Path Planning Based on Clustering and Improved ACO in UAV-assisted Wireless Sensor Network

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***Abstract*—UAVs as mobile nodes have been introduced into wireless sensor network (WSN) to assist information transmission and reduce the burden of communication. To minimize the path cost of UAVs for information transmission, this paper focuses on the path planning of UAVs. A multi-UAVs path planning combined K-means clustering algorithm and improved MAX-MIN ant system (MMAS) is proposed. This algorithm apply the K-means clustering algorithm to reduce the problem size and improve the search efficiency of subsequent path planning. By modifying the node search rules and proposing two optimal solution detection rules of the MMAS, the algorithm searching stagnation and failing into local optimal solution are effectively avoided.**

Keywords—UAV; K-means clustering algorithm; path planning; MAX-MIN ant system

I. INTRODUCTION

Low energy consumption, as one of the main requirements of WSN, limits the transmission distance and efficiency in some extend [1]. The participation of UAVs can not only assist the data transmission from wireless sensors, but also in recharging them. Hence, the rise of UAV is beneficial to enlarge the coverage of WSN. The process of UAV path planning is one of important steps in data collection ant colony algorithm (ACO) is one of the most common algorithms in UAV path planning [2]. With the increase of the number of nodes, the computational size of path planning increases significantly. Unfortunately, the traditional ACO is not suitable in this case [3]. To address this issue, this paper proposes an improved algorithm that the first step is to use K-means algorithm to cluster the sensor nodes, then the improved MMAS is proposed to solve the problem that the traditional algorithm easily falls into the local optimal solution.

The rest of this paper is organized as follows: Section II describes system model. Section III explains the proposed algorithm. Section IV provides the simulation results.

II. MULTI-UAVS PATH PLANNING MODEL

UAVs start from the base and return to the base after executing all sensor nodes. Consider M UAVs denoted as $V=\{V_1,V_2,\cdots,V_M\}$ and divide N sensor nodes $T=\{T_1,T_2,\cdots,T_N\}$ into a series of clusters $C=\{C_1,C_2,\cdots,C_k\}$, which meet:

$$\begin{cases} M=k \\ C_1\cup C_2\cup\cdots\cup C_k=T=\{T_1,T_2,\cdots,T_N\} \\ C_{k_1}\cap C_{k_2}=\Phi,\forall k_1\neq k_2;k_1,k_2=1,2,\cdots,k \\ C_k\neq\varnothing \end{cases} \tag{1}$$

i.e., the number of clusters is determined by the number of UAVs, and each sensor node is executed by only one UAV.

III. THE PROPOSED ALGORITHM

A. K-means Clustering Algorithm

The K-means clustering algorithm selects k nodes as cluster centers firstly and calculates the Euclidean distance between nodes and cluster centers [4]. For each target, it is divided into the nearest cluster. After each clustering, the center of the new clusters is the mean of each cluster. This process is repeated until the center of the cluster no longer changes or the maximum number of iterations is reached.

B. MAX-MIN Ant System

Thomas Stutzle et al. proposed the MAX-MIN ant system to solve the problem of premature convergence. m ants were randomly placed on the n sensor nodes, $m<n$. The transfer rule of each ant is shown in the formula (2).

$$p_{ij}^k(t)=\begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{j\in allowed_k}\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} & ,j\in allowed_k \\ 0 & ,j\notin allowed_k \end{cases} \tag{2}$$

where, $p_{ij}^k(t)$ is the state transition probability of the k^{th} ant from node i to node j at time t; $allowed_k$ is the searchable set of the k^{th} ant, i.e. $allowed_k=Tabu_k$; η_{ij} is the heuristic function, and generally $\eta_{ij}=1/d_{ij}$, d_{ij} is the the Euclidean distance between node i and node j; $\tau_{ij}(t)$ is the pheromone concentration for path section (i,j), $\tau_{ij}(0)=1$; α and β are information heuristic factors and expectation heuristic factors.

