

A Stable Clustering Algorithm based on Affinity Propagation Propagation for VANETs

Hamayoun Shahwani*, Toan Duc Bui*, Jaehoon (Paul) Jeong[†] and Jitae Shin*

* School of Electronic and Electrical Engineering, Sungkyunkwan University, Suwon, Republic of Korea

E-mail: hamayoun@skku.edu, toanhoi@skku.edu and jtshin@skku.edu

[†] Department of Interaction Science, Sungkyunkwan University, Suwon, Republic of Korea

E-mail: pauljeong@skku.edu

Abstract—This paper proposes a stable clustering algorithm based on Affinity Propagation (AP) for Vehicular Ad Hoc Networks (VANETs). In VANETs, vehicles share information for the safe and efficient driving by Dedicated Short Range Communications (DSRC). We present a trajectory-based clustering algorithm for VANETs using AP clustering technique. Our proposed algorithm considers vehicle trajectories to form more stable clusters. Simulation results show the better presentation of our algorithm. The performance of proposed algorithm is measured via cluster life time by choosing appropriate cluster head.

Keywords—Vehicular ad hoc network (VANET), Affinity Propagation (AP), clustering, trajectory, stability.

I. INTRODUCTION

Vehicular Ad Hoc Networks (VANETs) have been acquiring a considerable importance over the last decade due to the advancements in wireless technologies. Recently VANETs are one of the auspicious research areas for researchers [1]. Dedicated Short Range Communications (DSRC) was standardized for vehicular networks by IEEE [2].

Starting from the very beginning of VANETs, the main themes were, reducing the congestion of road traffic, preventing accidents, reducing the fuel consumption [3]. For achieving these goals, some research works were performed. Especially, some useful information is provided to satisfy safe driving, to give priority to emergency vehicles and so on. On the basis of these themes and goals, VANETs have been immensely researched recently. Vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and infrastructure-to-vehicle (I2V) communications are the three significant types of VANET networking.

In recent studies of VANETs, a large number of routing protocols have been proposed for safe and efficient driving but vehicles in VANET may face many difficulties in communication, such as scalability and hidden terminal problem with a larger number of nodes, which can be reduced by clustering of vehicles. Clustering has been shown to achieve efficient and reliable driving and to reduce data congestion. A Cluster Head (CH) is selected, which communicates to all other nodes and coordinate communication among cluster members (CMs). Much research has been done on cluster-based MAC protocols for VANETs [5][6]. Many papers have considered mobility as an important parameter in VANETs. Authors in [7], consider mobility for making stable cluster in VANETs and named

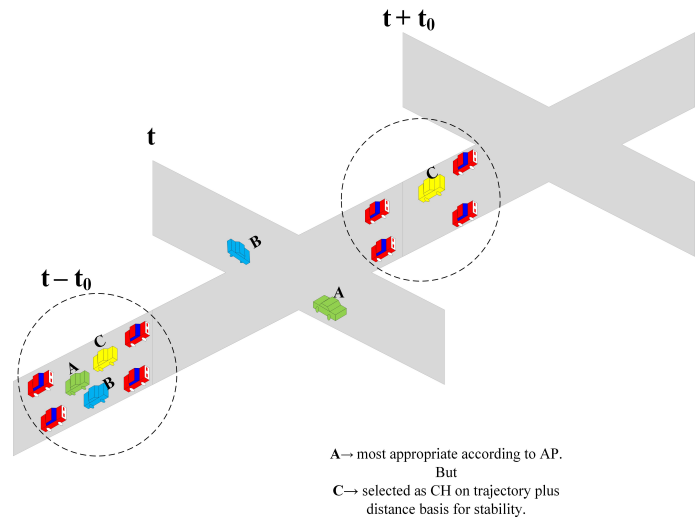


Fig. 1. An example of trajectory-based clustering in VANET. A being the most appropriate according to shorter distance from other vehicles, the second most appropriate is B, still C is selected as CH as it is less distant from other vehicles and has a common trajectory with majority of other vehicles.

