Networking and VANET Control For Data Aggregation

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Abstract— These In-network data aggregation is a useful technique to reduce redundant data and to improve communication efficiency however. They cannot be applied in highly mobile vehicular environments. We will try to implement an adaptive forwarding delay control scheme, namely Catch-Up, which dynamically changes the forwarding speed of nearby reports so that they have a better chance to meet each other and be aggregated together. The Catch-Up scheme to be designed will be based on a distributed learning algorithm where each vehicle learns from local observations and chooses a delay based on learning results. Traditional data aggregation schemes for wireless sensor networks usually rely on a fixed routing structure to ensure data can be aggregated at certain sensor nodes.

Index Terms— Data aggregation, Catch-Up, distributed learning algorithm, adaptive forwarding.

1 . Introduction

1.1 Basic Idea

Vehicular Ad-Hoc Network, or **VANET** is a technology that uses moving cars as nodes in a network to create a mobile network. VANET turns every participating car into a wireless router or node, allowing cars approximately 100 to 300 meters of each other to connect and, in turn, create a network with a wide range. As cars fall out of the signal range and drop out of the network, other cars can join in, connecting vehicles to one another so that a mobile Internet is created. It is estimated that the first systems that will integrate this . Data aggregation is a potential approach to improving communication efficiency. It consists of a variety of adaptive methods which can merge information from various data sources into a set of organized and refined information. The process of data aggregation can be performed in-network so that communication overhead can be effectively reduced soon after redundant reports are generated. We conduct simulation experiments with NS2 which demonstrate the effectiveness of our scheme.

1.2 Traffic Information Dissemination

Each vehicle periodically detects the traffic conditions around it, and then, forwards the information to vehicles following behind it.

1.3 Like congestion detection

- Multiple redundant copies for the same traffic status
- Consuming a considerable amount of bandwidth.

1.4 Motivation / Objective

- Our objective is to reduce the number of redundant reports and achieve a good trade-off between delay and communication overhead.
- In general ,our challenge is to ensure reports can be delivered to the same node at the same time in a distributed environment.

2 Literature Survey

In VANETs, several studies have implemented data aggregation mechanisms. In the Self-Organizing Traffic Information Systems, vehicles on a road segment periodically send out reports containing the traffic information on the current road segment. During the broadcast interval, a vehicle collects and aggregates information received from neighboring vehicles. This approach helps generate an overview of current traffic conditions by periodical broadcasting. However, periodical report broadcasting is not an efficient way for report propagation, and there is no guarantee that redundant reports from the same road segment can be aggregated together. Traffic View is another similar system which uses periodic report broadcasting for disseminating traffic information. Caliskan et al. proposed a hierarchical aggregation scheme for free parking place discovery. In this scheme, a city is divided into grids, which are further organized in a hierarchical grid-tree structure. Each vehicle maintains such a structure and periodically broadcasts this structure at a predefined interval. As stated by the authors, an optimal broadcast interval dynamically depends on a few factors, which the authors didn't further study.

In sensor networks, researchers have proposed a number of structure-based aggregation schemes. Which rely on a fixed routing tree to ensure reports can be merged at the tree forks. Certainly, these schemes are not suitable for dynamic vehicular environments. Fan et al. proposed a structure-free aggregation protocol based on randomized waiting. However, this probabilistic approach cannot guarantee the aggregation of all reports from a single event source.

Later, the authors presented a semi structured approach to improve the aggregation degree, but this approach still needs to maintain a routing structure. Several VANET projects, such as **Self-Organizing Traffic Information System (SOTIS)** and Traffic View, use periodical broadcasting for data aggregation. As time elapses, neighboring vehicles can get an overview of current traffic conditions in the vicinity by periodically exchanging information. However, content exchange based on periodical broadcasting may not be an efficient way in terms of communication overhead, and what is an optimal broadcast interval is still an unsolved issue.

3 Proposed Work

3.1

In our proposed work, each vehicle is a learner. Each vehicle maintains its local learning knowledge base and makes a decision on how much delay should be applied before forwarding a report to the next hop.

3.2

The main feature of our scheme is that a vehicle indirectly learns from other neighboring vehicles' action/reward pairs, whereas, in traditional learning algorithms, the learners learn from themselves' trial and error, and they usually encourage local information exchange for better learning performance.

