SELF-ORGANIZATION OF MULTIPLE-AGENTS USING INFORMATION THEORETIC INTERACTIONS

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Abstract: The recent sprout in the application of swarm intelligence to problems in varied fields has proved that this visionary technology is becoming practical. However, the organization and coordination of swarms is either heuristic or based on centralized approaches. In this paper, we propose a principled decentralized approach based on an information theoretic interaction principle to self-organize swarms. The goal of our algorithm is to spread the robots uniformly over a circular region using entropy maximization while guiding the collective towards a target. This algorithm minimizes the cost of the robots, since it is requires minimal hardware for its operation.

Keywords: Self-organizing systems, Decentralized Control, Mobile Robots, Maximum entropy.

1. INTRODUCTION

Swarm intelligence is biologically inspired by insect societies like ants and termites, which produce complex collective behaviour from the interactions of many simple individuals (Kube and Bonabeau, 2000; Resnick, 1997). The application of swarms in versatile fields like oceanographic sampling (Turner and Turner, 1998), communication networks (White and Pagurek, 1998), material transportation in hazardous zones (Genovese, *et al*., 1992) and planetary missions (Miller, 1990) has made it a hot research field.

Many researchers have attempted self-organization of swarms with a leader – follower strategy. But it is now widely accepted that decentralization is vital to swarms, since it brings robustness to the system. Some of the reasons for using a decentralized approach are:

- Having a central controller may not be feasible in some tasks like mine sweeping, since the failure of the controller means failure of the whole system.
- High swarm population would necessitate the controller to have extensive communication with agents.
- The complexity of the controller will make it costlier than having many simple robots.

Here we propose an information theoretic interaction (ITI) approach of implementing decentralized self-organization of swarms. The theory of physically interpreting data samples in entropy estimation as information particles (IPs) and the interactions between data samples as information forces (IF) can be applied to swarms by considering each robot as an IP (Principe, *et al*., 2000). The application of ITI to self-organization of swarms decreases the complexity and hence the cost of the individual robots, since:

- Each robot needs to have only a simple transmitter and receiver. The circuit complexity of the receiver does not increase with increasing the number of robots, since the signal from every robot has equal energy and is broadcasted to all the other robots.
- Each robot need not know its own absolute position as well as the position of the other robots.

The remainder of the paper is organized as follows. Section 2 briefly reviews the information theoretic interactions approach. Sections 3 and 4 describe the details of the information particle interaction algorithm for self-organization with simulation results. Section 5 provides a summary of our conclusions.

2. INFORMATION PARTICLES

The information particle interaction idea has been recently introduced (Principe, *et al.*, 2000) and has been successfully utilized in many problems including independent component analysis, nonlinear principal components analysis, and SAR image feature extraction. The principle was generalized into a general particle interaction framework (Erdogmus, *et al.*, 2002), which encompasses the original information particle interaction model for adaptation and self-organization as a special case corresponding to a specific choice of the particle potential functions. In this section, we will briefly describe the general particle interaction model for self-organization.

Renyi's entropy is a parametric family described by (Renyi, 1970)

$$H_\alpha(\mathbf{X}) = \frac{1}{1-\alpha}\log\int_{-\infty}^{\infty} f_{\mathbf{X}}^{\alpha}(\mathbf{x})d\mathbf{x} \tag{1}$$

where **X** is a random variable with the designated marginal and joint probability density functions (pdf), and α is the order parameter. We start by writing the entropy definition in (1) in a different way, using the expectation operator.

$$H_\alpha(\mathbf{X}) = \frac{1}{1-\alpha}\log E\left[f_{\mathbf{X}}^{\alpha-1}(\mathbf{X})\right] \tag{2}$$

The Parzen window estimator (Parzen, 1967) for the pdf is evaluated using a kernel function $\kappa_\Sigma(.)$, where Σ is a parameter that controls the width of the kernel function.

$$\hat{f}_{\mathbf{X}}(\mathbf{x}) = \frac{1}{N}\sum_{i=1}^{N}\kappa_\Sigma(\mathbf{x}-\mathbf{p}_i) \tag{3}$$

