Model Reference Adaptive Power Control for Cooperative Vehicle Safety Systems*

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Cooperative vehicle safety systems rely on vehicular networking for vehicle tracking and collision warning. The most pressing challenge in such systems is to maintain real-time tracking accuracy while avoiding network failure and congestion. In vehicular networking, vehicle density is changing rapidly. This unique characteristic can cause network disconnection or channel congestion. Moreover, the interference factors, such as hidden nodes, can cause the network performance to deviate from the ideal state, which heavily degrades the performance of vehicle tracking. To overcome the above two problems, in this paper, an adaptive power control framework for real-time vehicle tracking under the condition of dynamic vehicle density and interference factor is proposed. The framework consists of two parts: a prescriptive reference model and an adaptive power control model. The prescriptive reference model is used to predict, in a rolling-horizon manner, the desired network state based on the desired tracking accuracy by considering the dynamic vehicle density. The adaptive power control model integrates the desired network state and the current real network state that may be affected by interference to generate real-time power control strategy for accurate vehicle tracking. Experimental results show that the proposed framework can significantly improve the performance of real-time vehicle tracking.

Keywords: cooperative vehicle safety, vehicular networking, adaptive power control, vehicle tracking, vehicle density

1. INTRODUCTION

Vehicular networking, based on wireless communications between vehicles and with other infrastructures, enables a variety of new vehicular safety and automation applications. The most challenging application deployed over vehicular networking is Cooperative Vehicle Safety Systems (CVSSs) [1]. CVSSs rely on tracking neighboring vehicles and their movements to detect potential threats and provide warnings to the driver. The performance of vehicle tracking application is the basis for CVSSs [2]. To enable vehicle tracking among neighboring vehicles, each vehicle periodically broadcast state information (e.g., vehicle position, speed, and heading) over a shared wireless channel according to IEEE 802.11p and IEEE 1609 standards [3] defined under the DSRC framework [4], in order to predict possible collisions. Therefore, CVSSs play a critical
role in vehicle collision warning, and it has been showed that CVSSs could reduce over 75% of a nation’s crashes [5].

However, vehicle density is changing rapidly in vehicular networking. This unique characteristic has serious consequences on the performance of vehicle tracking applications in CVSSs. When the vehicle density is low, communication links between nodes may be disconnected and the channel resources could not be fully utilized. Vehicles cannot broadcast their state information to farther nodes and consequently, vehicles at far distance cannot track each other. On the contrary, when the vehicle density is high, an increased amount of packet collisions will happen, and therefore the vehicle cannot track its close neighboring nodes in real-time. It is more dangerous if a vehicle does not receive the state information of its closer nodes. Meanwhile, in vehicular networking, there are interference and uncertain factors, such as hidden nodes, which can cause the network performance to deviate from the ideal state. It has been shown that the probability of successful reception at the edge of the transmission range drops below 40% due to the interference of hidden nodes [6].

Controlling transmission power can be used to mitigate the adverse effects of dynamic change of vehicle density and interference factors. Transmission power is one of the most important adjustable parameters for network performance and tracking applications in CVSSs [7]. Transmission power could be decreased for high vehicle density to gain better tracking accuracy on closer vehicles while increased for lower vehicle density to gain better tracking accuracy on farther nodes. Power control is also an effective means for reducing the interference of hidden nodes [8].

However, the highly dynamic characteristic of vehicle density makes it hard to give good predictions of future vehicle density states, and hence it is difficult to adjust transmission power to maintain real-time tracking accuracy under the condition of dynamic change of vehicle density. Moreover, the rapid change of vehicle density aggravates the interference of hidden nodes, especially when the vehicle density is high. Therefore, it is imperative to design an effective real-time power control strategy that can mitigate the adverse effects of rapid change of vehicle density and interference factors in order to maintain accurate tracking accuracy for each node.

In the literature, several solutions [2, 5, 9, 10-12] have been proposed to tackle transmission power control problems in CVSSs. All these solutions, however, do not capture the highly dynamic characteristics of vehicle density and the effect of interference factors. These solutions rely on channel status, such as channel occupancy, to derive the optimal transmission power. However, it is hard to detect collisions and channel occupancy in a broadcast environment with no acknowledgement mechanisms in vehicular networks. Moreover, the detection mechanisms in these solutions will add delay during communication. This drawback makes these solutions unsuitable for real-time information delivery in vehicle tracking applications in CVSSs. In fact, in vehicular networking, channel status highly depends on the vehicle density. Therefore, an effective real-time power control strategy is expected to maintain the acceptable tracking accuracy for CVSSs in response to the continuous change of vehicle density and the effect of interference factors.

Against this background, in this paper, we propose a real-time power control framework to deal with the continuous change of vehicle density and the effect of interference factors for vehicle tracking in CVSSs. The framework is based on the Model Reference
Adaptive Control (MRAC) [13], which is a powerful adaptive control strategy with adjustable controller parameters in order to design an adaptive controller to guarantee robustness of a system against continuous dynamics, interference, and uncertain variations [14]. The proposed framework consists of two parts: a prescriptive reference model and an adaptive power control model. The prescriptive reference model maps probability of successful reception of packets to vehicle tracking accuracy by considering the continuous time-varying nature of vehicle density. It is then applied to predict, in a short-term and rolling-horizon manner, the desired reception probability of packets based on the acceptable vehicle tracking accuracy. The adaptive power control model evaluates the error between the desired network state and the current real network state and produces the real-time power control strategy. The real-time power control strategy will be finally implemented to guide the real vehicle tracking to the desired states. Simulations are carried out using traffic simulator VISSIM and network simulator NS3, and the results show that the proposed adaptive power control framework is robust to variations of vehicle density and can remarkably improve the performance of the real-time vehicle tracking.

