KANTS – A Stigmergic Algorithm for Data Clustering and Swarm Art

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KANTS is a swarm intelligence algorithm [1], proposed in [10, 2] for data clustering and classification. The term KANTS derives from *Kohonen Ants*, since the algorithm was partially inspired by Kohonen's Self-Organizing Maps [9]. The method was also based on Chialvo and Millonas' Ant System [6] and its working mechanisms are very similar to that model. However, differences in the local rules and pheromone concept makes KANTS a singular system, very different not only from Self-Organizing Maps and Ant System, but also, to the extent of the authors knowledge, from other ant-based clustering algorithms.

Instead of the 2-dimensional homogeneous lattice graph (or square grid) used in the Ant System [6] as the *habitat* (or *environment*) for the ants, KANTS swarm moves on a square grid with one vector of real-valued variables mapped to each cell or node. The *agents* also differ from Chialvo and Millonas model, since KANTS uses data samples (with the same size as the environmental vectors) as artificial ants while Ant System is a simplified model of real ant colonies. KANTS move through the grid, changing the values of the vectors (following Kohonen's approach [9]) so that they tend to be closer to their own values. At the same time, the ants are attracted to the sections of the habitat where the Euclidean distance between the ant's vector and the environmental vectors in that particular section is minimized. This means that the ants communicate via the environment, by changing that same environment, an ability that is a fundamental part of a process known as stigmergy [8]. The simple set of rules of the model leads to a global behavior in which clusters of ants/samples belonging to the same *class*[1] tend to emerge.

As stated above, the ants act upon the environmental grid, changing the values of vectors. Therefore, the grid of vectors acts as a kind of *pheromone map* that is shaped by the ants. In our exploration of KANTS as a *swarm art* tool, the maps are used for generating 2-dimensional colored images in the RGB system. The vectors are directly translated to the R, G, and B values (three-variable data samples are used here, which makes it easy to translate the values into RGB images, but other forms of translating vectors to RGB can be devised). Since the ants tend to cluster, thus changing the values in that region, it is expected that the pheromone map, after a certain number of iterations, shows non-random patterns, like a kind of fuzzy patchwork. Below, we give some examples of a recent project that uses KANT for generating abstract painting that result from the interaction of data samples, but first let us describe the simplified version of KANTS that is currently being used in our swarm art projects. The reader is referred to [10] for a detailed description of the original algorithm[2]. Please note that although KANTS is different from traditional Ant Algorithms [1], it is stigmergic, and directly inspired by the Ant System: its working mechanisms are extensions of the set of equations of Chialvo and Millona's model. Therefore we use here the metaphors and the terminology associated with this kind of algorithms and models: *ants*, *pheromone*, *reinforcement* and *evaporation*. With this in mind, we will describe now the KANTS algorithm in detail.

KANTS is based on the emergent properties of a set of simple units that travel through a grid. In KANTS, the grid is mapped to an array with size $N \times N \times d$, in which d is the dimension of the data vectors of the target problem, and $N \times N$ is the dimension of the grid. That is, each cell in the habitat is mapped to a d-dimensional vector. In addition, the ants also "carry" a d-dimensional vector that corresponds to a data sample: each ant is in fact one data sample of the data set. The main idea of the algorithm is having data samples (ants) moving on (and updating a) an array of real-valued vectors with the same size of the samples. The dimension of the habitat affects the performance. In general, a ratio between the number of data samples and the size of the grid (measured in number of cells) in the range $[{}^1/_3, {}^1/_2]$ provides a good basis for KANTS clustering ability, as given by [2].

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[1] *Class* here is in the context of *statistical classification* and *cluster analysis*.

[2] The source code of the original KANTS is available at: https://forja.rediris.es/plugins/scmsvn/viewcvs.php/KohonAnts/?root=geneura

The values of the grid's vectors are initially set to a random value with uniform distribution in the range $[0, 1.0]$. Then, the ants are randomly placed in the grid (after the vectors they "carry" are also normalized within the range $[0, 1]$). In each iteration, each ant is allowed to move to a different cell of the habitat and modify that cell's vector values. The ants move to neighboring cells using equations 1 and 2, taken from Ant System [5].

$$w(j) = \left(1 + \frac{\sigma}{1 + \delta\sigma}\right)^{\beta} \tag{1}$$

$$P_{i \to j} = \frac{w(\mathrm{j}).\mathrm{r}(\mathrm{j})}{\sum_{j \in M} w(\mathrm{j})} \tag{2}$$

Equation 1 measures the relative probability of moving to a cell j with pheromone density σ. The parameter β ($\beta \geq 0$) is associated with the osmotropotaxic sensitivity. Osmotropotaxis has been recognized by Wilson [12] as one of two fundamental types of an ant's sensing and processing of pheromone, and it is related to instantaneous pheromone gradient following. In other words, parameter β controls the degree of randomness with which the ants follow the gradient of pheromone. The parameter δ ($\delta \geq 0$) defines the sensory capacity ($1/\delta$), which describes the fact that each ant's ability to sense pheromone decreases somewhat at high concentrations. This means that an ant will eventually tend to move away from a trail when the pheromone reaches a high concentration, leading to a peaked function for the average time an ant will stay on a trail, as the concentration of pheromone is varied.

