

Data-driven feedback algorithms for automated position identification and environment reconstruction of autonomous vehicles

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Abstract: Independently of the automation level challenging aspects on unmanned vehicle management such as performance optimization processes, adaptive cruise control systems, steering and braking controls, are related to the assessment of the operational functioning degree of relevant responsive procedures. This paper states the problem of determining both the position and the environment of fully autonomous cars for safe and efficient car routing control. An *adaptive, closed loop policy* is proposed utilizing a minimum number of measurements available by principal car technology, a laser sensor and a smart camera. No additional investment is required on other devices where the costly continuous real time scans can be now reduced. The low computational complexity encourages for embedded designs providing real time responses. Missing or invalid sensor information is estimated by a first approach using neural network programming. Positions of mobile and immobile entities are determined and the related environmental context within the desired vehicle vicinity is precisely reproduced. The performance of the proposed methodology is evaluated through realistic simulation data fed by multiple ground truth recordings. Hence, multiple biases on direct information as generated by professional drivers leading to untruthful and unreliable conclusions are now minimized. A trajectory within Paris central areas and suburbs is considered involving varying traffic conditions and rich road infrastructure. Some first qualitative and quantitative results appraise the accuracy and performance of the proposed methodology while further research targets are discussed.

Keywords: target tracking, autonomous vehicle perception, environmental perception, highly-automated driving functions (HAF), lane identification.

1. INTRODUCTION

During the last years, the significant increase in the number of unmanned driving abilities is also accompanied by an increase in the complexity of the involved functional components. Planning and control modules are frequently associated with complicated tasks which at least must remain manageable if not optimized. Efficiency of most prediction and planning algorithms is massively influenced by a robust perception of the vehicle environment even when *conditional automation* is employed.

In 2007, team VictorTango successfully completed the DARPA Urban Challenge where Odin drove for several hours without human intervention Kammel et al. (2008). Despite the failures deep knowledge on unmanned driving was obtained. The crucial role of accurate environmental sensing was confirmed. The vehicle speed and path definition explicitly depend on the available space within lanes

and obstacle localization. In a tentative to cope with unpredictable real world events employment of cost effective sensors and fault tolerant schemes are required. A vision based algorithm for cost effective LDWS is suggested in Eldenstein (2015) specifically applied for low and medium range vehicles. Lane Keep Assist (LKA) is a camera based system allowing automatic detection of divider line markings on the road. The system provides steering assistance Porsche (2016), technology services (2017), Volvo-Cars-Support (2017).

Experiences have shown that navigation based on a global positioning system incorporated with an Inertial Measurement Unit (IMU) and digital cartography implies a satisfactory solution Sukkarieh et al. (1999), V.Milanes et al. (2008). Advanced methods for sensor signal processing are proposed in RobustSENSE (2016). Decisions on lane change possibilities taking into consideration perception uncertainties are examined in Ulbrich and Maurer (2015)

by means of a dynamic Bayesian network. When driving modes alternate between manually and automated ones new requirements on critical system components are imposed Becker and Helmle (2015).

Moreover, mesoscopic and macroscopic modeling of traffic flow comprised of vehicles moving within a single highway lane according to intelligent cruise control (ICC) and cooperative driving is studied in Li and Ioannou (2004). A Point Positioning technique is presented in Knoop and Buist (2012). A methodology identifying the lane position of the GPS-instrumented vehicles when located in a queue of a signalized intersection is presented in Rompis et al. (2017).

This paper proposes a methodology allowing precise dynamic configuration of the lane level position of any detected object including the ego vehicle, within any detection frequency. Minimal information resulting from laser sensor and a smart camera is employed whereas the involved number of lanes is given by a GPS cartography. Many similar works simultaneously resolve multiple problems: definition of the total number of lanes within the road segment, measurement of the lane width, road markers detection and finally determination of the object lane Chen (2010), Tiberius et al. (2012), Jing et al. (2013). Due to the increased complexity a decomposition into subproblems of different nature is considered. It merits to specify that no additional investment in extra devices is necessitated while elementary sensor measurements are utilized. The currently proposed scheme is significantly advanced regarding previous works as Lioris and et al (2018) were an elementary deterministic approach is presented requiring specific road infrastructures having a physical separator between the opposite flows. Another important novelty concerns the new developed techniques overcoming *major* previous limitations regarding observations. When no sensor (valid) signals are returned, the new scheme still responds where the scheme in Lioris and et al (2018) was unable to compute. Specific signal estimations are now considered when temporary missing detections occur. Despite the increased flexibility, the new decision making policy remains of very low complexity able to be incorporated to embedded vehicle structures. The remainder of the paper is organized as follows. §2 formalizes the dealing problem. The desired goals of this research are presented and mathematically modelled. §3 presents a first performance evaluation of the suggested approach. §4 resumes the most important outcomes of the study while it introduces the new goals of the ongoing research.

