A Multi-level Cooperative Perception Scheme for Autonomous Vehicles

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***Abstract*—This paper introduces a multi-level cooperative scheme for autonomous vehicles, using the sensors equipped on-board and a communication scheme with the deployed infrastructures. The proposed model focuses on the communication elements, delving into the cooperative aspect between the network components. The first level of the proposed scheme is composed of a multi-sensor data fusion framework using the measurements obtained from the vehicle on-board sensors, in order to detect obstacles in front of the vehicle. The obstacle detection is based on a liner regression fusion rule, which combines the obtained features from several sensors. Once the decision is taken, the vehicle responds consequently using implicit coordination and bringing the network to an uncertain status. Hence, the second level consists on achieving a stable network by applying explicit coordination between the vehicles and the deployed infrastructures. The third level controls the entire network from a centralized perspective using long-range communication links. Using the knowledge obtained from the centralized network, optimization can be achieved using a coordination scheme based on communication. To finalize, the theoretical framework is simulated under realistic conditions obtaining promising results, in terms of obstacle avoidance and network coordination.**

Keywords*—*VANETs, cooperative sensing, data fusion center, vehicular communications

I. Introduction

Autonomous vehicles have been attracting a lot of attention in recent years as a viable technology to reduce the number of casualties on the road [1]. To achieve this goal, the car manufacturers have to equip their vehicles with different autonomous mechanisms involving different kind of sensors. Nowadays, most of the modern cars are equipped with a driving assistance which helps the driver [2]. However, the future aim is to achieve a fully automated or high automated car. According to the SAE International Standard J3016 [3], a fully automated car is such with no human interaction while the rest of cars are also autonomous. Therefore, a fully automated car must have knowledge about the surrounding environment and should also be able to obtain and share information about the general traffic status.

The main goal is to obtain a global perception of the environment. For this purpose, different technologies have been developed involving communication between vehicles (V2V) and also to different infrastructures deployed alongside the road (V2I) [4]. Using V2V communication, local information is exchanged using short-range links to obtain knowledge of the vehicles surroundings. Since V2V communication acquires only local information, due to its short-range, V2I plays the role of extending their electronic horizon [5]. By combining both communication schemes, a general cooperative scheme among vehicles and infrastructures can be achieved [6].

However, the two previously mentioned communication schemes are not sufficient to completely sense the vehicle surroundings. Hence, and in addition to the obtained knowledge from different communication technologies, a widely used concept to perceive the near environment is to equip the vehicle with a large number of sensors. These sensors constitute the active safety system of each vehicle in order to bring integrity to the system [7]. Since the information coming from all sensors has a widely different nature, it is important to implement signal processing techniques to rapidly obtain the information. For this purpose, the vehicles in this paper are characterized by multi-sensor data fusion centers. Many different studies have focused their effort in obstacle detection using image recognition [8], however, this paper focuses solely on radio-wave technologies.

The main goal of this paper is to introduce a theoretical framework for autonomous vehicles, focusing on the active safety by presenting an obstacle avoidance framework involving a cooperative scheme. For this purpose, the aforementioned sensors, equipped on-board, aim to detect different unexpected obstacles in the trajectory of the vehicle, such as pedestrian, road obstacles or other vehicles. Many collision avoidance studies have been done under the perspective of system control [9], [10], however, in this paper, the collision avoidance along with the coordination scheme, are considered under the communication scope. This paper is organized as follows; the system model architecture is presented in Section II. In Section III, the different coordination schemes are analyzed. Finally, Section IV presents the simulation results and the paper is concluded in Section V.

