A Smart Compact Traffic Network Vision Based on Wave Representation

Walter Balzano, Aniello Murano, Loredana Sorrentino and Silvia Stranieri

Abstract VANET constitutes a huge research area due to its potential in traffic management and road safety. In this paper, we propose a novel, smart, and compact representation of vehicular networks. Starting from the standard graph representation, we extract a signal assigning a congestion factor to each vehicle, so that highly jammed traffic areas can be immediately detected by identifying the highest peaks of the wave. The way the signal is built provides useful information about vehicles distribution throughout the network, producing as result a simple but very meaningful wave characterizing the corresponding VANET.

***Keywords**: VANET, wave representation.*

1 Introduction

Wireless Sensor Networks (WSNs) are made of low-cost and low-power sensors able to communicate and perform distributed tasks, often by self-organizing into clusters. These networks can be largely employed for different purposes, such as sensing, event detection, localization ([8, 9, 11, 21]). The WSN features of congestion control, self-configuration, and energy awareness let their use keep growing. In particular, congestion in WSN constitutes a concrete challenging issue, since it

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determines a network performance decrease, as a consequence of an amount of requests which is higher than the ones it can be actually satisfied. As pointed out in [3], the increasing interest in the last years is due to the fact that rapid deployment and fault tolerance characteristics of sensor networks make them a promising sensing technique for military purposes. Moreover, the sensor ability of tracking the movement of small animals, as well as monitoring the surrounding ambient, makes them suitable for environmental aims.

An interesting application of WSN is in the vehicular context [22]: indeed, a new emerging field is the *vehicular ad hoc network*, where the vehicles play the role of sensors in a WSN [4]. Due to the increasing number of road accidents, the need for a stable communication system between vehicles is growing. Cars can broadcast data and information about exceptional events occurrence via wireless media, letting the rest of the vehicles be aware of the condition inside the network [16]. This mechanism has a significant impact not only on safety, but also in traffic management. Due to the importance of such a network, in this work we provide a smart VANET representation by including in a single compact wave a lot of useful information about node congestion, traffic, and network clusterization. Such a wave is obtained by computing the value of congestion, named *congestion factor*, of any vehicle in the network, so that highly jammed traffic areas can be immediately detected by identify the highest peaks of the wave. Essentially, we propose a way to obtain the highest amount of information about the network, with as few data as possible.

Outline of the paper

The rest of the paper is organized as follows. In Section 2, the state of the art is analyzed. In Section 3, our novel network representation is provided. Here we distinguish the phase in which the signal is built from the one in which the signal is analyzed and understood. In this section we also provide some examples of use, just for the purpose of illustration. Finally, Section 4 gives the conclusions and some hints for future developments of this paper, working mainly on the obtained wave.

2 Related Work

Vehicular ad hoc networks (VANETs) has become an active area of research due to its potential to improve vehicle and road safety, and traffic efficiency: as explained in [25], these kind of networks belong to Intelligent Transportation System (ITS) field, where each vehicle can receive or send information to the network. Vehicles are equipped with on-board units in order to be able to communicate not only between each other, but also with road infrastructure elements.

Each car in a VANET can communicate with its adjacent nodes directly and, via multi-hop, communication can be performed also with farther vehicles, as pointed out in [13]. Nowadays, VANETs are a hot research topic because of the variety of applications: in [15], they propose some of them, such as vehicle collision warning, cooperative driving, map location, automatic parking [5], path tracking [10], and so on.

Many researchers in the last years based their studies on VANETs issues, such as routing protocols, and clustering algorithms: in [18], they point out that routing is a challenge due to high dynamics of VANETs, and they analyze a position-based routing approach in city environment; similarly, in [19], they propose a Connectivity-Aware routing for inter-vehicular communication, by integrating the needs of locating destination and finding paths between source and destination. [17] provides a survey on routing protocols for VANETs.