2. PROBLEM STATEMENT

2.1 System Overview

A system defining the instantaneous ego vehicle environment potentially comprised of mobile and immobile objects with respect to the ego vehicle *level lane* and *in level* position is going to be determined. A laser detector-LIDAR provides information on captured objects within a multi-plane and long range vision angle. Observations are processed and after specific treatment various quantification and qualification measurements are returned. Intelligent use of these metrics may allow a detailed reconstruction of the actual vehicle environmental context.

Thus, the lateral and longitudinal coordinates of each referenced object are calculated, the object length and width, information on the related velocity, other variables characterizing the object nature etc. Among all available information, the present work employs the Cartesian coordinates of the tracked obstacles as well the object velocity in some particular cases. As Figure 1 represents, at a particular time t laser car equipment detects obstacles located within an angle in front of the car. For each such obstacle the pair (x, y) is defined with respect to the system origin $(0, 0)$ associated with the present ego vehicle position.

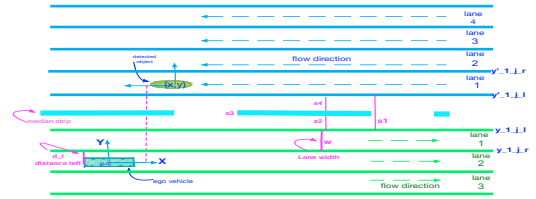


Fig. 1. Vehicle environment.

The embedded smart camera returns the distance between the ego vehicle and the left and right lane markers while the total number of lanes at the related road segment is supplemented by cartography. Lanes are identified and labeled with numbers starting with the far left lane. Once the ego vehicle level lane position is determined then all observations can be precisely distributed within the vehicle environment.

Remark 1: In the present study detections obtained by a laser sensor located in the front part of the vehicle are considered. Under the same approach observations from a laser detector positioned at the rear part of the vehicle can be also taken into consideration.

2.2 Defining the ego vehicle level lane positioning

Prior to redefining the vehicle environmental context at a given time t , we seek to determine the level lane identification within which the ego vehicle is located. For this purpose, the proposed lane estimation methodology combines two different types of decision policies. The first approach requires identification of the *central reservation* or *median strip object* or any fixed positioned obstacle. Alternatively mobile object detections moving within the opposite direction can be employed. In many contexts, this later approach can successfully stand alone for lane identification (not largely developed in the present work). The second type of decisions consists of computations determining whether a lane change vehicle behavior occurs. It is of worth to be accentuated that no future predictions are involved in the current scheme.

Left Median strip detection The median divider island located on the left side in the vehicle moving direction is aimed to be localized for any candidate lane. For this purpose, the y object coordinate will be considered at the decision time.

If $N(t)$ represents the total number of captured objects at time t at the maximal longitudinal distance then set \mathcal{P} comprised of pairs (x, y) of all detected elements at time t can be defined as follows

$$\mathcal{P}(t) = \{p_i(t) = (x_i(t), y_i(t)), i = 1, \dots, N(t)\} \quad (1)$$

with

$$\text{card}(\mathcal{P}(t)) = \begin{cases} > 0, & \text{if } N(t) > 0 \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

Temporarily set \mathcal{P} may become empty depending upon the actual vehicle context and/or sensor failures. In similar cases fusion procedures involving data from other sensors or additional estimation algorithms for noisy and irregular observations should be adopted in order to replace missing information. Keeping in mind that laser technology has a wide and long detection range of approximately 300 meters a practical policy would consist in defining an acceptable detection area \mathcal{N}_ϵ which can progressively enlarge depending upon the ϵ value.

Hence, at time t the considered observation set \mathcal{P}_ϵ can be defined as follows

$$\mathcal{P}_\epsilon(t) = \{p(t) \in \mathcal{P}(t) \cap \mathcal{N}_\epsilon(t) : y(t) > 0\} \quad (3)$$

Since the median strip positioned on the left side of the ego vehicle is aimed to be localized, observations associated with strictly positive y coordinates are taken into consideration as Eq.3 defines.

