Are Vehicular Networks Small World?

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***Abstract*—Daily, vehicles in transit in a city and during their trajectories encounter other vehicles. The regularity of these encounters is influenced by several elements, such as: vehicle's speed, destinations, traffic conditions, and the period of the day. It is possible to justify these elements by road conditions and the driver's behavior. People have routines and similar behaviors, which strongly impact the daily traffic evolution. An alternative to understand this evolution is to look to the vehicles' mobility under a social perspective. Thus, we present a social analysis of real and realistic traces that describe the mobility of a set of vehicles. Social metrics are computed and the obtained results are compared to random graphs. Initial results showed the presence of social characteristics in the vehicular mobility.**

I. Introduction

"Computer networks are inherently social networks, linking people, organizations, and knowledge"[1]. In this perspective, the concepts of Social Networks have been explored in different kinds of computer networks, mainly to better understand the evolution of the network topology and to analyze physical encounters of the nodes. The goal is to improve the performance of the network protocols. In Vehicular Ad hoc Networks (VANETs), vehicles transit along an area and during their trajectories they can encounter others vehicles. In this moment, they can exchange information and establish a communication.

Therefore, the mobility of vehicles is influenced by the driver's behavior and their routine. During the weekends, destinations such as camping, malls, churches, and theaters are chosen to leisure and entertainment. These places are not frequently visited. On the other hand, on weekdays people tend to repeat their paths at similar daily time and to the same destinations, such as school, work, university, restaurant. These are places visited everyday and, during their trajectories, vehicles can pass in the same streets and suffer the same traffic conditions. These presented features suggest the study of the vehicular mobility under a social perspective, in order to better understand its evolution and the interaction between vehicles. We believe such study can help to improve vehicular applications' performance and to better take profit of connectivity between vehicles.

In this direction, we focus on the study of the vehicular mobility under a social perspective, considering the encounters between vehicles during their trips. Thus, to execute this social analysis, we have chosen in literature two data sets, which describe vehicular mobility. Using these data sets, we create graphs and compute metrics aiming to find social behavior. (e.g., diameter and cluster coefficient). We then compare the results with the ones obtained using random graths, generated with the same degree properties of the data sets. Preliminary results show that it is possible to find social behaviors in VANETs, depending on the nature of vehicles such as: taxis, cars, buses and trucks.

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II. Modeling

The social analysis considers the encounter among vehicles, i.e., when two vehicles are within communication range of each other. In our evaluation, we consider communication range of 100 m , according to the protocol 802.11p. The traces describes the mobility in urban areas and highways, and we consider 25 km/h as the average speed. Thus, according to this speed and the communication range, we consider the minimum contact time of one encounter equal 15 seconds(s). Then, we map vehicles mobility and encounters described in the trace into a temporal graph. We first divide the whole trace into discrete time slots of duration $t = 1h$. Since vehicle traces usually describe fast changes in the topology, short time slots are recommended to better capture traffic changes. So, with the data in each slot we build a temporal graph. The temporal graph at the time t is an undirected and can be formally defined as a graph $G(t) = (V, E)$, where V represents the set with all vehicles v_i and E represents the set of edges e_{ij}. In $G(t)$, an edge $e_{ij}(t)$ exists between the vehicle v_i and v_j during time t, with $i \neq j$. Each metrics are evaluated hourly, considering the temporal graph $G(t)$ that aggregates all the encounters that happen in the period t. For each trace, 24 graphs $G(t)$ are generated, hourly describing the vehicles encounters during the day.

III. Preliminary Results

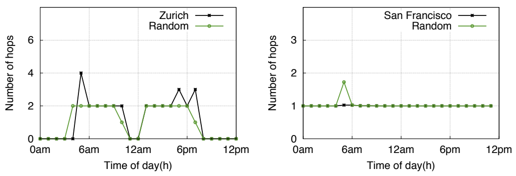
In our initial work [2], we showed an social analysis of a trace mobility. In this work, we had classified the metrics according to mobility features. In the same direction, in this section we present the traces evaluated and the results of two important metrics in social analysis: Distance and Cluster Coefficient.

A. Traces Evaluated

We select to analyze two public data set traces that describe the vehicle mobility along a city. The first trace chosen is the Zurich Trace [3]: a realistic data set based on mathematical models and generated in a mobility simulator that considerate the Zurich's census information. The trace represents the traffic evolution over the day, include the rush times and daybreak. It describes the trajectory of 260.000 vehicles over the day. The second trace chosen is the San Francisco Trace: a real data set describing GPS information of 551 taxis in San Francisco during four weeks [4]. The information is captured from GPS devices installed in each vehicle, minute-to-minute, over its trajectory. Next, we present the obtained numerical results and the comparison with the random graphs.

