Pass Permission Interpretation at Urban Intersections for Automated Driving Systems

David Perdomo and Rene Waldmann
Automated Driving Volkswagen Group Research, Wolfsburg, Germany
Email: {david.perdomo.lopez, rene.waldmann}@volkswagen.de

Raúl Rojas
Department of Mathematics and Computer Science, Freie Universität Berlin, Berlin, Germany
Email: rojas@inf.fu-berlin.de

***Abstract*—One of the most common challenges for autonomous driving at urban intersections is the proper analysis and interpretation of traffic lights and traffic signs in order to set the proper behavior of the ego vehicle. Among other problems, the inaccuracy of the perceived inputs and their time fluctuations increase the difficulty of understanding the current situation. Thus, we propose a new concept to interpret the pass permission at urban intersections in a simple manner. The main idea is to calculate the probability of every perceived input to generate a probability mass function in which every discrete state corresponds to one possible pass permission. In this sense, every resulting state indicates a certain behavior of the ego vehicle with respect to the intersection. This approach helps the system to set the proper maneuver automatically according to the European traffic rules.**

***Index Terms*—automated driving, scenario interpretation**

I. Introduction

The first matter of a human driver approaching an intersection is to determine how the traffic flow is controlled.

It is not only about estimating if one is allowed to pass the intersection or not. In fact, it is crucial to understand how one should pass the intersection and under which conditions. With this information, one is able to plan and execute the further maneuver according to the traffic rules. Obviously, this is a very simple task for a human, but the same problem represents a challenge for a self-driving car. In this context, such a system should first perceive the surrounding of the ego vehicle, then interpret it and finally set the appropriate driving strategy. In particular the system should recognize those inputs that control the traffic flow at the intersection (i.e. traffic lights, traffic signs and road signs). In this context, only normal situations should be considered, but not those such as emergency vehicles, indications of a police officer, temporal constructions sites, etc.

According to the Vienna Convention on Road Signs and Signals of 8 November 1968 [1], the traffic flow at intersections is normally controlled in three different ways: with traffic lights, with traffic signs or with the *right before left* rule.

In [2] the authors introduce a new approach to optimize the control of traffic lights at intersections. They consider a connected intersection system where all vehicles share information. To improve the traffic flow, the proposed controller makes real time decisions for the time duration of the traffic lights. There optimization is based on game theory algorithmic. Similarly, the same problem is solved based on a process synchronization approach in [3]. In this regards, the presented approaches enable to reduce the dead-lock and waiting time at intersections regulated by traffic lights.

Nevertheless, the big bottleneck of the interpretation is to handle uncertainty and fluctuations of the perceived inputs over time. Nevertheless, many authors take for granted that Vehicle-to-X communication is available to solve this problem. For example, in [4] the authors present two methods for priority conflict resolution. The first method uses some vectors that describe the turning possibilities of all vehicles and their corresponding priority signs. Then, an auxiliary table containing all possible vectors is associated with Boolean values to indicate if the ego vehicle has to move or stop. The second proposed method aims to interpret different priority levels (using an auxiliary truth table to detect potential conflicts with other vehicles). These two proposed methods depend on a predefined topology (in this case a two road intersection) and a vehicle-to-vehicle communication system is required.

In [5], a hierarchical finite state machine is used to plan the proper behavior of the ego vehicle. The movement of ego vehicle is divided in three different types: normal driving in streets, in intersections or in unstructured environments. To handle driving in intersections, three simple states are used: *stop* if the ego vehicle is in a yield-road, *driveInside* if it crosses the intersection on a priority road and *priorityStop* if stop and wait is needed. A different approach was introduced in [6]. The authors use description logic to describe an ontology that represents the road networks, objects, their relations, and traffic rules. The goal is to reason the relations *hasRightOfWay* and *hasToYield*, which is done executing augmentation rules according to the current situation. A simple and a complex

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intersection are used as example. Its reasoning takes approximately 1.6 and 3 seconds respectively.

Conversely, the authors in [7] use multi criteria based decision making to set the most appropriate maneuver. This decision making unit, which is modeled as a Petri net [8] is divided in two stages. The first stage aims to set the feasible maneuvers considering safety and traffic rules. Then, the second stage considers the calculated set of maneuver and the input of the route planner. In this respect, the traffic rules knowledge and its application is embedded in the execution of a Petri net. In fact, the core of the problem is to interpret the different recognized traffic lights and traffic signs in a proper manner, so that the system can plan and execute the desired maneuver considering the traffic rules.

This paper is organized in six sections. After introducing the problem, the main structure is explained in the second section in order to give the reader a quick overview of the main idea of our approach. In the third section the concept based on a probability mass function to model the pass permission at an intersection is explained in detail. This represents the core of our approach. Subsequently, the fourth section explains how the fluctuations are interpreted over time. Then, some experimental results are presented before the conclusion of the paper.

II. Main Architecture

The architecture of a generic self-driving system can be structured in four main modules: (1) perception, (2) scenario interpretation, (3) planning and (4) control. The low level processing of sensors and a priori data (e.g. image processing, object recognition and tracking, localization and mapping, etc.) is represented by the perception module. The scenario interpretation involves understanding the processed and described data. Then, the planning module makes the proper decisions and delivers them to the control module, which finally executes it, providing the adequate signals in terms of steering and acceleration. This simplified structure with the elements required in our approach is illustrated in Fig. 9.