At the decision time t , a two-dimensional coordinate system will dynamically be created for any candidate lane. For each such system and for any lane located on the left of the considered candidate lane, the y coordinates of both left and right lane boundaries will be determined. Thus, the left separator may be detected amongst the reference objects of set \mathcal{P}_ϵ at time t .

Let m be the total number of lanes in the ego vehicle direction, j the considered candidate lane where the system origin is placed with $1 \leq j \leq m$, $y_{i,j}^l(t)$ the y -coordinate of the left boundary of lane i regarding lane j at time t and $y_{i,j}^r(t)$ the y -coordinate of the right boundary of lane i regarding lane j at time t , for any $i \leq j$.

Moreover, if w denotes the lane width and d_l, d_r represent the distance between the ego vehicle and the left and right lane boundaries respectively then the values of $y_{i,j}^l$ and $y_{i,j}^r$ at time t can be calculated

$$y_{i,j}^l(t) = \begin{cases} d_l(t) + (j - i) \times w, & \text{if } i < j \\ -(d_r(t) + (i - j - 1) \times w), & \text{otherwise} \end{cases} \quad (4)$$

$$y_{i,j}^r(t) = \begin{cases} d_l(t) + (j - i - 1) \times w, & \text{if } i < j \\ -(d_r(t) + (i - j) \times w), & \text{otherwise.} \end{cases} \quad (5)$$

Let s_1 denote the max considered distance between the left barrier and the left boundary of the first lane (enumeration starts from left to right onwards the automobile direction)

while s_2 is the real distance of the left barrier from the left boundary of first lane with $s_2 \leq s_1$, (see also Fig. 1).

Set $\mathcal{S}_{j,\epsilon}$, can be defined with respect to the candidate ego vehicle lane j :

$$\mathcal{S}_{j,\epsilon}(t) = \{p(t) = (x(t), y(t)) \in \mathcal{P}_\epsilon(t) : y(t) \in [y_{1,j}^l(t), y_{1,j}^l(t) + s_1]\}. \quad (6)$$

Set $\mathcal{S}_{j,\epsilon}$ maybe empty for a particular candidate lane j in which case this lane will be rejected from the set of feasible ones. This result may occur either because the considered candidate lane does not correspond to the current vehicle location or when the left separator failed to be detected (unsuccessful sensor functioning, absent barrier, large dimensioned objects at the front vehicle sides blocking laser caption range etc.). Furthermore, it is possible that elements of set \mathcal{P}_ϵ may satisfy the constraints of $\mathcal{S}_{j,\epsilon}$ for more than one candidate lanes due to value shifts. This could be the case when the ego vehicle is located at an internal or last lane and is surrounded by other objects positioned in different lanes. In the present study, all candidate lanes are examined and when $\mathcal{S}_{j,\epsilon} \neq \emptyset$ for at least two candidate lanes no response is provided by this criteria. Consideration of additional constraints may diminish the appearance of similar situations. Thus, when $j = 1$ set $\mathcal{S}_{1,\epsilon}$ can be defined as follows

$$\mathcal{S}_{1,\epsilon'}(t) = \{p(t) = (x(t), y(t)) \in \mathcal{P}_\epsilon(t) : y(t) \in [y_{1,1}^l(t), y_{1,1}^l(t) + s_1], v_{a,p} \leq \epsilon', \epsilon' \simeq 0\}. \quad (7)$$

where $v_{a,p}$ defines the absolute velocity of the detected object p .

That is, when then candidate position lane of the ego vehicle is the first one, the median strip should be an object located at an appropriate distance from the first lane left boundary but also an object of which the related absolute velocity should be a very small number almost zero. Nevertheless, this additional constrain should be satisfied only when examining the first lane as a candidate one. When other mobile objects are positioned on the left side of the ego car while having a non-zero speed at the considered time, they may partially hide the left barrier. Hence, the laser detector may not be always able to distinguish whether the separator is a static or a mobile entity.

