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Vehicle Position Awareness in Roadside-to-Vehicle Communication

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Abstract: The roadside-to-vehicle communication system is an infrastructure network to be deployed along the roads, which is an important part of the vehicular Ad Hoc networks for future intelligent transportation systems. Vehicle position estimation is a key technology for roadside-to-vehicle communication. In this study, a roadside-to-vehicle communication system is proposed where a camera is fixed on the roadside infrastructure for taking snapshoot of the target vehicle. Then target detecting and pixels counting is performed through certain image processing technology. After that, the function relationship between the vehicular pixels and the distance between the vehicle and the infrastructure is obtained by using the machine learning method, whose training data comes from our field trial. The vehicle position information acquired will be used for the parameters selection of OFDM transmission. The simulation results show that in the vehicular wireless fading channel model, the roadside-to-vehicle system which has position awareness can effectively implement adaptive modulation and coding scheme and, thereby, achieve greater throughput over a fixed modulation and coding scheme.

Keywords: Adaptive modulation and coding, image processing, machine learning, roadside-to-vehicle communications

INTRODUCTION

Recently, lots of study is focused on the goal of enhancing the safety and efficiency of highway and urban transport by using the wireless communication and modern control technology. Research on how to use the latest mobile communication technology for the Intelligent Transportation Systems (ITSs) has become one of the focuses of research and application. The Federal Communication Commission (FCC) allocated the 5.850-5.925 GHz frequency spectrum spanning 75 MHz band for the Dedicated Short Range Communications (DSRC, 2012). IEEE 802.11 adds the Wireless Access to Vehicle Environment (WAVE) (IEEE, 2006) to form the IEEE 802.11p. Efforts on these physical layer standards make the Vehicular Ad hoc Networks (VANETs) possible.

VANETs Integrate Ad Hoc network, Wireless Local Area Network (WLAN) and cellular network technology, whose system architecture can be divided into different forms. From the vehicular communication perspective, the architecture can be categorized into Roadside-to-Vehicle Communications (RVC) (also called Car-to-Infrastructure, C2I) and Inter-Vehicle Communications (IVC) (also called Car-to-Car, C2C) (Vinel *et al*., 2009). The core idea of the RVC and IVC is to design the communication protocols to facilitate different kinds of information exchanging between vehicles, roadside sensors and even pedestrians when they are located within each others' wireless communication range. The transmit information through VANETs can be divided into two categories: commercial/entertainment/information services (e.g. on-board Internet access) and safety-related/emergency services (e.g. crash of the cars). Figure 1 shows the architecture of the VANETs (Liu *et al*., 2009). The On-Board Unit (OBU) is similar to the mobile terminal in spite of its communication mode and frequency. Furthermore, based on built-in processing unit, the processing ability of OBU is more considerable than normal mobile terminal. Gateway (GW) is used for connecting between access network and Internet network. Roadside Unit (RSU) is also called roadway unit or roadway device. It is in charge of the access to the OBU and mainly is referred to the roadway communication devices.

In the design of physical layer of RVC and IVC, Orthogonal Frequency Division Multiplexing (OFDM) modulation technique is often utilized, which can divide a channel with a higher rate data into multiple orthogonal sub-channels with a lower rate data. As a means to overcome frequency selective fading difficulties, OFDM is favorable to transmit high rate data in vehicular wireless channel.

The significance of the essay is to propose a RVC system design including vehicle position awareness. By

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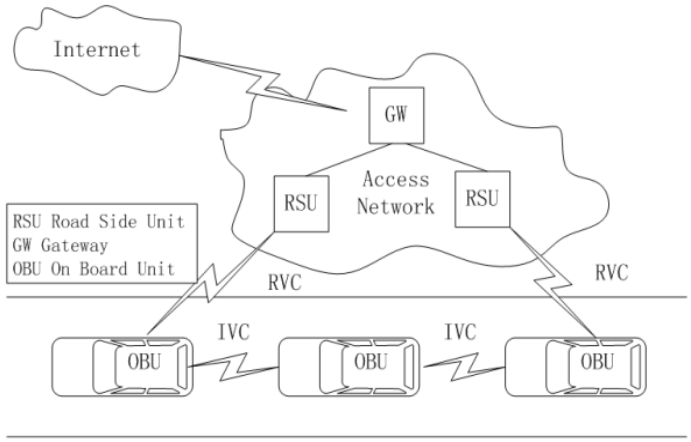

Fig. 1: Architecture of the VANETs

integrating the camera into roadside infrastructure and with the aid of the related image processing technology, we can realize target vehicle detection and position estimation of the identified vehicle through the supervised learning of the machine learning in order to enhance the performance of the Adaptive Modulation and Coding (AMC) in OFDM transmission.