Equation 2 models the probability of an ant moving from cell i to a specific cell j that belongs to the Moore neighborhood (M) of i: $P_{i \to j}$, defined after a discretization of time and space, is the probability of moving from cell i to j; $w(j)$ is given by equation 1 and $r(j)$ is set to 1 if the cell j is within the Moore neighborhood (with range $r1$) and 0 otherwise. The pheromone density σ in equation 1 is defined as the inverse of the Euclidean distance $d(\vec{v}_a, \vec{v}_c)$ between the vector carried by ant n $\vec{v}_{an}$ and the vector in cell (i, j) at time-step t, $\vec{v}_{cij}(t)$ – see equation 3. That is, the shorter the Euclidean distance is, the more *intense* is the pheromone level. Please note that in this algorithm the pheromone levels are not absolute values. Instead, they are relative quantities that depend on the ant that inspects the cell.

$$\sigma = \frac{1}{d(\vec{v}_{an}, \vec{v}_{cij}(t))} \tag{3}$$

With these rules, an ant tends to travel to cells that are mapped to vectors which are "closer" to its *own* vector. (Please note that $\vec{v}_{an}$ is a data sample and therefore constant, while the vectors mapped by the grid are modified by the ants). The ants update the vector in the cell where they are currently on, plus the vectors in the cell's Moore neighborhood (with a user-defined range $r1$) according to equation 4, where $\alpha \in [0,1.0]$ is a learning rate that controls how fast the cells' vectors acquire the information carried by the ants. This is the equation that modifies the environment and shapes the images given below. Please note that this *reinforcement* action is proportional to the Euclidean distance between the ant's vector and the cell's vector: an ant tends to travel to cells with vectors more "similar" to its own, and, at the same time, they change the values of that cell, approximating them to their own values, at a rate that is proportional to the distance between the vectors.

$$\overrightarrow{v_c}(t) = \overrightarrow{v_c}(t-1) + \alpha\left[1 - d\left(\overrightarrow{v_a}, \overrightarrow{v_{cij}}(t)\right)\right].\left(\overrightarrow{v_a} - \overrightarrow{v_{cij}}(t-1)\right) \tag{4}$$

$$\overrightarrow{v_c}(t) = \overrightarrow{v_c}(t) - k.\left(\overrightarrow{v_c}(t) - \overrightarrow{v_{ic}}\right) \tag{5}$$

Finally, the grid vectors are all evaporated in each time-step. Evaporation, in KANTS, is done by updating the vectors with Equation 5, where $k \in [0,1.0]$ (usually a small value, in the range $[0.001, 0.1]$) is the evaporation rate and $\overrightarrow{v_{ic}}$ is the vector's initial state (at $t = 0$). Basically, the evaporation step "pushes" the vectors towards their initial values.

In total, there are six parameters that need to be set before the run: β,δ,α,k and Moore neighbordhood ranges $r1$ and $r2$, plus the size of the environment $N \times N$, which must be set to a value that allows the communication and self-organization of the swarm (too big, and the ants may become too isolated for order to emerge; too small, and the ants won't able to move freely). Such a large parameter set can make some experiments with KANTS difficult. We are currently trying to reduce the set of parameters by using the state of the system during the run. For instance, α learning rate is now controlled by the average Euclidean distance of the ants to their neighboring cells (Moore neighborhood with range set to 1). This means that the learning rate decreases over time (just like in Kohonen's Self-Organizing Maps), favoring exploration in the beginning of the run, and moving towards more exploitive behavior when the run approaches the end. In addition, the range $r1$ is now defined for each ant and it is self-regulated by the number of neighbors (again, Moore neighborhood with range 1). In the first version of KANTS, local information and decisions cause the emergence of global patterns. We are now using local information for self-regulating the algorithm, thus reducing the tuning effort.

On one hand, reducing the parameter set or self-regulating some of the parameters facilitate the experiments and the analysis of the algorithm when clustering ability and self-organization of the swarm is the main objective of the research. On the other hand, a larger parameter set permits a wider range of aesthetical experimentation in swarm art projects. Some of the work that is currently being done with KANTS on swarm art uses fixed learning rate α and range $r1$.

