Setting up an extended perception in a vehicular network environment: A proof of concept

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***Abstract*— VANETs) that provides a vehicle with data about 1-hop neighboring vehicles. Data provided by this service can be used to support safety applications, such as the efficient selection of forwarders for safety messages and dissemination of early warnings to drivers about potential dangers of the road. This paper discusses the limitations of the beaconing service in providing vehicles with safety-related information. It also proposes a mechanism to let each vehicle have additional information about its surroundings in order to get an extended perception of its environment. This can help in considerably reducing accidents on the roads. Through simulations, we show that the additional overhead caused by the exchange of additional data can be kept low enough to prevent significant impact on overall network performance.**

Keywords— VANET; active safety; global perception; beaconing;

I. INTRODUCTION

Intelligent Transportations Systems (ITS) were introduced to increase the efficiency of transportation systems. The main idea behind ITS is to use emerging technologies, such as sensors and wireless communications to save lives, time and energy. A key component of ITS is vehicular ad-hoc networks (VANETs). These networks make use of Wireless Access for Vehicular Environment architecture (WAVE) [1] to communicate with each other and with the road infrastructure. WAVE defines how vehicles should communicate with each other (vehicle-to-vehicle communications) and with infrastructure equipment (vehicle-to-infrastructure communications) using DSRC (Dedicated Short-Range Communication); a wireless spectrum allocated by the regulator in the 5.850–5.925 GHz band[2].

Vehicular networks are an important research topic that has been around for over a decade. Different protocols and mechanisms were proposed to achieve better network performance or solve different issues related to the harsh VANET environment. Most of those contributions agree on the importance of the beaconing service where each vehicle periodically broadcasts Cooperative Awareness Messages CAM [3] containing information about vehicle position, speed, direction, etc. This information can be readily available for vehicles in range. Indeed, some vehicles embedded a range of sensors to give them some kind of local perception of their environment (LIDARs, cameras, etc.). Beaconing data give data about the surrounding vehicles when no local sensors are available. It also complements and may enhance information about neighboring vehicles when local sensors are available.

The importance of beaconing data ranges from improving application performance (e.g. helping vehicles make better routing decisions) to enhancing road safety (e.g. forward collision warning). The data can also be used to provide other threat alerts. Let us consider a scenario of bad weather where a neighboring vehicle (NV), to our vehicle of interest (VoI), is in range but cannot be seen directly by the driver due to bad visibility. Beacons can serve in such a scenario to warn VoI's driver about any potential danger from NV.

However, beacon messages have their limitations. Indeed, beacon messages can only be received by vehicles in range. In our previous example, when NV is out of range (e.g. 400m away from VoI, and if we have an effective transmission range of 300m), it can present a potential threat (i.e. accident) to VI.

In this paper, we propose to include additional data in beacon messages that can be used to provide threat alerts in scenarios of bad weather or involving threats with low mobility, such as temporary obstacles (construction work on the side of the road, road maintenance, etc.).The remainder of this paper is organized as follows. Section 2 highlights the limitations of the current "classical" beaconing service through some scenarios. Section 3 presents the concept of extended perception of the network and how it can improve safety applications. In Section 4, we present our extended perception scheme that allows vehicles to merge different local maps into an extended perception of the network and select information to be included in local map messages. We finally evaluate the additional overhead through simulations in section 5 and conclude the paper.

II. LIMITATIONS OF BEACONNING SERVICE

Exchanged beacons allow each vehicle to construct a neighbors table to keep track of the evolution of surrounding

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vehicles. Any potential threat detected (sudden change of velocity, very close vehicle, etc.) would trigger a warning signal to the driver and/or to surrounding vehicles. Although the current standard beaconing service is capable of detecting many potential threats in different situations (lane changing, overtaking of a bus or a truck, etc.), it remains insufficient for several other scenarios. In the following, we present two such scenarios.

TABLE I. BEACON MESSAGE FIELDS

Description	Size (in Bytes)
GPS coordinates	12
Time stamp	8
Vehicle speed	2
Vehicle acceleration	2
Vehicle heading	2
Vehicle size (length, width, height)	6
GPS antenna offset (relative XYZ)	4

A. Non DSRC capable vehicles

During the early stages of DSRC deployment, the penetration rate of the technology (i.e. percentage of vehicles on the roads equipped with an On Board Unit to communicate with neighbors using DSRC) will be limited (around 30% during the first four years of deployment) according to the US Department of Transportation[4]. In fact, even if the technology is enforced by law, the DoT expects about 70% penetration rate only after 10 years of the initial deployment.

