Adaptive Beacon Rate
Adjusting mechanism for safety communication in cooperative IEEE 802.11p-3G vehicle-infrastructure systems
Adaptive Beacon Rate Adjusting Mechanism for Safety Communication in Cooperative IEEE 802.11p-3G Vehicle-Infrastructure Systems

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Abstract—Cooperative active safety applications in WAVE employ periodic beacon broadcasting for status advertisement. High beacon rate enables each vehicle sense the traffic situation from its vicinity promptly. This timely information may assist the driver for safer driving experience. However, high beacon rate will congest the wireless medium due to the contention-based IEEE 802.11p MAC. In this paper, an Adaptive Beacon Rate Adjusting (ABRA) mechanism is proposed and studied. With the help of neural network and back propagation algorithm, a set of guide beacon rates can be obtained adaptively to decrease the performance deterioration caused by congestion. Extensive simulations validate that the proposed mechanism is effective.

Keywords—IEEE 802.11p, WAVE, beacon rate adjusting, neural network

I. INTRODUCTION

The wireless network in vehicular environment is designed to enable communications either between on board unit (OBU) and road side unit (RSU) or among OBUs. In such circumstances, IEEE 802.11p/1609.x protocol families [1-3], referred as WAVE (Wireless Access in Vehicular Environment) standard in many literature and papers, has been gaining more and more attentions in recent years. WAVE aims to provide an efficient and robust wireless access to adapt the dynamic network topology and complex channel conditions. In WAVE, the upper applications mainly focus on traffic safety [4], including Cooperative Collision Warning, Electronic Emergency Brake Light, Stopped Vehicle Alert and etc. By sharing with traffic situations among all OBUs and RSUs, vehicles can be alerted timely of traffic accidents or traffic jams in metropolitan areas.

Safety-related messages of these WAVE-based applications can be divided into two categories: non-periodic messages and periodic messages (heart-beat beacons). Non-periodic messages, usually invoked in emergency, are designed to indicate dangerous situations demanding for timely delivery with little latency. Periodic heart-beat messages are used for status (such as position, speed and direction) announcement, which are broadcast at regular intervals.

With periodic messages, each vehicle can collect enough information about its vicinity for active safety applications in the upper layer. It is necessary to broadcast these heart-beat messages frequently, so that vehicles can sense the traffic situation around precisely. On the other hand, high transmission rate will lead to QoS performance deterioration (i.e. severe packet loss and intolerable delay) due to contention-based EDCA mechanism derived from IEEE 802.11e. This kind of beacon loss will “blind” vehicles which will be a potential threat to traffic safety. So the question of how often these heart-beat messages should be broadcast should be studied carefully. Furthermore, the fairness should also be considered carefully, since even only one vehicle enduring severe performance deterioration will cause serious problem in a complex traffic situation.

In this paper, we propose an Adaptive Beacon Rate Adjusting (ABRA) mechanism to tune the heart-beat beacon transmission rate dynamically according to the QoS metrics such as delay and packet loss rate. With the help of our mechanism, a better QoS performance as well as fairness can be guaranteed.

II. RELATED WORKS

Much work has been done to adjust beacon transmission rate or power in order to balance the network load and accuracy of active safety applications. A traffic situation-adaptive beacon frequency adjusting was proposed in [5], so that the cooperative awareness accuracy can be guaranteed. The beacon rate here is determined by the movement of the target vehicles and its surroundings. In [6], a joint adaptive beacon rate and power mechanism was proposed. In which, beacon rate is adjusted based on so-called tracking accuracy as well as power control is also studied with a simple linear function of transmission range. That means the channel congestion can be avoided by tuning transmission power dynamically and the tracking accuracy can be maintain in a small scale. Both [5] and [6] focused on the accuracy of cooperative active safety applications in the upper layer rather than the QoS metrics from the perspective of network performance. [7] envisioned a Distributed Fair Power Adjustment for Vehicular Environments (D-FPAV) to control the load of periodic messages. At the same time, an Emergency Message Dissemination for Vehicular Environments (EMDV) was also proposed for fast and effective multi-hop information dissemination of event-driven
messages. Beacon transmission power control was investigated in terms of QoS metrics such as message reception probability and delay. However, the beacon rate adaptation was not included in this paper. Authors of [8] and [9] studied adaptive performance optimization of WLAN with the help of neural network, which shows fairly simplicity. Illuminated by [8] and [9], we proposed the ABRA mechanism using back propagation algorithm based on neural network in this paper. With the proposed mechanism, each vehicle modifies its beacon rate adaptively in order to mitigate the performance deterioration caused by channel congestion.