The perception module receives the detected traffic signs and traffic lights (e.g. from the camera or vehicle-2-X communication), the position of the ego vehicle (from the GPS or other localization approaches) and an a priori map that describes the road network. The assignment of the ego vehicle into a lane is done using its position and the a priori map as input. Once it is estimated on which lane the ego vehicle is, this information is used to achieve the assignment of the detected traffic lights (and traffic signs) into lanes. In other words, the association between every traffic light (and traffic sign) to every lane is estimated.

The scenario interpretation module receives the traffic lights and traffic signs associated to lanes. Then, this information is used to understand how the behavior of the ego vehicle at the intersection (namely the pass permission from an ego perspective) should be. Consequently, this state suggests the behavior of the ego vehicle, so that the proper maneuver can be provided to the planning module. Finally, the controller converts its input (a suggested trajectory) into acceleration and steering values.

III. Modeling the Pass Permission as a Probability Mass Function

Considering the represented architecture, the inaccuracy of the inputs can be caused by different reasons. For example in case that the localization is not accurate enough because of poor GPS signal, the traffic lights are erroneously detected or there are discrepancies between the a priori map and the real road network.

It is a fact that the probability that a particular traffic light is valid for the ego vehicle depends on the accuracy of previous modules. Therefore, it becomes a requirement to handle the uncertainty of the inputs provided by the perception module.

In this respect, the scenario interpretation module should deal with the probability of its input. Here, the term *probability* is used as a *bayesian probability*; that is to say, it does not indicate how frequently an event occurs, but how certain a given hypothesis is, so that a probability is assigned to it. As a simple example, if the location is very inaccurate (and hence it is improbable that the ego vehicle is assigned correctly to its lane), the hypothesis of achieving a perfect association of several detected traffic lights into lanes is very unlikely. The basic idea is to calculate the Bayesian probability $P(TL_k)$ of every traffic light state k considering the probability of previous modules as evidences. In the same way, $P(TS_l)$ is estimated for every traffic sign l. This is illustrated in Fig. 10.

$P(Pos)$ and $P(AM)$ correspond to the probability that the localization of the ego vehicle and the information of the a priori map is correct, respectively. The probability of the proper recognition of a detected traffic light phase i is denoted as $P(TLR_i)$. Similarly, $P(TSR_j)$ indicates the probability that a detected traffic sign $_j$ has been correctly recognized.

$P(AM)$ and $P(Pos)$ influence directly on how certain the assignment of the ego vehicle to a lane f is (i.e. $P(LA_f)$). The probability of the assignment of a traffic light phase i into a lane f is denoted as $P(TLA_{if})$. Because there is an independent probability for every association of every traffic light ($i = \{1, ...,I\}$) to every lane ($f = \{1, ..., F\}$), the resulting assignment probabilities can be expressed as a (IxF)-matrix in which every element represents an independent probability:

$$P(TLA_{if}) = \begin{bmatrix} P(TLA_{1,1}) & P(TLA_{1,2}) & \cdots & P(TLA_{1,F}) \\ P(TLA_{2,1}) & P(TLA_{2,2}) & \cdots & P(TLA_{2,F}) \\ \vdots & \vdots & \ddots & \vdots \\ P(TLA_{I,1}) & P(TLA_{I,2}) & \cdots & P(TLA_{I,F}) \end{bmatrix} \quad (1)$$

Note that this matrix (1) should not be misunderstood with a stochastic matrix. Every element of the matrix represents an independent hypothesis.

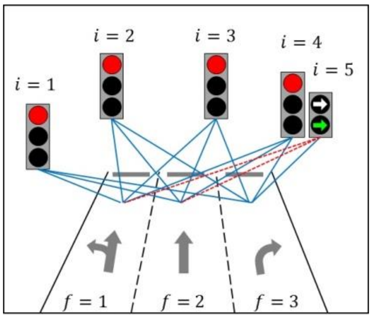

Figure 1. Example with 5 detected traffic lights (I = 5) and 3 lanes (F = 3).

The Fig. 1 shows an example with 5 detected traffic lights and 3 lanes. In this example, the first 4 traffic lights (*i = {1, 2, 3, 4}*) are valid for the 3 lanes (*f={1,2,3}*) and the fifth traffic light is valid just for the third lane. Therefore, an ideal assignment should provide the following probabilities:

$$P(TLA_{if}) = \begin{bmatrix} P(TLA_{1,1}) & P(TLA_{1,2}) & P(TLA_{1,3}) \\ P(TLA_{2,1}) & P(TLA_{2,2}) & P(TLA_{2,3}) \\ P(TLA_{3,1}) & P(TLA_{3,2}) & P(TLA_{3,3}) \\ P(TLA_{4,1}) & P(TLA_{4,2}) & P(TLA_{4,3}) \\ P(TLA_{5,1}) & P(TLA_{5,2}) & P(TLA_{5,3}) \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix} \quad (2)$$

In the same manner, the probability of the assignment of traffic signs into lanes $P(TSA_{jf})$ can be expressed as the following matrix:

$$P(TSA_{if}) = \begin{bmatrix} P(TSA_{1,1}) & P(TSA_{1,2}) & \cdots & P(TSA_{1,F}) \\ P(TSA_{2,1}) & P(TSA_{2,2}) & \cdots & P(TSA_{2,F}) \\ \vdots & \vdots & \ddots & \vdots \\ P(TSA_{I,1}) & P(TSA_{I,2}) & \cdots & P(TSA_{I,F}) \end{bmatrix} . \quad (3)$$

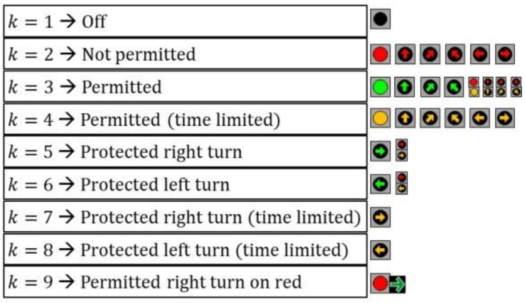

Figure 2. Different possible states k of the traffic light probability mass function.