it MOBIC in their paper. The basic idea of MOBIC is to consider mobility of every node with respect to its neighboring nodes. If a CH is selected with high mobility with respect to its neighbors, the probability of cluster fragmentation and re-clustering will be high. Thus, a CH with similar mobility with neighbor vehicles should be used. Previous research in VANETs based on clustering stimulates the desire for a stable clustering scheme for VANETs. In this paper, we propose a new trajectory-based clustering algorithm for stability of cluster. Stability here means that the duration of CH will be long and the changing of CH will be minimized along the trajectory of a cluster. We assume that the vehicles are equipped with GPS-based navigation system. Our algorithm is based on a well familiar clustering technique known as Affinity Propagation (AP). Our algorithm will form more stable clusters with the help of AP and vehicle trajectories. Fig. 1 shows the basic concept of our algorithm. When vehicle A in green color is selected as a CH, the cluster will not continue after the first junction as the CH will change its path. Hence, it is important to select the CH wisely considering both distance

and trajectory of CH.

The rest of the paper is structured as follows. Section II elaborates the formulation of our algorithm. Performance evaluation is performed in Section III. Finally, our paper is concluded along with future work in Section IV.

II. PROPOSED ALGORITHM

In this section we formulate our problem as follows.

- Our goal is to make stable clusters considering the trajectory of the vehicles.
- we use AP technique for clustering and for stability we use vehicles trajectories.

In general, the clusters are formed on the basis of distance. But in our algorithm, in addition to distance we use trajectories. Vehicles are classified in two types. One is CH and the other is CM. The procedure for the algorithm is as follows.

- **Step 1:** All vehicles share their location and end-to-end trajectories with each other.
- **Step 2:** The vehicle with less distant from other vehicles and sharing the farthest trajectory with the maximum number of vehicles in vicinity is selected as a CH.

A. The Trajectory-based Affinity Propagation Clustering

Frey and Duek in their paper [8] proposed the idea of Affinity Propagation (AP) that was extraordinary technique for clustering. As AP can make clusters with less error and less time, and also it does not require to have a fixed number of nodes to make a cluster, which is compared to other clustering techniques. AP takes similarity measures between data points as an input, by performing the exchange of real valued messages between data points to make clusters and select their exemplar as a CH. In our proposed scheme, we use vehicles instead of data points.

AP takes similarity, $s(i, j)$, as an input between vehicles, where $s(i, j)$ shows how vehicle j is suitable for the exemplar (i.e., CH) of vehicle i . In order to maximize similarity $s(i, j)$, the similarity between vehicles is set to a negative Euclidean distance. Each vehicle j has a self similarity $s(j, j)$, that is a *priori preference* value, which influences the fair number of clusters. The number of clusters is increased or decreased by increasing or decreasing *priori preference* value.

After similarity measures, vehicles exchange their end-to-end trajectory information to each other. Now instead of selecting an exemplar on the basis of distance, vehicles will select the one as an exemplar which is following their trajectory to the farthest in addition to the least distance with them. As demonstrated in Fig. 1, there are seven vehicles in the cluster. The most appropriate exemplar in according to the general AP is vehicle A in green, the second most appropriate is B in blue, and then the third one is C in yellow. But considering the stability of cluster, CMs will look at the least distance and the trajectory of the exemplar that follows the farthest path along with them.

Two types of messages are transferred between vehicles. The responsibility $r(i, j)$ message is sent from vehicle i to

exemplar j , which shows how well vehicle j is suitable as an exemplar for vehicle i . Formula for responsibility is:

$$r(i, j) \leftarrow s(i, j) - \max_{j' \neq j} \{a(i, j') + s(i, j')\} \quad \forall i, j. \quad (1)$$

The availability $a(i, j)$ message is sent from exemplar j back to vehicle i in response to the responsibility message, showing the inclination for vehicles to become the exemplar of vehicle i , considering the support from other vehicle j (as data points) that vehicle j should be selected as an exemplar. Formula for availability is:

$$a(i, j) \leftarrow \min \left\{ 0, r(j, j) + \sum_{i' \in \{i, j\}} \max\{0, r(i', j)\} \right\} \quad \forall i, j \quad (2)$$