When the road separator does not exist or it is not detected then set $\mathcal{S}_{j,\epsilon}$ becomes

$$\mathcal{S}_j(t) = \{p(t) = (x(t), y(t)) : y(t) = \min_{y'(t)} \{p'(t) = (x'(t), y'(t)), y'(t) > 0, v_{a,p'}(t) < 0\}\}. \quad (8)$$

Lane change detection Conditionally to the fact that a *recent and reliable* estimation of the ego vehicle lane position is made, we search to define the present vehicle lane location by detecting potential movements towards the adjacent lanes. With this purpose the automobile

distance from the side lane boundaries will be examined. If ϵ_l and ϵ_r define very small numbers close to zero, d_l and d_r the vehicle distance from the left and right lane markers and w the lane width then the following two sets of inequalities characterize the instants where cars move towards the left lane

$$\mathcal{L}_{\epsilon_l} = \{t \in \mathbb{R} : d_l(t) \leq \epsilon_l, \epsilon_l \simeq 0\} \quad (9)$$

$$\mathcal{L}_w = \{t \in \mathbb{R} : d_r(t) \geq w\}. \quad (10)$$

Whenever a left lane change is about to occur, the vehicle distance from the left lane marker becomes very small (in the perfect case it reaches zero). An alternative way to express a movement towards the left lane is when the vehicle distance from the right lane boundary exceeds the lane width. These two situations are illustrated by Eqs. 9 and 10, respectively.

Similarly the next two sets of inequalities formalise right lane changes of the ego vehicle

$$\mathcal{R}_w = \{t \in \mathbb{R} : d_l(t) \geq w\} \quad (11)$$

$$\mathcal{R}_{\epsilon_r} = \{t \in \mathbb{R} : d_r(t) \leq \epsilon_r, \epsilon_r \simeq 0\}. \quad (12)$$

Values of the left and right distances d_l and d_r are provided by the smart camera technology at any detection instant. However, depending upon various factors (vehicle context, meteorological conditions etc.) the values of d_l , d_r are not always valid. In the present study, missing or unreliable signal values, for both types of decisions, are estimated by means of supervised learning technique, Multilayer Perceptron (MPL). Taking into consideration that the laser sensor provides new detections within a frequency of 25Hz, whenever a lane change is detected, another decision algorithm is called in order to approve or reject this observation. As a vehicle moves towards an adjacent lane values of the left and right car distances d_l , d_r from the lane markers for consecutive time instants t may satisfy at least one of Eqs. (9), (10) (11), (12). In order to consider only movements towards different lanes within consecutive instants t a procedure examining the time of the last lane change acceptance is considered. Hence, let t_l denote the last instant at which a lane change was approved and t_c the current time for which a lane change is also observed. If p_t denotes a parameter expressing the min required time between two consecutive lane changes then a lane change at time t_c will be accepted whenever inequality $|t_l - t_c| \geq p_t$ is satisfied.

In this case the new vehicle lane position will be its current lane increased or decreased by one depending upon the observed direction of the lane change (right or left).

2.3 Determining the vehicle environment

Consider a fixed $\epsilon' > 0$ and define set $\mathcal{P}'_{\epsilon'}(t)$ as follows

$$\mathcal{P}'_{\epsilon'}(t) = \{p'(t) = (x'(t), y'(t)), p'(t) \in \mathcal{P}(t) \cap \mathcal{N}_{\epsilon'}(t)\} \quad (13)$$

Let $\tilde{\alpha}_v$ denote the ego vehicle lane identification at time t computed as discussed in §2.2. If m represents the total number of lanes at the present road segment, then $1 \leq \tilde{\alpha}_v \leq m$.

Concerning the position of any detection point $p' \in \mathcal{P}'_{\epsilon'}$ we have that:

$$p' = \begin{cases} \text{on the left side of the ego vehicle, when } y' > 0 \\ \text{on the right side of the ego vehicle, when } y' < 0 \\ \text{on the same level, otherwise} \end{cases} \quad (14)$$

For any real number a the ceiling function is defined as the least integer greater or equal to a ,

$$\lceil a \rceil = \min\{n \in \mathbb{Z} : n \geq a\}. \quad (15)$$

Let $q_{p'}$ be the number of lanes between the ego vehicle and the detected object p' , then

$$q_{p'} = \left\lceil \frac{y' - d_l}{w} \right\rceil \quad (16)$$

whereas w represents the lane width at time t , that is

$$w(t) = d_l(t) + d_r(t) \quad (17)$$

The lane identification of any detected object p' , denoted $\alpha_{p'}$ can be then calculated

$$\alpha_{p'} = \begin{cases} \alpha_v - q_{p'} & \text{if } y' > 0 \\ \alpha_v + q_{p'} & \text{otherwise.} \end{cases} \quad (18)$$

Remark 2: Concerning the ego vehicle environment, the validity of the suggested algorithm remains intact for any set \mathcal{P}_{ϵ} determined at time t .