This limited penetration rate will have an impact on the efficiency of safety applications and services which need beaconing services. In fact, many non-capable DSRC vehicles will be "invisible" to the surrounding cars; they will not be included in the list of neighboring vehicles and therefore cannot be monitored to check whether they pose potential threats.

B. Non DSRC capable vehicles

Vehicular networks use the wireless channel as a shared physical medium for communication. This medium presents, however, several limitations such as limited transmission range, noisy channel, interferences and the presence of obstacles that affect the signal power and the transmission range of beacon messages.

Let us consider the scenario shown both in Fig.1 and Fig.2 reconstructed using the Virage Simulation (VS) [5]; VS is a car driving simulator system with allows to simulate realistic driving environments. In this scenario, VoI is approaching a curve with a reduced visibility due to a natural obstacle (i.e. mountain). As shown in Fig.2, the driver can only see V1 because V1 already reached the curve in the opposite direction of VoI. V2 and V3 are hidden by the mountain. In addition, although the distance between VoI and V3 does not exceed 200m, both vehicles are not in communication range because of the obstacle that reduces the power of transmitted signals between both vehicles. Therefore, the beaconing service cannot help VoI driver perceive any potential danger. If V3 stops or significantly reduces its velocity, VoI will not be aware of the danger until it comes closer to the curve. In fact, the stopping distance for VoI would be:

$$d_{stop\_VOI} = d_{reaction\_VOI} + d_{breaking\_VOI} \tag{1}$$

where:

- $d_{reaction\_VOI}$ is the traveled distance from the moment the driver perceives the danger until the moment he starts breaking; it can be computed follows:

  $$d_{reaction\_VOI} = t_r * v_{VOI} \tag{2}$$

  where t_r is the average driver reaction time when seeing a danger and v_{VOI} is the velocity of VoI.

- $d_{breaking\_VOI}$ is the distance necessary to stop the vehicle after applying the brakes; it can be computed as follows:

  $$d_{breaking\_VOI} = \frac{v_{VOI}^{2}}{2\mu g} \tag{3}$$

  where g=9.8m.s^{-2} is the acceleration of gravity and μ is the friction coefficient between the road and the tires.

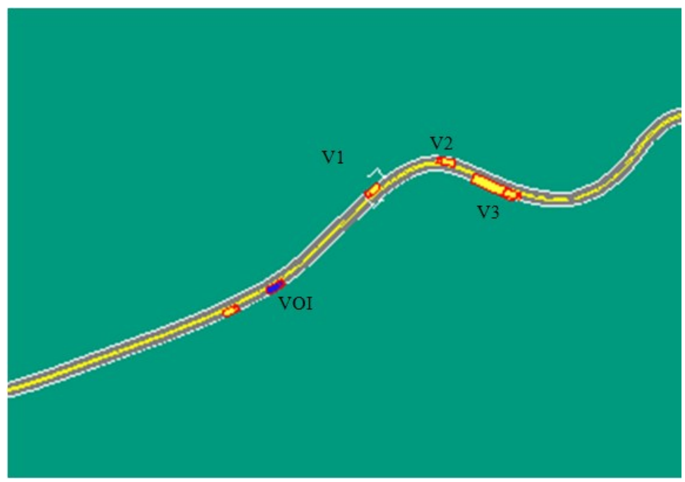


Fig. 1. Obstacle scenario (map)

In optimal conditions (alert driver, dry surface, sufficient tread depth of tires, etc.), t_r equals 0.8s and μ is about 0.8. This makes the minimum braking distance, when the velocity of VoI is 50km/h, equal to around 13m. In real case scenarios, this distance can be much longer depending on the condition of the breaks, the weather, the type of road (roadway or track). Therefore, if VoI is out of range of V_3 until few meters before the turn (due to the mountain), it is very likely that it will run into the stopped vehicle V_3.

In these kinds of scenarios, the driver needs additional data about vehicles that are not in the line of sight and/or are out of transmission range. This data will help him make decisions in time to avoid hazardous situations (e.g. accidents). We believe that an extended perception that allows a vehicle to get information about vehicles which are beyond range is necessary in these kind of conditions (e.g. snow, fog) because it will help the driver to decide, in time, whether to decelerate/brake to avoid possible accidents.