Availabilities and responsibilities are combined to select exemplar. The maximum value of $a(i, j) + r(i, j)$ identifies the exemplar. The formula for convergence to get exemplar Ex is as follows:

$$Ex = \operatorname{argmax}_j \{a(i, j) + r(i, j)\} \quad (3)$$

B. Assumptions

- Each vehicle is installed with a GPS-based navigation system.
- Each vehicle has to share its location and end-to-end trajectory in order to get a stable cluster for long time.
- Vehicle are moving in a uniform speed or they manage their speed in accordance to other vehicles in order to stay with in the group for long time.

III. PERFORMANCE EVALUATION

In this section, we evaluate the performance of our proposed trajectory-based algorithm in terms of stability, that is the average life time of the cluster.

Our performance is based on the following points:

- **AP-and-trajectory based clustering:** Our proposed algorithm gets clusters on the basis of Euclidean distance and end-to-end trajectories of the vehicles. It can construct a more stable group, which will live for a much longer time than other clustering algorithms.
- **Poisson Distribution:** Poisson distribution is used to get the probability of a stable cluster [9]. The probability is more if one CH is selected considering the average vehicular trajectory. The probability is very small if more than one CHs are selected through the trajectory. Such a probability is as follows:

$$P(k) = \frac{e^{-\lambda} \lambda^k}{k!} \quad (4)$$

where λ is the average number of CHs selected and k is the number of CHs selected through out the trajectory. In this case λ is equal to 1, because one CH is selected. Also we can calculate the probability by selecting more than one CH (value of k) for the entire shared distance among the CMs.

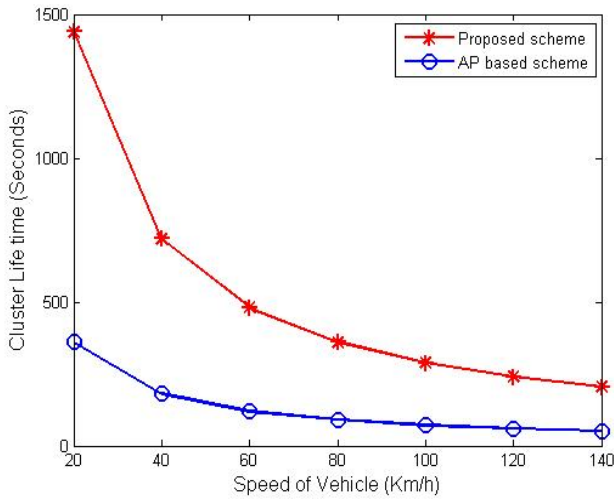


Fig. 2. Stability of cluster (cluster lifetime vs speed of vehicle).

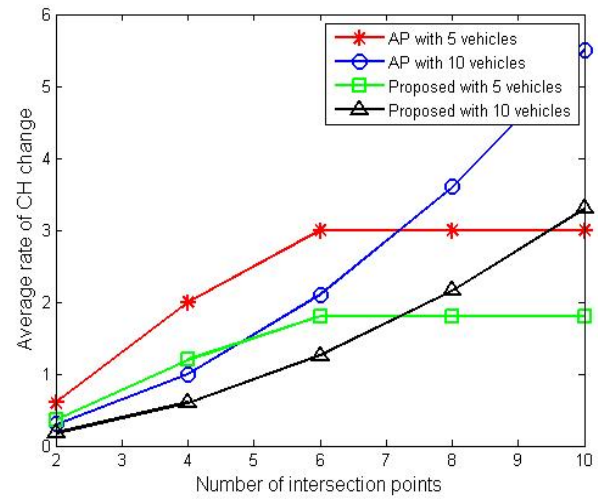


Fig. 4. Average rate of cluster head change with respect to number of vehicles and intersection points.

