Emergent Behaviors and Traffic Density among Heuristically-Driven Intelligent Vehicles using V2V Communication

Philippe Morignot, Oyunchimeg Shagdar, Fawzi Nashashibi

Emergent Behaviors and Traffic Density among Heuristically-Driven Intelligent Vehicles using V2V Communication

Philippe Morignot, Oyunchimeg Shagdar, and Fawzi Nashashibi
RITS Project-Team, INRIA Rocquencourt
Domaine de Voluceau, B.P. 105 78153, Le Chesnay, FRANCE
Email: {*philippe.morignot, oyunchimeg.shagdar, fawzi.nashashibi*}*@inria.fr*

***Abstract*—In this paper, we study the global traffic density and emergent traffic behavior of several hundreds of intelligent vehicles, as a function of V2V communication (for the ego vehicle to perceive traffic) and path-finding heuristics (for the ego vehicle to reach its destination), in urban environments. Ideal/realistic/no V2V communication modes are crossed with straight-line/towards-most-crowded/towards-least-crowded path-finding heuristics to measure the average trip speed of each vehicle. The behaviours of intelligent vehicles are modelled by a finite state automaton. The V2V communication model is also built based on signal propagation models in an intersection scenario and a Markov-chain based MAC model. Our experiments in simulation over up to 400 vehicles exhibit attractive insights: 1) communication's impact is positive for the performance of the emergent vehicles' behaviour, however, 2) the path-finding heuristics may not obtain their expected collective behaviour due to the communications errors in realistic road environment.**

I. Introduction

Wireless communication is expected to play an important role for road safety, efficiency, and comfort of road users. Particularly, vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications appear as mostly important for an intelligent autonomous vehicle to perceive outside traffic, in order to help to dynamically determine its path to its destination, e.g., avoiding perceived traffic jams in urban scenarios. To support such ITS applications the IEEE 802.11p (ETSI ITS G5 for the European usage) is standardized for V2X communications using the 5.9 GHz frequency bands. Furthermore, ETSI defined two types of message sets, cooperative awareness messages (CAM) and decentralized environmental notification messages (DENM), which are generated periodically and triggered by events, respectively [1]. A large number of research and development studies are made on signal propagation in realistic roads, channel capacity for dense traffic condition, message dissemination in a geographical area, and so on [2], [3]. These previous and ongoing efforts brought important insights on the remaining challenges of the communication technologies in various road and traffic scenarios.

The automated cooperative driving applications require efforts on multiple research domains including robotics, artificial intelligence, and communications to build a safe and intelligent collective driving behavior. While some studies show the potentials of the V2V communications for safer and smoother automated driving [4], [5], [6], it is still not clear if the standardized technologies can meet the strict requirements of the automated driving applications. More importantly, if the decisions for individual vehicles' control are based on the V2V communications, the communications performance must largely affect the "quality" of the collective behavior. Furthermore, since the decisions on e.g., path planning impact the traffic density, they consequently impact the performance of the wireless communications. To the best of our knowledge, the inter-dependency between communications and the behavior of automated vehicles is not yet explored. Motivated by this, in the current paper, we combine different V2V communication modes with different dynamic path-finding heuristics, over a population of several hundreds of intelligent vehicles, to observe convergence towards stable traffic. The various traffic stability levels are compared in order to exhibit most efficient combinations of communication modes and path-finding heuristics.

The next section presents the model (environment, vehicles, communication); Section III presents experimental results, and the last two sections compare our work to previous work and sum up our contributions.

II. Model

A. Environment

An urban environment is considered, with streets exclusively oriented North-South or East-West. Perpendicular streets cross at intersections. Parallel streets are separated by the same distance. As a first approximation (and for not limiting vehicles' motion), we assume that streets loop at the borders of the simulated environment (wrapped/circular environment), i.e., the rightmost (resp. topmost) extremity of a East-West (resp. North-South) street meets with its leftmost (resp. bottom) extremity. A street is composed of two lanes, one up and one down, and the vehicles circulate on the right lane of a street (North-American driving way). Formally, streets can be represented as a directed cyclic graph, where vertices are intersections and arcs are lanes (2 arcs in opposite directions between 2 nodes).

