Improved Particle Swarm Optimization for Wireless Intelligent Surveillance Path Planning using Wireless Sensor Network

Mr. R.Baskarane, Mr. T. Sendhil kumar, Mr. A.Parthiban

Abstract— **Context Aware Surveillance Device path planning is divided into off-line static path planning and real-time dynamic path planning. Actually, the flight situation is very complex for the devices; we have to adopt real-time path planning based on off-line static path planning. Wireless sensor network (WSN) technologies are expected to be integrated Robust Autonomous system, allowing for the global interconnection of heterogeneous smart objects with advanced functionality. Recent advances of microcontroller design and radio technologies have opened the way to an emerging category of wire-less network-enabled sensors that serve as smart agents equipped with a low-power dedicated high-performance microcontroller and a large memory space. The paper shows that the path planning strategy and proposes the basic ideas which meets the needs of real-time path planning. Moreover, it has better performance than other algorithm.**

Index Terms— **Surveillance Device [SD], Wireless Sensor Network [WSN], Particle Swarm Optimization [PSO], chaos particle swarms optimization [CPSO].**

I. Introduction

The primary task of SD path planning is off-line static path planning, which serves as a reference trajectory tracking control to make SD fly based on the flight path planned before. During the flight, the airborne sensor surveys barriers and threats; it will start real-time dynamic track re-planning once found new barriers or moving threats. It is a difficult points in the research of SD path planning that how to effectively do a track re-planning to avoid danger during the flight. At present, as a kind of outstanding optimization algorithm, the standard PSO is applied to the research of SD path planning with a good effect. Against shortcomings of PSO that it has a low convergence speed and it is likely to fall into the local optimum, many researchers have put forward improved measures. Reference [1] put forward the method of inertia weight. The larger ω can strengthen the ability of global search, while the smaller ω can strengthen the ability of local search. The value of ω in the standard PSO can be seen as 1, as a result, it has a lack of local search ability in the late iteration. The experimental results show that PSO has a higher convergence speed when the value of ω is during the interval of [0.8, 1.2]. Reference [2] set the value of ω to decrease linearly from 0.9 to 0.4, making PSO explore in a larger area at the beginning and rapidly locate the approximate location of the optimal solution, as the value of ω gradually decreases, particles slow down to start the local search. This method accelerates the convergence rate and improves the performance of PSO algorithm. However, when the problem to be solved is complex, this method makes the PSO lack of global search ability in the late iteration, and it fails to find the optimal solution required.

More and more researchers have proposed other improvements for PSO algorithm, which are main follows, Reference [3] proposed to change inertia weight and learning factor, reference [4] added chaos perturbation to PSO to improve the activity of particles, reference [5] proposed a kind of improved PSO based on the principle of avoiding disadvantages, reference [6] proposed a dynamic PSO with double variable subgroups. To cope with problems above, this paper proposes a hybrid PSO algorithm, which joins an adaptive strategy and a theory of chaos optimization search to increase the particle diversity, and it is combined with a variable structure optimization search theory. To cope with the problem of suddenly moving barriers in the real-time SD path planning, we should predict the barriers' movement path, based on which SD can start real-time path regenerative planning. Where, the real-time path planning is divided into three steps as follows, data acquisition and data fusion, reconstruction of maps of flight environment, path re-planning. Kalman filtering algorithm is used to forecast the track of moving barriers [7]. Through all above, it achieves real-time dynamic track re-planning of SD online.

*Mr .**R. Baskarane**, Senior Assistant Professor and HOD (CSE) Department, Christ College of engineering and technology, Pondicherry University, Pondicherry, India,*

***Mr. T. Sendhil kumar**, Student Final Year M.Tech, (CSE) Department, Christ College of engineering and technology, Pondicherry University, Pondicherry, India,*

***Mr. A. Parthiban**, Student Final Year M.Tech, (CSE) Department, Christ College of engineering and technology, Pondicherry University, Pondicherry, India.*

II. Related Work

In Particle Swarm Optimization [PSO] several Protocols designs to be considered for wireless surveillance. The basic requirements that need to be considered for protocol design are listed in the following.