In this study, we propose a design of the adaptive roadside-to-vehicle communication system which contains the vehicle position information awareness. we use the camera to take snapshoot of vehicles, with the aid of the background subtraction method of image processing to detect and identify the vehicle. Moreover, we predict the distance between vehicle and infrastructure by using the supervised learning of machine learning, which can be used for subsequent selection of the MCS in the OFDM transmission for obtaining the throughput and transmitted bits performance gain.

LITERATURE REVIEW ON DETECTION OF MOVING TARGET

Lots of study has been done on the detection of moving target in ITSs, traffic control, military surveillance, robotic vision and other relevant areas. The so-called target detection is to detect whether the image has a change in the image sequences. If the image has any change, the target moves; if not, there is no movement. Motion detection is being affected by many factors, including the gradual and sudden change of illumination, the moving and changing of the background objects, shadows etc. The current image motion detection methods commonly used are optical flow (Fejes and Davis, 1998), frame difference (Haritao *et al*., 2000) and background subtraction (Cucchiara *et al*., 2003). Optical flow method is the overall analysis of the time-varying characteristics of optical flow with the moving targets, which can be directly used for target detection under the camera motion. But in most of the optical flow methods the calculation is very complicated which need special hardware devices and are not suitable for real-time processing. Frame difference method extracts the movement area of the image through the change of time difference threshold of the pixels in adjacent frame with poor anti-noise performance. Background subtraction method requires a background image which uses the subtraction of current image and the background image to obtain the target image, namely, by comparing each input frame with the background image, it can detect the moving targets and can extract their images. Moreover, it has the advantage of simple calculation, real time processing and high anti-noise performance. Considering these virtues, we choose the background subtraction method for the detection of moving vehicles.

METHODOLOGY

System model: RVC system is an infrastructure network to be deployed along the roads for future intelligent transportation systems. Specially, the system not only supports voice and data transmission but also the multimedia service, for example, the real time video transmission under high mobility condition. RVC system requires numerous Base Stations (BSs) to cover long roads and meet high user mobility, which means we face two challenging issues:

- Optimize the number of BSs to make the system cost-effective;
- The system should have a fast and simple handover process to counter the high vehicle mobility.

Literature (Al-Raweshidy and Komaki, 2002) makes a detail discussion about the first issue to optimize the configuration of BSs. In RVC, each base station of the infrastructure usually needs to choose appropriate

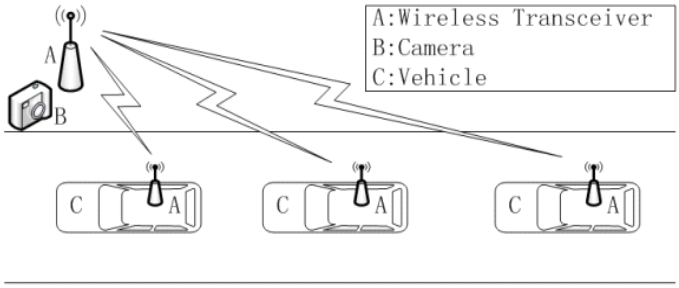

Fig. 2: Diagram of the RVC system architecture

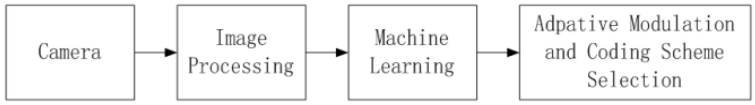

Fig. 3: The processing diagram

transmission parameters according to the distance between target vehicle and each base station, while the high mobility of the vehicle makes the choice difficult to achieve, so the second issue poses a great challenge to the practical application of RVC system. The study utilizes a kind of roadside infrastructure by adding cameras to obtain position information of vehicles scheme to provide high speed wireless data service for the position changing vehicles.

Figure 2 shows the diagram of the RVC system architecture in the study. A stands for the wireless transceiver and is used for short distance information transmission and reception between roadside and vehicle; B is camera for the detection of the target vehicle and estimation of the distance. When these cameras are used, the system requires some special image processing modules. By controlling the camera exposure time, we are able to capture clear images of vehicles; C denotes the moving vehicle including A.

