Vehicle Detection Assistance in Urban Intersection Using Data Exchange Between Road Infrastructure

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***Abstract*— This paper provides a new way of handling results related to safety algorithms used in urban area, in an intersection network. It denounces the waste of computing resources granted to run those algorithms while most mobile entities targeted may be detected several times during their journey through multiple interconnected intelligent intersections. A new approach is proposed, mixing detection algorithms and communications between intersection in order to reinforce consecutive detections of the same vehicles at different places. Experimentation in simulated environment leveraging a vehicular simulator called SCANeR Studio give some payoff on its performances: some improvements relative to the precision of vehicle detections but also a slight shift in detected position that may be corrected with an optimized data fusion algorithm.**

Keywords-vehicular simulation; sensors; communication; data fusion; prediction.

I. INTRODUCTION

Road safety have been considered primarily as a responsibility of each driver for a long time. Yet evolution of new vehicle technologies brought a renewal in this vision and allowed the development of new systems to assist drivers in their task: Advanced Driver Assistance Systems (ADAS) [1]. This possibility was granted thanks to the use of multiple on-board sensors and higher computational capabilities.

A similar trend was followed for road infrastructures and contributed to the development of new prevention techniques [2]. It is shown in [3] that these techniques correspond mainly to the analysis of vehicle and driver behavior and are based on detection, classification and tracking of different objects. These objects are evolving on a monitored location to prevent potentially dangerous situations and subsequently collisions and accidents. These new approaches oriented the choice of the different sensing systems to deploy on infrastructures, depending on the capabilities of the sensors and on the configuration on the chosen infrastructure itself. With more and more sensors involved to ensure better knowledge on the monitored area, data fusion has become a necessity. In [4], models, architecture, opportunities, and applications of data fusion among Intelligent Transport Systems (ITS) are described and show promising results.

Monitoring an intersection allows flexibility and the choice of sensors may be done by considering both the environmental factors and the particularities of the intersection. The concept introduced in this work offers a solution customizable to fit any road network and aims to perform with any type of sensors. In this regard, scenarios build in the chosen simulator are simple enough to accommodate all kind of sensors. Results presented in the review [5] outlined the good performances and relatively low-cost of camera-based solutions thanks to the progress of computer vision techniques. Although, their implementation requires most of the time the application of deep learning techniques. However, in order to keep the problem to a simpler state, other technologies are considered, such as: Radio Detection And Ranging (RADAR) or Light Detection And Ranging (LiDAR). Shirazi et al. in [3] give additional information on the trending sensors used for entity detection around intersections. While showing once again the potential of cameras, it also reveals comparable performances for LiDARs and rises only one main drawback: its high cost. However, this represents no obstacle for this project as simulations allow easy implementation without consideration of the cost. LiDAR will then be the chosen type of sensor at this stage.

Some more work has been exposed in [6], focused on the use of Dedicated Short-Range Communication (DSRC) and especially Vehicle-To-All (V2X) communications. It shows the potential of DSRC in intersection safety, as well as the implication of countries in its development. V2X demonstrates strong results while associated with the sensing equipment's that can be deployed in the infrastructure. Connected vehicles are considered as a highly potential step of the evolution of cars which may appear progressively, sooner than any automated driving vehicles from medium to high autonom level. Including communication technologies in any upcoming road safety solution should be a must.

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Advances in infrastructure technologies have also led to improvements in traffic management through intersection cooperation [7], enabled by vehicular communications. Once again, some very promising solutions have been presented, leading to new thoughts on the future of signalization. However, while independently showing very good results, intersection cooperation and vehicular safety analysis have not gathered as much interest and very few works have been done in the preservation of analysis results. While powerful algorithms run on a single intersection to ensure its safety, once any mobile entity leaves this intersection, all gathered data is lost and next intersections will have to execute similar processes to infer to the same information for its self-use. While taking advantage simultaneously of infrastructure equipped with multiple sensors, DSRC and data fusion techniques, this paper introduces the idea of shared data through an example of intersection network. For this purpose, a testing environment has been simulated on the vehicular simulator SCANeR Studio from AVSimulation where different scenarios were run to gather data from dedicated sensors, then processed in external models synchronized with the simulator.