This paper is organized as follows. Section 2 reviews related work in communication power control in CVSSs. Section 3 describes the vehicle tracking problem in CVSSs and MRAC theory. Based on MRAC, an adaptive power control framework is proposed in section 4. Section 5 provides the prescriptive reference model for vehicle tracking and Section 6 presents the adaptive power control model. Section 7 evaluates the proposed adaptive power control strategy based on the proposed framework and discusses experimental results. Finally, Section 8 concludes this paper and outlines directions for future research.

2. RELATED WORK

There are a variety of studies on adaptive power control by taking into account vehicle density to support safety application in vehicular networking. M. Artim and W. Robertson et al. [15] introduced a power adjustment strategy based on the local vehicle density to maintain the connectivity. This power control strategy, however, is mainly used to solve the problem of network connectivity. D. B. Rawat et al. [18] presented an adaptive power control strategy based on the estimated local vehicle density to change the transmission power dynamically. The strategy achieves better throughput and lower delay compared with other power control strategies. J. Mittag and F. Schmidt-Eisenlohr et al. [19] presented a segment-based power adjustment approach based on the distribution of vehicle density estimation. The approach reduces overhead while being effective in controlling the channel load. However, all these power control studies intend to improve the system connectivity, to maximize throughput, or to reduce packet loss probability, without taking into account the performance of tracking accuracy, and, therefore, are not applicable to the vehicle tracking applications in CVSSs.

Our primary focus is on vehicle tracking applications in CVSSs. To increase vehicle tracking accuracy, the work in [9] analyzed the effect of different choices of rate and range on the network performance, and then a feedback strategy for transmission power control based on the channel occupancy was designed to improve the vehicle tracking performance. C. L. Huang and Y. P. Fallah et al. [10] proposed a transmission control protocol that adapts communication rate and power based on the tracking accuracy and
channel occupancy. The packet generation rate and associated transmission power for safety messages are adjusted in an on-demand and adaptive fashion in order to realize an accurate tracking. The above methods assume that communication channel has no loss or delay. This assumption does not hold in reality.

In the presence of communication losses, based on tracking errors, Y. P. Fallah and C. L. Huang et al. [2] proposed an adaptive rate control algorithm based on the channel status and tracking errors. The proposed algorithm relies on the channel collision probability to determine whether to deliver vehicle state information or not. In [11], a transmission power control protocol was proposed to track all neighbors in real time. It adjusts communication power based on the observed channel status. S. Rezaei and R. Sengupta et al. [5] proposed a strategy of dynamic transmission rate adjustment with repetition to reduce the communication load while improving vehicle tracking accuracy. The above strategies rely on channel occupancy or channel collision probability to adjust transmission power to improve vehicle tracking accuracy. However, the channel occupancy and channel collision are hard to detect in a broadcast environment with no acknowledgement mechanisms in vehicular networking. Moreover, actions to control transmission power are undertaken only when high channel occupancy or a high channel collision probability has been detected. This means that it needs some time to recover from the channel congestion state, which is not suitable to real-time vehicle tracking in CVSSs. Channel load highly depends on the vehicle density in the surroundings. Therefore, it is necessary to design an adaptive power control strategy that uses the real-time vehicle density information to determine the current optimal transmission power for vehicle tracking applications.

3. PRELIMINARIES

3.1 Vehicle Tracking Problem

The vehicle tracking function blocks inside each vehicle are shown in Fig. 1. For \( n \geq 2 \) nodes (vehicles), each node \( i, i \in \{1, 2, \ldots, n\} \), has a plant and a bank of neighbor estimators. The plant describes the state of node \( i \) and the neighbor estimators operate simple kinematics models for estimating the state of the neighbors. Let \( \hat{x}_i(t) \) be the receiver \( j \)'s estimation of sender \( i \)'s position and \( \hat{v}_i(t) \) be the receiver \( j \)'s estimation of sender \( i \)'s speed. The kinematics model is formulated as a simple discrete equation, which is switched as following two modes [5]:

1. If no state information of node \( i \) is received at time \( t \) at receiver \( j \), use the estimated state of node \( i \) at time \( t-1 \) to estimate the state of node \( i \) at time \( t \),

\[
\begin{align*}
\hat{x}_i(t) &= \hat{x}_i(t-1) + \hat{v}_i(t-1)\Delta t, \\
\hat{v}_i(t) &= \hat{v}_i(t-1),
\end{align*}
\]

where \( \Delta t \) is the time interval in-between message transmissions.

2. Else if the state information of node \( i \) is received at \( t \), use it to reset estimation state of node \( i \).
\[
\tilde{x}_i(t) = x_i(t), \\
\tilde{v}_i(t) = v_i(t),
\]  
where \(x_i(t)\) is the actual position of node \(i\) and \(v_i(t)\) is the actual speed of node \(i\). Thus, the position error between the actual position and the estimated position of sender \(i\) at receiver \(j\) is calculated as follows:

\[
\varepsilon_{ji}(t) = x_i(t) - \tilde{x}_{ji}(t).
\]  
The objective of our power control is to make vehicle tracking error \(\varepsilon_{ji}(t)\) converge to a desired value \(\varepsilon_d(t)\) under the change of vehicle density and interference factors.

### 3.2 MRAC Theory

The idea behind the MRAC theory is to create a closed loop controller with parameters updated to better guide the controlled system to a desired state [13].