Our method minimizes the communication overhead in distributed learning in two aspects. First, we don't need the vehicles ahead, perhaps multiple hops away, to send back a message to show the reward for the previous action. In other words, we avoid the communication overhead for reward information exchange. Second, this model also avoids the exchange of Q tables among vehicles. Q table (function) is actually a local knowledge base, usually of large volume. Therefore, this learning-from-neighbors paradigm effectively reduces the communication overhead for distributed learning algorithms.

The extra communication overhead incurred by our learning process is little. As aforementioned, each vehicle attaches only three variables _; s; a to a report before forwarding it to the next hop. Since they are simple variables, the incurred communication overhead is little. We don't have extra message exchanges for the learning process. Actually, it is more important that our scheme can effectively reduce the number of redundant reports, which is a major contributing factor in wireless channel congestion and collision.

3.3 RESEARCH OBJECTIVE:

A) To formulate an adaptive forwarding delay control scheme for VANET

B) To formulate a distributed Markov Decision Process (MDP) model to be designed for individual vehicles with the objective of improving global performance through distributed cooperation.

C) To formulate a Qlearning – based scheme to reduce the exchange of entire local knowledge base.

D) Finally we propose a fuzzy rule base function approximation to speed up the learning process

E) Simulation of the scheme using NS2simulator

3.4 Algorithm:

We introduce the Catch-Up scheme—an adaptive forwarding delay control scheme for VANET data aggregation. The scheme is designed based on a customized distributed learning algorithm.

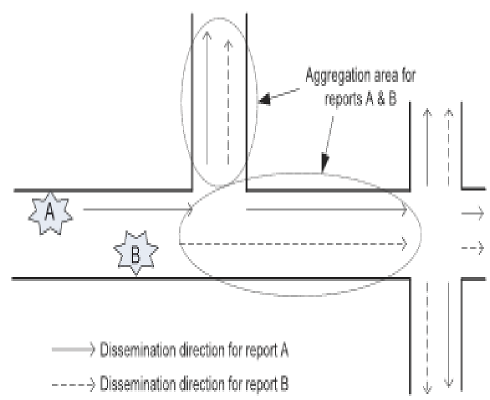


Fig.3. 1 Dissemination tree .If data from different events are propagating in the same direction, they can be aggregated for reducing communication overhead.

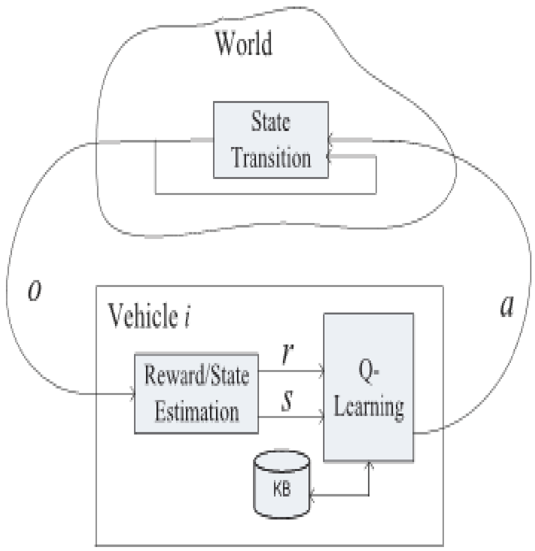
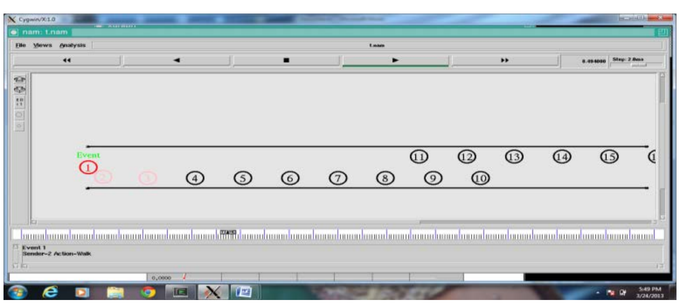


Fig.3.2 Distributed MDP model

The MDP model works as follows: Suppose that we have vehicles I and j. Before vehicle I forward a report to vehicle j, vehicle I attaches its local variables i ; si; ai to the report (as shown in (1)). After vehicle j receives the report, it calculates the reward Ri with (2). Evidently, reward Ri is obtained based on vehicle i's action a i. Vehicle j then uses si ;ai;Ri to update its local knowledge base and also calculates the optimal action (WALK or RUN) based on its local knowledge base. After a delay (WALK or RUN), vehicle j forward the report to the next hop. Please note that in this process vehicle j uses vehicle i's action/reward pair to update its local knowledge base. In other words, vehicle j learns from other vehicles' action/reward pairs. This important feature guarantees that little extra communication overhead is introduced by the learning proc.