Figure 3 gives the processing diagram. First, camera is used to capture the vehicle image. Then the target vehicle is detected through image processing techniques and the estimation of the vehicle position is made by the machine learning method. Hence, the transmission parameters are optimized after getting the vehicle position. With regard to the OFDM transmission, high rate data is transmitted to the vehicle in the base station of the infrastructure by selecting the appropriate type of modulation and coding scheme.

Detection of target vehicle: Background subtraction method can extract target perfectly through comparing the background to the input image. The design idea is to detect the changing of pixel intensity between current image and background in a short time interval, the obviously changed pixels are caused by the moving targets, the successive work is centered on these pixels. During the processing of extraction of the moving target, some noise will be produced. In order to remove the noise interference, we can make a binarization by choosing a fixed threshold on the subtraction between background and the current frame. The process is as follows:

The background subtraction method resolves the difference value between background and current frame (subtraction image) in accordance with the formula (1):

$$D_m(x, y) = |f_c(x, y) - f_b(x, y)| \tag{1}$$

in which $f_c(x, y)$ represents the pixel value of the c frame, $f_b(x, y)$ is the pixel value of original background and $D_m(x, y)$ denotes the subtraction value. As the actual image acquired is subject to noise pollution, the noise will be produced as a result while acquiring the subtraction image. The noise is approximately the Gaussian distribution. In order to highlight the target region, we should eliminate the image noise. Following the formula (2) we set a fixed threshold to eliminate the image noise and make the subtraction image binarization:

$$\begin{cases} D_m^{'}(x,y) = 0, D_m(x,y) < threshold \\ D_m^{'}(x,y) = 1, D_m(x,y) \geq threshold \end{cases} \tag{2}$$

Target vehicle position estimation: The Current vehicle position depends on the built-in GPS receiver to provide location information (Vinel *et al*., 2009). The study proposes a new method to estimate the vehicle position, whose key process is to determine the distance of the vehicle by the snapshoot image which we will use machine learning algorithms. Machine learning is generally divided into supervised learning, unsupervised learning and reinforcement learning (CS229, 2010). In our application, supervised learning is adopted. In this method of learning, a training set is given and then we attempt to

identify the relationship between input and output through a learning algorithm and then achieve a function h, called a hypothesis. When a new input x is given, we can get the predicted output y through the function h. Supervised learning consists of two important parts, namely, regression and classification. The difference between them is whether the predicted output is continuous or discrete. If the predicted output is continuous it is a regression problem, otherwise it is a classification problem. As the output in the study is continuous, we will consider the former one.

The simplest model for regression is one that assumes h to be a linear combination of the input variables x_i:

$$h(x, w) = w_0+w_1x_1+\ldots+w_{n-1}x_{n-1} \quad (3)$$

where $x = [x_1, \ldots, x_{n-1}]^T$. The model is often known as linear regression. Due to the nonlinear in the practical use, the model has a significant limitation. We, therefore, extend the model by considering linear combinations of fixed nonlinear functions of input variables:

$$h(x,w)= w_0 + \sum_{i=1}^{n-1} w_i\phi_i(x) \quad (4)$$

where, $\phi_i(x)$ is a basis function. Set $\phi_0(x) =1$, we can get:

$$h(x,w)=\sum_{i=0}^{n-1} w_i\phi_i(x)= w^T\phi(x) \quad (5)$$

where, $w = [w_1, \ldots, w_{n-1}]^T$ and $\phi(x) = [\phi_0(x), ..., \phi\ n-1\ (x)]^T$. In order to get the predication function h(x, w), we need to determine w and$\phi(x)$. Considering w, we first introduce the following cost function:

$$J(w)=\frac{1}{2}\sum_{j=1}^{m}\left(h^i(x,w)-y^i\right)^2 \quad (6)$$

where, m defines the number of the training data. The equation calculates the sum of the errors between the predict output value and the actual value and is known as the sum of error square rule. To minimize the sum of error square function J(w), we make derivation of formula (6) and can obtain the following form:

$$\nabla J(w)=\sum_{j=1}^{m}\left(\left(w^T\phi(x)\right)^i - y^i\right)\phi(x)^T \quad (7)$$

Set formula (7) to zero then get:

$$0=\sum_{j=1}^{m} y^i\phi(x)^T - w^T\left(\sum_{j=1}^{m}\phi(x)\phi(x)^T\right) \quad (8)$$

Solving w, we have the standard form:

$$w = (\Phi^T \Phi)^{-1} \Phi^T Y \quad (9)$$

This is the well-known normal equations for the least squares problem. Here $\Phi = [\phi^1(x), ..., \phi^m(x)]$ is an n*m matrix. $Y = [y^1, y^2, \ldots, y^m]^T$ is the whole corresponding output.