The basic function blocks of MARC are shown in Fig. 2, in which we can see that MRAC consists of four components: a model, a plant, a controller, and an adjustment mechanism.

**Model:** The model is a desired model, which produces the desired or ideal output with the reference input \(u_c\). Reference input \(u_c\) represents the system objective.

**Plant:** The plant is the controlled dynamic system.

**Controller:** The controller describes a set of parameters which are used to design a control law \(u\) to improve the system performance. It is a closed loop controller with parameters that can be modified adaptively.
Adjustment mechanism: The adjustment mechanism updates the controller parameters to match the response of the real plant to the output of the reference model.

As shown in the Fig. 2, \( y_{\text{model}}(t) \) is the output of the reference model and \( y_{\text{plant}}(t) \) is the output of the actual plant. The difference between them is denoted by \( e(t) \) as follows:

\[
e(t) = y_{\text{plant}}(t) - y_{\text{model}}(t).
\]  

In MARC, by defining the error \( e(t) \), adjustment mechanism updates the controller parameters to make the output of the actual plant converge to the output of a reference model having the same reference input. The MRAC is an effective method to maintain an optimal performance of the system in the face of abrupt variations and disturbances in the process dynamics. CVSSs are typical dynamical and uncertain systems due to the rapid change of vehicle density. In order to maintain the acceptable tracking accuracy under the change of vehicle density, in next section, an adaptive power control framework based on MRAC is proposed.

4. ADAPTIVE POWER CONTROL FRAMEWORK

Based on MRAC, a Model Reference Adaptive Power Control framework for real-time vehicle tracking is proposed in Fig. 3. The framework consists of three key parts: the prescriptive reference model, the adaptive power control model and the real vehicle tracking process.

Fig. 3. The proposed Model Reference Adaptive Power Control framework.

(1) The prescriptive reference model

The objective of CVSSs is to maintain acceptable tracking accuracy for each node. Therefore, we regard the acceptable tracking accuracy as the reference input in the Model Reference Adaptive Power Control framework. Based on the acceptable tracking accuracy, the prescriptive reference model produces the target or desired network state according to the current vehicle density from the real-world. The prescriptive reference model first collects the state from the real-world traffic, and then evaluates the current vehicle density and provides a desired reception probability of packets for the acceptable tracking accuracy. Meanwhile, the model seeks the perfect control strategies to achieve the desired reception probability of packets. Since only a short-time prediction for network state is feasible in a highly dynamic traffic scenario, the prescriptive reference model evaluates and predicts the network behavior in a short-term manner.
(2) The adaptive power control model
The adaptive power control model consists of two components: a power controller and an adjustment mechanism. The power controller is used to adjust the transmission power. The adjustment mechanism updates the power controller parameters to make the response to the real network equal to the reference model. In the framework, the adaptive power control model produces the real-time power control strategy based on the difference between the desired reception probability from the prescriptive reference model and the current real reception probability from the real vehicle tracking process, in order to make the response of the real vehicle tracking accuracy the same as that of the reference model.

(3) The real vehicle tracking process
The vehicle tracking process describes the physical dynamics of vehicle movement and the real communication process considering the effect of interference factor. In the paper, we use the traffic simulator VISSIM and network simulator NS3 to represent the real vehicle movement process and communication process, respectively. The produced power strategy from the adaptive power control model will be finally implemented to guide the real network behavior towards the desired reception probability of packets, so that accurate vehicle tracking can be achieved under various traffic conditions and interference factors. The procedure needs to be conducted cyclically in a rolling horizon fashion.

5. THE PRESCRIPTIVE REFERENCE MODEL

In CVSSs, a reliable and accurate tracking mainly depends on whether or not the state information can be successfully received by neighbors. The probability of successful reception depends on two main factors: the connectivity between vehicles and the channel contention. These two major factors, however, are all affected by vehicle density. In this section, we first present the effect of both connectivity among vehicles and channel contention on probability of successful perception. Then, the probability of successful reception model that takes into account the dynamic nature of vehicle density is given. Based on the probability of successful reception model, the prescriptive short-term prediction model for vehicle tracking accuracy is derived.

5.1 Effect of the Connectivity Among Vehicles on Probability of Successful Reception

The basic requirement of a successful reception of the state information in vehicular networking is that the sender and the receiver must be connected throughout the whole journey, that is, the maximum separation between two vehicles in the road segment must be lower than the communication range of the sender. Vehicles enter the highway as a homogeneous Poisson process with arrival rate $\alpha(t)$, which means that the number of the vehicle arrivals in time interval $(t_1, t_2]$ is Poisson with mean $\int_{t_1}^{t_2} \alpha(t)dt$. Vehicles speed in the road section has a uniform distribution with mean $\mu = \frac{v_1 + v_2}{2}$ and variance $\sigma^2 = \frac{(v_1 + v_2)^2}{12}$, where $v_1$ and $v_2$ are the minimum and maximum speed of vehicles, respectively. Considering a road segment with length $L$, the average number of vehicles in the road segment
with arrival rate $\alpha(t)$ is:

$$N_L(t) = \frac{\alpha(t)L}{\mu}.$$  \hfill (5)

Given the mean density of the road segment $\rho(x, t)$ at time $t$, a probability density function of the vehicles in the road section is defined as follows [20]:

$$f_L(x, t) = \frac{\rho(x, t)}{N_L(t)}. \hfill (6)$$

Therefore, $f_L(x, t)\Delta x$ represents the probability that a vehicle is located within the range $[x, x+\Delta x]$ at time $t$.

