A New Swarm Intelligence Coordination Model Inspired by Collective Prey Retrieval and Its Application to Image Alignment

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Abstract. Swarm Intelligence is the emergent collective intelligence of groups of simple agents acting almost independently. Algorithms following this paradigm have many desirable properties: flexibility, decentralized control, robustness, and fault tolerance. This paper presents a novel agent coordination model inspired by the way ants collectively transport large preys. In our model a swarm of agents, each having a different destination to reach, moves with no centralized control in the direction indicated by the majority of agents keeping its initial shape. The model is used to build an algorithm for the problems of image alignment and image matching. The novelty of the approach and its effectiveness are discussed.

1 Introduction

Swarm Intelligence (SI) is the property of a system where the behaviour of simple quasi-independent agents, interacting locally with their environment, cause intelligent global behaviour to emerge. Since intelligent behaviour should emerge from collaboration rather than from individual abilities, each agent is designed to be very simple. The agents should have a limited knowledge of the environment, which they should be able to modify only locally, and should be designed according to the reactive paradigm [1].

A feature distinguishing Swarm Intelligence from classical multi-agent systems is the concept of stigmergy. While in classical multi-agent systems, the agents communicate directly between each other, in the SI paradigm the agents communicate by modifying a shared environment. The alterations of the environment, amplified through a feedback process, may lead the system to self-organize. The state reached by the system should correspond to an optimal solution of the problem. A system with such characteristics is non-linear. The next state of the system does not depend solely on the current state of every agent. The prediction must be based also on the relationships among the various agents. Such complexity makes difficult for an agent to determine the action leading to the desired macroscopic behaviour.

Despite some interesting works [2,3,4], there is a lack of general theories and programming methodologies in the SI field. The difficulties have induced

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researchers to look for inspiration at biological phenomena. Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are optimization techniques inspired to coordination mechanisms used by, respectively, ants gathering for food [5] and birds flocking [6]. Other examples of biologically-inspired algorithms can be found in [7,8,9,10].

This paper presents a new agent coordination model named Democratic Collective Transportation (DCT). The model is inspired by ants collectively transporting large preys to the nest. In fact, some species of ants are able to transport a heavy prey by coordinating their forces through the prey itself. In our new model, the constraint that all agents try and move the prey toward the same destination (the nest) is removed: each agent has a desired destination. The group moves the prey toward the direction chosen by the majority of agents with no centralized control. Based on the introduced model, an algorithm for the Image Alignment problem has been devised. It is a population-based optimization algorithm but, unlike ACO and PSO, only one solution, obtained through a self-organizing mechanism, is generated at each iteration.

The paper is organized as follows. Section 2 describes the biological model. Section 3 presents the new model. Section 4 describes an algorithm for image alignment based on the presented coordination model and discusses its results. Section 5 presents some concluding remarks.

2 Collective Prey Retrieval

In order to overcome the limits imposed by their small size and limited capabilities, many species of ants have evolved by developing collaborative strategies. The carriage of a large prey into the nest is an example of such process. Some species of ants have specialized workers able to cut the prey into small pieces that a single ant can carry, while other species are able to collectively transport large preys. Experimental results show that the latter strategy, called collective transportation, is the most efficient one [5]. The species with the most interesting strategies are *Pheidole crassinoda, Myrmica rubra and Myrmica lugubris*. They exhibit the same behavioural patterns in solitary and group transport [11]. An high level description of collective prey retrieval is summarized below:

1. When an ant finds a prey, it tries to carry it.
2. If the ant does not succeed in moving the prey, it tries to drag it in various directions (realignment behavior).
3. If the prey does not move, the ant grasps the prey differently, then tries and drag it in various directions.
4. If the prey still does not move, the ant starts recruiting nest mates. First, it releases a secretion in the air in order to attract nearby ants (short range recruitment). If the number of recruited ants is not enough to move the prey, the ant goes back to the nest leaving a pheromone trail on the ground. Such trail will lead other ants to the prey (long range recruitment). The recruitment phase stops as soon as the group is able to move the prey.

Resistance to traction represents a positive feedback mechanism. As specified at point 4, recruitment stops when resistance to traction ends and the prey starts moving.

While moving toward the nest, coordination among the ants occurs through the prey itself. The change of the force applied by a single ant modifies the stimuli perceived by the other ants (which react accordingly). Such coordination strategy is an example of stigmergy.