The variables *i* and *j* represent the index of the detected traffic lights and signs respectively. In contrast, the variable *k* represents the index of every possible state of a traffic light and *l* indicates every type of traffic sign. In the case of traffic lights, the different colors (red, amber, green), forms (normal, left arrow, right arrow...) result in multiple combinations. We group together the combinations that indicate the same pass permission into 9 different states (*k = {1,2, ..., 9}*), so that the term *state* corresponds to a group (i.e. every group indicates a different behavior for the ego vehicle). This is clearly shown in Fig. 2.

On the other hand, $P(TL_k)$ corresponds with the probability that every possible state *k* is valid for the ego vehicle.

Using the assignments of the ego vehicle to lanes and traffic lights to lanes, it is calculated the conditional probability that every traffic light state *k* is valid for the ego vehicle ($P(TL_k)$):

$$\begin{aligned} &P(TL_k) = \\ &P(TL_k \mid TLA_{if}) \cdot P(TLA_{if} \mid LA_f, TLR_i) \cdot \\ &P(TLR_i) \cdot P(LA_f \mid AM, Pos) \cdot P(Pos) \cdot P(AM). \end{aligned} \quad (4)$$

Similarly, the probability that every vertical traffic sign state *l* is valid for the ego vehicle results:

$$\begin{aligned} &P(TS_l) = \\ &P(TS_l \mid TSA_{jf}) \cdot P(TSA_{jf} \mid LA_f, TSR_j) \cdot \\ &P(TSR_j) \cdot P(LA_f \mid AM, Pos) \cdot P(Pos) \cdot P(AM). \end{aligned} \quad (5)$$

Consequently, the set of states *k = {1, 2, ..., 9}* is expressed as a discrete random variable of a probability distribution. This resulting mass function indicates the probability that every state of the traffic light *k* is valid for the ego vehicle. Since every state is interpreted as a dependent hypothesis, the sum of the probabilities of every state is 1:

$$\sum_{k=1}^{K} P(TL_k) = 1. \quad (6)$$

Likewise, a probability mass function is calculated for the different traffic signs ():

$$\sum_{l=1}^{L} P(TS_l) = 1. \quad (7)$$

Since the main idea is to estimate the current pass permission state based on the traffic lights and signs, both functions are combined to calculate the probability of every pass permission state $P(PP_m)$:

$$\sum_{m=1}^{M} P(PP_m) = 1. \quad (8)$$

In this way, the pass permission from an ego vehicle perspective is simplified in states (*m = 1, 2, ..., M*) that indicate different behaviors of the ego vehicle at the intersection:

- ***Not permitted (m = 1).*** The ego vehicle shall not enter the intersection (for example, if a red light is valid for its lane).
- ***Permitted (m = 2).*** Passing is allowed if the driving corridor of ego vehicle is not congested. However, it shall yield the right of way to oncoming vehicles or vulnerable road users at parallel crosswalks/bike-lanes.
- ***Permitted (time limited) (m = 3).*** Ego vehicle shall

stop before the intersection unless the stopping cannot be made safely. Otherwise, the permission is interpreted as permitted.

- ***Protected (m = 4).*** While turning the ego vehicle is protected from oncoming vehicles and crossing bikes/pedestrians, which shall not be permitted to entrance the intersection.
- ***Protected (time limited) (m = 5).*** Ego vehicle shall stop before the intersection unless the stopping cannot be made safely. Otherwise, the permission is interpreted as protected.
- ***Permitted turn on red (m = 6).*** It is allowed to turn right just if the way is clear and the maneuver is safe from a collision with other road users.
- ***Right before left (m = 7).*** The ego vehicle shall yield the right of way to the vehicles crossing from the right.
- ***With precedence (m = 8).*** Other crossing vehicles shall give way to the ego vehicle.
- ***Yield (m = 9).*** Passing is allowed, but the ego vehicle has to yield the right of way to other vehicles.
- ***Stop (m = 10).*** The ego vehicle shall stop before entering the intersection and then give way to other possible crossing vehicles.

Once every pass permission state is explained, the key question is how to combine both traffic lights and traffic signs functions in a coherent way. This idea is illustrated in Fig. 3.

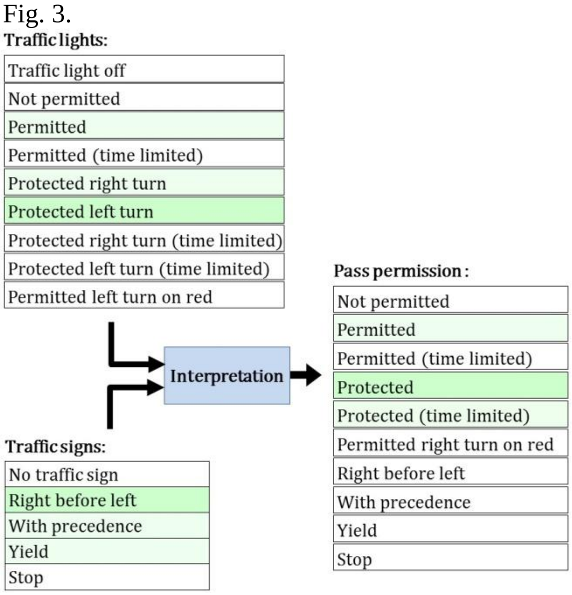

Figure 3. Combination of $P(TL_k)$ and $P(TS_l)$ to calculate the pass permission probability mass function $P(PP_m)$.

