

Self-Organized Data and Image Retrieval as a Consequence of Inter-Dynamic Synergistic Relationships in Artificial Ant Colonies^Δ

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Abstract. Social insects provide us with a powerful metaphor to create decentralized systems of simple interacting, and often mobile, agents. The emergent collective intelligence of social insects – swarm intelligence – resides not in complex individual abilities but rather in networks of interactions that exist among individuals and between individuals and their environment. The study of ant colonies behavior and of their self-organizing capabilities is of interest to knowledge retrieval/ management and decision support systems sciences, because it provides models of distributed adaptive organization which are useful to solve difficult optimization, classification, and distributed control problems, among others. In the present work we overview some models derived from the observation of real ants, emphasizing the role played by stigmergy as distributed communication paradigm, and we present a novel strategy (ACLUSTR) to tackle unsupervised data exploratory analysis as well as data retrieval problems. Moreover and according to our knowledge, this is also the first application of ant systems into digital image retrieval problems. Nevertheless, the present algorithm could be applied to any type of numeric data.

1. Introduction: Stigmergy and Distributed Awareness

Synergy, from the greek word *synergos*, broadly defined, refers to combined or co-operative effects produced by two or more elements (parts or individuals). The definition is often associated with the quote “the whole is greater than the sum of its parts” (Aristotle, in *Metaphysics*), even if it is more accurate to say that the functional effects produced by wholes are different from what the parts can produce alone. Synergy is a ubiquitous phenomena in nature and human societies alike. One well know example is provided by the emergence of self-organization in social insects, via direct (mandibular, antennation, chemical or visual contact, etc) or indirect interactions. The latter types are more subtle and defined by *Grassé* as stigmergy [5] to explain task coordination and regulation in the context of nest reconstruction in *Macrotermes* termites. An example [1], could be provided by two individuals, who interact indirectly when one of them modifies the environment and the other responds to the new environment at a later time. In other words, stigmergy could be defined as a typical case of environmental synergy. *Grassé* showed that the coordination and regulation of building activities do not depend on the workers themselves but are mainly achieved by the nest structure: a stimulating configuration triggers the response of a termite worker, transforming the configuration into another configuration that may trigger in turn another (possibly different) action performed by the same termite or any other worker in the colony. Another illustration of how stigmergy and self-organization can be combined into more subtle adaptive behaviors is recruitment in social insects. Self-organized trail laying by individual ants is a way of modifying the environment to communicate with nest mates that follow such trails [1]. Division of labor is also another paradigmatic phenomena of stigmergy. Simultaneous task performance (parallelism) by specialized workers is believed to be more efficient than sequential task performance by unspecialized workers. But by far more crucial to the present work and aim, is how ants form piles of items such as dead bodies (corpses), larvae, or grains of sand (fig. 1). There again, stigmergy is at work: ants deposit items at initially random locations. When other ants perceive deposited items, they are stimulated to deposit items next to them, being this type of cemetery clustering action,

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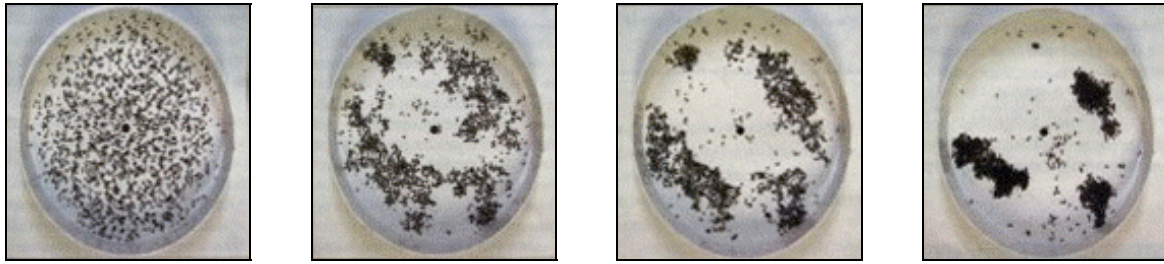


Figure 1. From left to right, a sequential clustering task of corpses performed by a real ant colony. 1500 corpses are randomly located in a circular arena with radius = 25 cm, where *Messor Sancta* workers are present. The fig. shows the initial state (left), 2 hours, 6 hours and 26 hours (right) after the beginning of the experiment [1].