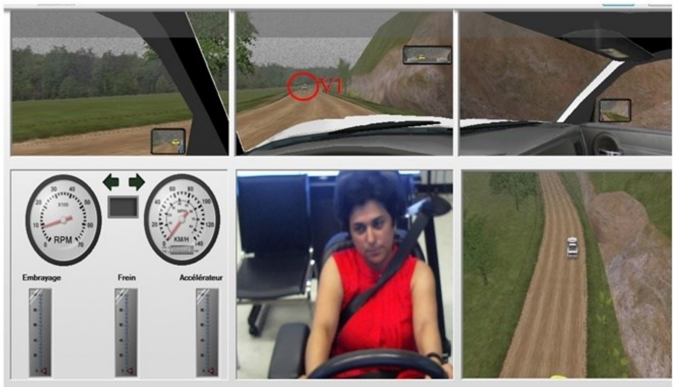


Fig. 2. Obstacle scenario (VOI perception)

III. ENHANCING THE BEACONING SERVICE: FROM LOCAL MAP TO EXTENDED PERCEPTION

The beaconing service relies essentially on GPS data. In fact, all information included in a beacon message (see Table.1) can be determined using a GPS unit and a digital map. However, additional information is available for the vehicle of interest and can be useful for safety applications.

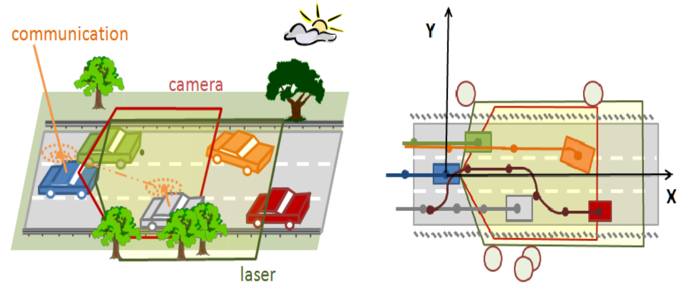
A. Concept of local map

In addition to the GPS unit, some vehicles may embed different sensing equipment such as front/rear cameras, lasers and radars. These equipments are able to provide exteroceptive feedback (e.g. presence of obstacles, surrounding buildings, state of the routes, curves, etc.). Other proprioceptive data about the vehicle can also be collected using embedded sensors. In fact, the number of automotive sensors in a single vehicle has been steadily rising over time. According to the MEMS Journal [6], each vehicle has 60-100 sensors on-board. This number is projected to increase to reach up to 200 sensors measuring a very broad range of parameters, including temperature, humidity, light, pressure, fluid levels, positioning, acceleration, speed, lamp status, oxygen flow and compass direction (geomagnetic).

All of these equipments enable the vehicle to operate as a sensing platform that gathers huge amounts of information, some of it may, however, be redundant and must be processed to generate a local map. After collecting and processing available data to explore redundancies and evaluate the accuracy of measurements, each vehicle in the network is capable of constructing an accurate local perception about its own status and its surrounding environment (Fig. 3).Using this perception, the vehicle is able to detect different dangerous situations (e.g. insufficient inter-vehicle distance) and to alert the driver.

B. Constructing a extended perception

Along with its own perception about its immediate neighborhood, exchanged beacons with 1-hop neighbors give additional information about the surrounding environment. This can be especially useful in situations where the presence of obstacles that reduce the efficiency of exteroceptive data collection (i.e. using a camera to detect the presence of a vehicle). An illustration of this example is shown in Fig. 4 where V_1 is moving right behind a bus. The only way to detect the presence of V_2 on the opposite direction is through exchange of beacons.



(a) scene as perceived by blue vehicle (b) local map of blue vehicle

Fig. 3. Construction of local map

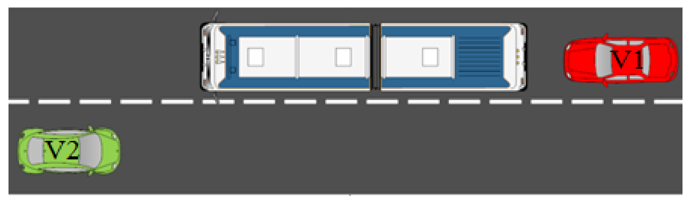
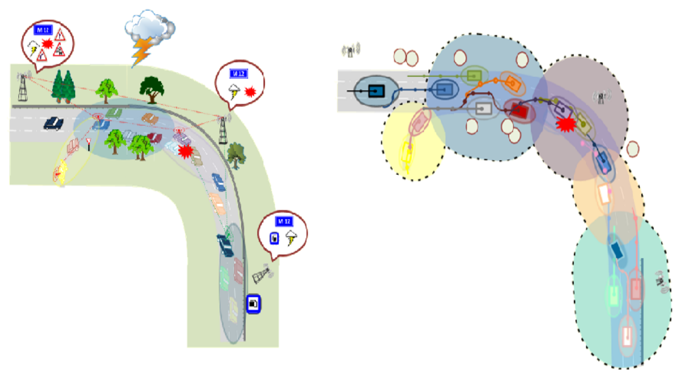


Fig. 4. Blocked view

However, this combination of beaconing service and local maps remains insufficient in many scenarios (see Section II). Available data about surrounding obstacles and one-hop neighbors are not always sufficient and need to be completed by additional information about objects (static or moving) that are beyond the communication range of the vehicle.



