Optimised secure communication and perception based on intelligent reflective surfaces

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Shuo Tang*, Tong Xi, Liang Wu

College of Information Science and Technology, Tibet University, Lhasa, Tibet, 850000, China *Corresponding author

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Abstract: Intelligent Reflecting Surface (IRS), as an emerging technology, brings a brand new optimization approach for future wireless communications and environment perception by dynamically regulating the propagation path of electromagnetic waves. This paper focuses on the optimization of secure communications and perception based on IRS, and proposes a joint optimization framework that aims to balance the needs of communication security and perception accuracy. By constructing a multi-objective optimisation model and designing an innovative algorithm, this paper achieves a significant improvement in secrecy capacity and signal-to-noise ratio (SNR) in single-user and multi-user scenarios. Experimental results show that the optimisation method combined with machine learning shows strong adaptability and performance advantages in dynamic environments. The research results of this paper provide technical support for scenarios such as the Internet of Things and driverless vehicles that require the coordination of communication and perception, and provide a theoretical basis for the intelligent design of next-generation wireless communication networks.

1. Introduction

In the field of modern wireless communication and perception, with the development of the Internet of Things (IoT), 5G, and future 6G technology, the importance of secure communication and environmental perception is becoming increasingly prominent. However, traditional communication systems face many challenges in terms of physical layer security and environmental perception accuracy, such as channel uncertainty, resource allocation limitations, the risk of eavesdropping attacks, and perception performance bottlenecks in complex environments. The introduction of the IRS provides a new technological paradigm to solve these problems [1]. IRS can dynamically adjust the propagation path of electromagnetic waves to enhance the strength and directionality of signals, bringing unprecedented possibilities for secure communication and environmental awareness optimisation.

The intelligent reflecting surface is composed of an array of controllable reflecting units. Its core technical advantages are low power consumption, high flexibility and high integration. Compared with traditional relaying technology, IRS does not require active signal amplifiers. It can intelligently guide signals simply by adjusting the phase and amplitude of the reflecting units, thereby optimising

the coverage and quality of wireless signals without increasing energy consumption. In secure communications, IRS can optimise channel gain by designing a phased array to enhance the secure capacity of the communication link of legitimate users and resist signal interference from eavesdroppers [2]. In environmental perception, IRS enhances the target echo through signal reflection to achieve high-precision detection and tracking of the target's position and status. Therefore, how to jointly optimise the configuration of IRS to meet the needs of both secure communications and perception tasks has become a key issue in current research.

In recent years, research on the application of IRS in secure communication and perception has made some progress. In terms of secure communication, existing research mainly focuses on optimizing beamforming through IRS to maximize the confidential capacity and suppress the performance of eavesdropping channels. In terms of perception optimization, IRS is used to enhance signal coverage and target detection capabilities. However, these studies usually treat communication and perception tasks separately, without fully considering the interaction between the two. In practical applications, communication and perception are often coupled tasks. For example, in intelligent transportation and intelligent manufacturing scenarios, it is necessary to ensure both the security of data transmission and high-precision perception of the environment [3]. Therefore, developing a joint optimization framework that considers the performance trade-offs between communication and perception is of great theoretical and practical significance.

This paper focuses on the optimization of secure communication and perception based on intelligent reflective surfaces and proposes a comprehensive joint optimization framework. By constructing an optimization model with multiple scenarios and multiple objectives, we aim to tap the potential of IRS in coupled communication and perception tasks and achieve efficient resource allocation and configuration optimization in dynamic scenarios through innovative algorithm design. The research results of this paper not only provide technical support for applications in fields such as the Internet of Things and driverless vehicles, but also provide theoretical basis and practical reference for the design of next-generation wireless communication networks.

