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***Abstract*—Connected vehicles are equipped with sensors that can detect surrounding objects. However, vehicles perception is limited by sensors range or by the presence of other obstacles. Collective perception can improve vehicles perception by allowing them to exchange information about detected obstacles. In this context, vehicles rely on on-board sensors in order to generate Collective Perception Messages (CPM) that are exchanged by means of LTE-V2X connectivity. In order to reveal hidden obstacles and obtain a coherent visualization about the environment, CPM fusion is then crucial. In this work, we propose a novel low complexity fusion algorithm for CPM. Moreover, we evaluate the impact of LTE-V2X connectivity performance, specially in terms of packets loss, on the fusion. Simulation results in a smart junction demonstrate the relevance and efficiency of our algorithm in terms of obstacles detection capabilities.**

***Keywords*—Collective Perception Message, Fusion Algorithm, Cooperative Collision Avoidance, LTE-V2X.**

I. Introduction

Nowadays, vehicle accidents increase drastically, specially on road intersections (60 % of accidents occur at intersections). This is due to several factors, mainly the obstructed view of vehicles and the limited perception capabilities, which can influence negatively the road safety and driving efficiency. Connected vehicles can improve their perception capabilities by exchanging traffic safety messages including sensor information via wireless technologies (ITS-G5 [1] and LTE-V2X [2]). This is known as collective perception which consists of the exchange of messages between vehicles and/or Road Side Units (RSUs) in order to reveal any hidden obstacles. More precisely, ETSI Technical committee [3] has designed Collective Perception Messages (CPM) that allow vehicles to exchange information about detected obstacles. ETSI standard describes then the generation rules of CPM messages while taking into account detection capabilities and wireless connectivity performance.

In this work, we propose a fusion algorithm for CPMs that contain a list of obstacles with their corresponding information such as: speed, position, heading, type, etc. More specifically, we consider the scenario where vehicles transmit CPMs to a fusion center via LTE-V2X connectivity. The latter will perform the proposed fusion algorithm in order to generate a merged CPM, that will be broadcast to all vehicles in range. The fusion of CPMs obstacles is important in order to maximize perception gains and obstacles detection capabilities. Several studies have tackled the problem of merging sensor data information. In [4], a fusion architecture for a cooperative perception system is proposed. The architecture solves the problem of correlated data by dividing the fusion into a local and a global part. Authors in [5] have studied the concept of cooperative perception via communication of localization and perception information between vehicles and infrastructure. This work compares three variants of the Covariance Intersection (CI) method used for state fusion in an Inter Vehicle Information-Fusion (IV-IF) System. The goal is to figure out which CI method out of the selection is the best choice for an active road safety application. In [6], authors propose a sensor data fusion architecture for emergency stop assistance. In this work, authors aim at simplifying the fusion process for an automotive application. The work in [7] presents an approach for 360 degree multi sensors fusion for static and dynamic obstacles. Obstacles perception is achieved by combining the object tracking and occupancy maps generated by each vehicle. In [8], authors propose a perception framework for merging information from on-board sensors and data received via CPM. For each vehicle, occupancy grids are calculated from sensor measurements and then merged in terms of occupancy and confidence. In [9], authors evaluate the impact of LTE-V2X connectivity performance on the fusion of local occupancy maps. Moreover, a study was conducted in order to define the best compromises between the physical layer configuration, occupancy maps resolution, message periodicity, and obstacle detection capabilities.

Among the before mentioned papers, few papers have considered the impact of the connectivity, specially in terms of packets loss, on sensor data fusion. None of these papers have considered a fusion algorithm that can analyze received CPMs according to the standardized generation rules. The occupancy maps impose the use of large packets and thus high Modulation Code Schemes (MCS) [9], which may affect the connectivity performance. Besides, the fusion of local occupancy maps proposed in [8] may induce computation complexity. Thus, in order to enhance V2X connectivity performance compared to [9] and reduce the fusion algorithm complexity in comparison with [8], we propose a low complexity fusion algorithm that can process CPM according to the ETSI generation rules, while taking into account the impact of V2X connectivity on the CPM fusion.

