Adaptive Messaging based on the Age of Information in VANETs

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***Abstract*—A significant challenge in 802.11p based vehicular ad hoc networks (VANETs) is that the cooperative awareness messages (CAMs) tend to experience collisions. In this paper, we propose an adaptive CAM messaging algorithm based on the emerging methodology of the age of information (AoI). Our objective is to minimize an age-penalty function in a trajectory prediction application. In our design, each vehicle will compute a local penalty which serves as an indicator on whether the CAM messaging frequency is appropriate for its mobility status; and at the same time, calculates an appropriate penalty associated with all its neighbors which serves as an indicator regarding the impact of network congestion on the trajectory prediction quality. The aggregated penalty score integrating both the local and neighboring parts will be used to adaptively control the CAM sending frequency. We are to present simulation results demonstrating that our adaptive messaging method can indeed mitigate network congestion while meet the driving safety requirements.**

***Index Terms*—adaptive messaging, AoI, CAMs, trajectory prediction, VANETs**

I. Introduction

The rapid development of vehicular technologies and mobile communication networks has transformed the traditional road transportation into the modern paradigm of intelligent transportation systems (ITS) [1]–[3]. A key element of ITS is the vehicular ad-hoc network (VANET), where vehicles and roadside infrastructure can form a multiple-hop ad hoc network, accessing Internet through vehicle-to-vehicle and vehicle-to-infrastructure communications [4]. VANETs are expected to enable a wide scope of applications for entertainment and driving safety. To facilitate safety applications, each vehicle is equipped with multiple types of sensors that generate safety-critical and time-varying data (e.g position, speed, heading, and acceleration), termed as cooperative awareness messages (CAMs), and broadcast the messages to all neighboring nodes within their communication range [5]. The performance of VANET fundamentally depends on the medium access control (MAC) protocol, where a distributed carrier sensing multiple access (CSMA) based protocol, defined in the IEEE 802.11p standard, is the popular MAC protocol for VANETs.

A significant challenge in 802.11p based VANETs is that the CAMs tend to experience collisions, especially in a congested situation, for example, a jammed traffic light with many vehicles queued on the road. As the CAMs are broadcasted without acknowledgement, serious collisions will cause the dropping of many CAMs, and thus, seriously impact the driving safety. In fact, it is possible to reduce unnecessary CAMs to mitigate the network congestion. For example, when vehicles are statically queued at a traffic light or move in a constant speed, the frequency of broadcasting CAMs can be reduced without impacting the safety applications. To achieve a stable and reliable VANET, thus, requires knowledge of the mobility pattern of vehicles. Considering the application-level requirement of improved driving safety, the wireless channel of a typical VANET is usually constrained by interference and collisions. As part of the design requirements for ITS, the European Telecommunication Standards Institute (ETSI) included a mandatory Decentralized Congestion Control (DCC) component in the access layer of the ITS-G5 protocol stack to reduce range degradation, radio channel overload, and self-interference [6], [7]. However, the DCC is limited to restricting the number of messages that each vehicle sends into the wireless channel, based on the channel busy ratio (CBR) [8]. We opine that the DCC does not justify the basis for congestion control from the application-level perspective. Beyond the DCC, more attention has been given to the mobility, routing and scheduling issues in VANETs, towards improving driving safety and achieving low latency in packet delivery [1], [9], [10]. However, only few studies have examined the application-level problems in VANET, such as the relevance and freshness of CAMs, which relies on the sampling frequency; these are complex optimization tasks, especially when congestion is critical.

In this paper, we propose an adaptive CAM messaging algorithm based on the emerging methodology of the *age of information* (AoI) [11]. The underpinning problem is that the frequency of sending CAMs is not monotonically related to the quality of the safety applications. Too frequent CAM messaging tends to cause network congestions, which will then negatively impact the safety application; too sparse messaging by a vehicle, otherwise, will not be enough for the neighboring ones to timely obtain its speed/location information and negatively impact the safety applications too. The AoI methodology exactly targets at the analysis of the complex interplay among sampling frequency of sensing messages, the sojourn time of those messages in the networking systems, and the information freshness at the receiving node, and is quite suitable for studying the CAM frequency issue in VANETs.

