Generating Colored 2-Dimensional Representations of Sleep EEG with the KANTS Clustering Algorithm

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ABSTRACT

Evolutionary Computation and Swarm Intelligence (SI) are currently some of the scientific research fields where scientists and artists seek for tools and inspiration for creating what is known as *generative art*. Within the SI field, social insects and the concept of stigmergy, in particular, have inspired several significant artworks that question the borders and nature of creativity. This paper addresses generative art created with SI systems and presents a set of images that correspond to a working mechanism of an ant-based clustering algorithm, which uses data samples that interact via the environment and generate what we call *abstract swarm paintings*. The algorithm, called KANTS, consists in a simple set of equations that model the local behavior of the ants (data samples) in a way that, when travelling on a heterogeneous 2-dimensional lattice of vectors, they tend to form clusters according to the class of each sample. The algorithm was previously proposed for clustering. In this paper, KANTS is used outside a purely scientific framework and applied to data extracted from sleep-Electroencephalogram (EEG) signals. With such data, the lattice vectors have three variables, which are used for generating the RGB values of a colored image. Therefore, from the action of the swarm on the environment, we get 2-dimensional colored abstract sketches of human sleep. We call these images *pherogenic drawings*, since the data used for creating them are actually visual representations of the algorithm's pheromone maps. As a visualization and creative tool, the method is contextualized within the swarm art field.

Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous

General Terms

Algorithms, Theory

Keywords: Generative Art, Artificial Art, Swarm Art, Ant Algorithms, Pherographia, Pherogenic Drawings, Stigmergy.

GECCO'12 Companion, July 7–11, 2012, Philadelphia, PA, USA.
ACM 978-1-4503-1178-6/12/07.

1. INTRODUCTION

Generative (or artificial) art is a contemporary trend in which autonomous systems are employed for generating artworks or ornamental objects. There may be more or less human interaction with the automatic process, but, in general, the core of a generative artwork results of a computational and sometimes emergent process. Swarm Intelligence (SI) is one of the techniques used by generative art practitioners, whether as computational simulations for creating digital art that can be later translated to a physical medium, or as guiding rules for groups of agents (like robots, for instance) that act directly (i.e., physically) on a canvas. This paper focuses on a digital approach and describes a SI algorithm for data clustering called KohonAnts [18] (or simply KANTS) that the authors use as a tool for generating 2-dimensional non-figurative images that represent a correlated data set of human sleep.

KANTS is an ant-based algorithm that was proposed by Mora *et al.* in [18] for data clustering and classification. The method is loosely based on the *Ant System* (AS) proposed by Chialvo and Milonas [2]. The equations that model AS depend on a set of parameters that, when properly tuned, guide the swarm to a self-organized state, causing complex patterns of global behavior to emerge. Instead of the 2-dimensional homogeneous lattice used in AS as an environment for the swarm, KANTS evolve on a 2-dimensional regular lattice with one vector of real-valued variables mapped to each cell. The agents also differ from Chialvo and Milonas model, since KANTS uses data samples (with the same size as the environmental vectors) of different classes as artificial ants[1]. These ants travel trough the grid, changing the values of the variables 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 sections' vectors is minimized, i.e, the ants communicate via the environment, an ability that is a fundamental part of a process known as stigmergy [10]: communication via the environment, with modification of that same environment. The model's simple set of rules leads to a global behavior in which

[1] Although KANTS is different from traditional Ant Algorithms, it is directly inspired by Chialvo and Millonas' Ant System and its working mechanisms are simple extensions of the model's set of equations. Therefore we use the terminology associated with this kind of algorithms and models: *ants*, *pheromone*, *pheromone maps* and *evaporation*.

clusters of ants/samples belonging to the same class tend to emerge.