Signal model and adaptive modulation and coding selection:

Signal model: In Daniels *et al*. (2008), Meng *et al*. (2011), Rappaport, (2001) and Andrea (2005), a wireless channel including path loss, shadow fading, small scale fading and additive background noise is considered. For transmit node i and receive node j, the multipath fading of the channel is modeled as a tapped-delay line with L_p taps with non-uniform delays:

$$h_{ij}(t)= \sum_{l=0}^{L_p-1} \alpha_{l,ij}\delta(t-\tau_l) \quad (10)$$

where, $\alpha_{l,\ ij}$ represents the discrete time-domain channel coefficient which is independent and identically distributed (i.i.d) complex Gaussian variable and τ_l denotes the path delay term.

The signal between transmit node i and receive node j can be represented as:

$$r_{ij}(t)= \sum_{l=0}^{L_p-1} \sqrt{P_t d_{ij}^{-\alpha}\beta_i}\ \alpha_{l,ij}\, s_i(t-\tau_l)+n_{ij}(t) \quad (11)$$

In Eq. (11), P_t is the transmission power and d_{ij} indicates the distance between node i and j. α denotes pass loss index and β_i refers to log-normal shadowing term, i.e., $10\log_{10} \beta_i \sim N(0, \sigma_{db}^2)$. $s_i(t)$ is the transmission signal from node i and n_{ij} denotes additive white Gaussian noise with zero mean and power spectral density N_0.

In the studied OFDM transmission scheme, the transmitter uses the cyclic prefix to mitigate the effect of Intersymbol Interference (ISI) due to the multipath propagation, which is removed in order to get the original signal at the receiver. In order to achieve an adaptive OFDM transmission, the base station should select a different square Quadrature Amplitude Modulation (QAM) according to the SNR of communication link.

The average frequency response of subchannel k in an OFDM receiver is $H_{ij}(k)$. For simplicity reasons, we ignore the subchannel index and define the gain of the subchannel as $G_i = d_{ij}^{-\alpha}\beta_i|H_{ij}|^2$. The transmission parameters of OFDM are: total subcarrier number K, subchannel number K, subcarrier spacing B (KHz) and channel spacing W (MHz). Therefore the receive SNR is

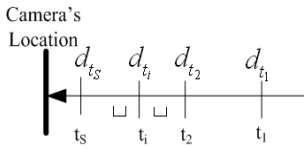

Fig. 4: Definition of distance threshold (arrowhead represents the direction of vehicle)

$$\gamma_i = \frac{P_i \frac{N}{K} G_i}{N_0 \frac{N}{K} B} = \frac{P_i . G_i}{N_0 . B} \tag{12}$$

where, P_i is the transmit power of subcarrier.

Adaptive modulation and coding scheme selection: The selection principle of AMC is to choose the appropriate scheme that makes the throughput of the vehicle transmission maximum in OFDM transmission. Considering the M-ary Quadrature Amplitude Modulation (M-QAM), the modulation level and coding rate of node i are M_i and C_i, respectively. In Yamamoto (2005), the practical Modulation and Coding Schemes (MCS) will cause the loss of SNR when the bit error rate p_b is considered. Then we consider the rate formula as:

$$f(\gamma_i, p_b) = \log_2(1 + \varphi\gamma_i), \varphi = -1.5 / \ln(5 p_b) \tag{13}$$

When M-QAM ($4 \le M \le 64$) is used for modulation level control, the bandwidth efficiency is approximated to formula (13) in the additive white Gaussian noise channel.