Traffic lights are modelled at the four entering lanes of each intersection, 2 opposed to 2, all with the same phase (no green wave).

B. Intelligent vehicles

1) Finite state automaton: The behavior of each intelligent vehicle is modelled by a finite state automaton:

1) Go straight on a lane and accelerate until reaching the speed limit, or decelerate because of other vehicles (collision avoidance) or red traffic lights (respect of traffic rules);
2) If the intelligent vehicle reaches its destination on its lane, assign a random new one to it (perpetual motion);

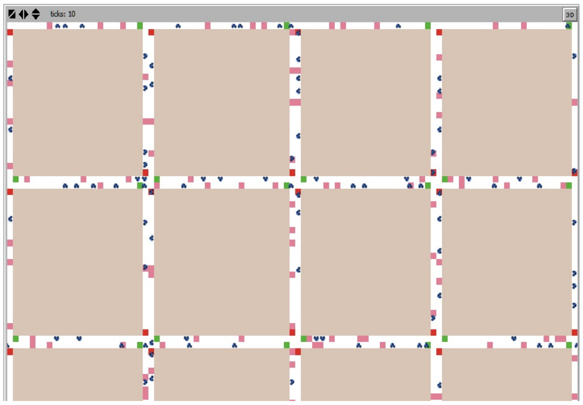

Fig. 1. Topology of the environment: intelligent vehicles (blue car icons) circulate on the right lane of streets (white patches), each intersection has one traffic light per entering lane (green/red patches), destinations are displayed (pink patches).

3) When the intelligent vehicle reaches an intersection, possibly communicate with the other vehicles in the four directions North/East/South/West to determine the perceived vehicles;
4) Once the intelligent vehicle has communicated, choose the exit direction of the intersection among the 4 possible ones North/West/South/East;
5) Once the intelligent vehicle has chosen its targetted exit in the current intersection, follow a 1- to 4-step plan to go to this exit through the intersection while avoiding collision with other vehicles on the intersection;
6) Go to state 1, until a timeout (end of simulation) has elapsed.

Longitudinally (state 1 of the automaton above), an intelligent vehicle accelerates when there is no vehicle in front of it on its lane (catching up), until it reaches the speed limit; it decelerates (and possibly stops) for not colliding a vehicle in front of it on its lane (collision avoidance), or when it encounters a red traffic light (respect of traffic rules).

When on a lane, an intelligent vehicle stays on its lane and never overtakes, i.e., we assume that continuous yellow lines hold in the middle of each road.

When an intelligent vehicle has reached its destination (state 2), a new random destination is assigned to it (any point on a lane which is not located at an intersection), for cars to run constantly (a.k.a. taxi called by customers, parking slots on the side of roads are not modelled).

2) Intersection management: Intelligent vehicles follow a 1- to 4-step plan to traverse an intersection and reach the exit lane they have heuristically chosen (state 5 of the previous automaton). Streets are composed of two lanes and vehicles run on the right lane of a street, leading to 4 patches at an intersection, labelled from 1 to 4 (see Fig. 2). If a vehicle, $V1$, has to make a right turn, it will go straight to patch 1, then make a right turn, and then go straight (1-step plan); If $V1$ has to go straight across the intersection, it will go straight to patch 1, then straight to patch 2, and then go straight (2-step plan); If $V1$ has to make a left turn, it will go straight to patch 1, then straight to patch 2, then make a left turn to patch 3, and then go straight (3-step plan); If $V1$ has to make a U turn, it will go straight to patch 1, then straight to patch 2, then make a left turn to patch 3, then make a second left turn to patch 4, and then go straight (4-step plan).

Each heading change for right or left turns is performed by 90 degrees addition to/subtraction from the current heading of the vehicle (see e.g. [7] for a discussion on more precise trajectory models).