As stated above, the ants act upon the environmental lattice, changing the values of the vectors. Therefore, this array of vectors act as a kind of pheromone map (pheromone is the chemical substance used by real ants to communicate) that is shaped by the ants. In this paper, those pheromone maps are visualized and used for generating 2-dimensional colored images in RGB format. The vectors' values are directly translated to the R, G, and B values, since a sleep data set with three variables is used here. Since the ants tend to gather in clusters, thus changing the values in that region, it is expected that the pheromone map, after a certain number of iterations, shows non-random patterns, something like a kind of a fuzzy patchwork. In addition, due to the stochastic nature of the process and the size and range of the data samples, these "sleep signatures" are unique, not only for each patient, but also for each night's sleep. We believe that these results not only represent an interesting imagery related to human sleep, but could also provide a motivating conceptual framework for artists and scientists to work with.

The present work is organized as follows. Section 2 discusses generative art in general and swarm art in particular, while giving a special emphasis on a set of works that preceded and inspired the KANTS-based drawings. Section 3 describes the simplified KANTS algorithm used for generating the EEG sleep data images. In Section 4, the EEG signals and the sleep staging problem is introduced. Section 5 presents the images generated by the algorithm on a set of sleep data recorded from voluntary sane adults. Finally, Section 6 concludes the paper and outlines future lines of work.

2. SWARM ART

Generative art is a term used for to classify art that, with varying degrees of human intervention, is mainly generated by artificial intelligence systems or other computational and autonomous models. There is an enormous amount of work in the area, and generative art is even gradually dividing itself into subfields, such as artificial music, and evolutionary art. From the large number of work created in the last decades, we will describe just a few, more related to the pherogenic drawings, technically or metaphorically.

Like KANTS, Leonel Moura's swarm paintings [19] are also based on Chialvo and Millona's swarm model. The author started by experimenting on-screen computer drawings, using the ant system described in [2]. However, the results were disappointing until he used a CAD machine and a brush to create physical objects. Since then, Moura has been experimenting with swarms, self-organization and robotics [20].

Like Moura, Monmarché *et al.* [17] also use ants for their research on the potentialities of swarms as "non-human artists". The authors discuss the ant paradigm as a tool for generating music and painting.

Using a common terminology in the History of Art, Moura and Monmarché swarm paintings may be categorized as abstract, while the proposal by Collomosse [4], for instance, which uses Evolutionary Computation to evolve aesthetically appealing techniques for photo rendering, is more related to figurative art. Semet *et al.* [24] also investigated the automatic generation of rendering. The authors propose a method for non-photorealistic rendering based on artificial ants. The ants move and sense the environment (image) and deposit "ink" on an output image, according to their location and the state of a short term memory. The user interacts with the ant colony, by choosing the parameters, defining "importance maps" and deciding when the rendering is finished.

In 2001, Ramos and Almeida [21] proposed a modification of the Chialvo and Milonas ant systems in which the ants interact on a grayscale image (i.e., the 2-dimensional lattice stores the pixel values of the picture) and detect the edges of that image, generating pheromone maps that are sketches of the environmental grayscale images. Later, Fernandes *et al.* [7] described an evolutionary extension to the model that radically changes the aspect of the pheromone maps. In 2010, Fernandes proposed the term pherographia (meaning *drawing with pheromones*) as a designation for the resulting pheromone maps of the system, and projected a line of creative work based on pherographia, that resulted in several artworks which were exhibited to an heterogeneous audience [8]. In a sense, the *pherogenic drawings* described in this paper are also pherographs, since KANTS comes from the same base-system, and the images may be considered the pheromone maps of the algorithm. However, we use here the term pherogenic drawings in order to differentiate from the images in [21] and [7], which are closely related to *photographia*, the inspiration of the term *pherographia.*

The above referred works do not rely on an explicit objective function to guide the exploration of the environment, but other approaches require a fitness functions that must be optimized. These approaches, usually termed as *evolutionary art*, may be divided in two classes: automated and interactive evolutionary art. Interactive evolutionary art is based on interactive Evolutionary Algorithms (EA) [26]. Interactive EAs use human evaluation for determining the quality of the solutions described by the population: i.e., one or more humans evaluate the solution and provide the algorithm with some measure of quality of the individual or guide the search by interacting with the reproduction process (human-guided EAs).

