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Routing networking technology based on improved ant colony algorithm in space-air-ground integrated network

Wuzhou Nie[1], Yong Chen[1], Yuhao Wang[1], Peizheng Wang[1], Meng Li[1] and Lei Ning[1*]

*Correspondence: ninglei@sztu.edu.cn

[1] College of Big Data and Internet, Shenzhen Technology University, Shenzhen, China

Abstract

Space-air-ground integrated networks comprise a multi-level heterogeneous integrated network that combines satellite-based, aerial, and terrestrial networks. With the increasing human exploration of space and growing demands for internet applications, space-air-ground integrated networks have gradually emerged as the direction for communication network development. These networks face various challenges such as extensive coverage, diverse communication node types, low-quality communication links, and simultaneous operation of multiple network protocols. However, the rapid development and widespread application of artificial intelligence and machine learning technologies in recent years have offered new perspectives and solutions for the communication architecture and routing algorithm research within space-air-ground integrated networks. In these networks, not all nodes can typically communicate directly with satellites; instead, a specific set of specialized communication nodes facilitates data communication between aerial and satellite networks due to their superior communication capabilities. Consequently, in contrast to traditional communication architectures, space-air-ground integrated networks, particularly in the terrestrial layer, often need to address challenges related to the diversity of communication node types and low-quality communication links. A well-designed routing approach becomes crucial in addressing these issues. Therefore, this paper proposes an AODV routing network protocol based on an improved ant colony algorithm (AC-AODV), specifically designed for the terrestrial layer within the space-air-ground integrated networks. By integrating information such as the type, energy, and location of communication nodes, this protocol aims to facilitate network communication. The objective is to guide information flow through nodes that are more suitable for communication, either by relaying communication or by connecting with satellites through specialized nodes. This approach alleviates the burden on ordinary nodes within the terrestrial communication network, thereby enhancing the overall network performance. In this protocol, specialized nodes hold a higher forwarding priority than regular nodes. When a source node needs to transmit data, it enters the route discovery phase, utilizing its own type, location, and energy information as heuristic data to calculate forwarding probabilities. Subsequently, it broadcasts route request (RREQ) messages to find the path. Upon receiving the RREQ message, the destination node sends an RREP message for updating information elements and selects the optimal path based on these information elements. Compared to AODV, AC-AODV shows significant improvements in performance metrics such as transmission latency, throughput, energy conversion rate, and packet loss rate.

Keywords: Space-air-ground integration, Terrestrial layer network, Ant colony algorithm, Routing networking protocol

1 Introduction

The concept of the space-air-ground integrated network (SAGIN) has seen rapid development over recent decades, amalgamating advanced technologies such as the Internet of Things (IoT), cloud computing, artificial intelligence, and big data. Its primary aim is the seamless integration and interconnectivity between the physical and digital realms. Its evolution can be traced back to the early notions of the IoT. With continual technological advancements and widespread applications, the SAGIN has transitioned into reality [22].

SAGIN boasts several distinct features. Firstly, it offers extensive connectivity, enabling various physical devices, sensors, and smart terminals to communicate and interact seamlessly. Secondly, SAGIN emphasizes real-time data and intelligent processing capabilities. Utilizing big data analysis and AI algorithms, it extracts valuable insights from vast data troves, facilitating intelligent decision-making. Additionally, SAGIN places significant emphasis on security and privacy, employing multi-layered security measures to ensure the safety of data and systems [13].

The future trajectory of SAGIN leans toward increased intelligence, efficiency, and sustainability. As technology progresses further, networks will become more adept at autonomous learning and adaptation to diverse environments and requirements. Moreover, SAGIN will prioritize efficient resource utilization and energy sustainability. By optimizing energy consumption and enhancing resource efficiency, it will deliver more benefits for society and the environment [19].

In the context of the space-air-ground integrated network (SAGIN), both the maritime and terrestrial surfaces can collectively be considered as the ground network layer. The ground routing networking protocol plays a pivotal role within this layer. It is responsible for managing and maintaining tasks such as route selection, data transmission, and resource management among communication nodes in the ground network. This role ensures the efficient operation and reliability of the SAGIN.