In vehicular networking, the receiver cannot communicate with the sender if the received signal strength is below a threshold. The received signal strength depends on the level of the transmission power, the relative distance between the sender and receiver and the path attenuation. The relationship between the transmission power and the received power is as follows [21]:

$$P_{r_j}(t) = \frac{\delta}{r_{ij}^{\alpha}}P_{t_i}(t),$$ \hfill (7)

where $P_{r_j}(t)$ is the received power level at receiver $j$ from sender $i$, $P_{t_i}(t)$ is the transmitted power of sender $i$, $r_{ij}^{\alpha}$ is the relative distance between sender $i$ and receiver $j$, and $\alpha$ is the path loss exponent, and $\delta$ is the shadowing coefficient.

In order to guarantee a reliable communication between the sender and the receiver, the received power level at a receiver has to be greater than a minimum power level, denoted by $P_{Min\,Recv}$. Given the transmitted power level $P_{t_i}(t)$ of node $i$ at time $t$, the reliable communication range between two vehicles is maximal if the received power equals the minimal value. The reliable maximum communication range is denoted as $r_{max}(t)$, and can be given as follows:

$$r_{max}(t) = \sqrt{\frac{\delta}{P_{Min\,Recv}}}P_{t_i}(t).$$ \hfill (8)

Given the communication range of the transmitting node, the probability that the receiving node at location $x$ is in the range of the transmitter at time $t$ is [20]:

$$P_L(t) = \int_{x-r_{max}(t)}^{x+r_{max}(t)} f_L(x, t)d(x).$$ \hfill (9)

The number of vehicles distributed on the road section is Poisson-distributed, thus, the probability that $n$ vehicles are located within the road section at time $t$ is:

$$P_N(N(L, t) = n) = \frac{\lambda(L)^n}{n!}e^{-\lambda(L)}.$$ \hfill (10)

The probability that a receiver is within the range of the sender is conditioned on
that the population size of the road section is nonzero. Thus, the probability that the receiver is connected with the forward sender is as follows:

\[
P_c(t) = \frac{P_r(t)}{1 - P_n(N(L,t) = 0)} = \frac{\int_{x} f_c(x,t)d(x)}{1 - e^{-\lambda(N(L,t))}}.
\] 

(11)

### 5.2 Effect of Channel Contention on Probability of Successful Reception

In CVSSs, a vehicle transmits a packet only when the channel is idle. Concurrent transmissions among vehicles will cause the contention for the channel resources. In this circumstance, the back-off mechanism is adopted to maintain the coordination of channel accesses. The model for the back-off process in IEEE 802.11p is constructed based on Markov chain model [22].

In the Markov chain, if the channel is sensed busy by a node at a slot time, a contention window \( W \) will be chosen from \([0, 1, 2, ..., W_s-1]\) for the node as a back-off counter, where \( W_s \) is the minimum contention window size. During the back-off process, if the channel is sensed idle, the back-off counter is decremented by 1 with probability \((1-p)\), where \( p \) denotes the probability that the channel is busy; otherwise, the back-off counter will be frozen until the channel is idle again. Once the back-off counter reaches the zero state, the node can broadcast its packet [23]. Based on Markov chain, the Markov chain model for the back-off process is defined as follows:

**Definition 1:** The Markov chain model for the back-off process is defined by a 4-tuple \( \Sigma = (S, T, M, \lambda, Q) \) verifying the following conditions:

1. \( S \): \( S \) is a finite set of states of Markov chain with \(|S| = W_s\), where \( W_s \) is the minimum contention window size.
2. \( T \): \( T \) is a finite set of transitions from one state to another state.
3. \( \lambda: T \rightarrow P \): \( \lambda \) is a function that assigns a probability to each transition, and \( P \) is a probability set with \( P = \{p, 1-p, p/W_s\} \).
4. \( M: S \rightarrow R \): \( M \) represents the state value of every state in \( S \), and \( R \) is the state space of the Markov chain with \( R = \{0, 1, 2, ..., W_s-1\} \).
5. \( Q: Q \) represents the state transition probability matrix with \( Q = [q_{ij}]_{m \times m} \), where \( q_{ij} \) is the transition probability from state \( i \) to state \( j \) and \( m=W_s \). \( q_{ij} \) is defined as follows:

\[
q_{ij} = \begin{cases} 
p, & \text{if } i = j \\
1-p, & \text{if } j = i+1 \text{ or } i = j+1 \\
p/W_s, & \text{if } i = 0 \text{ or } j = 0
\end{cases}
\] 

(12)

The first condition in Eq. (12) denotes that the transition probability from the state \{k\} to state \{k\} is \( p \). This transition probability means that the value of the back-off counter stays constant when the channel is sensed busy.

The second condition in Eq. (12) denotes that the transition probability from the state \{i\} to state \{i+1\} is \((1-p)\). This transition probability means that when channel is idle, the back-off counter is decremented by 1 with probability \((1-p)\).
The third condition in Eq. (13) denotes that the transition probability from the state \{0\} to another state is $p/W_s$. This transition probability means that a new packet following a successful transmission start the back-off process by randomly choosing a new back-off counter value from the zero state with a probability of $p/W_s$.

Fig. 4. Markov chain model for the back-off process.

Markov chain model for the back-off process is shown in Fig. 4. In the Markov chain, a vehicle transmits a packet only when the current state of the back-off process is in or reaches state 0. Therefore, the probability that a vehicle transmits a packet in a slot time is related to the steady-state probabilities of state 0. The steady-state probabilities of state 0 can be obtained by solving the steady-state equations. However, the existence of steady-state has to be satisfied. To verify the existence of steady-state of the Markov chain, we give the following properties of the Markov chain for the back-off process.