Considering the regulations indicated in [1], the traffic flow at intersections is first controlled by traffic lights, then traffic signs (if there are no traffic lights) or by the *right before left* rule. Taking this into account, the combination is done in a very simple manner: the mode of $P(TL_k)$ is considered to update the states of $P(PP_m)$ if the value of the mode is large enough. That is:

$$P(PP_m) = \begin{cases} h(P(TL_k)) & \text{if } E_{TL} \geq Th \\ h(P(TS_l)) & \text{else if } E_{TS} < Th \\ \text{default} & \text{otherwise.} \end{cases} \quad (9)$$

where $h(\cdot)$ is the mapping function that indicates which probability mass function is used to update the pass permission ($P(PP_m)$). The terms E_{TL} and E_{TS} represent the difference between the mode and the mean value of the traffic lights and traffic sign function, respectively:

$$E_{TL} = \text{mode}(P(TL_k)) - \sum_{k=1}^{K} \frac{P(TL_k)}{K}. \quad (10)$$

Here, Th corresponds to a threshold set empirically to *0.2*.

In other words, the pass permission is mapped considering the traffic light states if the value with the largest probability is at least 20% over the mean. Else, the traffic sign states are considered. Moreover, the default state is set to *right before left* if there is no traffic sign.

IV. Probability Mass Function Over Time

Another required task is to interpret temporal changes of the calculated probabilities in a proper manner. This section explains how the interpretation over time is done using the traffic light probability mass function $P(TL_k)$ as example.

In real situations, the traffic lights are often erroneously (or not) detected, so that the resulting probability varies over time in an illogical way (e.g. from *not permitted* to *permitted* suddenly, and back to *off*...). These errors are typically due to false detections of the camera, wrong assignment into lanes, occlusions, etc. An example of these typical fluctuations of the traffic light states over time ($P(TL_k, n)$) is shown in Fig. 4.

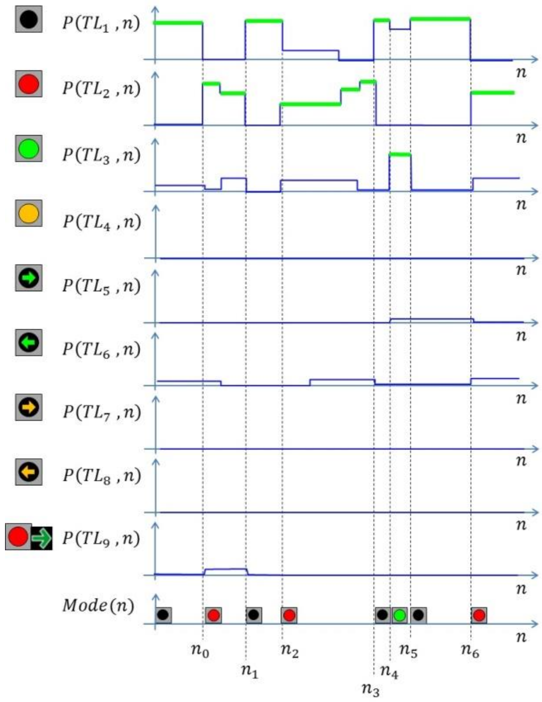

Figure 4. Example of a probability mass function representing the possible traffic light states over time $P(TL_k;n)$.

Thanks to this example, it is possible to note visually how often the mode value (*mode(n)*) changes over time. The mode is *off* (i.e. $k = 1$) until n_0, then it changes to *not permitted* until n_2, and so on. Consequently, it becomes obvious the need of mitigating suddenly changes over time. At first, in order to keep this smoothing very simple, the function is smoothed over time using a simple exponential moving average approach:

$$P^*(TL_k, n) = P(TL_k)(1-\alpha) + P(TL_k, n-1)\alpha \tag{11}$$

where $P^*(TL_k, n)$ represents the smoothed function and the smoothing factor ($\alpha = \{0, 1\}$) indicates how effective the smoothing is. Nevertheless, observing the values of the traffic light state *not permitted* (i.e $P(TL_2, n)$), it is easy to notice if a constant value of α is appropriate or not: an increasing and decreasing probability (see the fluctuation at $P(TL_2, n_0)$ and $P(TL_2, n_4)$) would smooth $P(TL_2, n)$ with the same value of α. From a logical point of view, a decreasing probability of *not permitted* requires a smaller value of α than an increasing one (since it could be unsafe to smooth the probability of a properly recognized red traffic light). Therefore, we use a conditional exponential moving average with different α values to increase and decrease probabilities (α_{in} and α_{de}):

$$\alpha = \begin{cases} \alpha_{in} & \text{if } P(TL_k, n) > P(TL_k, n-1) \\ \alpha_{de} & \text{otherwise} \end{cases} \tag{12}$$

Thanks to this concept, we can introduce the terms *conservative* and *non-conservative* smoothing. Accordingly, the smoothing is conservative when $\alpha_{in} < \alpha_{de}$. The concept of a conservative or non-conservative smoothing is graphically explained in Fig. 5 with an example.