The rest of this paper is organized as follows: the ABRA mechanism is proposed in Section 3. Section 4 describes the core algorithm of our ABRA mechanism exhaustively. Validation of the proposed mechanism through simulations is shown in Section 5. At last, Section 6 concludes this paper.

III. ADAPTIVE BEACON TRANSMISSION RATE ADJUSTING MECHANISM

As mentioned above, the performance metrics such as delay and packet loss rate are affected by beacon transmission rates. In other words, high beacon rates may lead to performance aggravation due to channel congestion on contention-based IEEE 802.11p MAC layer. On the other hand, the status of other vehicles cannot be collected by the subject vehicle timely if beacon transmission rate is low, which makes upper layer applications have an obsolete knowledge of the traffic situation in its vicinity. In this section, an Adaptive Beacon Rate Adjusting (ABRA) mechanism is proposed to control beacon transmission rate of each vehicle properly according to the network performance measurement.

A. Overview of ABRA

In general, vehicles are equipped with simple WAVE devices, which have low computation abilities. So the ABRA mechanism is mainly implemented in RSUs. Figure 1 illustrates the implementation scenario of the proposed ABRA mechanism whose details will be described in the following. The definition of Administration Region (AR) is given first. Administration Region is a region within which the beacon broadcasting of vehicles is controlled by the specific RSU. Note that AR should be larger than power coverage of the RSU. Vehicles which are out of the power scope can communicate with RSU by multi-hop. Once one vehicle enters AR of one RSU, it obeys the instructions of the RSU. Note that there is only one RSU in an AR (denoted as serving RSU). Of course, a vehicle can be only controlled by one RSU at one time. Vehicles equipped with GPS devices can sense which AR it belongs to by comparing the distances between itself and RSUs with certain distance threshold. The RSU whose distance to the vehicle is shorter than this threshold can be the serving RSU. And this vehicle belongs to the corresponding AR.

Figure 2 shows the procedure of the proposed ABRA mechanism. The network performance metrics such as delay and packet loss rate are being monitored by the RSU all the time, so that the network performance deterioration can be detected in time. Once some metric exceeds some certain tolerance threshold (e.g. packet loss rate higher than a certain threshold), the learning period is invoked. Enough data will be used to train the neural network, which depicts the current relationship between beacon rates and network performance. After that, back propagation (BP) algorithm based on the trained neural network calculates a set of guide beacon rates which can improve the performance on the whole. Finally, these new guide beacon rates can be applied to each vehicle, so that the performance deterioration can be mitigated. It should be noted that all these procedures are executed in the RSU.

![Figure 1. Architecture of ABRA](image1)

![Figure 2. Procedure of ABRA mechanism](image2)

The proposed ABRA mechanism is designed based on the following assumptions:

a) RSU is distributed densely (e.g. in metropolitan areas). RSUs are not far away from each other, so that vehicles can resident in the AR of one RSU most of the time;

b) Metropolitan scenarios: the vehicles’ speeds are relatively low, which means that the resident time of vehicles in one RSU’s coverage is long enough;

c) Vehicles are equipped with ITS sensors, GPS devices and digital map;

d) Vehicles are always in the coverage of 3G communication network.

B. Functional description

In ABRA, OBU's (vehicles) are in charge of sensing its own driving behaviors (e.g. speed, position and so on) using equipped ITS sensors and reporting them to the serving RSU. Furthermore, OBU's is responsible for reporting its transmission record to the serving RSU. The RSU is responsible for analyzing the network performance metrics (e.g. delay, packet loss rate) based on information submitted by vehicles, executing the BP algorithm based on neural network to calculate a set of guide beacon rates and disseminating these guide beacon rates to every vehicle in its AR.