II. Proposed Network Model

The hierarchical vehicular network proposed is divided into three different levels as depicted in Fig.1. The first level is formed by the on-board sensors of each individual vehicle which main task is to detect unexpected obstacles in front of the vehicle that may lead to a collision. The sensors feed their data to a fusion center in order to mix all the different obtained features and produce a more reliable decision. The majority of accidents due to an unexpected object are caused by pedestrians [11], which up until now, are not equipped with a localizer, so they are invisible to the network. Therefore, it is required to equip the autonomous vehicles with a set of sensors to avoid any collision with pedestrians. Since pedestrians will most likely remain immobile before an accident [12], the autonomous vehicle will make an evasive

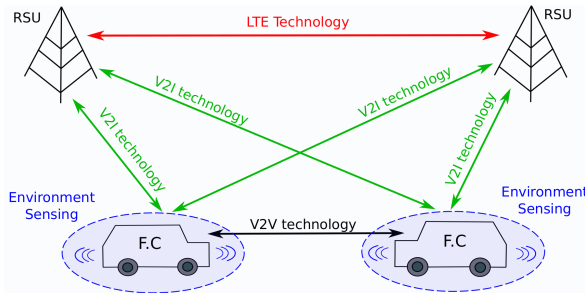

Fig. 1: General Network Framework

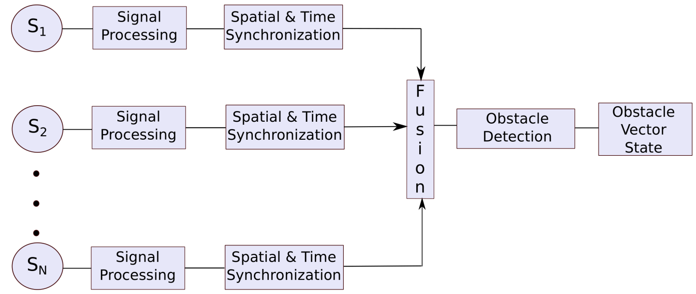

Fig. 2: Sensor Network Scheme

maneuver to avoid the pedestrian which is performed under the basis of an implicit coordination scheme, taking the surrounding scenario in consideration. The second level is the ad-hoc network formed by the autonomous vehicles. which are equipped with communication systems enabling V2V and V2I communication. This level handles the network state after an unexpected event, i.e., a vehicle making an evasive maneuver, using explicit coordination. In order to perform explicit coordination, firstly the vehicles and infrastructures exchange information updating their state and secondly, inform the network about any change in the network. The upper level focuses on long range communications, i.e., communication between the infrastructures themselves. Due to this long range communication, the global perception of the network can be extended, allowing different optimization schemes, such as vehicle routing or traffic jams avoidance.

III. Cooperative Vehicular Coordination Scheme

The first part consists on sensing the close range environment using the on-board sensors of the car. After mixing the features in the data fusion center, a decision is made whether an obstacle is detected or not. The second part uses explicit coordination between the cars to update the status of the network and inform about any unexpected event. The last part is used to extend the range of perception of each vehicle, i.e., using the deployed infrastructures, the vehicles acquire knowledge of the entire network. In the following subsections, the aforementioned coordination schemes are explained in detail.

A. Data Fusion Center Model

The features obtained from the N different sensors are first preprocessed and synchronized in time and space, using the external information obtained from the RSU as depicted in Fig. 2. It is noteworthy that external information from the RSU is required since the sensor network forms part of a mobile system, namely, the vehicle, making the obtained features relative to the mobile position. Therefore, the use of information from the RSU is needed to *anchor* the obtained information. Once the information is *anchored*, it is relevant to the entire network. Once all the features obtained from the sensors are synchronized in time and position, $\mathbf{x}^i(t)$ is obtained where $\{x_1^i(t), x_2^i(t), \ldots, x_k^i(t)\}$ with $k \in \{1, \ldots m\}$ are the different lectures obtained from each individual sensor $i \in \{1, \ldots, N\}$. In order to perform the sensor fusion, these features are modeled as rays using a ray-tracing algorithm, PIROPA [13], to obtain a realistic model. Using an optical physic model is possible to simulate the features from short and long range detection system as shown in Fig. 3.