2. Optimised design for secure communication

2.1. Physical layer secure communication technology

Physical layer secure communication technology based on IRS aims to use the flexible beamforming capabilities of IRS to dynamically adjust the reflection coefficient to optimise the signal propagation path and resist interference. In a typical communication scenario, legitimate communication nodes transmit signals via IRS, while a potential eavesdropper tries to steal the information [4]. By designing the phase shift and reflection amplitude of the IRS, the received signal strength of the legitimate user can be significantly enhanced, while the eavesdropper's reception capability is weakened.

The core of beamforming optimisation is to design the IRS phased array so that the signal superposition at the receiving end Bob is maximised. Assuming that the transmitted signal is s, the power is P_t , and the path gain of the signal reflected by the IRS from Alice to Bob is h_{AB} , then the received signal strength at Bob is:

$$|y_B|^2 = \left|\sqrt{P_t}h_{AB}\theta\right|^2\tag{1}$$

Among them, $\theta = [e^{j\theta_1}, e^{j\theta_2}, ..., e^{j\theta_N}]$ represents the phase vector of IRS.

In order to resist the interference of attackers, the design goal is to maximize the confidentiality capacity of legitimate communication while minimizing the received signal strength of the eavesdropper. The eavesdropping channel gain is h_{AE} , then the eavesdropper's received signal is:

$$|y_E|^2 = \left|\sqrt{P_t}h_{AE}\theta\right|^2\tag{2}$$

2.2. Optimization problem modeling

Confidentiality capacity is defined as the difference between the capacity of the legitimate user communication channel and the capacity of the eavesdropping channel:

$$C_s = \max\left\{\log_2\left(1 + \frac{|h_{AB}\theta|^2}{\sigma^2}\right) - \log_2\left(1 + \frac{|h_{AE}\theta|^2}{\sigma^2}\right), 0\right\}$$
 (3)

Where σ^2 is the noise power.

To achieve confidential communication, it is necessary to maximize the confidentiality capacity by optimizing θ . The optimization problem is formalized as:

$$\max_{\theta} C_s \text{s.t.} |\theta_i| = 1, \forall i$$
 (4)

In a multi-user scenario, IRS also needs to allocate resources fairly to ensure the confidentiality capacity requirements of different users. The goal of this problem is to maximize the sum of the weighted confidentiality capacity of all users:

$$\max_{\theta} \sum_{k=1}^{K} w_k C_s^{(k)} \text{s. t. } |\theta_i| = 1, \forall i$$
 (5)

Among them, w_k is the weight of the user.

2.3. Solution method and algorithm design

optimization

Since the problem contains non-convex constraints (constraints with a phase amplitude of 1), direct solution is relatively complicated. The method based on convex optimization is to relax the non-convex constraints into convex problems through the semidefinite relaxation (SDR) method and iteratively optimize [5]. Relax the constraints of θ into a semi-positive matrix optimization problem. Use convex optimization tools for solution. Extract approximate solutions based on the results and quantize them into actual phase values.

The dynamic optimization strategy combined with machine learning takes into account the dynamic changes of the communication environment, and the reinforcement learning (RL) method can quickly adapt to the environment. Taking deep Q learning (DQL) as an example, first define the state, including channel gains h_{AB} , h_{AE} and current IRS configuration. Secondly, the action adjusts the phase value of each reflection unit [6]. Finally, the reward function is positively correlated with the confidentiality capacity C_s . By training the DQL agent, fast dynamic beam optimization can be achieved in complex environments.

Method	Initial confidentiality capacity (bps/Hz)	Optimized confidentiality capacity (bps/Hz)	Increase (%)
No optimization	1.2	1.2	0
Based on SDR optimization	1.2	3.8	216.7
Based on DQL	1.2	4.2	250.0

1.2

Table 1: Confidentiality capacity improvement in single-user scenario

To verify the effectiveness of the optimization scheme, the performance in single-user and multiuser scenarios is simulated. From the data in Table 1, it can be seen that the optimization scheme has a significant effect on improving the confidentiality capacity in the single-user scenario. Initially, the

4.2

250.0

confidentiality capacity of the system without optimization was only 1.2 bps/Hz. After optimization, both the optimization method based on semidefinite relaxation (SDR) and the deep Q learning (DQL) method achieved significant performance improvements. Among them, the confidentiality capacity after SDR optimization increased to 3.8 bps/Hz, an increase of 216.7% compared to the initial value, while the confidentiality capacity after DQL optimization reached 4.2 bps/Hz, an increase of 250.0%.

