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MULTI-ROBOT CONTROL ALGORITHM FOR MAPPING THE RADIATION AREAS

1. Introduction

The task for the adaptive optimization algorithm in these environments is to find optimal results quickly after the change in environment is detected. Monitoring can be realized by continuously collecting sensory data from a distributed network of mobile multi-robot systems deployed in the field. Multi mobile sensor systems are reconfigurable wireless networks of distributed autonomous devices that can sense or monitor physical or environmental conditions cooperatively [1].

2.Brief Description of Algorithm.

Based on the PSO paradigm, each of particles represents a potential solution to an optimization problem, navigate through the search space [2]. The goal of algorithm is to converge to the global (over the search space) or local (into the particular cluster) optimum of a target function. Assuming that the set of particles with their parameters are given initial part of algorithm proceeds as follow steps [3]:

I. Initialize:

Each particle has three features:

p_k^i – for simplifying the calculation, the value of radiation in this position can be identified (this is the *i-th* particle at time or step *k*, notice vector notation) with the coordinates:

$$p_k^i = [x_k^i, y_k^i] \quad i = 1,2, \dots N \qquad (1)$$

The particles are assumed to move within the search space iteratively. This is possible by adjusting their *position* using a proper position shift, called *velocity* (similar to search direction, used to update the position) and denoted as: v_k^i

$f(p_k^i)$ – fitness or objective (determines which particle has the best value in the swarm and also determines the best position of each particle over time.

The swarm is defined as a set:

$$p_k = \{p_k^i\}, \qquad i = 1,2, \dots N \qquad (2)$$

(a) Set parameters N, c_1, c_2, x_{min}, x_{max} y_{min}, y_{min}, G, μ.

where: c_1, c_2 are weighting factors, called the *cognitive* and *social* parameter, respectively.

The parameters c_1 and c_2 are important control parameters that affect the PSO's convergence.

(b) Set $k \leftarrow 0$

Generate N particles (in 2-D space) with random locations i.e. positions with their coordinates (Figure 1) and «velocities» (*the steps) for each particle.*

(c) $p_o^i = p_{\min} + rand\ (p_{\max} - p_{\min})$

(3)

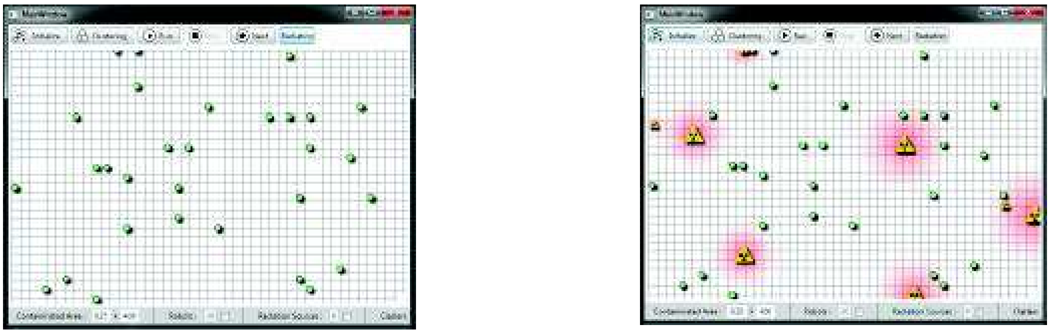
where: $p_{\min}$ and $p_{\max}$ are vectors of lower and upper limit values respectively.

Evaluate the fitness of each particle and store:

– particle best ever position (particle memory b^i here is same as p_o^i);
– best position in current swarm (influence of swarm).

Initial velocity is randomly generated.

$$v_0^i = \frac{p_{\min} + \mathrm{rand}(p_{\max} - p_{\min})}{\Delta t} \qquad (4)$$



a) random locations of particles b) particles with sources of radiation

Figure 2

II. Clustering:

(a) Fitness function $f(p_k^i)$ evaluation for each particle in given coordinates.

(b) Election the leader (or leaders) as best position and the outsiders in the cluster (or clusters) [4]. Given a set of leaders with their positions $l_r = \{p_k^i\}$, $r = 1,2, \ldots M$.

(c) Clustering of swarm (part of outsider particles around of each leader) by K-Means algorithm (Figure 2).

K-means clustering aims to partition the N outsiders into M sets: $L = \{l_r\}$, $r = 1,2, \ldots, M$, so as to minimize the within-cluster sum square:

$$\underset{L}{\arg\min} = \sum_{l_r=1}^{M} \sum_{p_k^i \in L} \| p_k^i - p_k^j \|^2$$

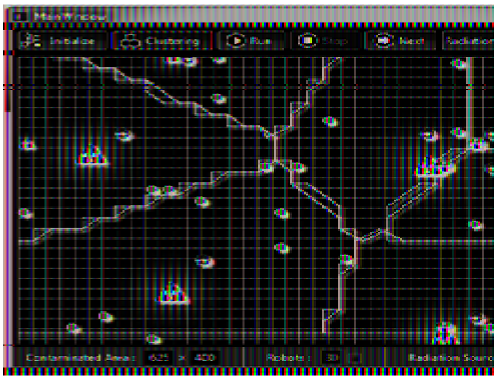


Figure 3

III. Updating:

(a) Velocity Update:

– Provides search directions.
– Includes deterministic and probabilistic parameters.
– Combines effect of current motion, particle own memory, and swarm influence.

$$v_{k+1}^{i} = wv_{k}^{i} + c_1 rand\,\frac{(\mathrm{p}_{k}^{l} - p_{k}^{i})}{\Delta t} + c_2 rand\,\frac{(\mathrm{p}_{k}^{g} - p_{k}^{i})}{\Delta t} \qquad (5)$$

where:

w – inertia factor;
p_{k}^{l} – local best position;
p_{k}^{g} – global best position;
wv_{k}^{i} – current motion;
$\frac{(\mathrm{p}_{k}^{l} - p_{k}^{i})}{\Delta t}$ – particle memory influence;
$\frac{(\mathrm{p}_{k}^{g} - p_{k}^{i})}{\Delta t}$ – swarm influence.

This paper evaluates an adaptive approach to tune the c_1 and c_2 based on proportions: $c_1 = \mathrm{p}_{k}^{l}/\mathrm{p}_{k}^{g}$, $c_2 = 1 - (\mathrm{p}_{k}^{l}/\mathrm{p}_{k}^{g})$

(b) Position Update:

Position of each particle is updated by own velocity vector.

$$p_{k+1}^{i} = p_{k}^{i} + v_{k+1}^{i}\Delta t \qquad (6)$$

Constraints: If a particle is infeasible, last search direction (velocity) was not feasible. Set current velocity to zero.

$$v_{k+1}^{i} = c_1 rand\,\frac{(\mathrm{p}_{k}^{l} - p_{k}^{i})}{\Delta t} + c_2 rand\,\frac{(\mathrm{p}_{k}^{g} - p_{k}^{i})}{\Delta t} \qquad (7)$$

(c) Memory Update:

At each iteration, after the update and evaluation of particles, best positions are also updated. Thus, the new best position p_{k+1}^{g} of leader l_{k+1}^{r} at iteration k+1 is defined as follows:

$$l_{k+1}^{r} = p_{k+1}^{g} = [x_{k+1}^{g}, y_{k+1}^{g}], \qquad r = 1,2, \ldots M \tag{8}$$

$$\mathrm{p}_{k+1}^{g} = \begin{cases} p_{k+1}^{i} & if\ f(p_{k+1}^{i}) \leq f(\mathrm{p}_{k}^{g}), \\ \mathrm{p}_{k}^{g} & Otherwise \end{cases} \tag{9}$$

(d) Set $k \leftarrow k+1$.

IV. Stopping Criteria

Particles convergence (and entropy, respectively) metrics, as one of the criteria, can be defined by measuring the location or dispersion around the leader and is more convenient to use in some cases.

(a) Calculate the movement of the best position of leader:

$$\partial_{k+1} = \left| f(\mathrm{p}_{k+1}^{g}) - f(\mathrm{p}_{k}^{g}) \right| \leq \mu \tag{10}$$

where:

μ - specified tolerance.

(b) Calculate the degree (or measurement) of convergence of particles into the cluster:

$$D = \frac{1}{N} \sum_{l=1}^{N} \sqrt{\left| p_{k}^{i} - p_{k}^{j} \right|^{2}} \leq G \tag{11}$$

where:

p_{k+1}^{c} - position of convergence central point

$$\mathrm{p}_{k+1}^{c} = \frac{1}{Q} \sum_{l=1}^{Q} \sqrt{\left| \mathrm{p}_{k+1}^{c} - \mathrm{p}_{k+1}^{i} \right|^{2}}, \qquad i \neq j. \tag{12}$$

(c) Calculate the current value of function:

$$S = \partial_{k+1} + D \Rightarrow min. \tag{13}$$

(d) Stopping criteria satisfied?

If "Yes", go to IV (e).

If "No", go to III (a).

(e) Output results.

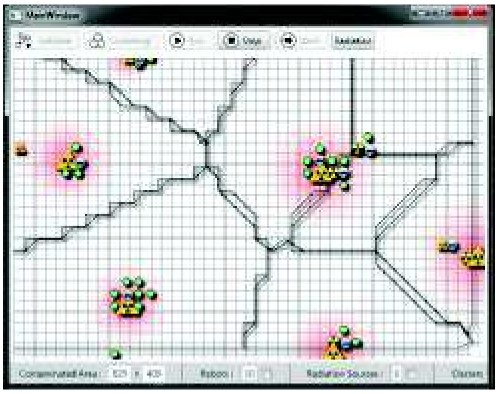


Figure 4 Final state

3. Conclusion

We have discussed the PSO algorithms as main tools for adaptive control of mobile sensor system. The task for the adaptive optimization algorithm in these environments is to find optimal results quickly after the change in environment is detected.

4. References

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