A. Radio signal planning

Smart home environments are typically characterized by severe multipath due to the presence of reflective surfaces

[14]. Radio planning is a useful tool which relies on the prediction of the wireless link quality. Prediction can be supported by independent radio measurement campaigns over typical indoor buildings and/or by empirical propagation models.

B. Low duty cycling operation

Wireless autonomous devices are battery powered. EPs are usually deployed in predefined spots and must remain active at least for 3 to 5 years. Thus it is stringent constraints on the sensor and the radio transceiver design for minimizing the energy consumption.

C. Channel immunity & Transmission collisions

The sensitivity of the system to channel variations and particularly to any attenuation increase, grade 1 service can support an attenuation increase of up to 3 dB, grade 2 to 6dB, grade 3 to 9dB, and grade 4 to 12dB.

The objective of the collision rate requirement is to ensure a high level of confidence during the transmissions of alarm and monitoring messages to avoid auto-interference (interference among devices of the same system).

D. Low duty cycling operation

Wireless autonomous devices are battery powered. EPs are usually deployed in predefined spots and must remain active at least for 3 to 5 years. Thus it is stringent constraints on the sensor and the radio transceiver design for minimizing the energy consumption.

E. Link consistency & Security

The link consistency measures the probability of information loss during the communication. It is set to $10-3$ for grades 1 to 2 (corresponding to 999 correctly interpreted messages out of 1, 000 [3]) and to $10-4$ for grades 3 to 4 (corresponding to 9, 999 correct messages out of 10, 000). The use of direct/indirect retransmissions (if allowed) can be optimally designed to comply with such specifics.

In order to prevent both unintentional and intentional device substitution, each transmitter shall be identified by an identification code. The security levels are characterized by the probability for an intruder to discover the identification code in less than 1 hr.

F. Cross-tier interference & System monitoring

The system robustness against cross-tier radio interference is measured in terms of in-band and out-of-band interference. Let F min and F max be the minimum and maximum carrier frequencies: the out-of-band carriers F1 and F2 are defined as $F1 = 0.95 \cdot F\ min$ and $F2 = 1.05 \cdot F\ max$.

The measurement of the noise and the interference level is implemented by a periodic message exchange. The period interval for link quality sensing depends only on the transmitter role in the system (e.g., EP or RE devices) and on the network topology. From grade 1 to grade 4, the system has to guarantee that the time interval is not greater than 60 min, 20 min, 100 s, and 10 s, respectively.

G. Wireless protocols for home and building automation

In the following, a review of the most suitable commercial systems for wireless networking in home and building automation is presented. The selection criteria include frequency bands, data rates, modulation techniques, routing schemes, topologies, interoperability, openness of the software architecture, standardization, and general suitability to support critical home automation applications and security [16]. A Bluetooth has been introduced in [17] using a primary network controller and a number of sub-controllers connected by star topology. A ZigBee-based WHAN has been proposed in [18]. Although ZigBee interface based on the IEEE 802.15.4- 2006 standard [19] provides an effective network solution for low-power wireless sensing, the overall size of the radio stack (between 45 and 100 kb) limits its applications to a small subset of smart home automation scenarios.

The use of CSMA as access technology for all sensors is unsuitable for critical delay-sensitive applications such as intrusion detection systems subject to real-time constraints. On the other hand, in beacon-enabled mode, a coordinator node (i.e., the personal area network coordinator) acts as a clock distributor to provide a framing structure by periodically transmitting beacon frames. The frame is the time between two beacons, and it is divided into three parts: a contention access period for CSMA/CA, a contention-free period for TDMA, and an inactive period to power-off devices. The Z-Wave protocol (Zen Systems, Hillsborough, NJ, USA) [20] was developed with an explicit focus on home control applications. Z-Wave operates at 908 MHz in the US and in the ISM band of 868 MHz in Europe, using FSK modulation with data rate 200 kbps. EnOcean is a proprietary environment not yet standardized at international level [21]. EnOcean offers its technology and its licenses through the EnOcean Alliance (San Ramon, CA, USA). The objective is to provide self-powered wireless devices, such as piezoelectric or mini solar panels, highly optimized for energy saving for the automation of homes and buildings. Wavenis is a wireless protocol operating at 868, 915, and 433 MHz, developed by Coronis System (Pérols, France) for monitoring and control applications in several environments such as homes and buildings [14]. The standard Wavenis, currently promoted and managed by Wavenis Open Standard Alliance, supports data rate up to 100 kbps and adopts Gaussian frequency-shift keying (GFSK) modulation in conjunction with fast frequency hopping spread spectrum (FHSS).