3 A New Coordination Mechanism Based on Collective Prey Retrieval

The new coordination model introduced in this paper is an extension of the last phase of the collective prey retrieval strategy: the coordination of forces during the transportation of the object to the nest. It introduces two significant differences with respect to the model described in section 2:

– in collective prey retrieval, each ant tries and carry the prey to the same destination (the nest). In our model each agent has its own destination for the prey. The group must move in the direction indicated by the majority of its agents.
– In section 2 the prey is considered a rigid body. A force applied to a rigid body is perceived instantaneously by all the carrying ants. The inclusion of a similar propagation mechanism in a model would lead to an unacceptable level of complexity: either the agents or the preys should be equipped with a broadcasting mechanism. In the democratic transportation model, the application of a force by an agent is immediately notified to its neighbouring agents only and is perceived by all the other agents after some instants. Such delayed propagation roughly corresponds to considering the prey as a non-rigid body. We show how such modification still allows the coordination of the agents, while keeping simple both the prey and the agent models.

3.1 Model Description

In order to obtain the democratic collective transportation model described in section 3, the biological model (section 2) is to be modified as follows:

1. each agent constantly applies a force on the prey toward his preferred destination V_p.
2. The intensity of the applied force is inversely proportional to the angle between V_p and the direction V_g chosen by the majority of the agents.
3. The direction V_g of the majority of the ants is estimated by each agent by simply looking at the movements of the prey in the previous time steps.

In the following we outline the functions needed for a formal description of the democratic collective transportation model.

p denotes a generic agent of the system. The agents are grouped in a set P. $p(t)$ is the position of agent p at time t. Each p has 0 initial velocity and moves according to F_n and F_p.

$\mathbf{F_n}$ propagates the individual forces applied to the item being transported to neighbouring agents. F_n is obtained constraining each agent to keep the initial distance from its neighbours at every time step:

$$F_n(p) = c \cdot \sum_{q \in P} \left(\frac{q(t) - p(t)}{\|q(t) - p(t)\|} \right) \cdot (\|q(t) - p(t)\| - \|q(0) - p(0)\|) \cdot \delta(p, q) \ , \quad (1)$$

with $0 \le c \le 1$. The first factor of eq. (1) is the versor from agent p to agent q. The second factor is the gap between the current and the initial distance between p and q. Function δ indicates whether p and q are to be considered neighbours: $\delta(p, q) = 1$ if $q \in neigh(p)$ and 0 otherwise. Function $neigh(p)$ determines the initial disposition of the agents. The function $neigh$, used in our work, is defined as:

$$neigh(p) = \left\{ q \in P : \ 0 < \|p(0) - q(0)\|_2 \le \sqrt{2} \right\} \ . \quad (2)$$

$\mathbf{F_p}$ controls the velocity of the agents p moving in their preferred directions. F_p can be expressed as:

$$F_p(p(t)) = \begin{cases} 0 & \text{if} \quad F_p(p(t-1)) + V_p \cdot A < 0 \\ \mathrm{Max}_{F_p} & \text{if} \quad F_p(p(t-1)) + V_p \cdot A > \mathrm{Max}_{F_p} \\ F_p(p(t-1)) + V_p \cdot A & \text{otherwise} \end{cases} \ . \quad (3)$$

At time $t = 0$, $F_p(p(0)) = 0$. The term A in equation 3 represents the increment in modulus of F_p at time t:

$$A = \lambda(V_p \cdot \hat{V}_g(p)) \ . \quad (4)$$

It is worth noting that F_p and V_p have the same orientation and the same direction. Since V_p and $\hat{V}_g(p)$ are versors, the parameter λ represents the maximum value of A. The increment of the modulus of F_p is inversely proportional to the angle between the direction chosen by the agent, i.e. the versor V_p, and the direction chosen by the majority of agents, i.e. the versor V_g.

In order to obtain the exact value of V_g, we should know the state of each agent in any iteration, but such assumption violates SI principles. An estimate $\hat{V}_g$ of V_g can be obtained by using local information only, namely comparing the current position of an agent to its position at time $t - k$:

$$\hat{V}_g(p) = \frac{p(t) - p(t-k)}{\|p(t) - p(t-k)\|} \ . \quad (5)$$

In order for eq. (5) to be consistent for every t, it is assumed that $p(-1) = p(-2) = \ \ldots \ = p(-k) = 0$. In the first k iterations each p receives a positive feedback from the system.

The position of agent p at time t is expressed as follows:

$$p(t) = p(t-1) + F_n\left(p(t)\right) + F_p\left(p(t)\right) \ . \quad (6)$$

In order to ease the description, we will identify agents with the points of the transported item.