Remark 3: Use of other available information related to object characterization will imply additional qualitative information to the lane positioning. For instance, one may also define the nature of the detection. Exploitation of signals related to object dimension allows distinction between cars and trucks etc. The current version does not considers such signals although they can be easily involved. Treatment of the reliability of the qualitative metrics is under progress.

3. EXPERIMENTAL CONFIGURATION

3.1 Data Model

The behavior of the proposed decision scheme is examined and performance evaluation is achieved through complex traffic scenes. Multiple ground truth scenarios were recorded by sensor equipped cars circulating in Paris region, under varying traffic contexts, numerous road infrastructures and rich environmental conditions. This information was then utilized by an accurate simulation tool able to provide reliable and detailed scenarios.

The case study network as shown in Figure 2 corresponds to a trajectory from Invalides to Orly airport (red points)

and then back to Paris with a final destination at Montparnasse (blue points). The followed trajectories (from and back to Paris) involve urban roadways (e.g. Boulevard des Invalides, Avenue de la Porte d'Orléans) and motorway stretches such as A106 and A6A. The two trips are comprised of different paths with some common parts related to the freeways. The selected trajectory constitutes a challenging test-bed for the proposed methodology. As a non-trivial combination of a road infrastructure involving on-ramps and off-ramps is incorporated a variety of lane-changing attitudes is yielded. Furthermore, occurring formation and dissipation of stretch-internal congestion states provide a rich driving behavior and equipment functioning as well.

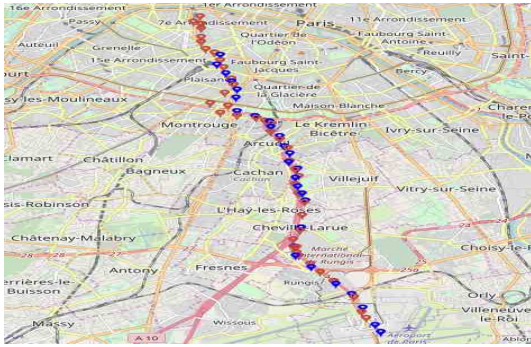


Fig. 2. Vehicle Trip.

A time discretization step of approximately 0.04 seconds is considered due to the laser detection frequency of 25 Hz.

3.2 Data validity

Within every sensor detection the lane estimation policy evaluates the current environmental context within the desired vehicle neighborhood. Collected data is verified and the necessary information is transmitted to the corresponding algorithm estimating the position of each detected entity. Nevertheless, sensor information may be judged unreliable and consequently it will be rejected by the proposed approach. Even more, no information may be available at particular time instances due to sensor failures, traffic context and congestions, meteorological conditions etc. To establish observability, employment of noisy data estimation schemes involving probabilistic approaches, model predictive schemes, artificial intelligence patterns will significantly improve the quality of the provided sensor information and thus the performance of the suggested methodology.

Figure 3 plots a variable measuring the cumulative number of calls of the lane estimation algorithm whenever invalid or no information occurs versus the related time instant. For the considered scenario, among the 70,500 distinct sensor detections, 5,534 times invalid data were returned.

Figure 4 quantifies the valid sensor detections for the employed series of recordings. Acceptable signals were available during the 92.15% of the total sensor functioning period while the 7.85% of the detections were judged invalid.

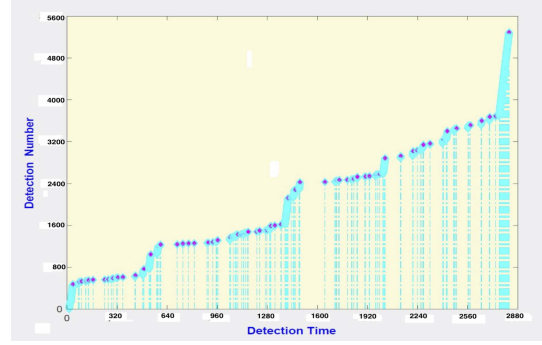


Fig. 3. Invalid sensor outputs.