**Theorem 1:** The Markov chain for the back-off process is irreducible.

**Proof:** The Markov chain for the back-off process in Fig. 4 consists of $W_s$ states and all $W_s$ states communicate with each other. Therefore, there is only one class (i.e., all states communicate) in the Markov chain and hence, the Markov chain for the back-off process is irreducible.

**Theorem 2:** The Markov chain for the back-off process is positive recurrent.

**Proof:** There are $W_s$ states in the Markov chain and hence, the Markov chain for the back-off process is a finite-state Markov chain. According to [21], all states in an irreducible finite-state Markov chain are positive recurrent. Based on Theorem 1, the Markov chain for the back-off process is positive recurrent.

**Theorem 3:** The Markov chain for the back-off process is aperiodic.

**Proof:** The period $d_i$ of state $i$ is the greatest common divisor of $\{n: P^{(n)}_i > 0\}$, $P^{(n)}_i$ is the $n$-step transition probabilities of state $i$. If $d_i = 1$, the state $i$ is aperiodic [21]. In the Markov chain of Fig. 4, for state $i$, $i \in \{0, 1, 2, \ldots, W_s-1\}$, as $P^{(n)}_i > 0$ and $P^{(n+1)}_i > 0$, state $i$ have period 1 and hence, state $i$ is an aperiodic state. Therefore, all $W_s$ states in the Markov chain are aperiodic and the Markov chain for the back-off process is aperiodic.

**Theorem 4:** The limiting distribution of the Markov chain for the back-off process uniquely exists.

**Proof:** Limiting distribution uniquely exists only when the Markov chain is irreducible and ergodic. A Markov chain is ergodic if all its states are ergodic states. In a finite-state Markov chain, positive recurrent states that are aperiodic are ergodic states [21]. From the above analysis, all states in the Markov chain for the back-off process are positive.
recurrent and aperiodic. Therefore, all states in the Markov chain are ergodic states and the Markov chain for the back-off process is ergodic. As a consequence, the limiting distribution (i.e. steady-state probabilities) of the Markov chain for the back-off process uniquely exists.

The probabilities of the steady states in Markov chain is denoted as a $W_s$-dimensional vector of $\pi=[\pi_0, \pi_1, \pi_2, \ldots, \pi_{W_s-1}]$, where $\pi_i$ denotes the probability that the back-off counter reaches the steady state $i$. Based on properties of Markov model [21], the $W_s$-dimensional vector satisfies the following steady-state equations:

\[
\begin{cases}
\pi Q = \pi \\
\sum_{i=0}^{W_s-1} \pi_i = 1
\end{cases}
\]  

(13)

where $Q$ is one-step transition probability matrix.

By solving the above equations, the vector $\pi$ can be observed as follows:

\[
\pi_i = \frac{W_s - k}{W_s} \frac{p}{1-p}, 1 \leq k \leq W_s - 1.
\]  

(14)

By using the formula $\sum_{i=1}^{W_s} \pi_i = 1$, the steady state probability $\pi_0$ can be obtained as given by Eq. (15):

\[
\pi_0 = \frac{2(1-p)}{2 - 3p + pW_s}.
\]  

(15)

A vehicle transmits a packet only when the current state of the back-off process is in or reaches state 0 with probability of $(1-p)$. Therefore, the probability that a vehicle transmits a packet in a slot time is given by:

\[
\tau(p) = \frac{2(1-p)^2}{2 - 3p + pW_s}.
\]  

(16)

The channel is busy if at least one vehicle within the communication range of the sender transmits a packet. Given the vehicle density $\rho(\tau, t)$ of the road segment and transmission power $P_i(t)$ of the sender $i$ at time $t$, the probability that the channel is busy is given by Eq. (17):

\[
p = 1 - (1 - \tau^\rho(\tau, t)_{\text{max}}),
\]

(17)

where $r_{\text{max}}(t)$ is the maximum reliable communication obtained from the Eq. (8) given $P_i(t)$.

Based on Eq. (17), we obtain:

\[
\tau^* (p) = 1 - (1 - p) \frac{1}{r^\rho(\tau, t)_{\text{max}}}. \]

(18)

This is a continuous and monotone increasing function in the range of $p\in(0,1)$ with $\tau^*(0)=0$ and $\tau^*(1)=1$. It is also easy to prove that equation $\tau(p)$ defined by Eq. (16) is a
monotone decreasing function in the range of \( p \in (0,1) \) with \( \pi(0)=1 \) and \( \pi(1)=0 \). Thus, the uniqueness of the solution of Eqs. (16) and (18) is proven. The solution to Eqs. (16) and (18) can be solved.

The number of vehicles in the communication range determines the busy time of the channel. However, the vehicle density in the road section is not constant, which makes the number of vehicles within the communication range variable. Thus, the dynamic characteristics have to be considered in the channel contention model. The probability \( P_s(t) \) that a successful transmission occurs at a slot time is given by the probability that exactly one node transmits on the channel. \( P_s(t) \) can be given by Eq. (18) as follows:

\[
P_s(t) = \rho(x,t)r_{\text{max}}(t)r(1-r)^{\min(x,r_{\text{max}}(t)-1)}.
\]

### 5.3 The Probability of Successful Reception Model

To derive the probability of successful reception by the receiver, it is imperative that the receiver has to be connected with the sender in a single-hop communication range. Moreover, no vehicle within the communication range transmits at the same slot time in which the sender is transmitting. By taking into account the dynamics of vehicle density, putting all the above conditions together, the probability \( P_{\text{succ}}(P_s(t)) \) that a vehicle successfully receives the packet with respect to transmission power \( P_s(t) \) of the sender is:

\[
P_{\text{succ}}(P_s(t)) = \frac{\int_{x_r}^{x_{\text{max}}(t)} f(x)dx}{1-e^{-\delta r_{\text{max}}(t)}} \rho(x,t)r_{\text{max}}(t)r(1-r)^{\min(x,r_{\text{max}}(t)-1)}.
\]

where \( r_{\text{max}}(t) = \sqrt{\frac{\delta}{P_{\text{Min Receiver}}}} \) based on Eq. (8), \( \rho(x,t) \) is the vehicle density of the road segment at time \( t \).