The remainder of this paper is structured as follows: in section II, we introduce the system setup. In section III, we present our proposed CPM fusion algorithm. We dedicate section IV to present the system evaluation and discussions. Finally, we conclude our paper in section V.

II. System Model

In this work, a road intersection scenario has been considered, where vehicles can generate CPM according to ETSI generation rules explained in section II-B. CPMs are transmitted to a RSU that takes the role of the fusion center. It is to be noted that the RSU is chosen as a fusion center entity because it is encountered with storage and computation capacity that allow the fusion process. Moreover, fusion capabilities can be performed by vehicles (on-board fusion), however in this study, the RSU is considered as fusion center because of its privileged position in the near center of the intersection which facilitates communication links. The fusion center will gather all successfully received CPMs and process them in order to generate a merged CPM that contains an exhaustive list of obstacles that are present in a certain region of interest at iteration t. The merged CPM is then broadcast, every $T_{CPM} = 100ms$, to all vehicles to inform them of all obstacles within the intersection (vehicles, vulnerable users, etc.). The objective being to announce a risk of collision or reveal hidden obstacles. In order to simulate this scenario, we consider a simulation framework (Fig. 1) that consists of four module:

- Physical mobility module: models realistic road traffic of a real-life urban intersection using Simulation of Urban Mobility (SUMO).
- V2X connectivity module: NS-3 [10] simulation of messages exchange between vehicles and fusion center, via LTE-V2X connectivity, based on mobility traces generated in SUMO. Details about LTE-V2X standard and simulation setup are explained in [9].
- CPM generation module: generates CPMs (following ETSI generation rules), based on Lidar sensor model.
- CPM fusion module: the local generated CPMs will be gathered by the fusion center while taking into account V2X connectivity. The fusion center executes the fusion algorithm then as explained in details in section III.

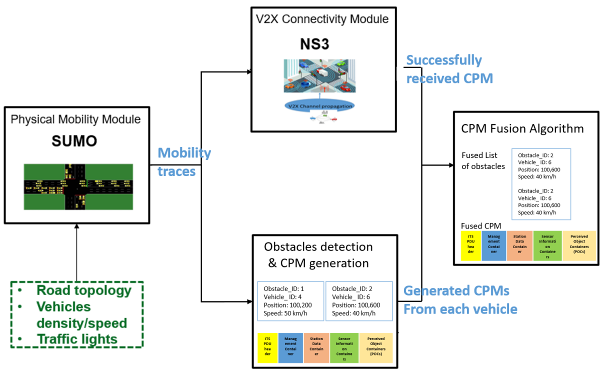


Fig. 1. Simulation modules and the interaction among them.

A. CPM Structure

According to ETSI standard [3], CPM messages (Fig. 2) include an Intelligent Transport Systems Protocol Data Unit (ITS PDU) header and 4 containers: Management Container, Station Data Container, Sensor Information Containers (SICs), and Perceived Object Containers (POCs). The ITS PDU header includes data such as the message ID and the vehicle ID. The Management Container is mandatory and provides basic information such as the position of the transmitting vehicle. SIC is optional and includes additional information about the transmitting vehicle (e.g. its speed, heading, etc.). Finally, the POCs provide information about the detected obstacles; their speed and dimensions.

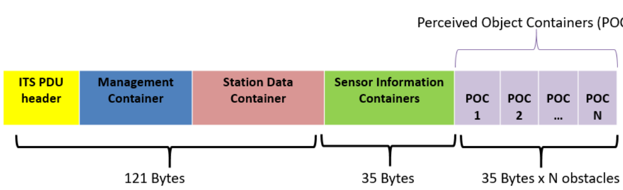


Fig. 2. CPM message structure.