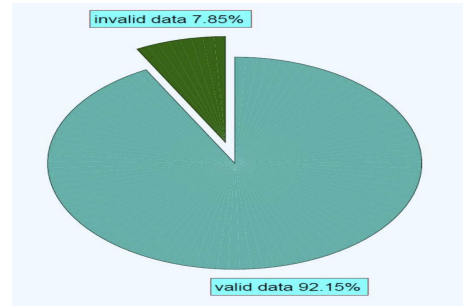


Fig. 4. Data validation measurement.

3.3 Lane estimation reliability measurement

The accuracy of the lane identification policy is going to be examined. In Figure 5 the calculated lane id (red line) is plotted versus the real value (green line) for any time of the trip trajectory. Clearly, the two values, coincide for most of the time. Nevertheless a few incompatibilities are observed for short time periods. Thus, at $t = 1503$ secs the car moves from lane 3 to lane 2 where the estimation scheme responds that this change occurs at $t = 1403$. Additionally, for $t \in [1860, 2320)$ the car follows lane 3 while the computed value indicates that the vehicle moves towards this lane at $t = 2000$ seconds. Finally at $t = 2320$ secs the car moves to lane 4 where this change is computed at 2250 seconds.

A microscopic statistical analysis explains that the algorithm underperformance is due to imprecise signal values. As sensors provided erroneous outputs, a specific data treatment was employed based on neural network programming. Missing and invalid values were estimated through a first approach utilizing Multilayer Perceptron Learning (MPL). An insufficiency related to the data and the employed MPL model led to wrong responses. However, all other MPL data estimations were accurate enough and the considered lane identification algorithm returned correct responses for the invalid signal values.

3.4 Vehicle environment representation

The current vehicle environmental context is going to be reconstituted for a particular time instant $t = 1855$ seconds randomly selected. For the sake of brevity and in order to deal with legible figures, a small vehicle vicinity is considered. However, the proposed methodology remains valid for any size of the detected area and any number of considered objects.

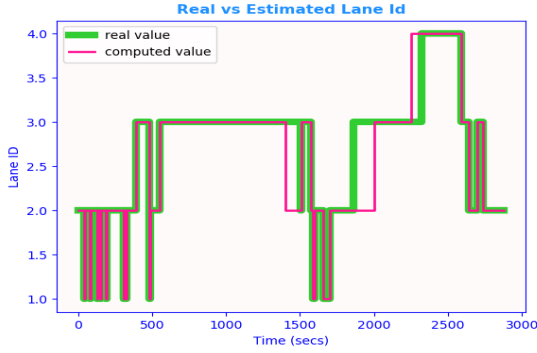


Fig. 5. Vehicle lane trajectory.

At present, eight captured obstacles are taken into consideration as detected by the laser sensor at $t = 1855$ seconds and within a longitudinal distance of 50 meters from the corresponding ego vehicle location. Figure 6 depicts the vehicle context at $t = 1855$ seconds within the considered area as seen by the embedded camera.

As Figure 6 shows the ego vehicle is positioned at lane 2 where four additional mobile obstacles can be observed. More precisely, on the same lane with the ego vehicle and in front of it another car is located, while one automobile circulates on lane 3. Finally, two more cars move simultaneously along the extreme lanes, one positioned at lane one and the other at lane four.



Fig. 6. Vehicle environmental context.

Immobile objects are also viewed. Hence, a left median strip area is also visible in Figure 6.

Application of computations discussed in §2 allow a precise reconfiguration of the present vehicle environment.

Figure 7 illustrates the level lane as well the in lane position of each one of the eight detected obstacles in the front part of the vehicle, by a colored lozenge. It should be noted that the separator on the left side on the ego vehicle direction is precisely located (light green lozenge). Moreover, the same figure shows that two of the detections correspond to objects positioned outside of the road segment (yellow lozenges on the right side of the road on the ego vehicle moving direction). Finally the wall located at the rightmost line of the road segment is identified and depicted by the bright yellow lozenge in Figure 7.

Comparison of Figures 6 and 7 implies that the outputs of the suggested lane-scheme reconstitution feature precisely the actual vehicle environment.