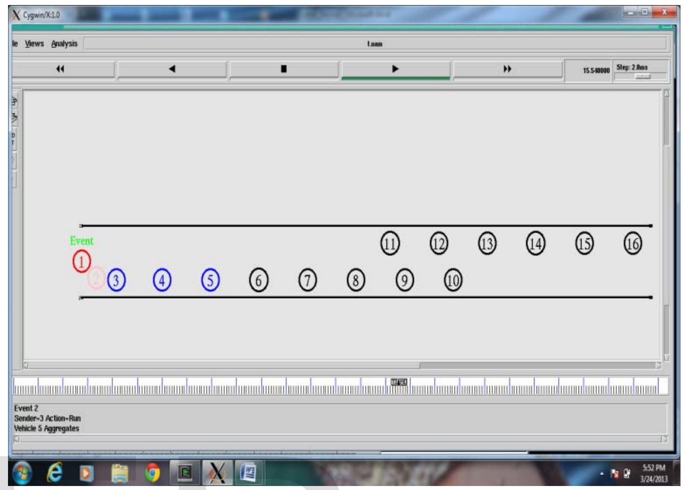
4 Implementation

4.1) Snapshot Event=1



In this 1st snapshot shows red node indicate event 1 ocure ,sender 2 and action is walk.Black-Default or the initial color of every node is black. Red - Indicates the event.Pink - The node which senses the event first , starts the data transmission and the node which receives this event turns to pink color.

4.2) Snapshot Event=2



In the second ,snapshot as compare to first event 2 is occurred ,sender 3 action run and vehicles 5 is aggregates .

Black - Default or the initial color of every node is black.

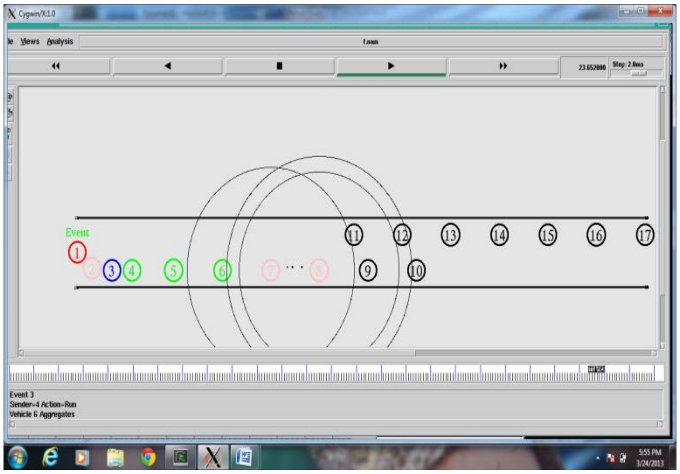
Red - Indicates the event.

Pink - The node which senses the event first, starts the data transmission and the nodes which receives this event turns to pink color.

Blue - The next node which senses the event , starts the data transmission and the nodes which receives this event turns to blue color.

Green - The further node which senses the event , starts the data transmission and the nodes which receives this event turns to green color.

4.3) Snapshot Between the node 7 and 8 broadcast,event 3 sender 4 action run and aggregates vehicles.



In this, snapshot as compare to first event 3 is occurred, sender 4 action run and Vehicle 6 is aggregates.

Black - Default or the initial color of every node is black.

Red - Indicates the event.