3.2 Model Validation

The democratic collective transportation model has been validated through a series of simulations. In order to prove the correctness of the model, we show that, in such model, each agent, after some iterations, starts following the direction chosen by the majority of the agents, independently by its initial direction.

The simulation is divided into two stages. At the beginning of the first stage, all the agents are still. The versors V_p are randomly selected and each agent starts moving. During the first $\frac{N}{2}$ iterations, where N is the total number of iterations of the simulation, the V_ps remain unchanged. At iteration number $\frac{N}{2}+1$, when the agents are moving along the direction of the majority of them, their V_ps are reselected. In this case, it is more difficult for a moving agent to modify its parameters and start following the majority.

The main issue for the model concerns the estimates of the majority direction $\hat{V}_g$ made by the agents. In order to verify such estimates, we used the following error measure:

$$E = \sum_{\forall p \in P} \left(1 - \hat{V}_g(p) \cdot V_g\right) \ . \tag{7}$$

Figure 1 shows the results of a single simulation. In that case the simulation was run for $N = 80$ iterations with a population of 900 agents and parameters set as follows: $c = 0.49$, $\lambda = 0.06$, $k = 3$, $\mathrm{Max}_{F_p} = 0.24$.

As the bottom right box of figure 1 shows, the sum of the errors rapidly decreases to 0 (the peak at iteration 40 is caused by the second selection of the preferred destinations). The slope of E depends on the percentage of agents willing to move in the direction of the majority. The slope of E does not depend on the number of agents: we ran simulations with up to 10000 agents obtaining similar results.

4 An Algorithm for Image Alignment and Matching

In this section we propose an algorithm for Image Alignment based on the democratic collective transportation model.

Image alignment is defined as the problem of finding an optimal spatial alignment of two images of the same scene/object taken in different conditions. For example, two images of the same object taken at different times or from different points of view or with different modalities [12]. Image alignment is the problem of finding an optimal transformation ω minimizing dissimilarities between an input image I_{input} and a target image I_{target}. The degree of dissimilarity is measured by a cost function f:

$$\omega_{min} = \mathrm{argmin}_{\omega \in \Omega} \ \{f(\omega(I_{input}), I_{target})\} \ . \tag{8}$$

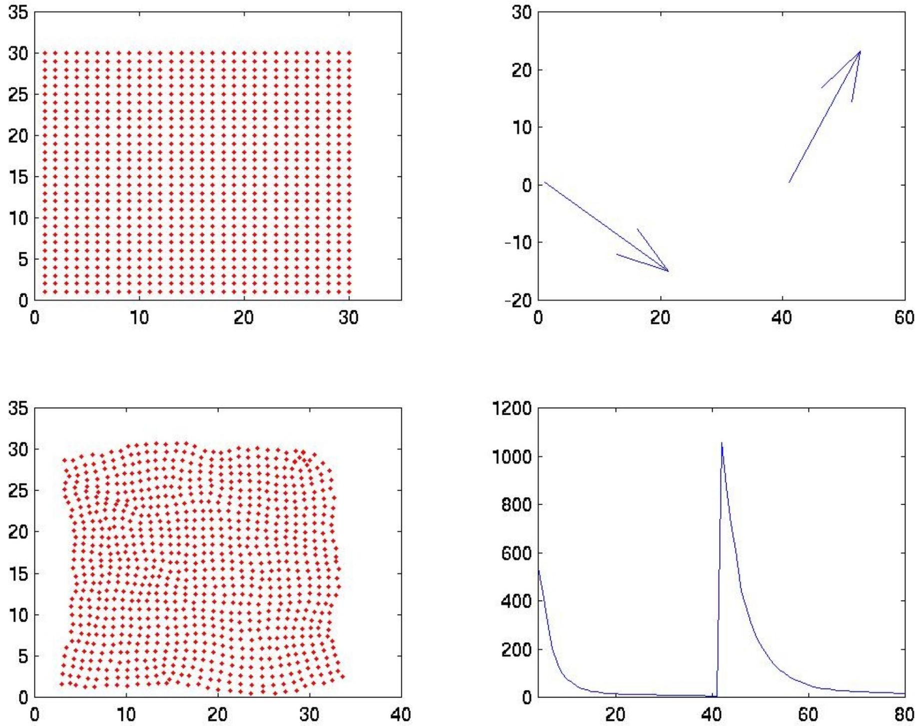

Fig. 1. A simulation of the democratic collective transportation model. From left to right, top to bottom: initial positions of the agents, qualitative idea of the direction chosen by the majority of the agents (from iteration one to 40: South-East, from iteration 41 to 80: North-East), final positions of the agents, plot of the error rate E, representing the error made by the agents in guessing the direction of the majority.

