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Air–ground integrated artificial intelligence of things with cognition-enhanced interference management

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Abstract

Integrated air–ground network enhances AIoT performance by improving spectral efficiency, achieving high-speed, stable network connectivity, and enabling sensing, learning, and decision-making. However, unmanned aerial vehicles (UAVs) can lead to local spectrum congestion and competition. To address this issue, intelligent signal processing techniques are employed to enhance AIoT system performance and stability through intelligent multi-channel sensing and communication. A novel communication framework inspired by brain cognition for UAV communication in heterogeneous environments is introduced. This framework iteratively determines the importance of signals, effectively eliminating unimportant signals with interference characteristics, and reducing their transmission power. Simulation results demonstrate the superiority of this method in terms of communication performance.

Keywords: AIoT, Unmanned aircraft, Space integrated network, Intelligent signal processing

1 Introduction

Wireless networks connect individuals, devices, and services, playing an indispensable role in modern society. The field of artificial intelligence of things (AIoT) leverages these networks by integrating artificial intelligence (AI) and Internet of things (IoT) technology, enabling intelligent and autonomous communication among smart devices [1]. AIoT devices, equipped with sensors and control units, gather real-time environmental data and employ AI algorithms for tasks like pattern recognition, object detection, and behavior analysis. Machine learning and deep learning techniques further enhance performance and adaptability, facilitating intelligent decision-making and interactions, such as the autonomous adjustment of parameters in smart home systems based on user habits [2–4]. Despite these advancements, AIoT faces limitations due to the significant wireless access demands of large-scale intelligent applications. These limitations stem from factors such as wireless co-channel interference, spectrum competition, and the intricate management of interconnected devices, hampering scalability, efficiency, and overall performance. Moreover, the interconnected nature of AIoT exacerbates these

limitations as IoT devices collaborate, creating dependencies and shared resource usage. This intensifies interference and competition issues, impeding seamless operation in comprehensive intelligent applications [5–7]. One solution to address these limitations involves exploring new wireless access opportunities in spatial domains. Most AIoT devices operate in relatively low-altitude terrestrial spaces, leaving much of the upper three-dimensional (3D) space underutilized. Unmanned aerial vehicles (UAVs) can alleviate local spectrum congestion through air–ground integrated (AGI) networks, supporting partial AIoT functionalities. UAVs offer several advantages, including enhanced spectral efficiency, stable network connections, relay capabilities for long-distance communication, and signal acquisition for interference research [8]. Additionally, UAVs possess the ability to sense, learn, and make decisions, integrating seamlessly into the AIoT system. Their flexibility and maneuverability make them suitable for various environments, optimizing wireless spectrum utilization. Equipped with advanced sensors and AI algorithms, UAVs enable efficient data collection and intelligent monitoring, enhancing wireless spectrum utilization accuracy and efficiency. Their automated detection and analysis capabilities improve frequency resource allocation, boosting task efficiency and accuracy. UAV technology holds significant potential for driving digital and intelligent transformation across industries, particularly in cross-domain applications.

However, it is essential to acknowledge the limitations of UAV integration in AIoT. While they can make better use of spectrum in 3D space, their high degree of freedom can lead to local spectrum congestion and competition. Therefore, in future AGI networks, UAVs may still face challenges similar to those in current two-dimensional ground networks, as UAVs cannot entirely solve the issue of spectrum congestion caused by airborne and ground devices. Under the background of combining numerous multimedia requests and AGI AIoT devices, multimodal sensation and communication face extremely challenge considering co-channel interference and access competition [9]. In this paper, we focus on the intelligent signal processing with novel cognitive approach to alleviate the uncontrolled interference and competition in large-scale AGI AIoT.

2 Brain cognition-enhanced AGI AIoT

In AGI AIoT, addressing wireless co-channel interference, spectrum competition, and management challenges for interconnected AGI devices is crucial to improve efficient communication protocols, network architectures, and high-bandwidth transmission technologies [10]. Real-time data analysis, edge computing, and intelligent algorithms significantly impact data traffic processing and decision-making.