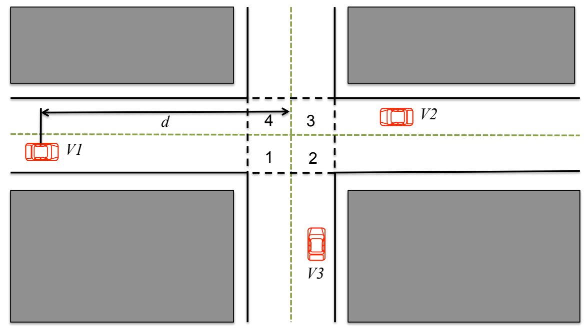

Fig. 2. Four patches at an intersection, labelled 1 to 4, for 1-step to 4-step plan for intersection traversal. The 3 other cases (i.e., a vehicle heading North/South/West) can be obtained by rotation.

The same rules as before on acceleration/deceleration hold for intersection crossing, which is sufficient to reach collision avoidance, and thus safety, during this phase. For example, we observed vehicles aiming at making a left turn at an intersection, waiting on patch 2 in the previous 3-step plan for other vehicles to pass on the opposite lane, before going straight to patch 3 when no more vehicle passes, and then going straight to the exit.

3) Heuristics: At each intersection (state 4 of the previous automaton), each intelligent vehicle can always choose among four directions, given the topology of the streets in our urban environment: right, straight, left and back (the vehicle performs a U-turn). When about to enter an intersection, each intelligent vehicle uses a heuristics to choose one of the four exits of the intersection, leading to its next lane. All vehicles use the same heuristics, for the population to be able to exhibit a global emergent behavior.

The 3 possible heuristics for an intelligent vehicle to choose its exit at an intersection are:

Compass. The intelligent vehicle runs as close as possible to a straight line to its destination. The vehicle is assumed to own a GPS sensor, computing the bird's fly ideal line from the current location to the destination. No V2V communication is performed. When entering an intersection, an intelligent vehicle computes the ideal angle which would lead to its destination if there was a direct straight lane towards it. The chosen angle among North/East/South/West is the one closest to the previous ideal angle. Given the topology of the environment (no curved streets, straight perpendicular streets only), such heuristics implements the shortest path to the vehicle's destination.

Towards least crowded ("No Ant"). When entering an intersection, an intelligent vehicle computes the ideal angle to its destination and the absolute difference with the angles corresponding to the four exits of the intersection, as previously. But now it considers the first two best angles: if the best one corresponds to the shortest path (see previous heuristics), the second best one could fit too because of the strictly perpendicular topology of streets: For example, going straight and making a right turn is almost equivalent to making a right turn and then making a left turn — the path might be slightly longer only. Therefore, there is a choice to perform among these first two best angles: the intelligent vehicle performs V2V communication to assess the number of other cars in each of these two directions. If the traffic is the same in these two directions, the first best angle is chosen as in the compass heuristics. But if one has strictly less traffic than the other, the former angle/direction/exit is chosen: This heuristics advises to avoid traffic whenever possible. Therefore the second best angle (possibly leading to a slightly longer path to destination) might be chosen when the traffic is less dense than on the first best angle.

Towards most crowded ("Ant"). This heuristics is close to the previous one, except for the choice among the first two best angles: This heuristics chooses the most crowded angle among the first two best angles. In practice, this heuristics is the opposite of the previous one (reversed test). Therefore the second best angle might be chosen when the traffic is denser than on the first best angle, possibly leading to choosing a slightly longer path, but for a reason opposite as in the previous heuristics. This heuristics is referred to as "Ant", since it is close in spirit to ant colony optimization algorithms [8] in which ant agents leave traces for further ant agents to follow them.

However, the last two heuristics may choose the second best angle several times in a row depending on traffic distribution, possibly leading vehicles to deviate too much from their ideal path (i.e., "Compass" heuristics) to destination — in early implementations of our model, some vehicles were endlessly running up and down the same portion of road and were making a U-turn at both ends, hence never reaching their destinations. To force these vehicles to choose their first best angle in the end of their path to destination, an attraction zone is introduced: when close enough (e.g., one block) to its destination, a vehicle switches from "Ant" or "No Ant" heuristics (possible second best angle) to "Compass" heuristics (no second best angle), hence defining a validity time period for those two heuristics.

C. V2V communication

The performance of the V2V communication largely depends on the wireless link quality as well as on the performance of the communication protocols, especially medium access control (MAC). In this subsection, we model the V2V communications performance in an urban road scenario by considering both the signal propagation and MAC.

