Joint Optimization in Intelligent Reflecting Surface-Aided UAV Communication for Multiaccess Edge Computing

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Intelligent reflecting surface (IRS) is a key enabling technology for 5G and 6G networks, which can provide a reconfigurable electromagnetic environment while reducing energy consumption. In this article, the communication link between user equipment (UE) and the base station (BS) is severely blocked, so we deployed IRS on the Unmanned Aerial Vehicle (UAV) to assist UE for offloading the computing task to the multiaccess edge computing (MEC) server on the base station, which provides mobile users with low-latency edge computing services. By jointly optimizing active beamforming of UE transmitter, passive beamforming of the IRS, UAV hovering position, and computing task scheduling, the response time of user tasks is minimized. In order to solve this complex nonconvex problem, we propose an alternating optimization (AO) algorithm combined with the genetic algorithm to decouple the problem, alternate optimization, until the convergence condition is met, to find the approximate optimal solution of the problem. Numerical results show that with the assistance of IRS, MIMO channels can significantly improve the performance of edge computing and meet the needs of users for high speed and low latency.

1. Introduction

The explosive growth of network traffic and computing demands has prompted the continuous integration of communication and computing technologies, thereby promoting the continuous innovation and evolution of 5G and 6G technologies [1–5]. Meanwhile, the continued evolution of user requirements and the emergence of new applications have resulted in higher demands on network infrastructure, such as delays, reliability, safety, and energy effectiveness. On the one hand, mobile cellular networks need to cope with the diverse and dynamic demands of massive UE. On the other hand, network operators are constantly confronted with high hardware costs and new demands, which require new technologies to reduce costs while improving quality of service (QoS) and energy efficiency.

MEC [6–8] is a key technology for the mobile communication system to enhance the capabilities of service applications. MEC [9] pushes services and functions of cloud computing to the edge of wireless access network, provides computing and caching services for local mobile users, and deeply integrates communication and computing technologies to meet the needs of mobile users in different scenarios, thereby improving the user experience and promoting network intelligence. MEC [10] uses network function virtualization (NFV) and software-defined network (SDN) to reduce equipment costs and improve equipment utilization; that is, MEC can provide users with low-latency network services at lower hardware costs by dynamically allocating communication and computing resources in real time. Computation offloading [11–14] is an important user-oriented use case in MEC, which is aimed at offloading computation tasks to MEC from resource-constrained UE to meet the real-time requirements of computation-intensive applications. In [6], the authors introduced the important framework of edge computing and categories of computation...
offloading and then illustrated the offloading model in terms of communication, computation, and energy harvesting. However, when we offload computation tasks, the channel strength between the mobile users and the edge of the network changes dynamically with time and frequency, especially when there are buildings, trees, hills, and other obstacles between the channels, which will cause signal attenuation. And this leads to higher energy consumption, deployment, backhaul, and maintenance costs and more serious and complex network interference problems.

In order to increase the channel gain, the cellular network can use higher frequency bands and package more antennas, i.e., the use of ultramassive multi-input multi-output (MIMO) and terahertz communication. However, this will increase hardware cost, energy consumption, and signal processing complexity. In the context of the above issues, the IRS [15] is considered a disruptive and innovative technology that can intelligently reconstruct the wireless propagation environment. The IRS [16] is an elaborately designed two-dimensional artificial surface. The amplitude and phase of the incident signal of each element IRS are regulated through the control circuit, thereby significantly improving the channel fading and interference problems, i.e., improving the spectral efficiency. Compared with traditional reflective antenna arrays and active surfaces, the IRS is composed of a large number of passive components; therefore, it has the advantages of cost and energy efficiency. Reference [17] proposed an alternating optimization approach to jointly optimize the MIMO input covariance matrix and the IRS reflection coefficients for maximizing the capacity of the IRS-enhanced MIMO system with narrowband and broadband transmission, respectively, and the numerical results showed that the algorithm for getting a suboptimal solution can significantly improve the capacity of the network.