H. Device Synchronization & Dynamic transmission power allocation

Wireless autonomous devices are battery powered. EPs are usually deployed in predefined spots and must remain active at least for 3 to 5 years. Thus it is stringent constraints on the sensor and the radio transceiver design for minimizing the energy consumption. A dynamic transmission power control algorithm is implemented to minimize the energy consumption during the periodic keep-alive message transmission. For each EP, the AP controller reads the received signal strength (RSS) from the RSS indicator (RSSI) of the received TI answer message.

I. Channel measurements and network planning

In this section, we analyze the impact of radio propagation at 868 MHz on the wireless alarm message delivery. For the experimental activity, we used eight EPs Texas devices deployed in different rooms and one AP controller. The effect of propagation in each office room has been characterized by calculating the average and the standard deviation of the RSS samples measured over each AP-EP link. The radio environment has been observed over a period of 48 h, during which the position of the AP was fixed while the EDs were moved over two different locations per room, every 24 h of operation.

J. Analysis of network lifetime

The energy consumption profile of a battery-equipped EP during a normal cycle of remote control. Measurements were obtained through an oscilloscope connected in parallel with the EP node itself. The absorbed current has been observed during five different phases: the wake-up period (Iwk = 10 mA with duration of Twk = 4 ms), the receive period (IRX = 23 mA), state message transmission (ITX = 40 mA for duration of TTX = 2ms), the acknowledge reception (Iack = 26mA for duration of Tack = 6ms) and the sleep mode (I sleep = 8 μA). To avoid the high background noise of the oscilloscope, the current absorbed during the sleep period was measured by a precision ammeter. The average power absorbed by the EP has been calculated on every frame with the aim of drawing relevant considerations for network lifetime prediction. To allow for general insights, the power consumption is modeled as a function of the number of keep alive messages transmitted per frame, ηk_alive, and the alarm transmission rate, η alarm, defined as the average number of alarm messages per frame.

III. PROPOSED WORK

PSO algorithm is a kind of evolution computing technology put forward by Kennedy and Eberhart based on swarm intelligence in 1995, which is inspired by birds, fish swarm, and the pattern of the human society.

A. Improved PSO Algorithm

The current position of particle i is xi=(xi1, xi2, ..., xiD) , and the current velocity is vi=(vi1, vi2, ..., viD) ; the historical optimal position of particle i is pi=(pi1, pi2, ..., piD) , the historical optimal position of all particles is pg=(pg1, pg2, ..., pgD) . Each particle flies in the solution space and updates its own position and velocity according to the optimal value of itself and groups, the specific updating formula is as follows:

$$\begin{cases} v_{id}^{k+1} = wv_{id}^{k} = c_1\, rand_1^{k}(pbest_{id}^{k} - x_{id}^{k}) + c_2\, rand_1^{k}(gbest_{d}^{k} - x_{id}^{k}) \\ x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \end{cases} \quad (1)$$

Although PSO algorithm owns such a powerful ability of optimization, it is likely to fall into local optimum and slow down the speed of convergence in the late iteration. In this paper, the adaptive strategy and chaos optimization search theory is added to the standard PSO algorithm. The adaptive strategy is a method to dynamically adjust the inertia weight factor ω and the learning factor $c1$ and c2 according to the change of the search process. As is mentioned above, ω is the key parameter in PSO, which could adjust the local and global search ability of algorithm. Usually, we expect particles to have strong global search ability in the early evolutionary search, while strong local search ability in the late evolutionary search. In order to meet the above requirements, this paper adopts adaptive strategy to dynamically adjust the inertia weight factor as follows:

$$\omega = \omega_{min} + (\omega_{max} - \omega_{min}) \times exp\,[-\lambda \times (\frac{t}{t_{max}})^2] \quad (2)$$