1) OBU

For information collecting, each vehicle is designed to contain a database, which stores the history transmission-receive records. The history records can be divided into two
categories: sending record and receiving record. Beacon sending record contains (as shown in TABLE I; take vehicle A as an example): beacon sequence number (No.), current position of the vehicle, sending time of the beacon (hh:mm:ss:ms) (Tx time), beacon transmission rate (ms) (the interval between two consecutive beacons’ broadcasting). Whereas beacon receiving record contains (as shown in TABLE II; take vehicle C as an example): beacon sequence number (No.), current position of the vehicle, receiving time of the beacon (Rx time), the sender ID of the received beacon. The database can be updated when a vehicle broadcasts or receives a beacon. The history records should be deleted once its lifespan is expired (e.g. 30s) for memory efficiency. These history records should be submitted by vehicle to its serving RSU periodically or event-drivenly.

<table>
<thead>
<tr>
<th>No.</th>
<th>Tx time</th>
<th>Position</th>
<th>Beacon rate (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>11134</td>
<td>10:15:34:935</td>
<td>(23.1,56.5)</td>
<td>103</td>
</tr>
<tr>
<td>11135</td>
<td>10:15:35:038</td>
<td>(22.4,58.6)</td>
<td>103</td>
</tr>
<tr>
<td>11136</td>
<td>10:15:35:136</td>
<td>(20.3,59.5)</td>
<td>98</td>
</tr>
<tr>
<td>11137</td>
<td>10:15:35:234</td>
<td>(19.6,60.4)</td>
<td>98</td>
</tr>
</tbody>
</table>

The transmission of these beacon records should also be considered carefully. Although IEEE 802.11p has the ability to conduct multi-hop routing to transmit data between distant vehicles, the stability and timeliness can not be guaranteed because of the dynamic vehicular topology and limited channel resource. While the traffic safety requires integrity and accuracy of the information, the stable and high-speed 3G communication network with high market penetration rate is chosen as the data uplink path instead of IEEE 802.11p. These beacon history records can piggyback with normal information through 3G interface periodically or event-drivenly in order to update the beacon history records in its serving RSU.

<table>
<thead>
<tr>
<th>No.</th>
<th>Sender ID</th>
<th>Rx time</th>
<th>Position</th>
</tr>
</thead>
<tbody>
<tr>
<td>11134</td>
<td>A</td>
<td>10:15:35:089</td>
<td>(13.1,44.5)</td>
</tr>
<tr>
<td>11134</td>
<td>B</td>
<td>10:15:35:093</td>
<td>(13.1,44.5)</td>
</tr>
<tr>
<td>11135</td>
<td>B</td>
<td>10:15:35:099</td>
<td>(13.2,44.6)</td>
</tr>
<tr>
<td>11137</td>
<td>A</td>
<td>10:15:35:457</td>
<td>(13.2,45.6)</td>
</tr>
</tbody>
</table>

2) RSU

There is also a database located in RSU, which stores the aggregated records of every beacon broadcasting in its AR. Each entry in this database is shown as in TABLE III.

<table>
<thead>
<tr>
<th>No.</th>
<th>Sender ID</th>
<th>Rx time</th>
<th>Position</th>
</tr>
</thead>
<tbody>
<tr>
<td>11134</td>
<td>A</td>
<td>10:15:35:089</td>
<td>(13.1,44.5)</td>
</tr>
<tr>
<td>11134</td>
<td>B</td>
<td>10:15:35:093</td>
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<td>10:15:35:099</td>
<td>(13.2,44.6)</td>
</tr>
<tr>
<td>11137</td>
<td>A</td>
<td>10:15:35:457</td>
<td>(13.2,45.6)</td>
</tr>
</tbody>
</table>

C. Procedural description

Figure 1 illustrates the proposed mechanism as an example. Vehicle A is in the AR of RSU 2. The updating of history records between A and RSU 2 is conducted every second through the 3G communication network. RSU 2 collects these history records for further analyzing. Once RSU 2 senses intolerable performance deterioration, a new set of guide beacon rates is generated by BP algorithm. The set of these guide beacon rates is broadcasted by RSU 2. Upon receiving the guide beacon rate setting, vehicle C adjusts its own beacon rate accordingly and relays the beacon rates setting message to other vehicles of the same AR. The path of this message to A is RSU2-C-D-B-A. Finally, every vehicle in the AR adjusts its beacon rate to the optimized guide value.