1) Signal propagation in urban environments: A number of path loss models, including two-ray ground reflection (TRG), and two-ray interference (TRI), are developed to approximate radio signal quality. In [2], the applicability of the models is studied for vehicular communications and it is shown that TRI provides better estimation than TRG (which is more commonly used). In realistic road environments, the quality of the link, i.e., signal quality, is largely affected by the surrounding objects (e.g., buildings), which results in signal blockage and/or multi-path fading effects. This may result in that the TRI and TRG models, where only 2 rays are taken into account, are not appropriate in urban road scenarios. Motivated by this, we first study the applicability of TRG and TRI to an intersection road scenario by comparing the models to results of the ray-tracing model for the IEEE 802.11p system for 10 MHz bandwidth and 20 dBm of transmission power [9].
TRG calculates the signal quality using free-space model for near distances and two-ray model far distances:

$$L_{trg}[dB] = \begin{cases} L_{fs} = 20log_{10}(4\pi\frac{d}{\lambda}), & \text{if } d \leq d_c \\ L_{tr} = 20log_{10}(\frac{d^2}{h_t h_r}), & \text{otherwise} \end{cases} \quad (1)$$

Here, d is the distance between the transmitter and the receiver, λ is the wave length, and h_t and h_r are the antenna heights of the transmitter and receiver, respectively. d_c is the extent of the Fresnel zone $d_c = 4\pi h_t h_r/\lambda$.
The TRI model takes account of the phase difference, φ, of the two interfering rays:

$$L_{tri}[dB] = 20log_{10}(4\pi\frac{d}{\lambda}|1 + \Gamma_\perp e^{i\varphi}|). \quad (2)$$

Here $\Gamma_\perp$ and φ are the reflection coefficient. The reflection coefficient and the phase difference can be found as

$$\Gamma_\perp = \frac{sin\vartheta - \sqrt{\varepsilon_r - cos^2\vartheta}}{sin\vartheta + \sqrt{\varepsilon_r - cos^2\vartheta}}, \quad \varphi = 2\pi\frac{d_{los} - d_{ref}}{\lambda}.$$

where, ε_r is the reflectivity coefficient of the material and ϑ is the incidence angle, which can be easily calculated based on the antenna heights and the distance (d).
The ray-tracing estimation is made for an intersection road scenario assuming that tall buildings are at each corner (see Fig. 2). The roads have 1-lane per-direction and the width of the lane is 3 meters. The receive powers at the nodes $V2$ and $V3$, which are 15 m and 30 m from the junction respectively, are calculated for signals emitted from $V1$. As illustrated in the figure, $V1$ and $V2$ are on the same road, which crosses with tha tof $V3$.
Figure 3 compares the models. Despite only 2 rays are taken into account, TRG and TRI can roughly estimate the signal power at the receiver that is on the same road as the transmitter ($V2$). The receive power characteristic at $V3$, on the other hand, is largely different, drops quickly below the receive threshold of 6 Mbps coding rate (which is the typical setting for safety applications) as soon as the distance of $V1$ from the junction is larger than 10 meters, obviously due to the signal blockage. Our results indicate that the receive signal power can be estimated by the TRG or TRI models for vehicles which are on the same road of the transmitter, and it is difficult to expect communications between vehicles on crossing roads unless the distance to the junction is very small.

2) MAC model: As mentioned earlier, ETSI defined the CAM frames for periodical information exchange between vehicles and infrastructure allowing the road users to know the existence and the state of each other. We believe that the CAM frames can indeed serve for path planning applications.

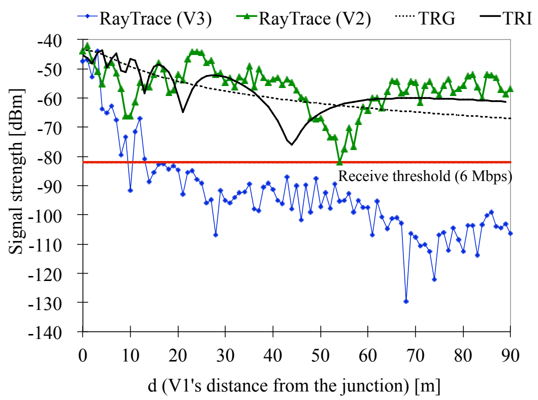

Fig. 3. Receive signal strengths at V2 and V3 from V1 are calculated using ray-tracing, TRG, and TRI models.