To overcome these challenges, it is essential to enhance the performance and applicability of AGI AIoT in wireless communication networks, promoting its widespread application and development across various domains [10]. The complexity and heterogeneity of AGI AIoT devices require faster processing speeds and improved signal processing capabilities to mitigate interference and competition. Cognitive radio, based on AI and machine learning, enables wireless communication devices to autonomously sense, infer, and adapt to the radio environment [11]. Cognitive insight leverages brain cognitive concepts to automatically diagnose network issues and optimize system performance. The AGI AIoT system efficiently processes intricate information patterns in four steps (as shown in Figs. 1 and 2), applying a brain

cognitive approach). Combining cognitive heuristics with massive complex information processing capabilities, AGI AIoT systems adeptly manage complex information and interference patterns for multi-device connectivity and data storage.

Three cognitive heuristics (familiarity, cognitive, and propensity) can assist in path selection, information and device association, and problem-solving in AIoT networks. In the AIoT network, wireless communication, brain cognitive technology, and UAV technology are pivotal in advancing AIoT applications in smart homes and smart cities [12]. While wireless communication technology brings convenience to AGI AIoT, it also introduces challenges like self-multiplexing and complex interference control.

Conventional solutions often rely on wasting large amounts of spectrum resources, resulting in resource congestion and scarcity, creating new problems. [13] Problems in typical wireless communication methods include:

- Cellular networks, which struggle with signal coverage, infrastructure costs, and spectrum congestion [14].
- Wi-Fi networks, which require adjustments for limited signal strength, scalability, frequency interference, and data security.
- Bluetooth networks, tailored for short-range demands with low data rates and interoperability issues.
- Satellite communication, hindered by high costs, signal latency, and susceptibility to weather conditions [15].
- Infrared communication, with limited range, susceptibility to obstructions, and line-of-sight requirements.
- RFID (Radio Frequency Identification), using antenna technology to extend transmission distance but limited by data capacity and close-range receiver requirements.

Therefore, this paper advocates for brain cognitive multimodal computing, simulating human brain cognitive abilities and multimodal perception. It facilitates the understanding, analysis, and processing of diverse data types and interference, enhancing system efficiency and performance. Implementing brain cognitive multimodal computing in AGI AIoT entails learning and reasoning with multimodal data, augmenting environmental perception, and adaptability across diverse scenarios.

3 Brain cognition-based interference management for AGI AIoT

Interference is a common issue in wireless communication, stemming from non-ideal characteristics of devices like local oscillators, power amplifiers, mixers, and signal leakage. In the AGI AIoT system, diverse devices and applications necessitate different wireless resources, leading to additional heterogeneous interference that impairs wireless communication accuracy and efficiency.

In an ideal scenario, the AGI AIoT system experiences two types of interference: 1) isomorphic interference, resulting from imperfect wireless communication controlling and difficulties in large-scale adaptive protocols; 2) heterogeneous interference, stemming from the diverse functions, protocols, and locations of devices within the AIoT system [2].

In the presence of interference, a received signal in the AGI AIoT system is denoted as

$$y = \sum_{i=1}^{M} \sqrt{P_{d^i}} h_s^i x_s^i + \sum_{j=1}^{N} \sqrt{P_{d^i}} h_{\text{int}}^j x_{\text{int}}^j + n, \tag{1}$$

where P_{d^i} represents the power of intended/interference signal (x_s^i / x_{int}^i) decayed at distance d, h is the corresponding channel coefficient, and n is additive noise with power P_n. In Eq. (1), the total interference power can be expressed as $\sum_{j=1}^{N} P_{d^j} |h_{\text{int}}^j|^2$. In large-scale networks, an increase in the number of devices N significantly reduces the signal-to-interference plus noise ratio (see Eq. (2)) required for the desired signal, i.e., $\lim_{N \to +\infty} SINR = +\infty$, potentially impacting AGI AIoT networking efficiency and control accuracy.

