Beamforming design based on particle swarm algorithm in IRS-assisted communication system

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Abstract. 5G and the next generation of wireless technologies are designed to meet the needs of vertical industrial applications like Smart Cities, Industry 4.0, and Smart Grid. These requirements necessitate increased network capacity in order to provide a ubiquitous wireless connection for a large number of devices. Many technologies, such as mm-wave (MMW) communications, massive MIMO systems, and ultra-dense networks (UDN), have been developed in recent years to achieve these goals. However, these technologies have high implementation costs or consume a lot of energy. Intelligent Reflective Surface (IRS) is a low-cost, energy-efficient meta-surface made up of several low-cost passive components. When controlled by the controller, the IRS components can reflect an occurrence signal with a predetermined phase shift for beamforming. This not only improves system performance, but it also addresses the millimeter wave penetration performance issue (MMW). In this paper, a mathematical model of a wireless communication system with IRS in the line-of-sight (LoS) case is developed, as well as a channel model between the base station, the smart reflecting surface, and the user, and a millimeter-wave large-scale fading model. It is investigated the beamforming matrix optimization problem on the base station surface and the intelligent reflecting surface.

Keywords: mmWave, IRS, PSO, Beamforming.

1. Introduction

Wireless technologies such as 5G and post-5G have been developed to meet the needs of industry applications such as smart grids and smart cities. This necessitates a significant increase in network capacity as well as extensive wireless connectivity of various major devices. However, due to its inability, 5G cannot fully automate and deliver an intelligent network. We developed a low-power consumption technology with an intelligent reflective surface (IRS), which helps to reduce costs while increasing network capacity. Intelligent reflective surfaces, or IRS, are technologies that are paving the way for low-cost, high-efficiency wireless communications in terms of frequency and power consumption in the future. The IRS, in particular, is a subsoil densely packed with low-cost passive devices. When operating at a modulatable phase shift, each passive element can independently reflect incident information. This allows a three-dimensional (3D) passive beam forming task to be performed concurrently without ever reaching the transmit radio frequency (HF) chain.

All of the work described above is done in full channel state information settings (CSI). Estimating the CSI between the IRS and the base station or between the IRS and the user has become significantly more difficult. Although some tasks may present solutions to this issue, (1) IRS must be a multifrequency (RF) chain; (2) IRS requires both phase control and amplitude control, which increases system complexity; (3) the channel must be a spur, which is generally only possible in millimeter wave systems less than 6 GHz; (4) IRS requires both phase control and amplitude control, which increases system complexity; and (5) IRS requires both phase control and amplitude control, which increases system complexity. (4) Because the amount of work involved in training grows in direct proportion to the number of IRS or BS elements, we propose a method for solving the beamforming optimization problem in IRS and BS that employs a generalized beamforming optimization algorithm based on particle swarm optimization (PSO) [2].

In this study, we use an intelligent reflection surface, also known as an IRS, to investigate the channel that exists between a multi-antenna base station (BS) and a single-antenna user (UE). Numerous RF chains and a significant amount of training work are required to obtain channel state information (CSI), which is actually difficult to execute. This is due to the IRS having a large number of distinct components that must be handled separately. The goal of this file, which does not use the CSI optimized beamforming of BS and IRS, is to keep the signal-to-noise ratio (SNR) as low as possible while reducing the amount of transmission power used. To solve the previously mentioned nonconvex optimization problem, a method known as particle swarm optimization (PSO) was used. The distance between the base station and the user of a single antenna is different [3]. This paper analyzes and compares the effect of varying inertia weights on the particle swarm method.

2. Channel Model

Figure 1 depicts a model of an IRS-assisted single-user millimeter-wave radio communication system with line-of-sight propagation between the base station (BS) and the user (UE). The reflective elements on this smart reflective surface's phase and amplitude are controlled. In the Figure 1, it shows A single-user millimeter-wave radio communication system with IRS assistance. M denotes the total number of IRS reflecting elements, whereas N denotes the total number of transmitter antennas [4].