### 5.4 Prediction Model for Vehicle Tracking

Based on Eq. (19), the vehicle tracking accuracy model can be derived. According to the vehicle tracking functional blocks as shown in Fig. 1, receiver \( j \)'s estimation of sender \( i \)'s position is equal to the actual position of sender \( i \) if the state information of sender \( i \) is successfully received at time \( t \). The probability of successful reception is \( P_{\text{succ}} \); meanwhile, if the actual position of sender \( i \) is not received at \( j \), Eq. (1) is used to estimate the position of node \( i \). The probability that the actual position of sender \( i \) is not received is \( 1-P_{\text{succ}} \). Thus, putting the two cases together, node \( j \)'s estimation of sender's position can be given as follows:

\[
\hat{x}_j(t) = x_i(t)P_{\text{succ}} + (\hat{x}_j(t-1) + \tilde{v}_j(t-1)\Delta t)(1-P_{\text{succ}}).
\]

Putting \( \hat{x}_j(t) \) in Eq. (21) into Eq. (3), we can obtain:

\[
\epsilon_j(t) = |x_i(t) - \hat{x}_j(t)| = |x_i(t) - x_i(t)P_{\text{succ}} - (\hat{x}_j(t-1) + \tilde{v}_j(t-1)\Delta t)(1-P_{\text{succ}})|
\]
Eq. (22) presents the relationship between vehicle tracking accuracy and successful reception probability of packets. We use Eq. (22) as the predictive model and the prediction model is expressed as follows:

\[
U_i(P_{t_i}(t)) = ([v_j(t) - \bar{v}_j(t-1)](1 - P_{\text{succ}}(P_{t_i}(t))))
\]

where \(U_i(P_{t_i}(t))\) is the objective function regarding transmission power \(P_{t_i}(t)\), \(P_{\text{succ}}(P_{t_i}(t))\) is the successful reception probability of packets as defined in Eq. (20), \(\bar{v}_j(t)\) is the receiver \(j\)'s estimation of sender \(i\)'s speed, and \(v_i(t)\) is the actual speed of node \(i\).

Given the acceptable vehicle tracking accuracy, the desired probability of successful reception of packets at time \(t\) will be derived by Eq. (23). The desired successful reception probability of packets will serve as a reference point for the adaptive power control. Then, based on Eq. (20), the desired power control strategy will be determined. Therefore, the desired transmission power can be used as a reference when designing the control strategy. Since the vehicle density in vehicular networking is highly dynamic, only a short-term power control is reliable. Therefore, the prediction model works in a rolling horizon manner. At the beginning of each horizon, the vehicle density can be considered fixed.

6. THE ADAPTIVE POWER CONTROL MODEL

In vehicular networking, even if the value of desired transmission power is assigned to the network, the inevitable interference, such as hidden nodes, will cause the network state to deviate from the predictable and desired value. To alleviate the impact of the disturbance, the parameters for designing the power feedback controllers have to be adjusted in a timely manner to produce a real-time power control strategy. The parameters are updated by the MRAC strategy, based on the difference between the desired probability of successful reception from the reference model and the current probability of successful reception from the real network. The produced real-time power will better guide the real network state to the desired value. The objective of the adaptive control is to make the error converge to zero.

As depicted in Fig. 3, the MRAC based power control framework consists of two major feedback loops: the ordinary feedback loop and the adaptive feedback loop. The ordinary feedback loop provides the error between the output of the real network state and the output of the reference model. The adaptive feedback loop adjusts the controller parameters based on the error. In this paper, the controller is designed based on the proportional-integral-derivative controller (PID controller) [22]. A PID controller is a control loop feedback controller that adjusts the process parameters to reach the target performance based on the errors between a measured process state and a desired setpoint. In this paper, we use a proportional-integral controller (PI) to design the controller. The PI
controller is a special case of the PID controller \[24\]. The PI controller is designed as follows:

\[ P_{i}(t) = K_{i}^{p} e_{i}(t) + K_{i}^{i} \int_{0}^{t} e_{i}(t) dt, \quad \text{(24)} \]

where \( e_{i}(t) = u_{i}(t) - \tilde{u}_{i}(t) \) with \( \tilde{u}_{i}(t) \) denoting the desired probability of successful reception generated by the reference model, \( u_{i}(t) \) is the actual probability of successful reception from the real network model at time \( t \), and \( P_{i}(t) \) is the transmission power at time \( t \). Due to the highly dynamic nature of the vehicle density, the parameters \( K_{i}^{p} \) and \( K_{i}^{i} \) are not constant, rather, they will change over time due to the uncertainties of the vehicle density. We define a utility function as follows:

\[ J(\theta_{i}) = \frac{1}{2} e_{i}^{2}, \quad \text{(25)} \]

where \( \theta_{i} = [K_{i}^{p}, K_{i}^{i}] \).