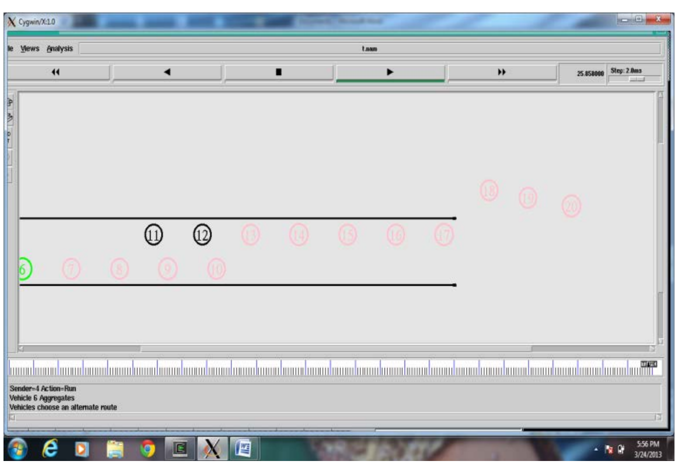
Pink - The node which senses the event first, starts the data transmission and the node which receives this event turns to pink color.

Blue - The next node which senses the event, starts the data transmission and the nodes which receives this event turns to blue color.

4.4) Snapshot Vehicle 6 is aggregates ,vehicles choose an alternate route.

In this, snapshot as compare to previous one event 4 is occurred, sender 4 action run and Vehicle 6 is aggregates, vehicles choose an alternate route.

Black - Default or the initial color of every node is black.



In this, snapshot as compare to previous one event 4 is occurred, sender 4 action run and Vehicle 6 is aggregates, vehicles choose an alternate route.

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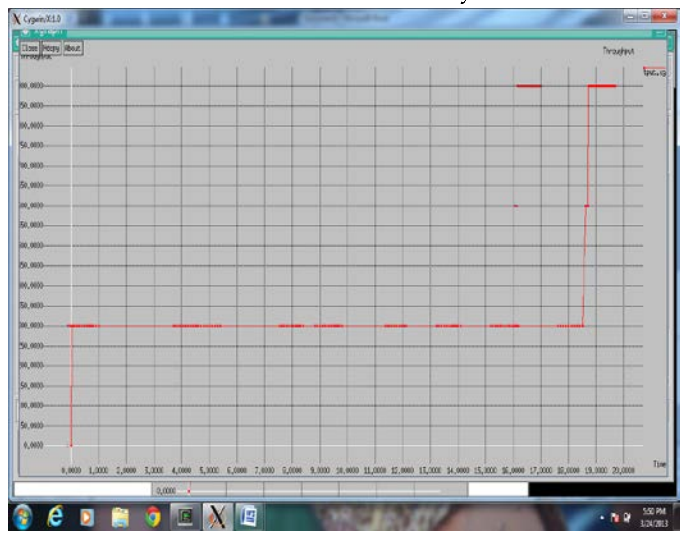

Fig 4.5 Graph 1 between the Time Vs Throughput

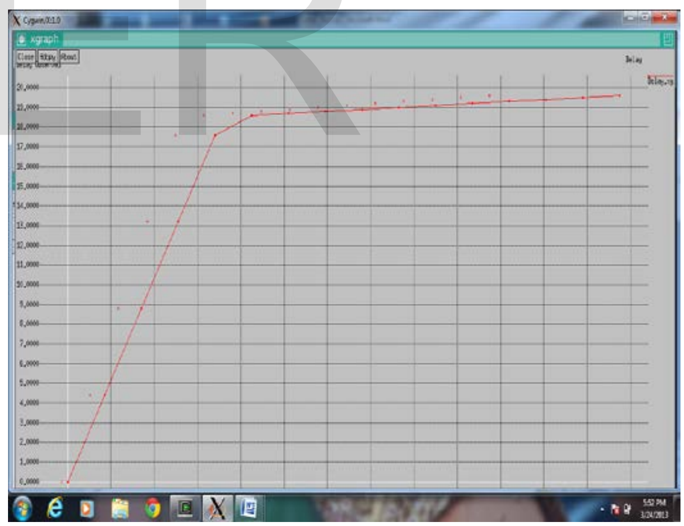

Fig 4.6 Graph 2 Graph between the Distance Vs Delay

5 Conclusion and Future Scope

In this paper, we have presented a data aggregation scheme for VANETs based on distributed learning. Essentially, the difference in propagation speed helps reports encounter each other, and we formulate this issue as a distributed learning problem where vehicles adaptively choose forwarding delays to make nearby reports have a better chance to meet each other. In order to avoid introducing extra communication overhead, we propose a new paradigm of distributed learning—"Learning-From-Others." We design a Q-learning-based algorithm to implement this new paradigm, and our simulation results demonstrate the effectiveness of our scheme.