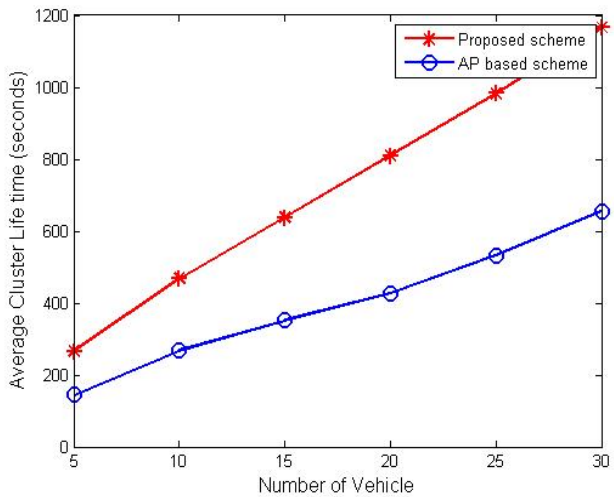


Fig. 3. Stability of cluster (Average cluster lifetime vs number of vehicles).

- **Clustering Performance Metric:** To evaluate the stability of cluster, we use cluster life time (i.e., CH duration) as a performance metric.
- **Evaluation Parameters:** We evaluate the cluster life time with respect to two parameters: *Vehicles Speed* and *Number of Vehicles*, and also the average rate of CH change with respect to the number of intersecting points.

We show the results of our proposed algorithm in MATLAB in term of cluster life time. We consider a cluster of vehicles formed by AP and trajectory-based algorithm. We assume that after every two kilometers, there is an intersection and any of the vehicle can leave the group at the intersection, which can be a CH or CMs. Fig. 2 shows the life time of cluster with respect to the speed of vehicles. As the speed of vehicles increases, the CH duration becomes shorter. In our proposed

algorithm, the CH is selected on trajectory basis, so it is more likely to get better CH duration. Our algorithm first checks for the most appropriate CHs, and then among those CHs, it selects the one whose trajectory is mostly common with the maximum number of CMs. In Fig. 3, we can see the stability of cluster that is average cluster life time with respect to number of Vehicles. The CH selected by AP-based clustering is the one, which is least distant from other CMs in spite of the fact that it can leave the cluster at first intersection or it can move to the end of the road segment. In our proposed algorithm, the CH is always wisely selected to improve the stability of the cluster. Blue line with circles shows the AP and red line with asterisk shows our proposed algorithm. Random vehicles are selected in both cases, but in our proposed case, the vehicle selected as a CH, is almost moving to the end of the road segment with in the highest number of vehicles. Fig. 4 shows the average rate of CH change. It can be seen that if there are more intersection points with in the trajectory of cluster, there is a higher chance of a CH change on any intersection. For 5 vehicles in one group, the CH changes is increased when the number of intersection points are increased but the average CH change remains same when the intersection points are more than the number of vehicles. The average CH change with 10 vehicle is less than that of 5 vehicles because with in 10 vehicles the probability of selecting the CH that can go to the end of trajectory is more. Obviously this CH change rate is less in our proposed algorithm than AP-based one because our algorithm selects a CH among the best suitable CH candidates on the basis of both distance and trajectory.

IV. CONCLUSION

In this paper, we proposed a stable clustering algorithm based on AP for Vehicular Ad Hoc Networks (VANETs). As the vehicles are equipped with GPS navigation system and

DSRC devices, its easier to use the positions and end-to-end trajectories of vehicles for betterment of VANETs. Our algorithm used the trajectories of vehicles to increase the duration of CH and make the cluster stable for longer distance and time. As a future work, we will design a new algorithm for the communication between two groups and also splitting and merging of CMs from one group to another.

ACKNOWLEDGMENT

This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIP) (No. B0101-16-0033, Research and Development of 5G Mobile Communications Technologies using CCN-based Multi-dimensional Scalability).