organization, and brood sorting a type of self-organization and adaptive behavior. There are other types of examples (e.g. prey collectively transport), yet stigmergy is also present: ants change the perceived environment of other ants (their cognitive map, according to [3]), and in every example, the environment serves as medium of communication [1]. Nevertheless, what all these examples have in common is that they show how stigmergy can easily be made operational. As mentioned by *Bonabeau* in [1], that is a promising first step to design groups of artificial agents which solve problems: replacing coordination (and possible some hierarchy) through direct communications by indirect interactions is appealing if one wishes to design simple agents and reduce communication among agents. Finally, stigmergy is often associated with flexibility: when the environment changes because of an external perturbation, the insects respond *appropriately* to that perturbation, as if it were a modification of the environment caused by the colony's activities. When it comes to artificial agents, this type of flexibility is priceless: it means that the agents can respond to a perturbation without being reprogrammed to deal with that particular instability. In our context, this means that no classifier re-training is needed for any new sets of data-item types (new classes) arriving to the system, as is necessary in many classical models, or even in some recent ones. Moreover, the data-items that were used for supervised purposes in early stages, can now, along with new items, be re-arranged in more optimal ways. Classification and/or data retrieval remains the same, but the system reorganizes itself in order to deal with new classes, or even new sub-classes. Recently, several papers (for a good revision see [1]) have highlighted the efficiency of stochastic approaches based on ant colonies for different problem solving. Data clustering is also one of those problems in which real ants can suggest very interesting heuristics for computer scientists. One of the first studies using the metaphor of ant colonies related to the above clustering domain is due to *Deneubourg* [4], where a population of ant-like agents randomly moving onto a 2D grid are allowed to move basic objects so as to cluster them. This method was then further generalized by *Lumer et al.* [10], applying it to exploratory data analysis, for the first time. Our aim is to improve these models, introducing some radical changes and different ant-like heuristics, developing a model without any local memory and/or hybridization with more classical approaches. Moreover, the present work will be applied for the first time to image retrieval and exploratory data analysis. The datasets represent a collection of the most representative 14 types of Portuguese grey granites (fig.3), with a total set of 237 images, each represented by 117 Mathematical Morphology [16,9,12] features. Some chinese granites were also used as a test, since they can mislead several human experts, leading to a total of 244 images x 177 features. Sections III -IV describe the present proposal, while results are in sections V-VI.

2. Corpse Clustering and Variants into Exploratory Data Analysis

In several species of ants, workers have been reported to sort their larvae or form piles of corpses – literally cemeteries – to clean up their nests. *Chrétien* (see [1]) has performed experiments with the ant *Lasius niger* to study the organization of cemeteries. Other

experiments include the ants *Pheidole pallidula* reported in [4] by *Denebourg* et al., and many species actually organize a cemetery. Figure 1 (section I) shows the dynamics of cemetery organization in another species: *Messor sancta*. If corpses, or more precisely, sufficiently large parts of corpses are randomly distributed in space at the beginning of the experiment, the workers form cemetery clusters within a few hours, following a behavior similar to aggregation. If the experimental arena is not sufficiently large, or if it contains spatial heterogeneities, the clusters will be formed along the edges of the arena or, more generally, following the heterogeneities. The basic mechanism underlying this type of aggregation phenomenon is an attraction between dead items mediated by the ant workers: small clusters of items grow by attracting workers to deposit more items. It is this positive and auto-catalytic feedback that leads to the formation of larger and larger clusters. In this case, it is therefore the distribution of the clusters in the environment that plays the role of stigmergic variable. *Denebourg* et al. [4] have proposed one model (hereafter called BM, for basic model) to account for the above-mentioned phenomenon of corpse clustering in ants. The general idea is that isolated items should be picked up and dropped at some other location where more items of that type are present. Let us assume that there is only one type of item in the environment. The probability P_p for a randomly moving, unladen agent (representing an ant in the model) to pick up an item is given by (Eq. 2.1):

$$P_p = \left(\frac{k_1}{k_1 + f} \right)^2 \quad (2.1) \quad P_d = \left(\frac{f}{k_2 + f} \right)^2 \quad (2.2)$$

where f is the perceived fraction of items in the neighborhood of the agent, and k_1 is a threshold constant. When $f \ll k_1$, P_p is close to 1, that is, the probability of picking up an item is high when there are not many items in the neighborhood. P_p is close to 0 when $f \gg k_1$, that is, items are unlikely to be removed from dense clusters. The probability P_d for a randomly moving loaded agent to deposit an item is given by Eq. 2.2., where k_2 is another threshold constant: for $f \ll k_2$, P_d is close to 0, whereas for $f \gg k_2$, P_d is close to 1. In their simulations, *Denebourg* et al. [4] have used $k_1 = 0.1$ and $k_2 = 0.3$, testing the spatial sorting organization of 400 items of two types, on a 100 x 100 grid, using 10 agents and $T = 50$; 5,000,000 iterations were needed to accomplish a feasible visual result. As expected, the depositing behavior obeys roughly opposite rules.

As we shall see, the algorithms later described (as well as those proposed) in the present work, are inspired by this idea, but rely on a more direct evaluation of f . This procedure should, therefore, be taken as an example among many possible procedures, and changing the detail how f is perceived does not drastically alter the results, according to *Bonabeau* [1]. Among other differences proposed later, are also those directly related to how the agents move on the spatial grid. For instance, real ants are likely to use chemical or tactile cues to orient their behavior. In their simulations, however, *Denebourg* et al. [4] have taken the option of using randomly moving agents, while in here and due to our aim, we suggest the use of ant-like spatial transition probabilities (section III), based on chemical pheromone non-linear weighting functions. Significantly more interesting to the present proposal is however, *Lumer's* and *Faieta* model [10]. Both authors have generalized *Denebourg* et al.'s BM [4], to apply it to exploratory data analysis. The idea is to define a distance or dissimilarity d between objects in the space of object attributes. Let $d(o_i, o_j)$ be the distance between two objects o_i and o_j in the feature space. Let us also assume that an agent is located at site r at time t , and finds an object o_i at that site. The "local density" $f(o_i)$ with respect to object o_i at site r is then given by:

$$f(o_i) = \max \left\{ 0, \frac{1}{s^2} \sum_{o_j \in \text{Neigh}_{(xxx)}(r)} \left[1 - \frac{d(o_i, o_j)}{\alpha} \right] \right\} \quad (2.3)$$