In terrestrial wireless networks, IRS [18] can be deployed on the exterior walls of buildings, ceilings, and billboard. By controlling reflections to avoid obstacles, establish a virtual line-of-sight (LOS) link between UE and BS, thereby significantly improving communication throughput. The performance of a wireless system still depends on its channel, that is, reflection, refraction, diffraction, and path loss in the channel before reaching the receiver. In [19], the authors presented an AO algorithm to jointly optimize resource scheduling, IRS reflection coefficients, and UAV trajectory for maximizing the sum rate in the IRS-assisted UAV system. The results showed that the IRS and UAV increase the degrees of freedom for communication system design and bring promising performance gains such as energy efficiency, passive beamforming, and channel. Reference [20] proposed a successive convex approximation (SCA) algorithm to iteratively optimize active beamforming, the trajectory of UAV, and passive beamforming for maximizing the received signal power, which can reduce the complexity of the solution. Compared with ground IRS, deploying IRS on a rotary-wing UAV to dynamically adjust its hovering position can establish a sustainable LOS link between UE and IRS and between IRS and BS. The aerial intelligent reflection surface (AIRS) [21] communication framework is presented for maximizing the worst-case signal-to-noise ratio (SNR) by jointly optimizing transmit power, AIRS location, and phase shifts of the IRS with the suboptimal solution.

The wireless relaying system aerial intelligent reflecting surface (AIRS) [21] can extend the coverage area of cellular network and improve the network performance. The authors proposed a suboptimal solution to tackle the maximizing worst-case signal-to-noise ratio (SNR) problem by jointly optimizing transmit power, AIRS position, and reflection coefficients. To improve the QoS of wireless network, the IRS-assisted single-input single-output (SISO) MEC system [22] was presented to offload the computational task to the edge node of the access point (AP). The presented system was aiming at maximizing the total computational bits by jointly optimizing the CPU frequency, the offloading time assignment, and the transmit power allocation, as well as the IRS phase shifts for promoting the performance of applications. The IRS-assisted MIMO system [17] can achieve increased capacity by a convex relaxation-based alternating optimization method. The authors optimized the transmission covariance matrix and the IRS reflection factors to get a suboptimal solution of achievable rate. Inspired by above views, we propose a UAV-IRS (UIRS) enhanced MIMO MEC system to assign computing and communication resources for offloading the computation tasks to the MEC server on the BS, which is shown in Figure 1. Obstacles in urban and suburban environments can block LOS links, which cause signal loss and attenuation. Therefore, the UAV can provide a higher LOS probability than the ground link. We assume that the radio signal from the transmitter to the receiver is severely blocked by obstacles (i.e., buildings) and the signal is interrupted. In this scenario, we place the IRS on a highly maneuverable rotary-wing UAV to expand the coverage of the IRS which makes it easier to establish a virtual LOS link between the UE and the BS, which can assist mobile users in computation offloading. Our objective is to minimize the computational offloading time by jointly optimizing transmit beamforming, IRS passive beamforming, UAV hovering location, and computing task allocation. To solve the above-mentioned nonconvex optimization problem, we use the AO algorithm combined with the genetic algorithm to decompose the complex problem into four subproblems for iterative optimization to reduce the computational complexity, so that the algorithm can at least accelerate the convergence to a local optimal solution. Moreover, the main notations presented in this article are summarized in Table 1.
As shown in Figure 2, we propose an edge computing system that deploys IRS on UAV to assist UE’s computation tasks for offloading. The UE’s signal is severely blocked by the building; then, the user’s intensive computing tasks cannot be directly offloaded to the base station. At this time, the IRS on the UAV can provide UE with intelligent reflection in the air to assist in offloading the user’s computing tasks. The UAV plays a role as a mobile communication base station but only for acquiring channel state information (CSI) for enhancing IRS’s signal reflection. In this paper, the channel is assumed to be quasistatic flat fading; i.e., the channel state, the reflection coefficient, and UAV’s and UE’s location are unchanged and independent over each transmission block.