The design of the ground routing networking protocol encounters multiple challenges. Firstly, owing to the heterogeneity of the SAGIN, the ground network encompasses various types of communication nodes, including sensor nodes, relay nodes, and base station nodes. These nodes exhibit diverse communication capabilities and coverage ranges. Broadly, these nodes can be classified into two types: ordinary nodes and special nodes. Ordinary nodes possess standard communication capabilities, such as communication range, bandwidth, transmission speed, battery power, etc., and generally cannot directly communicate with space-based or aerial networks. In contrast, special nodes have enhanced communication capabilities and can directly communicate with satellite or aerial networks.

Therefore, the ground routing networking protocol needs to consider these disparities in node types. It must intelligently select and manage communication paths among nodes to provide routing services adaptable to different application scenarios. Furthermore, the protocol must address challenges such as low communication link quality, high communication link time overhead, and the network expense incurred due to flood-based broadcast route request packets. Therefore, a rational research approach for communication networking within the ground network layer is crucial in overcoming these challenges [21].

With the continuous advancement of artificial intelligence (AI) technology, an increasing number of researchers are delving into the integration of machine learning algorithms to address technical challenges within the terrestrial network communication domain. These challenges encompass transmission channels, resource allocation, mobile access management, and network routing. For example, in the paper [11], the researchers proposed a study on maximizing communication throughput. Additionally, some scholars have integrated machine learning-based routing algorithms with distributed satellite cluster network routing algorithms to conduct studies within the space-based network domain. This paper primarily focuses on the design and implementation of routing algorithms in the space-air-ground integrated (SAGIN) network's terrestrial layer. Hence, it predominantly emphasizes the research domain of machine learning-based routing algorithms, proposing a routing networking protocol based on an enhanced ant colony algorithm [1].

The routing protocol based on an improved ant colony algorithm leverages the foraging behavior of ants to optimize the route selection process within the network, simulating the mechanism of pheromone deposition and evaporation in ants' path selection. Building upon the traditional ant colony algorithm, researchers have integrated machine learning techniques to enhance the performance and adaptability of the routing protocol [17]. Within this protocol, the establishment of an appropriate pheromone model serves as the initial step. By monitoring information such as communication quality, network topology, and node status, these data are mapped to initialize the pheromone values, dynamically adjusting them based on real-time network conditions. Subsequently, machine learning techniques are employed to learn from historical data and network state information, optimizing the pheromone update strategy. This adaptation addresses various communication demands and network fluctuations, addressing issues such as low communication link quality and the substantial network overhead caused by flood-based broadcast route request packets. There are also many researchers studying the integration of new research areas, such as RIS-UAV, to maximize the worst-case downlink secrecy rate for mobile vehicles [12].

In summary, we make the following contributions:

(1) A routing networking technology based on an improved ant colony algorithm tailored for space-air-ground integrated scenarios is proposed. This technique integrates the ground network routing technology of space-air-ground integrated networks with the ant colony algorithm from machine learning. It adapts the conventional ant colony algorithm model to suit the heterogeneous communication node scenarios within the existing ground network. This adaptation incorporates node types, communication locations, and remaining node energy into the state transition equations and pheromone update equations of the ant colony algorithm.

(2) In response to the network overhead issues caused by the traditional AODV routing protocol's reliance on minimum hop count path selection and flood-based broadcast route request data, enhancements were made considering the ground-level network scenarios within the space-air-ground integrated framework. Modifications were applied to the frame formats of RREQ and RREP messages. Additionally, OMNeT++ was employed for communication simulation, demonstrating notable improvements in communication performance metrics such as throughput, packet loss rate, and average end-to-end delay.

This paper is organized as below:

After the introductory section, the subsequent section delved into the current research status and motivations within the related field. Following that, the third section delineated the construction of the system model for space-air-ground integrated networks, while the fourth section elucidated the detailed process of algorithmic research. Moving on to the fifth section, we presented the parameters used in the simulation experiments and the resulting simulation outcomes. Finally, in the sixth section, we provided a comprehensive summary of the paper.

2 Related research and motivation

In this section, we briefly introduced the current status of related research in the field and the motivation behind this paper's study.

2.1 Related research

Although AODV routing protocol and ant colony algorithms were proposed by researchers over a decade ago [8, 16], many scholars in the modern field of communication networks still consider AODV as a starting point for achieving efficient routing and enhancing network communication performance. They often utilize machine learning techniques such as ant colony algorithms and genetic algorithms to optimize solution selection problems [2].