Section 2 explains the new concept presented in this document. Then, Section 3 gives more details about the mathematical models used. Section 4 introduces the system implemented and the corresponding scenarios put together to test the performances of the system. And eventually, a fifth section gives hints for improvements before the conclusion.

II. System and Data Sources

This section presents the overall idea of the described system along with the different data sources handled.

A. *General Idea*

The concept presented here is about data exchange between road infrastructures. While equipped with a set of sensors, each intersection can produce some knowledge about the vehicular situation at its surroundings. These data are valuable and require important resources to be generated but are also generally thrown away as soon as the detection is lost. Thus, the idea is to keep this awareness and to share it with other intersections in order to simulate sensor inputs for connected intersections. Based on this, a detection and prediction process are put together to anticipate the arrival of the travelling announced vehicle. In this paper, the performance of such a system are questioned and results are showed. The intention is to create an anonymous track of vehicles on the road, while alleviating the computed detection task of each intersection.

B. *Data sources*

Sensors chosen to gather data at intersection are DSRC and LiDARs. Both represent popular sensors adapted to the automotive industry. They can get data about all kind of vehicles with a stronger confidence for connected vehicles.

1) *DSRC*

DSRC is a vehicular communication protocol based on broadcasting messages, called Basic Safety Messages (BSM), to inform connected entities within the communication range about vehicles intentions [8]. It participates in the creation of an ad hoc network of vehicles, exchanging data in order to evolve in a secure environment. Among the information contained in every BSM, the position of the emitting vehicles, its current speed and acceleration are the ones that are the most interesting for this work. By gathering those data, it will be possible to keep an awareness of all connected vehicles present at the intersection.

An important note to make here is that this paper is not focused on disputing communication scheme. This point may be addressed in future works. That’s why, at this point, all communications are assumed perfect.

2) *LiDAR*

LiDAR is an active light-sensitive sensor that allows detection of obstacles in a specific field of view. Its strength rests on its ability to give accurate information of obstacle detected up to hundreds of meters [9]. It has the advantage of providing distance data and performing by day or night. But it may be affected by extreme weather (heavy rains, fogs) and some reflective surfaces.

3) *Intersection data*

Intersection data corresponds to the addition we are putting forward in this paper. It corresponds to the shared information that each intersection will send to other adjacent intersections. These data are based on the prior output of any detection and classification algorithm achieved by other sensors: the LiDAR and DSRC in this case.

From its knowledge, any intersection will be able to determine leaving vehicles with their status: exit used, last speed and acceleration measured. It will then inform connected intersections of the arrival of a new vehicle. Upon reception of the intersection message, the target infrastructure is expected to build a continuous prediction model corresponding to the evolution of the anticipated vehicle until it appears in the field of detection of its own sensors (if it appears).

A big interest of this new element relies on the fact that it can convey any type of data for any detected object that the intersection is capable of detecting. With LiDARs and DSRC chosen, each intersection should be able to detect any vehicle passing by the intersection, with a stronger belief in detection of connected vehicles. Although, intersections can only send data about vehicles monitored: it will not be able to predict the apparition of a newcomer.

III. MATHEMATICAL MODELS

This section focuses on a description of the equations used in the processing of the data from each described sensor.

A. *Cluster and single detection*

1) LiDAR

Simulated LiDARs in SCANeR Studio 1.7 return a matrix of all distances measured by each programmed beam including: obstacles: vehicles as well as roads and signalization sign. For the environment set in this simulation and to minimize the data processing task, a 375-beam configuration has been chosen. It corresponds to a matrix of 15 rows and 75 columns, each beam separated by 3 degrees. This configuration ensures best processing performance but shows less accurate detections at long distance where beams are widely separate, increasing the detected position error. Two lidars, face to face, are monitoring each intersection as represented in Fig. 1. All measures returned are perfect.