It can be observed from the data that the improvement of SDR optimisation and DQL optimisation is different. The reason behind this is the optimisation mechanism and adaptability of the two methods. SDR optimisation mainly finds a configuration that is relatively close to the global optimum through relaxation and iterative solution of non-convex problems, which can effectively improve the signal gain of legitimate users and suppress the reception ability of eavesdroppers. However, the SDR method may lead to the loss of the optimal solution during the relaxation process, so its improvement is slightly inferior to that of DOL. DOL optimisation has significant dynamic learning capabilities and can adaptively adjust the IRS configuration according to changes in the channel environment, thereby more accurately optimising the secrecy capacity in complex and ever-changing communication scenarios. This characteristic enables DQL to achieve a higher performance ceiling in the single-user scenario, demonstrating the advantages of intelligent algorithms in dynamic optimisation. Although both optimisation methods significantly improve the secrecy capacity, the secrecy capacity in the unoptimised scenario remains at the initial value of 1.2 bps/Hz, indicating that the IRS fails to effectively enhance the legitimate communication link or resist the threat of eavesdropping channels under the default configuration. This further verifies the importance of an optimised configuration for achieving physical layer security.

Figure 1 shows the relationship between the secure capacity and the number of IRS reflecting units, reflecting the key role of intelligent reflecting surfaces (IRS) in improving the security performance of secure communications. The increase in secrecy capacity is greater when the number of reflecting units is low (e.g. 32 to 128 units). This is because at this stage, each additional unit provides more precise beamforming for the target signal, while effectively suppressing the signal strength of the eavesdropping channel. The potential of the IRS to optimise channel conditions and enhance signal coverage is fully utilised, significantly improving the system's secrecy performance. However, when the number of reflecting units is further increased (e.g. from 256 to 512 units), the increase in security capacity begins to decrease, reflecting the diminishing marginal returns. This phenomenon can be explained by the saturation effect of signal superposition: when the directivity and gain of the target signal are already close to optimal, the performance improvement of additional reflecting units becomes limited.

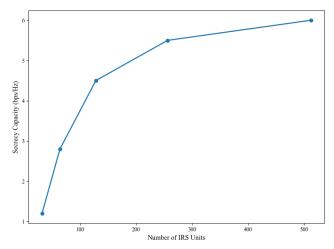


Figure 1: Relationship between the capacity for confidential data and the number of IRS reflection units

The data in Table 2 shows the significant impact of IRS-based optimisation on the total system secrecy capacity in a multi-user scenario, as well as the performance of SDR optimisation and DQL optimisation in multi-user communication. As can be seen from the table, as the number of users increases, the total system secrecy capacity increases significantly, but the performance of different optimisation methods also reflects their differences and potential advantages.

Number of
usersSDR-optimised confidential capacity
sum (bps/Hz)DQL-optimised confidential
capacity sum (bps/Hz)27.47.8515.216.51029.532.1

Table 2: Performance in multi-user scenarios

When the number of users is small, the performance gap between SDR and DQL optimization is small. The total confidentiality capacity of SDR optimization is 7.4 bps/Hz, while that of DQL optimization is 7.8 bps/Hz. The difference between the two is about 5.4%. This shows that in a simple multi-user scenario, channel resources are relatively sufficient, optimization problems are relatively controllable, and SDR optimization can effectively meet user needs. However, even in this case, DQL optimization is still slightly ahead, reflecting its potential advantages in dynamic adjustment and global resource allocation.