In the multidimensional pdf estimation case, this can be a vector or the covariance matrix of the kernel function. In general, we suggest using joint kernels of the type

$$\kappa_\Sigma(\mathbf{x}) = \prod_{o=1}^{n}\kappa_{\sigma_o}(\mathbf{x}^o) \tag{4}$$

where $\mathbf{x}^o$ is the o^{th} component of the input vector. We can now replace the expected value in (2) by the sample mean and obtain the following nonparametric estimator for Renyi's entropy (Erdogmus et al, 2002).

$$H_\alpha(\mathbf{X}) \approx \frac{1}{1-\alpha}\log\frac{1}{N^\alpha}\sum_{j=1}^{N}\left(\sum_{i=1}^{N}\kappa_\Sigma(\mathbf{p}_j-\mathbf{p}_i)\right)^{\alpha-1} \tag{5}$$

This nonparametric estimator allows the designer to choose any entropy order α and any kernel function κ_Σ. For the special choices of quadratic entropy (α =2), and Gaussian kernels, (5) reduces to the estimator defined by Principe except for a change in kernel size (Principe et al, 2000).

$$\begin{aligned} &H_2(\mathbf{X}) \approx -\log V_2(\mathbf{X}) \\ &V_2(\mathbf{X}) = \frac{1}{N^2}\sum_{j=1}^{N}\sum_{i=1}^{N}G_{\Sigma\sqrt{2}}(\mathbf{p}_j-\mathbf{p}_i) \end{aligned} \tag{6}$$

It is interesting to point out that this definition is achieved without any sample approximations as in (5) due to the mathematical properties of the Gaussian kernel.

Now, suppose that the particles $\{p_1,\ldots,p_N\}$, correspond to the robot position coordinate vectors in the current application. For simplicity, assume we are dealing with single dimensional random variables (extension to multi-variable case is trivial). We assume that each particle emanates a potential field. If the potential field that is generated by each particle is $v(\xi)$, we require this function to be continuous and differentiable (except possibly at the origin), and to satisfy the circular symmetry condition $v(\xi) = v(\|\xi\|)$. With these definitions, we observe that the potential energy of particle $\mathbf{p}_j$ due to particle $\mathbf{p}_i$ is $V(\mathbf{p}_j|\mathbf{p}_i) = v(\mathbf{p}_j\text{-}\mathbf{p}_i)$. The total potential energy of $\mathbf{p}_j$ due to all the particles is then given by (2)

$$V(\mathbf{p}_j) = \sum_{i=1, i\neq j}^{N} V(\mathbf{p}_j\,|\,\mathbf{p}_i) = \sum_{i=1, i\neq j}^{N} v(\mathbf{p}_j-\mathbf{p}_i) \tag{7}$$

Defining the interaction force between these particles, in analogy to physics, as

$$\begin{aligned} \mathbf{F}(\mathbf{p}_j\,|\,\mathbf{p}_i) &= \partial V(\mathbf{p}_j\,|\,\mathbf{p}_i)/\partial\mathbf{p}_j \\ &= \partial v(\xi)/\partial\xi\big|_{\xi=(\mathbf{p}_j-\mathbf{p}_i)} \\ &= \nabla v(\mathbf{p}_j-\mathbf{p}_i) \end{aligned} \tag{8}$$

(3

we obtain the total force acting on particle $\mathbf{p}_j$

$$\begin{aligned} \mathbf{F}(\mathbf{p}_j) &= \sum_{i=1, i\neq j}^{N}\mathbf{F}(\mathbf{p}_j\,|\,\mathbf{p}_i) \\ &= \sum_{i=1, i\neq j}^{N}\nabla v(\mathbf{p}_j-\mathbf{p}_i) \end{aligned} \tag{9}$$

Notice that the force applied to a particle by itself is zero. In the self-organizing context, since each agent is considered a particle, the gradient of the potential with respect to the particle position, which is called the interaction (information) force, can be immediately utilized as a command signal for self-organization. In the present application, we assume that each robot in the swarm transmits an RF signal with certain amplitude and frequency. This signal is also coded in order to improve the robustness of the system under noise and hostile jamming. Explicitly, the potential field emanated by each particle is given by

$$v(\xi) = \frac{A}{\xi^T \xi} \tag{10}$$

which is a circularly symmetric function decreasing quadratically with distance. The fact that this potential function is physically realizable motivates its use in this application. It is possible to show that maximization of entropy in a fixed region can be achieved using the above formulation (Erdogmus, *et al*., 2002). The maximization of entropy over a fixed-region leads to a uniform distribution of the particles (Principe, *et al*., 2000).

