Intelligent Reflecting Surface Aided Vehicular Communications

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***Abstract*—We investigate the use of an intelligent reflecting surface (IRS) in a vehicular communication network. An intelligent reflecting surface consists of passive elements, which can reflect the incoming signals with an adjustable phase shift. By properly tuning the phase shifts we can improve communication. This is known as phase optimization or passive beamforming. We consider the achievable rate maximization problem in the uplink utilizing an IRS. However, using an IRS brings more challenges in terms of channel estimation. We propose two schemes to reduce the channel estimation overhead for the IRS, one method uses the grouping of reflecting elements and the other one performs passive beamforming based on the position of the devices. We perform numerical simulations and the results show IRS can bring significant improvements to existing communication. Further, we use a ray-tracing based simulation to validate the benefits of using an IRS.**

***Index Terms*—Intelligent reflecting surfaces, vehicular communications, mmWave communications, passive beamforming, ray tracing.**

I. INTRODUCTION

Wireless Propagation Environment is random and uncontrollable in nature. Recently intelligent reflecting surfaces has been proposed as a means of having some control over it with the help of software-controlled reflections [1]. An IRS consists of a planar array of passive reflecting elements that can reflect the incoming rays with adjustable phase shifts and gains. These elements can work together to achieve fine grained three-dimensional reflect beam forming [1]. A survey on IRSs is presented in [2].

The information transfer capabilities of intelligent reflecting surfaces are analyzed in [3] and it is established that the normalized capacity is linearly proportional to the average transmitted energy per square meter, which is an improvement over massive MIMO. The uplink data rates of an IRS based large antenna array system is analyzed asymptotically in [4], considering the practical issues such as channel estimation errors and hardware impairments. The simulation results show that the asymptotic derivations closely agree with exact mutual information in the presence of large number of antennas and devices.

Most theoretical work on IRSs assume that perfect channel state information (CSI) is available at the IRS for transmitter to IRS and IRS to receiver channels. However, since the reflecting surfaces consist of passive elements, channel estimation becomes challenging. Two schemes that can be used for channel estimation is proposed in [5]. In their work they consider an IRS having few active elements in addition to the passive elements. These active elements can be used to take measurements of the channel. First method uses compressive sensing to construct the complete channel state information from the sparse measurements taken. In the second method a deep learning model is trained to interact with the incident signal, given the channel measured by the active elements.

We can utilize IRSs to improve the communication over existing communication networks. For example, the received signal power at the user can be increased by controlling IRS phase shifts with the reflected signal being added constructively. The interference can be reduced by controlling IRS phase shifts with the reflected signal being added destructively. The transmit beamforming must be jointly optimized with the reflect beam forming at the IRS based on base station (BS)-IRS, IRS-user and BS-user channels, in order to fully reap the network beamforming gain. An efficient algorithm to tackle this optimization problem based on alternating optimization of the phase shifts and transmit beamforming vector in an iterative manner is proposed in [6]. This is further extended in [7] to consider discrete phase shifts at the IRS, which is how the practical implementation can be done. Here the problem is to minimize the transmit power required at the access point (AP) by jointly optimizing the beam forming at the AP and discrete phase shifts at the IRS. Unfortunately, this is an NP-hard problem. However, they propose a sub-optimal algorithm with zero-forcing (ZF) based linear precoding at the AP for low-complexity implementation.

Vehicular communication networks have been studied extensively to realize the concept of intelligent transportation systems (ITS) [8]. Various vehicular applications are been considered, including wide variety of safety-oriented, comfort and entertainment applications [9]. These applications bring great challenges to existing communication and networking technologies. The introduction of data-intensive sensors such as laser imaging detection and ranging (LIDAR) has resulted in vehicular communication networks having to support Gb/s data rates [9]. A large system bandwidth is needed for such high data rates. These facts have motivated to utilize millimeter wave (mmWave) frequency band (10 GHz-300 GHz) that has a large available bandwidth [9] for vehicular communications. However, mmWave frequencies experience a higher path loss, thus reducing the transmission range. Recently, IRSs have been proposed in [10] to overcome these challenges. They consider a scenario where multiple IRSs are deployed to assist mmWave communications. The received power is maximized by jointly optimizing transmit beamforming at the BS and passive beamforming at the IRS.