In recent years, especially in the emerging field of vehicular ad hoc networks, the AODV routing protocol has proven to be a highly efficient and effective communication solution due to the utilization of high-energy and computational resources of vehicular nodes. In this paper [4], Sbayti and colleagues integrated ant colony optimization (ACO) into link state routing to minimize network overhead and enhance routing efficiency in vehicular ad hoc networks. In this paper [23], Zheng integrated ant colony optimization into the cross-layer routing algorithm for space-air-ground integrated networks. Meanwhile, in the paper by Liu [9], a joint communication and trajectory optimization scheme for multi-UAV mobile vehicular networks was proposed. Additionally, the paper by Bijalwan et al. used the most adaptive node clustering to enhance vehicular ad hoc networks using ant colony optimization [14].

Moreover, AODV routing protocol has found application in the realm of unmanned aerial vehicles (UAVs). In the paper [6], Gupta compared and evaluated OLSR, DSDV, AODV, and DSR dynamic routing protocols in UAV scenarios, demonstrating that AODV outperformed all other protocols in such scenarios. In the paper [10], the researchers proposed fair and energy-efficient resource optimization techniques for unmanned aerial vehicle (UAV) Internet of Things (IoT) networks. Furthermore, in paper [3], researchers proposed an algorithm called 'access residual energy-based efficient routing (AREBER),' incorporating the remaining energy of communication nodes as a vital evaluation parameter in conjunction with MANET for simulation assessment.

2.2 Mobility modeling

Due to the complexity of the space-air-ground integrated network, there exists a vast array of heterogeneous communication nodes in the ground layer network. These encompass various sensors, terminal devices, and network infrastructure. Hence, mobile ad hoc networks are better suited for the current scenario, bridging the gap between the space-based and ground-based networks. However, the communication capabilities of these nodes, including communication range, node energy, and transmission speed, vary significantly. Therefore, using traditional ad hoc on-demand distance vector (AODV) networking technology could result in challenges such as reduced communication efficiency and substantial network overhead due to the heterogeneous nature. These limitations constrain the performance and reliability of the ground layer network, consequently impacting the overall communication capabilities of the space-air-ground integrated network.

To overcome these challenges, this study integrates traditional AODV networking technology with the ant colony algorithm from machine learning. By incorporating the type, location, and remaining energy of communication nodes into the ant colony algorithm's information pheromones, intelligent routing decisions are made to enhance the communication efficiency and stability of the ground layer network within the space-air-ground integrated network [15]. The ant colony algorithm, simulating the behavior of ant colonies, is an optimization algorithm characterized by its distributed and adaptive nature. It effectively tackles the challenges posed by the heterogeneity of communication nodes in the ground layer network. By introducing the ant colony algorithm, this research aims to intelligently select communication paths, allowing the communication links in the ground layer network to better meet communication requirements, thereby enhancing data transmission reliability and real-time capabilities [7, 18].

3 System model

The space-air-ground integrated (SAGI) network is a heterogeneous network that incorporates sea, land, and air layers. It can be broadly categorized into satellite networks, aerial networks, and terrestrial networks, with the terrestrial layer encompassing both sea and land surfaces.

As shown in Fig. 1, the SAGI model comprises communication satellites in the space-based network, drones in the aerial network, and signal towers, ships, and land-based communication devices in the terrestrial network [5, 20].

In this paper, we primarily focus on the routing issues in the ground layer communication network. The communication infrastructure in the ground layer network mainly includes buildings, vehicles, communication stations, signal towers, ships, and so on. These communication facilities constitute the main components of the ground layer communication network.