2.1. Channel Model. We assume that the UE and BS are equipped with K antennas and L antennas, respectively, which are placed in uniform linear array (ULA) and vertical to the ground, i.e., the XOY plane. In this three-dimensional (3D) coordinate system, we take the midpoint of the transmit ULA, receive ULA, and the center point of IRS as the reference point to represent their location. We set the coordinate of K antenna reference point as \( \mathbf{m} = [X_m, Y_m, Z_m]^T \), the coordinate of IRS’s reference point as \( \mathbf{s} = [X_s, Y_s, Z_s]^T \), and the coordinate of L antenna reference point as \( \mathbf{b} = [X_b, Y_b, Z_b]^T \). The IRS is equipped with \( N = N_x \times N_c \) elements, i.e., placed in a uniform planar array (UPA) with \( N_x \) as the number of IRS elements along the x-axis and \( N_c \) as the number of elements along the y-axis, where the nth element is \( n \in \mathcal{N} = 1, 2, \ldots, N \) and parallel to the XOY plane. The intervals between adjacent elements along the x-axis and y-axis are both \( \lambda/2 \), where \( \lambda \) is the carrier wavelength. In view of the air traffic control (ATC), we suppose that UAV can only fly at a fixed area and altitude; that is, \( X_{\text{min}} \leq X_s \leq X_{\text{max}}, \quad Y_{\text{min}} \leq Y_s \leq Y_{\text{max}}, \quad \) and \( Z_{\text{ref}} \), is a constant. The vertical distance from the reference point of the UE antenna to the plane where the IRS is located and that from the BS antennae reference point to the IRS plane can be written as \( d_{\text{m}} = |Z_s - Z_m| \) and \( d_{\text{b}} = |Z_s - Z_b| \), respectively. Meanwhile the distance between the reference point of UE’s antenna and the reference point of IRS can be given by \( d_{\text{m}} = |\mathbf{m} - \mathbf{s}| \) and also, the distance from IRS’s reference point to BS antenna’s reference point can be denoted by \( d_{\text{b}} = |\mathbf{s} - \mathbf{b}| \).

As the direct link between UE and BS is blocked, IRS is deployed on UAV for assisting offloading computation tasks. We adopt the Rician fading channel model, and thus, the channel matrix \( H \in \mathbb{C}^{N_c \times K} \) between the UE and IRS is expressed by

\[
H = \frac{\sqrt{\mathcal{R}}H_{\text{los}} + H_{\text{nlos}}}{\sqrt{\mathcal{R}} + 1},
\]

where \( \mathcal{R} \) is the Rician factor.

**Table 1: Main notations.**

| Notation | Definition |
|----------|------------|
| \( \mathbf{m} \) | UE antennae vector |
| \( s \) | IRS position vector |
| \( b \) | BS position vector |
| \( N \) | Number of IRS element |
| \( d_{\text{m}} \) | Distance between UE and IRS |
| \( d_s \) | Distance between IRS and BS |
| \( \mathcal{R} \) | Rician factor |
| \( H \) | UE-IRS channel matrix |
| \( G \) | IRS-BS channel matrix |
| \( \theta_n \) | Reflection coefficient of the nth element |
| \( \beta_n \) | Reflection amplitude of the nth element |
| \( \theta_n \) | Phase shift of the nth IRS element |
| \( B \) | Bandwidth |
| \( \sigma^2 \) | Noise power |
| \( Q \) | Input covariance matrix |
| \( R \) | Transmission rate of UE |
| \( A \) | Data size of computation task |
| \( A_l \) | Data size of local execution |
| \( A_b \) | Data size of edge server execution |
| \( W \) | Workload of computation task |
| \( T_l \) | Delay of the local execution |
| \( T_b \) | Delay of the computation offloading |

The rest of this article is organized as follows. Section 2 introduces the UAV-IRS MEC system model and problem formulation and formulates the problem to minimize the computation task delay. Section 3 proposes an alternate optimization algorithm, which is used to solve each subproblem decomposed in different closed forms and obtain the optimal solution. Section 4 presents the numerical results and analysis. Section 5 summarizes this paper.

2. System Model

As shown in Figure 2, we propose an edge computing system that deploys IRS on UAV to assist UE’s computation tasks for offloading. The UE’s signal is severely blocked by the building; then, the user’s intensive computing tasks cannot be directly offloaded to the base station. At this time, the

**Figure 2: The illustration of UAV-IRS-enhanced MEC.**
where $\mathcal{H}$ is the Rician factor, $H_{\text{los}} = e^{-j(2\pi/\lambda)d(n,k)}$, $d(n,k)$ is the distance matrix between IRS’s $n$th element and UE’s $k$th antenna, $k \in \{1,2,\cdots,K\}$, $H_{\text{los}}$ is independent and identically distributed (i.i.d.), and $H_{\text{los}} \sim \mathcal{CN}(0,1)$. The channel matrix $G \in \mathbb{C}^{L \times N}$ between IRS’s $n$th element and BS’s $l$th antenna is given by

$$ G = \frac{\sqrt{\mathcal{H} G_{\text{los}} + G_{\text{nl}}}}{\sqrt{\mathcal{H} + \mathcal{I}}}, $$

(2)

where $G_{\text{los}} = e^{-j(2\pi/\lambda)d(I,n)}$, $d(I,n)$ is the distance matrix from BS’s $I$th antenna to IRS’s $n$th element, and $I \in \{1,2,\cdots,L\}$; $G_{\text{nl}}$ is i.i.d. according to $\mathcal{CN}(0,1)$.