$$SINR = \frac{\sum_{i=1}^{M} P_{d^i} |h_s^i|^2}{\sum_{j=1}^{N} P_{d^i} |h_{\text{int}}^j|^2 + P_n} \tag{2}$$

To address interference in AGI AIoT, we present the AGI AIoT framework in Fig. 1, with the cognitive process central to interference management. Figure 2 illustrates the brain cognitive technology employed in this paper to mitigate interference issues in AIoT wireless communication, ultimately optimizing AGI AIoT performance.

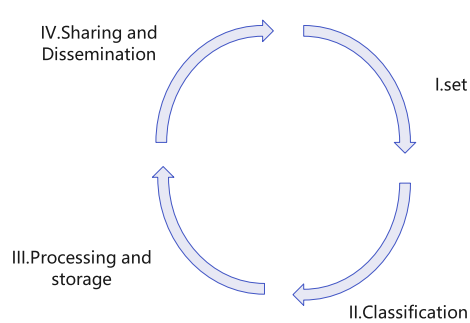

Fig. 1 The basic functions of AGI AIoT

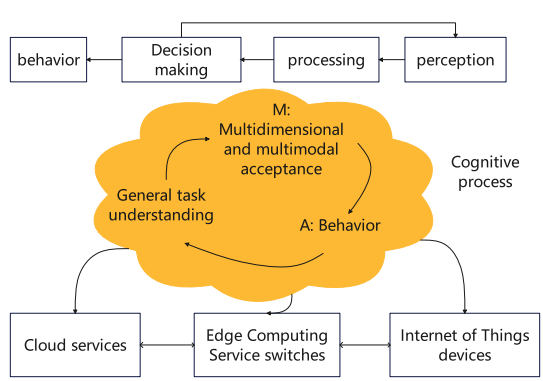

Fig. 2 Overall framework of brain cognitive AGI AIoT

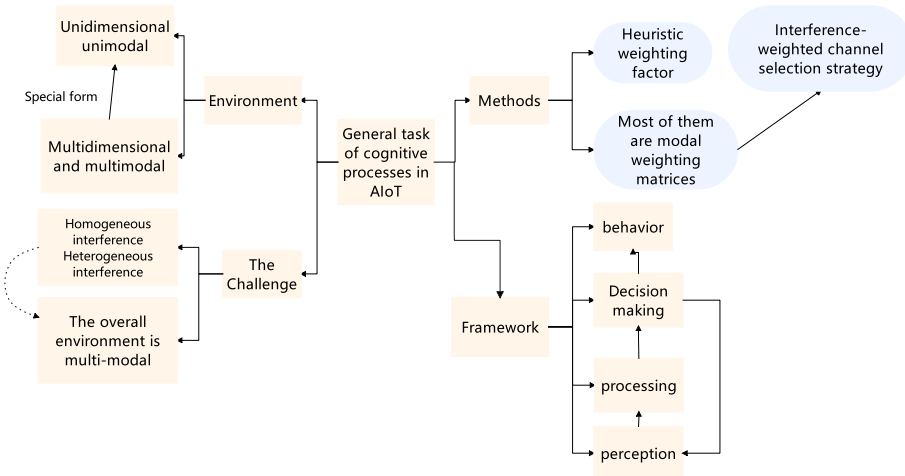

Fig. 3 The overview of designed architecture

Building on the overall task cognition depicted in Fig. 3, we differentiate between isomorphic and heterogeneous interference and delve into solutions for multimodal problems through straightforward single-mode information transmission.