IV. BACK PROPAGATION ALGORITHM BASED ON NEURAL NETWORK

The core of our ABRA mechanism is back propagation algorithm based on neural network. In this section, we describe the BP algorithm based on neural network to adjust beacon rate adaptively in order to improve the fairness. With BP algorithm, a set of guide beacon rates can be obtained. As a matter of fact, our BP algorithm consists of two phase: neural network training and BP based beacon rate adjusting.

A. Neural network training phase

As mentioned above, performance metrics of WAVE network (such as delay, packet loss rate and etc) are affected by beacon transmission rate of each vehicle. Furthermore, the relationship between beacon transmission rate and system fairness can be evaluated in terms of such metrics [10]. So we take both the QoS performance and fairness into consideration in the ABRA mechanism.

Consider $M$ vehicles with each one transmitting heart-beat beacons for safety message delivery. Since the QoS metrics are affected by beacon transmission rate of all vehicles, so we denote correlation function $f(\cdot)$ as following:

$$f(\beta_1, \beta_2, \ldots, \beta_M)$$

(1)
For simplicity, we only choose $K$ QoS metrics to represent the performance of the whole vehicular network.

In order to evaluating the fairness of the WAVE network, we define cost-reward function as following:

$$C = \sum_{i=1}^{\infty} (\text{QoS}_i - \text{QoS}_\text{THR}_i)^2 \quad (2)$$

where $\text{QoS}_\text{THR}_i$ is the QoS requirement of the $i$-th vehicle which demands better QoS performance. In other words, we call $\text{QoS}_\text{THR}_i$ as the optimization goal. Clearly, the QoS performance is improved and the wireless medium is fairly shared according to the QoS requirement if the cost-reward function $C$ is minimized. Thus, the goal of our optimization is to find a set of proper beacon transmission rates (i.e. a set of guide beacon rates) which make $C$ minimum.

The nonlinear correlation function $f(\cdot)$ can be obtained with the Multi-Layer Perceptron (MLP) neural network (shown in Figure 3). With a large amount of training data which take beacon transmission rate as input and QoS metrics as output, the neural network can be established. We employ a three-layer MLP here. The number of neurons in the input layer equals to the amount of vehicles $M$. There are $2M$ neurons in the hidden layer. In the output layer, the number of neurons equals to $K$. We denote it as an $M$-$2$-$M$-$K$ MLP.

In the $M$-$2$-$M$-$K$ MLP neural network, the output of the $i$-th neuron at the $l$-th layer can be described as following:

$$u_i(l) = \sum_{j=1}^{N_i(l)} a_{ij}(l)a_j(l-1) + \theta_i(l) \quad (3)$$

$$a_{ij}(l) = h[u_i(l)] \quad 1 \leq i \leq N_i, l = 1, 2 \quad (4)$$

where $N_i(l)$ is the number of neurons at the $l$-th layer (i.e. $N_0 = M, N_i = 2M, N_i = K$), $u_i(l)$ is the activation function and $a_i(l)$ is the output of the $i$-th neuron at the $l$-th layer. $a_{ij}(l)$ is the weight connecting the output of the $j$-th neuron at the $(l-1)$-th layer to the activation of the $i$-th neuron at the $l$-th layer; $\theta_i(l)$ is the bias. The transfer function $h(\cdot)$ is the sigmoid function at the hidden layer and linear at the output layer:

$$h[u_i(l)] = \begin{cases} u_i(l) & l = 2 \\ \frac{e^{u_i(l)} - e^{-u_i(l)}}{e^{u_i(l)} + e^{-u_i(l)}} & l = 1 \end{cases} \quad (5)$$

From Eq (3) and (4), we can say that the neural network has been trained only when the weights of the neural network is determined.