As a result of blocked LOS link, IRS-assisted virtual LOS link channel matrix between UE and BS is denoted by

$$ \mathcal{G} = \sqrt{\rho^{-1}}G\Theta H, $$

(3)

where $\rho$ is the free-space path loss and, according to [23–25], can be expressed by

$$ \rho = \frac{256\pi^2((d_m)^2 + (d_l^2)^{\frac{1}{2}})}{\lambda^3((d_m/d_n) + (d_b/d_s))^{\frac{3}{2}}}, $$

(4)

and $\Theta \in \mathbb{C}^{N \times N}$ is the reflection coefficient matrix which is expressed by

$$ \Theta = \text{diag}\left(\beta_1 e^{\theta_1}, \beta_2 e^{\theta_2}, \cdots, \beta_N e^{\theta_N}\right), $$

(5)

where $\beta_n \in [0,1]$ is the reflection amplitude of the $n$th passive element and $\theta_n \in [0,2\pi]$ is the phase shift of the $n$th passive IRS element. Therefore, the computation offloading transmission rate of UE according to [10] is denoted by

$$ R = B \log_2 \det\left( I + \frac{\mathcal{G}Q\mathcal{G}^H}{\sigma^2} \right), $$

(6)

where $B$ is the bandwidth, $\sigma^2$ is the noise power, and $Q \in \mathbb{C}^{K \times K}$ is the input covariance matrix.

2.2. Computing Model. Considering the limited computation resources of UE, we focus on partial offloading: computation-intensive part of the task is offloading to the edge server for remote executing, and the remaining part is computed locally. The UE’s computation tasks are characterized by the tuple $\langle A_l, W, f_l \rangle$, where $A_l = A_{l1} + A_{l2}$ (in bits) is the total amount of the computing task and $W$ (in cycles/bit) is the required workload of the task. Therefore, the delay of the user computation task is split into two parts in parallel, and the delay of the local execution part is

$$ T_l = \frac{A_l W}{f_l}, $$

(7)

where $A_l$ is the data size of local execution and $f_l$ is the local computation capacity. Generally, the results of computation task are very small compared to the input data; thus, the delay of returning the results can be ignored and the delay of the computation offloading is

$$ T_b = \frac{A_b}{R} + \frac{A_b W}{f_b}, $$

(8)

where $A_b$ is the data size of edge server execution and $f_b$ is the computing capacity of MEC server. The total delay of computation task is

$$ T = \max \{ T_l, T_b \}. $$

(9)

2.3. Problem Formulated. In this paper, we aim to minimize the delay of computation tasks for single UE by jointly optimizing the transmission covariance matrix $Q$, the IRS reflection coefficients $\Theta$, and the computation task allocation $A_l, A_b$, and the UAV hovering location is the $s$. Then, the problem of offloading time is formulated as

$$ \begin{align*}
    &\text{(P1) minimize } T \quad \text{s.t.} \quad \text{Tr}(Q) \leq P_t, \quad Q \succeq 0, \\
    &\quad A = A_l + A_b, \\
    &\quad A_l \geq 0, \quad A_b \geq 0, \\
    &\quad X_{\min} \leq X_s \leq X_{\max}, \\
    &\quad Y_{\min} \leq Y_s \leq Y_{\max}, \\
    &\quad 0 \leq \theta_n \leq 2\pi, \\
    &\quad \beta_n \in [0,1], \quad \forall n \in \{1,2,\cdots,N\},
\end{align*} $$

(10)

where (11) is the transmission power constraint, i.e., the active beamforming constraint, (12) denotes the task assignment constraint, (13) restricts the area of UAV hovering, and (14) is the passive beamforming constraint of the IRS, i.e., the phase shifts $\theta_n$ and the amplitude $\beta_n$, $\forall n \in \{1,2,\cdots,N\}$.

It is worth noting that the controller is embedded in the UIRS. UIRS can calculate the phase shifts and the amplitude according to the CSI and send the instructions to the controller to adjust the reflection coefficient for assisting UE in computation offloading. Moreover, the P1 problem is a non-convex optimization problem and there are four optimization variables coupling into the min-max formulation, which makes it more difficult to tackle.