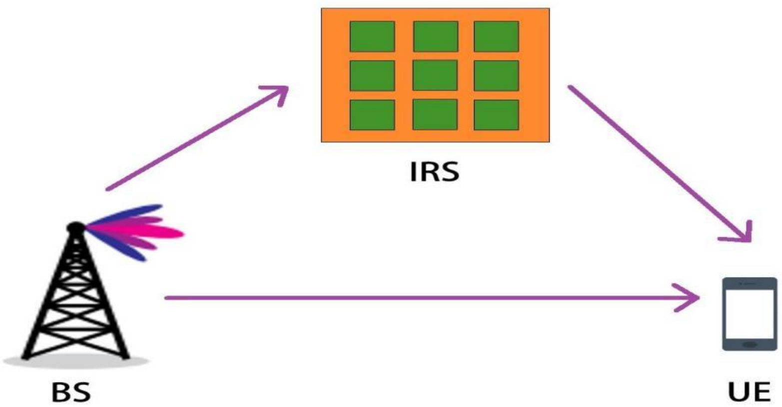

Figure 1. Line-of-Sight (LoS) propagation intelligent reflective surface-assisted single-user MMW communication system (original).

The signal that is received by the receiver after it has traveled through the channel and been transmitted by the transmitter can be expressed as:

$$y = \left(h_r^H \Theta \mathrm{G} + \mathrm{h}_\mathrm{d}^H\right)\mathrm{w}s + n \qquad (2-1)$$

where $h_r^H \in \mathbb{C}^{1\times M}$ refers to the channel vector from the smart reflector to the user (IRS-UE), $h_r^H \in \mathbb{C}^{1\times M}$ refers to the channel matrix from the base station to the smart reflecting surface (BS-IRS), $\mathrm{h}_\mathrm{d}^H \in$

$\mathbb{C}^{1\times N}$ refers to the channel vector from the base station to the user (BS-UE), $\mathrm{w} \in \mathbb{C}^{N\times 1}$ refers to the beamforming of the signal sent from the base station vector, s refers to the signal sent by the base station, which is an independent random variable with mean zero and variance 1, and n refers to the additive Gaussian white noise at the user with power σ^2. In addition, $\Theta = \mathrm{diag}(\beta_1 e^{j\theta_1}, \dots, \beta_M e^{j\theta_M})$, where $\theta = [\theta_1, \dots, \theta_M]$ refers to the phase shift vector, $\theta_M \in [0, 2\pi)$ .The amplitude reflection coefficient is $\beta_m \in [0, 1]$. For the sake of simplicity, we consider β_m=1, the maximum signal reflection for each IRS element.

When addressing fading on a small scale, it is assumed that each channel has a Les attenuation and a logarithmic distance path loss. This is done so in order to simplify the analysis. It is important to keep in mind that signals that have been reflected by the IRS more than twice will not be considered. As a result of the low dispersion that millimeter waves experience, their mode of propagation is mostly through the line-of-sight; hence, millimeter waves will be considered scarce when they are being transmitted. The BS-IRS channel matrix can be described in this manner by the following characteristics [5]:

$$G = \sqrt{PL(d)}\left(\sqrt{\frac{\beta}{1+\beta}}G^{LoS} + \sqrt{\frac{1}{1+\beta}}G^{NLoS}\right) \qquad (2-2)$$

$$PL(d) = C_0\left(\frac{d}{d_0}\right)^{-\alpha} \qquad (2-3)$$

where $C_0$is the path loss at the reference distance d_0, d refers to the distance from the base station to the user, α is the path loss index, β is the Rice factor, and G^{LoS} and G^{NLoS} represent the deterministic LoS component and the NLoS component, respectively. The elements in the non-visual component G^{NLoS} obey independent identically distributed complex Gaussian random distributions with mean 0 and variance 1. The visual component G^{LoS} is generated by

$$a_X(\vartheta) = \left[1, e^{j\frac{2\pi d}{\lambda}sin\vartheta}, \dots, e^{j\frac{2\pi d}{\lambda}(X-1)sin\vartheta}\right]^T \qquad (2-4)$$