In the context of a static LiDAR placed at a known position, detecting new object C_{L} in the environment can be made by taking a capture of the empty intersection C_{Ref} and comparing each new capture C_{c} with this reference (capture).

$$C_{\mathrm{L}} = C_c - C_{\mathrm{Ref}} \tag{1}$$

This method works well in a simulated environment with a few possibilities of noise due to uncontrolled elements appearing in the scenario. Thus, to reduce these possibilities, a filter is required. In this case, where this problem is not specifically approached, a simple two-bound threshold is applied to guarantee that all detected objects may correspond to vehicles. From the resulting matrix C_{L}, we can retrieve clusters of active beams corresponding to detected obstacles. The isolation of each of these clusters, in each column of a new matrix SC_{L}, allows the inference of listing spatial points forming each cluster. Hence, each cluster can be assimilated to a single center of gravity and its possible dimensions in final LiDAR detection matrix D_{L}.

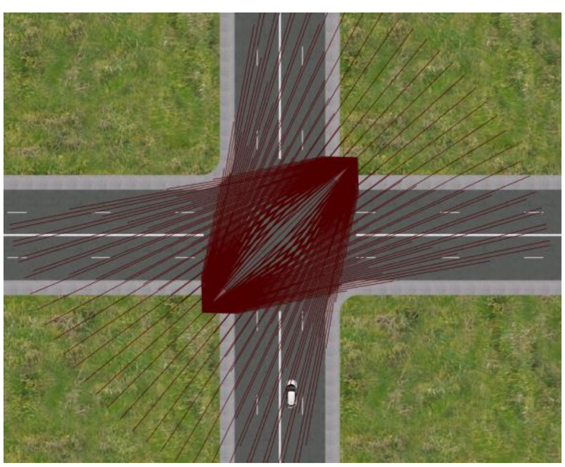

Figure 1. LiDARs field of view.

$$Pos_i = \begin{bmatrix} x_i \\ y_i \\ z_i \end{bmatrix} = \begin{bmatrix} \overline{x}_{SC_L,i} \\ \overline{y}_{SC_L,i} \\ \overline{z}_{SC_L,i} \end{bmatrix} \tag{2}$$

for $i \in [0, \text{nb cluster}]$

$$Dim_i = \begin{bmatrix} S_{X_i} \\ S_{Y_i} \\ S_{Z_i} \end{bmatrix} = \begin{bmatrix} Max(x_{SC_L,i}) - X_i \\ Max(y_{SC_L,i}) - Y_i \\ Max(z_{SC_L,i}) - Z_i \end{bmatrix} \tag{3}$$

$$D_{L,i} = \begin{bmatrix} Pos_i \\ Dim_i \end{bmatrix} \tag{4}$$

Where $x_{\mathrm{SCL},i}$, $y_{\mathrm{SCL},i}$ and $z_{\mathrm{SCL},i}$ are the coordinates of each point belonging to cluster i, respectively.

2) DSRC

Data returned by the DSRC correspond to position, speed and acceleration of connected vehicles. From this, a simple noise µ corresponding to GPS error (set to five meters) is applied to the perfect position returned by the system [10].

$$D_{\mathrm{DSRC},j} = \begin{bmatrix} Pos_j \\ v_j \\ a_j \end{bmatrix} + \mu \tag{5}$$

for $j \in [0, \text{nb connected vehicle}]$

$$\text{with } Pos_j = \begin{bmatrix} x_j \\ y_j \\ z_j \end{bmatrix} \text{ and } \mu = \aleph(0, P) \tag{6}$$

where Pos_j corresponds to the coordinates of the connected vehicle j, v_j to its speed and a_j to its acceleration. Lastly, μ represents a white Gaussian noise with a covariance P corresponding to the GPS location error.