Use of IRSs to assist a vehicular network has been briefly considered in literature. An IRS enabled vehicular network is considered in [11] to improve the physical layer security. Two vehicular network models have been presented in [11]. One model with an IRS based AP and other model with an IRS based relay. Analysis of outage in IRS assisted vehicular networks is considered in [12]. The outage performance of traditional vehicular networks and IRS aided vehicular networks are compared [12]. However, IRSs bring new challenges interms of channel estimation, even more with high mobility in vehicular networks. Estimating the channel coefficients for each reflecting path takes a large overhead.

In this paper we propose to use an IRS in a mmWave vehicular communication system. Although rate maximization problem for IRS aided systems have been considered in various studies in the literature [13], [14], to the best of the authors' knowledge this is the first work that considers this problem for vehicular communication. We use a successive refinement [7] based algorithm to optimize the IRS phase shifts. We propose two schemes for IRS phase optimization that reduces the channel estimation overhead, and facilitate the use of large reflecting arrays. One method is based on the grouping of reflecting elements in the IRS. The other method utilizes position based passive beamforming. Numerical simulations are carried out and it is shown that the achievable rate can be significantly improved by using an IRS. Further, we evaluate the performance of the system under mobility with a commercial ray tracing tool, Wireless InSite [15]. The results further validate that large reflecting arrays can provide significant benefits over existing communication.

The rest of the paper can be summarised as follows. The system model and problem formulation is presented in section II. The phase optimization algorithm and two phase optimization schemes are proposed in section III. Finally, the results and conclusion are presented in sections IV and V.

II. System Model and Problem Formulation

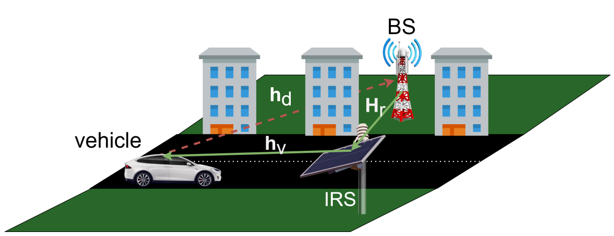


Fig. 1. An illustration of IRS-aided vehicular communication network

This section presents the system model and problem formulation. Here, we consider a vehicular network consisting of a single base station (BS) with M antennas and a vehicle with a single antenna, and focus on the uplink. An IRS with N reflecting elements is used to assist the communication. An illustration of this system is shown in Fig. 1. Let $\boldsymbol{H}_r \in \mathbb{C}^{M\times N}$ denotes the channel between IRS and BS, $\boldsymbol{h}_v \in \mathbb{C}^{N\times 1}$ denotes the channel between the vehicle and IRS, and $\boldsymbol{h}_d \in \mathbb{C}^{M\times 1}$ denotes the direct channel between the vehicle and BS.

Reflecting elements of the IRS can induce phase shifts in the incoming signals. We consider these phase shifts to be one of L discrete levels. For simplicity, we assume these phase shifts take one of the values obtained by uniformly quantizing the interval $[0, 2\pi)$. Thus, the set of discrete phase shifts at each reflecting element is given by

$$\mathcal{F} = \{0, \Delta\theta, ..., (L-1)\Delta\theta\}, \tag{1}$$

where $\Delta\theta = 2\pi/L$. Let the, phase shifts of i^{th} reflector of IRS be, $\theta_i \in \mathcal{F}$. We denote the reflection matrix of the IRS by $\boldsymbol{\Theta}$, where $\boldsymbol{\Theta} = \text{diag}([\exp(j\theta_1), \exp(j\theta_2), ..., \exp(j\theta_N)]^T)$.