B. CPM Generation Rules

CPM generation rules, standardized by ETSI, define when vehicles should transmit a CPM, and what is the information, i.e. the list of obstacles and sensors information, that should be included in a CPM. Two generation rules have been considered: the periodic and dynamic rules. First, the periodic method, which is a reference method, is used to compare with other policies. It indicates that CPMs are generated every T_{CPM} and they include all the detected objects. The CPM should be transmitted even if no objects are detected. With the dynamic generation rule, the transmitting vehicle checks every T_{CPM} if the environment has changed in order to transmit a new CPM. More precisely, a vehicle generates a new CPM if it has detected a new object, or any of the following conditions are satisfied for any of the previously detected obstacles:

1) The obstacle's absolute position has changed by more than 4 meters (m) since the last time (T_{update}) it was included in a CPM.
2) The obstacle's absolute speed has changed by more than 0.5m/s since the last T_{update}.
3) The last time the object was included in a CPM was 1 second ago ($T_{update} > 1$ sec).
4) The obstacle is classified as Vulnerable Road User (VRU) or an animal.

C. Obstacles Detection

In this work, in order to determine the list of obstacles detected by vehicles, LiDARs sensors model is implemented in Matlab® relying on *measurement* and *beam sensor* models. For the measurement model, the measurements collection is defined based on the sensor range, azimuth angle and frequency cycle. The measurement output corresponds to a set of pairs (distance; angle). The beam sensor model is represented by probabilistic curves that compute the probability of existence/absence of obstacles in each beam direction. For more details about the sensor model, readers may refer to [11]. Based on these models, we cluster the occupied cells (cells with high occupancy probability values) into objects, according to the DBSCAN algorithm. From the clustered cells, an estimation of the surrounding objects is achieved, extracting also different characteristics such as: position, velocity, type, etc.

III. CPM Fusion Algorithm

In this section, we present the proposed CPM fusion algorithm which is illustrated in Fig. 3.
According to this algorithm, at each time iteration t, the fusion center executes the following steps, in order to generate a temporary list of obstacles List_Obstacles_Temp(t) (LOT(t)). This list is analyzed in order to generate a final list of obstacles that should be integrated in the merged CPM. Every T_{CPM}, the fusion center gathers successfully received CPM (as indicated by NS-3 traces files) in order to generate a merged CPM. CPM fusion proceeds as follows:

- First, the fusion center checks if the received CPM includes new obstacles. More precisely, a CPM includes a tuple $(vehicle_{ID}, obstacle_{ID})$, if this tuple is not included in the LOT(t-1), then the obstacle is considered to be new.
- Second, the fusion center checks if already existent obstacles in LOT(t-1) are updated. An already existent obstacle is defined as an obstacle with the tuple $(vehicle_{ID}, obstacle_{ID})$ included in LOT(t-1). In this case, the fusion center updates the obstacle information.
- If there is remaining obstacles in LOT(t-1) that are not updated or processed, the fusion center will check if $T_{update} \leq 1sec$, and include the obstacles in LOT(t) without changing T_{update} nor the obstacles information.

In case of no received CPMs at t, the fusion center will search for already existent obstacles in LOT(t-1). If this list is not empty, the fusion center adds only obstacles with $T_{update} \leq 1sec$ to LOT(t).
The final step of the fusion algorithm consists of processing the LOT(t) in order to define the final list included in the PoCs of the merged CPM. This is achieved following these steps:

- The first step consists of merging obstacles with close positions. Given two obstacles in LOT(t), one can calculate