3. SELF-ORGANIZATION ALGORITHM

If every robot is considered as a particle, then the robots can distribute themselves uniformly over a certain region by maximizing their entropy. We take the simplest region, a circle, as the case for simulation of this algorithm. The circular region is commonly used in self-organizing swarms case studies. For example, Unsal uses an algorithm that spreads the robots uniformly over a circular region. However, this algorithm, quite restrictively, requires all the robots to know the absolute positions of every robot (Unsal and Bay, 1994).

To spread robots uniformly over a circle of certain radius needs some controlling force at the boundary of the circle so that the robots remain within the circle. This is achieved by comparing the total potential field measured by the robot to a preset threshold, which is a function of the transmitted signal power, number of agents, and the desired radius. Since the determination of an analytical function for the threshold in terms of the mentioned parameters is involved (it requires solving a complicated optimization problem), the solution was found experimentally. For a given number of agents, the threshold was computed through Monte-Carlo simulations for unit-power transmitted signal and unit-radius. Assuming spherical signal propagation, it is simple to generalize the obtained result to various radius and transmitted signal power levels. An exponential curve is then fitted to this data to get a simple and generalized threshold function in terms of the signal power (A), number of agents (N), and the desired radius (r). The experimental data and the fitted curve are shown in Fig. 1. The generalized threshold function is found to be

$$\gamma = 0.21128 \cdot A \cdot N^{1.5107} / r^2 \tag{11}$$

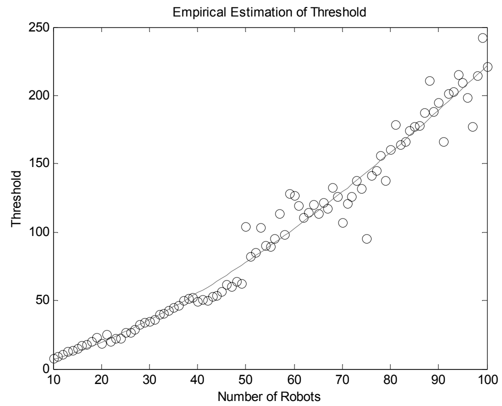

Fig. 1. Empirical estimation and approximation of threshold

In the figure, we can see that the variance of actual values from the approximation increases as the number of robots increase. This can be attributed to the fact that the simulation was run for the same number of iterations for any number of robots and hence the accuracy of the estimated thresholds decreases as the number of robots increase.

For transmission and reception of signals, pseudo-noise (PN) signals are used, since they offer a secure way of transmission and are robust to jamming. PN sequences used in CDMA based wireless communication must have low cross-correlation since the receiver must be able to de-spread only one particular PN sequence from many PN sequences for better reception of the desired signal. In this scenario, however, we require that the robots do not use different seeded PN sequences, because then, as the swarm size increases, hardware complexity of the receivers will also increase. Hence, all the robots must use the same PN sequence (with different phases) and autocorrelation property of the PN sequence assumes importance. The autocorrelation function of an m-sequence (Haykin, 1994) is constant at a very small value (-1/M, where M is the sequence period) for non-zero lags and is 1 at zero lag. Hence, they can be beneficially used in this application. Since every robot is at different distances from a particular robot, the received signal will have the same PN sequence arriving in different phase shifts. Then, when there are N robots, the received signal $r_i(t)$ at the i^{th} robot can be written as

$$r_i(t) = \sum_{k=1, k \neq i}^{N} A_{ik}\, g(t - \Delta_{ik}) \tag{12}$$

where A_{ik} is the amplitude of the signal coming from robot k. For a spherical propagation model, we would have $A_{ik} = A / d_{ik}^2$, where d_{ik} is the distance between the i^{th} and k^{th} robots. Also, we let $g(t)$ be the assumed PN sequence, which is common to all the robots. The phase Δ_{ik} depends on the time-of-arrival of the signal, which is a function of the distance d_{ik}.