Interactive evolutionary art is based on interactive and human-guided EAs. Karl Sims [25], for instance, used a human-guided EA for generating 2-dimensional abstract forms. Sims has an extensive body-of-work on artificial and evolutionary art that has been exhibited in art galleries and important art festivals. Another important author in this field is William Latham. Like Sims, he used evolutionary algorithms and computer graphics in the early 1990s to generate digital images [27]. Since then, several researchers and artists have been working on interactive evolutionary art, which has been also used in combination with swarm art.

Aupetit *et al.* [1], for instance, use an interactive EA for evolving the parameters used by a swarm of artificial ants that interacts with the environment (canvas). Each ant competes with the other ants for color placement. Given a set of parameters, the ants are able to draw complex images, and they can even paint for several hours, giving a different painting in each moment. The sensory mechanism of the ants in [1] was modeled in such a way that they are responsive only to the luminance values of the colors.

Greenfield [11] follows a different approach and uses ants that are responsive to tristimulus color values. Furthermore, he uses a non-interactive EA by designing fitness functions for evolving ant behavior. Later, the author increased the complexity of his model and designed ants that are responsive to both environmental stimulus and other ants' direct stimulus, thus increasing the role of stigmergy in the model [12].

These are just a few examples of swarm and evolutionary art, more related to the work described in this paper. There are many variants of generative art and other authors have been providing interesting compilations and state-of-the art reviews. Romero and Machado [23], for instance, edited a book on evolutionary and artificial art that gathers some of the most relevant proposals in the field. Lewis [15] provides an exhaustive review on the state of the art, not only on interactive and human-guided evolutionary art, but also on other types of artificial art. In this paper, we aim at contributing to this motivating field that blends art and science by applying the KANTS clustering algorithm as a swarm-art creative tool. For that purpose, we use a simplified version of the algorithm that is described in the following section.

3. KANTS

The KANTS algorithm [18] is an ant-based method for data clustering and classification. The term KANTS derives from *Kohonen Ants*, since the algorithm was partially inspired by Kohonen's Self-Organizing Maps [14]. However, KANTS is also based on Chialvo and Milona's AS and its working mechanisms are very similar to the algorithms in [2] and [21]. The way the concept of pheromone is implemented is the main difference when comparing KANTS with AS and Ramos and Almeida's algorithm.

In this section, a simplified version of KANTS is described. This is the used for generating the pherogenic drawings of sleep data described in Section 5. Since performance is not an issue here, the algorithm has been deprived of some parameters and constants that can be useful for fine-tuning its behavior, but are not fundamental when using the algorithm for generative art. The reader is referred to [18] for a detailed description of the original KANTS.

KANTS is based on the emergent properties of a set of simple units that travel through a 2-dimensional grid. In KANTS, this habitat 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 habitat (measured in number of cells) in the range $[\frac{1}{3}, \frac{1}{2}]$ provides a good basis for KANTS clustering abbility.

The values of the grid's vectors are set to a random value with uniform distribution in the range $[0, 1.0]$ in the beginning of the search. Then, the ants are randomly placed in the grid (after the vectors they "carry" are also normalized within the range $[0, 1.0]$). 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 AS [3].

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

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 [28] as one of two fundamental types of an ant's sensing and processing of pheromone, and it is related to instantaneous pheromone gradient following (the other type, klinotaxis, refers to sequential following, and it is not modeled in AS nor KANTS). 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.

The second equation, which models the probability of an ant moving to a specific cell in the habitat j belonging to the current cell's (i) Moore neighborhood, is defined after the discretization of time and space:

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

$P_{i \to j}$ 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 a user-defined radius centered on the cell i (or any other type of permitted target-region defined by the user) and 0 otherwise.

The pheromone value 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 the ant n $\vec{v}_{an}$ and the vector in the cell (i, j) at time step t, $\vec{v}_{cij}(t)$:

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

This way, 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 vary with time t, modified by the ants). In addition, the ants update the cell's vector where they are currently on, according to equation 4:

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

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 environmental and shape the images presented in Section 5. 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 vector, and, at the same time, they change that cell's values, approximating them to their own values, at a rate that is proportional to the distance between the vectors.