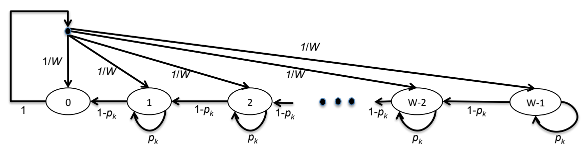

Fig. 4. The MAC protocol behaviour is modelled using Markov chain.

This subsection presents a simple MAC model to characterize the CAM delivery performance between vehicles. Since we consider only 1 type of information traffic and CAMs are broadcast packets, it is enough to express the protocol's behavior by a 1 dimensional Markov chain as illustrated in Fig. 3. Note that the Markov-chain is built for the saturated channel condition, but we will later extend the model for non-saturated cases. The state $b(i)$ of the Markov chain represents the contention window countdown states. p_k is the channel blocking probability, i.e., the probability of channel being busy due to activities at the nodes other than the tagged node (i.e., the node which is the subject to the Markov chain) and W is minimum contention window size for the AC. Solving the Markov chain, *i.e.*, $\sum_{i=0}^{W-1} b_i$=1, the channel access probability is found as

$$\tau_s = b(0) = \left[1 + \frac{W-1}{2(1-p_k)}\right]^{-1}. \tag{3}$$

The channel access probability for general channel conditions can be formulated as:

$$\tau = q \times \tau_s, \tag{4}$$

where q is the probability of a pending packet at the node. Since message generation can be modelled by the Poisson process, the probability of a pending packet is

$$q = 1 - \exp\left(-\lambda Y_s\right). \tag{5}$$

Here, λ is the frame generation rate, Y_s is the average channel service time. Letting T be the time required for a transmission of a frame (including the arbitrary inter-frame space, AIFS), and σ be the slot time, the average channel service time is

$$Y_s = p_b T + (1-p_b)\sigma, \tag{6}$$

where p_b is the probability of busy channel. The probabilities of busy channel and channel blocking events, p_b and p_k, can be expressed by the number of transmission nodes in the sensing range.

$$p_b = 1-(1-\tau)^N,\ p_k = 1-(1-\tau)^{N-1} \tag{7}$$

Finally the probability of successful reception of a given CAM frame at a given receiver is calculated as

$$P_s = (1-\tau)^{N-1}. \tag{8}$$

As it can be easily seen in Eq. (8), the current model takes into account the impact of packet collisions. Although the model should be extended to take the other effects (e.g., hidden terminal) into account, due to its simplicity, we decide to not extend the model for the current paper. Finally, the model is solved by iterative calculation using Eqs. (3) – (8).

III. Experiments

Experiments with the model of section II were performed in simulation using the NetLogo software environment [10], a graphical multiple-agent simulation tool — real experiments with hundreds of automated intelligent vehicles seem impossible nowadays. We chose to use NetLogo for two reasons: 1) it is a multi-agent simulation tool, and hence it naturally fits for investigations of the behaviour of vehicle-agents 2) although the network simulators including NS3 and OMNET are more popular in the field of communications, due to their packet-level processing, they are extremely time costly for a system with hundreds and thousands of nodes; in contrast, NetLogo is based on models and thus allows simulations of the fundamental communications characteristics in large-scale systems. Figure 1 illustrates the road scenario, where the distance between 2 parallel roads is assumed to be 200 meters. One simulation runs up to time tick 10000.