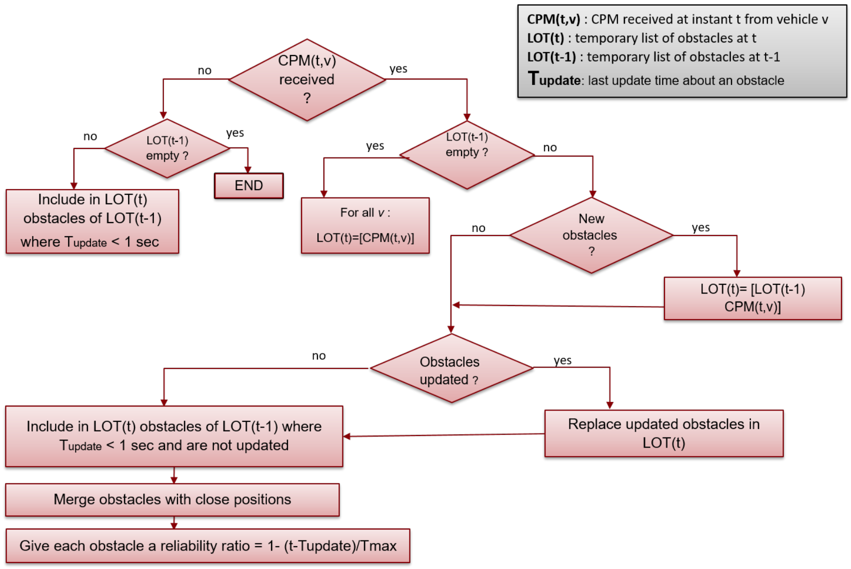


Fig. 3. CPM fusion algorithm

the best objects association by computing the difference between their positions and checking if it is lower than a predefined threshold.
An important challenge appears when handling ambiguous cases. For example, in case two different trajectories followed by two vehicles intersect and/or get close enough, this leads to suggest a merging erroneously. In this case, using only the distance between the current object observations may not be sufficient, and may lead to wrong associations. To overcome this, we consider that the detected obstacles in the final list will be assigned an identifier merged_obstacle_id. Each tuple in LOT(t) is associated to the corresponding merged_obstacle_id. This will avoid merging tuples corresponding to different merged_obstacle_id. Concerning new obstacles in LOT(t), the association is done based on the position only.

- Second, by giving identified obstacles a reliability value: $\beta = 1 - \frac{(t-T_{update})}{T_{max}}$; where T_{max} is a design parameter defining the maximum valid object age before it is discarded ($T_{max} = 1sec$). This is achieved in order to let vehicles know about the possibility of finding an obstacle in a certain position at time t.

This algorithm is simple to deploy and presents low costs in terms of run time and processing. Compared to the work proposed in [8], extracting the list of obstacles then calculating occupancy maps is more time consuming. Moreover, the fusion algorithm based on the occupancy map is complex (iterative fusion pixel per pixel). In addition, the interpretation of a merged occupancy map to generate the global CPM adds more time processing to the fusion algorithm and may induce obstacle misdetection specially for ambiguous cases where it is difficult to extract obstacles type or distinguish two close obstacles.

IV. Performance evaluation

A. Simulation Scenario

We consider a real intersection of two main streets located in Lyon (France). Each street is four lanes wide, with two lanes in each direction. This intersection constitutes the center of a 400m x 400m area. The RSU, placed at the north-west corner of the intersection, plays the role of the fusion center. Simulated vehicles can reach a maximum speed of 50 km/h. In Matlab®, we setup a 2D LiDAR with a horizontal field of view of 110^o (azimuth aperture) for all equipped vehicles. The complete setup of LiDAR sensors can be found in [11].
For each considered scenario, we run 10 NS-3 simulations with a duration of 60 seconds each.

1) Packets size: According to the dynamic generation rule policy, CPMs present variable size based on the number of obstacles included in the PoCs and other containers included in the CPM. In this work, containers are included in CPMs according to ETSI dynamic generation rule. Containers size are calculated in [3]. Moreover, concerning packets headers, due to the use of PC5 mode 4, we are considering MAC, RLC and PDCP layers headers with a respective size of 10, 3 and 2 Bytes; this gives an overhead of 15 Bytes to CPM packets. We note that, the physical layer configuration, specially MCS, varies according to CPM packet size. In this work, physical layer configurations are based on [12].

B. Key Performance Indicators (KPIs)

The Packet Deliver Ratio of Vehicle to Infrastructure (PDR V2I) is calculated. First PDR (denoted by PDR UL for simplicity) assesses the communication link from vehicles to RSU to evaluate its capacity to collect CPMs from the vehicles. Second, the communication link from RSU to vehicles (DL) evaluates the capacity of the RSU to share CPMs with all the vehicles in the intersection. PDR in UL is defined as the ratio between the number of packets received by the RSU and the number of packets sent by the vehicles. The PDR in DL is the number of vehicles actually receiving a packet over the total number of active vehicles in the intersection for each transmission from the RSU. The second KPI is the Obstacle Misdetection Ratio (OMR), that accounts the number of misdetected obstacles compared to the real scenario. An obstacle is considered as misdetected if it is missing compared to the real scenario or whenever the difference between the detection position and the real obstacle position is higher than a predefined threshold Th.