Finally, the vectors of the grid are all evaporated in each time step. Evaporation, in KANTS, is done by updating the values according to Equation 9:

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

where $k \in [0,1.0]$ (but 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, i.e., at $t = 0$. Basically, the evaporation step "pushes" the values of the vectors towards their initial values.

With this simple set of equations, the ants (data samples) 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 outcome of this *stigmergic* behavior of KANTS when applied to the iris flower data set [9].

The iris dataset consists of samples of vectors, 50 of each of three species (classes) of iris flowers. Each vector has four variables, representing the four features from each sample. Therefore, KANTS evolves with a population of 150 ants in a habitat of size . Parameters and are set to and respectively, while is set to and the evaporation rate is set to . Figure 1 shows the state of the swarm at different time-steps. Each color represents a class (i.e., if red, the class of the ant is Setosa). The graphics show that after 50 iterations the ants start to form clusters. At , the Setosa cluster (red) is defined and separated. Versicolor and Viriginica are not separable but the algorithm has an interesting capacity of congregating Virginica samples (blue) in a region of the habitat. The stochastic nature of the algorithm, and the lack of any local refinement mechanism, makes that sometimes the clusters tend to desegregate — see . However, these results, and others described in [18], validate the KANTS algorithm as an ant-based non-supervised clustering algorithm.

Mora *et al.* [18] also describe a classification algorithm that uses the information retrieved by the state of swarm at the end of the run. However, the pheromone maps (i.e., the grid of vectors) are used by the algorithm only for the ants to communicate and they are discarded by the end of the run. The important components of KANTS as a problem solver are the clusters (the ants' final positions in the grid) and the classification maps. Section 5 shows how this grid of vectors can be visualized as a kind of data's fingerprints. But first, Section 4 introduces the sleep staging problem and describes the data used for generating the pherogenic representations of sleep.

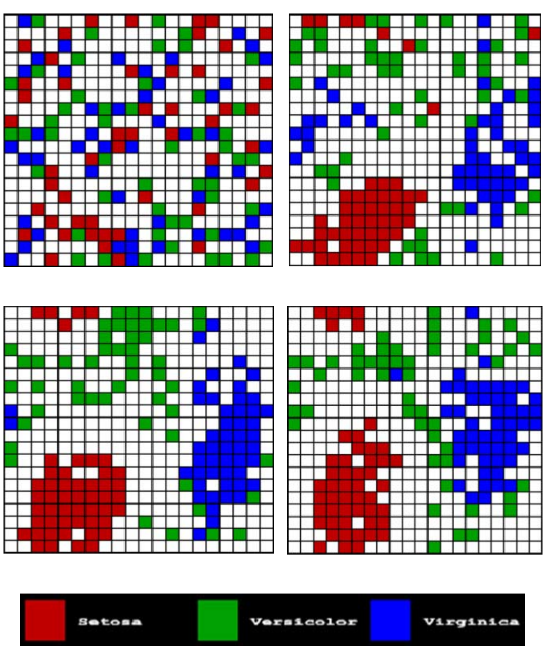

Figure 1. KANTS: Evolution of the position of the ants in the grid . Iris flower data set.

4. SLEEP SIGNALS

Sleep is a state of reduced and filtered sensory and motor activity, within which there are different stages, each one with a distinct set of associated physiological and neurological features. The correct identification of these stages is very important for diagnosis and treatment of sleep disorders such as apneas, narcolepsy and insomnia. However, sleep classification is not completely standardized and usually experts from different research centers have slightly different approaches

Usually, sleep experts make the classification by visual methods, that is, they analyze the signals and then, according to the patterns of the signal in a specific time period, decide in which stage the patients were at that precise period. This method is time-consuming and prone to errors. Therefore, it is very important for biomedical sleep research to devise methods to extract the proper information that is later used for classification. However, automatic sleep stage classification is a hard computational problem that requires efficient solutions at different levels of the process.

