Location Optimization of Wireless Sensor Network in Intelligent Workshop Based on the Three-Dimensional Adaptive Fruit Fly Optimization Algorithm

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Abstract—The production process of modern manufacturing industry is complex and changeable, manufacturing resources have extensive dynamic characteristics. For effectively managing and controlling manufacturing resources, realizing real-time location data collection of intelligent workshop, a manufacturing resource location sensing architecture based on the wireless sensor network is proposed. For ensuring real-time accuracy of manufacturing resource location data in the intelligent workshop, a three-dimensional adaptive fruit fly optimization algorithm is designed to estimate the location coordinates, the new algorithm introduced the adaptive inertial weight coefficient, retained the advantage of strong local search ability of fruit fly optimization algorithm, improved the ability of global optimization, effectively solved the problem of three-dimensional location in intelligent workshop. The simulation results show that, the algorithm in this paper is applied to the location calculation of triangulation, which has smaller location error and shorter operation time, it improves the accuracy of the location data and meets the real-time location requirements of manufacturing resources such as intelligent workshop staff, materials, logistics vehicles etc. facilitate resource sensing and scheduling management, thereby improving management standards and product quality.

Keywords—intelligent manufacturing, wireless sensor network, node location, fruit fly optimization, location error

1 Introduction

As a new type of manufacturing mode, Internet of manufacturing things is a technology contains highly integrated and mixed together with electronic information technology, intelligent sensing technology and advanced manufacturing technology. It is beneficial to the intelligent upgrading and transformation of manufacturing process and the realization of intelligent workshop. Modern manufacturing industry has features like product variety, complex process and numerous suppliers and customers. Its production process is complex and changeable. The manufacturing resources such as raw material, equipment, tooling mold, site and operator have extensive dynamic characteristics, for effectively management and control manufacturing resources, to ensure the safety of the enterprises, improve the production efficiency, promote the intelligent development of the manufacturing industry, real-time and effective production data location collection becomes very necessary.

The traditional location application GPS cannot solve the problem of manufacturing workshop location effectively because of the limitation of manufacturing workshop scene, installation cost and other factors. As a new information sensing technology, wireless sensor network (WSN) is composed of a large number of static or mobile sensing nodes, with the characteristics of low cost, low power consumption, self-organization, large coverage area, etc., which have been widely used and popularized in military, industry, agriculture, medical and other fields to complete things detection, event detection and target tracking in the network deployment area.

In the current engineering application field, range-based localization algorithm with higher accuracy is often adopted. However, under the effects of electromagnetic interference and manufacturing resources in manufacturing workshop, it exists low location accuracy, poor real-time and high location failure rate and other problems. Therefore, it is necessary to optimize the localization algorithm to improve the location accuracy and ensure the accuracy of location data. In recent years, particle swarm optimization (PSO), ant colony algorithm (ACO), artificial bee colony algorithm (ABC), fruit fly optimization algorithm (FOA) and other swarm intelligence optimization algorithms have been widely used in WSN node location optimization, achieved significant results. However, in the manufacturing workshop environment, three-dimensional (3D) location data collection of manufacturing resources can better reflect the integrity of the data, but only few researches on the optimization of 3D spatial location of WSN nodes.

Accordingly, in order to meet the need of high-precision 3D location of manufacturing resources in intelligent workshop, introduces an adaptive inertial weight coefficient to the FOA and proposes a 3D adaptive fruit fly optimization algorithm (3D-AFOA) to the calculation of triangulation to optimize node location in WSN. On the basis of preserving the local search ability of FOA, the design algorithm improves the running efficiency and enhances the ability of global optimization. The simulation results show that the design algorithm has strong local optimization ability and high efficiency of operation, can effectively find the minimum estimated coordinates of location error, efficiently locate 3D nodes and is conducive to achieving high precision location in the workshop to promote the realization of intelligent manufacturing.

