Distributed Intelligence in Multi-Agent Systems

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Introduction

Distributed intelligence refers to systems of entities working together to reason, plan, solve problems, and learn. Here, entities can be defined as any type of intelligent processor or system, including agents, robots, humans, smart sensors, and so forth. Distributed intelligence is desirable under dynamic environment due to its robustness, flexibility, scalability and reliability. The main challenge for distributed multi-agent systems is to adapt agents' behaviors through local interactions with environment and other agents so that global coherence can be achieved.

Four ongoing projects:

- Distributed biological-inspired multi-agent cooperation
- Distributed multi-agent learning using correlated multi-Q
- Distributed multi-robot task allocation for border defense
- Swarm intelligence based particle filter for object tracking

Algorithms

1. Distributed biological-inspired multi-agent cooperation

A stigmergy-based algorithm using the distributed pheromone to guide agent's individual movements

$$\mu_{ij}^k(t) = w_{ij}^k(t)e^{-\gamma} = \left(1 + \frac{\tau_{ij}^k(t)}{1+\tau_{ij}^k(t)/\delta^k}\right)^{\lambda} e^{-\gamma} \qquad \eta_{ij}^k(t) = \max\left(\frac{\delta^k}{d_i^k(t)}, 1\right)$$

Interaction-based algorithm to achieve global coherence through the interactions among the agents using the PSO-based algorithm

$$v^k(t+1) = w_e r_e v^k(t) + c_1 r_c (p_c(t) - x^k(t)) + c_2 r_s (p_s(t) - x^k(t))$$

$$p_s(t) = \max(\mu_{ij}^k(t)) \qquad p_c(t) = \max(\eta_{ij}^k(t)) \qquad x^k(t+1) = x^k(t) + v^k(t+1)$$

2. Distributed multi-agent learning using correlated multi-Q

The goal of this paper is to develop a decentralized cooperative multi-Q reinforcement learning algorithm, where each robot learns to make optimal decisions cooperatively with other robots based on its own Q value and the correlated Q values of other robots in a team.

$$\Delta Q_i(s_i, a_i) = -\alpha Q_i(s_i, a_i) + \alpha\left(R_i(s_i, a_i) + \gamma \frac{1}{n}\sum_{j=1}^{n} V_j(s_j)\right)$$

$$\Delta \mathbf{Q}(\mathbf{s},\mathbf{a}) = \mathbf{R}\alpha + \mathbf{W}\mathbf{V}(\mathbf{s}) - \alpha\mathbf{Q}(\mathbf{s},\mathbf{a})$$

$$\Delta\mathbf{Q}(\mathbf{s},\mathbf{a}) = [\Delta Q_1(s_1,a_1), \Delta Q_2(s_2,a_2), \ldots, \Delta Q_n(s_n,a_n)]^T$$

$$\mathbf{R} = [R_1(s_1,a_1), R_2(s_2,a_2), \ldots, R_n(s_n,a_n)]^T$$

$$\mathbf{V}(\mathbf{s}) = [V_1(s_1), V_2(s_2), \ldots, V_n(s_n)]^T$$

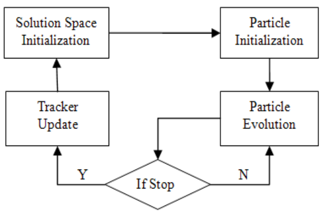
$$\mathbf{Q}(\mathbf{s},\mathbf{a}) = [Q_1(s_1,a_1), Q_2(s_2,a_2), \ldots, Q_n(s_n,a_n)]^T$$

3. Distributed multi-robot task allocation for border defense

A motivation-based distributed cooperation method is developed to control a multi-robot system with Fiber Optic Sensors for border defense. The basic idea is that the FS will sense the perimeter intrusion and act as a cueing sensor to an ensemble of robots which in turn engage in the surveillance and/or neutralization of the intrusion.

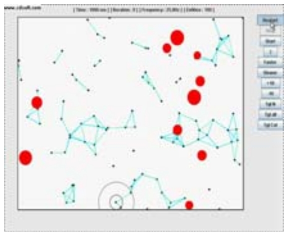
4. Swarm intelligence based particle filter for object tracking

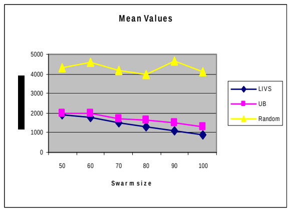
- Use particles dynamically looking for solutions;
- Particles communicate and share info to accelerate search;
- Tracking is executed in a high-dimensional space with multiple parameters adjusted simultaneously

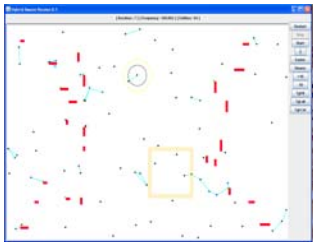


Experimental Results

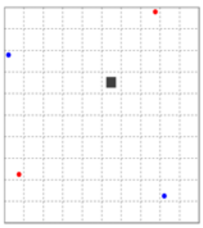
1. Distributed biological-inspired multi-agent cooperation

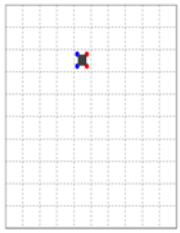


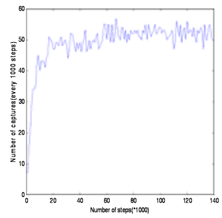




2. Distributed multi-agent learning using correlated multi-Q







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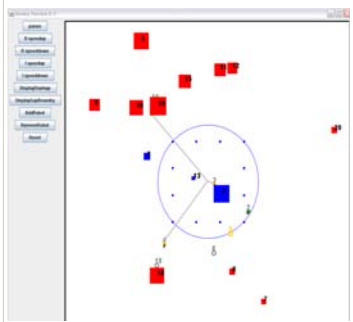
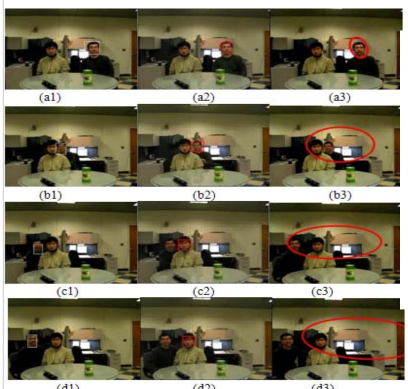
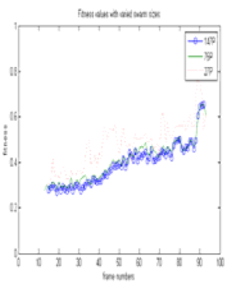


4. Swarm intelligence based particle filter for object tracking





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