Assume the length of the packet is L, the Packet Error Rate (PER) is $P_e = 1-(1-p_b)^L$, define the throughput of node i is TP, where:

$$TP = N.B.C_i.\log_2{}^{M_i}.(1 - P_e) \tag{14}$$

Assume the MCS that the communication system deployed at time t_i is s_i, $i \in \{1, 2, \ldots, S\}$ and S represents the highest modulation and coding mode. According to formula (14), the system can select a MCS at a given receive SNR that makes the throughput of system maximum. Only under the path loss conditions, can the distance between vehicle and roadside infrastructure determine the average received SNR. Define the distance threshold between vehicle and roadside infrastructure is d_{t_i} and it will correspond to a type of modulation and coding s_i and sequentially the average throughput TP_{s_i}. As shown in Fig. 4, the distance threshold is the interval boundary. By deploying adaptive MCS of the roadside-to-vehicle we can choose different types of the MCS according to the distance threshold and can achieve maximum throughput performance. In the adaptive transmission scheme, when the vehicle is at the interval i between boundary d_{t_i} and $d_{t_{i+1}}$, the type of the communication system fixes at s_i; when the vehicle is at the interval i+1 between boundary $d_{t_{i+1}}$ and $d_{t_{i+2}}$, the type of the communication system fixes at S_{i-1}.

Assume that the vehicle speed in the roadside-to-vehicle communication system is V, while deploying fixed MCS, the transmit bits under a certain threshold is:

$$TB_f = TP_{si} \cdot d_{ti}/V \tag{15}$$

To facilitate the calculation of the total transmit bits of adaptive MCS, here define a nominal distance threshold $d_{t_{S+1}} = 0$. In addition, the modulation and coding type that is used at starting time (the moment of the camera obtain the snapshot of the vehicle) is *Q*. The transmit bits of the corresponding use of adaptive MCS is

$$TB_a = \sum_{i=Q}^{S} TP_{s_i} \cdot \left(d_{t_i} - d_{t_{i+1}}\right) / V, 1 \le Q \le S \tag{16}$$

SIMULATION AND RESULTS

The image of the vehicle (type: Peugeot 307) is obtained from practical measurement in the simulation. The camera is fixed on the roadside in the RVC system with the lens focal length of 12 mm and the image resolution of 720*576 pixels. Owing to that when the vehicle is far from the camera, the vehicle size is small and vice versa. In order to simplify the issue, we assume there is only one vehicle in the camera lens at a certain time and the vehicle drives at a constant speed of V = 36km/h. We take a snapshot of the vehicle per 10 m and choose the range from 10 to 80 m, respectively in our practical measurement. Figure 5a and b give the background image and the vehicle image at a distance of 20 m, respectively.

Using the background subtraction method, we can handle the vehicle image at different distance and then get the binary image. The threshold selection is very important. If the threshold is too large, few pixels of detected moving targets will be obtained; if the threshold

(a) (b)

Fig. 5: (a) Background image, (b) vehicle image at distance 20 m

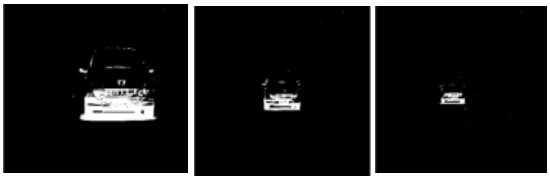

Fig. 6: The binary image at distance 10, 20 and 30 m, respectively

Table 1: The pixels of the detected vehicle at different distance

Distance (m)	Detected pixels
10	4545
20	4266
30	3939
40	3897
50	3807
60	3792
70	3768
80	3642

is too small, the noise will be mistaken as pixels of moving targets. Set the threshold at 50 in our simulation, parts of processing vehicle images are given in Fig. 6. The vehicle detection works well and the contour of the vehicle in the image is clear. Table 1 shows the pixels of processed binary image for different distance.

For the plane curve fitting, n points on the plane generally can always be completely fitted by using n−1 order polynomial fitting. However, even though the fitted curve can pass through the points perfectly, we can not definitely say that the curve is a best prediction. There are two major issues for the curve fitting: over-fitting and under-fitting. In the learning process, we predict the distance between the target vehicle and the camera by different vehicle pixels in the binary image. In general, compared with the actual model, the order of under-fitting is lower, consequently, most of the data are not well fitted. Over-fitting has higher order than actual model. Though most of the data can be well fitted, over-fitting has a poor ability of prediction. The selection of the order plays a decisive role in the curve fitting. We employed a 3-rd order fitting and the under-fitting, over-fitting and the 3-rd fitting results are shown in Fig. 7a, b and c, respectively.