In future, we can improve our scheme to detect any delay sensitive events like an accident report and to forward this report without applying any delay (run) to any nearby hospitals in emergency cases.

6 References

[1] "Dedicated Short Range Communications Project," http://www.leearmstrong.com/DSRC/DSRCHomeset.htm, 2011.

[2]"The Network Simulator—ns-2,"http://www.isi.edu/nsnam/ns/, 2011.

[3]"GrooveNetProject,"http://www.seas.upenn.edu/rahulm/Research/GrooveNet/, 2011.

[4] R. Mangharam , D.S. Weller, D.D. Stancil, R. Rajkumar, and J.S.Parikh , "GrooveSim: A Topography-Accurate Simulator for Geographic Routing in Vehicular Networks," Proc. Second ACM Int'l Workshop Vehicular Ad Hoc Networks (VANET '05), 2005.

[5] C. Intanagonwiwat, R.Govindan , and D. Estrin , "Directed Diffusion: A Scalable and Robust Communication Paradigm for Sensor Networks," Proc. ACM MobiCom '00, pp. 56-67,2000.

[6] S. Madden, M.J. Franklin, J.M. Hellerstein, and W. Hong, "TAG: A Tiny Aggregation Service for Ad-Hoc Sensor Networks," Proc.Fifth Symp. Operating Systems Design and Implementation (OSDI '02),2002.

[7] S. Madden, R. Szewczyk, M.J. Franklin, and D. Culler, "Supporting Aggregate Queries over Ad-Hoc Wireless Sensor Networks,"Proc. Fourth IEEE Workshop Mobile Computing Systems and Applications, 2002.

[8] C. Intanagonwiwat, D. Estrin, R. Govindan, and J. Heidemann,"Impact of Network Density on Data Aggregation in Wireless Sensor Networks," Proc. 22nd Int'l Conf. Distributed Computing Systems, 2002.

[9] K. Fan, S. Liu, and P. Sinha, "On the Potential of Strucuture-Free Data Aggregation in Sensor Networks," Proc. IEEE INFOCOM, 2006.

[10] K. Fan, S. Liu, and P. Sinha, "Scalable Data Aggregation for Dynamic Events in Sensor Networks," Proc. Fourth Int'l Conf.Embedded Networked Sensor Systems (SenSys '06), 2006.

[11] L. Wischhof, A. Ebner, H. Rohling, M. Lott, and R. Halfmann,"SOTIS—A Self-Organizing Traffic Information System," Proc.57th IEEE Vehicular Technology Conf. (VTC '03-Spring),pp. 2442-2446, Apr. 2003.

[12] L. Wischhof, A. Ebner, and H. Rohling, "Information Dissemination in Self-Organizing Intervehicle Networks," IEEE Trans.Intelligent Transportation Systems, vol. 6, no. 1, pp. 90-101, Mar.2005.

[13] T. Nadeem, S. Dashtinezhad, C. Liao, and L. Iftode, "TrafficView:Traffic Data Dissemination Using Car-to-Car Communication,"ACM SIGMOBILE Mobile Computing and Comm. Rev., vol. 8, no. 3,pp. 6-19, 2004.

[14] M. Caliskan, D. Graupner, and M. Mauve, "Decentralized Discovery of Free Parking Places," Proc. ACM Third Int'l Workshop Vehicular Ad Hoc Networks (VANET '06), 2006.

[15] H. Wu, R. Fujimoto, R. Guensler, and M. Hunter, "MDDV: A Mobility-Centric Data Dissemination Algorithm for Vehicular Networks," Proc. ACM First Int'l Workshop Vehicular Ad Hoc Networks (VANET '04), 2004.

[16] F.J. Ros, P.M. Ruiz, and I. Stojmenovic, "Reliable and Efficient Broadcasting in Vehicular Ad Hoc Networks," Proc. IEEE Vehicular Technology Conf., 2009.

[17] A. Broder and M. Mitzenmacher, "Network Applications of Bloom Filters: A Survey," Internet Math., vol. 1, no. 4, pp. 485-509,2005.

[18] L. Panait and S. Luke, "Cooperative Multi-Agent Learning: The State of the Art," Autonomous Agents and Multi-Agent Systems, vol. 11, no. 3, pp. 387-434, Nov. 2005.

[19] S.J. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, second. Prentice Hall, 2003.