ENTROPY-BASED METRICS IN ROBOT SWARM CONTROL

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Abstract

The spatially distributed multi-agent systems must yield coordinated behavior from individually autonomous actions. The movements of the particles around in the search-space are guided by their own best known position in the search-space as well as the entire swarm's best known position. The main claim of this paper is that the relation between self-organization in multi-agent systems and entropic concepts which can provide quantitative, analytical guidelines for designing and operating agent systems. We explain the link between these concepts by way of a simple suggestion how they can be applied in measuring the behavior of multi-agent systems. In this paper we have discussed different kind of metrics to robotic groups behavior such as order and entropy, which will help us in evaluation of performance of the swarming behavior.

Keywords: Sensor systems. Swarm intelligence. Entropy.

1. Introduction

Multi-mobile sensor systems are reconfigurable wireless networks of distributed autonomous devices that can sense or monitor physical or environmental conditions cooperatively. Swarm intelligence is an exciting new research field still in its infancy compared to other paradigms in artificial intelligence. The movements of the particles around in the search-space are guided by their own best known position in the search-space as well as the entire swarm's best known position. Particle swarms are attractive to the user as they do not require gradient and derivative information, are intuitive to understand and can be parallelized [1]. Particle swarm optimization (PSO) is a promising new population based optimization technique, which models a set of potential problem solutions as a swarm of particles moving about in a virtual search space.

2. Problem formulation

According to the literatures overview, it's easy to know that the canonical PSO model consists of a swarm of particles, which are initialized with a population of random candidate solutions. Each particle has a position represented by a position-vector x_i (i is the index of the particle), and a velocity represented by a velocity-vector v_i [2].

The swarm is defined as a set: $X = \{x_1, x_2, \cdots, x_N\}$, of N particles or individuals (candidate solutions), defined as:

$$x_i = (x_{i1}, x_{i2}, \cdots, x_{in})^T \in A, \quad i = 1,2,\cdots,N \tag{1}$$

where A is the searching space.

The particles are assumed to move within the search space, A, iteratively. This is possible by adjusting their *position* using a proper position shift, called *velocity*, and denoted as:

$$v_i = (v_{i1}, v_{i2}, \cdots, v_{in})^T, \quad i = 1,2,\cdots,N \tag{2}$$

Velocity is also adapted iteratively to render particles capable of potentially visiting any region of A. If t denotes the iteration counter, then the current position of the i-th particle and its velocity will be henceforth denoted as $x_i(t)$ and $v_i(t)$, respectively. Velocity is updated based on information obtained in previous steps of the algorithm.

This is implemented in terms of a memory, where each particle can store the *best position* it has ever visited during its search. For this purpose, besides the swarm, *X*, which contains the current positions of the particles, PSO maintains also a *memory* set:

$$P = \{P_1, P_2, \cdots, P_N\} \tag{3}$$

which contains the best positions:

$$P_i = (P_{i1}, P_{i2}, \cdots, P_{in})^T \in A, \quad i = 1,2,\cdots,N \tag{4}$$

ever visited by each particle.

These dynamic parameters are defined as:

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1 (P_{ij} - x_{ij}(t)) + c_2 r_2 (P_{gj} - x_{ij}(t)) \tag{5}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{6}$$

$$i = 1, 2, \cdots, N, \quad j = 1, 2, \cdots, n$$

where: *t* stands for the iteration counter;

r_1 and r_2 are random variables uniformly distributed within [0,1];

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

At each iteration, after the update and evaluation of particles, best positions are also updated. Thus, the new best position of x_i at iteration *t*+1 is defined as follows:

$$P_i(t+1) = \begin{cases} x_i(t+1), & if \quad f(x_i(t+1)) \le f(P_i(t)), \\ P_i(t), & otherwise \end{cases} \tag{7}$$

The presented approach is a distributed algorithm that partitions the supply chain network into a set of locally clusters. This is achieved by deriving a set of weight coefficient or estimation of effectiveness d_{il} between every pair of subtask T_l $(l = \overline{1,M})$ and agent $A_i \in A$, $(i = \overline{1,N})$ within the locality of each subset for selecting the best node of its neighborhood to become its leader. We envisage every the values of decision or management $D_i(t)$ as the "velocity" of each particle in given iteration. Moreover, the each pace is varied inversely of particular velocity.

The fundamental claim of this paper is that the relation between self-organization in multi-agent systems and entropic concepts which can provide quantitative, analytical guidelines for designing and operating agent systems. We explain the link between these concepts by way of a simple suggestion how they can be applied in measuring the behavior of multi-agent systems.

3. Metrics in robot swarm control. Brief overview

We are interested in having a cohesive of robot swarm that aligns to a common direction in a given time. In this section we review some approaches to estimate the robot swarm control that can be used to evaluate coherence of the multi-robot system. Entropy, order, and average angular velocity metrics can be defined to measure the alignment, positional order and energy consumption of the group, respectively. The average forward velocity metric is also utilized as a secondary measure of the energy consumption, and is more convenient to use in some cases.