As the number of users increases to 5 or 10, the total confidentiality capacity increases significantly, and the advantages of DQL optimization become more and more obvious. For example, in 5 user scenarios, the total confidentiality capacity optimized by DQL is 16.5 bps/Hz, which is an increase of 8.6% compared to the 15.2 bps/Hz optimized by SDR. In 10 user scenarios, the total confidentiality capacity optimized by DQL reached 32.1 bps/Hz, exceeding the 29.5 bps/Hz optimized by SDR, with an increase of 8.8%. This trend shows that as the number of users increases and the complexity of resource allocation increases, DQL optimization, through its reinforcement learning mechanism, can more efficiently find approximately optimal reflection matrix configurations in complex scenarios, further improving the confidentiality performance of the system.

The data also reveals that the growth trend of the total confidentiality capacity in multi-user scenarios is not linear. This phenomenon can be attributed to limited system resources, such as the number of reflection units and channel bandwidth of IRS. When the number of users increases, the system needs to allocate resources among users. This resource competition may cause the channel gain of some users to be limited, thereby reducing the growth rate of the overall system performance. However, DQL optimization can cope with this resource competition more efficiently and show better performance by learning the resource allocation weights among users and adjusting IRS configuration in real time.

3. Perceptual optimization design

3.1. Application of IRS in environmental perception

IRS provide strong support for environmental perception by dynamically adjusting signal reflection paths. In environmental sensing scenarios, IRS can achieve spatial focusing and coverage expansion of signals by precisely controlling the direction and phase of reflected signals, thereby improving the performance of target detection and tracking [7]. Taking target detection as an example, IRS can redirect the incident signal from the signal source to the area of interest, enhancing the target's echo signal strength while suppressing interference in non-target areas. This capability is particularly suitable for weak target perception in low SNR environments.

Assuming that the target is located at coordinate position x_t , the echo signal received by the sensor

is:

$$y = \mathbf{h}_{IRS}^H \Theta \mathbf{h}_t s + n \tag{6}$$

Among them, h_t is the channel vector between the target and IRS, h_{IRS} is the channel vector between IRS and the receiver, Θ is the reflection matrix of IRS, s is the transmitted signal, and n is the additive noise [8].

By optimizing Θ , the signal can be focused more strongly at the target position, while reducing the leakage signal strength in other directions, thereby improving the detection probability of the target signal.

3.2. Perception Optimization Modeling

In perception optimization problems, SNR is usually used as the main indicator to measure target perception performance [9]. Assume that the power of the target received signal is $P_s = |\mathbf{h}_{IRS}^H\Theta\mathbf{h}_t|^2 P_t$, and the noise power is σ^2 , then the SNR of the target detection channel is:

$$SNR = \frac{P_S}{\sigma^2} = \frac{|\mathbf{h}_{IRS}^H \Theta \mathbf{h}_t|^2 P_t}{\sigma^2}$$
 (7)

To maximize the perceived performance, the optimization problem can be formalized as:

$$\max_{\Theta} SNRs. t. |\Theta_{ij}| = 1, \forall i, j$$

Among them, $|\Theta_{ij}|$ represents the reflection coefficient amplitude constraint of the IRS unit.

Further, in order to improve the overall perception capability of the system, the detection problem of multi-target areas is considered [10]. Assume that the system needs to perceive K targets, and the channel of each target is $\mathbf{h}_t^{(k)}$. The optimization goal can be expanded to maximize the weighted detection probability of multiple targets:

$$\max_{\Theta} \sum_{k=1}^{K} w_k SNR^{(k)}$$
 (8)

Among them, w_k is the priority weight of target perception.

Perceived performance is directly affected by IRS configuration. When the number of IRS units is increased or the configuration is optimized, the focusing effect of the sensing signal is better and the SNR is significantly improved, thus enhancing the sensing accuracy.