REFERENCES

- [1] Q. Xu, R. Sengupta, D. Jiang, "Design and analysis of highway safety communication protocol in 5.9 GHz dedicated short range communication spectrum," in *Proceedings of the Vehicular Technology Conference, VTC*, IEEE, 2003.
- [2] Y. L. Morgan, "Notes on DSRC & WAVE Standards Suite: Its Architecture, Design, and Characteristics," in *IEEE Communications Surveys & Tutorials*, vol. 12, no. 4, pp. 504-518, Oct. 2010.
- [3] Hannes Hartenstein and Kenneth P. Laberteaux, "VANET: Vehicular Application and Inter-Networking Technologies," *John Wiley and sons, Ltd, Publication*. 2010.
- [4] W. Chen and S. Cai, "Ad hoc peer-to-peer network architecture for vehicle safety communications," *Communications Magazine*, IEEE, vol. 43, no. 4, pp. 100-107, April 2005.
- [5] Y. Gunter, B. Wiegel, and H. Grossmann, "Cluster-based medium access scheme for vanets," *Intelligent Transportation Systems Conference, ITSC* 2007. IEEE, pp. 343348, 30 2007-Oct.
- [6] H. Su and X. Zhang, "Clustering-based multichannel mac protocols for qos provisionings over vehicular ad hoc networks," *Vehicular Technology, IEEE Transactions on*, vol. 56, no. 6, pp. 3309-3323, Nov. 2007.
- [7] P. Basu, N. Khan, and T. Little, "A mobility based metric for clustering in mobile ad hoc networks," *Distributed Computing Systems Workshop, 2001 International Conference on*, pp. 413-418, Apr 2001.
- [8] Brendan J.Frey and Delbert Dueck, "Clustering by Passing Messages between Data Points," in *Science Magazine*.vol. 315, pp. 972-976, 2007.
- [9] Moslem Noori and Maoud Ardakani, "A probability model for lifetime of wireless sensor networks," in *Design, Automation and Test in Europe*. Vol. 1, pp. 202-203, 2007.



Hamayoun Shahwani received the B.S. degree from Balochistan University of Information Technology, Engineering and Management Sciences in 2010. He is currently an integrated (MS leading to PhD) student in the Department of Electronic, Electrical and Computer Engineering, College of Information and Communication Engineering, Sungkyunkwan University, Rep. of

Korea. His research interests include Machine to Machine communication, 5G communication systems, and Vehicular ad-hoc networks.



Toan Duc Bui received the B.S. degree from Hanoi University of Science and Technology, Vietnam in 2012 and the M.S. degree in electrical engineering from Sungkyunkwan University, Republic

of Korea in 2014. He is working toward the Ph.D. degree at Media System Lab, College of Information and Communication Engineering, Sungkyunkwan University, Republic of Korea. His research interests include image processing, machine learning, channel coding, with a special focus in image segmentation, level set-based methods, and deep learning.



Jaehoon (Paul) Jeong is an assistant professor in the Department of Software at Sungkyunkwan University in Korea. He received his Ph.D. degree from the Department of Computer Science and Engineering at the University of Minnesota in 2009. He received his B.S. degree from the Department of Information Engineering at Sungkyunkwan University and his M.S.

degree from the School of Computer Science and Engineering at Seoul National University in Korea, in 1999 and 2001, respectively. His research areas are vehicular networks, cyber-physical systems, Internet of things, wireless sensor networks, mobile ad hoc networks, network softwarization, and network security. His two data forwarding schemes (called TBD and TSF) for vehicular networks were selected as spotlight papers in IEEE Transactions on Parallel and Distributed Systems in 2011 and in IEEE Transactions on Mobile Computing in 2012, respectively. Dr. Jeong is a member of ACM, IEEE and the IEEE Computer Society.



Jitae Shin received his B.S. degree from Seoul National University in 1986 and his M.S. degree from Korea Advanced Institute of Science and Technology (KAIST) in 1988. After working around eight years at Korea Electric Power Corp. and the Korea Atomic Energy Research Institute, he returned to study and received M.S. and Ph.D. de-

grees in electrical engineering from the University of Southern California, Los Angeles, in 1998 and 2001, respectively. He is a professor in the College of Information and Communication Engineering of Sungkyunkwan University, Suwon, Republic of Korea. His current research interests include image/video signal processing, video transmission over wireless/mobile communication systems, and multimedia network control/protocol issues.