For synchronization purpose, BSMs are supposed to be all send at the same time and queued by the nearest intersections in communication range. Target intersection will then be able to build the current vehicle situation according to this input.

3) Intersection data

Intersection data depend on the result of the data fusion of all providing sources. Once this data fusion gives the current result, obstacles are located within the intersection and if some of them are flagged as leaving at a specific exit, then last fused data F_l are sent to the corresponding intersection.

$$F_l = \begin{bmatrix} Pos_l \\ v_l \\ a_l \end{bmatrix} \quad (7)$$

$$\text{for } l \in [0, \text{nb leaving object}]$$

Where Pos_l correspond to the fused coordinate of leaving object l, v_l to its last registered speed and a_l to its last registered acceleration.

The broadcasted data corresponds to the set of objects leaving the intersection at the specific exit. It mainly contains the moment of exit and, if available, the speed and acceleration of the object. This last data may not be accessible in the case of a non-connected vehicle, as no tracking is implemented for objects detected by LiDARs.

Upon reception of any intersection data, the target intersection is expected to resort to a prediction model of the listed vehicles possibly incoming. At this stage, each intersection knows the position of each connected intersection, the configuration of the road section in between (topology and speed limit) and the last position and possible speed and acceleration of the departing object are known by the target intersection.

For this simple scenario, the prediction part of a simple Kalman Filter is applied. In order to do so, the linearization of the vehicle dynamic is done by projecting the three Cartesian position coordinates to a single straight road between both involved intersections. In the case of this particular scenario topology, reducing the location to a one-dimensional problem (represented by variable d_k) is made by a compelling projection corresponding to the Manhattan distance (8) between the two involved intersections (with target intersection as origin).

$$d_0 = proj(Pos_l) \quad (8)$$

This projection gives a rather good estimate of the position of the vehicle during time but rests on the need of a mapping table. Then, the prediction part of the Kalman filter is applied with all known data.

$$\begin{cases} d_k = d_{k-1} + \Delta t \times v_{k-1} + \dfrac{\Delta t^2}{2} \times a_k \\ v_k = v_{k-1} + \Delta t \times a_k \end{cases} \quad (9)$$

Where d_k corresponds to the distance remaining to the next intersection (based on the projection of the coordinate), v_k corresponds to the predicted speed of the vehicle and a_k to its acceleration. With the state vector being $X_k = \begin{bmatrix} d_k & v_k \end{bmatrix}^T$ with $X_0 = \begin{bmatrix} d_0 & v_l \end{bmatrix}^T$, we deduce the model, as follows:

$$X_k = F_k \times X_{k-1} + B_k \times U_k \quad (10)$$

with $F_k = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$ as the state transition matrix and the control part corresponding to the acceleration influence and defined as follows:

$$U_k = \begin{cases} 0 & \text{if } v_{k-1} = \text{speed limit} \\ a_l & \text{otherwise} \end{cases} \quad (11)$$

$$B_k = \begin{bmatrix} \dfrac{\Delta t^2}{2} \\ \Delta t \end{bmatrix} \quad (12)$$

In (11), the acceleration is assumed to be constant until speed limit is reached. This acceleration corresponds to the last acceleration measured for the leaving vehicle a_l.

The prediction part of the covariance matrix P_k according to the Kalman filter is then defined as:

$$P_k = F_k \times P_{k-1} \times F_k + Q_k \quad (13)$$

$$\text{with } P_0 = 10^{-6}.diag(2) \quad (14)$$

$$\text{and } Qk = \begin{bmatrix} \Delta t^2 & \dfrac{\Delta t^3}{2} \\ \dfrac{\Delta t^3}{2} & \dfrac{\Delta t^4}{4} \end{bmatrix} \quad (15)$$

Where Q_k corresponds to the covariance matrix of the acceleration influence. Such that the final prediction model corresponds to:

$$\begin{cases} X_k = F_k \times X_{k-1} + B_k \times U_k \\ P_k = F_k \times P_{k-1} \times F_k + Q_k \end{cases} \quad (16)$$

For every returned state vector X_k, it is possible to infer to the corresponding d_k to the actual Cartesian position thanks to the projection table.