(a) complex scene: each vehicle transmitting its perception of the environment

(b) after the exchange of few beacons, all vehicles will have the same extended perception of the environment

Fig. 5. exchange of local perceptions to form an extended perception

By including local maps in the beaconing messages, each vehicle will be able to construct an extended perception of existing obstacles and vehicles of its own 2-hop neighborhood. This concept can be further generalized by including all available information about the environment in exchanged beacons. After few exchanges of beacons, each vehicle will have an extended perception of the environment, including the local maps of vehicles that are few hops away. Fig.5 illustrates this concept of an extended perception of the network. This perception contains information about all vehicles that are in the neighborhood. It would provide drivers with information about potential threats that are outside of Line of Sight (LoS) like in the obstacle scenario (Fig.3)

IV. PROPOSED SYSTEM

This paper proposes a system of cooperative perception of the road based on the exchange of local perception information. Our main design concern is to reduce the control overhead during beacon exchanges to avoid network performance degradation. Fig. 6 shows the proposed architecture of our system. It consists of a cooperative perception module that uses collected data (from beacons, received perception data from neighbors and vehicle's own sensors/equipments) to construct its extended perception of the network and then share it with its own neighbors. This module encloses four sub-modules:

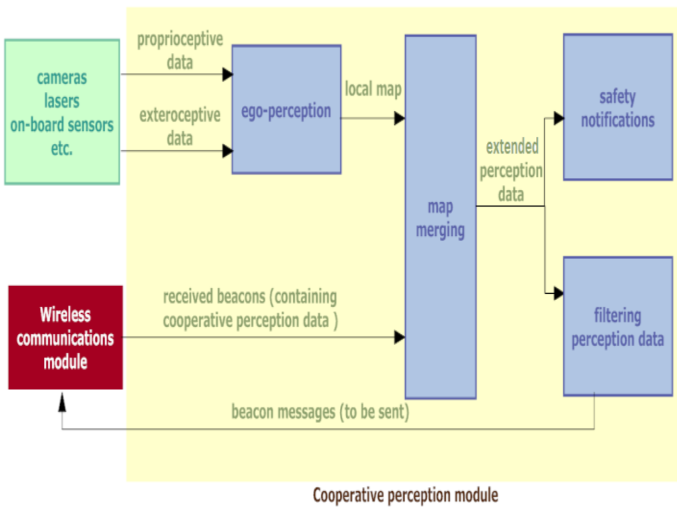


Fig. 6. Scheme of the cooperative Extended perception module

A. Ego-perception

The ego-perception module collects data from both proprioceptive and exteroceptive sensors to construct the ego-vehicle's own perception of its surroundings. There are several contributions that propose solutions for the fusion of information collected from different sensors [7] [8] [9] [10].

The construction of the ego-perception is outside the scope of our work as we concentrate on the communication aspect of the proposed system. This ego-perception represents what the VoI is detecting using its own equipments (without wireless communications) to form a local map of the objects in its immediate surroundings. In the rest of this paper, we consider that each vehicle has already built its own local map.

B. Map merging

Upon receiving different perception data from neighbors, this sub-module processes received data in order to fuse it properly with the current ego-perception. In the literature, there exist several different approaches [11-20] for map merging. This problem is outside of the scope of our work. We consider that upon receiving a perception message, a vehicle is able to merge the received map with its own map.

C. Safety Applications Module

Merging the VoI's local map with other maps received from neighboring vehicles allows the VoI to have an extended perception that goes up to few kilometers away from VoI. This extended perception is used by the active safety sub-module to perform early detection and notification of potential dangers.

This sub-module includes a decision model that allows assessing the current situation of the vehicle and determining whether it is necessary to intervene and warn the driver about potential dangers; this warning being a visual or sound alert. The automated assessment of threats was studied in many contributions in the open literature [21-26].

D. Perception data filtering

One of the key challenges in designing a cooperative perception scheme is to establish a trade-off between the amount of exchanged data to construct the extended perception and the network performance. This sub-module is therefore responsible for filtering the content of perception that are sent to neighbors.