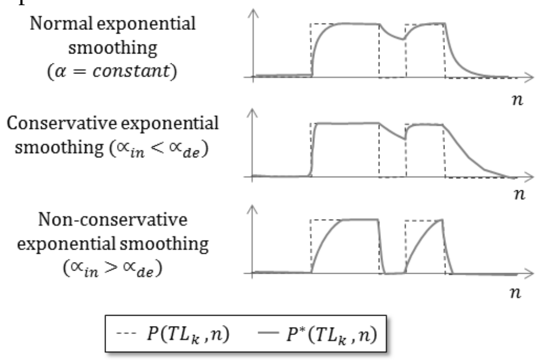

Figure 5. Examples of different exponential smoothing over time (normal, conservative and non-conservative).

Nevertheless, the position of the ego vehicle with respect to the intersection has to be taken into account in order to update the changes of the probability mass function over time. For example, let's say one is approaching the intersection with the intention of turning left. Firstly, the focus of a human driver approaching the intersection is to interpret how to pass it. Once the ego vehicle is inside the intersection, the perceived pass permission remains valid until one has completed the left turn maneuver. In other words, a human driver pays special attention to the possible changes over time when approaching the intersection. Then, once inside it (i.e. the traffic light is behind the ego vehicle), the last interpreted pass permission is kept fixed until the end of the whole maneuver. In order to imitate this behavior in our approach, the factor δ(d) is introduced in the equation (11), so that the resulting smoothed function $P^*(TL, n)$ also depends on the distance d from the rear axis of the ego vehicle to the start of the intersection:

$$P^*(TL_k, n) = P(TL_k)(1-\alpha\delta(d)) + P(TL_k, n-1)\alpha\delta(d) \tag{13}$$

with

$$\delta = \begin{cases} \delta_{\min} & \text{if } C = 0 \\ \left(\dfrac{1-\delta_{\min}}{d_{fov} - d_b}\right)(d - d_b) + \delta_{\min} & \text{if } C = 1 \text{ or } d < d_{fov} \\ 1 & \text{else} \end{cases} \tag{14}$$

where the variable $C = \{1, 2, 3\}$ represents the crossing state of the ego vehicle with respect to the intersection (i.e. *crossing*, *approaching* and *unknown* respectively).

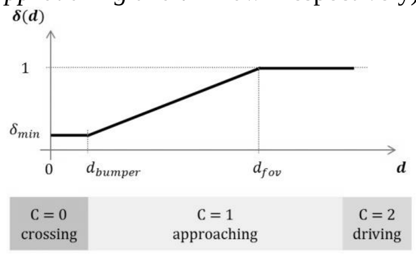

Figure 6. Value of δ depending on the distance to the start of the intersection d and the crossing state C.

As it can be seen in Fig. 6, the value δ_{min} ensures that even when the ego vehicle is already inside the intersection, the smoothing is always active (the closest $\delta(d)$ to 0.0 is, the slower is the update of the states over time). Based on experimental results, we set the value of δ_{min} to 0.01. On the other hand, the variables d_b and d_{fov} indicate the distance from the rear axis to the front bump of the ego vehicle and the optimal field of view distance to detect traffic lights, respectively.

TABLE I: SELECTED VALUES OF A_{DE} AND A_{IN}

	α_{de}	α_{in}
Traffic lights		
Off	0.5	0.01
Not permitted	0.1	0.5
Permitted	0.1	0.3
Permitted (limited)	0.1	0.3
Protected right turn	0.1	0.3
Protected left turn	0.1	0.3
Protected right (limited)	0.1	0.3
Protected left (limited)	0.1	0.3
Permitted right on red	0.1	0.3
Traffic signs		
No traffic sign	0.5	0.5
Right before left	0.5	0.5
With precedence	0.5	0.5
Yield	0.5	0.5
Stop	0.5	0.5
Pass permission		
Not permitted	0.5	0.9
Permitted	0.8	0.8
Permitted (limited)	0.8	0.8
Protected	0.8	0.8
Protected (limited)	0.8	0.8
Permitted right on red	0.5	0.5
Right before left	0.5	0.5
With precedence	0.5	0.5
Yield	0.5	0.5
Stop	0.5	0.5

Table I shows the selected values of α_{de} and α_{in} for every state. These values have been selected and optimized empirically based on experimental results.

V. Results

The main objective of the following experiments is to test the proposed approach in real traffic conditions. That is to say, the focus is not to analyze the detection/recognition of traffic lights/signs and corresponding assignment to lanes, but how the outputs of the perception module are interpreted to set the pass permission. For this purpose, we tested our approach in several routes in the Wolfsburg city. However, we selected two representative scenarios that help the reader to understand how our approach works in real situations. The location of these two scenarios in the selected route is illustrated in Fig. 7.

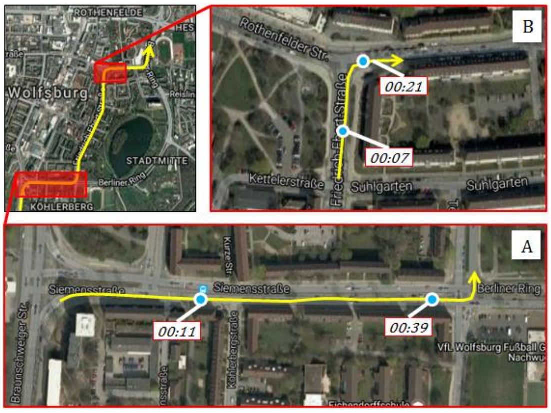

Figure 7. Route selected for testing the proposed approach. The image at the top-left illustrates the selected route in Wolfsburg city. The two rectangles marked in red represent the scenario A (bottom) and B (top-right). The driving path is marked with a yellow arrow along the route.