Let x denote the information bearing symbol of the vehicle's transmission. The received signal at the BS is

$$\boldsymbol{y} = (\boldsymbol{h}_d + \boldsymbol{H}_r\boldsymbol{\Theta}\boldsymbol{h}_v)x + \boldsymbol{n}, \tag{2}$$

where, $\boldsymbol{n} = [n_1, n_2, ..., n_M]$ with $n_m \sim \mathcal{CN}(0, N_0)$ being the complex additive white Gaussian noise (AWGN) at BS antennas. The BS applies a linear beamforming vector $\boldsymbol{w}$ to decode x, i.e.,

$$\hat{y} = \boldsymbol{w}^H(\boldsymbol{h}_d + \boldsymbol{H}_r\boldsymbol{\Theta}\boldsymbol{h}_v)x + \boldsymbol{w}^H\boldsymbol{n}. \tag{3}$$

For simplicity we assume maximal-ratio combining (MRC) beamforming at the BS with $\boldsymbol{w} = (\boldsymbol{h}_d + \boldsymbol{H}_r\boldsymbol{\Theta}\boldsymbol{h}_v)$. For a transmission power of P, the signal to noise ratio (SNR) can be written as,

$$\text{SNR} = \frac{P\|\boldsymbol{h}_d + \boldsymbol{H}_r\boldsymbol{\Theta}\boldsymbol{h}_v\|^2}{N_0}. \tag{4}$$

Using the SNR expression in (4), the achievable rate can be expressed as,

$$R = \log_2\left(1 + \frac{P\|\boldsymbol{h}_d + \boldsymbol{H}_r\boldsymbol{\Theta}\boldsymbol{h}_v\|^2}{N_0}\right) \text{bit/s/Hz}. \tag{5}$$

As we can see from (5), the achievable rate is dependent on the reflection matrix at IRS. Therefore it should be possible to achieve higher rates by properly tuning the reflection matrix. This is known as passive beamforming or phase optimization. We consider the phase optimization problem at the IRS, where the achievable rate is maximized by choosing the optimum discrete phase shifts:

$$\begin{aligned} &\text{maximize} \quad R \\ &\text{subject to} \quad \theta_i \in \mathcal{F}, \text{for i=1,2,...,N}, \end{aligned} \tag{6}$$

where, θ_i for all i=1,2,...,N are the optimization variables.

III. Algorithm Development

The optimization problem in (6) is non-convex due to discrete phase shifts. If brute force is used, the algorithm has to go through N^L possibilities, which is not feasible for large reflecting arrays. However, it is possible to come up with a simple algorithm based on successive refinement [7] by expanding the channel gain expression. Let us define $\boldsymbol{\Phi} = \boldsymbol{H}_r \text{diag}(\boldsymbol{h}_v)$ and $\boldsymbol{v} = [\exp(j\theta_1), \exp(j\theta_2), ..., \exp(j\theta_N)]^T$. Also, let $\boldsymbol{A} = \boldsymbol{\Phi}^H \boldsymbol{\Phi}$ and $\boldsymbol{b} = \boldsymbol{\Phi}^H \boldsymbol{h}_d$. The channel gain is given by,

$$\|\boldsymbol{h}_d + \boldsymbol{H}_r \boldsymbol{\Theta} \boldsymbol{h}_v\|^2 = \boldsymbol{v}^H \boldsymbol{A} \boldsymbol{v} + 2Re\{\boldsymbol{v}^H \boldsymbol{b}\} + \|\boldsymbol{h}_d\|^2. \quad (7)$$

We can focus on a single reflecting element, v_n considering all the other reflecting elements (v_i, $i \neq n$) fixed. We can write the channel gain as,

$$2Re\{v_n^* \kappa_n\} + \tau_n, \quad (8)$$

where, $\kappa_n = \sum_{j \neq n} A_{nj} v_j + b_n$ and $\tau_n = \sum_{j \neq n} \sum_{i \neq n} v_i^* A_{ij} v_j + 2Re\{\sum_{i \neq n} v_i^* b_i\} + A_{nn} + \|\boldsymbol{h}_d\|^2$. Here, A_{ij} and b_i represent the individual elements of $\boldsymbol{A}$ and $\boldsymbol{b}$ respectively.