B. *Data fusion*

Data fusion is applied on three nodes, as in Fig. 2:

- Between data from both LiDARs
- Between data from LiDAR and intersection data (IT Data)
- Between previous fused data and DSRC

All three of these data fusion correspond to a data association processed with a method inspired from the covariance intersection method [11]. The principle is to get both the set of position and covariance matrix measured or predicted in detection methods above and trying to find the best match between each sensor to fuse. Covariance Intersection method states that:

$$P_{pf}^{-1} = w_1 \times P_{p_1}^{-1} + w_2 \times P_{p_2}^{-1} \quad (17)$$

$$Pos_f = P_{pf} \times (w_1 \times P_{p_1}^{-1} \times Pos_1 + w_2 \times P_{p_2}^{-1} \times Pos_2) \quad (18)$$

Where Pos_i corresponds to the Cartesian position of considered points and P_{p_i} corresponds to the covariance matrix associated to Pos_i. All position measures are made relative to the center of the intersection processing the vehicle detected. The optimization problem, where w_k must be computed, is not of interest in this situation. More simply, this same variable is estimated (19) with each covariance matrix from sensors to fuse (P_{p_1} and P_{p_2}) and then the fused position (Pos_f) and covariance matrix (P_{pf}) are determined and compared to both initial positions (Pos_1 and Pos_2) to

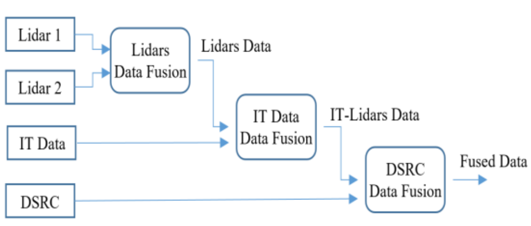

Figure 2. Data Fusion Scheme.

assess possibility of matching.

$$\frac{w_1}{w_2} = \frac{m_1}{m_2} = \alpha \quad (19)$$

with $m_k = Max(P_k(i, j))$

$$\text{And } w_1 + w_2 = 1 \text{ so } w_2 = \frac{1}{1+\alpha} \quad (20)$$

$$\begin{cases} dist(Pos_f, Pos_1) < m_1 \\ dist(Pos_f, Pos_2) < m_2 \end{cases} \Rightarrow S = \{Pos_f\} \quad (21)$$

Where $dist(Pos_f, Pos_k)$ corresponds to the Euclidean distance between the two position vectors and S corresponds to the set of all fused position vector verifying the condition in (19).

An area estimation of each matching possibility ($A(S(l))$) is then calculated and the wider area is retained as best match (BM).

$$BM = S(k) = Pos_{f,k} \quad (22)$$

$$\text{where } A(S(k)) = Max(A(S)) \quad (23)$$

$$\text{and } A(S(l)) = \pi \times \prod P_{f,l}(i,i) \quad (24)$$

It is to be noted that each captured data frame is considered independent of the others. For this purpose, no tracking was implemented during active detection of mobile entities, except when the detected vehicle was considered as leaving the intersection. Region-based comparisons grant this distinction and trigger a tracking process where a Kalman Filter is used to follow leaving vehicles.

IV. EXPERIMENT AND RESULTS

This section depicts the configuration of the scenarios built to tests this system, the experiments conducted, and the results obtained.

A. *System presentation*

For the purpose of this article, a simulated environment has been built using the vehicular simulator SCANeR Studio from AVSimulation. This environment consists of a succession of three intelligent intersections highlighted in Fig. 3. While all these intelligent intersections are equipped with sensors, we focus the study on the intersection in the middle. The other intelligent intersections are assumed to host perfect sensors and only their detection outputs are sent to the monitored intersection.