3.3 Solution methods and implementation

Due to the non-convex constraint of $|\Theta_{ij}| = 1$, direct optimization is more complicated. The fast optimization algorithm based on gradient descent converts non-convex optimization problems into iterative solutions by relaxing constraints in the gradient descent method. Specific steps include initializing Θ as a matrix of random phase values, and then calculating the gradient of the objective function SNR:

$$\nabla_{\Theta} SNR = \frac{\partial SNR}{\partial \Theta} \tag{9}$$

And update Θ :

$$\Theta \leftarrow \Theta + \eta \nabla_{\Theta} SNR$$

Among them, eta is the learning rate. Map the updated Θ to the constraint set such that $|\Theta_{ij}| = 1$. The multi-IRS cooperative sensing mechanism is that in complex scenarios, the coverage capability of a single IRS may be insufficient, and multiple IRS cooperative sensing becomes an

important means. Each IRS optimizes its reflection matrix independently and improves the overall sensing performance through joint optimization. The steps of the collaboration mechanism include each IRS independently optimizing local Θ_i . Carry out global optimization at the central node, coordinate the reflection configuration between IRS, and improve the overall SNR of the system [11]. In the distributed algorithm, IRSs exchange part of the channel information through limited communication to reduce the optimization complexity.

The data in Table 3 intuitively demonstrates the significant impact of the number of IRS units on perceptual performance (measured by signal-to-noise ratio SNR) in a single-target scenario. By optimizing the configuration of IRS, the system can effectively improve the signal quality of target detection, thereby significantly improving the SNR level. It is worth noting that the SNR improvement after optimization gradually increases as the number of IRS units increases, but the increase shows a certain flattening trend.

Number of IRS units	Initial SNR (dB)	Optimized SNR (dB)	Increase (%)
32	8.2	14.5	76.8
64	10.4	20.2	94.2
128	12.7	25.3	99.2

Table 3: Perceptual performance improvement in single target scenario

Judging from the initial SNR performance, the number of IRS units directly affects the signal quality of the unoptimised system. When the number of IRS units is 32, the initial SNR is 8.2 dB, and as the number of units increases, the initial SNR increases to 10.4 dB (64 units) and 12.7 dB (128 units). This trend shows that IRS can significantly enhance signal coverage and increase signal strength at the target location by increasing the number of reflecting units. However, the unoptimised SNR increase is limited, mainly due to the scattering of the IRS reflection signal and the path loss in the unconfigured case. The optimised SNR data further demonstrates the importance of IRS configuration. When the number of units is 32, the optimised SNR increases to 14.5 dB, an increase of 76.8% compared to the initial value. When the number of units is increased to 64 and 128, the optimised SNR reaches 20.2 dB and 25.3 dB, respectively, an increase of 94.2% and 99.2%. From these data, it can be seen that optimisation has a significant effect on improving SNR, especially when there are a large number of IRS units. Optimisation can more effectively focus signal energy and greatly enhance the signal strength at the target position. At the same time, the data also reveals the characteristic of gradual stabilisation of the increase. From 32 units to 64 units, the increase in SNR after optimisation is 17.4%, while the increase from 64 units to 128 units drops to 5.1%. This phenomenon can be attributed to the gradual decrease in the marginal contribution of IRS units. When the number of units is small, the contribution of each additional unit to the reflected signal is significant. However, when the number of units increases to a certain level, the signal energy in the target area is close to saturation, and the benefit of further increasing the number of units begins to decrease.

As can be seen in Figure 2, in the multi-target scenario, the signal-to-noise ratio (SNR) of different target areas all increased significantly with the number of IRS units, but the growth rate and performance of the areas showed obvious differences. When the number of IRS units was small, the SNR of all target areas was at a low level. This is because the number of reflecting units is insufficient to fully focus the signal energy, the signal gain in the target area is relatively limited, and the resource allocation among multiple targets may further dilute the performance. As the number of IRS units increases to 128 or 256, the SNR of each target area improves significantly, especially the SNR of the better performing target 1, which increases the most. This shows that the IRS configuration begins to play its full role at this stage, improving the efficiency of focusing signals on target areas by flexibly

adjusting the reflection matrix.