The array response vector $a_X(\vartheta)$ of the uniform linear array can be expressed as

$$a_X(\vartheta) = \left[1, e^{j\frac{2\pi d}{\lambda}sin\vartheta}, \dots, e^{j\frac{2\pi d}{\lambda}(X-1)sin\vartheta}\right]^T \qquad (2-5)$$

where d is the antenna cell spacing, λ is the carrier wavelength, X is the dimension of the vector, and ϑ is the angle, which can be expressed as the angle of departure (AoD) or the angle of arrival (AoA). Thus, the LoS component can be expressed as [6]:

$$h_d^{LoS} = a_N(\vartheta_d)$$

$$h_r^{LoS} = a_M(\vartheta_r)$$

$$G^{LoS} = a_M(\vartheta^{AoA})a_N(\vartheta^{AoD}) \qquad (2-6)$$

where h_d^{LoS} refers to the line-of-sight (LoS) component in the base station (BS) to user (UE) channel model, h_r^{LoS} refers to the line-of-sight (LoS) component in the intelligent reflecting surface (IRS) to user (UE) channel model, and G^{LoS} refers to the line-of-sight (LoS) component in the base station (BS) to intelligent reflecting surface (IRS) channel model. ϑ_d, ϑ_r are the signals AoA or AoD from the base station to the user and IRS to the user, respectively, and ϑ^{AoA} and ϑ^{AoD} are the signals AoA and AoD from the base station to the IRS, respectively.

Finally, the signal-to-noise ratio at the user under line-of-sight propagation conditions is given by the following equation.

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$$SNR = \frac{\left|\left(h_r^H \Theta \mathrm{G} + \mathrm{h}_\mathrm{d}^H\right)\mathrm{w}\right|^2}{\sigma^2} \qquad (2-7)$$

3. Particle swarm algorithm

In a typical PSO, a swarm of particles will navigate through a search space of D dimensions in order to locate the optimal answer. Each individual particle i possesses a current velocity vector donated by $V_i = [v_{i1}, v_{i2}, \ldots, v_{iD}]$ as well as a current position vector donated by $X_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$, where D is the dimension. The PSO procedure begins with a randomization of the starting values for V_i and X_i . Then, in each iteration, the historical best position $Pbest_i = [Pbest_{i1}, Pbest_{i2}, \ldots, Pbest_{iD}]$ of that particle found by particle i , and the global best position $Gbest = [Gbest_1, Gbest_2, \ldots, Gbest_D]$ of all particles found by the whole particle population, and guides particle i through $Pbest_i$ and $Gbest$ to update its velocity and position through Eqs (3-1) and (3-2) as follows [7].

$$v_{id}(t+1) = wv_{id}(t) + c_1 r_1\left(Pbest_{id}(t) - x_{id}(t)\right) + c_2 r_2\left(Gbest_d(t) - x_{id}(t)\right) \qquad (3-1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \qquad (3-2)$$

where w is the inertia weight; c_1 and c_2 are the cognitive and social acceleration coefficients, respectively; r_1 and r_2 are two random values generated in the interval of [0,1], which obey uniform distribution [8].

The particle swarm algorithm's main process is as follows: (1) Initialize the algorithm's coefficients, such as inertia weights w, acceleration coefficients $c_1$and c_2, and so on. Initialize the velocity as well as the position of each particle. (2) Determine the fitness value of each individual particle, ascertain whether or not the particle satisfies the restrictions, and locate the ideal solution for each individual particle as well as the optimal solution for all individual particles overall. (3) Go back to the second step to continue iterating the algorithm until it fulfills the halting condition. At this point in the process, the values for each particle's velocity and position will be updated [9].