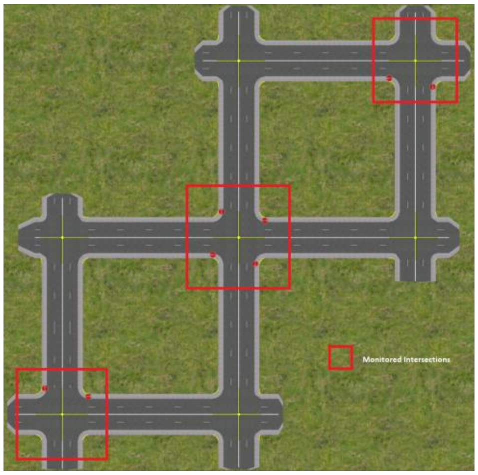

Figure 3. Simulated environment with monitored intersections highlighted.

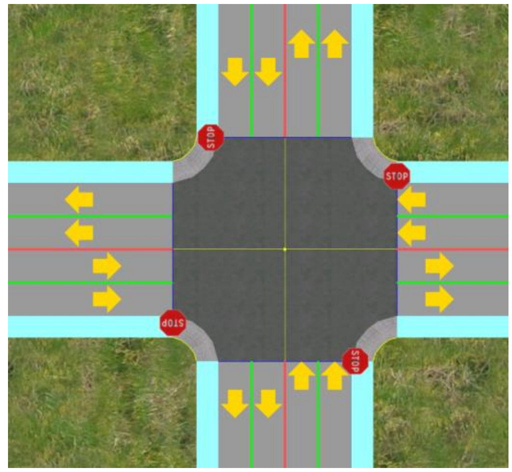

Figure 4. DSRC Entries and exits of each intersection.

This simulated topography is based on the modern representation of urban road network with a Manhattan grid network. It also allows easier distance calculation when needed. However, the vehicle flow is limited to few vehicles compared to real urban scenarios where hundreds of vehicles may be present. This scenario will be used as an early stage of the concept introduced.

All three of these intersections are identical and composed of four pairs of entries/exists following two axes, as shown in Fig. 4: north-south and east-west. Each of these entries is marked by a stop sign and contains two lanes: left lane allows only left turn while right lane allows all remaining other directions.

The scenario also contains four vehicles of different dimensions driving within the intersections and following a specific pre-defined path assigned to each of them.

For the processing part of each intersection, control models have been implemented externally to compute all exchanged data. Simulated environment and control models communicate through UDP and are synchronized so that reaction models depend on the vehicular simulator outputs. In this regard, these models are configured to ran at a faster rate than the simulator to efficiently process all data in due time.

The physical platform is currently only composed of a Windows 10 computer running SCANeR Studio version 1.7. But this system has been thought so that it can be implemented on a real-time platform to perform Software-In-The-Loop (SIL) based validation. Indeed, data exchange through UDP allows the communication with any external devices such as, for example, a real-time platform from Opal-RT Technologies. This would allow easy handling of any synchronization matter within the platform and ensures the access to greater computing resources for more complex systems.

B. Experiments details

Two main experiments will be realized to attest the performances of this system. First, the contributions of the new system will be observed through the comparison of the result of the data fusion with IT Data and with the initial output of the lidars data fusion.

Second, as the main sensors are LiDARs and DSRC, the number of connected vehicles may have some effect on the performance of the system. For that reason, four scenarios are considered in Table 1.

These scenarios can relate to the evolution of the vehicle population with time (DSRC penetration ratio), following the progress of the automotive industry. And, as a matter of fact, may show the relevance of the proposed system.

Performance factors will correspond to the influence of the intersection data on the detection of vehicles entering the new intersection. For this analysis, comparison factors correspond to:

- Position error of the detected vehicle compared to its true position;
- Data covariance ratio between results of data fusion with and without Intersection Data.