1) Limiting the perception range set

The extended perception aims essentially to extend the perception range of the vehicle beyond a one hop range and the line of sight (LoS) of the driver the ego-perception range of the VoI, and the communication range of the beaconing messages. An extended perception could theoretically extend the perception range of the VoI to a few kms away, up to an entire city or area. It is worth noting, however, that the farther an object is from the VoI, the less likely it will come to affect or interact with it. Having an "infinite" perception range is therefore not only "useless", it may also affect overall system performances as it increases communication overhead.

2) Limiting frequency of transmitted perception data

We perceive the extended perception as an extension to the beaconing service. Therefore, we consider that exchanged perception data are to be included in beacon messages transmitted periodically. In the literature, it is suggested that beacon messages are sent with the frequency of 10Hz. The frequency of perception data exchanges can however be lower. In fact, depending on the topology and the surrounding environment, the exchanged perception data per beacon may become a burden on the network itself; indeed, large data messages exchanged with high frequency can affect the success rate of received beacon messages and throttle the dissemination of high priority messages[27].

V. EVALUATING THE GENERATED OVERHEAD OF EXTENDED PERCEPTION

In this section we study the overhead generated to build an extended perception of vehicles. We assume that all sensor data are collected and fused at vehicles, into local maps providing accurate information about surrounding objects. Local maps will be merged by simply appending/updating objects in the extended perception map. In this section, we propose a message format for exchanged perception data. Then, we evaluate the generated perception data overhead in different situations.

A. Extending the beacon message

We propose to include a new data set (see Fig. 7), in the beacon message, which will be used to compute the global perception. We assume that the size of perception data is variable depending on vehicle density, topology of the road, etc. We classify perception data into two classes: dynamic objects (e.g. vehicles) and static objects (e.g. buildings). Data about a moving object include position, speed, heading, acceleration, size and time stamp (see table. II); data about static objects is shown in Table. III. It is worth noting that the number of bytes that we are dedicating is always sufficient to represent the perception data compared to other data set representation proposed in recent research works as shown in [21-26].

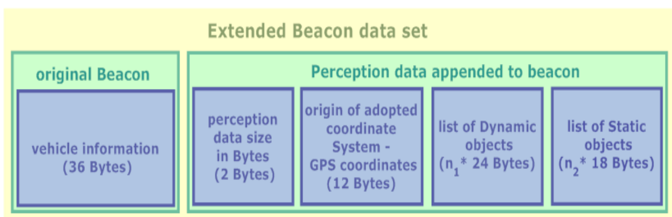


Fig. 7. Extended beacon message

We propose to make use of a relative coordinates system R since it can be represented on a smaller number of Bytes than the geographical coordinate system (Used with GPS). The origin of the selected coordinate system needs to be appended so that neighbors can convert relative positions to their own relative coordinates system before proceeding to map merging. This helps reducing the space complexity of the proposed as each dynamic object entry (vehicle entry) in the beacon would only add 24 Bytes in the beacon size.

TABLE II. DYNAMIC OBJECT DATA SET

Description	Size (in Bytes)
offset (relative XYZ)	4
Time stamp of last recorded information	8
speed	2
acceleration	2
heading	2
size (length, width, height)	6

TABLE III. STATIC OBJECT DATA SET

Description	Size (in Bytes)
offset (relative XYZ)	4
Time stamp of last recorded information	8
Size(length, width, height)	6

B. Evaluation scenarios

To perform simulations, we used OMNeT++ [28] integrating MIXIM/Veins [29] project as the network simulator and SUMO[30] as the traffic simulator. Veins uses an enhanced two-ray interference model that accounts for strong signal attenuation[31]. Both simulators are able to communicate in real time via a TCP connection, allowing bidirectional exchange of data and commands during simulations. In our simulations, we use a 10 kilometers, 2-ways highway segment with 3 lanes in each direction. The key metrics, we used in the evaluation, are:

1) The impact of perception range

Fig. 8 shows the overhead variation, for high (10Hz) and medium (5Hz) beaconing frequencies, with the perception range (a vehicle will append exchanged data about objects that are within this range)

We observe that the overhead increases with perception range. This is expected since when perception range increases, the amount of data exchanged increases. Fig. 8 shows that the overhead does not increase in a linear fashion; the variation of overhead when the perception range increases from2500m to3000m does not exceed 200 Bytes/s/vehicle while this variation is about 1000Bytes between 500m and 1000m. In fact, with the limited number of nodes in the simulation, having a high range will not increase drastically the number of objects that are within perception range especially when nodes are on the edges of the network.