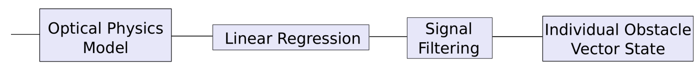

Fig. 3: Obstacle Detection Block Diagram

The main advantage of our modeling is that shooting rays in all directions allows us to detect many different obstacles, rather than a single ray detecting the obstacle, increasing the reliability of the decision. Moreover, since the vehicle is equipped with N sensors, the final decision is determined after mixing all the individual decisions in the fusion center, increasing the accuracy.

The idea of obstacle detection relies on the correlation between the scatterers bounced from the same object. Using the assumption that the speed of the obstacles relative to the vehicle speed is nearly zero, the delay between the different echoes remains constant. Therefore, by applying a linear regression model to the different samples, $\mathbf{x}^i(t)$, obstacles can be detected. The obstacle detection equation is as follows:

$$\boldsymbol{\tau}(t) = \mathbf{x}^i(t) + \Delta\epsilon \tag{1}$$

where $\boldsymbol{\tau}(t)$ is the delay value from the different rays reaching the sensor at each time instant t, and $\Delta\epsilon$ is the term used to simulate the noise inherent to the sensor receiver. At this point, all the different features are grouped in terms of the same delay τ, obtaining the potential obstacles in front of the vehicle. However, this decision is not reliable based solely on a time instant t, since the obstacle has to be persistent in the sensor readings, i.e., the obstacle must be detected in sequential time instants. For this purpose, it is assumed that the obstacle is relatively static, where the obstacle speed is negligible in comparison with the vehicle speed. Therefore, in the fusion center a linear regression technique [14] is applied to estimate the delay

$$\hat{\boldsymbol{\tau}}(t+1) = \boldsymbol{\tau}(t) + \boldsymbol{\beta}(t) \tag{2}$$

where $\Delta\delta = 0$ due to the previous static assumption. In the case of the linear regression terms $\boldsymbol{\beta}$, they are calculated using the following formula:

$$\beta(t) = \frac{v(t)}{c} \cdot \Delta t \tag{3}$$

where $v(t)$ is the speed of the car, c is the speed of light and Δt is the time difference between two consecutive reads. Therefore, by applying these coefficients, it is possible to estimate

the grade of certainty obtained by the obstacle detector.
The obstacle detection problem turns into a sequential detection using the Neyman-Pearson Test [15] with the aim of minimizing the probability of missing detection P_{M_i}. We assume that the different observations $\boldsymbol{\tau}(t)$ are independent, making the sequential detection likelihood ratio as follows

$$\Lambda(\boldsymbol{\tau}(t)) = \frac{P(\boldsymbol{\tau}|H_1)}{P(\boldsymbol{\tau}|H_0)} = \prod_{i=1}^{N} \frac{P(\tau_i|H_1)}{P(\tau_i|H_0)} \quad (4)$$

at this point, it is needed to determine the threshold η_0 and η_1, in terms of missing detection P_M and false alarm probability P_F. Hence, we define them as $P_F = \alpha_1$ and $P_M = \alpha_2$. In consequence, the sequential test is implemented as

$$\Lambda(\boldsymbol{\tau}(t)) \geq H_1 \quad (5)$$
$$\Lambda(\boldsymbol{\tau}(t)) \leq H_0 \quad (6)$$

B. Implicit Coordination Scheme

If all the network members are considered, the number increases greatly making infeasible the coordination of all the members using a communication scheme due to the delay. Therefore, a different coordination approach has to be developed for safety maneuvers where the delay is critical.
Implicit coordination is used to describe the kind of coordination which does not require exchange of information, but it is based on the shared knowledge between the network members [16]. Coordination is needed when the network members cannot act independently from the rest, and in this case, it is obvious that the safety of all the vehicles is a team coordination effort. Implicit coordination uses the shared knowledge of the network, which is defined as the combination of the local knowledge, information obtained by the on-board sensors, and the exchanged information with the rest of the network. This shared knowledge helps to anticipate the actions of the rest of the vehicles in the network. The general framework of the implicit coordination scheme is represented in Fig. 4.