C. Evaluation Methodology

In order to demonstrate the efficiency of the proposed fusion algorithm, we compare the following scenarios: 1) Dynamic generation rule with perfect connectivity and V2X connectivity, i.e, in this scenario, packets losses induced by V2X connectivity are considered and calculated based on simulated NS-3 traces. 2) Periodic generation rule with perfect connectivity and V2X connectivity. 3) Scenario with local occupancy maps. We consider the work similar to our previous work in [9], where vehicles exchange local occupancy maps of 1685 Bytes packets size every 100 ms. The goal here is to show the impact of using CPMs instead of occupancy maps. To this end, we consider that vehicles send maps to the fusion center. The latter extracts the list of obstacles, performs the fusion and retransmits a merged global occupancy map.

D. Results

1) CPM Generation Analysis: We proceed first by evaluating the CPM frequency (Fig. 4) and CPM periodicity (Fig. 5) using the dynamic generation rule. To this end, we consider three cases of traffic density: low density (20 vehicles), medium density (50 vehicles) and high density (100 vehicles). Fig. 4 demonstrates that the percentage of low CPM frequency increases with the traffic density. Indeed, in case of high vehicle density, the speed will decrease and thus the frequency of changing the position and speed will decrease accordingly. It is to be noticed that the maximum speed is 50 km/h. Thus, the vehicle will detect the change 3.44 times per second in average. However, in this case, we notice that there is a non negligible percentage of vehicles that transmit between 6 and 10 CPM per second. This is the case of vehicles that generate CPM as soon as they detect changes in obstacles position more than 4m. If the detected vehicle is changing its position more than 4m at different times, the vehicle will need to generate different CPMs. This explains the presence of non negligible percentage of 10 Hz in case of high density.
Regarding low and medium densities, we can observe that the percentage of 1 Hz is lower because vehicles will send more messages per second due to high speed. Vehicles satisfy more frequently the conditions of the changing environment (i.e. change in position more than 4m and speed more than 0.5 m/s). Fig. 5 shows that messages are sent in average every of 390 ms in case of 20 vehicles. This period increases to reach 600 ms in case of 100 vehicles. This is correlated with the frequency values in Fig. 4. Fro low vehicle density, messages periodicity will be low because the frequency is high (high percentage of 6 and 7 Hz compared to medium and high densities). However, in case of 100 vehicles, the percentage of 1 Hz is the highest which justifies the average period of 600 ms.