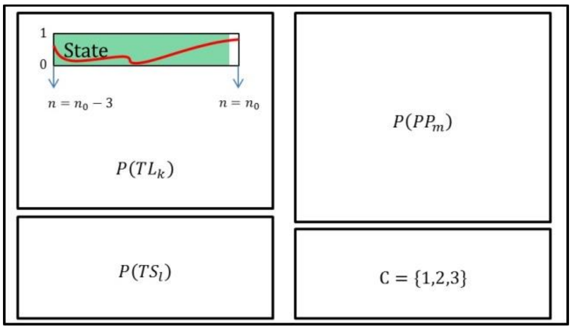

Figure 8. Explanation of the result's view: traffic lights (top-left), traffic signs (bottom-left), pass permission (top-right) and crossing state (bottom-right). Inside the top-left rectangle, a state example is illustrated to clarify its meaning: every state of a probability mass function is represented as a rectangle and colored in green according to its current probability value. Its probability over time is plotted in red, so that the right border indicates the current time ($n = n_0$) and the left one indicates three seconds later ($n = n_0 - 3$). For example, if the probability of a state decrease linearly in three seconds from 1.0 to 0, its corresponding plot would show a red line from the bottom-right (P(state, $n = n_0$) = 0.0) to the top-left of the rectangle (P(state, $n = n_0$-3) = 1.0).

In order to present the results and their changes over time in the scenarios A and B, Fig. 11 and Fig. 13 illustrate a plot of the probability of every state. Moreover, Fig. 12 and Fig. 14 show the results in 4 different instants (see time reference in Fig. 7). Namely, every figure contains 4 columns that represent 4 different moments. At the top of every column it is shown an image of the front camera. Hereunder, the second image from the top illustrates the corresponding road-graph visualization [9]. This format represents the road network as graphs, in which every graph can be instanced with different attributes as traffic lights, traffic signs, speed limits, etc. The *road-graph* corresponds to the output of the perception module (i.e. the assigned traffic lights/signs to lanes). Furthermore, the image at the bottom corresponds to the result of the interpreted pass permission. The distribution of its content is graphically explained in Fig. 8.

The result in scenario *A* is illustrated in Fig. 11 and Fig. 12. Here it can be seen how the proposed approach interprets the pass permission at three different intersections. First, the ego vehicle drives through an intersection controlled by a green traffic light, so that the resulting pass permission state is *permitted*. The changes of the pass permission state can be seen in the first and second column (i.e. from time 00:11 to 00:15), in which the ego vehicle approaches the second intersection. First, the pass permission changes from *permitted* to *right before left* as default and suddenly a *priority road* traffic sign is detected so that the corresponding probability increases over time. In other words, $P(TS_{l=3})$ increases from *0.0* to ≈1.0 when the traffic sign is detected (see camera image in the second column). In the third column a very representative situation is illustrated: the next intersection is not controlled any more by the *priority road* traffic sign, but by the red traffic light. Therefore, the corresponding pass permission changes quickly to the state *not permitted* (time 00:27). It is to say, that the probability of the most probable traffic light state $P(TL_{k=2})$ was large enough (see equation (9)), so that the pass permission is mapped directly with the probability of the traffic light states and the probability of the traffic signs $P(TS_{l=3})$ is not considered any more. In the fourth column it is illustrated how the traffic light color changes from red to green being yellow for approximately one second (time 00:39).

On the other hand, Fig. 13 and Fig. 14 illustrate the results for a less common situation: an additional traffic light with a not detected right arrow. In the first column (time 00:07), it is possible to see the change between the states *right before left* and *not permitted*, due to the recognized red traffic light. The next column illustrates how the traffic light with a right arrow is not detected (see the second column at time 00:11). For this reason, the pass permission is interpreted as *permitted*. In the third column of Fig. 14 (time 00:14) it is to be noted that both traffic lights are outside the image and, consequently, there is no input from the perception. In fact, this causes an smoothing: i.e. the value of $P(TL_3)$ decreases very slowly but is still the mode of the function. Therefore, the pass permission probability mass function is updated with the traffic lights even if the traffic sign *yield* is detected. Finally, once the ego vehicle leaves the intersection (i.e. the crossing state changes from *crossing* to *unknown*), the default state *right before left* increases its probability.

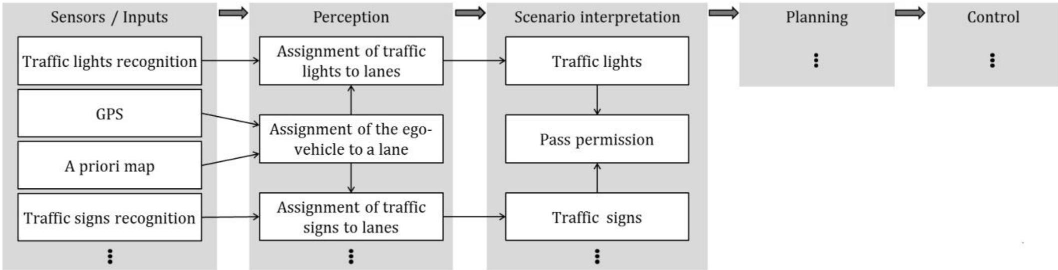

Figure 9. Simplification of the main system architecture.