Where, t is the current iteration times, tmax is the maximum iteration times, ωmax and ωmin, respectively, are the given maximum and minimum value of the inertia weight factor, λ= 3 is the factor to control the degree of change smoothing. In the standard PSO, c1 is a self-learning factor and c2 is a social-learning factor, both of which are referred to set as 2. In the early evolutionary search, we require particles have strong self-learning ability and weak social-learning ability, which makes particles fly in the entire search space; while in the late evolutionary search, we require particles have weak self-learning ability and strong social-learning ability, which makes particles fly towards the global optimal solution. In order to get better search performance, the dynamic adjustment strategy of c1 and $c2$ should be as follows:

$$\begin{cases} c_1 = (c1min - c_{1\max}) \times \frac{t}{t_{max}} = c_{1\max} \\ c_2 = (c2man - c_{2\mathrm{mix}}) \times \frac{t}{t_{max}} = c_{2\max} \end{cases} \quad (3)$$

Where, c1max and c1min, respectively, are the maximum and the minimum of c1, c2max and c2min, respectively, are the maximum and the minimum of c2. By means of dynamically adjusting the inertia weight actor ω and the learning factor c1 and c2, the global and local search ability of PSO algorithm is greatly improved.

However, the problem that it is likely to fall into local optimum still exists, which is due to the lack of diversity of the particle swarm. This paper proposes to add chaos optimization search theory to the standard PSO algorithm, which adds chaos perturbation to particles to increase the diversity of the swarm. Chaos as a non-linear phenomenon is very common in the nature; the messy state shown in the process of change on the surface does not disguise its inherent regularity, precisely because of the randomness, periodicity and regularity of the chaotic system, in which we can optimize the search. Logistic map is a typical chaotic system as follows:

$$z_{n=1} = \mu z_n\,(1 - z_n),\ \ n = 0, 1, 2 \quad (4)$$

Where, μ represents control variable, the system is totally at chaotic state when μ=4 and 0 $\leq z_0 \leq$1. All above are improvements for the weakness of the standard PSO algorithm in the process of search. However, there is still a problem of the "curse of dimensionality" in the PSO algorithm, that is, the performance of the algorithm drops sharply with the increase in the number of problem solution space dimension.

Considering the characteristics of the PSO algorithm and the needs of track planning, an optimization search theory of variable structure is proposed in this paper to alleviate the curse of dimensionality. The core idea of this optimization search theory is as follows: the entire track line can be searched in sub-block at first, and then we can form a complete track line by combining those blocks. This theory exactly matches the idea of reducing the dimension in the high-dimensional particle optimization search, and it can effectively forbid the PSO algorithm to fall into the problem of the "curse of dimensionality". By reducing the dimension of the particle optimization search, it can effectively avoid the "curse of dimensionality". However, in order to get the complete optimization search track line, they should share the information of the optimization search. As a result, this paper proposes an information sharing structure, chain structure. We decompose the high-dimensional particle into the low-dimensional minimum search particles which are equal to each other. We adopt a recursive mode. For the reason that the order of the decomposition of high-dimensional particle is according to the order of track directions movement, the search of decomposed low-dimensional particles can also be in order of track forward. The optimal solution searched by each low-dimensional particle will impact the search of the next adjacent particle. Finally, we will achieve the optimal solution for the entire track. For the reason that it costs little time for each search, this search method with chain structure allows real-time path planning.

B. *Forecast of the Track of the Barrier*

Based on kalman filter and predict the position of moving targets, SDs realized online local track re planning in dynamic environments. Concrete implementation method of Kalman filter is as follows. At first, process model of the system is used to predict the next state of the system, according to the state equation of the system, as shown in Equation (5), that is to say, we use the previous state of the system to predict the current state:

$$X(k|\, k\text{-}1) = AX(k\text{-}1 \mid k\text{-}1) + BU(k) \qquad (5)$$

Here $X(k|\, k\text{-}1)$ is the predicted results using a precious state, $X(k\text{-}1|\, k\text{-}1)$ are the optimal result of a previous state, U (k) is the control variable of the current state, A and B are system parameters.