By using the gradient method, the parameter \( \theta_{i} \) is adjusted in the negative gradient direction in order to make \( J \) converge to the minimum quickly.

\[ \frac{d\theta_{i}}{dt} = -\gamma_{i} \frac{dJ}{d\theta_{i}} = -\gamma_{i} e_{i} \frac{de_{i}}{d\theta_{i}}, \quad \text{(26)} \]

where \( \gamma_{i} \) is the step, \( \frac{de_{i}}{d\theta_{i}} \) indicates how the error is changed by adjusting the parameters.

To implement the method in the computer, we must discretize Eq. (24) as follows:

\[ \Delta P_{i}(t) = \Delta m_{i}(t) + \Delta n_{i}(t), \quad \text{(27)} \]

where \( \Delta P_{i}(t) = p_{i}(t) - p_{i}(t-1) \), \( \Delta m_{i}(t) = m_{i}(t) - m_{i}(t-1) \), \( \Delta n_{i}(t) = n_{i}(t) - n_{i}(t-1) \), in which:

\[ m_{i}(t) = K_{i}^{p} e_{i}(t), \quad m_{i}(t-1) = K_{i}^{p} e_{i}(t-1), \]

\[ n_{i}(t) = TK_{i}^{i} \sum_{j=0}^{t} e_{i}(j), \quad n_{i}(t-1) = TK_{i}^{i} \sum_{j=0}^{t-1} e_{i}(j). \]

\[ \text{where } t \equiv kT (k = 0, 1, 2, \ldots, n) \text{ and } T \text{ is the sampling period.} \]

Thus, the discrete version of Eq. (24) is expressed by Eq. (29):

\[ P_{i}(t) = P_{i}(t-1) + K_{i}^{p} (u_{i}(t) - \tilde{u}_{i}(t)) - (u_{i}(t-1) - \tilde{u}_{i}(t-1)) + K_{i}^{i} (u_{i}(t) - \tilde{u}_{i}(t)). \]

\[ \text{(29)} \]

The discrete version of Eq. (26) is given by:

\[ \theta_{i}(k) - \theta_{i}(k-1) = -\gamma_{i} e_{i} \frac{e_{i}(k-1) - e_{i}(k-2)}{\theta_{i}(k-1) - \theta_{i}(k-2)}. \]

\[ \text{(30)} \]

By solving Eq. (30) iteratively, the adjustable parameter \( \theta_{i} \) can be obtained after each iterative process, which in turn can be applied in designing the feedback controller in Eq. (29). Thus, the real-time the power control strategies can be produced.
7. PERFORMANCE EVALUATION

7.1 Simulation Settings

To test the performance of our adaptive power control strategy based on the proposed framework, we have conducted traffic/network simulation using VISSIM [25] and NS3 [26] simulators for road traffic and network simulations, respectively. The main simulation scenario in VISSIM is a straight 1-km of a 4-lane highway. The flow rate entering the highway is a random variable and yields in the interval [0.25, 3.75] vehicles/second. Vehicle trajectories are then fed to NS3 in which vehicles communicate over a DSRC channel by following the DSRC channel model in [27]. For the acceptable tracking accuracy in CVSSs, S. E. Shladover and S. K. Tan [28] have derived the accuracy required in position estimate to produce warnings of reasonable accuracy. They suggested the accuracy requirements on longitudinal tracking position error are nominally 0.5m. We use their work to set the acceptable tracking accuracy used in our adaptive power control strategy to 0.5m. Table 1 lists the simulation parameters used in the experiments.

During the simulation, we sample at 20Hz to collect the vehicle state information, such as vehicle position, speed and heading. At each 50ms time step, every node generates a packet and broadcasts it to its neighbors. Total simulation time is 30s for each run. Each rolling horizon is 150ms and the time interval is 50ms. Rolling horizon will be moved 50ms forward once it finishes current period. During the next period of 50ms, another adaptive power control process will be started. In each simulation, we calculate the average positioning errors over all neighboring nodes to explore the performance of the adaptive power control strategy based on the proposed framework.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>5.9GHz</td>
</tr>
<tr>
<td>Message size</td>
<td>300 bytes</td>
</tr>
<tr>
<td>Message and Header Sizes</td>
<td>512, 64Bytes</td>
</tr>
<tr>
<td>Slot time</td>
<td>$13\mu$s</td>
</tr>
<tr>
<td>Exponent factor $\alpha$</td>
<td>2.00</td>
</tr>
<tr>
<td>Received power threshold</td>
<td>3.162e-13W</td>
</tr>
<tr>
<td>Vehicle Speed</td>
<td>80-120Km/h</td>
</tr>
<tr>
<td>State packets rate</td>
<td>10 packets/s</td>
</tr>
<tr>
<td>Minimum contention window size</td>
<td>15</td>
</tr>
<tr>
<td>Number of lane</td>
<td>4</td>
</tr>
<tr>
<td>Acceptable tracking accuracy</td>
<td>0.5m</td>
</tr>
</tbody>
</table>

7.2 Simulation Results

In highway scenarios, the vehicle density is mainly affected by the vehicle arrival rate. Fig. 5 shows the vehicle density versus vehicles arrival rate in a 4-lane highway. As can be seen, as the number of vehicles crossing the starting point in each lane increases, vehicle density increases until it reaches a point where it stays constant. This is a jam scenario where traffic congestion happens in the highway section.
To validate the proposed vehicle tracking model, we compare the computed tracking errors from the tracking model with the experiment results. Fig. 6 shows the tracking errors over the probability of successful reception with different successful reception rates. As can be seen, the vehicle tracking model is highly accurate. The analytical results practically coincide with the simulation results (relative errors are less than 0.5%). This result proves the effectiveness of the proposed vehicle tracking model under various traffic conditions.