A correct identification of the sleep stages requires competent classification tools, but, before that, it is necessary to extract the proper information from the signals associated with sleep: the electroencephalography (EEG), electromyography (EMG) and electrooculography (EOG) signals. Even though several attempts have been made to automate the classification process, so far no method has been published that has proven its validity in a study including a sufficiently large number of controls and patients of all adult age ranges.

Traditional sleep classification is normally divided in three steps. First, significant data is acquired from the subjects. Then a human expert identifies, for each epoch, the relevant patterns. Finally, according to those patterns, the expert decides the sleep stage of the patient. Usually, the classification of sleep stages is made under the Rechtschaffen and Kales [22] guidelines (R&K classification rules), which divide sleep into five stages: REM, NREM1, NREM2, NREM3 and NREM 4, with WAKE as an additional stage. The complete EEG, EOG and EMG records, divided in epochs, usually, each one with 30 second. Therefore, an 8-hour night-sleep consists in samples of six possible classes.

An automatic tool for classifying this set of data may be constructed under two different principles. First, the manual classification may be mimicked and translated into an automatic process. Under this approach, certain typical characteristics of the signal associated with each stage are searched, identified and measured and then some method is used to decide the stage.

The second approach aims to extract relevant information from the signals, quantify it and then use traditional numerical classification system. In 1975, B. Hjorth [13] proposed a set of three parameters for describing the EEG signal. The first parameter is a measure of the mean power representing the *activity* of the signal. The second, called *mobility*, is an estimate of the mean frequency. The third parameter estimates the bandwidth of the signal and represents *complexity*. The main advantage of Hjorth parameters is its low computational cost when compared to other methods. Furthermore, the time-domain orientation of Hjorth representation may prove suitable for situations where ongoing EEG analysis is required.

However, our choice of the Hjorth parameters is merely practical: the three variables may be directly translated to RGB values and generated the desired 2-dimensional colored representation of the sleep signals. Besides Hjorth and power spectrum, there other feature extraction methods and, in fact, this is still an open problem. This paper does not deal directly with the sleep staging classification problem and therefore, novel techniques for extracting relevant features from the sleep signals are not required. The following section describes the resulting KANTS pheromone maps when applying the algorithm to a set of Hjorth parameters describing EEG signals of five adult sane patients.

5. RESULTS

For testing KANTS and retrieving its pheromone maps as images in the RGB format, real data from five adult sane patients were used. The patients are labeled as $p01$, $p02$, $p03$, $p04$ and $p05$.

The EEG signals were analyzed and each epoch classified within one of the R&K classes by a medical expert team. Then, the Hjorth parameters were extracted from those EEG signals. Five files with the Hjorth parameters corresponding to the EEG signals of each patient were created. The files contain 844, 907, 769, 685 and 865 samples (please remember that one sample corresponds to 30 seconds of sleep), respectively, from $p01$ to $p05$. Each vector is labeled with the class assigned by the experts. Each test uses one file: for instance, KANTS with patient $p01$ uses 844 ants (data samples). Since there are three parameters in the data set, the ants are described by $\vec{v}_a = (v_{a1}, v_{a2}, v_{a3})$, where v_{a1} is the Hjorth *activity* value in the data set, v_{a2} is the *complexity* of the same vector in the data set value and v_{a3} is *mobility* value (see equation 3).