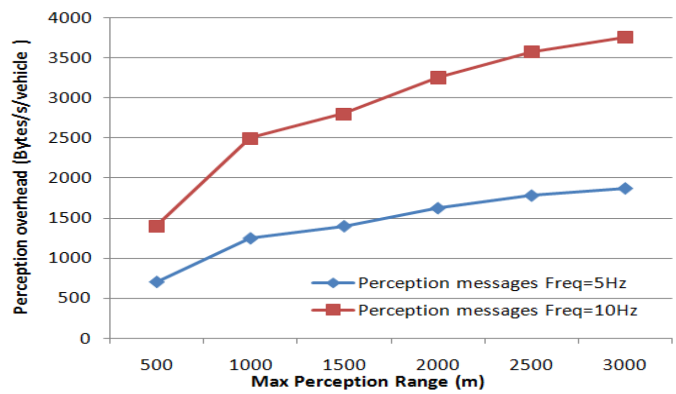


Fig. 8. Perception Range Vs Perception Overhead

2) The impact of message exchange frequency

Fig. 8 shows that reducing the frequency of beacon messages from 10Hz to 5Hz almost halved the perception data overhead. Perception overhead could be controlled when varying message frequency to avoid congestion. However, beacon messages are usually exchanged with a frequency of 10Hz. To achieve an efficient control over overhead without compromising beaconing service data, perception messages are piggybacked to few beacons per second only. In this scenario (Fig. 9), we measure the resulting overhead per second per vehicle depending on the frequency of perception data messages. Results are shown for 2 different vehicle densities while the perception range is fixed to 1km.

Results confirm that the perception overhead is proportional to the frequency of perception messages. Vehicles are therefore able to avoid congestion in the network by reducing the frequency of their perception messages without affecting the beaconing rate. A trade-off should, however, be established between messages frequency and congestion since lower frequencies implie less accurate data for the global perception. This trade-off will be examined in future work.

3) The impact of vehicle density:

We vary the density of vehicles per km per lane and measure the generated overhead per second per vehicle for three different dissemination message frequencies: high (10Hz), medium (5Hz) and low (2Hz) and a perception range of 1km.

Fig. 10 shows that perception overhead increases with density: as vehicle density increase to 8veh/s/km, each node will be in transmission range with a high number of vehicles on all the highway lanes, thus more perception data is exchanged between vehicles. We also observe that perception overhead increases proportionally with the dissemination frequency of messages. A low frequency keeps a relatively small overhead (less than 1000 Bytes) while higher frequency causes the exchange of relatively "big" messages multiple times per second and thus causes a faster increase of perception overhead.

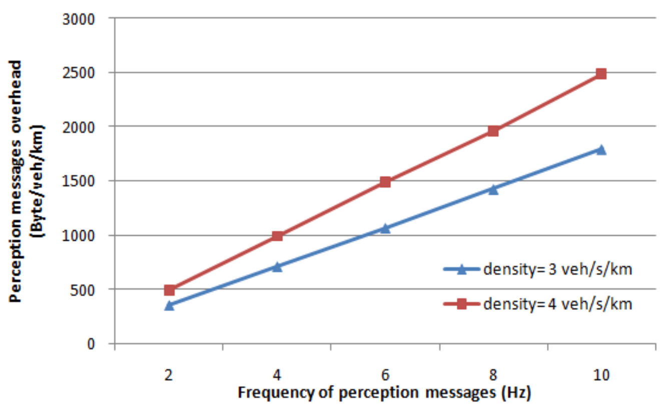


Fig. 9. Perception message Frequency Vs Perception Overhad

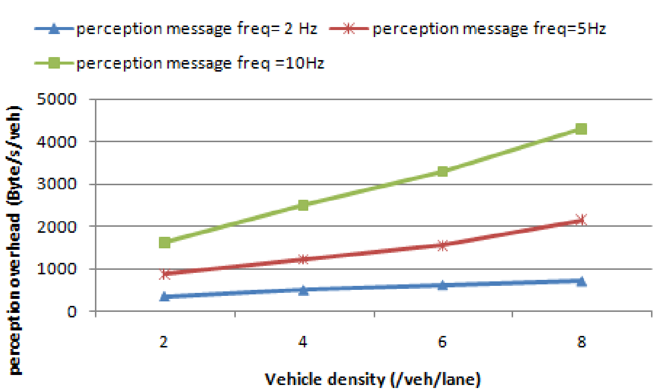


Fig. 10. Vehicle density Vs Perception Overhad

4) The impact of DSRC technology penetration:

The penetration rate of DSRC technology will impact the accuracy of our perception given that only DSRC capable vehicles are able to exchange their positions and their ego-perceptions. The presence of other ordinary (non-DSRC) vehicles is detected by communicating vehicles using on board sensors and scanners and then appended in the perception messages.