Based on the channel gain expression in (9) we can maximize the channel gain by matching the reflect array phase shift v_n to the phase of κ_n. For discrete phase shifts we can formulate the successive refinement algorithm as presented in algorithm 1 [7]. Here, ϵ is the stop threshold for the convergence.

In order to perform passive beamforming we need to estimate all the channels involved. In addition to the direct channel between the vehicle and BS, there are individual channels through each reflecting element of the IRS. An IRS generally consists of large number of reflecting elements. This makes the channel estimation very challenging. In the next two subsections we propose two phase optimization schemes that can be followed to reduce the channel estimation overhead.

Algorithm 1: Successive Refinement algorithm

initialize $\boldsymbol{\Theta} = \boldsymbol{\Theta}^{(0)}$
set $k = 0$
$R^{(0)} = \log_2 \left(1 + \frac{P\|\boldsymbol{h}_d + \boldsymbol{H}_r \boldsymbol{\Theta} \boldsymbol{h}_v\|^2}{N_0}\right)$
while $|R^{(k)} - R^{(k-1)}| > \epsilon$ **do**
  for *n=1 to N* **do**
    $\theta_n^* = \arg\min_{\theta \in \mathcal{F}} |\theta - \underline{/\kappa_n}|$
    $k = k + 1$
    $R^{(k)} = \log_2 \left(1 + \frac{P\|\boldsymbol{h}_d + \boldsymbol{H}_r \boldsymbol{\Theta} \boldsymbol{h}_v\|^2}{N_0}\right)$
  end
end

A. Grouping based IRS Phase Optimization

One approach to reduce the channel estimation overhead is to divide the reflecting array into subgroups, and perform phase optimization per sub group. Here, all the elements in the subgroup are considered as a single element. Therefore, we only need to estimate the channel for each group, not for all the reflecting elements. Also, we can run the phase optimization algorithm considering subgroups, without going through all the individual elements.

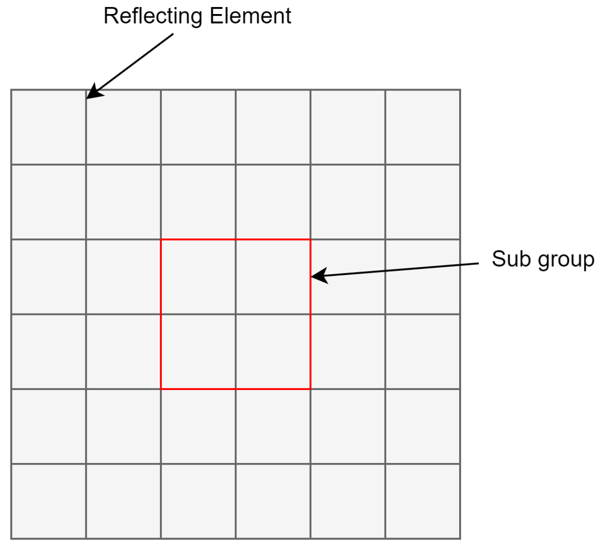


Fig. 2. Reflect array divided into subgroups

For example, Fig. 2 shows a 6×6 reflecting array. It is divided into 2×2 sized subgroups. Each subgroup is considered as a single reflecting element. Therefore, passive beamforming is effectively done for a 3×3 reflecting array. This reduces the channel estimation overhead as well as the complexity of successive refinement algorithm. After the phase shifts are found, phase shifts of all the reflectors in the group are set to the same value for the sub group.