Some related works have proposed AoI as an application metric for determining the frequency of CAMs generation. The design of an analytical model that statically sets the time interval between two consecutive beacon message generation has helped to minimize the AoI metric, but suffers performance degradation when the vehicle density is high [12]. Similarly, an information-age-aware method was proposed in [8] to configure the legacy ETSI DCC mechanism, while minimizing AoI and achieving satisfactory channel busy ratio (CBR). The method adopted *platooning* for the ITS application, where a human driver leads other vehicles behind it, and the other vehicles depend on the CAMs that is being exchanged [8], [13]. With this method, the benefit of autonomous driving in VANET is lost and we opine that the CBR is not sufficient to reflect traffic congestion in VANETs; this is because vehicles tend to have different mobility patterns.

To address some of the challenges highlighted from previous works, and considering the application-level problems in VANETs, in this paper, we rely on AoI-based analysis to adaptively adjust the CAM sending frequency at a vehicle based on the network congestion level and the vehicle mobility states, while guarantee the driving safety. Specifically, the AoI at a certain moment at a receiving node is defined as the time that has elapsed since the generation time (at the sending node) of the latest message it received. A non-decreasing function of the AoI, termed as an *age-penalty* function [11], [14] can be defined to link the AoI with more human-perceptible application performance. In our scenario, we use a trajectory prediction application to evaluate the driving safety through CAM messaging. That is, one vehicle A will predict the current location and speed of a neighboring vehicle B based on the latest CAM generated by vehicle B and the AoI of that message. The deviation of the predicted trajectory from the true value is defined as our age-penalty function, termed as $pAoI$.

In our design, each vehicle will compute a local penalty $pAoI_{local}$ based on its GPS ground truth and its own CAMs; the local penalty serves as an indicator on whether the CAM sampling frequency is appropriate for its mobility status. At the same time, each vehicle also calculates a penalty $pAoI_{neighbors}$ with weighted averaging over penalties associated with all its neighbors; the neighboring penalty serves as an indicator regarding the impact of network congestion on trajectory prediction quality. The aggregated penalty score integrating both $pAoI_{local}$ and $pAoI_{neighbors}$, compared against a predefined threshold based on security criteria, will be used to adaptively control the CAM sending frequency. We are to present simulation results demonstrating that our adaptive messaging method can indeed control the CAM sending frequency at an appropriate level while balancing the network congestion level and driving safety requirements.

The remainder of this paper is organized as follows. We describe the system model in Section II. We discuss our adaptive cooperative awareness messaging algorithm in Section III. Next comes the numerical results in Section IV, and the conclusion in Section V.

II. System Model

A. Cooperative Awareness Messaging in VANETs

The ITS in most of its applications ensures that nodes generate CAMs to achieve connectivity, automation and driving safety. Specifically, in VANETs, nodes usually generate and broadcast CAMs independently, and because the wireless channel is shared, there is a significantly large probability for congestion and collision of CAMs, especially with larger number of vehicles. Fig. 1 shows a typical VANET scenario where the driving safety of autonomous vehicles is negatively impacted by the congestion of CAMs. Since the information contained in CAMs are safety-critical and time-dependent, it is important that each node has up-to-date knowledge about the trajectory of other nodes within its communication range. For most applications, the CAMs usually contain the speed, position, acceleration and other vehicle-related parameters. The timeliness of the CAMs forms the basis for decision making in a VANET; such decisions can include the rate of maneuver of a vehicle at a given time. However, we need to understand that CAMs are periodic updates which are timestamped and carry critical data; thus, we require the AoI metric, which measures the degree of freshness of status updates. This metric helps to facilitate the prediction of a vehicle's trajectory.