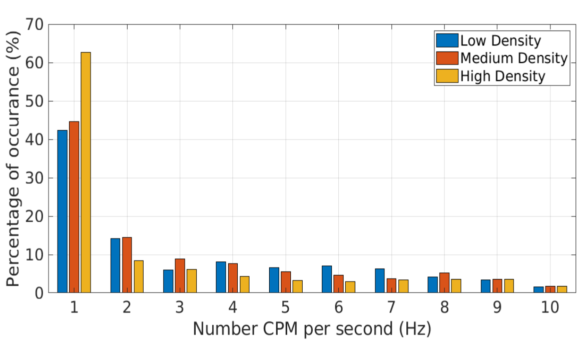


Fig. 4. Occurrence rate of CPMs Frequency

2) Packet Delivery Ratio: As shown in Fig. 6, the PDR decreases with the increase of vehicles density. Moreover, we can notice the gains brought by the dynamic generation rules compared to periodic one. With the dynamic policy, PDR is high even with high vehicles density (91% of PDR for 100 vehicles for the dynamic policy instead of 62% in case of the periodic policy). This is explained by a lower channel load. Indeed, in the dynamic case the average message periodicity for 100 vehicles is 600ms compared to 100 ms for the periodic generation rule. Furthermore, in the periodic scenario, CPM messages include all obstacles which implies an increase in packet size and therefore the use of higher MCS to transmit in 1 TTI. This results in a degradation of the connectivity performance [12]. For the occupancy maps scenario, where packets present larger size compared to CPMs, the probability of loosing packets sent to the RSU (UL) is higher, which may have an impact on the fusion result (PDR decreases from 71% for 10 vehicles to 43% for 100 vehicles). Fig. 6 shows that the PDR in DL is high because the RSU is strategically located in visibility of all the road users. It is noteworthy that, in case of occupancy maps, PDR DL is the lowest because packets sent from RSU to vehicles present a higher packet loss ratio. This may be critical in case of a collision warning.

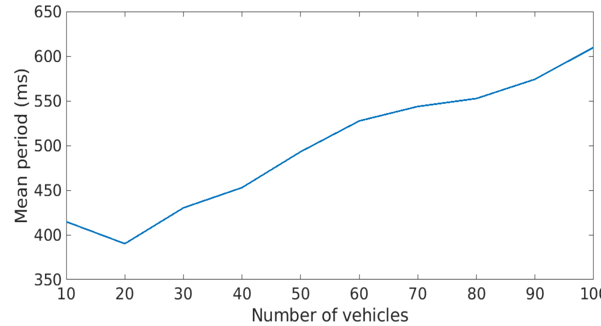


Fig. 5. Mean CPM period

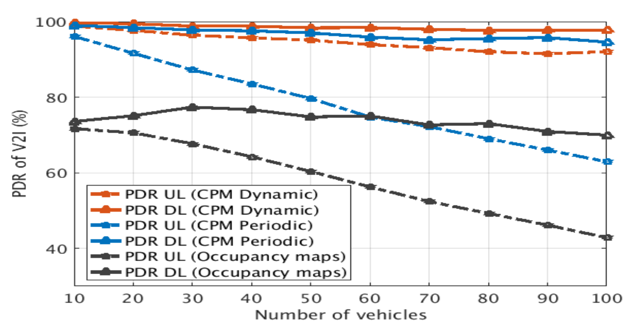
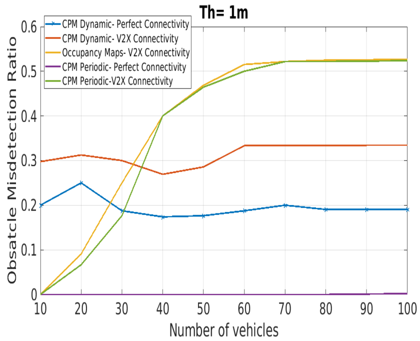
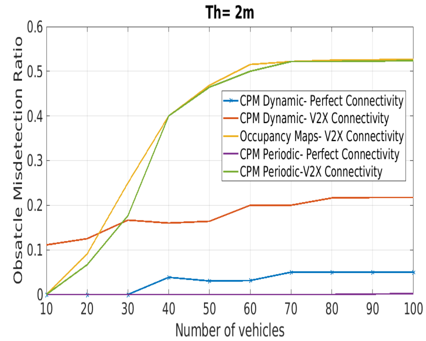


Fig. 6. PDR of V2I communication

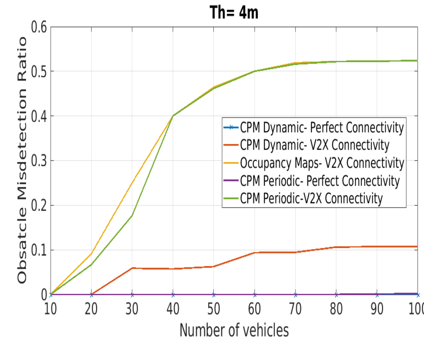
3) Obstacle Misdetection Ratio (OMR): OMR is assessed in order to demonstrate the effectiveness of the proposed algorithm and to show the impact of LTE-V2X connectivity on the merged list of obstacles. Results are illustrated in Fig. 7 for different values of obstacles position error threshold Th. Fig. 7 highlights the fusion algorithm advantages in terms of obstacles detection capabilities. Moreover, compared to the occupancy maps scenario, results confirm that the use of CPMs improves the communication performance and detection capabilities. In fact, the exchange of occupancy maps will impose the use of large packets (1685 Bytes), sent every 100 ms. This may induce packets loss due to high channel load. For the case of periodic scenario with V2X connectivity losses, with low traffic density, OMR is lower than the dynamic policy. In fact, with the periodic generation rules, vehicles are sending CPMs