We investigated the performances of the "No-ant" and "Ant" behaviors, when the vehicles 1) do not communicate, 2) have a complete set of information about all other vehicles (ideal communication, i.e., zero communication error), and 3) communicate following the IEEE 802.11p technology (realistic communication). The "realistic" communication is implemented following the PHY (signal propagation) and MAC models developed in the previous section. Specifically, having the 6 Mbps coding rate in mind, the receive and carrier sense threshold are set to -82 and -94 dBm, respectively. Applying the TRG model, we get 500 of transmission range and 800 meters of sensing range. Therefore, vehicles on the same road can communicate and are in the sensing range of each other if the distance is within the above mentioned values. Without much loss of generality, we assume that vehicles on crossing roads are within each others transmission range if they are in the intersection area. In the experiments, the individual vehicles behave following a finite state automaton model (see Section II) and broadcast CAM messages (200 Bytes) in every 100 ms. The success probability for a CAM message from a given vehicle is calculated for other vehicles in the transmission range following the MAC model (Eqs. (3) – (8)). It should be noted that because the width/height of the actual topology is smaller than double of the interference range, for accuracy of interference calculation, the roads are virtually extended containing "virtual" vehicles, with the equal density to that of the corresponding actual road.

A. Communications impact

Figure 5 compares the standard deviation of the number of vehicles on the individual streets.

We observe that in the "ideal" communication, the ant strategy creates extremely biased vehicle distribution (e.g., most of vehicles are in the same street), while no-ant strategy shows more balanced road usage. This is expected because in "ant" strategy, vehicles are attracted to other vehicles, and hence create congested roads. In contrast, in no-ant strategy, the vehicles try to take the scarce roads, creating a situation, where there is neither too congested nor too scarce road.

In the case of realistic communication, while STD value is again larger for "ant" than for "no-ant", the difference is small, showing that both the strategies fail to show the collective behavior as they intend to. This indicates that the collective behavior can be very different from the "expected" behavior, if there are communication errors. Figure 6 compares the average success probability of realistic communication for ant and no-ant cases. The results are obvious for the point that the success probability degrades with the increase of the number of vehicles (the increase of "N" in Eq. (8) results in degradation of the success probability). Moreover, it is expected that since "ant" behavior creates congested roads, the communication error is more severe in "ant" case compared to "no-ant" case. However, as can be seen in Fig. 6, while the success probability is better for "no-ant", the difference is very small. Figure. 5 explains the reason. As mentioned before, due to communication errors, the "ant" and "no-ant" strategies do not show their expected behaviors (i.e., the one in the "ideal" communication). Hence the vehicle distribution is not too biased for "ant" case, consequently "N" in Eq. (8) is not very different for "ant" and "no-ant" cases.

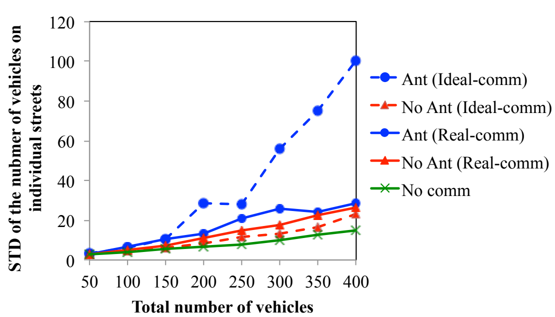

Fig. 5. Comparison of STD of the number of vehicles on the individual streets.

B. Emergent behaviors

For each simulation, at each time tick, the average of the instantaneous speed towards destination (in patch/tick) of each vehicle is measured. This speed is the manhattan distance (including the circular/wrapped environment) between the previous goal location (or initial location, at time tick = 0) and the current one, divided by the number of time ticks elapsed for a specific vehicle to reach these these two goal locations. Each vehicle updates its speed-towards-destination each time it has reached its destination.

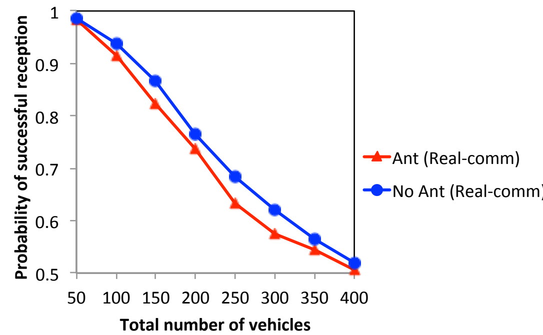

Fig. 6. Success Probability of the CAM frames.

For each simulation (each point in Fig. 7 and in Fig. 8), we observe stabilization of the measured speed-towards-destination to a specific value, after a sharp increase in the beginning (lasting approximately 2 to 3000 time ticks). To avoid this increase and compare stable values only, we plot the mean of values over the last 6000 time ticks among 10000 (see Fig. 7), leaving 4000 ticks for passing this increase, and the last value, at time tick 10000 (see Fig. 8). (Note that each point of the results represent the performance achieved from one simulation run, 10000 ticks.)