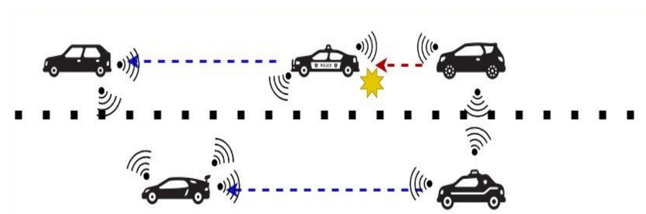

Fig. 1. Driving safety impacted by CAMs congestion in VANET

B. Age of Information Basics

The concept of age of information, popularly referred to as AoI or simply *age* has emerged in network research to analyse the difference and relationship between network delay and freshness of updates [11]. This is because timely updating is not the same as having updates with minimum delay [11], [14], [15]. In a complex system, such as VANETs, a source broadcasts fresh CAMs to the network, which is delivered to destination nodes; each node keeps track of the age of CAMs and uses it to make application-level decisions. For example, a node that receives an update with timestamp u is said to have age $t-u$ at a time $t \geq u$. An update is said to be fresh when its timestamp is the current time t and its age is zero. When the freshest received update at time t has time-stamp $u(t)$, then, the age [11] is a random process:

$$\Delta\left(t\right) = t - u\left(t\right) \tag{1}$$

Consider that fresh updates are sent at times $t_1, t_2, ..., t_n$ and received at corresponding times $t'_1, t'_2, ..., t'_n$, this yields to sawtooth shape function which reflects the age of the updates when it is delivered at the destination. Since in the absence of updates, the age $\Delta(t)$ grows linearly at a unit rate, this means that the last received update gets stale until a fresh one arrives. Although, the AoI $\Delta(t)$ grows linearly over time, the performance degradation due to information aging may not always be a linear function of time [11]. In the literature, the dissatisfaction with information staleness can be represented by a non-decreasing age-penalty function $p(\Delta(t))$.

C. Adaptive CAMs meeting the Safety Requirements

Our objective is to design a mechanism for a vehicle to adaptively adjust its CAM messaging frequency based on its own mobility pattern and the network congestion level, while meet the safety requirement. We use a trajectory prediction application to evaluate the driving safety through CAM messaging. That is, one vehicle A will predict the current location and speed of a neighboring vehicle B based on the latest CAM generated by vehicle B and the AoI of that message. The deviation of the predicted trajectory from the true value is defined as our age-penalty function. Hence, our adaptive messaging aims to minimize the penalty function.

III. Adaptive Cooperative Awareness Messaging

In this part, we will first present the modeling details of our trajectory prediction application and then give the details of our adaptive messaging protocol.

A. Trajectory Prediction

When vehicle A generates a CAM at t_1, it contains its trajectory $\vec{g_{t_1}}$, that is, position $p_{1_{xy}}$, speed $v_{\vec{1_{xy}}}$, and acceleration $a_{\vec{1_{xy}}}$. At a time t_2 ($> t_1$) before another CAM, this CAM message can be leveraged by vehicle A itself or a neighbor of A to predict the trajectory $\vec{g_{t_2}}$ of A at t_2 as follows:

$$\Delta(t_2) = t_2 - t_1 \tag{2}$$

$$\vec{g_{t_2}}' = \begin{bmatrix} p_{1_{xy}} + v_{\vec{1_{xy}}}\Delta(t_2) + \frac{1}{2}a_{\vec{1_{xy}}}\Delta(t_2)^2 \\ v_{\vec{1_{xy}}} + a_{\vec{1_{xy}}}\Delta(t_2) \\ a_{\vec{1_{xy}}} \end{bmatrix} \tag{3}$$

where $\Delta(t_2)$ is the AoI of the CAM at t_2. We use $\vec{g_{t_2}}$ and $\vec{g_{t_2}}'$ to denote the true trajectory and predicted trajectory of vehicle A respectively. Both $\vec{g_{t_2}}$ and $\vec{g_{t_2}}'$ are considered as column vectors with each element representing position, speed and acceleration.