B. Position based Passive Beamforming

A reflecting element in the IRS captures the incoming signal and re-scatters it in every direction [16]. The effective path loss is the product of the path losses of individual links through IRS. Therefore, the direct link from vehicle to BS will be stronger in general. Yet, IRS aided system can get a benefit in a scenario where, the vehicle to BS link is weak and, the link through IRS have strong line-of-sight links. Since, line-of-sight links will be prominent in this case, it will be possible to do passive beamforming based on the position of the devices. Here, the network will track the position of the devices and also, the departure and arrival angles. Then, the channel matrix can be re-constructed assuming that antenna dimensions are known.

Assuming planar arrays at both the BS and IRS, the LOS channel between BS and IRS can be expressed as,

$$\boldsymbol{H}_{r,los} = \sqrt{L_{los}} \exp\left(\frac{-j2\pi d}{\lambda}\right) \boldsymbol{a}_{bs}(\phi^{bs}, \theta^{bs}) \boldsymbol{a}_{irs}^H(\phi^{irs}, \theta^{irs}), \quad (9)$$

where, d is the distance between BS and IRS, $\boldsymbol{a}_{bs}(\phi^{bs}, \theta^{bs}) \in \mathbb{C}^{M \times 1}$ is the array response of BS for the considered azimuth and elevation arrival angles, and $\boldsymbol{a}_{irs}(\phi^{irs}, \theta^{irs}) \in \mathbb{C}^{N \times 1}$ is the array response of IRS for the considered azimuth and elevation departure angles. Similarly, $\boldsymbol{h}_{v,los}$ and $\boldsymbol{h}_{d,los}$ can be defined. The system performs passive beamforming based on the estimated line-of-site channel. Here, we only need to estimate arrival and departure angles for the whole reflect array. Then, the channel matrix can be reconstructed based on the prior knowledge of antenna dimensions. This takes less overhead than estimating the channel for individual reflecting elements.

IV. Numerical Results

In this section we present the results of numerical simulations to validate the algorithms and to gain an insight into IRS aided vehicular communications. We initially present the results of stochastic simulations under static conditions. Later, we present the results of ray tracing based simulation results using Wireless InSite [15] that take mobility into account as well. In our simulations we consider millimeter wave communications in the 28 GHz band with carrier frequency $f_c = 24.2$ GHz.

A. Stochastic Simulations

The position of the devices in the stochastic simulation is shown in Fig. 3. BS has a 4×2 uniform planar array (UPA) antenna panel and, IRS has a planar reflecting array of 16×16 reflecting elements. Vehicle has a single antenna. IRS is placed on the YZ plane at a height $a_{irs} = 1$ m. BS is placed on the XZ plane at a height $a_{bs} = 2$ m and at distances of $b_{bs} = 20$ m, and $c_{bs} = 10$ m from the origin. Vehicle antenna is placed at a height $a_v = 1$ m and at distances of $b_v = 1.5$ m, and c_v from the origin.