In this scenario, we vary the penetration rate of DSRC technology and measure how accurate is the perception (i.e. if all non DSRC vehicles that are within perception range exist in the vehicle's own perception) compared to the perception as perceived by an oracle during the simulation.

Several equipments such as laser scanners are available on the market and have a scanning range between 80m and 250m[32]. In this scenario (Fig. 11) we assume that every DSRC capable vehicle is using basic sensors to detect and estimate the position of surrounding vehicles within 100m and 150m[11].

Fig. 11 shows that perception accuracy increases with penetration rate; indeed, when more DSRC vehicles are present on the roads, more local maps are exchanged increasing the accuracy of the extended perception. For 85% perception accuracy, the penetration rate has to be between 60 and 70%. But it is also interesting to notice that perception rates of 30% can provide an accuracy of over 50%. We also observe that sensor detection range has minimal impact on the perception accuracy. In fact, sensors can only detect the first adjacent vehicle in each direction; other vehicles may be in sensor range but cannot be detected. This explains the limited impact of sensor range on perception accuracy (an increase of 50m in sensor range has improved accuracy by 3% only).

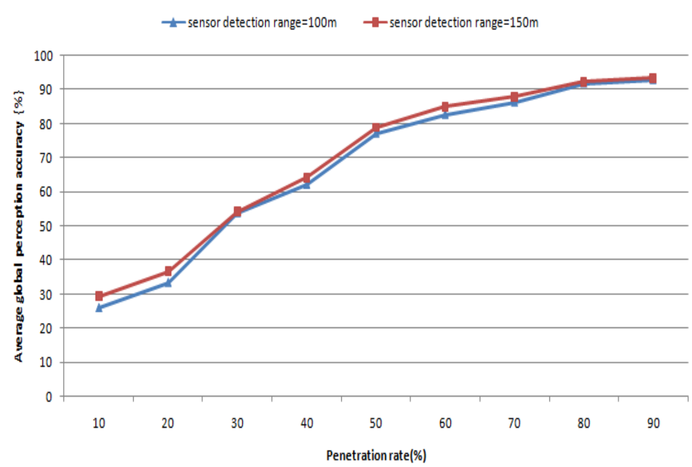


Fig. 11. Penetration Rate Vs Average perception accuracy

VI. CONCLUSION

The beaconing service provides limited information about one-hop neighbors. In this paper, we highlight the benefits of extending this service to exchange data about other surrounding elements and propose a new cooperative extended perception module that handles both beacon and extended perception messages. Through simulations, we study the perception overhead to show that it can be controlled to limit its effect on overall network performance and highlight the importance of penetration rate of DSRC technology on the effectiveness of the global perception.

References

[1] "IEEE Guide for Wireless Access in Vehicular Environments (WAVE) - Architecture," IEEE Std 1609.0-2013, pp. 1-78, 2014.

[2] "Trial-Use Standard for Wireless Access in Vehicular Environments (WAVE) - Resource Manager," IEEE Std 1609.1-2006, pp. 1-71, 2006.

[3] E. T. ETSI, "102 638 Technical Report, V1. 1: Intelligent Transport Systems (ITS), Vehicular Communications (VC), Basic Set of Applications, Definitions," ed: June, 2009.

[4] "AASHTO Connected Vehicle Infrastructure Deployment Analysis," 2011.

[5] Virage Simulator. Available: http://viragesimulation.com/vs500m-car-simulator-training-and-research/

[6] (2015). MEMS Journal Automotive sensors and electronics 2015. Available: http://www.automotivesensors2015.com/

[7] D. Gruyer, A. Cord, and R. Belaroussi, "Vehicle detection and tracking by collaborative fusion between laser scanner and camera," in Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on, 2013, pp. 5207-5214.

[8] B. Steux, C. Laurgeau, L. Salesse, and D. Wautier, "Fade: a vehicle detection and tracking system featuring monocular color vision and radar data fusion," in Intelligent Vehicle Symposium, 2002. IEEE, 2002, pp. 632-639 vol.2.

[9] R. Labayrade, C. Royere, D. Gruyer, and D. Aubert, "Cooperative Fusion for Multi-Obstacles Detection With Use of Stereovision and Laser Scanner," Auton. Robots, vol. 19, pp. 117-140, 2005.

[10] O. Ludwig, C. Premebida, U. Nunes, and R. Araujo, "Evaluation of Boosting-SVM and SRM-SVM cascade classifiers in laser and vision-based pedestrian detection," in Intelligent Transportation Systems (ITSC), 2011 14th International IEEE Conference on, 2011, pp. 1574-1579.