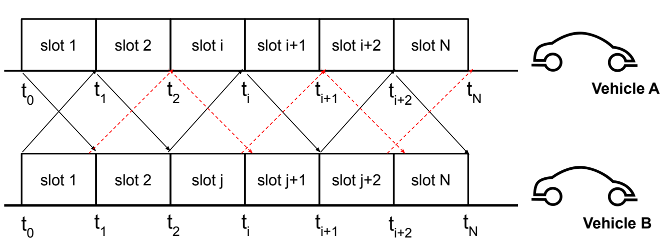

Fig. 2. CAMs scheduling in VANET

B. Age-penalty Function in VANETs

The measure of dissatisfaction caused by the linear growth of AoI of CAMs, which is characterized by the non-decreasing age-penalty function $p(\Delta(t))$, is used as an application-level metric to control when it is appropriate to send a new CAM. To meet the driving safety requirement in VANET, we define age-penalty $p(\Delta(t_i))$ as the square root of l_2Norm between the true vehicle position $p_{i_{xy}}$ and the predicted vehicle position $p'_{i_{xy}}$. That is,

$$p(\Delta(t_i)) = \sqrt{\left|\left|p_{i_{xy}}, p'_{i_{xy}}\right|\right|}, \quad \forall i \in \{1, 2, ..., N\}. \tag{4}$$

Note that our age penalty function has the physical meaning of distance and is an appropriate metric to evaluate driving safety.

We use Fig. 2 to illustrate the scheduling of CAMs, where each slot has a fixed time-frame, within which a vehicle can receive or send CAMs to its neighbors. When vehicle A and vehicle B both send CAMs to each other at time t_0, the CAM is received before the end of duration of slot 1. Each vehicle uses the AoI of it's last received CAM to predict the next trajectory of its neighbor before the end of slot 2. The decision to delay CAMs or send CAMs immediately, depends on the trajectory prediction quality, which reflects the level of congestion in the network; this is based on the age penalty function. As shown in Fig. 2, at t_2, t_{i+1}, and t_N, vehicle A did not receive any message from vehicle B; at t_i and t_{i+2}, vehicle B did not receive any message from vehicle A, each represented by red broken lines. The AoI function based on the CAMs sending frequency is shown in Fig. 3.

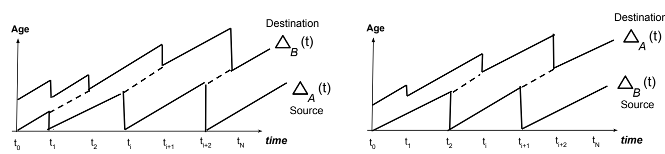

Fig. 3. AoI process in a simple VANET

C. Local Penalty and Neighbor Penalty

The equations (3) can be used by vehicle A to compute a local penalty over its own CAMs. The local penalty can serve the important purpose to evaluate whether the CAM messaging freqency is appropriate regarding its current mobility pattern. For example, if the current CAM messaging interval is large and vehicle A is doing rapid acceleration, the computed local penalty will be large.

The ultimate goal of CAM messaging from a vehicle A is for A's neighboring vehicles to correctly predict the trajectory of vehicle A, thus maintaining safe distance in driving. We thus compute a neighbor penalty for this purpose. The neighbor penalty serves as an indicator regarding the impact of network congestion on trajectory prediction quality. As illustrated in Fig. 3, if vehicle B didn't receive vehicle A's CAM due to network congestion (that caused the dropping of the message), it will get a large penalty in predicting A's trajectory.

A challenge in computing neighbor penalties in a distributed environment is that it is hard for vehicle A to know how accurate its neighbor B could predict its trajectory. To address this issue, we leverage a *symmetric assumption*: for any two neighboring vehicles A and B communicating with the same channel, the trajectory prediction accuracy of vehicle B regarding vehicle A, its neighbor, is roughly the same as that of vehicle A regarding vehicle B.

D. Adaptive Messaging Algorithm

Based on the symmetric assumption where each vehicle gets the knowledge about its local age-penalty and that of its neighbors, it becomes realistic to adaptively adjust the sending frequency of CAMs, while still meeting the driving safety requirement in VANETs.

In contrast with a computer network, for VANETs, congestion control is usually affected by driving patterns such as the mobility and speed of vehicles, which cannot be optimized by merely restricting the number of messages that each vehicle sends into the wireless channel, based on the CBR. For example, a slight change in the speed of a vehicle can affect the application-level decision making processes of other vehicles in the network, where status updates are critical and time-dependent.