C. *Dynamic Path Planning Strategy In Real-time*

During the SD cruise flight, if the airborne sensor detects moving barriers in front of the SD, the autonomous control system of SD will call the real-time dynamic path planning strategy. Forecast of the Track of the Barrier. The airborne sensor could get the current position and velocity information of barriers, and then, it could obtain the optimal estimation of the barrier position at the next moment through the process of the Kalman filter algorithm. As a result, we could get the prediction of the barrier position of the current state, A and B are system parameters. The improved PSO algorithm and chain structure is used to search.

a) *Settings of the Particle Swarm*

The size of the particle swarm is set as m; the dimension of the particle is n, which is equal to the number of track control points. We divide the X-axis direction between the starting and ending into n +1 equal portion, so that the horizontal axis of the n track control points locate in these bisectors. Now we just do the random search for the n control points in the Y-axis coordinate. In order to search with chain structure, the minimum search particle dimension is set as N, these N track control points are the numerical points required to be planned for each time in chain structure.

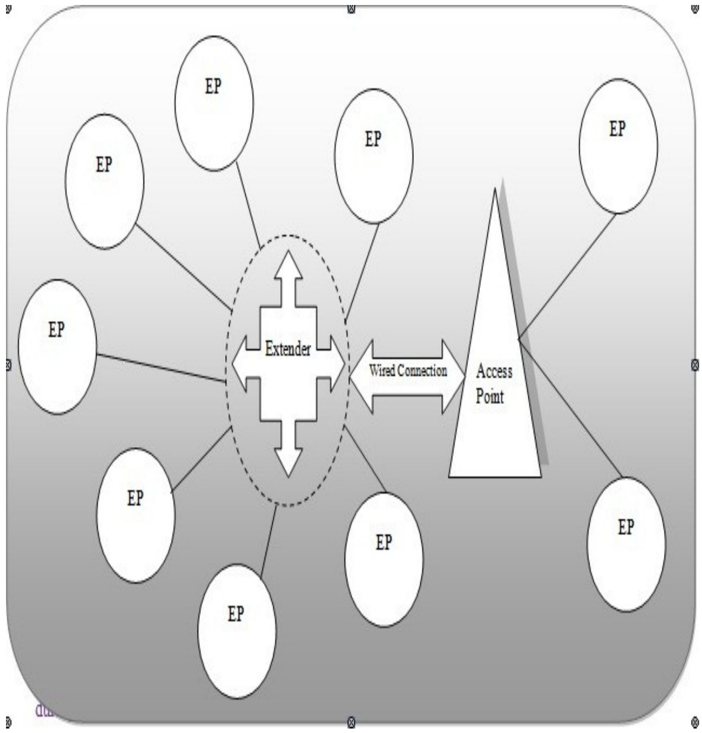

Fig. 1 Dynamic Path Planning

b) *Initialization of the Particle Swarm*

Compared to the global static path planning, the starting point of real-time dynamic path planning is set as \the current SD location, while the end point does not change. At the beginning of the algorithm, it initializes the position and velocity of the N track control points from the starting point. As the search algorithm is carried out, it will save the optimal results if the former particle of the chain structure gets an optimal solution. During the initialization of the latter particle of the chain structure, the starting point of search in the next section is set as the last point of the control points searched before, the same for the initialization of the next consecutive N-track control points.

c) *Calculation and Preservation of the Particle*

Fitness Value At first, we could calculate the threat cost function value for each particle, from which we could synthesize to get the fitness value of each particle. Then, we could preserve the individual optimum searched by each particle and the global optimum searched by the particle swarm. In the calculation process of the threat cost value, considering the movement characteristics of the barrier and the dynamic process of the threat scope, the distance between the two adjacent track control points is designed to be equal to the flight distance of the SD in unit time. Thus, in the calculation of the threat cost, the effect of the current moving barrier on each control point needs to be considered. Based on the traditional update of the velocity and position, the chaotic disturbance is added to the optimization process. Finally, those update particles with higher values are saved.