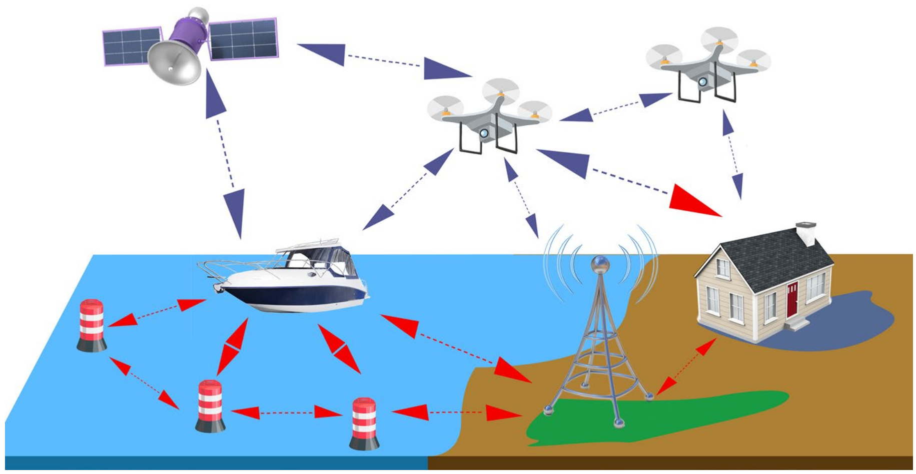

Fig. 1 The system model of space-air-ground integrated network

The routing issues within the communication network of the ground layer can be understood as the establishment and utilization of routing tables to guide data flow, ultimately maximizing network performance based on certain metrics. For each node in the network, the aim is to use local routing tables to select the optimal transmission path, directing incoming data toward their intended destinations.

In ground layer network communication, the communication nodes are initially categorized into special nodes and regular nodes. Only special nodes can communicate directly with satellites, all nodes are equipped with location devices that can translate their geographical position information into corresponding coordinates. The communication scenarios in the ground layer network are subdivided into the following scenarios:

(1) When regular nodes proactively establish communication among other regular nodes or special nodes, to expedite network establishment, priority is given to utilizing more robust communication-capable special nodes (network base stations, dedicated communication relay nodes, etc.).
(2) When special nodes need to relay instructions or signals issued by satellites to regular nodes, selecting paths involving special nodes takes precedence to reduce energy consumption in regular communication nodes and improve transmission speed and communication quality, thereby transferring the burden of the regular node link to the special nodes with stronger communication capabilities.

4 Ant colony optimization-based AODV routing for network formation

The ant colony optimization (ACO) is an optimization algorithm that simulates the collective behavior of ants searching for food. It was proposed by Italian computer scientist Marco Dorigo in 1992, inspired by the cooperative behavior of real ant colonies. The core idea of the algorithm is to mimic the movement of ants in exploring solution spaces to find the optimal solution for a given problem. It is primarily used for solving combinatorial optimization problems like the traveling salesman problem, scheduling problems, path planning, among others. The basic principle of the ACO algorithm is as follows:

(1) Ant Movement Simulation: In the solution space of the problem, each possible solution is regarded as a node on a path. Ants move through this solution space based on certain rules, navigating via these nodes. Each ant probabilistically selects the next node based on two factors: the concentration of pheromones on the path and heuristic information between nodes.
(2) Pheromone Update: Ants release a substance known as "pheromones" along their path. The concentration of pheromones indicates the quality of the path; the more frequently an ant chooses a specific path, the higher the concentration of pheromones on that path. Mechanisms for pheromone evaporation and update ensure a continuous update of pheromones to prevent getting stuck in local optimal solutions.
(3) Heuristic Information: Apart from pheromones, ants are also influenced by heuristic information during their movement. This heuristic information provides prior knowledge about nodes in the solution space, guiding the ants' movements. It can include details like distances, costs, or other relevant node information.
(4) Global Pheromone Update: Once all ants complete their movement, there is a global update of pheromones, impacting the next round of ant movements.
(5) Iteration: Through multiple iterations, the ant colony algorithm gradually converges toward the optimal solution or an approximate optimal solution for the problem.

The improved ant colony algorithm-based protocols for wireless ad-hoc networks typically perform path discovery by sending multiple control messages (akin to ants in the ant colony algorithm). With an increase in the number of control messages, the accumulated pheromones on well-performing links also increase, thereby accelerating the algorithm's convergence. Eventually, this leads to the selection of a path that meets specific metric criteria.

The traditional AODV routing protocol uses distance vectors as a measure for routing, establishing route paths based on the minimum number of hops. However, in the context of the space-air-ground integrated terrestrial networks, the presence of heterogeneous communication nodes with varying communication capabilities (limited communication capabilities and energy constraints for ordinary nodes) and the requirement for specific special nodes to communicate with the space-based network render the minimum hop count unsuitable as a measure.

Therefore, there is a need for a new metric, aiming to introduce node forwarding probabilities to reduce the number of control message transmissions by ordinary nodes. Hence, it is possible to selectively adopt the concept of pheromones from the ant colony algorithm into AODV to assess the state of links. By incorporating heuristic information regarding type, energy, and location into the state transition probability model and pheromone update model, the aim is to fully leverage the advantages of special nodes. This approach prioritizes the selection of special nodes and determines forwarding probabilities by computing link states, effectively reducing the transmission of control messages by ordinary nodes, thereby alleviating congestion in the ground-based network.