(a) OMR with $Th = 1m$



(b) OMR with $Th = 2m$



(c) OMR with $Th = 4m$

Fig. 7. OMR as the function of Th: (a) OMR with $Th = 1m$ and (b) OMR with $Th = 2m$ (c) OMR with $Th = 4m$

every $100ms$ and include all detected obstacles. This enhances the detection capabilities. However, with a higher number of vehicles, packets collision is more frequent as confirmed by Fig. 6 where PDR decreases to reach 62 %. This explains the increase of OMR values for higher traffic densities. For the dynamic policy, in case of perfect connectivity, OMR increases by 20 % for $Th = 1m$ compared to the periodic scenario, that is 20 % of obstacles are given with a position shifted by 1m to 2m from their real positions. For $Th = 2m$ (Fig. 7(b)), one can notice that few obstacles are misdetected by more than 2m. Moreover, $Th = 4m$ is considered (Fig. 7(c)) in order to show that the fusion algorithm works correctly. In fact, with the dynamic policy, information about obstacles are included in a CPM each time the obstacle changes its position by 4m or more. Therefore, in case of perfect connectivity, all obstacles should be updated, and no obstacle should be misdetected by more than 4m. Fig. 7(c) shows that OMR in this case is null, which confirms our analysis and highlights the effectiveness of the proposed algorithm. For the dynamic policy with V2X connectivity, the OMR is higher by 10 % than the scenario of perfect connectivity. This is in accordance with the PDR values given in Fig. 6.

4) Position Error: In the following, we will give an idea about the average position error obtained in each case. It is to be noted that this work considers a perfect GPS positioning. Fig. 8 shows that the mean error for dynamic policy with perfect connectivity is close to zero at first, then this error increases with high vehicles density to reach 0.2m due to vision obstruction. For the dynamic policy with loss, the mean error is 1.25m. While for the periodic policy with loss, the error is low at first with low density, since packets losses are low. However, with the increase of traffic density this error increases to reach 3m due to packets losses and PDR decrease.

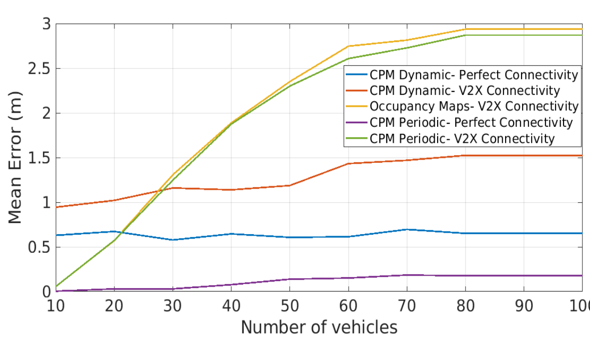


Fig. 8. Position Error

V. Conclusion

In this paper, we have proposed a fusion algorithm that can merge Collective Perception Messages in order to generate a global CPM that contains more reliable information about vehicles environment. The proposed fusion algorithm is simple to implement, with low complexity compared to literature approaches. Moreover, this paper evaluates the impact of LTE-V2X connectivity on the fusion results. Performance evaluation has shown the effectiveness of our fusion algorithm in terms of obstacles detection capabilities. Moreover, this algorithm can cope with packets losses caused by LTE-V2X connectivity performance degradation. In addition, we showed that the use of CPM is more advantageous than occupancy maps in our scenario. As future perspective, we aim at evaluating the integration of more realistic errors in obstacles detection and CPMs fusion.

Acknowledgments

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