d) Termination of the Judgment

In the track search process of each N particle, it needs to judge whether or not that the number of iterations is maximum, or the evaluation function is optimal, according to which it choose to continue or terminate the operation of the track search. If the termination condition is not satisfied, it needs to follow the chain link to jump to the 2nd step of the algorithm. Then, the search for the next N track control points begins. If the termination condition is satisfied, it ends the search process. Then, track control points are fitted to a curve

With B-spline curve fit. The fitted curve is projected onto a digital map of the security zone, which is regarded as the reference track for the next SD flight.

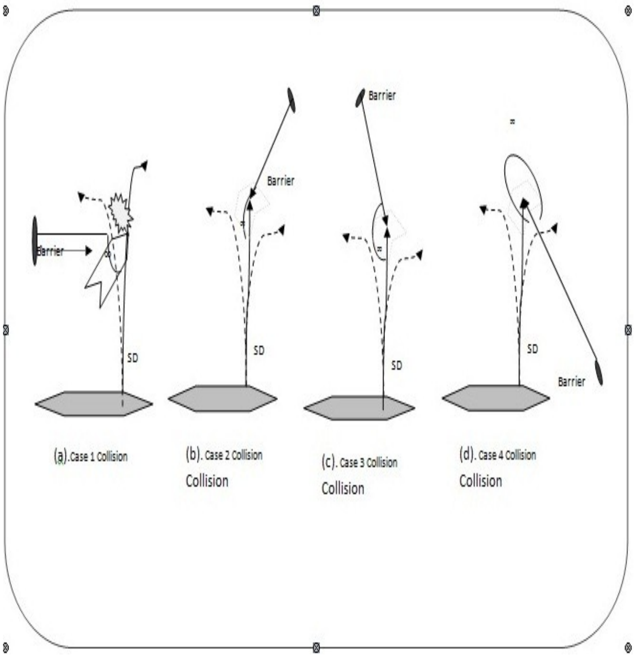

Fig. 1 Collision detection on varring angle

In order to make the track planning more efficient, this paper proposes a barrier avoidance strategy to accelerate the arithmetic operations. We can abstract the impact of the moving barriers on the SD flight safety to the problem of space objects encounter. For the reason that the planning algorithm is implemented in the two-dimensional plane, according to the relationship between the SD flight direction and the moving barrier movement direction, barrier avoidance strategy is divided into four cases.

IV. CONCLUSION

This paper proposed a kind of adaptive chaos PSO, which is successfully applied to SD path planning in the practical flight environment. Before the start of path planning, the terrain environment is pretreated, including the extraction of terrain contours and the fitting of the terrain with an oval. Then, the variable structure optimization search strategy based on improved PSO, which successfully completed the SD real-time path planning. Moreover, our implementation of the real-time dynamic path planning strategy produces superior trajectories to the standard PSO and immune PSO algorithm. The proposed protocol uses a very basic core API, allowing for a more flexible network design. The medium access scheme has been designed to jointly exploit both scheduled and random access to guarantee low-power periodic keep-alive message exchange and real-time alarm propagation with minimum latency, respectively.

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AUTHOR BIOGRAPHIES

Mr. R.Baskarane, currently working as Head of the Department (CSE), CHRIST College of **Engineering** and Technology, affiliated to Pondicherry University, Pondicherry. Completed Post Graduation M.E (CSE), in Anna University, Chennai. More than 10 years experience in teaching as Assistant Professor.
Mr. T.Sendhil kumar, pursuing M.Tech (CSE) - final year, CHRIST College of Engineering and Technology, affiliated to Pondicherry University, Pondicherry. Completed **Master Degree** M.C.A, at **Krishnasamy college** of Engineering and Technology, affiliated to **Anna University**.

Mr. A.Parthiban , pursuing M.Tech (CSE) - final year, CHRIST College of Engineering and Technology, affiliated to Pondicherry University, Pondicherry. Completed Bachelor Degree B.Tech(CSE) at **Pauls Engineering College**, affiliated to **Anna University**.