4.1 The improved ant colony algorithm's state transition probability model

The node type, remaining energy, and node position are three key factors that need to be carefully considered when designing routing protocols for the ground-level network. To reduce energy consumption among regular nodes and improve the speed and quality of network communication, we have chosen to utilize these three factors to assess the quality of communication link status.

In the traditional AODV routing protocol, the RREQmessage is typically broadcasted, meaning it does not specify the next hop address, and all nodes within the transmission range of the sending node can receive this message. Therefore, concerning the state transition probability model, the decision for the current node to forward depends on the link status between the previous hop and the current node itself.

Therefore, if the next node is within the communication range of the current relay node, the forwarding probability $P_{i,j}$ for the current intermediate node i when forwarding the RREQ message is calculated as follows:

$$Pij = 2\arctan\left(\frac{[\tau(\mathrm{s,i-1})]^{\alpha}[\eta(\mathrm{i-1,i}]^{\beta}}{\tau(\mathrm{s,i})}\right) \tag{1}$$

where $\tau\left(i,j\right)$ represents the concentration of information pheromone from node s to node i in the network, and $\left(i,j\right)$ denotes the heuristic information from node i to the previous hop node $(i-1)$. If node j is not within the communication range of node i, the probability received is 0.The factors α and β represent the pheromone and heuristic influence factors, respectively, governing the significance of the pheromone concentration and heuristic information on probability. Equation (1) normalizes the forwarding probability using an arctan function.

$$\eta(i-1,i) = \frac{\alpha\mu(i-1,i) + b\sigma}{H_k} \tag{2}$$

Equation 2 represents distance vector heuristic information computed based on location data; σ_i signifies the energy heuristic information derived from node energy data; a and b are constants representing the weighting parameters for distance vector and energy heuristic information, respectively; H_k indicates the number of hops in the routing path. To maximize the communication advantage of the special node, the weighting parameters a and b for the special node should be greater than those for the regular node.

$$\mu(i-1,i) = \frac{d}{R} \tag{3}$$

In Eq. 3, the R represents the transmission range radius of the node, d signifies the distance between the relay node and the previous hop node, where $0 \le \mu(i-1,i) \le 1$.

$$\sigma_i = \frac{E_c}{E_i} \tag{4}$$

The E_c represents the current remaining energy of the node, and the E_i stands for the initial energy of the node, where $\le \sigma(i-1,i) \le 1$.

Type	J	R	G	D	U	Reserved	Hop count
RREQ ID							
Destination IP address							
Destination Sequence Number							
Originator IP Adress							
Originator Sequence Number							

Fig. 2 The original RREQ frame format

Type	R	A	Reserved	Prefix Size	Hop count
Destination IP address					
Destination Sequence Number					
Originator IP Adress					
Lifetime					

Fig. 3 The original RREP frame format

4.2 The improved ant colony optimization information update model

When the destination node has been reached, it is necessary to increase the corresponding information along the return journey. This allows for a preference in subsequent communication processes to select paths with better link states, directing more data packets toward special nodes. This minimizes the hop count for ordinary nodes and their energy consumption. In the RREP message, the concentration of information will be updated to:

$$\tau(s,i) = (1-\rho)\tau(s,i-1) + \Delta\tau(i-1,i) \tag{5}$$

In this context, ρ represents the information evaporation factor, while $(1-\rho)$ denotes the information retention factor. $\Delta\tau(i-1,i)$ refers to the increment in information concentration needed from the previous hop node $i-1$ to node i:

$$\Delta\tau(i-1,i) = \frac{a\mu(i-1,i) + b\sigma_i}{H_k} \tag{6}$$

4.3 AC-AODV

The conventional AODV (ad hoc on-demand distance vector) networking protocol utilizes distance vector standards to select the next-hop node. Furthermore, it only initiates a route request when a node requires routing to transmit data. AODV operates with three primary control packets: Route Request (RREQ), Route Reply (RREP), and Route Error (RRER). Additionally, nodes in AODV transmit HELLO packets to maintain neighboring information.