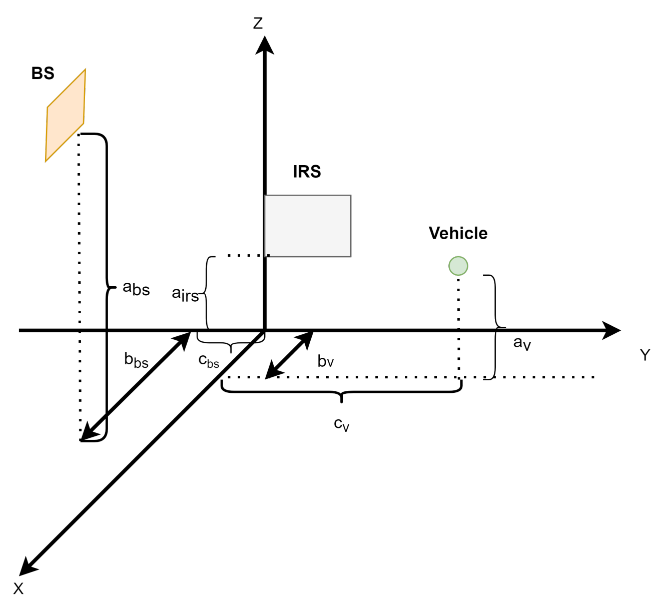


Fig. 3. Device positions in the stochastic simulation

All the channels involved are modeled with a Rician fading model. To model path loss, 3GPP TR 38.901 UMi - Street Canyon path loss model [17] is used. We use $\beta_r = 2$ for IRS-BS link, $\beta_v = 1$ for vehicle-IRS link and $\beta_d = \infty$ for the direct link.

Fig. 4 shows the variation of the achievable rate as we change the vehicle position by changing c_v. We see that the IRS gives a significant increase in the rate when the vehicle is close to IRS. It shows the highest rate at the closest point $c_v = 0$. However, the gain in the rate decreases as the vehicle moves further away from the IRS.

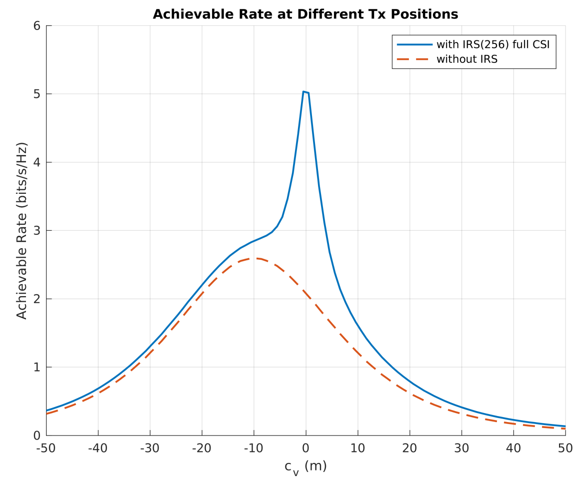


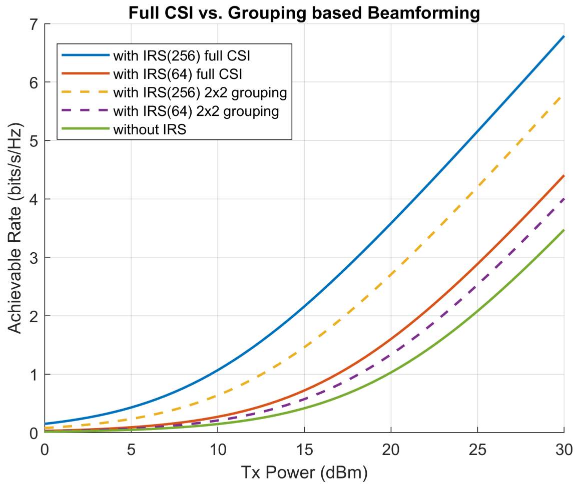
Fig. 4. Variation of achievable rate as c_v is changed

Next, we fix the vehicle position at the closest point to IRS, which is at $c_v = 0$. The achievable rate is compared for reflecting array sizes of 16×16 and 8×8, while changing the transmit power. Sub group based phase optimization is compared in Fig. 5(a). We see that there is a decrease in the performance when grouping is used. However, there is a performance gain compared to the system without an IRS. When a 16×16 reflecting array is used with 2×2 grouping, it effectively acts as a 8×8 panel in-terms of passive beamforming. Yet, it gives better performance than utilizing a 8×8 reflecting array with full CSI. Therefore, grouping provide a practical means to utilize large reflecting arrays, reducing the overhead for channel estimation.