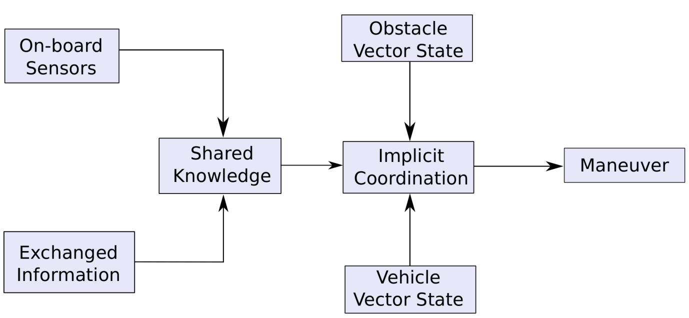

Fig. 4: Implicit Coordination Scheme Block Diagram

In order to perform the implicit coordination, the following information is extracted:

$$\Omega \equiv \text{ road positions} \quad (7)$$
$$\mathcal{U} \equiv \text{occupied positions} \quad (8)$$
$$\vec{v} := \{p(t), s(t), h(t)\} \quad (9)$$
$$\mathcal{Y} \equiv \text{obstacle positions} \quad (10)$$

where $\mathcal{Z}$ is the set of valid future positions for the vehicle defined as:

$$\mathcal{Z} \equiv \Omega - \{\mathcal{U} \cup \mathcal{Y}\} \quad (11)$$

However, the vehicle can only move to a restricted number of positions $z_i \in \mathcal{Z}$, which are in function of the speed, position and direction, i.e., the vehicle vector state $\vec{v}$. Therefore, after estimating all the possible future positions, the coordination scheme clusters them, in order to reduce the complexity. For each obtained cluster, the center of gravity, speed and direction of the car are used to select the optimal next position. The implicit coordination scheme stated here considers only the state-information stored in the vehicle and the state-information of the obstacle estimated by the on-board sensors. Therefore, the vehicle and the obstacle are in conflict [17], if there exist $t \geq 0$ such that

$$\|(p + tv) - (\hat{p}_i + t\hat{v}_i)\| \leq D_{th} \quad (12)$$

being p_0 and v_0 the position and velocity of the vehicle, respectively. $\hat{p}_i$ is the estimated position of the obstacle and $\hat{v}_i$ the estimated speed which is considered zero. Hence, if the set of positions $\mathcal{Z}$ defined in Eq. (11) with the parameters p, v and $\hat{p}_i$ fulfill the safety criterion in Eq. (12) there is no required evasive maneuver.

C. Explicit Coordination Scheme

The explicit coordination concept implies the coordination of the network elements using communication protocols in order to improve the network cognition. The main benefit of the communication between the vehicles and the different infrastructures is to extend the electronic horizon, due to the short-range of communication obtained with the vehicular communication technology 802.11p [18]. This is the main reason why deploying the infrastructures alongside the road improves the range of network communication. In order to accomplish optimal coordination, three different layers are implemented:

1) V2V communication: between the cars which are in the same cluster and in a short-range. Using the V2V scheme, the vehicles share their local knowledge. In order to perform the communication, a similar framework as the one introduced in [19] is used, where the vehicles are clustered based in their similarity using spectral clustering. The vehicles share their knowledge using a beacon:

$$m_i(t) := (p_i(t), v_i(t), h_i(t)),$$

where $p(t)$ is the absolute car position, $v(t)$ is the current speed and $h(t)$ is the heading of the vehicle. The main application of V2V is to share the local knowledge of cars in the same cluster, in order to obtain the complete knowledge of their surroundings.

