. Hence, every vehicle slows down in a similar way, causing the adapted algorithm to not detect the differences between slowing down for an incoming right turn maneuver or just slowing down for respecting the yield sign. In our ongoing work, we intend to improve the algorithm to detect these situations. Nevertheless, we were able to show the behavior of the adapted algorithm in the presence of packet loss. In the case of a delay analysis, it is crucial to have a low latency communication network since the *TTC* is as short at 1 second on average, which means that when adding the other delays, the total window frame goes down to 0.2 seconds.

TABLE V
ACCURACY IN THE PRESENCE OF PACKET LOSS

Packet Loss	**Accuracy**
0%	0.58
0.5%	0.56
1.0%	0.54
1.5%	0.52
2.0%	0.48
2.5%	0.43

V. CONCLUSIONS AND FUTURE WORK

In this paper, we have proposed an adaptation for a driver's intent inference algorithm for urban intersections [8]. The algorithm is intended for use in a system to alert cyclists of possible collisions. We have presented our approach that proposes the processing of the inference algorithm outside the vehicle, following IoT design principles [4] and considering cloud and edge computing as main technologies for deployment. We have implemented and used a predicting model for successfully identifying the driver's intention of turning right at an intersections in a way that it is possible to alert cyclists of possible collisions. We have performed an evaluation of the proposed adaptation by considering metrics such as delay and accuracy in the presence of packet loss.

Considering the results, we conclude that a good network performance is needed to achieve the minimum requirements for the inference algorithm, because if the delay and packet losses are high, the algorithm does not perform good enough to infer driver's intent and raise the proper alert on time to the cyclists. Since the goal is to prevent cyclists' deaths, it is important to improve the network reliability to facilitate these kinds of algorithms to operate at their full capacity. Improving the results of the proposed adapted algorithm can be done by improving the effectiveness of the inference algorithm together with improving the communications network reliability to receive data from the vehicles and deliver data to the cyclists.

Future work considers testing the algorithm with different network delays and packet losses considering a variety of network architectures. We also intend to mitigate the packet loss as it impacts directly on the accuracy of the inference algorithm, and finally we are working on improving the algorithm to adapt with the incoming data of each vehicle to make better models and have an improved accuracy.

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