System simulation parameters are partially based on IEEE 802.11p, The channel spacing, the number of the subcarriers, the subchannels, subcarrier spacing is W = 10 [MHz], N = 52, K = 4 and B = 156.25 [KHz], respectively. The carrier frequency is 5.9 [GHz]. A quasi-static six-path fading channel model is considered, whose Rician coefficient is 0.6 and standard deviation of log-normal shadowing is 8 dB. The power gain in each tap is defined as [0.0-1.0-9.0-10.0-15.0-20.0] [dB] with reference to M.1225 in vehicle environment, high antenna and linear path delay and is normalized and converted into power values as [0.4850 0.3853 0.0611 0.0611 0.0485 0.0153 0.0049]. The relative delay in each tap is T = 1/W

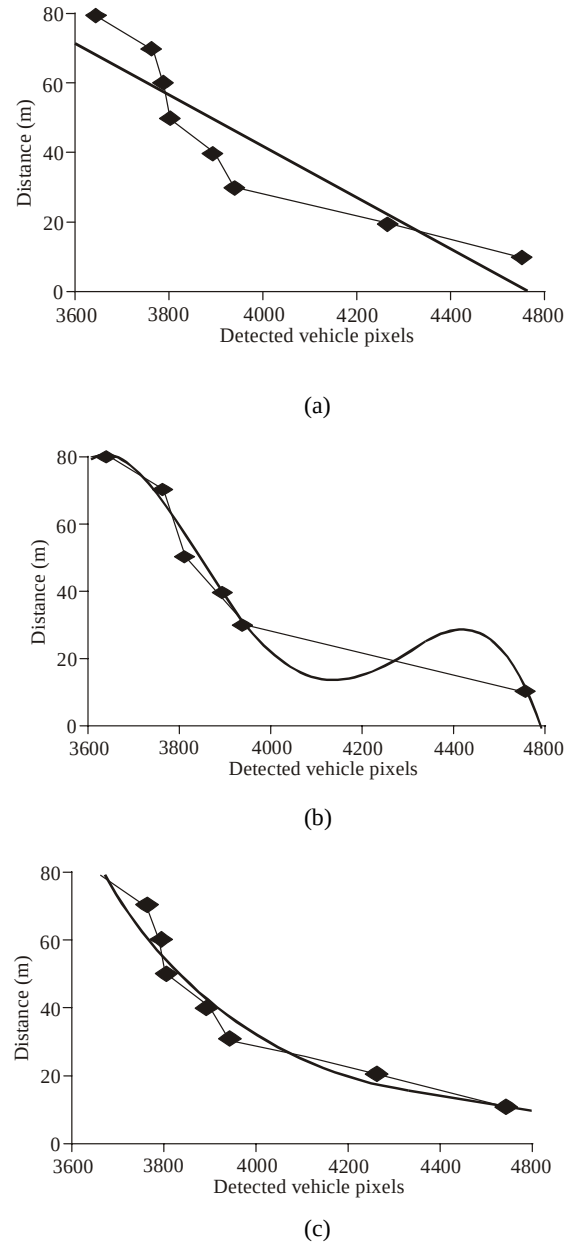

Fig. 7: (a) Under-fitting, (b) over-fitting, (c) 3-rd fitting

as [0 310 710 1090 1730 2510] [ns] and converted into the number of path delay as [0 3 7 11 17 25]. In the simplified path-loss model (Andrea, 2005), a reference distance, d_0 = 10 [m], is defined and the corresponding normalized distance is defined as (d_0/d). Five MCS are considered S = 5, i.e., QPSK-1/2, QPSK-3/4, 16QAM-1/2, 16QAM-3/4 and 64QAM-3/4. Assume under the idea channel estimation. all the subcarriers can obtain equal treatment and all subcarriers use the single QAM modulation scheme in an interval of fading block at the base station. When packet length is 1000 bytes, we have