2) V2I communication: between several cars and the infrastructure they belong to. This method of coordination is an extension of the V2V communication scheme shown before. The shared knowledge contained in the beacons is, in this case, sent to the RSUs which store all the information from the nodes. Hence, the RSUs play the role of a Data Center Unit (DCU) while the vehicles serve as sensors of a bigger network. Applying this

knowledge, each RSU manages a single cluster where many cars are included. As shown in [19], the best way of managing the clusters is to select one or many different head-clusters using the information stored in the beacons.

3) I2I communication: between different infrastructures using a long-range communication protocol, namely LTE. The last communication scheme aims to spread the information among the different network elements obtaining a fully connected network. The final application of the I2I scheme is to optimize the traffic routing using all the gathered information.

IV. Simulation

In this section, the proposed model is simulated under realistic conditions using a real-world scenario. The scenario is simulated using 2 LTE eNodeB and a maximum of 50 vehicles, simultaneously. The simulation has been performed using SUMO [20] software in order to create the mobility scenario, and VEINS [21] to simulate the communication network.

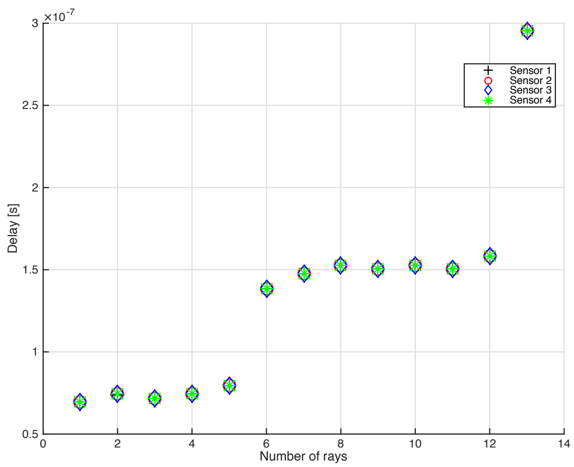

Fig. 5: Obstacle at 22 meters

As shown in Fig. 5, the detection of an obstacle occurs when Eq. (1) is fulfilled, i.e., there is a constant delay in the obtained features. In addition, by using several sensors for the same obstacle detection, the final detection is more accurate. Using concepts from radar detection, the estimated distance is:

$$\hat{d}_i = \frac{c \cdot \hat{\bar{\tau}}}{2} = \frac{3 \cdot 10^8 \frac{m}{s} \cdot 1.5 \cdot 10^{-7} s}{2} \approx 22.5 \text{ m}$$

where c is the speed of light, since electromagnetic waves are used. $\hat{\bar{\tau}}$ is the estimated mean delay for the obtained features of all the sensors and the obtained distance is divided by 2, due to the used radar concept, i.e., the delay contains the reflection of the wave. As shown in Fig. 5, there are two different set of points where the delay is constant fulfilling Eq. (1). Therefore, it is needed to observe if the obstacle is persistent in time, in order to detect it correctly and also to avoid false alarm detections.

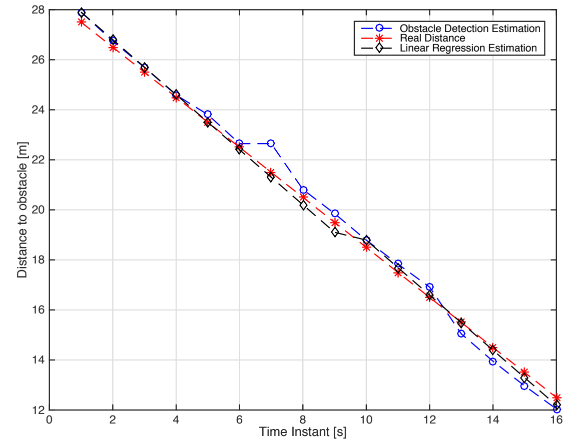

Fig. 6: Comparison of different obstacle detection methods

The next step is to compare the obstacle detection algorithm with real measurements. In Fig. 6., a static obstacle is placed in front of a vehicle driving at a constant speed of 30 km/h. In the one hand, the results show that the estimation done using the ray-tracing algorithm is quite accurate, but it suffers from noise in the measurements and from the dependency in the non-variability of the scenario. On the other hand, the estimation using linear regression show a better match with the real measurements, but in contrast, it has the dependency of required the vector state of the vehicle $\vec{v}$ at every time instant. The mean square error for both methods is:

$$\sigma_{obs-det} = 0.2061 \tag{13}$$

$$\sigma_{lin-reg} = 0.0550 \tag{14}$$

Finally, the exchange of local information between the vehicles in the same cluster is simulated in Fig. 7. This cluster is formed by vehicles with similar $v(t)$, $h(t)$ and $p(t)$ during 400 seconds in a urban scenario. The simulation parameters are as follows:

TABLE I: Communication Parameters

Parameter	Value
V2I using LTE	2.4 GHz
V2V using 802.11p	5.9 GHz
V2I beacon frequency	1 s
V2V beacon frequency	0.1 s

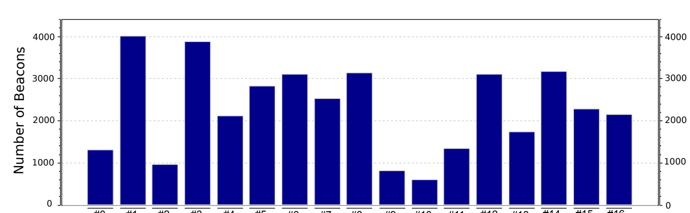

Fig. 7: Number of V2V beacons received per car

The simulation exhibits a high number of beacons successfully delivered to the vehicles. This high number of beacons allow to have an updated local information exchange. Moreover, in further studies, it will be interesting to obtain the optimal rate of sent beacons, in order to not collapse the network with unnecessary information.

V. Conclusion

Autonomous vehicles are an emergent technology within the few next years will be a reality in our daily life. In this paper, a communication framework for vehicular networks is proposed focusing on the cooperation among all the network elements. The proposed framework is divided in three layers; the first one sensing the close-range environment and implementing an obstacle/pedestrian avoidance mechanism. This active safety mechanism is simulated using a ray-tracing algorithm, emulating the close range radar systems, displaying great results in terms of accuracy with a reasonable amount of sensors. The second layer involves an explicit coordination scheme where the vehicles share their local knowledge in order to extend their electronic horizon. The simulations show that the network has enough information to perform the coordination scheme in a reasonable time, showing the feasibility of the proposed framework. The last layer is used to share the high level knowledge using LTE links between the RSUs in order to optimize the traffic routing. Applying this concept, the re-routing of the traffic is greatly improved. To sum up, the proposed multi-level network performs well-enough and it brings a new concept to vehicular networks such as the share of knowledge in order to obtain a multi-cooperative network.

References

[1] L. Hobert, A. Festag, I. Llatser, L. Altomare, F. Visintainer, and A. Kovacs, “Enhancements of v2x communication in support of cooperative autonomous driving,” *IEEE Communications Magazine*, vol. 53, no. 12, pp. 64–70, Dec 2015.

[2] S. Greengard, “Automotive systems get smarter,” *Commun. ACM*, vol. 58, no. 10, pp. 18–20, Sep. 2015. [Online]. Available: http://doi.acm.org/10.1145/2811286

[3] S. International, “Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems, sae j3016,” 2014.

[4] D. Jiang and L. Delgrossi, “Ieee 802.11p: Towards an international standard for wireless access in vehicular environments,” in *Vehicular Technology Conference, 2008. VTC Spring 2008. IEEE*, May 2008, pp. 2036–2040.

[5] Y. Horita and R. S. Schwartz, “Extended electronic horizon for automated driving,” in *ITS Telecommunications (ITST), 2015 14th International Conference on*, Dec 2015, pp. 32–36.