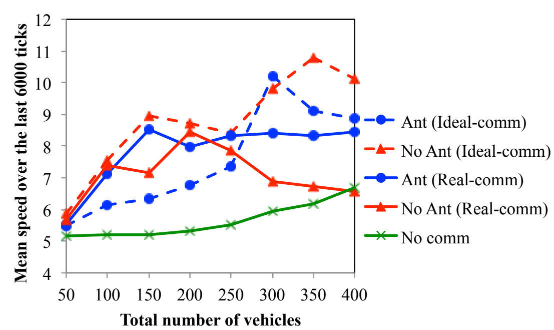

Fig. 7. Mean over the last 6000 time ticks of the averaged instantaneous speed of vehicles towards destination, as a function of the number of vehicles (50 to 400 by step of 50 vehicles), for combinations of communication modes and path-finding heuristics: Ideal communication with No/Ant heuristics, realistic communication with No/Ant heuristics, no communication with compass heuristics (No/Ant heuristics are not applicable in this case).

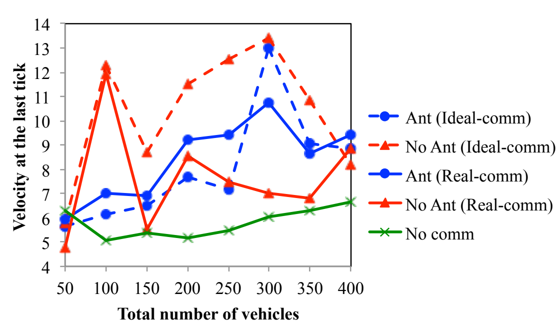

Fig. 8. Last value (at tick = 10000) of the same measures as in Fig. 7.

Fig. 7 and 8 suggest that: (1) Communication's impact is large for the performance of the emergent behaviour, i.e., No-Communication gives the worst speed-towards-destination, vehicles boldly following their path to destination without communicating is worse than any other path-finding heuristics with communication. (2) When communication is ideal, the No-Ant behaviour outperforms the Ant one, i.e., when there is a choice, fleeing traffic leads to higher speed-towards-destination than following traffic. (3) When communication is realistic, the difference between the No-Ant behaviours is smaller with regards to the ideal case, but the Ant heuristics behaves slightly better for a large number of cars.

IV. Related Work

Much effort has been made to study the applicability of the IEEE 802.11p to the ITS applications. The authors of [2] compared the TRI and TRG models to experimental results, and concluded that while TRI is computationally expensive it fits well to the signal propagation characteristics in vehicular environments. The focus of our work is in urban scenarios and it is not clear if the TRG and TRI, which take account of only 2 rays, can be be used. To this reason, we compared the models to ray-tracing results, and showed that the models can be used for vehicles that are on the same street. Due to its simplicity, we chose TRG for our simulations. A large number of work have been made to model the MAC for wireless communications. Bianchi made the pioneering work to model the Distributed Coordination Function using a 2D Markov chain. Ma et al. presented a 1D Markov chain to describe the broadcast throughput, delay, and packet reception ratio by taking channel freezing into account. Our model is similar to that presented in [3], except the channel blocking effect is considered.

In the context of automated driving, the authors of [6] studied how the penetration rate of communication enabled vehicles improves the braking effort of individual vehicles. Sakaguchi et al. [4] defined communications protocol for inter and intra platoons for safe automated platooning control. The authors of [11] define high level definition of message exchange between vehicles and supervisor (infrastructure) that are required from trajectory planning in crossroads.

Several authors have studied communication under the multiple agent systems (MAS) paradigm [12] [13]. However they define communication protocols for natural language per se (*speech act*), and ignore the physical sending/receiving of messages. Our work is different from the previous efforts in the points that 1) we study the applicability of the standardized technology for automated driving especially route planning of automated vehicles 2) we showed how realistic communications perform in comparison to the "ideal" cases, which are often assumed in majority of work in the context of automated driving.