This paper focuses on comparing the differences between the three inertia weights [10]:

(1) Static and random inertia weights

$$w_1 = 1 \qquad (3-3)$$

$$w_2 = 0.5 + \left(random(0,1)\right) \div 2 \qquad (3-4)$$

(2) Time-varying inertia weights

$$w_3 = (w_{max} - w_{min})\left(\frac{T-t}{T}\right) + w_{min} \qquad (3-5)$$

where w_{max} and w_{min} are the final and initial values of inertia weights, respectively. T is the maximum number of iterations, and t is the current number of iterations.

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4. Experimental results

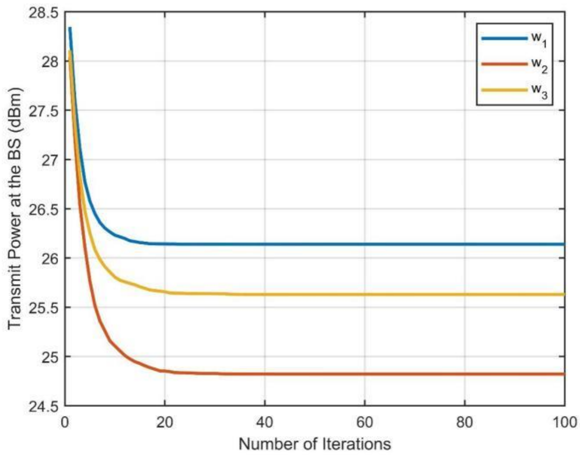

Figure 2. Comparison chart of different inertia weights(original).

The curves in the figure show the feasibility of the particle swarm algorithm in this problem and that the use of random inertia weights works best in this problem.

The following simulation parameters are set: $N = 4$ for the number of antennas at the base station's transmitting end. And the Les factors of the BS-UE, IRS-UE and BS-IRS channels are: $\beta_{BU} = \beta_{IU} = 0$, $\beta_{BI} \to \infty$, respectively. The path loss indices of the BS-UE, IRS-UE and BS-IRS channels are: $\alpha_{BU} = 3.5$, $\alpha_{BI} = 2.0$, $\alpha_{IU} = 2.8$, respectively. The reference distance of channel fading $d_0 = 1m$, the large scale fading path loss $C_0 = -30dB$ for distance d_0, the noise power $\sigma^2 = -80dBm$, the distance $d_v = 2m$ from UE to the BS and the IRS, and the distance $d_h = 51m$ from the BS to the IRS.

5. Conclusion

The performance of an IRS-assisted millimeter-wave MISO single-user wireless communication system under line-of-sight (LoS) conditions is investigated. The convergence and efficiency of the particle swarm algorithm are studied, along with the effect of different inertial weights on the method's performance, and the beamforming matrices of the base station and smart reflective surface are improved using the particle swarm algorithm.

The results indicate that the applicability of particle swarm algorithms to such situations and the various inertia weights have a substantial effect on their performance. On such problems, better algorithm performance can be obtained by choosing random inertial weights.

There are many flaws in this paper that can be further explored in the future based on the model as well as the conclusions of this paper.

1) The combined optimization of the base station (BS) beamforming matrix and the intelligent reflecting surface (IRS) is performed in this paper without taking channel estimates into account (CSI). The effect of channel estimates on the particle swarm method's convergence rate and training effort can be found in and will be investigated further in the future.

2) In this study, the phase shift of the beamforming matrix has been adjusted to continuous phase shift. The difference in base station transmit power required to achieve the minimum signal-to-noise ratio for continuous and discrete phase shifting in future work. In any case, it is possible to consider both the rate at which the particle swarm algorithm converges and the amount of work required to train it. These elements are critical to consider.

3) The intelligent reflecting surface has a reflection amplitude that ranges from 0 to 1. For the sake of simplicity, the reflection amplitude has been set to 1 throughout this article, which corresponds to the

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greatest amount of signal reflection generated by each individual IRS component. Both the amplitude changes and the phase change that occurs after IRS can be studied concurrently in future work.

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