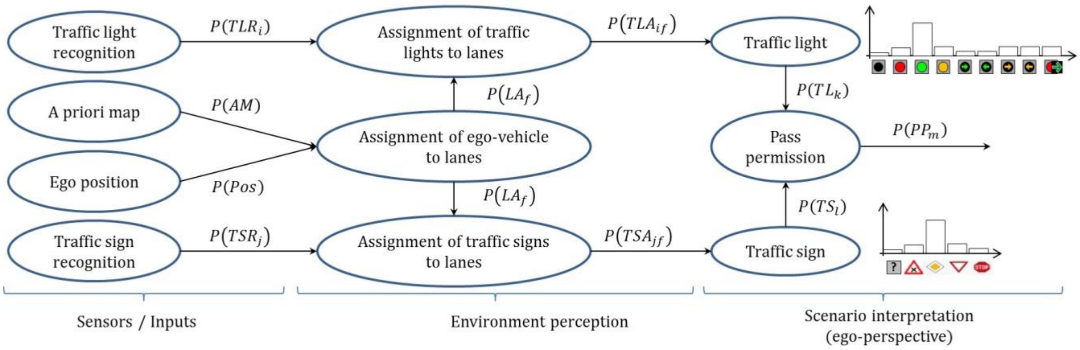

Figure 10. Probability calculation of the assignment of traffic lights and traffic signs to the ego lane.

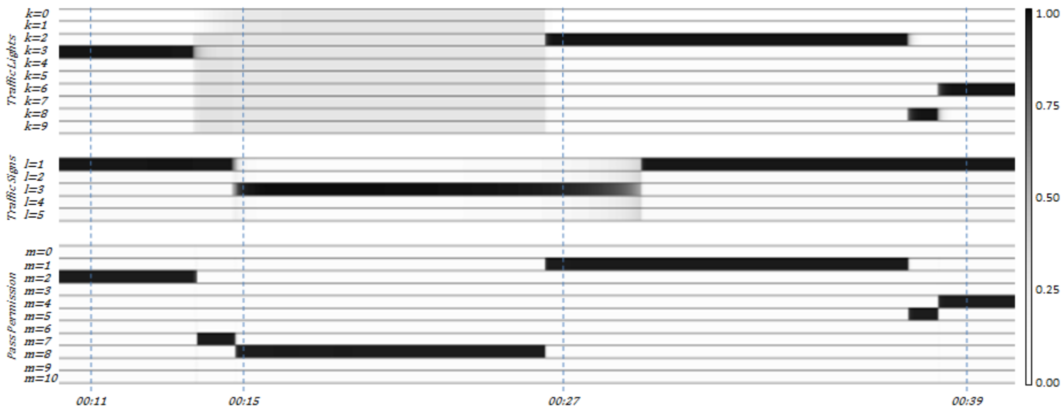

Figure 11. Result of scenario A: plot of the probability of all states over time.

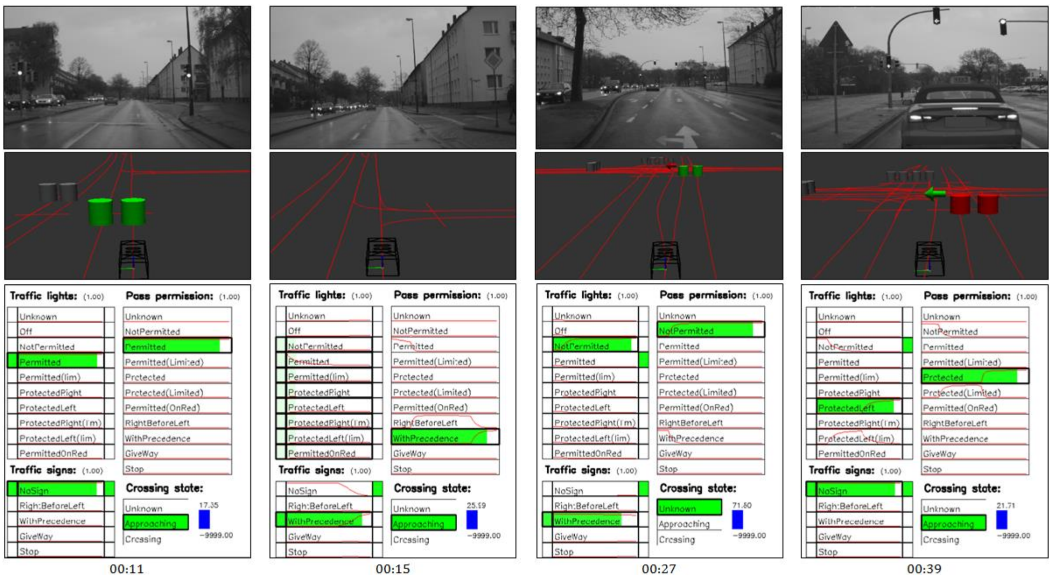

Figure 12. Result of scenario A: 4 representative frames in different times.

