Machine Learning-Based Beam Selection for V2X Communication

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Abstract

In this paper, we develop a machine learning (ML) framework for vehicular networks that aid beam selection in the presence of the other road users. The frequency of beam selection is determined by the speed of the vehicle, the channel coherence time and blockages between the transmitter and receiver. The results shows that the selection overhead can be greatly reduced even in a high-speed communication scenario. Subsequently the system throughput can b by allocating more time to data transmission.

I. Introduction

Millimeter wave (mmWave) beam management usually the communication bottle in vehicular scenario due to the high-speed mobility and frequent blockage arising from the other road users such as trucks, and busses. Exploiting information from onboard sensors in vehicles has been considered to gain information such as position to reduce the beam selection overheads [1].

Although position information has shown tremendous improvement in reducing the selection overhead compared to traditional exhaustive search scheme, the effect of blockage is an issue that still have to be addressed. To this end, this paper conceptually exploits the location information and type of vehicles in the vicinity of the transmitting and receiving vehicle to aid beam selection.

To this end, we propose a ML framework to map the situation information obtained by observing vehicular sensor data with the optimal beam between the transmitting and receiving vehicles. We propose a method of integrating deep learning and situational awareness learning for beam selection.

II. System Model

The proposed system relies on exploiting situational awareness information from vehicular systems. To gain situational awareness information between the vehicle information such as speed, location, heading, type of vehicles, etc., are shared with predefined beams. Our goal is to predict the beams to be used in sharing such information in the next transmission time given the currently situation information. This will improve system reliability, reduce beam selection overhead and high system throughput.

a. Signal Model

We assume beam codebooks $\mathcal{B}_t = \{v_1, v_2, \dots, v_{|B_t|}\}$ and $\mathcal{B}_r = \{w_1, w_2, \dots, w_{|B_r|}\}$ at the transmitting and receiving vehicles respectively. The received signal at the receiver vehicle k is given by

$$y_{(p,q)}(n+1) = \mathbf{w}_q^H(n)\mathbf{H}(n+1)\mathbf{v}_p(\mathrm{n})s(n+1) + n_r \quad (1)$$

where s is the signal carrying the absolute position information of the transmitting vehicle. Note that sharing the absolute position information s with other vehicles at time instant n requires that the transmit and receive beams are predetermined to maximize the signal power.

b. Beam selection

By omitting the time parameter n in (1), the beam selection at vehicle k is determined by the normalized signal power

$$y_{(p,q)}^k = \left|\mathbf{w}_q^H \mathbf{H}_k \mathbf{v}_p\right|^2, \quad (2)$$

where n_r is the zero mean Gaussian noise at the receiving vehicle. The optimal beam pair which is determined by the situation between the transmitting vehicle i and the receiving vehicle k is $(\hat{p}, \hat{q}) = argmax_{p,q} y_{(p,q)}^k$.

To address the beam selection issue in a high mobility environment, we aim to gain situational awareness from the sensor data and map the information to the optimal beams from the codebook as shown in Fig 1.

III. Beam Selection Problem Formulation for V2X Communications

The objective of this paper is to select the best beamformer for a given situational information which will enable information exchange in a vehicular scenario. We aim to efficiently predict the situation information between the connected vehicles to reduce the beam training overhead while maintaining the situational awareness tracking accuracy. Hence given a predicted situational information, the optimal transmit/receive beamformer which will be used to share the sensor data is selected for transmission for the next slot.

Specifically, the selected beamformer from the k-th vehicle for $k \in \{1,2 \dots, K\}$ is accomplished through a codebook based approach $\mathcal{B}_t$ and $\mathcal{B}_r$ at the transmitter and receiver respectively.