A further hot topic in this field is clusterization, that provides a clever way to disseminate data through the network, by improving communication and reducing redundancy. This is the reason way many authors made an effort to propose new clustering algorithms suitable for vehicular networks. As instance, we mention authors in [26], which propose a multi-hop clustering schema to enstablish stable vehicle groups. Furthermore, we have already faced some VANETs issues in our recent work, by also focusing on clusterization techniques. In particular, in [12], we provide a non-exclusive clustering approach, by modifying the DBSCAN algorithm, by revisiting the standard communication framework with a centralized approach. Indeed, we observed that a centralized system brigs different benefits, among them: (*i*) the simplification of clustering process, (*ii*) a full knowledge of the network topology, and (*iii*) the ability of collecting data and providing statistics. Moreover, in [6], we propose a new clustering technique based on two kind of cluster-head election, according to the road configuration (one-way or two-ways). Specifically, the cluster-head is chosen as the farthest node from the source of information. This choice allows to optimized the node distribution in clusters, and to minimize redundancy in transmission. For further details on VANETs clustering proposals consult [24].

Although many authors focused on VANETs aspects and challenges, as far as we know, this is the first work addressing the VANETs representation. Even in *Google Maps*, the most popular mapping app used by more than 150 millions of unique users monthly according to a 2018 statistics reported in [2], a road representation emphasizing the traffic congestion is not treated enough. Here, we provide a smart and compact representation of such a network, by computing a congestion factor for each vehicle belonging to it, aimed to map the network to a wave on a Cartesian coordinate system. The result is a very intuitive representation of the starting VANET, providing useful information, such as traffic distribution and network clusterization.

3 Wave Construction over Traffic Network

In this section we propose a novel algorithm to produce an opportune wave representation of a generated traffic network. Before focusing over the core of our work, we provide the definitions of some terms used in this section.

3.1 Preliminaries

As follows, we provide some basic concepts used in the rest of the paper. As these are common definitions, an expert reader can skip this part.

We consider a traffic network as a undirected graph $G = (V,E)$ in which the set of nodes V corresponds to the vehicles in the network, with $|V| = n$, and the set of edges E corresponds to the links, if any, between the nodes, with $|E| = m$.

We define R as the *distance coefficient*, i.e. the maximum value within which two vehicles can communicate with each other. Such a value is calculated referring to the measurement of the power present in a received radio signal, i.e. the *received signal strength indicator (RSSI)*. The RSSI values are measured in dBm and have typical negative values ranging between 0 dBm (excellent signal) and -110 dBm (extremely poor signal)[20]. In particular, it is intuitive to say that increasing the distance, the RSSI decreases. Moreover, given two nodes $\mathtt{u}, \mathtt{v} \in \mathtt{V}$, we define $d(u,v) \in [0,R]$ the euclidean distance between u and v. We can state that an edge $(u,v) \in E$ **exists** iff $d(u,v) \leq R$, and we indicate with $weight(u,v)$ its weight.

Since in a vehicular network $d(i,j) \neq d(j,i)$ (with $i \neq j$), we directly provide a normalized graph, by computing the average of these two distances and by assigning this value to the edge linking i and j, so that the corresponding adjacency matrix is symmetric. Finally, for each $v \in V$ define $neig(v) = \{v' | (v,v') \in E\}$ and $degree(v) = |neig(v)|$ as the set of v-neighbors and its number, respectively.

3.2 Construction Phase

The idea of our algorithm is to construct a smart compact vision of traffic network based on wave representation, starting from randomly generated points in the space (based on the normal distribution). In order to obtain a signal that reflects the congestion of any vehicle in the network regardless the way it is visited, we compute a *congestion factor* through a function f for each node of the network:

$$f : V \longmapsto [0,1] \tag{1}$$

This factor is parametric on R and is computed as the difference between the *ideal congestion* and the *local congestion*. Given the node v, the ideal congestion represents the situation where all the neighbors are at maximum distance from v:

$$ideal(v) = degree(v) * R \tag{2}$$

Instead, the local congestion is an arithmetic average over the adjacents of v:

$$local(v) = \frac{\sum_{u \in neig(v)} weight(u,v)}{degree(v)} \tag{3}$$

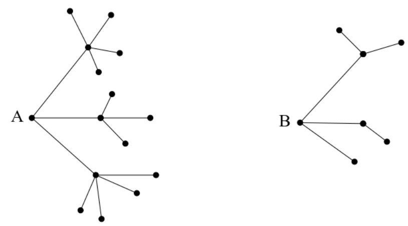

Fig. 1: Example of misleading congestion factor computation

We can observe that the congestion degree of a node does not depend only on the number of its neighbors, but mostly on their congestion. Thus, we need to take into account the congestion of each neighbor of the considered node, in order to avoid the situation as the one shown in Figure 1, in which the nodes A and B have the same number of neighbors, but the congestion of such neighbors is different. Indeed, in the left side we have a higher congestion level with respect to the right side, but with the previous formula A and B would have had the same congestion factor.