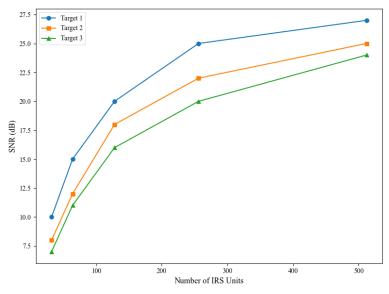


Figure 2: SNR Distribution in Multi-Target Scenarios

The data in Table 4 shows the significant improvement in system perception performance achieved by collaborative optimisation in the multi-IRS collaborative perception scenario. By comparing the SNR values of non-collaborative and collaborative perception, it is clear that the multi-IRS collaborative mechanism has obvious advantages in improving signal quality and enhancing target perception capabilities, especially when the number of IRSs increases, the potential for collaborative optimisation becomes more prominent.

Number of IRSs	Non-cooperative sensing SNR (dB)	Cooperative sensing SNR (dB)	Increase (%)
2	15.8	19.4	22.8
3	17.3	22.1	27.7
1	18.0	24.8	31.2

Table 4: Multi-IRS collaborative perception performance

From the non-collaborative perception of SNR data, it can be seen that as the number of IRSs increases, the initial SNR of the system shows a gradual upward trend. It increased from 15.8 dB with two IRSs to 17.3 dB with three IRSs and 18.9 dB with four IRSs. This shows that even without collaboration, increasing the number of IRSs can create stronger signal coverage of the target area through independent signal reflection. However, due to the lack of coordination between the IRSs, the focusing ability of the signal is limited, and interference from the reflected path may result in insufficient increase in signal strength in the target area. The cooperative perception SNR data further demonstrates the optimisation effect of multi-IRS cooperation. When two IRSs cooperate, the perceived SNR increases to 19.4 dB, an increase of 22.8%; when the number of IRSs increases to 3 and 4, the cooperative SNR increases to 22.1 dB and 24.8 dB, an increase of 27.7% and 31.2%. This trend shows that multi-IRS collaboration can effectively reduce signal scattering interference and enhance signal superposition in the target direction by globally optimising the reflection matrix of each IRS, significantly improving the signal-to-noise ratio of target perception.

The data also reveals that the collaborative gain gradually increases with the number of IRSs. When the number of IRSs is small, a single IRS contributes more to the target area, and the relative benefit of collaborative optimisation is limited. However, when the number of IRSs increases, the

synergy between IRSs becomes more significant, which can control the signal distribution more finely and improve the focusing ability of the signal in the target area. This characteristic shows that the performance advantages of multi-IRS collaboration are more significant in large-scale systems. Although the collaborative sensing SNR increases significantly with the number of IRSs, the marginal effect of the increase weakens. The increase from 2 to 3 IRSs is 4.9%, while the increase from 3 to 4 IRSs decreases to 3.5%. This phenomenon can be attributed to the limitation of system resources and the diminishing returns of collaborative optimisation when the target signal strength approaches saturation. This indicates that in the actual system design, an optimal balance needs to be found between the number of IRSs and performance improvement to avoid wasting resources.

4. Discussion

The proposed optimization framework for secure communication and perception based on IRS systematically explores how to improve communication confidentiality and perception performance by optimizing IRS configuration, from theoretical modeling to algorithm design and simulation verification. In our study, we found that the multifunctional characteristics of IRS are not completely independent of communication and perception tasks, but are deeply coupled. Signal optimisation during communication has a direct impact on perception performance, while the reflection path design in the perception scenario can in turn improve the effectiveness of the communication channel. How to balance the resource allocation of the two is a key issue that requires further research.