Given the situational information, the receive beamforming vector $\mathbf{w}_q(n)$ for the i-th receive vehicle is chosen from $\mathcal{B}_r$ to maximize the channel gain as follows

$$\mathbf{w}_q^*(n) = \underset{\mathbf{w}_q \in \mathcal{B}_r}{\operatorname{argmax}} \left| \mathbf{w}_q^{\mathbf{H}}(n)\mathbf{H}(n)\mathbf{v}_p(n\text{-}1) \right|^2, \qquad (3)$$

Similarly, the transmit beamforming vector $\mathbf{v}_\mathrm{p}(n)$ for the k -th transmit vehicle is chosen from $\mathcal{B}_t$ to maximize the channel gain as follows

$$\mathbf{v}_p^*(n) = \underset{\mathbf{v}_p \in \mathcal{B}_r}{\operatorname{argmax}} \left| \mathbf{w}_q^{\mathbf{H}}(n\text{-}1)\mathbf{H}(n)\mathbf{v}_p(n) \right|^2, \qquad (3)$$

IV. Proposed ML based Beam Selection

As shown in Fig. 1, the main objective of this paper is to establish a framework of learning situation information via onboard vehicle sensor data, where $\mathbf{x}_k = [x_k, y_k, \dot{x}_k, \dot{y}_k, \ddot{x}_k, \ddot{y}_k]$ is the input vector consisting of position, velocity and acceleration data observed from the sensors in vehicle k. Since all the vehicles shares their sensor data each vehicle concatenated the data as input to the ML.

a. Offline Training

In the offline training stage, $\mathbf{X} = [\mathbf{x}_k], \forall k$ situational information and the labels are employed to train the ML. The DNN generates the optimized analog beamforming vector index $\hat{p}$ and $\hat{q}$, by minimizing the loss function.

b. Online Deployment and Testing

In the online deployment stage, the actual situation is observed from the sensors are applied to the ML as input and the optimized beamformer is selected. It is worth noting that perfect CSI is only required to compute the loss during the offline training stage. When deployed online, all parameters of the DNN have already been fixed and the well-trained DNN only accepts the imperfect CSI as the input and directly outputs the analog beamformer.

V. Results and Discussion

Table 1: Summary of simulation parameters

SNR = 10dB	$\lvert\mathcal{B}_r\rvert$=16,32,64
K = 10	Length=50
$\lvert\mathcal{B}_t\rvert$=16,32,64	Width =20

A summary of the simulation parameters are presented in Table 1. The simulation scenario is generated in MATLAB simulator.

Fig. 2 and Fig. 3 show the situational awareness and beam training accuracy of the machine learning. In the simulation, we generate 100 data set for each beam in the codebook with which we train the machine learning. We note that as the codebook size increases, performance accuracy also improves slightly. Further investigation is required to study an efficient codebook size that obtains the best accuracy. The validation and testing accuracy can also be improved by increasing the data size, however, the results are promising, and such techniques can reduce the beam selection overhead in vehicular networks. Finally, the results also shows that the ML based technique can be used to predict the optimal beams for the next transmission time, and hence, can be used for sensor information exchange.

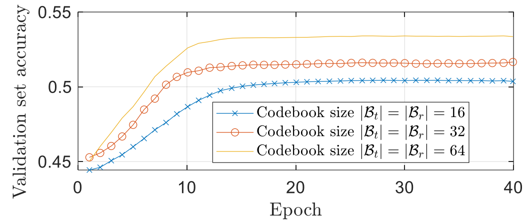

Fig. 2. Training accuracy with different codebook size versus number of Epoch

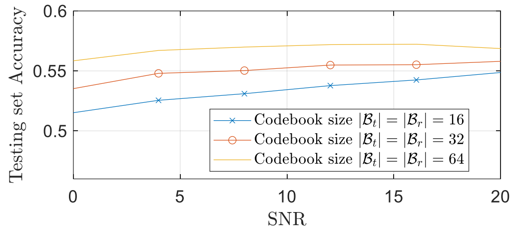

Fig. 3. Testing accuracy with different codebook size versus SNR

VI. Conclusion

In this paper, we present a situational awareness learning method to map the optimal beams set to the sensor data. The result shows a promising research direction in V2X communication. In addition, beam training and beam search overhead can be efficiently reduced by gaining situational awareness information. In the future, we aim to extend the system to actual situation information.

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