Another problem with the original KANTS was the tendency for formed clusters to "break". The dynamics of the swarm, with every ant moving in every time-step, did not favor the stability of the clusters. Therefore, we have recently introduced a probably test that restricts the movement of the ants: an ant only moves if a random value uniformly distributed in the range [0,1] is above a probability value p defined by Equation 6:

$$p = \frac{1}{neighbors} \times d(cells) \times d(neighbors) \tag{6}$$

where $d(cells)$ is the averaged Euclidean distance to the neighboring cells (range 1), $d(neighbors)$ is the averaged Euclidean distance to the neighbors and $neighbors$ is the number of ants in the Moore neighborhood (including the ant itself). If there are no other ants in the neighborhood except the ant itself, $d(neighbors)$ is set to 1. The pseudo-code of the algorithm is given below.

Algorithm KANTS

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1. Initialize an array $N \times N \times d$ with random values in the range [0, 1], where $N \times N$ is the size of the habitat and d is the dimension of the data samples
2. Store n data samples in an array of size $n \times l$, $ants[n][l]$, where l is the number of variables of the vectors.
3. Distribute the ants randomly on the environment.
4. For each ant do:
    5. Update habitat (grid) vectors: apply equation 4 to the vectors in the Moore neighborhood (range $r2$) of the ant.
    6. Determine $neighbors$ (number of ants in neighborhood, with range 1), average distance to neighbors and average distance to the neighboring cells.
7. For each ant do if random[0,1] < p (p is defined by equation 6):
    8. Compute $P_{i \to j}$ for each possible destination cell (not occupied and within the Moore neighborhood with range $r1 = (0.5 \times N)/neighbors$).
    9. Decide where to go by *roulette wheel* selection. Move to selected cell.
10. For each cell in the environment evaporate pheromone: apply equation 5 to the vector in the cell.
11. If stop criteria not met return to 4

With this set of equations and rules, the ants shape the environment, communicate via that environment, self-organize, and, after a certain number of iterations, congregate in clusters that more or less represent each class in the data set. Figure 1 exemplifies the KANTS' stigmergic behavior when applied to the iris flower data set [7]. The iris dataset consists of 150 samples of vectors, 50 of each of three classes of iris flowers. Each vector has 4 variables, representing the 4 features from each sample. Therefore, KANTS works with a population of 150 ants in a 20×20 habitat. Parameters β and δ are set to 32 and 0.2 respectively, while α is set to 0.5 and evaporation rate k is set to 0.01. Figure 1 shows the state of the swarm at different time-steps. Each color represents a class. The cluster start to emerge at early iterations (see $t = 50$, which correspond to 486 movements). At $t = 1000$, the Setosa cluster (red) is defined and separated. Versicolor and Viriginica are not separable but the algorithm has an interesting capacity of congregating Versicolor (green) and Virginica (blue) samples in different regions of the habitat. These results and others in [2, 10] validate the algorithm as a non-supervised clustering algorithm.

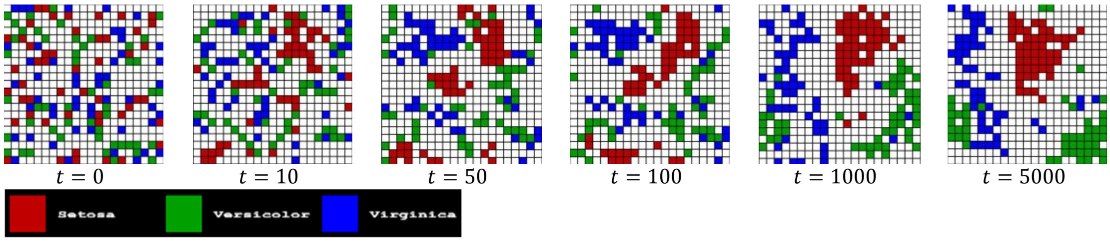

Figure 1. KANTS: position of the ants in the grid. Iris flower data set. At $t = 5000$ the swarm had completed 9071 movements.

Mora *et al.* [10] also describe a classification tool that uses information retrieved by the state of swarm. However, the pheromone maps (i.e., the environment) are used by the algorithm only for the ants to communicate, being discarded by the end of the run. The important components of KANTS as a problem solver are the clusters and the classification maps. Meanwhile, Fernandes started to experiment with KANTS as a swarm art technique, following his line of work on generative art [3, 4, 11]. In [5], Fernandes used data extracted from Electroencephalogram (EEG) signals of sleeping patients for generating the swarm. Then, after running KANTS, he translated the resulting pheromone maps into grey-scale triptychs.