[11] E. D. Nerurkar, S. I. Roumeliotis, and A. Martinelli, "Distributed maximum a posteriori estimation for multi-robot cooperative localization," in Robotics and Automation, 2009. ICRA '09. IEEE International Conference on, 2009, pp. 1402-1409.

[12] L. Carlone, M. K. Ng, J. Du, B. Bona, and M. Indri, "Simultaneous localization and mapping using rao-blackwellized particle filters in multi robot systems," Journal of Intelligent & Robotic Systems, vol. 63, pp. 283-307, 2011.

[13] D. Nister, O. Naroditsky, and J. Bergen, "Visual odometry," in Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on, 2004, pp. I-652-I-659 Vol.1.

[14] A. Großmann and R. Poli, "Robust mobile robot localisation from sparse and noisy proximity readings using Hough transform and probability grids," Robotics and Autonomous Systems, vol. 37, pp. 1-18, 2001.

[15] A. Censi, L. Iocchi, and G. Grisetti, "Scan Matching in the Hough Domain," in Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on, 2005, pp. 2739-2744.

[16] S. Rusinkiewicz and M. Levoy, "Efficient variants of the ICP algorithm," in 3-D Digital Imaging and Modeling, 2001. Proceedings. Third International Conference on, 2001, pp. 145-152.

[17] P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 14, pp. 239-256, 1992.

[18] Y. Chen and G. Medioni, "Object modeling by registration of multiple range images," in Robotics and Automation, 1991. Proceedings., 1991 IEEE International Conference on, 1991, pp. 2724-2729 vol.3.

[19] A. Birk and S. Carpin, "Merging Occupancy Grid Maps From Multiple Robots," Proceedings of the IEEE, vol. 94, pp. 1384-1397, 2006.

[20] L. Hao, M. Tsukada, F. Nashashibi, and M. Parent, "Multivehicle Cooperative Local Mapping: A Methodology Based on Occupancy Grid Map Merging," Intelligent Transportation Systems, IEEE Transactions on, vol. 15, pp. 2089-2100, 2014.

[21] Y. Lee, Y. Ji Hyun, E. Feron, and V. Kulkarni, "Development of a performance-based approach for a rear-end collision warning and avoidance system for automobiles," in Intelligent Vehicles Symposium, 2003. Proceedings. IEEE, 2003, pp. 316-321.

[22] R. Kiefer, M. Cassar, C. Flannagan, D. LeBlanc, M. Palmer, R. Deering, et al., "Refining the CAMP Crash Alert Timing Approach by Examining" Last Second" Braking and Lane Change Maneuvers under Various Kinematic Conditions," Accident Investigation Quarterly, 2004.

[23] A. Polychronopoulos, M. Tsogas, A. Amditis, U. Scheunert, L. Andreone, and F. Tango, "Dynamic situation and threat assessment for collision warning systems: the EUCLIDE approach," in Intelligent Vehicles Symposium, 2004 IEEE, 2004, pp. 636-641.

[24] M. Green, "" How Long Does It Take to Stop?" Methodological Analysis of Driver Perception-Brake Times," Transportation human factors, vol. 2, pp. 195-216, 2000.

[25] A. Eidehall and L. Petersson, "Statistical Threat Assessment for General Road Scenes Using Monte Carlo Sampling," Intelligent Transportation Systems, IEEE Transactions on, vol. 9, pp. 137-147, 2008.

[26] A. Gray, M. Ali, G. Yiqi, J. K. Hedrick, and F. Borrelli, "A Unified Approach to Threat Assessment and Control for Automotive Active Safety," Intelligent Transportation Systems, IEEE Transactions on, vol. 14, pp. 1490-1499, 2013.

[27] N. Chaabouni, A. Hafid, and P. K. Sahu, "A collision-based beacon rate adaptation scheme(CBA) for VANETs," in Advanced Networks and Telecommuncations Systems (ANTS), 2013 IEEE International Conference on, 2013, pp. 1-6.

[28] (September 11, 2015). OMNeT++ the open simulator. Available: http://www.omnetpp.org/

[29] C. Sommer. (October 20, 2012). Veins - Vehicles in network simulation. Available: http://veins.car2x.org/

[30] (September 10, 2015). SUMO - Simulation of Urban MObility. Available: http://sumo.sourceforge.net/

[31] C. Sommer, S. Joerer, and F. Dressler, "On the applicability of Two-Ray path loss models for vehicular network simulation," in Vehicular Networking Conference (VNC), 2012 IEEE, 2012, pp. 64-69.

[32] S. Velupillai and L. Güvenç, "Laser scanners for driver-assistance systems in intelligent vehicles [applications of control]," Control Systems, IEEE, vol. 29, pp. 17-19, 2009.