To achieve the driving safety requirement based on AoI, the decision regarding when it is important to send a measured trajectory through CAMs is, thus, regulated by comparing the age-penalty score $p(\Delta(t))_{score}$, which is the weighted average between the local age-penalty of the source node and that of its neighbors, against a predefined threshold $p^*(\Delta(t))$ based on security criteria. Every time there is a new CAM (generated every 100 ms in our experiment), each vehicle computes its local age-penalty $p(\Delta(t))_{local}$. It then uses the CAMs received from neighboring vehicles to compute $p(\Delta(t))_{neighbors}$ as described in Algorithm 1, where the weight w_j of the age-penalty for each node is a function of the normalized distance z_j and the time $u_j(t)$ since the last update was received. For example, the further any node is from the source node, the less *relevant* is the information.

On the other hand, when more time has elapsed since the last received update, the more relevant is the age-penalty of the node. The age-penalty score can, thus, be obtained.

$$p(\Delta(t))_{score} = \alpha p(\Delta(t))_{local} + (1-\alpha)\sum_{j\neq i} w_j p_{ij}(\Delta(t)) \quad (5)$$

where $p_{ij}(\Delta(t))$ is the age-penalty of node j computed at node i and $\alpha \in [0,1]$ is a controlling parameter, which can be determined based on experiments. The remaining parameters are computed as:

$$z_j = \frac{D - d_j}{D} \quad (6)$$

$$u_j(t) = \frac{1}{1 + e^{-\frac{1}{5}(t-15)}} \quad (7)$$

$$w_j = z_j u_j(t) \quad (8)$$

$$\sum_j w_j = 1 \quad (9)$$

We define d_j to be the distance of node j from node i and D is the distance of the farthest node from node i, that is, we have $d_j \leq D$. The time portion $u_j(t)$ of the weights w_j is calculated using a non-linear sigmoid function, which approximates the time contribution to the weight with a range between 0 and 1.

In our setting, for $u_j(t)$, a node whose CAM's AoI is ≥ 15 seconds contributes largely to the $p(\Delta(t))_{neighbors}$.

Algorithm 1 Compute $p(\Delta(t))_{neighbors}$

Input $\vec{A} \leftarrow [\Delta(t)_1, \ldots, \Delta(t)_i, \Delta(t)_N]$ (AoI of each node), $\vec{P} \leftarrow [p_1(\Delta(t)), \ldots, p_i(\Delta(t)), p_N(\Delta(t))]$ (Penalty AoI of each node), $\vec{D} \leftarrow [d_1, \ldots, d_i, d_N]$ (distances to each node)
Output $p(\Delta(t))_{neighbors}$
procedure COMPUTE_GENERAL_PAOI($\vec{A}, \vec{D}, \vec{P}$)
    $\vec{W} \leftarrow [w_1, \ldots, w_i, w_N]$
    for $\Delta(t)_i, d_i, w_i$ in $\vec{A}, \vec{D}, \vec{W}$ **do**
        $w_i \leftarrow$ Compute node weights using Eq. 6, Eq. 7 and Eq. 8.
    end for
    $\vec{W} \leftarrow$ Normalize weights using Eq. 9
    $p(\Delta(t)) \leftarrow 0$
    for $w_i, p_i(\Delta(t))$ in $\vec{W}, \vec{P}$ **do**
        $p(\Delta(t))_{neighbors} \leftarrow p(\Delta(t)) + w_i p_i(\Delta(t))$
    end for
    Return $p(\Delta(t))_{neighbors}$
end procedure

The adaptive messaging control, is then a function $I(t)$, where 0 means CAM frequency should be reduced by a certain step value and 1 means to increase CAM frequency; this corresponds to increasing and decreasing the CAM sending interval by 100 ms respectively, in our experiment.

$$I(t) = \begin{cases} 0 & \text{if } p(\Delta(t))_{score} \leq p^*(\Delta(t)) \\ 1 & \text{otherwise} \end{cases} \quad (10)$$

$$p^*(\Delta(t)) = k \in [0, \infty) \quad (11)$$

The age-penalty score $p(\Delta(t))_{score}$, thus, encodes the information on how the CAM sending frequency and network congestion impact on the trajectory prediction quality; it models the complex relationship among sampling, scheduling, and age of information. Noteworthy is the feasibility of applying our adaptive messaging algorithm to a typical VANET.