During the discussion, we noticed that the optimisation results in this paper for single-user and multi-user scenarios are mainly based on idealised channel models and hardware assumptions. However, in actual deployment, the performance of IRSs may be affected by hardware non-idealities and complex environments. These factors may cause the actual performance of the optimisation algorithm to be lower than the theoretical prediction. Therefore, future research needs to further incorporate hardware constraints into the optimisation framework, evaluate their impact on communication and perception performance, and design more adaptable and robust optimisation algorithms.

In addition, multi-IRS collaborative optimisation has shown significant performance advantages in experiments, but its scalability and communication overhead in actual deployment still need to be further discussed. Collaboration between multiple IRSs requires some control information exchange, which may bring a double burden of calculation and communication when the number of IRSs increases or the scene changes dynamically. Therefore, how to reduce the collaboration overhead through distributed or decentralised optimisation methods while ensuring overall performance improvement is an important challenge that needs to be solved in the future.

Another issue that requires in-depth exploration is the potential for IRS technology to integrate with other emerging technologies. For example, combining with massive MIMO can further enhance the spatial focusing ability of the signal; combining with millimeter wave communication can expand the bandwidth and capacity of the system; and combining with artificial intelligence technology can achieve more accurate dynamic optimisation and resource prediction. Exploring these integrated technologies will not only compensate for some of the limitations of IRS, but also stimulate its wider application in the fields of communication and perception.

In summary, although this paper has verified the effectiveness of IRS-based secure communications and perception optimisation at the theoretical and simulation levels, it still faces many challenges in actual deployment. Future research needs to pay further attention to the practical constraints of hardware implementation, the optimisation overhead of multi-IRS collaboration, and the deep integration with other technologies to provide comprehensive solutions for building smarter and more efficient communications and perception systems. These explorations will lay an important

foundation for the practical application of intelligent wireless networks.

5. Conclusion

This paper studies the optimisation of secure communications and perception based on intelligent reflecting surfaces (IRSs), and proposes a joint optimisation framework to address the challenges currently faced by wireless communication systems in the fields of physical layer security and environmental perception. By thoroughly analysing the unique advantages of IRSs in signal enhancement, path control and resource optimisation, this paper achieves dual improvements in communication confidentiality and perception performance, providing important theoretical support and technical paths for the intelligent and secure development of future wireless networks.

The research results show that IRS can effectively enhance the channel gain of legitimate users and weaken the eavesdropping ability of eavesdroppers by dynamically adjusting the phase and amplitude of the reflecting unit, thereby significantly improving the secrecy capacity of the system. In addition, the flexible configuration of IRS enables it to focus the reflected signal strength in the target area, improving the accuracy and robustness of target detection and environmental perception. This paper verifies the optimisation effect in single-user and multi-user scenarios through simulation. The data fully demonstrates the adaptability and performance advantages of IRS-based optimisation algorithms in complex scenarios.

This paper also explores the coupling relationship between communication and perception tasks in multi-user collaboration and dynamic perception scenarios, and solves the problem of resource allocation and performance trade-offs by constructing a multi-objective optimization model. The experimental results show that the optimization method combined with machine learning can significantly improve the system's real-time responsiveness and overall performance in dynamic environments. In practical deployment, this optimization framework can be widely used in fields such as the Internet of Things, intelligent transportation, and driverless vehicles, where communication and perception need to work together.

Future research can further explore the impact of IRS hardware implementation constraints on optimisation performance, especially how to balance system complexity and performance improvement in scenarios with low power consumption and high integration requirements. At the same time, with the development of 6G technology, the integration of IRS with other emerging technologies will also be an important direction. The research in this paper not only provides theoretical support for IRS-based wireless communication and perception optimisation, but also lays the foundation for the design and application of next-generation intelligent wireless networks.

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