3.5 Algorithm response frequency

The present approach proceeds to a complete reconstruction of the vehicle surrounding context only when a unique

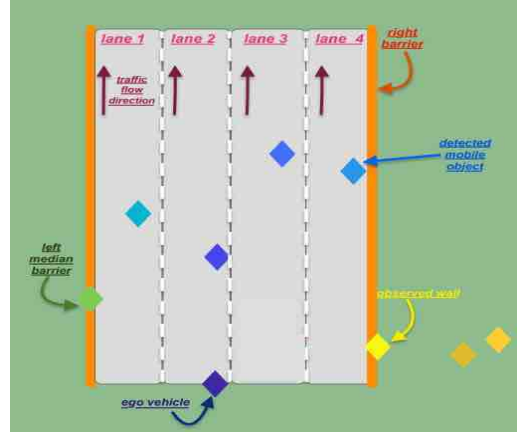


Fig. 7. Reconstruction of the vehicle environment, $t = 1855$ secs.

response is obtained regarding the object lane identification. If at a particular time instant more than one feasible solutions exist, no response is returned at that time. Nevertheless, specific algorithm schemes are about to be modeled, not considered in the present work, aiming at a successful response selection when multiple feasible answers are implied.

Whenever a situation associated with a response impossibility occurs the currently suggested decision structure is penalized. Thus, the performance of the proposed methodology is evaluated in terms of a unique lane identification ability of the detected objects. Histogram in Figure 8 illustrates the percentage of time where the vehicle environment was successfully configured. Hence, for the 99.42% of the recording time (where valid information was available) the proposed approach identified the ego vehicle lane position as well the in level lane locations of all the detected objects while only for the 0.58% no response was provided.

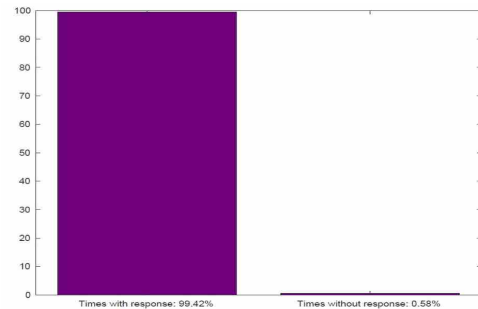


Fig. 8. Response frequency.

4. DISCUSSION-FUTURE WORK

The present work aims to reconstitute the current environmental context of an equipped vehicle based upon detection measurements provided by an embedded camera, a smart laser sensor in association with a GPS cartography. The proposed scheme is operational for trips within divided highway infrastructures and urban areas. A feedback decision-making scheme is developed identifying the level lane position of each captured object at any desired time. Minimum sensor information provided by the existing vehicle technology is exclusively employed, requiring

no extra investments for additional devices. Missing or invalid signal values are estimated by a first approach based on Multi Layer Perceptron models. Whenever the in level lane position of considered ego vehicle is identified mobile and/or immobile objects located at any desired neighbourhood are also identified and appropriately positioned within the car environment. The effectiveness of the proposed methodology was examined through carefully designed experiments covering a trajectory within Paris area. Realistic scenarios resulting from an accurate simulation tool using multiple and complex ground truth recordings are employed, minimizing biases generated by professional drivers. Statistical analysis provided a first quantified and qualified appraisal of the suggested scheme.

Thus, the response frequency of the proposed methodology is considered in two terms:

- (1) valid data acquisition ability: 92.15% of the provided data were validated by the suggested structure
- (2) feasibility of calculation: 99.42% of the considered recording time a unique response was provided.

It should be emphasized that this study forms only a part of an ongoing research of which the next shortcoming and further goals should be considered. Consequently, at this stage no definite conclusions should be taken.

Hereafter, are presented some tasks which are about to be developed aiming at improved performance of the presented lane decision approach:

- measurement of the system sensitivity in order to model the involved parameters,
- performance evaluation on multiple datasets,
- employment of additional available signals with the aim to achieve object characterisation such as measured obstacle dimensions, type qualifications etc.
- improvement of data quality. Development of estimation algorithms for noisy and missing data, advanced approaches of MPL contributing to reliable signal estimation.
- development of multiple complementary schemes allowing reliable detection of road merges, bifurcations, etc.

The suggested approach has several advantages for future possible real world applications, involving

- ★ the development of an independent or complementary scheme, exploring and reconstructing the vehicle environmental context at any desired time;
- ★ a low cost methodology accurately reconfiguring the considered ego vehicle neighbourhood. No additional devices are required, only a limited number of the existing vehicle equipment is used. Moreover, a small part among the available sensor measurements is required by the proposed scheme;
- ★ a carefully designed model avoiding risky, complicated and expensive calculations.

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