For this reason, we introduce a *weighted ideal congestion*:

$$weighted\_ideal(v) = \sum_{u \in neig(v)} (degree(u) - 1) * ideal(v) \tag{4}$$

Notice that when we compute the degree of the neighbors of a given node v, we decrease it by 1 in order not to consider v again. Once the congestion factors are computed, they are normalized, dividing them by the maximum congestion factor of the considered network.

The network representation we want to build is $f(V)$, with f as defined in equation 1. A key point in the wave representation is the order in which the nodes are placed on the x axis. Our goal is to obtain a signal that immediately highlights the most congested areas and which points belong to them. For this reason, we propose a cluster-oriented visit of the network that, starting from a random point, continues the visit of neighbors, putting them in the same connected area, as long as a certain distance is not overcome. With "connected area" we mean a set of related nodes. It is important to notice that this is not a new clusterization technique, but an alternative way of visiting a network by detecting areas of nodes connected within a certain distance. To this aim, we introduce a tolerance ε such that, given a node v and its neighbor u, if $d(v,u)) \leq R - \varepsilon$, u is in the same connected area as v. It is necessary to notice that we distinguish the congestion factor of isolated nodes by the one of nodes having only edges with weight $\geq R - \varepsilon$, by preserving them in the network. Once the connected areas are obtained, the nodes are placed on the x axis in such a way that the ones belonging to the same connected area are contiguous. In particular, for each connected area we put the elements belonging to it in increasing order with respect to the congestion factor. This choice makes easier the detection of connected areas looking at the signal.

3.3 Signal rendering

In this section, we propose some examples of network transformation, by analyzing all the information we can infer. The examples below are generated according to the following parameters: the number of nodes n, maximum distance R allowed between two nodes, a tolerance ε introduced in the section above, and the standard deviation sd, used to produce random points through a normal distribution.

Starting from the wave representation, we are able to understand the network congestion, as well as identify the different connected areas. Indeed, according to how the signal is built, a null congestion factor corresponds to an isolated node, and each high-low transition induces a new connected area, but the opposite does not hold in general. Hence, this is a *necessary* but not a *sufficient* condition for the starting of a new area. This means that there could be changes of area hidden by the signal, when the highest congestion factor of the first connected area is smaller than the lowest one of the second connected area, introducing *false negatives*. As shown in Figure 2(b), which is the signal corresponding to the graph 2(a), it is intuitive to observe that the most congested nodes are 24 and 29. Another information easy

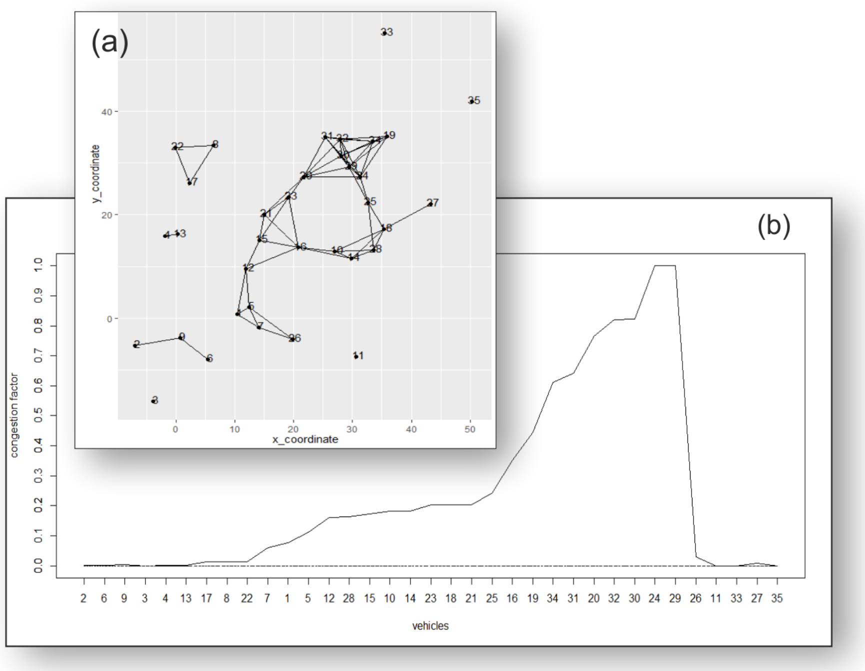

Fig. 2: Random generation of a network with $n = 35$, $sd = 10$, $R = 10$, $\varepsilon = 0.3$ (a) and the corresponding wave representation (b)