B. Numerical Results

Distance: In a vehicular networks, the Distance can represent the existence of a common interest between two vehicles. The short distance means that the vehicles visit same places, or cross in the same routes, and long distance means that vehicles pass in distinct regions.

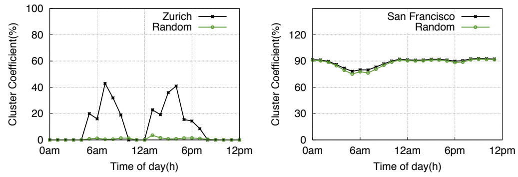


(a) Zurich. (b) San Francisco.

Fig. 1. Daily Average Distance evolution.

In the Zurich trace, Figure 1-(a), we attribute the distance 0 to the hours where there is no traffic. However, in hours with high traffic, the number of vehicles in transit increases and consequently, the encounters probability increases too. Despite this, the distance does not suffer a huge increase. This happened because in the downtown there are many traffic jams that increase the encounters probability, contributing to keep small average distance value. Also, we note that the results obtained from random graphs G^R present a small difference. These are graphs generated in random way, where the edge between two vertices obeys a probability; differently of the temporal graphs where the existence of an edge respects the direction limits of the public roads, and in the random graphs the edge insertion can create shortcuts. In addiction, in the Figure 1-(b), we can see the average distance of the San Francisco trace. As expected, the trace presents a small distance during all the day, and the curve has a constant behavior. Similarly, the random graph G^R presents the same behavior; all the vehicles can reach each other with just one hop. This happen because this trace particularly describes taxis mobility, and due the mobility pattern and the high density, during one hour many taxis encounters one each other, which describing a graph with a higher number of edges and short distance among the vertices. According to the *small world phenomenon*, this phenomenon can be seen in the two traces; a larger number of vertices with a short distance among them.

Cluster Coefficient: The cluster coefficient is an important metric to analyze in the context of social network, because it indicates the presence of communities and users with common interests. In the traditional paper [5], Watts and Strogatz present an discussion about the small worlds networks and comparison with random graphics. It is showed that the cluster coefficient of a social graph is one order of magnitude of the one of a random graph G^R. In the Zurich Trace, Fig. 2-(a), we found a difference of one order of magnitude; the G^R presents a low cluster coefficient compared to the temporal graphs. With this result, we can found social behaviors in Zurich trace. On the other hand, we could not found this difference in the San Francisco trace, as shown in Fig. 2-(b): the curves for the two graphs present the same behavior. This happens due to the high number of encounters in this trace, which make the temporal graph a complete graph.



(a) Zurich $\times$ Random. (b) San Francisco $\times$ Random.

Fig. 2. Daily Cluster Coefficient evolution.

IV. Conclusion and Next Steps

In this work, we presented the social analysis of two vehicular traces describing the mobility of vehicles in the metropolitan area. We analyzed the Zurich trace and San Francisco trace that have different duration and routines. Considering the assumptions defining an encounter, the analyses tof the Zurich trace showed that it presents a small world behavior. Moreover, it presents features that indicate the presence of communities and people with similar interest. The San Francisco trace also presents the small world behavior. Nevertheless, when we look at the cluster coefficient results, it is not possible to conclude the presence of social behavior. As next steps, we intend to extend the evaluation with the computation of other metrics. Additionally, we plan to extend the analysis by varying the parameters impacting the temporal graph generation, such as: encounter duration, slot time windows, communication range, and others. Beyond that, we intend to study the spatio-temporal correlation, aiming to capture the difference of values in different points of the city.

References

[1] B. Wellman, “Computer networks as social networks,” *Science*, vol. 293, no. 5537, pp. 2031–2034, 2001. [Online]. Available: http://www.sciencemag.org/content/293/5537/2031.abstract

[2] F. Cunha, A. Carneiro Viana, R. A. F. Mini, and A. A.F. Loureiro, “How effective is to look at a vehicular network under a social perception?” in *1st International Workshop on Internet of Things Communications and Technologies (IoT’13) (IoT’2013)*, Lyon, France, Oct. 2013.

[3] V. Naumov, R. Baumann, and T. Gross, “An evaluation of inter-vehicle ad hoc networks based on realistic vehicular traces,” in *Proceedings of the 7th ACM international symposium on Mobile ad hoc networking and computing*, ser. MobiHoc ’06. New York, NY, USA: ACM, 2006, pp. 108–119. [Online]. Available: http://doi.acm.org/10.1145/1132905.1132918

[4] M. Piorkowski, N. Sarafijanovic-Djukic, and M. Grossglauser, “Crawdad trace,” Downloaded from http://crawdad.cs.dartmouth.edu/, Feb. 2009.

[5] D. J. Watts and S. H. Strogatz, “Collective dynamics of ’small-world’ networks,” *Nature*, vol. 393, no. 6684, pp. 440–442, Jun. 1998. [Online]. Available: http://dx.doi.org/10.1038/30918