TABLE I. LIST OF SCENARIOS

#	Scenarios
A	Only connected vehicles
B	Number of connected vehicles greater than 50%
C	50% of connected vehicles
D	Number of connected vehicles lesser than 50%

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Three minutes long scenarios corresponding to the ones described in Table 1, are monitored. Each of these scenarios presents eleven intersection crosses by vehicles from the simulation, nine of them announced by other intersections. Details about detections made in main intersection are registered at each time and saved for processing, for a total of 12 GB of data. Next section presents a condensed study of this data, depending on the comparison factors chosen.

C. Results and discussions

From the first experiment, two graphics are generated. Fig. 5 presents the distance error between the real position of the vehicle and the detected position. Values from the result of IT-LiDARs data fusion are compared with LiDARs fusion. This measure is limited to each time that a fusion is operated with an IT Data and then occurred only when a vehicle from another intersection is coming in range of the target intersection.

Fig. 5 shows that the fusion with IT Data tends to move detections away from their true position with some extreme cases as for the third successful fusion attempt where the resulting fusion comes from two separated vehicles detected by each sensors with a covariance large enough for the data fusion algorithm to consider it possible. However, the average distance error of the IT-LiDARs fusion results (counting the wrong fusion) remains around ten meters, still corresponding to a standard GPS error.

On the other hand, Fig. 6 shows the ratio of covariance for the same detections as before, comparing results from the LiDARs fusion and results from IT-LiDARs fusion. It shows that in second case, the covariance is reduced in average by approximatively thirty percent. This implies a better precision of the detection even with a bigger distance error to the real position. The fusion error specified earlier can also be observed in this new graphic where the covariance ratio exceed one in value. Furthermore, another exceeding value can be observed which also corresponds to a fusion error. This gives hint of improvement for the algorithm.

The second experiment focuses more on the study of the impact on the system of communicating vehicles. From it, we obtain both boxplots diagram in Fig. 7 and 8. In this case, all detections are considered, and pertinent data are summarized in presented graphs.

Fig. 7 presents the distance errors between detected and real position of vehicles for each scenario described in Table 1. And Fig. 8 details the covariance ratio between the scenarios with IT Data and the ones without it. Results obtained allow to confirm the ones obtained in the previous experiment: slight distance shift of the detection position and better covariance ratio. Also, what is more interesting to notice here is the relative absence of changes between the

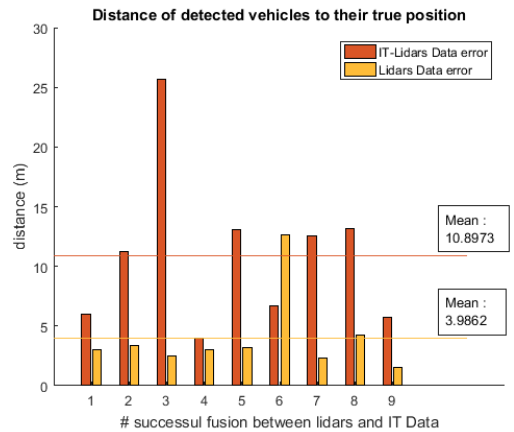

Figure 5. Distance error between detections and real position.

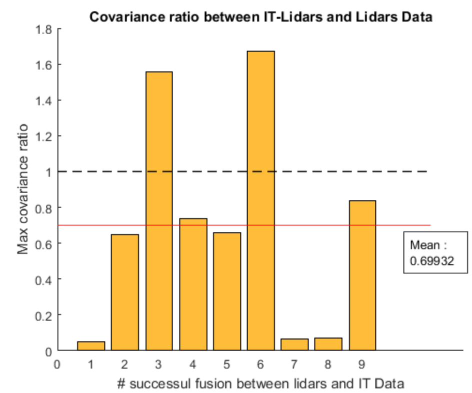

Figure 6. Covariance ratio between IT-LiDARs and LiDARs Data.