- **Homogeneous interference problem in AGI AIoT**:

  Isomorphic interference arises when devices within wireless communication employ the same protocols or frequencies. This leads to terminals that should coordinate to avoid interference instead receiving unwanted signals on the same frequency. Consequently, terminals experience interference they should have been spared from.
- **Heterogeneous interference problem in AGI AIoT**:
  AIoT encompasses a vast array of devices, networks, and applications distributed across diverse geographical locations. Variations in features, protocols, and institutions create a complex and heterogeneous environment. Interference and resource contention occur among various devices and applications, resulting in heterogeneous interference that detrimentally affects communication quality and availability.

3.1 Homogeneous interference mitigation

In Fig. 4, interference occurs during transmission to the destination terminal due to the broadcast feature covering nodes that should not receive the information. Node 2, in addition to the destination terminal A, receives the broadcast signal, causing interference. The node that should receive the broadcast information, Terminal B, enhances its own signal transmission capability to improve the broadcast coverage. In AIoT networks, as the number of devices increases, congestion issues such as limited bandwidth and increased sources of disturbance may arise. These issues can degrade communication quality and rates. The total available bandwidth (B) is inversely affected by the number of interference sources (N). In frequency divisions, this leads to a reduction in the lowest available bandwidth, while in time slot-based divisions, it decreases the lowest achievable rate. Coordination of co-channel interference through homogeneous protocol consistency often results in competition.

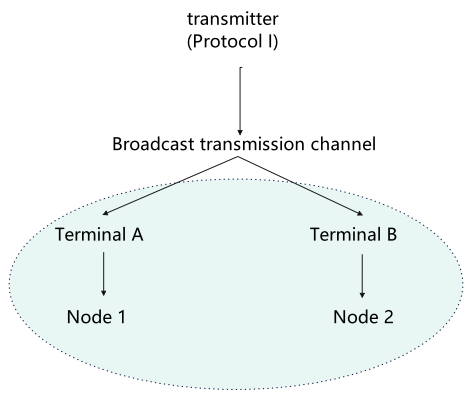

Fig. 4 Broadcast channel and homogeneous interference

Assuming equal transmission probabilities for each device, the probability (P) of successfully transmitting data while competing determines the probability of failure ($1 - P$). The number of successfully transmitting devices (k), represented by a binomial distribution denoted as $B(N, P)$, also indicates the communication rate.

To address the interference problem caused by device density and bandwidth competition in homogeneous devices, we use the heuristic factor method shown in Fig. 3. We introduce a weight coefficient vector A and utilize current and historical information to optimize actions. The power weight (see Eq. (7)) selected through the reinforcement learning process is the most stable and reduces interference signal in the channel, enabling optimal transmission efficiency [16].

We set the power weight value as $a_i \in \{a_1, a_2, a_3, \cdots, a_i\}$ to adapt each devices' transmit power. In time slot $t + 1$, a weight table is built up on a single independent link and is updated according to the transition function in Eq. (3) when a file transmission is finished. We have

$$Q_{a_i}(t+1) = Q_n + Q_p = Q_{a_i}(t) + R_{a_i}(t), \tag{3}$$

where Q_n and Q_p are current and historical information. R_{a_i} is the current reward at action time slot t defined by

$$R_{a_i} = \begin{cases} 1 \\ -1 \end{cases}, \tag{4}$$

where Q_{a_i} is an accumulation of historical rewards. The initial weight value $Q_{a_i}(0)$ is set to 0. Equation (3) can be rewritten as

$$Q_{a_i}(t+1) = \sum_{k=0}^{t-1} R_{a_i}(k) + R_{a_i}(t). \tag{5}$$

By generalizing the R_{a_i} from action time 0 to t, the proportion of current information in $Q_{a_i}(t+1)$ is

$$Prop\left(\frac{Q_n}{Q_n + Q_p}\right) = \frac{R_{a_i}}{(t-1)R_{a_i} + R_{a_i}} = \frac{1}{t}. \tag{6}$$

In Eq. (6), the impact of Q_n decreases at a rate of $\frac{1}{t}$ as the number actions t increases, which results in the weight value varying more during the initial stage, and thereafter gradually becoming stable as more actions are taken. With the increase of time, the power weight value a_i tends to stabilize, and the channel quality when the weight value is stable is optimal for current signal transmission quality. Thus, the power weight can be adjusted using the heuristic weighting factor to adjust the signal transmission power of each AIoT device. This enables intelligent control of transmission power, selection of better channels for transmission, and reduction of interference while ensuring effective transmission.