3. Proposed Method

The P1 problem in the previous section is a high-complexity nonconvex problem. In order to solve this problem, we use an alternating optimization method to decouple multiple variables of the problem, that is, iteratively optimize the active beamforming, the UAV hovering location, the
computation task scheduling, and passive beamforming variables while the other variables are fixed. In each iteration, we use a heuristic genetic algorithm to get a feasible solution to the optimization problem to be solved in acceptable time and space cost. Specifically, the P1 problem can be transformed into more solvable formulation by changing the optimization variables in task assignment and passive beamforming. We set a task allocation factor \( \varphi \) to replace the \( A_t \) and \( A_p \), i.e., \( A_t = \varphi A, \) \( A_p = (1 - \varphi)A, \) and \( \varphi \in [0, 1] \). The reflection factors are continuously adjusted and can be defining \( \Theta_s = \beta_s e^{\varphi_1} \) as the coefficient per element, that is, \( |\Theta_s| \leq 1 \) for simplicity. Therefore, the P1 problem can be transformed as follows:

\[
(P2) \text{ minimize } T \\
\text{s.t. } \text{Tr}(Q) \leq P_t, \quad Q \succeq 0, \\
|\Theta_s| \leq 1, \quad \forall n \in \{1, 2, \ldots, N\} \\
A_t = \varphi A, \\
A_p = (1 - \varphi)A, \quad \varphi \in [0, 1], \\
X_{\min} \leq X_s \leq X_{\max}, \\
Y_{\min} \leq Y_s \leq Y_{\max}.
\]

To solve the P2 problem, we use the alternating optimization [26] to decompose the nonconvex problem into four optimization variables, which can be denoted by

\[
\begin{align*}
\tilde{s}^{i+1} &= \arg \min_s T(s, \varphi^i, Q^i, \Theta^i), \\
\varphi^{i+1} &= \arg \min_\varphi T(\tilde{s}^{i+1}, \varphi, Q^i, \Theta^i), \\
Q^{i+1} &= \arg \min_Q T(\tilde{s}^{i+1}, \varphi^{i+1}, Q, \Theta^i), \\
\Theta^{i+1} &= \arg \min_\Theta T(\tilde{s}^{i+1}, \varphi^{i+1}, Q^{i+1}, \Theta),
\end{align*}
\]

where \( \tilde{s}^i \) is the UIRS hovering location, \( \varphi^i \) is the task assignment factor, \( Q^i \) is the transmit covariance matrix, and \( \Theta^i \) is the reflection factors in the \( i \)th iteration. Then, in the iteration, we first update the location \( s \) by genetic algorithm (GA) [27, 28] when all the other variables are fixed, then put the updated \( s \) into the fitness function to update the allocation factor \( \varphi \) while the matrix \( Q \) and \( \Theta \) are unchanged; next, we put the new factor \( \varphi \) to the objective function to update the matrix \( Q \). Finally, we update the active beamforming \( \Theta \) with hovering location \( s \), task allocation coefficient \( \varphi \), and passive beamforming \( \Theta \) fixed.

The detailed GA process is given in Algorithm 1.

GA can use very complex fitness functions (i.e., objective functions) and place limits on the range of variables. GA is not always the best optimization strategy, but it can find good solutions, even in very complex feasible set. For any specific optimization problem, adjusting the parameters of the GA can make the problem converge quickly. That is to say, the GA can jump out of the local optimum and find the global optimum. Therefore, our proposed hybrid optimization method of GA and AO algorithm can find a suboptimal solution to the P2 problem.

### 4. Simulation Results

In this section, we provide extensive simulation results to corroborate the performance of our presented UIRS-enhanced MEC system.
enhanced MEC system. The simulation is for narrowband flat-fading channels under MIMO as well as single-user setups. The channel between UE and BS is interrupted because of severe blockage, and the mobile user offloads computation task to the MEC server by the UE/UIRS link and UIRS-BS link. The execution of computing tasks is divided into the following three ways:

(i) Local execution: the computation resources of the UE are sufficient to perform computation task locally; thus, the task allocation factor $\phi = 1$

(ii) Full offloading: the UE’s computation resources are limited, and the whole computation task can be off-loaded to the MEC server, i.e., the task assignment factor $\phi = 0$

(iii) Partial offloading: the UE offloads partial computation task to the edge server, and the rest of the task is executed locally; that is, the task scheduling factor $\phi \in (0, 1)$

In the simulations, our proposed system is a 3D coordinate system, the BS is located at the origin coordinate; the UE is located on the $x$-axis. Their antennas are both equipped with the ULA perpendicular to the $XOY$ plane, and the spacing of antenna is $\lambda/2$. The IRS is deployed on the UAV and is equipped with the UPA parallel to
the XOY plane. The system parameters are summarized in Table 2.