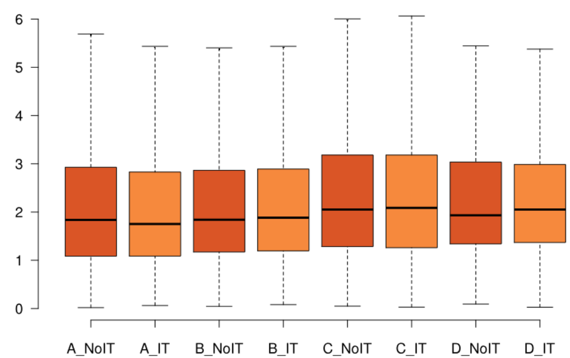

Figure 7. Distance errors between detected and real vehicles for each described scenarios – with and without Intersection Data.

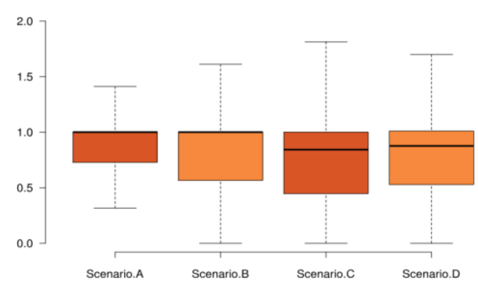

Figure 8. Covariance ratio between results with Intersection Data and without for each scenarios.

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different scenarios. From this observation, we can conclude that the system is quite robust against the variation of communicating vehicles and allow to perform a relatively more precise detection of all vehicles in the vicinity of the intersection.

The scenario presented for this system is simple and does not take into consideration all variations that may happen in most real-life scenario: vehicles driving through the road network may leave at any moment without any warnings, stop in a place between two intersections or even face any sort of possible obstacles that may slow down its progression. All those possible outcomes will have an impact on the system, resulting in the loss of the data gathered about this vehicle or its mix with other data from another vehicle circulating on the same road sections. The first case does not represent much trouble as following detection of the vehicle will only be considered as new. However, the second case might lead to some data mismatch which may affect the detected behavior of vehicles on some road sections between intersections. The comparison of the results obtained in these simulations with the data from real-life scenarios is of great interest and will be the topic of a future work. It is to be noted that some adjustments may be needed to guarantee that the vehicular simulator can handle further vehicle loads in order to match more realistic urban scenarios.

V. CONCLUSION AND FUTURE WORK

Among all the assumptions made in this work, communications are considered perfect which surely affect positively the results presented. A more realistic simulation should involve more realistic communication models. That's why it would be necessary to switch to a later version of the vehicular simulator used or even add an intermediary software specialized in communications and include DSRC to enhance the current model.

Detection algorithms used in this work lacks optimization. The covariance intersection method implemented searches only for a possible fusion result and elect the best choice based on the largest common covariance area between two detections. Better adjustments could be made to enhance the potential of this data fusion and reduce the covariance factors of detections.

On a similar thought, the Kalman prediction performed to follow vehicles between intersections is also open to better performances. Some pre-study of typical vehicle dynamic evolution could be used to set a speed profile for better anticipation. This could contribute to real improvement of the results gathered in this work and lead to an acceleration of the detection.

Also, other type of sensors and data fusion methods will be applied to guarantee good results of the introduced concept. This analysis will be introduced as soon as scenarios with heavier vehicle load will be implemented for closer fidelity to urban scenario.

To conclude, the work presented in this article introduces a different handling of the data gathered by intelligent road infrastructures in urban area. The recycling of old detection data towards the whole intersection network was presented as a mean of preparation for smart cities to welcome intelligent and automated driving vehicles among other vehicles. Results presented have demonstrated that the system is effective with no regards to the number of communicating vehicles present. It still needs to be improved but already has some interesting outputs when applied to the discussed scenarios.

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