2 Location sensing architecture for intelligent workshop

Currently the main problems in modern manufacturing industry include: backward technology of real-time manufacturing information collection; weak real-time monitoring ability of production process; low level of production site control; inflexible mechanism of data sharing and feedback in production. In view of the existing problems of modern manufacturing enterprises, intelligent workshop can realize the interconnection of production workshop automatic control equipment and manufacturing execution system, the data such as production plan and task execution and quality information of in-process products are collected in real-time and interacted with the enterprise management information system to realize the cooperative application of information data.

Therefore, this paper proposes a location sensing architecture for intelligent workshop as shown in Figure 1, which can effectively match the manufacturing resources of the intelligent workshop, the real-time location data of manufacturing resources are collected and analyzed and integrated with enterprise resource management system and workshop manufacturing execution / control system. Through collecting effective real-time location information to consummate the integrality of manufacturing data, strengthen the management and business application of manufacturing data thus can forecast, monitor and analyze the events in manufacturing process and provide decision basis for production managers.

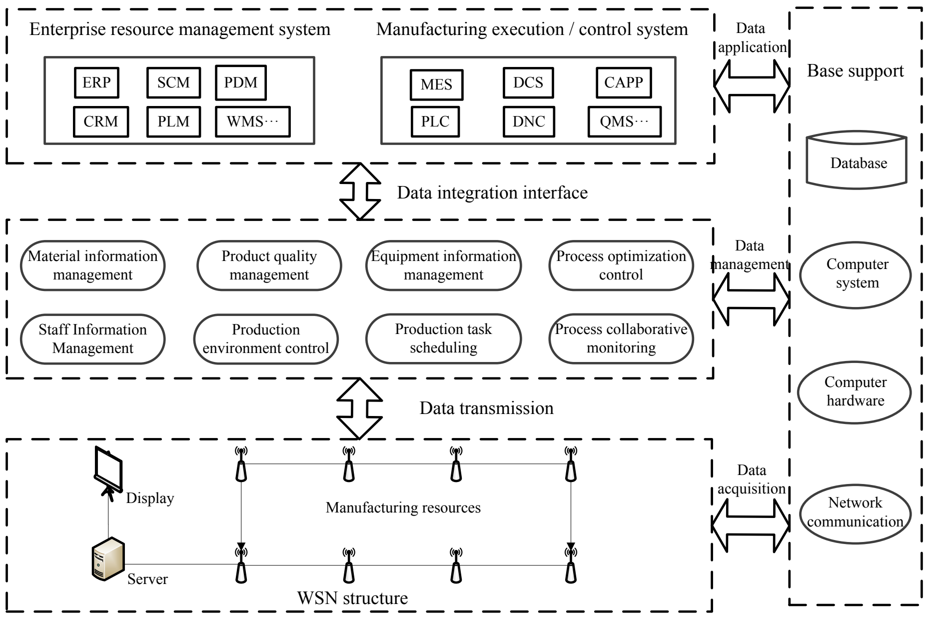

Fig. 1. Location sensing architecture for intelligent workshop

3 The optimization of location method based on the 3D-AFOA

3.1 The 3D-AFOA

FOA is a new swarm intelligence optimization algorithm, which was proposed by Taiwanese scholar Pan Wenchao in 2011, he studies the complex foraging relationship of fruit fly. Compared with other traditional swarm intelligence optimization algorithms, this algorithm has the advantages of easy to understand, less parameter setting, small computing space and strong global optimization ability. It is widely used in solving various practical problems of optimization.

In order to overcome the disadvantages of FOA which is easy to fall into local optimum, combined with the strong global optimization ability of PSO, aiming at the need of 3D location of manufacturing resources in intelligent workshop. By introducing adaptive inertia weight coefficient from PSO, a 3D-AFOA is proposed, in which the specific flow of the algorithm is as follows:

Step 1: Algorithm initialization. Setting the population size of fruit fly *Size pop*, iteration times of algorithm *Maxgen*, and initializing the population position of fruit fly (X_{axis}, Y_{axis}, Z_{axis}), introducing adaptive inertial weight coefficient ω where is shown in formula (1), g is the current iteration number;

$$\omega = cos\left(\frac{g\times\pi}{4\times Maxgen}\right) \tag{1}$$

Step 2: Random search. The initialized fruit fly individuals (X_i, Y_i, Z_i) use olfactory to carry out random search for food sources, where X_i, Y_i, Z_i are shown in formula (2), (3), (4);

$$X_i = \omega \times X_{axis} + 2 \times Rand - 1 \tag{2}$$

$$Y_i = \omega \times Y_{axis} + 2 \times Rand - 1 \tag{3}$$

$$Z_i = \omega \times Z_{axis} + 2 \times Rand - 1 \tag{4}$$

Step 3: Calculate the judging value of taste concentration. By calculating the euclidean distance D_i from the individual to the origin of fruit fly melanogaster, the judging value of taste concentration S_i was calculated, where D_i, S_i are shown in formula (5), (6);

$$D_i = \sqrt{{X_i}^2 + {Y_i}^2 + {Z_i}^2} \tag{5}$$

$$S_i = \frac{1}{D_i} \tag{6}$$

Step 4: Calculate the fitness. According to step 3, the taste concentration of fruit fly melanogaster $Smell_i$ was calculated, where is shown in formula (7);

$$Smell_i = Function(S_i) \tag{7}$$

Step 5: Find out the present best. According to the calculating results of the taste concentration of fruit fly melanogaster population in step 4, the fruit fly with the highest taste concentration was selected as the contemporary optimum. By greedy selection method to find the fruit fly with the highest taste concentration;

$$[bestSmell\ bestIndex\ ] = min(Smell) \tag{8}$$

Step 6: Update the optimal location. To record step 5 the maximum flavor concentration and select current optimum individual coordinate position of fruit fly melanogaster;

$$Smellbest(g) = bestSmell \tag{9}$$

$$X_{axis} = X(bestIndex) \tag{10}$$

$$Y_{axis} = Y(bestIndex) \tag{11}$$

$$Z_{axis} = Z(bestIndex) \tag{12}$$

Step 7: If the maximum number of iterations *Maxgen* is reached, the algorithm ends with the optimal output value, otherwise, we will continue the algorithm to search for optimization iterations.

The flow chart of the optimization algorithm described above is as shown in Figure 2:

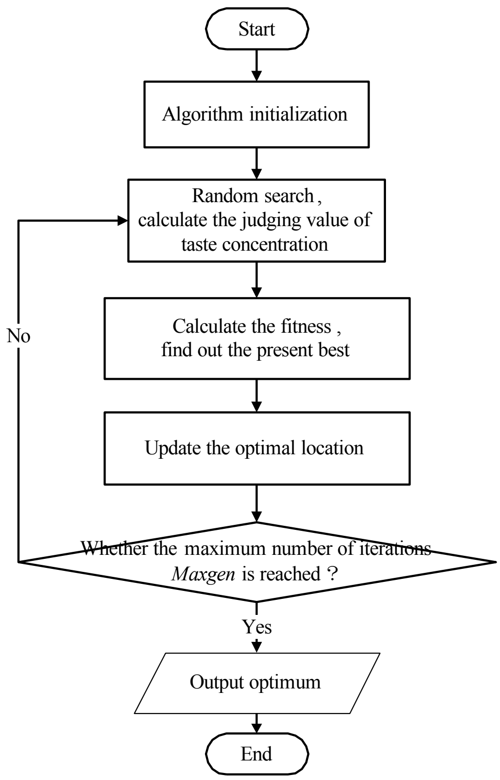

Fig. 2. The flow chart of the 3D-AFOA

3.2 Design and implementation of location method

The triangulation is a location method based on the anchor node and the distance between the unknown node and the anchor node to estimate and the location of the unknown node. In this article, 3D-AFOA is applied to solve the triangulation, and the location error is iteratively optimized thus to improve the location accuracy.