Here, we add a_i to achieve a channel selection strategy, where the probability of selecting a channel depends on its interference level. A lower selection probability will be allocated to those channels with higher interference levels, thus achieving low interference at terminals of the link.

$$a_i = \frac{1}{\sqrt{n + I_{a_i}}}, \tag{7}$$

where I is the interference level, and n is the noise. Based on Eqs. (5) and (7), the optimal signal received by the terminal is then given by

$$y = \sum_{i=1}^{M} \sqrt{P_{d^i}} h_s^i x_s^i + \sum_{J=1}^{N} \sqrt{a_i P_{d^i}} h_{\text{int}}^j x_{\text{int}}^j + n, \tag{8}$$

where the relative strength of information in the signal can be controlled by multiplying itself with the power weight a_i, and noise and channel interference are added to the signal.

With Eq. (7), the lower interference channels have higher probability to be selected, and vice versa.

In comparison with Eq. (1), the optimal signal form obtained in Eq. (8) increases the power weight in the interference part to adjust the weight value according to the change in channel quality described by Eq. (5). When the SINR exceeds a certain threshold, i.e., $SINR > \gamma_{th}$, the number of successful transmissions can increase and be added to the number of historical successes, and vice versa. This approach enables intelligent control of transmission power and the selection of better channels for transmission, ensuring effective transmission while reducing interference.

Under isomorphic conditions, interference in the channel remains constant, meaning that its amplitude and characteristics do not change. In this scenario, we can utilize the aforementioned methods to choose communication channels and minimize the impact of interference on the signal.

However, under heterogeneous conditions, interference in channels becomes variable due to unstable channel states, variations in multipath effects, and interference from other devices. In such cases, we combine the aforementioned approach with multimodal perception to enable adaptable signal processing and interference cancelation, allowing us to handle diverse interference situations more effectively.

Table 1 Multimodal matrix

Function	Visual	Speech	Sensor	Text
Camera	1	0	0	0
Identifying objects	1	1	1	1
Image	1	0	0	0
Sound	0	1	1	0
Emotion recognition	1	1	0	1
Status	1	1	1	1

Based on the 0-1 states in the matrix, suitable eigenvalues that can serve as normalization features in multimodal matrices can be obtained

1 indicates that the mode can be detected

0 indicates that the mode cannot be detected

3.2 Heterogeneous interference mitigation

The same isomorphic protocol can be considered as single-modal communication, while heterogeneous protocols mostly involve multimodal communication. Single-modal communication is the simplest form of multimodal communication. Therefore, we address the issue of isomorphic and heterogeneous interference by transforming it into a multimodal problem [17].

Perception tasks differ from computational tasks, as computational tasks focus on processing and analyzing data for meaningful outcomes, while perception tasks aim to interpret and understand input signals to provide information about the environment or objects.

Moreover, when processing perception tasks in communication systems, it is important to consider priority and resource allocation in conjunction with other tasks. Given that perception tasks require real-time and low latency, allocating sufficient bandwidth, computing resources, and energy to these tasks during communication system design is necessary to ensure reliable and timely perception results.

In conclusion, the specific requirements for perception tasks may vary in different application scenarios during communication system design.

To adapt to the multimodal scenario, we establish a multimodal matrix (Fig. 3 and Table 1) that selects channels with fewer interference signals to regulate interference.