to deduce is about the areas of the network made by single nodes. Indeed, they are identified by the points whose congestion factor coincides with the dashed line, i. e. 3, 11, 33, and 35. In order to detect the remaining connected areas, we need to retrieve the high-low transitions, corresponding in this network to the points 9, 29, 26, and 27. By analyzing the network in Figure 2(a), we would have expected a change of area between the nodes $4, 13$ and $8, 17, 22$, that is hidden by the signal because of false negatives. The same happens between the nodes 22 and 7.

The signal obtained as shown in the examples, is determined by visiting the nodes of the network starting from the one having the smallest x-coordinate. By changing the starting point, clearly the congestion factor of each node stays the same, but the resulting wave can be a permutation of the peaks in the current signal. This could be a limitation for comparisons between waves. For this reason, we introduce a *canonical form* of the signal, obtained by changing the order of the nodes on the x axis: not only the nodes are ordered in increasing order of congestion factor inside each connected area, but also each connected area is ordered in decreasing order of maximum congestion factor on the x axis. Through this normalization, we obtain a signal having the connected area with the highest congested node on the left side, and the single nodes on the right side.

With this approach, false negatives are also reduced. Indeed, it is no longer possible that the highest congested factor of a previous connected area is smaller than the lowest factor of the next area, since they are ordered, but false negatives can still occur, as formally reported in the following theorem:

Theorem 1. *Given two successive connected areas a_1 and a_2, let h_i and s_i (with $i \in [1,2]$) be the highest and lowest congestion factors respectively for the corresponding area, then:*

$$\textit{false negative} \implies a_2 \textit{ made of a single node having as congestion factor } h_1$$

Proof. Let us assume the premise true, thus we have a false negative. The following inequalities hold:

$$\begin{cases} h_1 \geq h_2 & \textit{by construction} \\ h_1 \leq s_2 & \textit{by definition of false negative} \\ s_2 \leq h_2 & \textit{trivially} \end{cases}$$

Hence, the only possibility is that $s_2 = h_2 = h_1$.

□

The example in Figure 3(b) shows the signal construction following the random generation of the corresponding network in Figure 3(a). As expected, the peaks decreases from left to right (with 21 the most congested vehicle), each high-low transition indicates a change of connected area, and the nodes whose values correspond with the dashed line are isolated vehicles $(2, 10, 19, 35)$.

By slightly changing the standard deviation value, we generate a more connected network such as the one shown in Figure 4(a). Analyzing the corresponding signal