When all ants searched for the next respective node, the local pheromone is updated as shown in (3) [5].

$$\tau_{ij} = (1-\rho)\tau_{ij} \tag{3}$$

where ρ is pheromone evaporation coefficient.

When the ant completes the full path search the global update of the pheromone is needed, which is described by

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho / L_{\min} \tag{4}$$

where $L_{\min}$ is the minimum path value in this iteration.

At the same time, in order to avoid algorithm stagnation, pheromone concentration on the path needs to be limited to $[\tau_{\min}, \tau_{\max}]$.

C. Improved MAX-MIN Ant System

Before global pheromone update we propose two optimization rules, that is cross-comparison and optimal solution detection, and redefine the formulas of $\tau_{\min}$ and $\tau_{\max}$.

The first rule randomly selects two sensor nodes on the path and reverse the order of all nodes between them. Then it calculates the path length and chooses the shorter path. In order to avoid the algorithm falling into the local optimal solution, the optimal solution detection rule is applied. If the shortest path length doesn't change within 40 iterations, the value of β is adjusted to try to jump out of the current optimal value. β is described by

$$\beta = \beta / N*best\_ant \tag{5}$$

where $best\_ant$ is the total number of ants on the optimal path in this iteration.

The formulas of $\tau_{\min}$ and $\tau_{\max}$ are redefined. $\tau_{\min} = 1/10n$ is the minimum concentration of pheromone on the path; $\tau_{\max} = 1/\rho L_{\min}$ is the maximum concentration of pheromone on the path.

IV. Simulation Result and Analysis

Both MMAS and improved MMAS set up parameters as $m = 30$, $\alpha = 1$, $\beta = 5$, $\rho = 0.1$, the maximum number of iterations is 100. UAV base coordinate is (0,0), and the sensor nodes are within $x \in [50,100], y \in [50,100]$. Three UAVs collect data from 40 sensor nodes.

The paths of MMAS and Improved MMAS algorithm are illustrated in Fig.1. The minimum distance and the average distance of two algorithms are shown in figure 2. We can observe that path length obtained by improved MMAS is shorter. After 80 iterations, the improved MMAS adjusts the β value to jumps out of the local optimal solution.

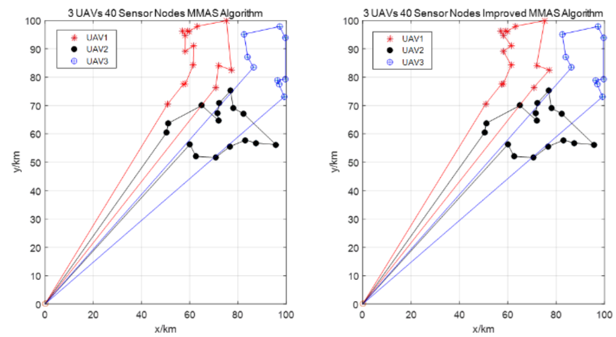

Fig.1. The Path Planned by MMAS and Improved MMAS

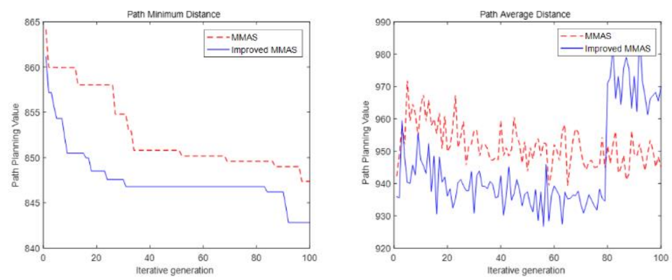

Fig.2. Minimum Distance and Average Distance

We testify the effectiveness of improved MMAS by comparing the shortest path length generated by two algorithms. Each case was be simulated 200 times as shown in Table 1.

TABLE I. Result of Simulation

Number of nodes	10	20	30	40
Optimization rate	0.011%	0.028%	0.056%	0.266%
Number of nodes	50	60	70	80
Optimization rate	0.368%	1.013%	1.575%	2.008%

As seen from Table 1, the performance of the improved algorithm is better with the increase of the number of nodes.

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