In heterogeneous scenarios, we introduce the ability to maximize information retrieval by considering factors such as unit data (ρ), the amount of data in the event space (D), the attention mechanism ($\overrightarrow{A}$) (similar to a_i in Eq. (5)), and the overall amount of information generated by all events (I). Our goal is to obtain the highest proportion of effective information in heterogeneous environments, based on:

In summary, when designing communication systems, the specific requirements for perception tasks may vary depending on specific application scenarios.

$$\rho = \frac{\max ||A \otimes \sum_{i=1}^{m} I_i||}{D}. \tag{9}$$

The key is the generation of vector $\overrightarrow{A}$, which iterates and determines its importance, thereby removing unimportant signals with interference characteristics and reducing

their transmission power. This process can be inspired by the brain cognition and simplified as follows:

$$\overrightarrow{A}(n) = \alpha \overrightarrow{A}(n-1) + \Delta(n), \tag{10}$$

where $\alpha \in (0, 1)$ determines the proportion of 'old' experience in the next information acquisition. α helps determine the deviation caused by shortcuts and decide whether our $\overrightarrow{A}$ needs improvement and update $\Delta(n)$. The flowchart of the adaptive function design is shown in Fig. 5.

Compared to the problem of isomorphic interference, heterogeneity introduces more complex dynamic tasks. Before creating a multimodal matrix, we need to address the process of semantic feature extraction, as shown in Fig. 6.

In order to solve the problem of protocol inoperability between heterogeneous devices, we need to organize and align the original data of received multimodal information, extract and fuse features, and perform normalization to convert scores from different models into a common scale. In the following, Z-score normalization is used, where the mean and standard deviation are calculated for each feature. The normalized value, denoted as x', is computed as follows:

$$x' = \frac{x - mean}{std}, \tag{11}$$

where x is the original value, *mean* is the mean of is the mean obtained for each feature value, and *std* is the standard deviation. By recording the information within the range of mean 0 and standard deviation 1 as the successful state and adding one, we obtain the information processed by normalization [18]. Finally, the normalized values are multiplied, and the larger the value, the better the link with the best performance.

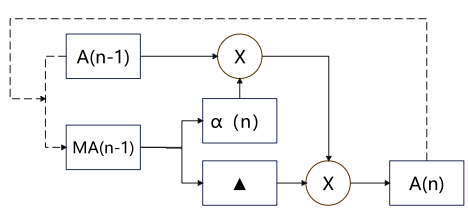

Fig. 5 Flowchart of the adaptive function design

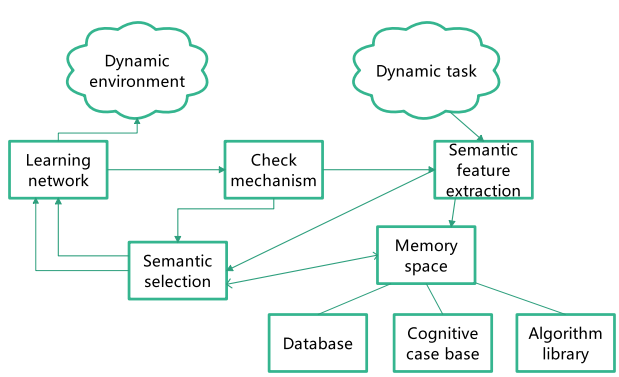

Fig. 6 Multimodal weighting mechanism design

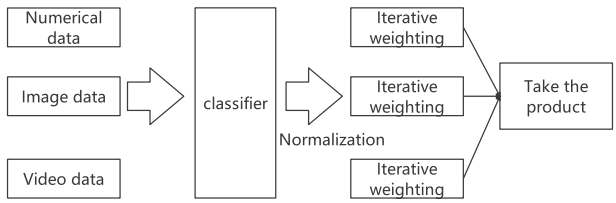

Fig. 7 Process of cognition processing

Each row of the matrix represents a function that can be carried out by a certain mode, and each column represents the modes that can complete the task. Among them, the object recognition function is common to multiple modes, which makes it the common mode. As a function after classifier classification, it participates in normalization processing and subsequent brain cognition (Fig. 7).