As mentioned above, enough data samples for training are indispensable when building the nonlinear correlation function $f(\cdot)$ with neural network. So that the mean square error (MSE) between training data and output of the neural network can be very small, which means the trained neural network can reflect the correlation well. Obviously, larger amount of training data produces smaller MSE. Nevertheless, due to the computation time limit constrained by the real-world implementation, we suggest that the initial weights of the neural network should be obtained roughly through offline training. Based on these coarse weights, a few of more precise modifications can be made later in real vehicular scenarios (online training).

![Figure 3. Architecture of neural network](image)
Eq (7) means that the $\lambda^e_l(\ell)$ of $l$-th layer is determined by the $\lambda^e_{l+1}(\ell+1)$ of the $(l+1)$-th layer. Note that, $\alpha^j_{l+1}(\ell+1)$ means the weight connecting the output of the $j$-th neuron at the $l$-th layer to the activation of the $j$-th neuron at the $(l+1)$-th layer. $h^j$ is the derivate of the transfer function.

For the trained neural network consisted of three layer, $\lambda^e(2)$ can be first derived from the cost-reward function. So $\lambda^e(1)$ and $\lambda^e(0)$ can be successively derived with Eq (7).

The detail procedure is shown in TABLE IV.

V. SIMULATIONS

In our simulations, we consider packet loss rate and transmission delay as the optimization goal respectively. In other words, packet loss rate and delay of periodic messages among vehicles are used to reflect the performance of vehicular network.

![Back propagation Algorithm](image)

TABLE IV. BP Algorithm

<table>
<thead>
<tr>
<th>Back propagation Algorithm: Find a proper set of beacon rate to mitigate the performance deterioration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: while abs(beta_new-beta) &gt; err_threshold</td>
</tr>
<tr>
<td>2: beta = beta_new</td>
</tr>
<tr>
<td>3: calculate $\lambda^e(2)$ with the trained neural network</td>
</tr>
<tr>
<td>4: for $i=1$ to $N_{\text{output}}$</td>
</tr>
<tr>
<td>$\lambda^e(i) = -\frac{\partial C}{\partial a_i(2)}$</td>
</tr>
<tr>
<td>5: end for</td>
</tr>
<tr>
<td>6: end while</td>
</tr>
<tr>
<td>7: for $i=1$ to $N_{\text{hidden}}$</td>
</tr>
<tr>
<td>$\lambda^e(i) = \sum_{j} \lambda^e(j) h^j u_i(2)$ $\omega_{ij}(2)$</td>
</tr>
<tr>
<td>8: end for</td>
</tr>
<tr>
<td>9: for $i=1$ to $N_{\text{input}}$</td>
</tr>
<tr>
<td>$\lambda^e(i) = \sum_{j} \lambda^e(j) h^j u_i(1)$ $\omega_{ij}(1)$</td>
</tr>
<tr>
<td>10: end for</td>
</tr>
<tr>
<td>11: update beta_new with Eq. 6</td>
</tr>
<tr>
<td>12: beacon rate = beta_new</td>
</tr>
</tbody>
</table>

We conduct simulations with NCTUns6.0 tools [11] in a dense urban scenario without intersection. The density of vehicles is relatively high (i.e. the average interval between vehicles is 100m) which may cause serious performance deterioration. The simulation time is 200s. The number of vehicles is 20. In our simulation, we ignore the transmission power settings, so we suppose that every vehicle can communicate with each other all the time.

Due to the computation limitation, six communication pairs are chosen to represent the performance of the whole WAVE network. Thus a three layer 20-40-6 MLP neural network is built whose training consists of two phase: offline training and online training. The stopping criterion of the neural network training is either when the mean square error (MSE) falls below 1E-10 or when the training epochs exceed 1000 times.

Clearly, a lot of training should be done to obtain precise neural network weights. However, using a large amount of data to train the neural network at run time is unwise since computations consume too much time. So a lot of offline training is conduct before ABRA started. During the offline training phase, the initial weights of the neural network are obtained using 100 data samples collected in a sample environment in order to provide coarse values which are effective in improving the reaction speed of ABRA. In online working phase, our simulation takes appropriate amount data to train the neural network in order to do some small-scale modifications to the weighs. In order to validate the effectiveness of the ABRA, the neural network based BP algorithm is executed every 10s rather than when the performance deterioration exceeds the threshold.