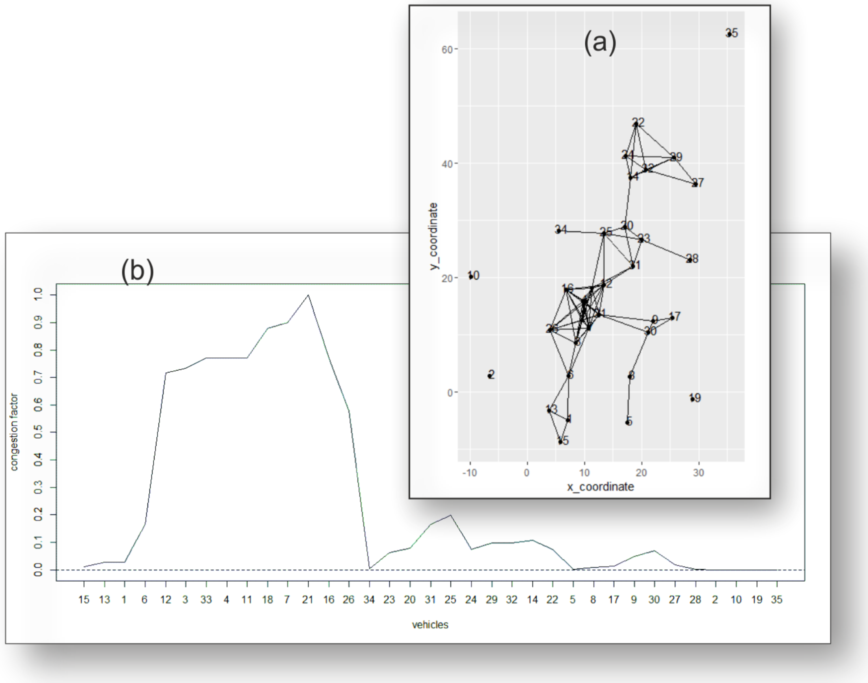

Fig. 3: Random generation of a network with $n = 35$, $sd = 10$, $R = 10$, $\varepsilon = 0.2$ (a) and the corresponding wave representation (b).

in Figure 4(b), we can deduce that the most congested node is 18, there are three isolated nodes $(4, 34, 10)$, and high-low transitions occur correspondingly to the nodes 18, 3, 15, 5, 28 and 34 identifying the end of a connected area.

Other examples my be obtained by modifying the input parameters: the result is a network with a different distribution of nodes. By decreasing the maximum distance allowed between any pair of nodes, we automatically make the radio signal less powerful. As a consequence, the visibility between nodes is reduced and we produce a network which is more disconnected. The corresponding signal, hence, presents an higher number of isolated nodes (whose congestion factor correspond to the zero line).

On the other hand, if we increase the tolerance, we have a higher probability that nodes far *enough* do not belong to the same connected area, despite being linked. Indeed, the greater is the tolerance, the less is the maximum distance allowed for two nodes to be in the same connected area.

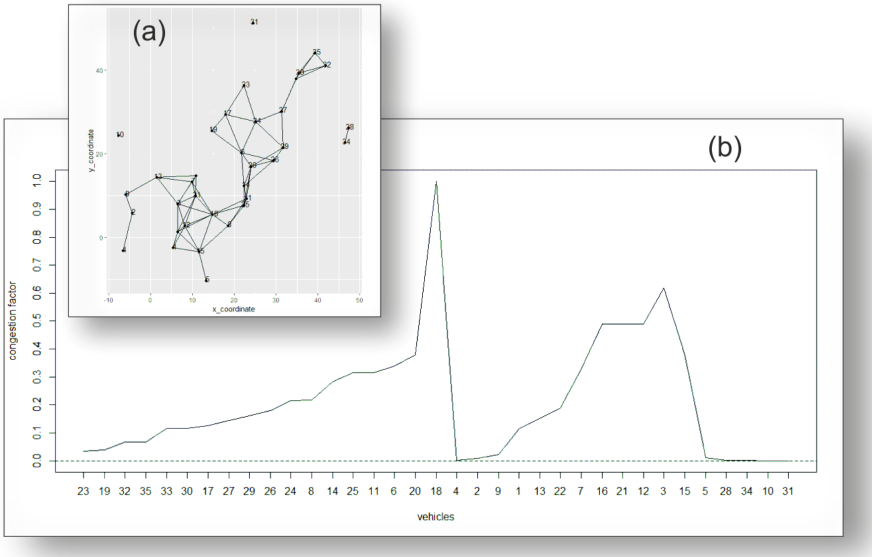

Fig. 4: Random generation of a network with $n = 35$, $sd = 8$, $R = 10$, $\varepsilon = 0.2$ (a) and the corresponding wave representation (b).

4 Conclusions and Future Works

VANET constitutes a very promising research field due to the increasing number of vehicles equipped with wireless devices. This number, according to how estimated in [1], will have increased more than three times the 2018 value in seven years. Vehicular environments represent challenging but fascinating scenario in which we find a huge amount of applications [7]. Among the best known, we mention the *Traffic information systems* [23], as well as parking techniques development [14].

In this work, we provide a smart wave representation of a network, where vehicles are linked to each other according to RSSI value. The obtained signal allows to indentify the traffic condition of a certain environment, and how the vehicles form connected areas according to their distribution. This work opens up several possible future scenarios. Indeed, we are planning to exploit this representation to preform comparisons between the waves, corresponding to networks, and to extract similarity measures.

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