$f(o_i)$ is a measure of the average similarity of object o_i with the other objects o_j present in the neighborhood of o_i . That is, $f(o_i)$ replaces the fraction f of similar objects in the BM model, while α is a factor that defines the scale of dissimilarity: it is important for it determines when two items should or should not be located next to each other. Then, and inspired by *Denebourg* et al.'s functions [4] (Eqs. 2.1 and 2.2), *Lumer* and *Faieta* [10] defined picking up probabilities similarly, where f was substituted by $f(o_i)$, and dropping probabilities as $P_{\bar{d}} = 2f(o_i)$ for $f(o_i) < k_2$, and $P_{\bar{d}} = 1$ for the remaining cases. *Lumer* and *Faieta* [10] have used $k_1 = 0.1$, $k_2 = 0.15$ (while BM uses $k_2 = 0.3$) and $\alpha = 0.5$, with $t_{max} = 10^6$ steps. In order to illustrate the functioning of their algorithm, the authors used a simple example in which the attribute space is R^2 , and the values of the two attributes for each object correspond to its coordinates (x, y) in R^2 . The same distribution was later used for tests in the present work – see fig. 2a, section V. *Lumer* and *Faieta* [10] have then added three features to their system, due to the fact that are generally more clusters in the projected system than in the initial distribution. These features help to solve this problem, even if they are computationally intensive and broadly bio-inspired. They are: (1) ants with different moving speeds, (2) a short term memory, and (3), behavioral switches.

3. From Randomly Moving Agents to Bio-Inspired Spatial Probabilities

Instead of trying to solve some disparities in the basic LF algorithm by adding different ant casts, short-term memories and behavioral switches (described in section II) which are computationally intensive, representing simultaneously a potential and difficult complex parameter tuning, it is our intention (within the present ACLUSTER proposal) to follow real ant-like behaviors as possible (some other features will be incorporated, as the use of different response thresholds to task-associated stimulus intensities, discussed later at section IV). In that sense, bio-inspired spatial transition probabilities are incorporated into the system, avoiding randomly moving agents, which tend the distributed algorithm to explore regions manifestly without interest (e.g., regions without any type of object clusters), being generally, this type of exploration, counterproductive and time consuming. Since this type of transition probabilities depend on the spatial distribution of pheromone across the environment, the behavior reproduced is also a stigmergic one. Moreover, the strategy not only allows to guide ants to find clusters of objects in an adaptive way (if, by any reason, one cluster disappears, pheromone tends to evaporate on that location), as the use of embodied short-term memories is avoided (since this transition probabilities tends also to increase pheromone in specific locations, where more objects are present). As we shall see, the distribution of the pheromone represents the memory of the recent history of the swarm, and in a sense it contains information which the individual ants are unable to hold or transmit. There is no direct communication between the organisms but a type of indirect communication through the pheromonal field. In fact, ants are not allowed to have any memory and the individual's spatial knowledge is restricted to local information about the whole colony pheromone density. In order to design this behavior, one simple model was adopted (*Chialvo* and *Millonas*, [3]), and extended (as in [13]) due to specific constraints of the present proposal. As described in [3], the state of an individual ant can be expressed by its position r , and orientation θ . It is then sufficient to specify a transition probability from one place and orientation (r, θ) to the next (r^*, θ^*) an instant later. The response function can effectively be translated into a two-parameter transition rule between the cells by use of a pheromone weighing function (Eq. 3.1):

$$W(\sigma) = \left(1 + \frac{\sigma}{1 + \delta\sigma}\right)^\beta \quad (3.1)$$

$$P_{ik} = \frac{W(\sigma_i)w(\Delta_i)}{\sum_{j/k} W(\sigma_j)w(\Delta_j)} \quad (3.2)$$