In AC-AODV, modifications to the frame formats of the original RREQ and RREP packets from AODV are required. The frame formats before modification are shown in Figs. 2 and 3, while the improved frame formats are shown in Figs. 4 and 5. In the RREQ

<table>
<tr><th>Type</th><th>J</th><th>R</th><th>G</th><th>D</th><th>U</th><th>Reserved</th><th>Hop count</th></tr>
<tr><td colspan="8">RREQ ID</td></tr>
<tr><td colspan="8">Destination IP address</td></tr>
<tr><td colspan="8">Destination Sequence Number</td></tr>
<tr><td colspan="8">Originator IP Adress</td></tr>
<tr><td colspan="8">Originator Sequence Number</td></tr>
<tr><td colspan="5">Node Type</td><td colspan="3">Location Information</td></tr>
<tr><td colspan="8">Pheromone Content of Path List</td></tr>
</table>

Fig. 4 The improved RREQ frame format

<table>
<tr><th>Type</th><th>R</th><th>A</th><th>Reserved</th><th>Prefix Size</th><th>Hop count</th></tr>
<tr><td colspan="6">Destination IP address</td></tr>
<tr><td colspan="6">Destination Sequence Number</td></tr>
<tr><td colspan="6">Originator IP Adress</td></tr>
<tr><td colspan="6">Lifetime</td></tr>
<tr><td colspan="4">Node Type</td><td colspan="2">Pheromone Increment</td></tr>
<tr><td colspan="6">Pheromone Content of Path List</td></tr>
</table>

Fig. 5 The improved RREP frame format

packet, additional fields are introduced, including node type to differentiate between ordinary and special nodes, location information for computing distance vector heuristic data, and added fields to store path list information element contents. Similarly, in the RREP packet, node type is added to distinguish between ordinary and special nodes. Additional fields are included to store information element increments and path list information element contents.

The route discovery mechanism in AODV is achieved through RREQ (Route Request) and RREP (Route Reply) packets. AODV periodically sends HELLO messages to establish a neighbor routing table. When a source node has data to transmit but lacks a valid path to the destination node, it sends an RREQ packet for route discovery. Each intermediate node that receives this packet broadcasts it, and this process continues until the destination node is found or until a valid path to the destination node is discovered. Subsequently, an RREP packet is sent back to update the routing table entry.

During the route discovery process, there is a significant amount of RREQ packet exchanges. In the energy-constrained environment of ground-level networks, this is highly unfavorable due to the scarcity of energy resources. Hence, an improved routing protocol should aim to minimize the number of RREQ broadcast instances to reduce energy consumption. Additionally, this protocol should introduce a novel metric, no longer prioritizing minimal hop count but favoring the transmission of information through nodes with stronger communication capabilities, notably the special nodes.

The routing diagrams for AODV and AC-AODV are depicted in Figs. 4 and 5. Black nodes represent regular nodes, while blue nodes represent special nodes. Blue arrows indicate the transmission paths for RREQ, and orange arrows denote the transmission paths for RREP. Node A is the source node, and G is the destination node. When node A intends to send data to node G but does not possess a valid route to node G via node E, it initiates a route discovery phase.

Node A generates an RREQ packet and broadcasts it. The entire network uses a flooding mechanism to propagate the RREQ packets until the destination node is located. However, the flooding propagation can lead to broadcast storms, causing network congestion, and in severe cases, network paralysis. Additionally, when the number of hops for regular nodes decreases, node E chooses the path A-C-E-G and responds with an RREP packet.

In AC-AODV, as nodes C and E are regular nodes with relatively weaker communication capabilities, the link status can be considered poorer. Consequently, the calculated transmission probabilities based on heuristic information are smaller, thereby reducing the dissemination of RREQ packets to some extent. Upon receiving the RREQ packet, the destination node then selects a path containing special nodes based on the information element. At this point, node G selects the path A-B-D-F-G and responds with an RREP packet.

(1) If the routing table does not contain a forwarding path to the destination node, the source node broadcasts an RREQ packet.
(2) The intermediate node receiving the RREQ packet checks whether it is the destination node or if there exists a valid route to the destination. If affirmative, it proceeds to step 3. If not, it evaluates whether it is a special node, computes the transition probability using formula (1) based on values a and b, and broadcasts a new RREQ packet according to this probability.
(3) The destination node receives the RREQ packet or the intermediate node has already found a valid route to the destination. According to formula (5), it calculates the required information update, writes it into the RREP packet, and then sends it.
(4) The intermediate node receives the RREP packet from the destination within the specified time, updates the information accordingly, calculates the necessary updates based on formula (5), writes them into the RREP packet, and continues unicasting.
(5) The source node, upon receiving the RREP packet from the destination within the specified time, updates the information related to the information elements, updates its local routing table to the destination, directly sends data packets to the next-hop node, and initiates data transmission.