Sleep data is an alluring raw material for the swarm art practitioner. Since the ants tend to cluster, thus changing the values in the clustering region, it is expected that the pheromone map, after a certain number of iterations, shows non-random patterns, like a kind of a fuzzy patchwork. In addition, the stochastic nature of the process and the size and range of the data samples, make these *sleep signatures* unique, not only for each patient, but also for each night's sleep. The resulting *pherogenic drawings* not only represent an interesting imagery related to human sleep, but can also be a basis for a conceptual framework for artists and scientists to work with. For long, sleep was a mysterious state that science and philosophy tried to study and interpret. In addition, dreams, an inseparable feature of the human sleep, added a mystic aura to this physiological state. Having the opportunity of generating representations of a night's sleep with a novel bio-inspired and self-organized algorithm is surely inspiring. Furthermore, the whole process is based on a kind of distributed creativity, i.e., the drawings are in part generated by the person/patient, since the data samples shape the environment, and in part created by the swarm and its local rules, from which global and complex behavior emerges. Under this motivation, Fernandes, with Mora and Merelo, have been recently working on the the *Pherogenic Sleep Drawings* project. With a representation of the sleep EEG that describes the signal with three variables, they use KANTS for generating three-variable pheromone maps which are then translated into a RGB image (see Figure 2).

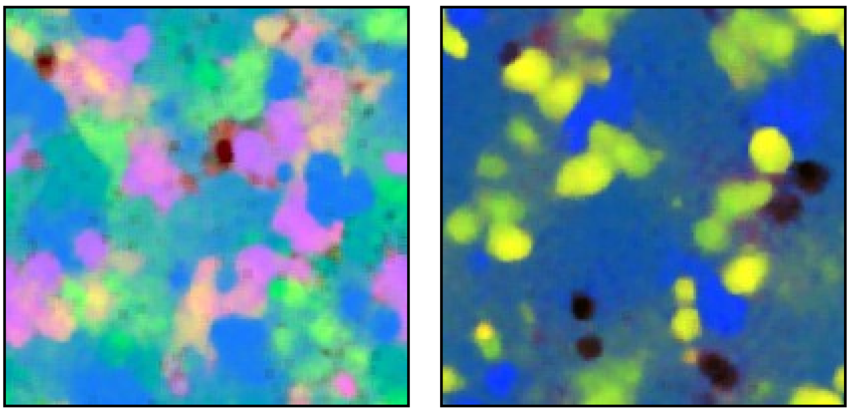

Figure 2. Pherogenic Sleep Drawings. Two pheromone maps generated by sleep data from two different patients. $\beta = 16$; $\delta = 0.2$;$\alpha = 0.1$; $k = 0.005$; $r1 \ = \ 25$; $r2 = 2.$; $p = 1$

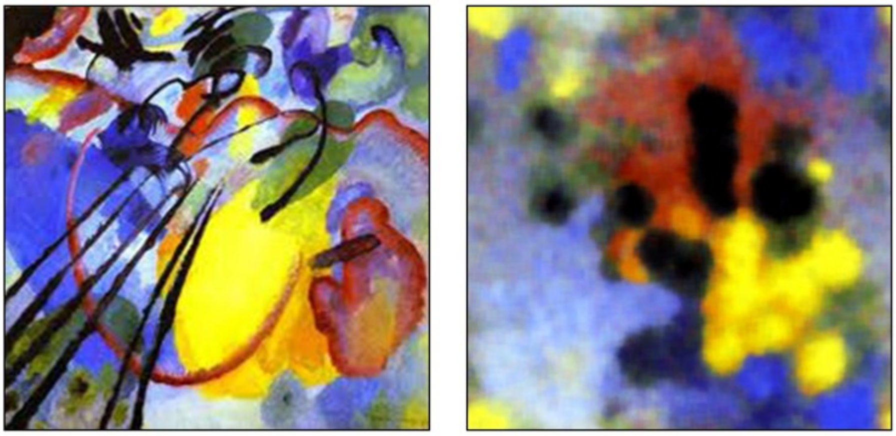

Figure 3. Carlos M. Fernandes, *Abstracting the Abstract #4*, 2012; (left) Kandinsky's *Improvisation*, which was used as a source of data samples for KANTS; (right) the resulting pheromone map, after 100 iterations. Size of the data set: 14400 samples (taken from a 120×120 digital image of Kandinsky's painting). Size of the grid: 200×200. Parameters: $\beta = 16$; $\delta = 0.2$;$\alpha = 0.1$; $k = 0.001$; $r1 = 50$; $r2 = 2.$; $p = 1$

More recently, Fernandes devised a project called *Abstracting the Abstract*, in which KANTS swarms are used for "reinterpreting" famous nonfigurative paintings of the twentieth century. In this work, the data samples are extracted from the paintings. The original image is first translated to an array with RGB values. Then, those values are used as KANTS data samples, i.e., the data samples represent the RGB values of the original painting. The resulting pheromone map (or pherogenic drawing) is translated again to RGB, displaying a range of chromatic values that are similar to the original, although with radically different patterns. Figure 3 shows an example with a Wassily Kandinsky's painting. *Abstracting the Abstract* is Fernandes's proposal for GECCO's Evolutionary Art Competition. Its motivation, details and complete set of images are described in the artist statement.

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