This equation measures the relative probabilities of moving to a cite r (in our context, to a grid location) with pheromone density $\sigma(r)$. The parameter β is associated with the osmotropotaxic sensitivity (a kind of instantaneous pheromonal gradient following), and on the other hand, $1/\delta$ is the sensory capacity, which describes the fact that each ant's ability to sense pheromone decreases somewhat at high concentrations. In addition to the former equation, there is a weighing factor $w(\Delta\theta)$, where $\Delta\theta$ is the change in direction at each time step, i.e. measures the magnitude of the difference in orientation. As an additional condition, each individual leaves a constant amount η of pheromone at the pixel in which it is located at every time step t . This pheromone decays at each time step at a rate k . Then, the normalised transition probabilities on the lattice to go from cell k to cell i are given by P_{ik} [3] (Eq. 3.2), where the notation j/k indicates the sum over all the pixels j which are in the local neighbourhood of k . Δ_i measures the magnitude of the difference in orientation for the previous direction at time $t-1$. That is, since we use a neighbourhood composed of the cell and its eight neighbours, Δ_i can take the discrete values 0 through 4, and it is sufficient to assign a value w_i for each of these changes of direction. *Chialvo et al* used the weights of $w_0 = 1$ (same direction), $w_1 = 1/2$, $w_2 = 1/4$, $w_3 = 1/12$ and $w_4 = 1/20$ (U-turn). In addition, coherent results were found for $\eta = 0.07$ (pheromone deposition rate), $k = 0.015$ (pheromone evaporation rate), $\beta = 3.5$ (osmotropotaxic sensitivity) and $\delta = 0.2$ (inverse of sensory capacity), where the emergence of well defined networks of trails were possible. For a detailed mathematical discussion of this model, and other conditions readers are reported to [3] and [13]. In order to achieve emergent and *autocatalytic* mass behaviours around item groups on the *habitat*, which can significantly change the expected ant colony cognitive map (pheromonal field), instead of a constant pheromone deposition rate η used in [3], a term not constant is included. This strategy follows an idea implemented by *Ramos et al.* [13], while extending the *Chialvo* model into digital image habitats. In here, however, this term is naturally related with the amount of items found in one specific region. So for instance, if we use Δ_h as that measure (i.e., the number of items present in one neighborhood), the pheromone deposition rate T for a specific ant at that specific cell (at time t), should change to a dynamic value (p is a constant = 0.0025): $T = \eta + p\Delta_h$. Notice that, if no objects are present, results expected by this extended model will be equal to those found by *Chialvo* and *Millonas* in [3], since Δ_h equals to zero.

4. Stressing the Role of Response Thresholds to Task-Associated Stimulus Intensities

In order to model the behavior of ants associated to different tasks, as dropping and picking up objects, we suggest the use of combinations of different response thresholds. As we have seen before, there are two major factors that should influence any local action taken by the ant-like agent: the number of objects in his neighborhood, and their similarity (including the hypothetical object carried by one ant). *Lumer* and *Faieta* [10], use an average similarity (Eq. 2.3, section II), mixing distances between objects with their number, incorporating it simultaneously into a response threshold function like the one of *Denebourg's* (Eq. 2.1, 2.2, section II). Instead, in the present proposal, we suggest the use of combinations of two independent response threshold functions, each associated with a different environmental factor (or, stimuli intensity), that is, the number of objects in the area, and their similarity. Moreover, the computation of average similarities are avoided in the present algorithm, since

this strategy can be somehow blind to the number of objects present in one specific neighborhood. In fact, in *Lumer* and *Faieta's* work [10], there is an hypothetical chance of having the same average similarity value, respectively having one or, more objects present in that region. But, experimental evidences and observation in some types of ant colonies, can provide us with a different answer. After *Wilson* [17], it is knowned that minors and majors in the polymorphic species of ants *Genus Pheidole*, have different response thresholds to task-associated stimulus intensities (i.e., division of labor). Recently, and inspired by this experimental evidence, *Bonabeau* et al. [2], proposed a family of response threshold functions in order to model this behavior. According to it, every individual has a response threshold θ for every task. Individuals engage in task performance when the level of the task-associated stimuli s , exceeds their thresholds. Authors defined s as the intensity of a stimulus associated with a particular task, i.e. s can be a number of encounters, a chemical concentration, or any quantitative cue sensed by individuals. One family of response functions $T_\theta(s)$ (the probability of performing the task as a function of stimulus intensity s), that satisfy this requirement is given by (Eq. 4.1) [2]:

$$T_\theta(s) = \frac{s^n}{s^n + \theta^n} \quad (4.1) \quad \chi = \frac{n^2}{n^2 + 5^2} \quad (4.2) \quad \delta = \left(\frac{k_1}{k_1 + d} \right)^2 \quad (4.3) \quad \varepsilon = \left(\frac{d}{k_2 + d} \right)^2 \quad (4.4)$$