IV. Numerical Results

A. Simulation Setting

We simulated a network of vehicles to implement our adaptive cooperative awareness messaging model. In our simulation, we assumed a typical urban traffic environment with streets and intersections. This is to capture several practical driving scenarios such as changing lanes, increasing speed,

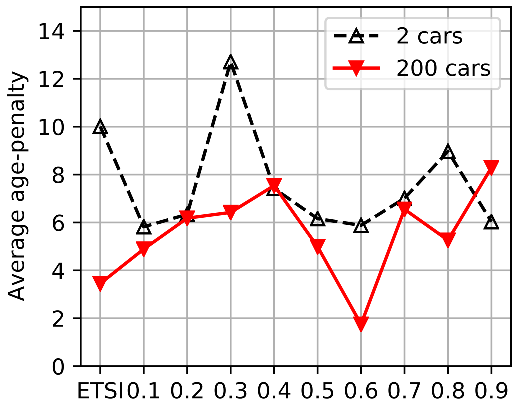

Fig. 4. Average age-penalty comparison between ETSI standard and adaptive messaging control model

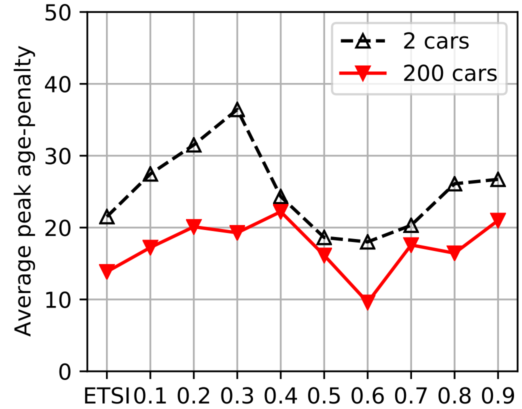

Fig. 5. Average peak age-penalty comparison between ETSI standard and adaptive messaging control model

maneuvers, and observing traffic lights. In our design, we leveraged the SUMO traffic simulation tool to create realistic car trajectories in VANETs. The network event simulation tool, OMNet++, provides functionalities for routing packets within the network, where CAMs are broadcasted and congestion is controlled using our proposed method of adaptive messaging decision. Our view on network congestion, is that, when vehicles slow down and wait at a traffic light, network is now becoming congested due to many vehicles queued at the intersection. However, the trajectory prediction is becoming very accurate due to the small (or zero) mobility, and our $p(\Delta(t))_{score}$ will be low, thus the CAMs will be reduced, and network congestion can be alleviated. When vehicles start to move and the speed keeps increasing, a low CAM sending frequency will cause inaccurate trajectory prediction (both local and regarding neighbors) and then the $p(\Delta(t))_{score}$ will increase, till crossing the threshold and the triggering CAM frequency increases.

In a typical driving situation with moderate number of neighbors around, network may have certain degree of congestion. It is possible that $p(\Delta(t))_{local}$ is good, that is, sampling frequency is enough for local trajectory prediction, but the penalties of neighbor nodes might be high as some CAMs get lost due to congestion. Since our $p(\Delta(t))_{score}$ incorporates the impact of the neighbors' penalties, if $p(\Delta(t))_{score}$ is higher than the threshold, the vehicle will then send more CAMs to compensate the loss due to moderate congestion.

B. Results and Analysis

In this section, we discuss the numerical results of applying our method on two network sizes - a small network of two cars and a large network of two hundred cars. These networks represent a lightly-loaded and densely-loaded traffic environment respectively. We compare the performance of our adaptive messaging control model with the ETSI standard for VANETs.

For all experiments under either small- or large-sized network setting, we aim to evaluate performance using the following metrics:

a) Average age-penalty: This is a measure of the average trajectory prediction error. It reflects the quality of predictions, and it is the lower the better.

b) Average peak age-penalty: This is the average of all the local-maxima of the age-penalty. It corresponds to the highest penalty that can be possibly observed over a period of time. Similar to the average prediction error, it is the lower the better.

c) Packet received ratio: This is the ratio of successfully received CAMs to the total CAMs sent between vehicles in the network. It serves as an important indicator for congestion of CAMs, alongside the peak age-penalty. When there is less congestion of CAMs, the packet received ratio is higher.