By integrating the concept of information elements from ant colony optimization, combining node types, computing energy, and positional information to derive the concentration of information elements as a new metric, in the process of probabilistic forwarding, it is possible to reduce the signaling interaction between nodes with poorer link states. This aims to reduce energy consumption, improve communication speed and quality, while amplifying the importance of special nodes. Consequently, during the routing process, priority is given to selecting special nodes, reducing the hop count for communication links involving ordinary nodes.

5 Performance evaluation

This research utilizes the OMNeT++ communication simulation software, with a simulated network area measuring 10 km in length, 5 km in width, and 0.1km in height. The primary focus is on simulating the ground-layer network. Within this ground-layer network, several special and ordinary nodes are randomly distributed. As shown in Table 1, the simulation parameters are presented with the conventional AODV protocol selected as the control.

(1) End-to-end delay: The comparative transmission delays for varying node counts are depicted in Fig. 6. Generally, AC-AODV exhibits slightly lower transmission delays compared to AODV.

During the initial stages of operation, when nodes need to send data packets without finding valid paths, these packets must be stored in queues. The delay caused by queuing

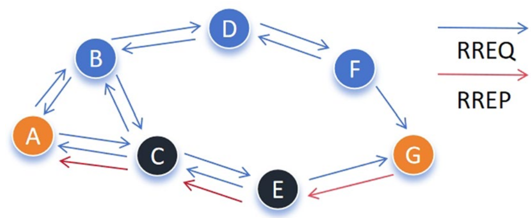

Fig. 6 The schematic diagram for AODV route discovery

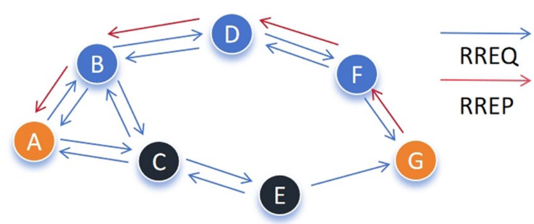

Fig. 7 The schematic diagram for AC-AODV route discovery

Table 1 Simulation parameters

	Parameter	Value
1	Number of normal nodes	10,20
2	Number of special nodes	5
3	Transmission range of normal nodes	1km
4	Transmission range of special nodes	2km
5	Normal node energy	5000J
6	Special node energy	20000J
8	Packet length	200 byte
9	Packet transmission interval	5s
10	α, β, ρ	0.4,2,0.4
11	Weight parameters a,b of normal nodes	1,1
12	Weight parameters a,b of special nodes	0.4,0.4
13	Data bandwidth of normal nodes	125k
14	Data bandwidth of special nodes	1M
15	Operating frequency of nodes	2.4G

and waiting causes an increase in average delay. As the simulation continues, the communication environment stabilizes gradually, leading to stabilized delays.

(2) Transmission success rate: As shown in Fig. 7, the success rate of transmission stands as a crucial metric in network performance, impacting both reliability and efficiency. Congestion within the network can lead to increased collisions and delays, subsequently resulting in a higher rate of packet loss. In such instances, some data packets might fail to reach their destination due to the excessive load on the network. Network congestion tends to trigger packet conflicts and transmission delays, thereby diminishing the overall transmission success rate.

(3)The forwarding count for route request packets: AC-AODV calculates information pheromones based on node type, energy, and location data. Utilizing these calculated probabilities, it forwards RREQ route request packets. This approach helps reduce the frequency of RREQ route requests, alleviating the communication pressure along the entire network links. Figure 8 illustrates the total forwarding count of RREQ route request packets within the network during the initial 300 s. As observed, AC-AODV exhibits significantly fewer forwarding instances compared to AODV (Figs. 9, 10).