where $n > 1$ determines the steepness of the threshold (normally $n=2$, but similar results can be obtained with other values of $n > 1$). Now, at $s = \theta$, this probability is exactly $\frac{1}{2}$. Therefore, individuals with a lower value of θ are likely to respond to a lower level of stimulus. In order to take account on the number of objects present in one neighborhood, Eq. 4.1, was used (where, n now stands for the number of objects present in one neighborhood, and $\theta = 5$), defining χ (Eq. 4.2) as the response threshold associated to the number of items present in a 3×3 region around r (one specific grid location). Now, in order to take account on the hypothetical similarity between objects, and in each ant action due to this factor, a Euclidean normalized distance d is computed within all the pairs of objects present in that 3×3 region around r . Being a and b , a pair of objects, and $f_a(i), f_b(i)$ their respective feature vectors (being each object defined by F features), then $d = (1/d_{max}) \cdot [(\sum_{i=1, F} (f_a(i) - f_b(i))^2)]^{1/2}$. Clearly, this distance d reaches its maximum ($=1$, since d is normalized by d_{max}) when two objects are maximally different, and $d=0$ when they are equally defined by the same F features. Then, δ and ε (Eqs. 4.3, 4.4), are respectively defined as the response threshold functions associated to the similarity of objects, in case of dropping an object (Eq. 4.3), and picking it up (Eq. 4.4), at site r . Note that these functions are similar to those proposed by *Denebourg* et al. [4] (k_1 and k_2 , are threshold constants), while defining probabilities for picking up or to deposit an item (Eqs. 2.1, 2.2, section II). In here, however, we use them in reversed order, substituting f by d (where f represented, for *Denebourg* et al., the perceived fraction of items in the neighborhood of one agent, having in mind a robotic implementation). As we can observe, the probability δ for a specific moving loaded agent to deposit an item at site r , is given by Eq. 4.3. When $d \ll k_1$ (i.e., d close to 0), δ is close to 1, that is, the probability of dropping an item is high when the similarity between the loaded object and one present in the region around r , is high.

Now, in every action taken by an agent, and in order to deal, and represent different stimulus intensities (number of items and their similarity), present at each site in the environment visited by one ant, the strategy uses a composition of the above defined response threshold functions (Eq. 4.2, 4.3 and 4.4). These composed probabilities are resumed in table 1, and were used as test functions in one preliminar test (section V) proposed in [10] in order to illustrate the functioning of the algorithm.

TYPES OF HYBRID RESPONSE FUNCTIONS USED

Function Types	Picking Probability	Dropping Probability
#1	$P_p = (1-\chi).\varepsilon$	$P_d = \chi.\delta$
#2	(a) $P_p = (1-\chi).\varepsilon$ (b) $P_p = \varepsilon$	(a) $P_d = \chi.\delta$ (b) $P_d = \delta$
#3	(a) $P_p = 1-\chi$ (b) $P_p = \varepsilon$	(a) $P_d = \chi$ (b) $P_d = \delta$
#4	<i>Lumer & Faieta</i> (see section II)	<i>Lumer & Faieta</i> (see section II)

Table 1 – Types of picking (P_p) and dropping (P_d) probability functions used for several tests. In #2,3 half of the ants used one probability function (a), while the rest used the other function (b). In #4, the LF algorithm (section II) was fully implemented and followed, but using a toroidal grid.

On the other hand, to evaluate the algorithm behavior, a simple entropy definition is proposed. For a finite number of n type A items, placed into a finite area grid, the entropy of A type objects can be defined as the normalized sum, over all n , of the number of empty cells e (or occupied by objects different from A), surrounding each item A ($e_{max} = 8$, in 3×3 regions), that is, $E_A = (\sum e_i) / (n \cdot e_{max})$. As its obvious, several configurations lead to different values of entropy, where E_A reaches its maximal value ($E_A = 1$) when all type A items are disconnected from each other. Disconnected clusters of type A items, lead also to an increase in the value of entropy.

5. Results on a “4 Classes X 200 Gaussian Distributed Points” Problem

As mentioned before, we decide to test the algorithm using the same problem as *Lumer* and *Faieta*, introduced by them in [10]. This problem consists of 800 points, represented by two features each. That is, the attribute space is R^2 , and the values of the two attributes for each object correspond to its coordinates (x,y) in R^2 . Four clusters of 200 points each were then generated in attribute space, with x and y distributed according to Normal (or Gaussian) distributions $N(\mu,\sigma)$ of average μ and variance σ^2 - see figure 2.a) for details. The 800 data points (items) were then assigned at random locations on a 57×57 non-parametric toroidal grid, and the clustering algorithm was run with 80 ants, using the function types specified in table 1. Generally, the following empirical rules were followed, since they lead to good results: $A=4.n_o$, $n_a=A/40$, and $n_a/n_o=0.1$, where A is the grid area, n_o is the number of objects, and n_a the number of ants used. As a final result, objects that are clustered together belong generally to the same initial distribution, and objects that do not belong to the same initial distribution are found generally in different clusters. In figure 2.b), the evolution of total entropy ($E_{total}=E_A+E_B+E_C+E_D$), for 10^6 iterations (as those used in [10]) was plotted for four different type functions. It is clear to see that probabilistic functions type #3, are the worse in terms of clustering the different items, while the rest (including the algorithm proposed by *Lumer* and *Faieta* [10]) have similar behaviors, and indeed reduce drastically the value of entropy of those configurations. We can also get an idea of how the new algorithm clusters the different items, while the algorithm proceeds (fig. 2.c,d,e,f). In this case type function #1 was used, and as observed, initially randomly deposited items at $t=1$ in the toroidal grid, are then at $t>0$ spatially distributed according to their similarities.

6. Applications into Digital Image Retrieval: A Case Study within a Granite Database

Ornamental stones are quantitatively characterised in many ways, mostly physical, namely, geological-petrographical and mineralogical composition, or by mechanical strength. However, the properties of such products differ not only in terms of type but also in terms of origin, and their variability can also be significant within a same deposit or quarry [12].