In some cases the differences between the two images should not be corrected since they might contain relevant information. For example, the diagnosis obtained by some image-based medical examinations relies on the differences between two images acquired at different times. Any registration algorithm should correct all the differences caused by misalignment and should preserve all the other ones. A detailed description of the image alignment problem and an overview of classical and new approaches can be found in [13,12].

As eq. (8) suggests, image alignment can be seen as an optimization problem, where Ω is a family of functions differing only for a set of parameters. Classical optimization techniques as well as popular swarm intelligence methods, such as Particle Swarm Optimization [14] and Ant Colony Optimization [15], have been applied to the image alignment problem. Such methods require a global cost function (or error function) to drive the system toward an optimal choice for the parameters of ω. The algorithm we propose does not use a global cost function: each agent has its local cost function.

4.1 Description of the Algorithm

Before describing in full details the algorithm, we will sketch its relationship with the introduced model:

1. I_{input}, the image to be registered, is considered the object that has to be moved.
2. Pixels of I_{input} are considered as points (and therefore agents) moving in a bi-dimensional space. Each agent has 8 neighbours corresponding to the neighbourhood of the pixel in I_{input}.
3. An application of a force on the object to be transported causes the pixel in I_{input} to move.
4. Each agent p has a set $Dest(p)$ of possible destinations, corresponding to the coordinates of the points in I_{target} that are similar, according to eq. (10), to p.
5. Each agent selects a point q in $Dest(p)$ and tries to move toward q.

The functions of the model are modified as follows:

p is a generic agent of the system. Pixels of I_{target} are grouped in a set O. At $t = 0$ the agents form a grid of points. A function $Color$ maps the agents to the gray values of the corresponding pixels in I_{input}.

$\mathbf{F_p}$ modifies I_{input} in order to make it as similar as possible to I_{target}. The idea is to let regions of I_{input} with a high gradient be attracted by corresponding regions of I_{target}. The only difference with the democratic transportation model concerns the V_p definition. Each $p \in P$ has an associated set of pixels $Dest(p)$, composed by the pixels of I_{target} which are similar to p according to eq. (10):

$$Dest(p) = \{q \in O | sim(p, q) \geq d_{sim}\} \ , \tag{9}$$

where d_{sim} is the similarity threshold. The similarity function used is:

$$sim(p, q) = |Color(p) - Color(q)| + \|\nabla p - \nabla q\|^2 \ , \tag{10}$$

where ∇p is the gradient of the image I at coordinates (p_x, p_y). Each p tries to reach a position corresponding to an element of $Dest(p)$ stored in $CurrentDestination(p)$. $CurrentDestination(p)$ is modified every g iterations according to probability density ρ defined as:

$$\rho(p, q) = \left((1 + \|p(t) - q\|) \cdot \sum_{o \in Dest(p)} \frac{1}{1 + \|p(t) - o\|} \right)^{-1} \ . \tag{11}$$

By reselecting $CurrentDestination(p)$ every g iterations, the system explores more solutions. Since in the selection process closest destinations are preferred, when a good solution has been found each agent tends, with high probability, to go back to the same point.

V_p is the versor with direction from p to its current destination:

$$V_p = \frac{CurrentDestination(p) - p(t)}{\|CurrentDestination(p) - p(t)\|} \ .$$

The dynamic of the algorithm pushes the majority of I_{input} pixels in the direction of their current preferred destination. With high probability I_{input} will move to a position "satisfying" the majority of the agents. In this paper we hypothesize that this position is the one with the highest probability to correctly align the image.

4.2 Results and Discussion

The algorithm has been tested on Magnetic Resonance images of the human brain. We ran several test using different images and different degree of noise. In each case the target image was obtained by 1) removing the background in the original image, 2) translating the filtered image to South-East and 3) by adding noise. The typical results of such experimentations are shown in fig. 2, which contains the output of three tests on 116 x 137 images. In the first row a 45% salt & pepper noise was added to I_{input}. In the second row a 16% speckle noise was added. In the last row a 16% speckle noise and a 35% salt & pepper noise were added. The last image in each row represents the final result of the algorithm. In every case the swarm needed few seconds on an AMD 1800+, with 1 GB of RAM, to compute the correct registration. The algorithm still finds the correct transformation on larger images, even if it takes longer. The results show that the algorithm corrects the differences caused by the translation.