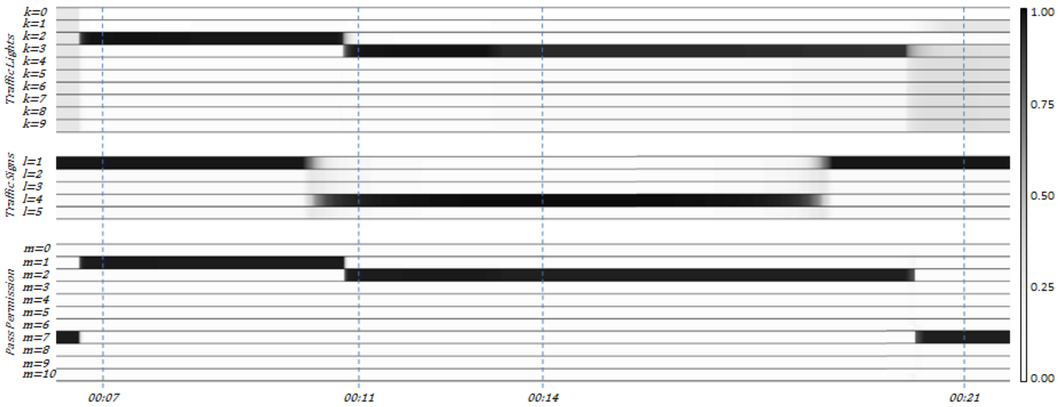

Figure 13. Result of scenario B: plot of the probability of all states over time.

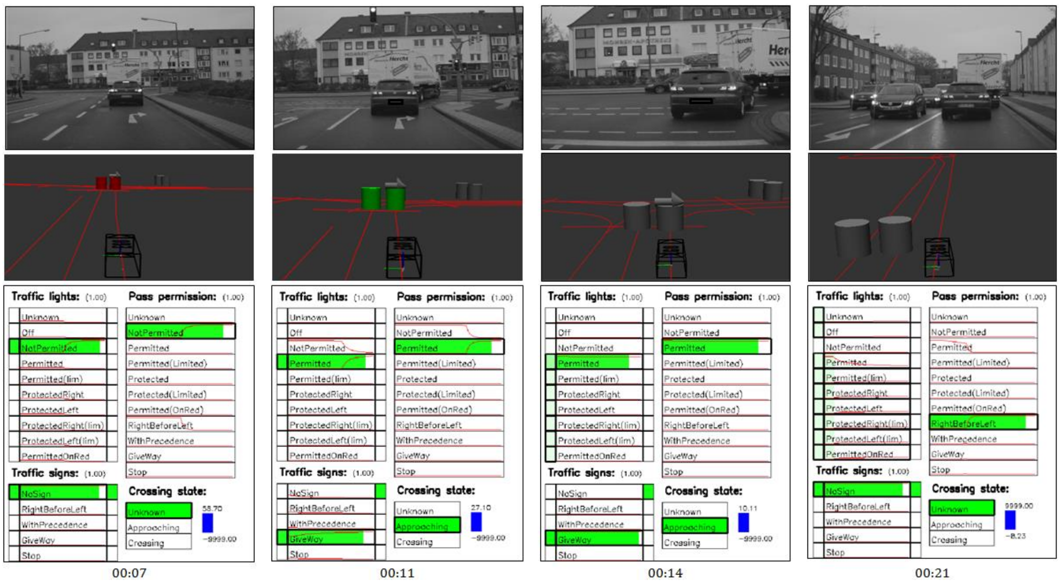

Figure 14. Result of scenario B: 4 representative frames in different times.

VI. Conclusion

In this paper a concept to interpret the pass permission at urban intersection has been introduced. The main goal of the proposed approach is to calculate the conditional probability of every input and fit them into a probability mass function in which every discrete state corresponds to one concrete pass permission. In other words, the idea is to combine the probability that every possible state of traffic lights and traffic signs is valid for the ego vehicle and generate a set of pass permission states with its corresponding probabilities. This approach should enable to handle uncertainty and fluctuations over time in very simple manner. Compared to state-of-the-art solutions, a very important advantage of our system is that it may be applied without Vehicle-2-X communication.

Experiments in real world scenarios illustrate how the proposed system works in real situations as well as ease to identify the advantages and disadvantages when some information is missing.

Future research will focus on optimizing the process of combining traffic lights and traffic signs. Furthermore, next steps and future research work will be achieved to improve the interpretation of fluctuations over time.

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David Perdomo was born in Las Palmas de Gran Canaria (Spain) in 1986. He received his Bachelor’s degree of Telecommunication Engineering from Universidad de Las Palmas de Gran Canaria in 2010, and the M.Sc. degree from Technische Universität Braunschweig (Germany) in 2015. He is currently pursuing the Ph.D. degree from Freie Univesität Berlin (Germany). At present Mr. Perdomo is a Ph.D. candidate in the Volkswagen Group Research / Automated Driving. His research interest include machine learning, scenario interpretation, signal processing and decision making with focus on applications for autonomous vehicles.

Rene Waldmann was born in Brunswick (Germany) in 1981. He received his Diploma Degree in Computer Science in 2007 and Ph.D. in 2012 at Technische Universistät Braunschweig.
Dr. Waldmann is currently software engineer and project manager at the Volkswagen Group Research / Automated Driving. His research interest includes Machine Learning, scenario understanding, trajectory planning and artificial intelligence.

Raúl Rojas was born in Mexico City (Mexico) in 1955. He received his Bachelor of Mathematics in 1977 and his Master of Science (Mathematics) in 1980 at the Department of Mathematics, National Polytechnic Institute, Mexico. In 1980 he received his Master of Economics at the Department of Economics, National Autonomous University of Mexico (UNAM). He obtained his Ph.D. at the Otto Suhr Institute, Free University of Berlin in Economics and Social Sciences. He is currently leader professor at the Dahlem Center for Machine Learning and Robotics at the Free University of Berlin, Germany. His research areas are machine learning, computational science, robotics, autonomous driving, i.a.