Algorithm. High-level description of *ACLUSTER*.

```

/* Initialization */
For every item  $o_i$  do
Place  $o_i$  randomly on grid
End For
For all agents do
Place agent at randomly selected site
End For
/* Main loop */
For  $t = 1$  to  $t_{max}$  do
For all agents do
 $sum = 0$ 
Count the number of items  $n$  around site  $r$ 
If ((agent unladen) and (site  $r$  occupied by item  $o_i$ )) then
For all sites around  $r$  with items present do
/* According to Eqs. 4.2, 4.4 and Table 1 (section 4) */
Compute  $d, \chi, \varepsilon$  and  $P_p$ 
Draw random real number  $R$  between 0 and 1
If ( $R \leq P_p$ ) then
 $sum = sum + 1$ 
End If
End For
If ( $(sum \geq n/2)$  or ( $n = 0$ )) then
Pick up item  $o_i$ 
End If
Else If ((agent carrying item  $o_i$ ) and (site  $r$  empty)) then
For all sites around  $r$  with items present do
/* According to Eqs. 4.2, 4.3 and Table 1 (section 4) */
Compute  $d, \chi, \delta$  and  $P_d$ 
Draw random real number  $R$  between 0 and 1
If ( $R \leq P_d$ ) then
 $sum = sum + 1$ 
End If
End For
If ( $sum \geq n/2$ ) then
Drop item  $o_i$ 
End If
End If
/* According to Eqs. 3.1 and 3.2 (section 3) */
Compute  $W(\sigma)$  and  $P_{ik}$ 
Move to a selected  $r$  not occupied by other agent
Count the number of items  $n$  around that new site  $r$ 
Increase pheromone at site  $r$  according to  $n$ , that is:
 $P_r = P_r + [\eta + (n/\alpha)]$ 
End For
Evaporate pheromone by  $K$ , at all grid sites
End For
Print location of items
/* Values of parameters used in experiments */
 $k_1 = 0.1, k_2 = 0.3, K = 0.015, \eta = 0.07, \alpha = 400,$ 
 $\beta = 3.5, \gamma = 0.2, t_{max} = 10^6$  steps.

```

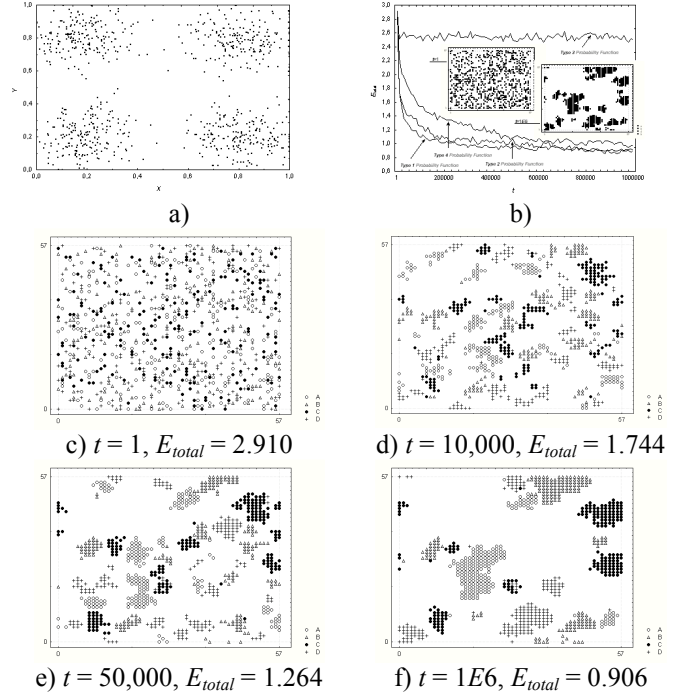


Fig. 2. **a)** Distribution of points in “attribute space”: 4 clusters of 200 points each were generated in attribute space, with x and y distributed according to Normal (or Gaussian) distributions $N(\mu, \sigma)$: $A = [x \approx N(0.2, 0.1), y \approx N(0.2, 0.1)]$, $B = [x \approx N(0.8, 0.1), y \approx N(0.2, 0.1)]$, $C = [x \approx N(0.8, 0.1), y \approx N(0.8, 0.1)]$, $D = [x \approx N(0.2, 0.1), y \approx N(0.8, 0.1)]$, for objects type A, B, C and D , respectively. **b)** Total entropy, $E_{total} = E_a + E_b + E_c + E_d$, in time, as the swarm evolves new solutions in clustering four type of objects. Four graphs are shown which correspond to four types of Probability functions (dropping and picking) analyzed (see table 1). **c, d, e, f)** Spatial distribution of 800 items on a 57×57 non-parametric toroidal grid at several time steps. At $t=1$, four types of items are randomly allocated into the grid. As time evolves, several homogenous clusters emerge due to the ant colony action, and as expected the total entropy decreases. In order to illustrate the behavior of the algorithm, items that belong to different clusters (fig. 2.a), were in here represented by different symbols: $\circ, \Delta,$ and $+$. Type 1 probability function was used with $k_1=0.1$ and $k_2=0.3$.