In fig. 3 the results of a different experimentation are shown. In this case the goal was to locate a small image in a larger one. In this case also the algorithm is able to correctly locate the input image.

The algorithm described in this paper is different from classical population based optimization techniques such as genetic algorithms (GA), ACO, and PSO. In GA, ACO, and PSO at each iteration every agent proposes a complete solution to the problem. The best solutions are then selected and influence the creation of the solutions in subsequent iterations. Such approaches require a global cost function able to evaluate how good each proposed solution is. In the approach described in this paper, only one solution is generated at every iteration. There is no need of a global cost function: each agent uses a local cost function which is much simpler than common global cost functions. The system is able to discard the contribution of those agents whose cost function would lead to a poor solution and to promote those agents whose cost function would increase the quality of the solution.

5 Conclusions and Future Work

In this paper we presented a new agent coordination model based on the collective prey retrieval strategy of some species of ants. In the model a swarm of agents, each having a different destination to reach, is able, with no centralized control, to move in the direction indicated by the majority of the agents keeping, at the same time, the initial shape of the swarm.

From this coordination model an algorithm for Image Alignment and Matching in which simple agents collaborate to move an input image toward a target

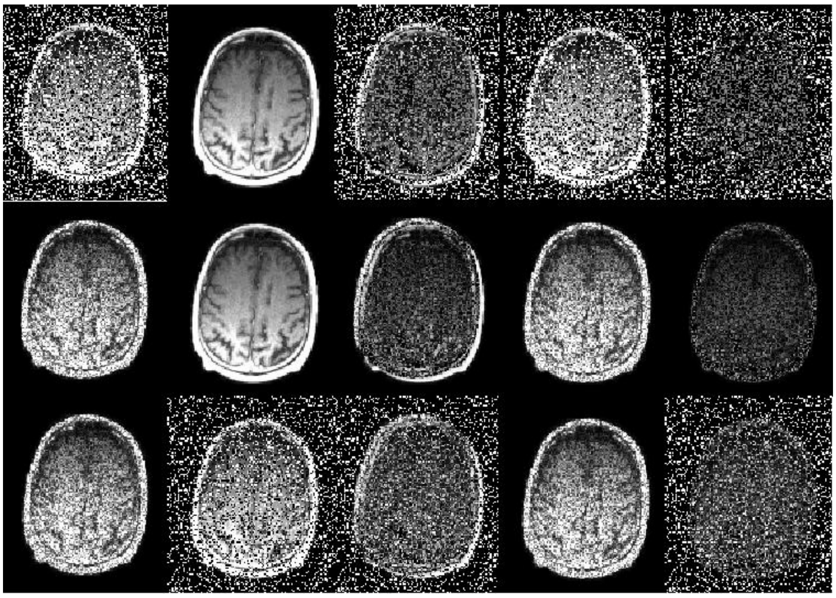

Fig. 2. Example of the execution of the algorithm. For every row, from left to right: I_{input}, I_{target}, differences between I_{input} and I_{target}, the output of the algorithm (the aligned image), the difference between I_{target} and the output of the algorithm.

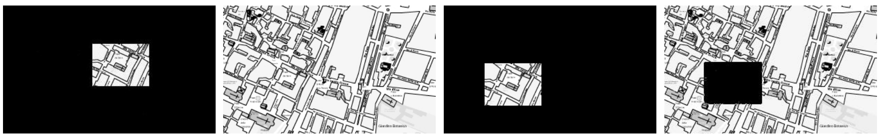

Fig. 3. Example of application of our algorithm to the Image Matching problem. In this case the goal is to find the location of the patch I_{input} in I_{target}. From left to right: I_{input}, I_{target}, the output of the algorithm, the differences between I_{target} and the estimated location of I_{input} in I_{target}. The black box means that the algorithm was able to correctly locate the patch over I_{target}.

one has been devised. According to the current results, the algorithm is tolerant to noise, but we need to further investigate its dynamic behaviour by using a larger set of test images.

The algorithm is able to correct translations only, but the results obtained so far induce us to further investigate the capabilities of our approach. The short-term goal is to extend the algorithm in order to match rotated images and to compare its performance against standard approaches. The long-term goal is to introduce new interactions that should enable the image alignment with elastic deformations and other types of noise.

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