To verify the performance of real-time response to the dynamic changes of vehicle density, we assume that at $t=100$s, the flow of vehicles entering the highway changes from a constant 0.75 vehicle/s to 1.25 vehicle/s, at $t=400$s, the flow of vehicles returns to 0.75 vehicle/s, and at $t=500$s, the flow of vehicles changes from 0.75 vehicle/s to a constant rate of 1.5 vehicle/s. From Fig. 5, we can see that the above arrival rates will not cause a high traffic load. There are fewer interactions between vehicles and thus the Poisson distribution is valid. Fig. 7 shows how the adaptive power control strategy based on the proposed framework reacts when the vehicle density changes. The adaptive power control strategy based on the proposed framework converges to the desired value fast during each stage when the vehicle density changes. Fig. 8 shows the convergence rate of the adaptive power control strategy based on the proposed framework. We can see that, after only 5 iterations, the adaptive power control strategy converges to the optimal value, which fully demonstrates that the adaptive power control strategy based on the proposed framework has a good real-time responding characteristic.
Fig. 9 shows how the transmission power varies when the vehicle density changes using the proposed adaptive power control strategy. Through the adaptive power control strategy, we can identify the power to maintain the desired tracking accuracy under different traffic conditions.

Fig. 9. Evolution of the power under MRAC.

Fig. 10. Effective power versus vehicle density when the tracking error is 0.5m.

Fig. 10 depicts the change of transmission power over time when the vehicle density is set from 0.05vehicle/m to 4vehicle/m. It is clear that, as the vehicle density increases, the transmission power decreases. This means that, to achieve the acceptable tracking performance for any vehicle density, vehicles have to reduce their communication power based on Fig. 10.

To test the capacity and effectiveness of the adaptive power control strategy, we compare the tracking errors of the proposed adaptive power control strategy with those of the fixed power strategy in Fig. 11 and Table 2. Fig. 11 plots the comparison of tracking errors for the fixed power strategy and the adaptive power control strategy, respectively, with respect to the change of vehicle density. Table 2 shows the tracking errors using the fixed 28dBm transmission power, which is the standard solution suggested by VSCC, and the proposed adaptive power control strategy, when the vehicle density is 0.1vehicle/m, 0.2vehicle/m and 0.3vehicle/m, respectively.

![Fig. 11. Tracking errors versus vehicle density.](image)

From Fig. 11 and Table 2, we can see that during each stage of change of the vehicle density, the adaptive power control strategy performs well and tracking errors are all close to the desired values. The tracking errors using the fixed power strategy, however,
Table 2. Tracking errors and relative error (Comparison among adaptive power and fixed power).

<table>
<thead>
<tr>
<th></th>
<th>0.1 vehicle/m</th>
<th>0.2 vehicle/m</th>
<th>0.3 vehicle/m</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tracking error</td>
<td>Relative error (%)</td>
<td>Tracking error</td>
</tr>
<tr>
<td>Adaptive power</td>
<td>0.471663</td>
<td>5.6674</td>
<td>0.482103</td>
</tr>
<tr>
<td>Fixed power</td>
<td>0.350881</td>
<td>-29.8238</td>
<td>0.687597</td>
</tr>
</tbody>
</table>

are quite high, especially when there is a high density of vehicles. The relative errors of the standard solution suggested by VSCC reach 96.747% when the vehicle density is 0.3 vehicle/m. The fixed power strategy suffers from more consecutive packets losses and thus higher tracking errors when there is a high vehicle density. Although for low vehicle density, the fixed power strategy work better than the adaptive power control strategy, the channel is not used to its potential and the vehicles at far distance cannot be accurately tracked. Our proposed strategy adaptively increases the transmission power when facing low vehicle density, and hence, leaves the shared channel to faraway vehicles that have larger tracking error to broadcast state information, rather than to the close nodes to send information.

Therefore, our proposed design adapts its power according to the vehicle density; thus, tracking errors are maintained at the desired values for different traffic conditions. When the vehicle density is low, the adaptive power control strategy based on the proposed framework increases the power and leaves the shared channel to faraway neighbors. When the vehicle density is high, the proposed strategy gives up remote nodes and tries to gain better tracking accuracy on nearby vehicles.

7. CONCLUSIONS

CVSSs enable each vehicle to track its neighboring vehicles in real-time in order to allow each vehicle to detect potential collisions. However, the dynamic vehicle density and interference factors, such as hidden nodes, affect the performance of the CVSSs tracking applications. In this paper, we propose an adaptive power control framework based on MRAC for real-time vehicle tracking under the continuous change of vehicle density and the effect of interference factors. In this framework, a dynamic reference model generates the desired network state (i.e., the probability of successful reception of packets) to achieve the optimized tracking performance, and an adaptive power control model produces the actual power control strategy. Simulation results show that the proposed power control framework can significantly improve the network performance and considerably maintain the real-time vehicle tracking accuracy under the situation of dynamic change of vehicle density and interference factors.

Our proposed framework can be extended in several ways to study the tracking performance under more complicated traffic scenarios. For example, one future work can be implementing the proposed framework for vehicle tracking on the signalized urban road systems with interactions in the segment and arrival and departure of vehicles at road junctions. Furthermore, power and rate control should be jointly designed in an
adaptable fashion for the optimum performance of the vehicle tracking, particularly in intersections with a high vehicle density.

REFERENCES


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