Though useful, these methods do not fully solve the problem of classifying a product whose end-use makes appearance so critically important. Appearance is conditioned not only by the kind of stone but also depends on the subjective evaluation of beauty and hence of economic value, which are strongly influenced by supply and demand. Traditionally, the selection process is based on visual inspection, giving a subjective characterisation of the appearance of the materials. Thus, one suitable tool to characterise the appearance of these natural stones is digital image analysis. In the present work we use mathematical morphology (MM, [16]) as a feature extraction method, as used in past works by Ramos et al. [12]. Generically, the extraction of features by means of image analysis and mathematical morphology techniques is implemented in 2 stages: a global and a local analysis. It consists on the extraction of features before (global analysis) and after (local analysis) the segmentation or mineral phase classification procedures. This approach is general and can be applied not only to characterise slab surfaces of granites as also other types of ornamental stones. The method fully described

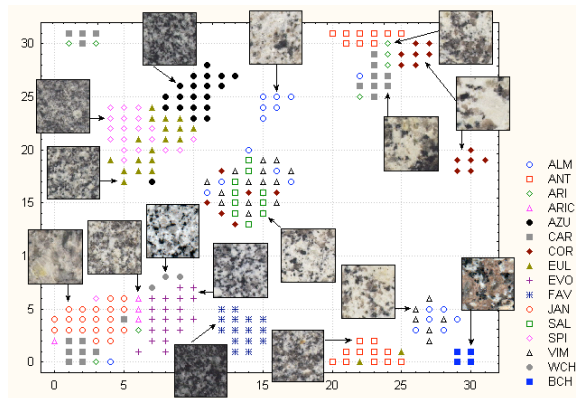


Figure 3 – Spatial distribution of 244 images (representing 14 types of Portuguese Granites + 2 types of Chinese Granites), at $t=1,000,000$. Each image (point in the environment) is composed by 117 morphological and intensity features. Type 1 probability function was used with $k_1=0.1$ and $k_2=0.3$.

in [12] uses the opening MM operator (erosion followed by dilation) and the closing (dilation followed by erosion), since they have granulometric properties [11] once are increasing, extensive (closing) and anti-extensive (opening) and idempotent. From here, a size-intensity diagram [9], can be extracted and used as a feature vector for each image. Data was collected for 14 types of Portuguese grey granites, with a total set of 237 images, each represented by 117 MM features. Some chinese granites were also used as a test, since they can mislead several human experts, leading to a total of 244 images \times 177 features. Since we had 244 items (images) to self-organize by the swarm, 24 ants were used (see section V), on a 31×31 non-parametric toroidal grid. Fig. 3 shows the final result at $t=10^6$, as well as the type of granite textures clustered.

7. Conclusions

We have presented in this paper a new ant-based algorithm named ACLUSTER for data unsupervised clustering and data exploratory analysis, while sketching a clear parallel between a mode of problem-solving in social insects and a distributed, reactive, algorithmic approach. Some of the mechanisms underlying corpse clustering, brood sorting and those that can explain the worker's behavioral flexibility, as regulation of labor and allocation of tasks have first been introduced. As in similar past works applied to document clustering and text retrieval [14], the role of response thresholds to task-associated stimulus intensities were stressed as an important part of the strategy, and incorporated into the algorithm by using compositions of different response functions. These compositions allows the strategy not only to be more accurate relatively to behaviours found in nature as avoids short-term memory based strategies, and the use of several artificial ant types (using different speeds), present in some recent approaches. Behavioral switches as used in [10], were also avoided, in order to maintain simplicity and to avoid complex parameter settings to be performed by the domain expert. At the level of agent moves in the grid, a truly stigmergic model was introduced (section III) in order to deal with clusters of objects, avoiding randomly moves which can be counterproductive in the distributed search performed by the swarm, and adopted by all past models. In fact, the present algorithm, along with [14], were the first to introduce pheromone traces on agents to deter random explorations and encourage objects cluster formation, a successful feature not implemented even in some recent proposals [7,6]. Results speak for themselves (fig.2,3). While achieving similar results compared to *Lumer's* model [10], as pointed by the spatial entropy of solutions at each time iteration (fig.2b), the present algorithm is by far more simple. Moreover, for some of response thresholds compositions used, results are superior while using the present algorithm for the majority of time iterations, that is, entropy is always lower, even if at the end they tend to the same

value. As a final advantage, ACLUSTER does not require any initial information about the future classification, such as an initial partition or an initial number of classes. This novel strategy was then applied for the first time to digital image retrieval via k -NNR. Generally, similar types of images tend to be homogeneously clustered together. But more impressive is that this type of stigmergic map can be used to classify new images, arriving to the system at any moment. In fact, using 50 randomly chosen images as a test set (from the initial 244; several sub-sets were used), an average classification and retrieval rate of 94% was achieved by using k -NNR classification methods (*Nearest Neighbor Rule* – i.e., a label of an unknown item is determined by the label of his first k neighbors; $k=3$ was used). Finally, and as verified by other tests [15] on ACLUSTER, a robust nonstop classifier could be achieved, which produces class decisions on a continuous stream data, allowing for continuous mappings. As we know, many categorization systems have the inability to perform classification and visualization in a continuous basis or to self-organize new data-items into the older ones (evenmore into new labels if necessary), unless a new training happens. This disadvantage is also present in more recent approaches using Self-Organizing Maps [8], as in *Kohonen* maps. While a benchmark comparison of the above cited methods should be interesting to explore, the ability of ACLUSTER to perform continuous mappings and the incapacity of the latter to conceive it, tend to difficult any serious comparison.