We can define state, and thus entropy, in terms either of location or direction. Location-based state is based on a single snapshot of the system, while direction-based state is based on how the system has changed between successive snapshots. Each approach has an associated gridding technique. Our approach participates to this caveat.

Entropy-based metrics in robotic control. Entropy measures the positional disorder of the swarm. Entropy is used in a number of classical approaches to clustering, as a means to drive the clustering process. This metric is calculated by finding every possible cluster combination, finding Shannon's information entropy of these clusters and then sum them up [3].

Several approaches in metrics are directly applicable to the problem of swarm clustering. They include the *entropy* (*S*) measures as the positional disorder of the swarm [4]. It is calculated by finding every possible cluster via changing the maximum distance (*h*) between the position vectors of robots in a same cluster. Shannon's information entropy H*(h)* of a cluster with a maximum distance *h* is defined as:

$$H(l) = -\sum_{k=1}^{K} P_k \log_2(P_k) \tag{8}$$

Where P_k is the proportion of the individuals in the *k*-th cluster and *M* is the number of clusters for a given *h*. The rate of change of the entropy (dS/dt) is considered as metrics. These entropy values are integrated over all possible *h*'s ranging from 0 to ∞ to find the total entropy (*S*):

$$S = \int_0^{\infty} H(l)dl \tag{9}$$

The angular order. The order (coherence or synergy) measures the angular order of the sensors [5].

$$\psi(t) = \frac{1}{M}\left|\sum_{k=1}^{M} e^{i\theta_k}\right| \tag{10}$$

Where M is the number of sensors in the cluster and θ_k is the heading of the *k*-th sensor at time *t*.

Swarm order can be estimated by the value between 0 and 1 and is calculated by collecting the heading value of the distributed sensors. When the group in an *ordered* state, the order parameter approaches to 1, and inversely, when the group is unaligned, the system is in a *disordered* state and the order parameter is close to 0.

The swarm velocity as metrics. This metric, which is the average velocity of the geometric center of the swarm during the whole course of its motion, can be calculated by dividing the displacement of the geometric center of the swarm by the duration of flocking.

$$\vec{V}_s(t) = \frac{1}{N}\left|\sum_{i=1}^{N} \vec{V}_i(t)\right| \tag{11}$$

4. Proposed approach

Based on this brief review of metrics to evaluate the quality of mobile sensor swarm behavior, we argue that entropy of swarm cluster, as degree of disorder, can be also calculated using relative positions or average angular velocity by collecting the heading value of the sensors. Further, they will be utilized in comparing the performance of different behaviors achieved through setting controller parameters or sensing characteristics to different values than the default ones. We consider the entropy of dynamic system as an internal behavioral incompatibility or antagonism, certain contradiction between disoriented components behavioral vectors [6]. Hence, the robot swarm behavior metric, which consists in estimation of disoriented robot behavioral vectors can be derived as below.

This approach is based on vector algebraic addition of the velocity-vectors $\vec{v}_i(t)$ of mobile robots at time *t*. Metric of whole robot group in time *t* can be measured as:

$$H(t) = -\sum_{k=1}^{K} P_k(t) \log_2(P_k(t)) \tag{12}$$

where:

$$p_k(t) = \frac{\sum_{i=1}^{N} \vec{v}_i(t)}{\sum_{i=1}^{N} |\vec{v}_i(t)|} \tag{13}$$

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რეზიუმე

სივრცულად განაწილებული მულტი-აგენტური სისტემის ქცევა ინდივიდუალური ავტონომიური ქმედებებით არის განპირობებული. საძიებელ არეში ნაწილაკების მოძრაობა განისაზღვრება მათი საუკეთესო პოზიციით, რომელიც იმავდროულად მთლიანი სისტემის საუკეთესო პოზიციასაც განაპირობებს. სტატიაში წარმოდგენილი მიდგომა ადგენს გარკვეულ რაოდენობრივ თანაფარდობას თვითორგანიზებისა და ენტროპიულ ცნებებს შორის, რომლებიც შეიძლება გამოყენებულ იქნას მულტი-აგენტური სისტემების ქცევის შეფასების თვალსაზრისით. სტატიაში განხილულია რობოტული ჯგუფების ქცევის სხვადასხვა სახის მეტრიკა, მათ შორის მოწესრიგებულობა და ენტროპია, როგორც ქაოტურობის ზომა.

ОСНОВАННАЯ НА ЭНТРОПИЮ МЕТРИКА В УПРАВЛЕНИИ ГРУППОЙ РОБОТОВ

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Резюме

Поведение пространственно распределенных мульти-агентных систем обусловлено индивидуальным автономным поведением. Перемещение частиц в поисковом пространстве оценивается собственной наилучшей позицией, которое обусловливает наилучшую позицию системы в целом. В статье представленный подход установливает определенное количественное соотношение между понятиями самоорганизации и энтропией, что может бить применен для оценки поведения мульти-агентных систем. С этой точки зрения, в качестве метрики поведения группы роботов в работе рассмотрены упорядоченность, а также энтропия, как мера хаотичности.