The above interference cancelation technology is based on resource allocation methods. By correctly planning and optimizing the spectrum, selecting power and time slot resources in the network, the system is able to find the links with the least interference between different networks. Through weighted iteration, the system is able to find the links with the lowest probability of information retransmission and the best channel quality. For example, in heterogeneous networks, interference caused by collisions is distributed through power weights to different networks within the same frequency band. Dynamic power control and time slots reduce the impact of interference signals Fig. 10.

4 Numerical results

To evaluate vector $\overrightarrow{A}$ generation accuracy in the AIoT system, the method of model classification can be adopted. By analyzing these classification results, the model accuracy can be evaluated and the performance of the AIoT system can be optimized. Higher values of $\overrightarrow{A}$ indicate better classification accuracy for this deep learning model [14, 15].

$$O = \frac{TP + TN}{TP + TN + FP + FN}, \tag{12}$$

where TP, TN, FP, and FN, respectively, represent correctly predicted positive cases, correctly predicted negative cases, incorrectly positive cases, and incorrectly predicted negative cases. By counting and analyzing classification results, we can evaluate the accuracy of the model and optimize the performance of the AIoT system. A higher value of A implies better classification accuracy for this deep learning model.

Using the above approach, the power of the interference signal in different channels is kept floating at a certain value until the simulation results shown in Fig. 8. The power of the interference signal decreases through several iterations of the heuristic weighting factor. Once a certain number of iterations is reached and the power of the interference signal no longer changes, the optimal transmission channel is found.

From Fig. 9, it can be observed that the probability of the base station selecting different channels is nearly equal when no learning is involved. There are approximately six highly popular channels.. Therefore, it is recommended to avoid using these six channels since adjacent links between transmitters and receivers on the same base station cannot effectively reuse channels.

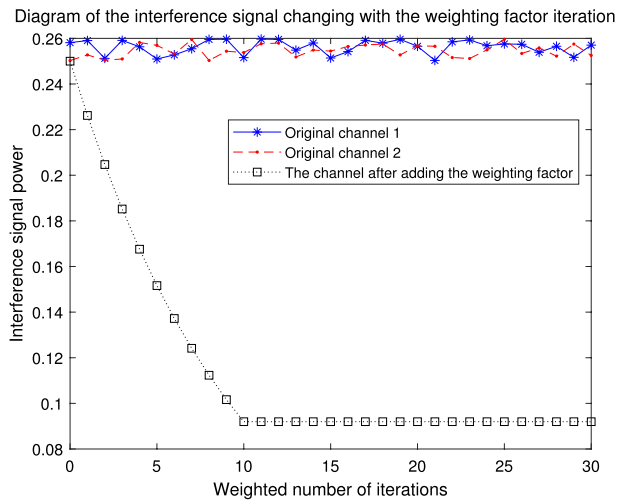

Fig. 8 Graph of iterative change of weighting factor

The heuristic weighting factor used in this paper for reinforcement learning is a delayed process. The base station needs to learn from experience by taking actions. The convergence rate, which reflects the time required for the base station to learn the preferred channel, is an important parameter to measure learning efficiency. Slow convergent learning in the initial phase can have harmful effects in terms of excessive interference at the base station. Figure 10 provides the time performance over an average of 10 simulation runs to represent the speed of the learning scheme. After reinforcement learning, the channel retransmission probability is minimized, and it can further reduce the retransmission probability through time accumulation.

5 Conclusion

By utilizing cognitive heuristics and deep learning in AGI AIoT brain cognition, this study proposes a comprehensive multimodal communication technology and weighting factor method to solve the separation of interference signals and improve communication quality in multimodal AGI AIoT communication. First, we utilized cognitive heuristics and deep learning techniques to extract relevant features between multiple perceptual modalities in AGI AIoT brain cognition. This allowed us to successfully separate interference signals and improve communication quality in multimodal AGI AIoT communication. The multimodal communication technology combines different modes of communication, such as audio, visual, and tactile, to enhance the communication capabilities of AGI AIoT systems. This allows for more robust and reliable communication, as multiple modalities can be used simultaneously to transmit information. Furthermore, we introduced a weighting factor method to optimize the communication quality. By assigning different weights to different modalities or channels, the system can dynamically adjust the allocation of resources based on the importance and reliability of each modality. This ensures that the most reliable and relevant information is given priority in the communication process.