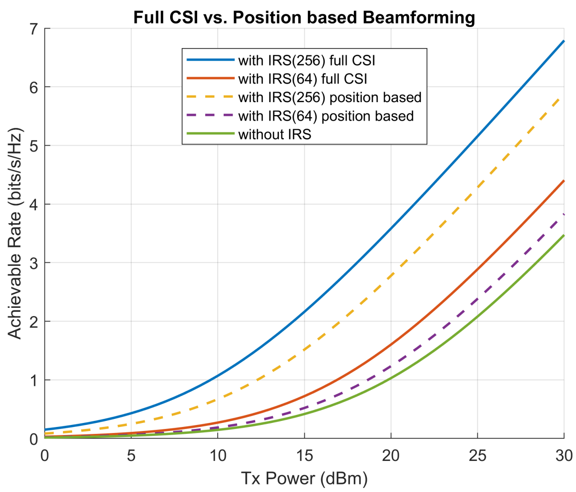
Position based phase optimization is compared in Fig. 5(b). This scheme also has a reduction in performance compared to when full CSI is available. Yet, it gives a significant increase in the rate for a 16×16 reflecting array compared to the system without an IRS. However, the rate of 8×8 reflecting array lies closely by the rate curve without IRS. This suggests that position based beamforming is more suitable for large reflecting arrays.

The convergence of the successive refinement algorithm is shown in Fig. 6. We see that, the algorithm converges quite fast for both 8×8 and 16×16 reflecting arrays. Here, we have set the initial values of phase shifts to zero ($\theta_i = 0$, for all $i = 1, 2, .., N$).

Fig. 7 illustrates the effects of quantizing the phase shifts. As we can see, 1 bit phase shifts hardly give any benefits over existing communication without IRS. As we increase discrete phase shift levels to 2 bits the performance improves dramatically. The performance gain when we further increase the number of quantization bits to 3, is not that significant. Therefore, we can conclude that reflecting arrays with even 2



(a)



(b)

Fig. 5. Comparison of variation of achievable rate with Transmit Power a) with grouping vs. full CSI and b) with position based beamforming vs. full CSI