Figure 4 illustrates the details of average beacon rate adjusting with the ABRA mechanism in our simulation. The beacon rate here represents the interval between two consecutive beacons. For comparison, we set the beacon interval of each vehicle at 100ms as the original mechanism. As mentioned above, cooperative active safety applications require frequent broadcasting of beacons, so that each vehicle can sense traffic situations in its vicinity precisely. The results in Figure 4 show that our proposed ABRA mechanism maintains a little larger interval of beacon transmission comparing with the original one, so that the network performance can be guaranteed. From Figure 4, we can conclude that the ABRA doesn’t suppress the frequency of beacon transmission very much, which the accuracy of cooperative active safety applications in the upper layer can also be maintained. Even in the worst cases, the largest broadcasting interval of ABRA mechanism is only about 20ms larger than the original one, which will not deteriorate the traffic situation sensing accuracy so much.

![Figure 4. The adjusting of average beacon rate](image)

![Figure 5. Average delay of the network](image)
Figure 5 shows the average delay of the network using the original mechanism and our ABRA mechanism. The optimization goal is to maintain the average delay at about 200ms. From Figure 5, we can conclude that our proposed ABRA mechanism can reduce the transmission delay to a low level, which can guarantee the timely heart-beat messages delivered soon after generated.

The overall packet loss rate improvement is shown in Figure 6. In this scenario, the optimization goal is packet loss rate which is set as 10%. Comparing to the original one, the ABRA mechanism brings considerable performance improvement. The packet loss rate is suppressed at a low level.

VI. CONCLUSIONS

Cooperative active safety applications, which demand for periodically self-status broadcasting, are the most important services provided by ITS. Thus, heavy network load may be introduced due to its periodicity of transmission. In this paper, we propose an Adaptive Beacon Rate Adjusting (ABRA) mechanism to dynamically tuning the beacon rate in order to mitigate the performance deterioration caused by channel congestion. Our mechanism consists of four parts: performance monitoring, neural network training, beacon rate adjusting and new guide rate applying. With enough training data collected in the monitoring phase, the relationship between beacon rate and system performance can be obtained. Therefore, the back propagation algorithm can be executed to find proper guide beacon rates for mitigating the performance deterioration. Through simulation results, it is concluded that our ABRA mechanism can work well in dynamic vehicular environment. The performance in terms of packet loss and delay is improved a lot with the help of our ABRA.

ACKNOWLEDGMENT

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APPENDIX

In order to obtain $\lambda^*_n(l)$, we have

$$\lambda^*_n(l) = \frac{\partial C}{\partial a^*_n(l)} = \sum_{j=1}^{N} \Lambda^*_n(l+1) \frac{\partial a^*_j(l+1)}{\partial u^*_j(l+1)} \frac{\partial u^*_j(l+1)}{\partial a^*_n(l)}$$

Clearly, we have

$$\frac{\partial C}{\partial a^*_n(l+1)} = -\lambda^*_n(l+1)$$

$\frac{\partial a^*_n(l+1)}{\partial u^*_j(l+1)}$ is the gradient of $\lambda^*_n(l+1)$ with respect of $u^*_j(l+1)$, so we can denote it in terms of transfer function as

$$\frac{\partial a^*_n(l+1)}{\partial u^*_j(l+1)} = h'[u^*_j(l+1)]$$

As for $\frac{\partial u^*_j(l+1)}{\partial a^*_n(l)}$, we have

$$u^*_j(l+1) = \sum_{k=1}^{N} \omega^*_j(l+1)a^*_k(l) + \theta^*_j(l+1),$$

so

$$\frac{\partial u^*_j(l+1)}{\partial a^*_n(l)} = \omega^*_j(l+1)$$

From Eq (2), (3) and (4), we have

$$\lambda^*_n(l) = -\frac{\partial C}{\partial a^*_n(l)}$$

$$= \sum_{j=1}^{N} \lambda^*_n(l+1) \cdot h'[u^*_j(l+1)] \cdot \omega^*_j(l+1)$$

REFERENCES