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- [1] Bonabeau E., M. Dorigo, G. Théraulaz. *Swarm Intelligence: From Natural to Artificial Systems*. Santa Fe Institute in the Sciences of the Complexity, Oxford University Press, New York, Oxford, 1999.
- [2] Bonabeau, E., Théraulaz, G., Deneubourg, J.-L., “Quantitative Study of the Fixed Response Threshold Model for the Regulation of Division of Labour in Insect Societies”. *Roy. Soc. B*, 263, pp. 1565-1569, 1996.
- [3] Chialvo, Dante R., Millonas, Mark M. “How Swarms Build Cognitive Maps”. In Luc Steels (Ed.), *The Biology and Technology of Intelligent Autonomous Agents*, (144) pp. 439-450, NATO ASI Series, 1995.
- [4] Deneubourg, J.-L., Goss, S., Franks, N., Sendova-Franks A., Detrain, C., Chretien, L. “The Dynamic of Collective Sorting Robot-like Ants and Ant-like Robots”, *SAB'90 - 1st Conf. On Simulation of Adaptive Behavior: From Animals to Animats*, J.A. Meyer and S.W. Wilson (Eds.), 356-365. MIT Press, 1991.
- [5] Grassé, P.-P. “Termitologia, Tome II” *Fondation des Sociétés. Construction*. Paris; Masson, 1984.
- [6] Handl, J., Meyer B. “Improved Ant-based Clustering and Sorting in a Document Retrieval Interface”, in J.J. Merelo, J.L.F. Villacañas, H.-G. Beyer, P. Adamidis (Eds.), *PPSN VII - 7th Int. Conf. on Parallel Problem Solving from Nature*, Granada, Spain, Sept. 2002.
- [7] Hoe, K.M., Lai, W.K., Tai, T.S.Y. “Homogeneous Ants for Web Document Similarity Modeling and Categorization”, in M. Dorigo, G. Di Caro and M. Sampels (Eds.), *3rd Int. Works. on Ant Algorithms*, Springer-Verlag, Brussels, Sept. 2002.
- [8] Kohonen, T. *Self-Organizing Maps*, Springer-Verlag, Berlin, 1997.
- [9] Lotufo, R.A., Trettel, E., “Integrating Size Information into Intensity Histogram”, in Maragos P., Schafer R.W., Butt M.A.(Eds.), *Mathematical Morphology and its Applications to Image and Signal Processing*, pp. 281-288, Kluwer Academic Publishers, Boston, 1996.
- [10] Lumer E. D. & Faieta B. (1994), Diversity and Adaptation in Populations of Clustering Ants. In Cliff, D., Husbands, P., Meyer, J. and Wilson S. (Eds.), *in From Animals to Animats 3*, Proc. of the 3rd Int. Conf. on the Simulation of Adaptive Behavior. Cambridge, MA: The MIT Press/Bradford Books, 1994.
- [11] Matheron G. *Random sets and Integral Geometry*, Wiley, New York, 1975.
- [12] Ramos, Vitorino, Pina, P. and Muge, F. “From Feature Extraction to Classification: A Multidisciplinary Approach applied to Portuguese Granites”, *11th Scan. Conf. on Image Analysis*, pp. 817-824, Greenland, 1999.
- [13] Ramos, Vitorino, and Almeida, F. “Artificial Ant Colonies in Digital Image Habitats - A Mass Behaviour Effect Study on Pattern Recognition”, in Marco Dorigo, Martin Middendorf and Thomas Stützle (Eds.), *Proc. of ANTS'00 – 2nd Int. Workshop on Ant Algorithms*, pp. 113-116, Brussels, Belgium, 7-9 Sep. 2000.
- [14] Ramos, Vitorino and Merelo, Juan J. “Self-Organized Stigmergic Document Maps: Environment as a Mechanism for Context Learning”, in E. Alba, F. Herrera, J.J. Merelo et al. (Eds.), *AEB'02 - 1st Int. Conf. on Metaheuristics, Evolutionary and Bio-Inspired Algorithms*, pp. 284-293, Mérida, Spain, 6-8 Feb. 2002.
- [15] Ramos, Vitorino., “Swarms on Continuous Data”, to appear in Ahmad Lotfi, Bob John and Jon Garibaldi (Eds.), *Recent Advances in Soft Computing*, Springer-Verlag, Nottingham, UK, 12-13 Dec. 2002.
- [16] Serra J., *Image Analysis and Mathematical Morphology*, Academic Press, London, 1982.
- [17] Wilson, E.O., *The Insect Societies*, Belknap Press, Cambridge, 1971.