The CAMs sending frequency is expressed in per-minutes term, while the average prediction error and average peak prediction error are both expressed in meters (for the physical meaning of distance).

Our experiments show the relationship and correlation between the CAMs sending frequency and the trajectory prediction quality, using a predefined penalty threshold $p^*(\Delta(t)) = 6$ (meters). In our experiments, we find a good controlling parameter $\alpha \in [0, 1]$ that minimizes trajectory prediction error and improves the CAMs messaging frequency. Fig. 4 and Fig. 5 show the trajectory prediction quality, as a function of the average age-penalty and average peak age-penalty respectively, for the two cars and two hundred cars. The horizontal axis represents the comparison between the ETSI standard and our method using different α steps. We observed that setting $\alpha = 0.6$, our method achieves better performance than the ETSI standard, especially for the two hundred cars scenario, where driving safety is more critical. However, the performance degrades for $0.1 \leq \alpha \leq 0.3$; this is because, the algorithm allows a vehicle to take into account the network congestion indication by neighbor vehicles, while giving less attention the CAMs sampling frequency caused by its mobility states. For $\alpha \geq 0.7$, the reverse is the case; thus, $\alpha = 0.6$ serves as a trade-off between CAMs sampling frequency and

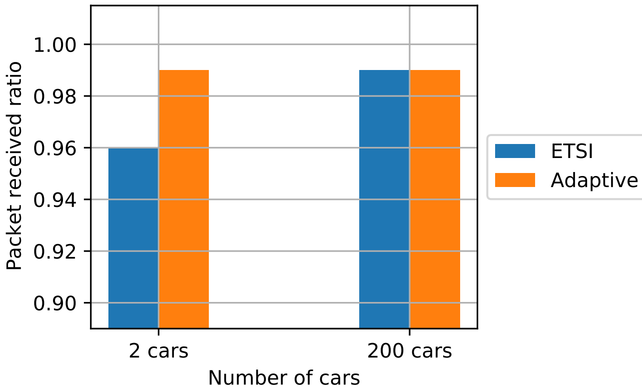

Fig. 6. Packet received ratio as a measure of congestion reduction in VANETs

congestion control.

Table 1 shows the results of comparing the ETSI standard with our adaptive messaging control model, based on AoI methodology. The significant improvement of 41.27% and 49.27% on trajectory prediction quality, as a function of the average age-penalty for the two cars and two hundred cars respectively, can guarantee driving safety in VANETs, while maintaining very minimal packet loss due to network congestion as shown by the packet received ratio in Fig. 6, where our method achieved a success rate of 0.99 for each network size.

From our experiments, the driving safety requirement in VANETs, through trajectory prediction quality, becomes more stringent with increase in the number of vehicles. This means that large-sized networks will have lower age-penalties. An important knowledge extract from the two-car scenario and two-hundred car scenario is the robustness of our method to different network sizes and vehicle mobility.

TABLE I
PERFORMANCE COMPARISON BETWEEN ETSI STANDARD AND ADAPTIVE MESSAGING METHOD

	ETSI (2 cars)	Adaptive (2 cars)	ETSI (200 cars)	Adaptive (200 cars)
Average age-penalty	10.01	5.88	3.45	1.75
Average peak age-penalty	21.52	18.01	13.85	9.60
Average CAMs sent per minute	140	144	144	135
Packet received ratio	0.96	0.99	0.99	0.99

V. CONCLUSION

In this paper, we present an innovative method to reduce the rate of unnecessary CAM update in a typical VANET where driving safety is critical. Our proposed adaptive messaging control model satisfied our system design requirement in achieving close-to-optimal prediction of vehicles' trajectory with low network congestion, towards enhancing driving safety. Optimizing the trajectory prediction model to account for road-side infrastructures and pedestrians, and to further improve on network congestion control, is an open research direction.

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