The proposed multimodal communication technology and weighting factor method offer a promising solution to improve communication quality in AGI AIoT systems.

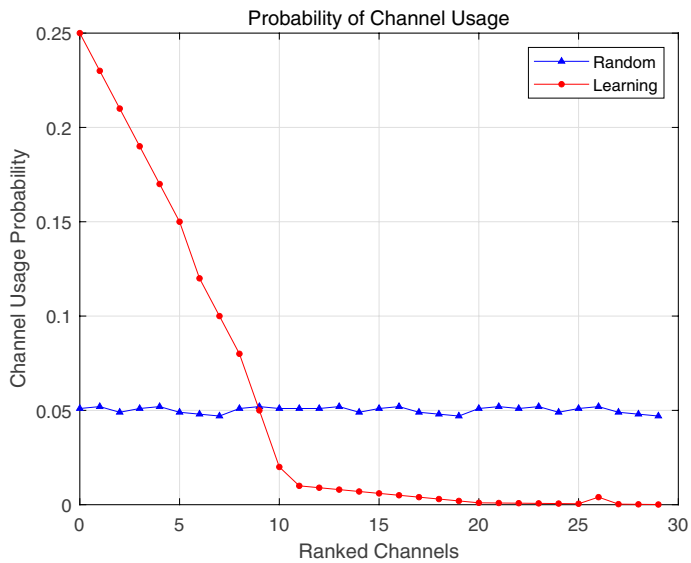

Fig. 9 Probability of channel usage

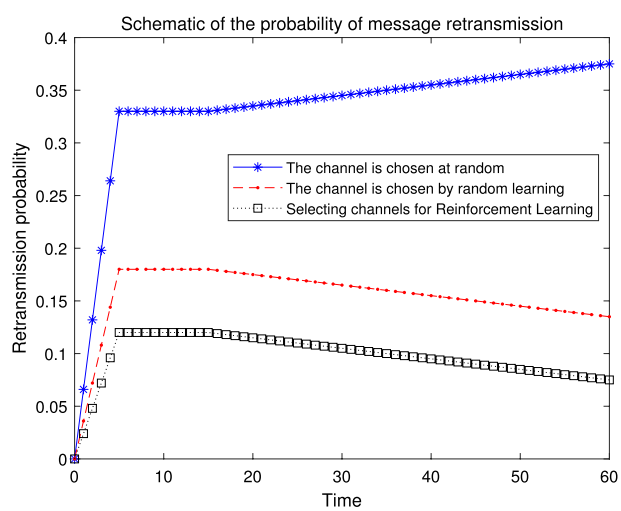

Fig. 10 Plot of information retransmission probability

The comprehensive utilization of AGI AIoT brain cognition and deep learning provide an effective solution to the interference problem in multimodal communication. These research findings contribute to the advancement of cognitive heuristics and deep learning in the field of AGI AIoT and have practical implications for the design and optimization of such systems. We encourage further research to delve into and optimize multimodal communication technologies, creatively employ cognitive heuristics and deep learning algorithms, and consider additional factors such as energy efficiency and security. These efforts will enhance the performance and practicality of AGI AIoT systems.

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Author contributions
CR provided the conceptualization and methodology design of the whole paper. JS performed the data analysis and implementation of the computer code and supporting algorithms. MQ and XW performed the formal analysis. YL performed the validation. CR and JS wrote the manuscript.

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Availability of data and materials
The data that support the findings of this study are available on request from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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