Figure 3 shows the average distance between individuals in each generation, which is a good measure of population diversity. From Figures 3(a) to 3(d), we can find out that as the population evolves, the average distance between individuals approaches 0 as the number of mutations decreases. Figure 4 shows the decay trend of fitness function (i.e., the computation offloading time), and the optimal value can be obtained after generations iteratively. We use the
parameters in Table 1 as the initial parameters to search optimal solution with GA. The optimized UIRS hovering location, task assignment factor, active beamforming, and passive beamforming can be found while all the other variables are fixed.

In addition, the bandwidth and the number of IRS reflecting elements also affect the response time of computation offloading. Under the premise of the optimal solutions obtained from previous experiments, Figure 5 plots the computation task delay with system bandwidth under three task execution ways. The local execution is independent of bandwidth, and all the variables are optimized. As a result, it is a straight line in the figure. The full offloading requires offloading all the computation task to the MEC server, and the task delay is affected by the IRS parameter and bandwidth. Partial offloading divides computing tasks into local execution and edge execution, and the two are executed in parallel, so the task latency is less than the full offloading latency. We observe that the full offloading and partial offloading decrease with increasing bandwidth, which is due to the fact that the transmission rate is affected by system bandwidth. As the bandwidth

\[ \text{Bandwidth (MHz)} \]

\[ \text{Task delay (s)} \]

\[ 0.1 \quad 0.2 \quad 0.3 \quad 0.4 \quad 0.5 \quad 0.6 \]

\[ 0.7 \quad 0.8 \quad 0.9 \quad 1 \]

\[ 25 \quad 100 \quad 225 \quad 400 \quad 625 \quad 900 \quad 1225 \quad 1600 \quad 2025 \quad 2500 \quad 3025 \quad 3600 \]

\[ \text{Local} \quad \text{Full} \quad \text{Partial} \]

\[ \phi = 0.1 \quad \phi = 0.2 \]

**Figure 5:** Computation task delay versus system bandwidth.

**Figure 6:** Computation task delay versus IRS elements.
increases, performance of UIRS-aided MEC begins to outperform the local execution, and the gap becomes more pronounced, which further illustrates the important role of IRS in the proposed system.

Figure 6 shows that the computation task delay obtained by local execution, full offloading, and partial offloading under the different numbers of IRS elements, where the task assignment factor $\phi = 0.1$ and $\phi = 0.2$. It can be observed that as the number of IRS elements increases, the task response time of UIRS-assisted system decreases, while the exception of local execution latency is unchanged due to the irrelevant with the IRS. Another important finding is that the number of IRS elements cannot grow indefinitely. On the one hand, it is due to the constraints of hardware cost and control complexity. On the other hand, it can be seen from Figure 6 that when the number of IRS elements increases to a certain extent, the task delay will not be significantly improved. We can also observe that our presented UIRS system can significantly improve the MEC performance of the UE; that is, the IRS can play an important role in wireless network. Moreover, the partial offloading outperforms the full offloading, and the gap between them depends on the task allocation factor. We can get this conclusion from the variety of the polyline when $\phi = 0.1$and $\phi = 0.2$in Figure 6.

5. Conclusions

In this paper, we present an alternating algorithm based on GA for computation task delay optimization in the UIRS-enhanced MEC system. Due to the severe blockage, UIRS can provide virtual LOS link between the UE and BS. The BS provides MEC service for the UE so as to obtain more efficient power management, fewer storage requirements, and higher application performance. We aim to minimize the task latency and jointly optimize the UIRS hovering location, task allocation factor, active beamforming, and passive beamforming to find the suboptimal solution in limited time. The IRS and UAV provide new degrees of freedom to further improve the performance of wireless links, paving the way for the convergence of computing and communications. Simulation results validate the effectiveness of the proposed solution and that MEC can significantly decrease the delay of computation task and improve the performance of UE. In general, our proposed method is an efficient, parallel, global search method suitable for running on hardware with limited memory or computational power. Meanwhile, our proposed method can also be used as a benchmark for future work. In addition, there are still some challenging problems that can be completed in the future. For example, discrete reflection coefficient and multiuser computation offloading problem should be considered in our future work.

Data Availability

The data used to support the findings of this study are included in the article. Some or all data used during the study are available from the corresponding author by request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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