If the PN sequence is $g(t)$, then the decoded signal will be at a particular phase shift L of the PN sequence

$$y_i^L = E[r_i(t)g(t-L)] \tag{13}$$

Then, substituting the received signal in the above equation gives

$$y_i^L = E\left[\sum_{k=1}^{N} A_{ik}\, g(t-\Delta_{ik})g(t-L)\right] \tag{14}$$

The autocorrelation of the PN sequence,

$$C_{ik}^L = E[g(t-\Delta_{ik})g(t-L)] \tag{15}$$

For the specific case of an m-sequence,

$$C_{ik}^L = \begin{cases} 1 & \text{if } L = \Delta_k + zM \\ -\dfrac{1}{M} & \text{if } L \neq \Delta_k + zM \end{cases} \tag{16}$$

where M is the length of PN sequence and z is any integer. Then, the decoded received signal becomes as shown in (17), where j=1,2,….,N where N is the number of robots. Thus, a reasonable threshold can be set to get the amplitudes A_{ij}, j=1,2,…,N.

$$y_i^L = \sum_{k=1}^{N} A_{ik} C_L^k = \begin{cases} -\dfrac{1}{M}\displaystyle\sum_{k=1,k\neq i}^{N} A_{ik} & \text{if } L \neq \Delta_1,...,\Delta_N \\ A_{ij} - \dfrac{1}{M}\displaystyle\sum_{k=1,k\neq i}^{N} A_{ik} & \text{if } L = \Delta_j \end{cases} \tag{17}$$

The potential V_i for a particular robot is the sum of the received signal amplitudes A_{jk} from all other robots.

$$V_i = \sum_{k=1}^{N} A_{ik} = \sum_{k=1}^{N} \frac{1}{d_{ik}^2} \tag{18}$$

This is compared to the threshold calculated according to the desired radius to specify the sign on the direction of the information force (IF), which is the gradient of the potential. Approximating the discontinuous *sign* function with *arctan*, the expression for the IF for the i^{th} robot becomes

$$\mathbf{F}_i = arctan(\gamma - V_i)\frac{\partial V_i}{\partial \mathbf{p}_i} \tag{19}$$

The gradient of the potential with respect to the robot's position $\mathbf{p}_i$ is estimated from the measurements taken by a rectangular grid of receiver antennas (located on the robot) by a first-order difference approximation of the derivatives.

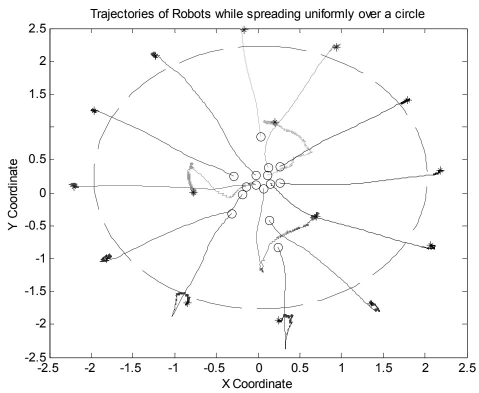

Fig. 2. Trajectories of robots while spreading themselves uniformly over a circle

This algorithm was simulated with the following specifications:

Number of robots, N = 15
Radius of the circle, r = 2
Length of the maximum sequence, M = 127
Number of antennas in the receiver array = 9
Number of iterations = 1000
Integration time step = 0.03

The results are shown in the figure above, but many other simulations produced similar results. The circles show the initial position of robots, where they are randomly distributed. Stars depict the final position of robots where all the robots have spread themselves almost uniformly over a circle. It must be noted that the final positions of robots can differ depending on their initial positions. The uniformity of the distribution can be estimated from the variance of the nearest neighbour distances for each robot, which is 0.0031 for this simulation. The robots have spread slightly outside the circle due to the curve-fitting approximation in the threshold.

4. CONVERGING ON THE TARGET

In addition to spreading, target guidance is also an important problem. Our approach to target guidance does not assume any beacon signal from the target (Parunak and Brueckner, 2001), since this is an unrealistic assumption in some applications like bombing or surveillance of a military target. Instead, two base stations are used to transmit direction information to all robots.