6 Conclusion

In this paper, we analyzed the routing and networking protocols of the ground layer network in the space-air-ground integrated (SAGI) system. It combines the ant colony algorithm from machine learning and proposes an AC-AODV routing protocol based on the improved AODV, considering node type, position, and energy. AC-AODV defines distinct state transition probability models and information update models for regular and special nodes. To address the vast and diverse communication nodes in the existing SAGI ground layer network, the enhanced AODV prioritizes evaluating the communication link quality during route discovery and calculates forwarding probabilities for route discovery packet forwarding. This effectively reduces data packet exchange between regular nodes or nodes with weaker communication link quality, minimizes communication hops, and leverages nodes with stronger communication capabilities, thereby enhancing the overall communication capabilities of the ground layer network. Compared to

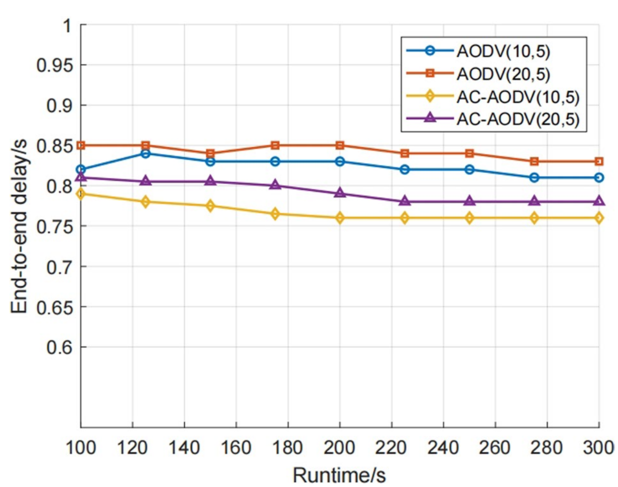

Fig. 8 The end-to-end delay diagram

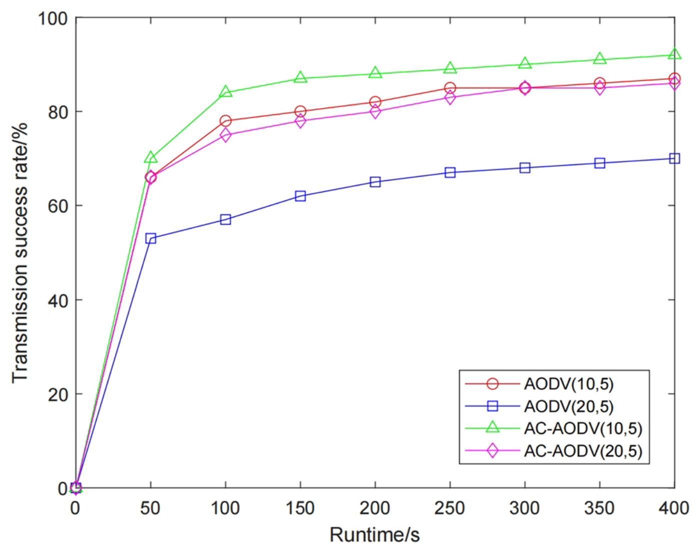

Fig. 9 The transmission success rate diagram

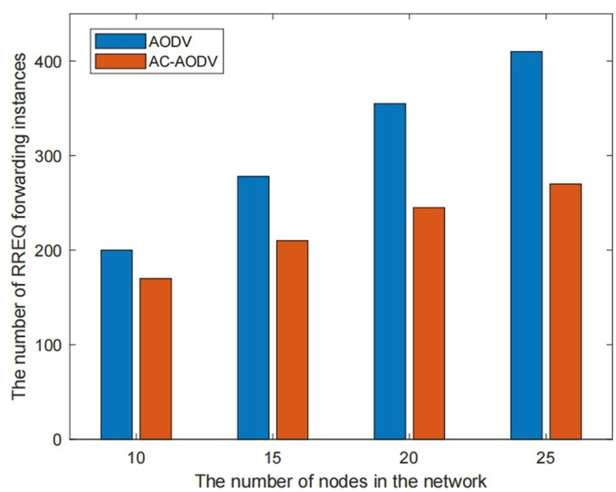

Fig. 10 The forwarding count for route request packets

traditional AODV networking protocols, AC-AODV exhibits improvements in communication metrics such as packet loss rate, end-to-end transmission delay, and route discovery packet forwarding counts.

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Author Contributions
WN and YC were responsible for research design, experimental operations, data collection and analysis, and manuscript writing. YW handled the literature processing. PW and ML provided guidance and support. LN was responsible for guiding the manuscript revisions and provided valuable suggestions and comments throughout the research design, result interpretation, and manuscript writing stages.

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Consent.

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

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