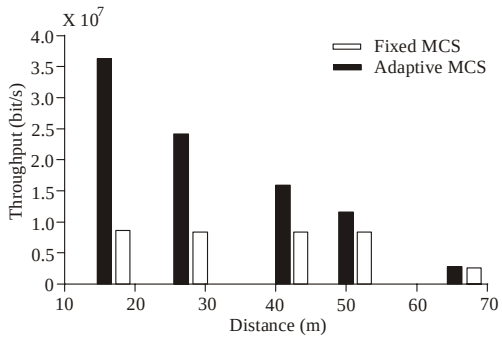

Fig. 8: Comparison of the throughput under the two schemes

Table 2: The distance threshold of different MCS

MCS	Distance (m)
QPSK 1/2	66.0869
QPSK 3/4	50.8231
16QAM 1/2	42.0090
16QAM 3/4	27.8829
64QAM 3/4	17.1592

Table 3: Value comparison of the throughput under the two schemes

Distance (m)	Fixed MCS (Mbits)	Adaptive MCS (Mbits)	Gain performance (%)
66.0869	2.4355	2.4350	100.00
50.8231	8.1246	11.351	139.72
42.0090	8.1250	15.690	193.11
27.8829	8.1250	23.840	293.41
17.1592	8.1250	35.953	442.49

Table 4: Value comparison of the transmitted bits under the two schemes

Distance (m)	Fixed MCS (Mbit/s)	Adaptive MCS (Mbit/s)	Gain performance (%)
66.0869	16.095	123.14	765.09
50.8231	57.692	119.43	207.01
42.0090	65.912	109.42	166.01
27.8829	66.472	87.26	131.27
17.1592	61.692	61.69	100.00

L = 8000 [bits]. According to Eq. (14) we calculate the objective function and select the MCS that makes the value of the objective function maximum.

Distance has a great influence on transmitting rate in wireless communication. By averaging the selection of MCS at different distance we can obtain the distance threshold in a certain MCS as shown in Table 2, which can be used for the OFDM transmission. Figure 8 compares the average throughput of fixed MCS to AMC solutions, in which calculation method is formula (14) and the unit is b/s. The fixed MCS uses a single QPSK-3/4 in Fig. 8, adaptive MCS selects the type of modulation and coding scheme according to the distance derived from the snapshot of vehicle. The adaptive MCS throughput performance is increasing with the decrease of the distance, while deploying fixed MCS, the throughput performance is no longer increase within distance 50.8231 m. Value comparison of the two is shown in Table 3.

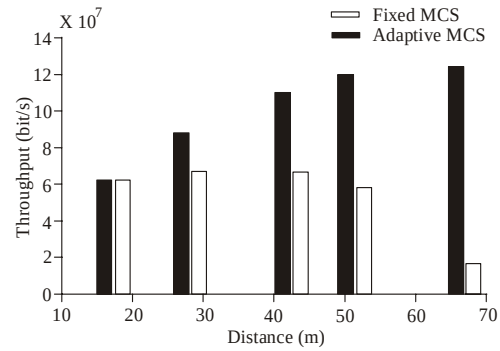

Fig. 9: Comparison of the transmitted bits under the two schemes

After acquiring the vehicle snapshot, the base station at the infrastructure should transmit as many bits as possible to the vehicle. Based on the measurement as defined in formula (15) and (16), we calculate the total transmitted bits of fixed MCS and adaptive MCS, respectively and the unit is bits. Therefore we achieve the performance curve as shown in Fig. 9 and the value comparison is shown in Table 4. When the distance between the vehicle and infrastructure is less than 27.8829 m, the total transmitted bits are basically the same. When the distance is higher than the threshold, the adaptive scheme has distinct gain on the measurement of the total transmitted bits. Specially, when the distance is 66.089 m, the total transmitted bits increase to 765.09%.

In the final section we will compare the feature of fixed MCS and adaptive MCS. It is easy to implement fixed MCS implements and does not need to establish a feedback link between the communication vehicle and infrastructure. Based on the vehicle position estimation of the adaptive MCS as described in the study does not require feedback channel quality information, which only needs to use a camera and associated image processing module. As the impact of the shadow of the wireless link and the small-scale fading affect the channel quality, the selection of the MCS on the basis of path loss in the study might not be necessarily the optimum.

CONCLUSION

In this study, we propose a design of the adaptive roadside-to-vehicle communication system which contains the vehicle position information awareness. We use the camera to take snapshoot of vehicles, with the aid of the background subtraction method of image processing to detect and identify the vehicle. Moreover, we predict the distance between vehicle and infrastructure by using the supervised learning of machine learning, which can be used for subsequent selection of the MCS in the OFDM transmission for obtaining the throughput and transmitted bits performance gain.

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