V. Conclusion

In this paper, we studied the emergent traffic performances of several hundreds uniform vehicles as a function of communication modes and dynamic path-finding heuristics (straight-towards-destination, towards-more-traffic "Ant", towards-less-traffic "No Ant") in a urban (Manhattan-like, wrapped/circular) environment. An implementation of the model using NetLogo multiple agent simulation software [10] suggests that V2V communication and dynamic path-finding heuristics lead to better emergent average speed (i.e., global traffic with better performances) than no communication (i.e., vehicles following their compass to destination only); and that, whenever there is a secondary path in an urban environment, fleeing from traffic leads to better global performances than following traffic.

Our future work includes an extended MAC model that takes account of the hidden terminal and capture effects. For the aspect of the vehicles' behaviour, we will include the agent/group/role MAS paradigm (e.g., using the MadKit software [14]) to: (1) separate vehicles into different behavioral groups, each group having its own heuristics (e.g., taxi, bus, car), instead of having all vehicles sharing the same behavior/heuristics; (2) change the currently unique global behavior of the infrastructure to measure the resistance of intelligent vehicles to perturbation.

References

[1] *ETSI TR 102 638; Intelligent Transport Systems (ITS); Vehicular communications; Basic set of Applications*, Std., Feb. 2009, draft V1.0.4.

[2] C. Sommer, S. Joerer, and F. Dressler, "On the applicability of two-ray path loss models for vehicular network simulation." *VNC*, vol. 12, pp. 64–69, 2012.

[3] X. Ma, X. Chen, and H. H. Refai, "Unsaturated performance of ieee 802.11 broadcast service in vehicle-to-vehicle networks," in *Vehicular Technology Conference, 2007. VTC-2007 Fall. 2007 IEEE 66th*. IEEE, 2007, pp. 1957–1961.

[4] T. Sakaguchi, A. Uno, and S. Tsugawa, "Inter-vehicle communications for merging control," in *Vehicle Electronics Conference, 1999.(IVEC'99) Proceedings of the IEEE International*. IEEE, 1999, pp. 365–370.

[5] L. C. Bento, R. Parafita, and U. Nunes, "Intelligent traffic management at intersections supported by v2v and v2i communications," in *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*. IEEE, 2012, pp. 1495–1502.

[6] Q. Xu, K. Hedrick, R. Sengupta, and J. VanderWerf, "Effects of vehicle-vehicle/roadside-vehicle communication on adaptive cruise controlled highway systems," in *Vehicular Technology Conference, 2002. Proceedings. VTC 2002-Fall. 2002 IEEE 56th*, vol. 2. IEEE, 2002, pp. 1249–1253.

[7] T.-C. Au and P. Stone, "Motion planning algorithms for autonomous intersection management." in *Bridging the Gap Between Task and Motion Planning*, 2010.

[8] M. Dorigo and T. Stützle, *Ant Colony Optimization*. MIT Press, 2004.

[9] *IEEE Standard for Information technology — Telecommunications and information exchange between systems — Local and metropolitan area networks — Specific requirement, Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications*, IEEE Computer Society Std., July 2010, iEEE Std 802.11p-2010.

[10] U. Wilensky, "NetLogo, available online at http://ccl.northwestern.edu/netlogo," *Center for Connected Learning and Computer-Based Modeling. Northwestern University, Evanston*, 1999.

[11] O. Mehani and A. de La Fortelle, "Trajectory planning in a crossroads for a fleet of driverless vehicles," in *Computer Aided Systems Theory–EUROCAST 2007*. Springer, 2007, pp. 1159–1166.

[12] P. Populaire, Y. Demazeau, O. Boissier, and J. Sichman, "Description et implmentation de protocoles de communication en univers multi-agents," *1eres Journes Francophones sur lIAD et les SMA, AFCET & AFIA, Toulouse, IRIT*, April 1993.

[13] J.-P. Briot and Y. Demazeau, Eds., *Principes et Architecture des Systmes Multi-Agents*. Traité IC2, Hermès, November 2001.

[14] O. Gutknecht, J. Ferber, and F. Michel, *The Madkit Agent Platform Architecture*, LIRM, Université de Montpellier II Std., May 2000.