Each base station is assumed to use a simple radar by which it decides whether the center of the circle in which the robots reside are to the left or right of the target line-of-sight (LOS) and accordingly changes the sign of the transmitted PN sequence. The base stations have their unique PN sequences in order to facilitate their distinguishing from each other and the other robots. For the robots, the amplitudes of the base station signals give the gradient information to calculate the IF towards the target while the sign of those signals change the direction of the IF towards the target depending on the region of the robots as depicted in Fig. 3.

The results of the above guidance algorithm are shown in Fig. 4. It must be noted that the spreading of the robots and guidance towards the target occur simultaneously. This is due to the fact that the total IF experienced by each individual robot is a superposition of the forces due to inter-robot interactions and the interactions with the base stations.

In summary, the following are the operations performed by every robot while tracking a target.

1. From the received signal amplitudes at various antenna elements, find V and $\partial V / \partial p$ due to the interaction of robots by decoding using the appropriate signature.
2. Compare V with threshold and determine the direction of IF due to interaction of robots (see 13).
3. By using the signature sequences of base stations, find the sign commands and $\partial V / \partial p$ due to base stations.
4. Rotate this gradient according to the signs to determine the direction of IF due to base stations.
5. Superimposing IFs due to robots and base stations gives the total IF providing the direction in which the robot is moved.

It is possible to use the same algorithm to track a moving target. In that case, the base stations need to continuously adjust their LOS to the target so that correct direction information is conveyed to the agents.

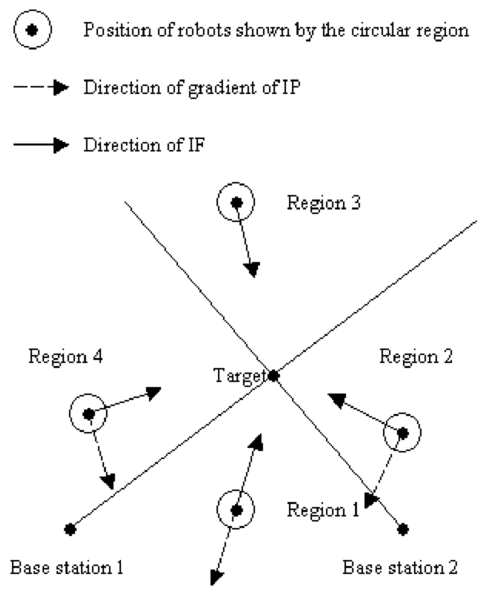

Fig. 3. Guiding of robots towards a target

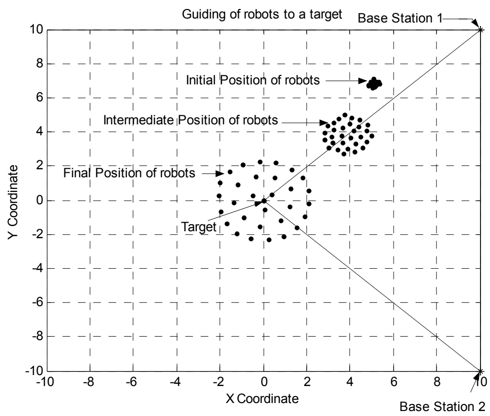

Fig. 4. Target guidance of robots

5. CONCLUSION

Research on swarm robots is increasing its popularity due to many possible applications. The focus is currently on designing effective and efficient self-organizing algorithms that would lead the group of agents to accomplish a task collectively. This requires communication and cooperation between the individuals of the collective.

In this paper, we have proposed a self-organizing and collective control principle based on particle interactions through a predefined interaction law. The approach is based on the recently developed particle interaction and information particle principles in adaptation. In this approach, each agent is considered an information particle, which emanates a potential field that allows communication with the other agents in the collective. The proposed self-organization (maximizing entropy over a circular region) and target tracking algorithms are tailored to be hardware efficient, in order to facilitate practical implementation of the proposed system, while maintaining the underlying information particle interaction principle.

The optimisation problem addressed in this paper is similar to the famous sphere-packing problem in mathematics with the main difference being the formulation as a global cost function (entropy) optimization. In sphere packing, the circles packed optimally inside a bigger circle have equal size, while the final solution obtained with our solution achieves the same objective, but with slightly different sized circles.

Currently, the use of PN sequences is proposed to introduce robustness to noise and immunity to hostile jamming. Future work will explore the performance of the proposed algorithms under such hostile operating conditions.

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