Based on the 3D-AFOA, the reciprocal distance is taken as the judging value of taste concentration, then the fitness function is put in to find the optimal taste concentration. Set D_i as the location error of the unknown node to the anchor node i, where is shown in formula (13);

$$D_i = \left|\sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2} - r_i\right| \quad (13)$$

$(\hat{x}, \hat{y})$ is the estimated coordinates of unknown nodes, $(x_i, y_i)$is the coordinates of anchor nodes i, r_i is the distance from unknown nodes to anchor nodes i.

Take the node location error as the judging value of the taste concentration S_i, add the fitness function to solve the $Smell_i$ concentration so that the node location error will be minimized that can find the precise location coordinate. To carry out iterative optimization to find the minimum location error and obtain the estimated coordinates of unknown nodes with the highest location accuracy.

4 Experimental simulation and analysis

4.1 Experimental environment

In order to verify the performance of the 3D-AFOA designed in this article, based on the experimental platform Win10/MATLAB(R2016a), computer configuration: Intel(R)Core(TM)i3－M330CPU@2.13GHz, 4.00GB RAM, 64-bit operating system, a simulation program based on MATLAB is designed. By comparing and analyzing the positioning accuracy and performance of different algorithms to verify the superiority and efficiency of the algorithm.

4.2 Algorithm analysis

Because the FOA is mainly used in the two-dimensional location optimization of WSN nodes and has limited reference value, this article compares the 3D-AFOA with the three-dimensional fruit fly optimization algorithm (3D-FOA)to evaluate the superiority of the design algorithm.

The parameters of the experimental environment are set as follows: to simulate the layout of the intelligent workshop, the experimental space is set at 80m × 30m × 6m, the coordinates of the three anchor nodes are assumed to be the same, using the node location method in this article to simulate the manufacturing resource of the node P (5, 10, 2). Among them, the population *Size pop* of 3D-AFOA and 3D-FOA are both set to 50, the iterative times of the algorithm *Maxgen* are all set to 500. 3D-AFOA adopts the adaptive inertia weight coefficient as shown in formula (1). In the 3D-FOA, the default inertia weight coefficient ω is 1. To compare the location error of formula (14). The simulation results are as follows in Figure 3:

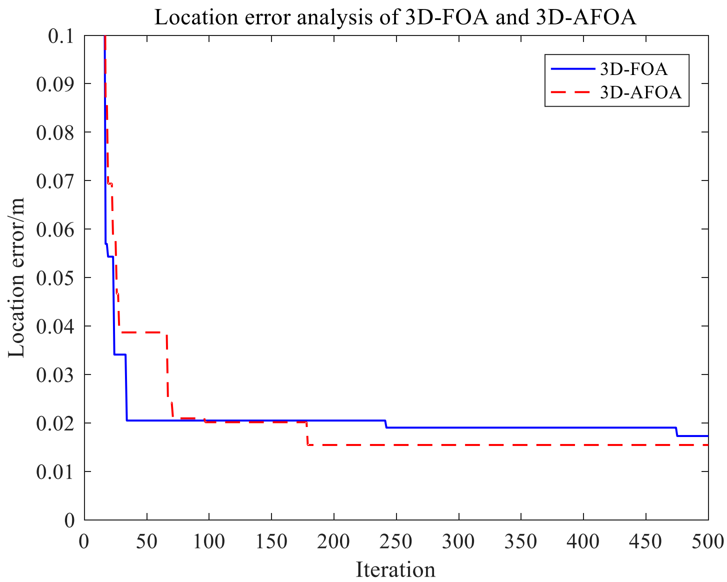

Fig. 3. Location error analysis of 3D-FOA and 3D-AFOA

As shown in Figure 3, the red dotted line is the simulation curve using the 3D-AFOA to solve the minimum location error, and the blue solid line is the simulation curve of the 3D-FOA. From the diagram, we can get the minimum location error of 1.54 cm for 179 iterations of the 3D-AFOA, and 1.73 cm for 475 iterations of the 3D FOA. It can be seen that the former's ability to jump out of the local optimum is greatly enhanced, the location error is reduced, and the coordinates of unknown nodes can be obtained more accurately. Therefore, in the WSN node location optimization, the 3D-AFOA is more accurate than the 3D-FOA.