[6] H. j. Gunther, O. Trauer, and L. Wolf, “The potential of collective perception in vehicular ad-hoc networks,” in *ITS Telecommunications (ITST), 2015 14th International Conference on*, Dec 2015, pp. 1–5.

[7] M. Wrner, F. Schuster, F. Dlitzscher, C. G. Keller, M. Haueis, and K. Dietmayer, “Integrity for autonomous driving: A survey,” in *2016 IEEE/ION Position, Location and Navigation Symposium (PLANS)*, April 2016, pp. 666–671.

[8] Mobileye. (2015) Collision avoidance system. protecting your fleet and improving your bottom line. [Online]. Available: http://www.mobileye.com

[9] J. Funke, M. Brown, S. M. Erlien, and J. C. Gerdes, “Prioritizing collision avoidance and vehicle stabilization for autonomous vehicles,” in *2015 IEEE Intelligent Vehicles Symposium (IV)*, June 2015, pp. 1134–1139.

[10] ——, “Collision avoidance and stabilization for autonomous vehicles in emergency scenarios,” *IEEE Transactions on Control Systems Technology*, vol. PP, no. 99, pp. 1–13, 2016.

[11] S. Oikawa, Y. Matsui, T. Doi, and T. Sakurai, “Relation between vehicle travel velocity and pedestrian injury risk in different age groups for the design of a pedestrian detection system,” *Safety Science*, vol. 82, pp. 361 – 367, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0925753515002647

[12] A. Soni, T. Robert, F. Rongieras, and P. Beillas, “Observations on pedestrian pre-crash reactions during simulated accidents,” *Stapp Car Crash J*, vol. 57, pp. 157–183, Nov 2013.

[13] F. Schröder, M. Reyer, and R. Mathar, “Efficient implementation and evaluation of parallel radio wave propagation,” in *EuCAP 2011 - 5th European Conference on Antennas and Propagation*, EUR Congressi in Rome, Italy, Apr. 2011, pp. 2466–2470. [Online]. Available: http://www.ti.rwth-aachen.de/publications/output.php?id=791&table=proceeding&type=pdf

[14] H. Wang and F. Hao, “An efficient linear regression classifier,” in *Signal Processing, Computing and Control (ISPCC), 2012 IEEE International Conference on*, March 2012, pp. 1–6.

[15] P. K. Varshney, *Distributed Detection and Data Fusion*, 1st ed. Secaucus, NJ, USA: Springer-Verlag New York, Inc., 1996.

[16] A. Espinosa, J. Lerch, R. Kraut, E. Salas, S. M. Fiore, and J. A. C. bowers (editors, “Explicit vs. implicit coordination mechanisms and task dependencies: One size does not fit all,” 2002.

[17] A. J. Narkawicz and C. A. Munoz, “State-based implicit coordination and applications,” 2011.

[18] S. Eichler, “Performance evaluation of the ieee 802.11p wave communication standard,” in *2007 IEEE 66th Vehicular Technology Conference*, Sept 2007, pp. 2199–2203.

[19] J. A. L. Calvo and R. Mathar, “A two-level cooperative clustering scheme for vehicular communications,” in *The 6th International Conference on Information Communication and Management*, Hertfordshire, United Kingdom, Oct. 2016, pp. 205–210. [Online]. Available: http://www.ti.rwth-aachen.de/publications/output.php?id=1056&table=proceeding&type=pdf

[20] D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, “Recent development and applications of SUMO - Simulation of Urban MObility,” *International Journal On Advances in Systems and Measurements*, vol. 5, no. 3&4, pp. 128–138, December 2012.

[21] C. Sommer, R. German, and F. Dressler, “Bidirectionally Coupled Network and Road Traffic Simulation for Improved IVC Analysis,” *IEEE Transactions on Mobile Computing*, vol. 10, no. 1, pp. 3–15, January 2011.