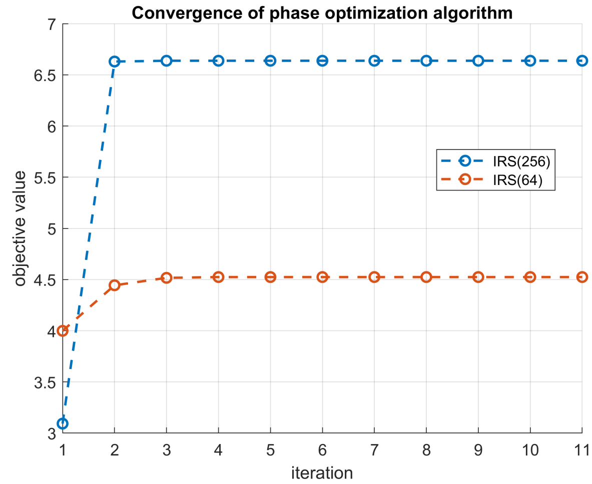


Fig. 6. Convergence of the successive refinement algorithm

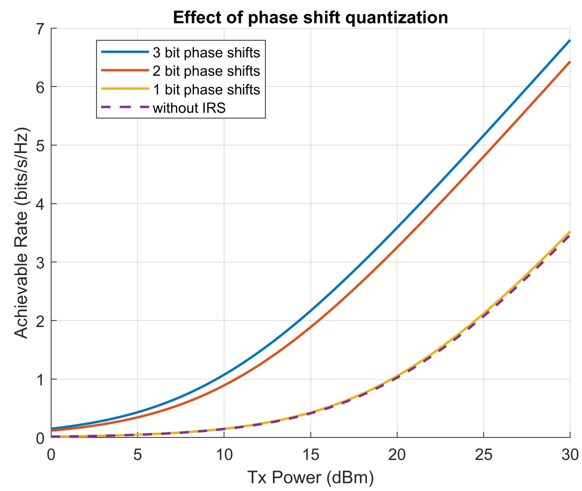


Fig. 7. Illustrating the effects of quantizing the phase shifts

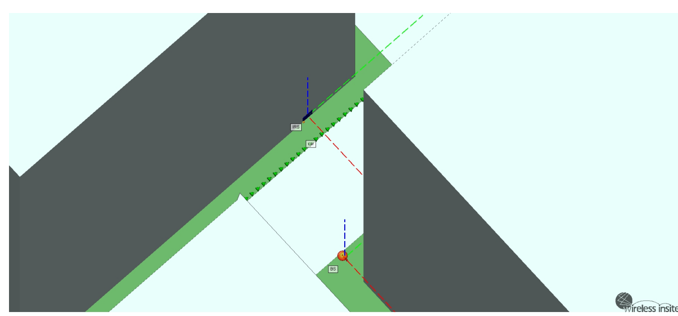


Fig. 8. Simulating IRS aided system in Remcom Wireless InSite [15]

bit phase shifts are sufficient to improve the existing communication. This is beneficial because practical implementations of IRSs can only support limited number of phase shift levels.

B. Ray Tracing based Simulation

Although stochastic simulations in the last section provide some insights on the IRS aided system, they rely on simplified assumptions. They do not take mobility into account either. We need a more complex simulation to model mobility and the environment conditions in detail. Ray tracing is considered as a reliable methodology to estimate complex propagation characteristics in mmmWave vehicular networks [18].

The IRS aided system is modeled in Remcom Wireless InSite [15] as shown in Fig. 8. The IRS is modeled as a rectangular array of patch antennas. A route for the transmitter in the vehicle is defined with an average speed of 10 m/s. The system is modeling an urban scenario with buildings and roads. BS is positioned at one side of the road. Vehicle is moving on the other side of the road. IRS is placed closer to the vehicle's path. Vehicular traffic is not considered for simplicity. The channel matrices are obtained using the ray tracing simulation and phase optimization is carried out. Fig.

9 shows the plots of achievable rates for reflecting array sizes of 8×8 and 16×16. Here, we have considered the closest point of the vehicle to IRS and have calculated the rate while changing transmit power. A significant increase in rate is seen for the 16×16 reflecting array. The 8×8 reflecting array only provides a slight improvement over existing communication without IRS. This suggests that large reflecting arrays are needed to improve the system performance considerably.

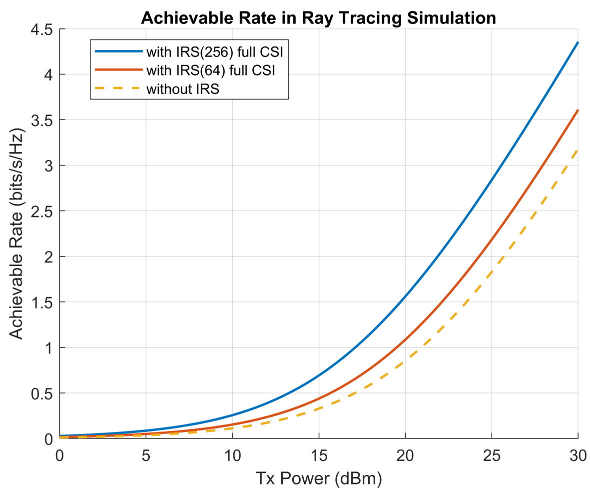


Fig. 9. Achievable rate with transmit power for the ray tracing simulation

V. Conclusion

In this paper, we have analyzed the usage of an IRS in a mmWave vehicular network to maximize the achievable rate. A ray tracing based simulation is used to validate the benefits of using an IRS in a vehicular network. We have proposed two passive beamforming schemes that can be utilized to reduce the channel estimation overhead. We have compared the performance of these methods through numerical simulations based on a stochastic channel model. The numerical results suggest, although the performance of these schemes is lower than when full CSI is available, these schemes still provide significant improvements to the existing communication. They provide practical ways to utilize large reflecting arrays.

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