To further verify the effectiveness of the algorithm, three anchor nodes A(0, 0, 6), B(80, 0, 6), C(80, 30, 6), four anchor nodes A(0, 0, 6), B(80, 0, 6), C(80, 30, 6), D(20, 0, 6) and five anchor nodes A(0, 0, 6), B(80, 0, 6), C(80, 30, 6), D(20, 0, 6), E(40, 0, 6) are used to locate the manufacturing resources of the node P (5, 10, 2), to compare with the minimum positioning error, analyze the superiority of the optimization method that obtains the contrast curve as shown in Figure 4.

By analyzing the positioning error curve of different number of anchor nodes shown in Figure 4 obtained a comparative table of location error analysis as shown in Table 1. According to the Table 1, with the increase of the number of anchor nodes, the convergence speed of the algorithm is obviously accelerated, and the location error is improved at the same time. Because there is only one unknown node in the simulation experiment, the number of anchor nodes has little effect on the location error, but in the actual manufacturing workshop environment, the number of unknown nodes is more than the number of anchor nodes, with the increase of the number of anchor nodes, the location error will be reduced obviously, and further research will be done at the later stage.

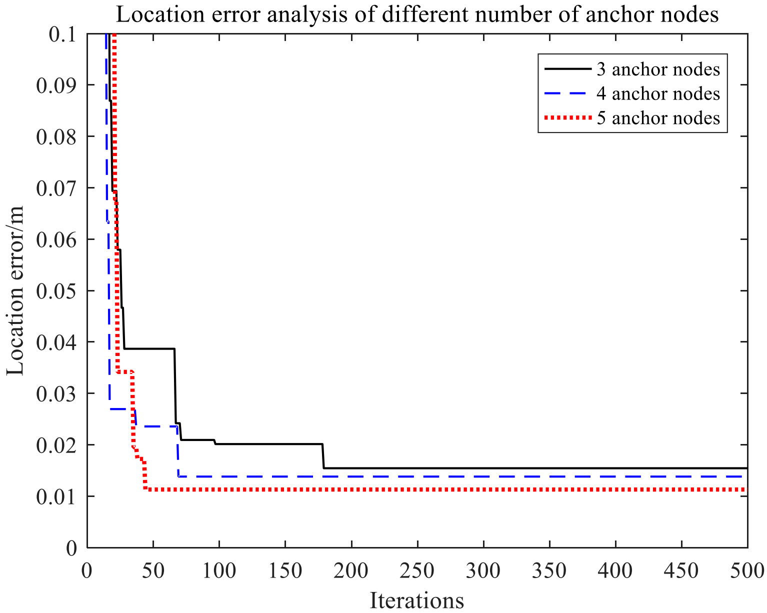

Fig. 4. Location error analysis of different number of anchor nodes

Table 1. The table of location error analysis

Number of anchor nodes	Minimum location error	Generation of convergence
3	1.54cm	179
4	1.38cm	73
5	1.13cm	44

5 Conclusion

In this paper, by analyzing the requirement of 3D location of manufacturing resources in intelligent workshop, a location sensing architecture based on WSN for intelligent workshop is proposed. In order to improve the real-time accuracy of manufacturing resource location data in intelligent workshop, aiming at the disadvantage that FOA is easy to fall into local optimum, considering the advantages of PSO and FOA, propose the 3D-AFOA. The new algorithm is applied to the calculation of the positioning coordinates of the triangulation, which can find the estimated coordinates of the minimum location error, reduce the location error and improve the accuracy of the location algorithm. The simulation results show that the 3D-AFOA has a strong ability to jump out of the local optimum, it is simple, fast and easy to realize. It is highly feasible to apply to WSN node location algorithm and has low hardware requirements; The 3D-AFOA is superior and efficient for node location, not only the location time is obviously shortened, but also the location error is obviously reduced, which can meet the requirement of location accuracy in intelligent workshop.

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