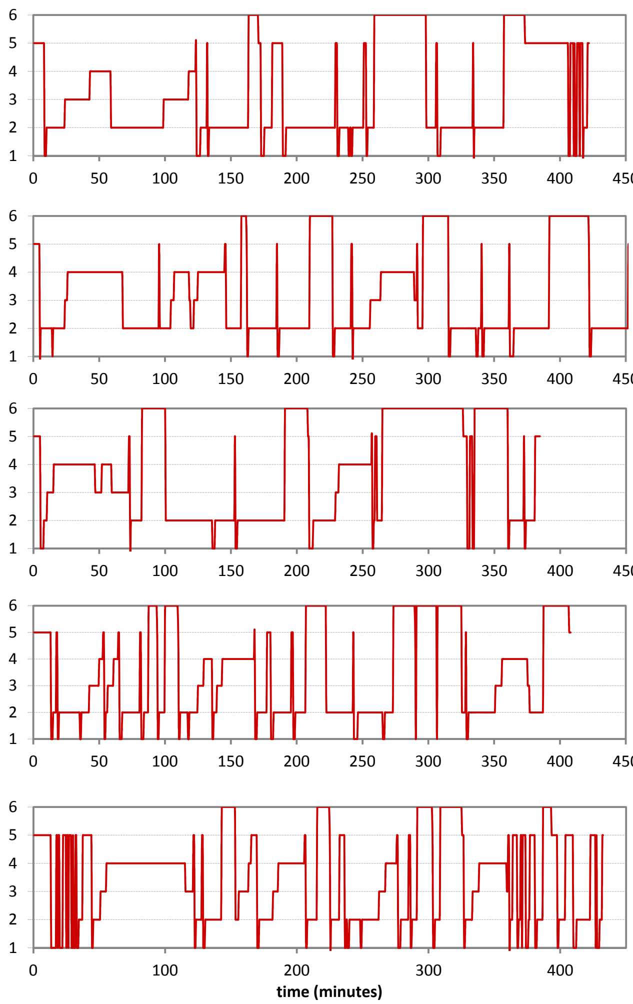

Figure 2. Hypnograms of patients $p01$, $p02$, $p03$, $p04$ and $p05$ (top to bottom). States, y-axis: 1 (NREM1); 2 (NREM2); 3 (NREM3); 4 (NREM4); 5 (Awake); 6 (REM).

The habitat size is set to 175×175. With this size, the ratio between the number of ants and the number of environmental vectors is much smaller than the range suggested in Section 3. However, the objective of this work is not to optimize the clustering ability of KANTS, but instead to generate appealing images during the process. Given the size of the data sets, using the suggested ratio would generate very small images that could not be properly visualized and valued. Therefore, input files of each patient's data with 10 copies of each sample were created. The results in this section are the pheromone maps created by these enlarged sets, with sizes 8440, 9070, 7690, 6850 and 8650.

Figure 2 shows the hypnograms of each patient. A hypnogram is a graphical representation of the stages of person's sleep in a time-domain. This state-time graphic allows a quick observation of a night's sleep and the identification of possible sleep disorders. This study uses data from sane adults without diagnosed sleep disorders, which, if present, would disturb a normal hypnogram, but it is possible to observe that each patient generates rather different hypnograms. When applied to a stochastic algorithm like KANTS, it is expected that the resulting pheromone maps are also very different.

The algorithm was tested with the following settings. Parameters ρ and δ are set to 32 and 0.2. These values are in the range of the parameter space that in [18] puts the system in the self-organized state. The learning rate α is set to 0.5 and evaporation rate k is set to 0.01. The algorithm stops after 50 iterations and the grid's vector values are then normalized into the range [0,255].

A previous art project was conducted by translating the resulting pheromone maps into gray-scale images. Figure 3 shows an example of those works. The images were created by normalizing the final environmental vectors $\vec{v}_c = (v_{c1}, v_{c2}, v_{c3})$ (see equation 3) into the range [0,255], where v_1 represents the environmental values affected by the Hjorth's parameter *activity*, v_2 by *complexity* and v_3 by *mobility*. Each set of values was stored in 175×175 arrays and then each array was used to create the gray-scale images represented in Figure 3.

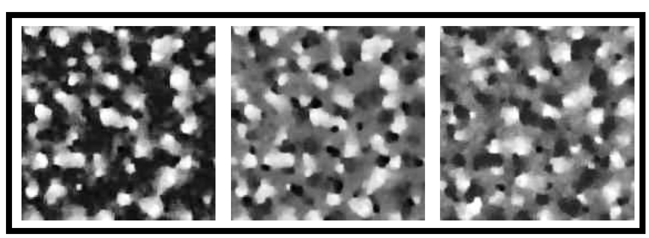

Figure 3. Abstract monochromatic pherographic drawings created by KANTS from sleep data. Each image corresponds to one of the three vectors' variables mapped to the Hjorth's parameters: activity (left), complexity (center), mobility (right). Patient $p05$

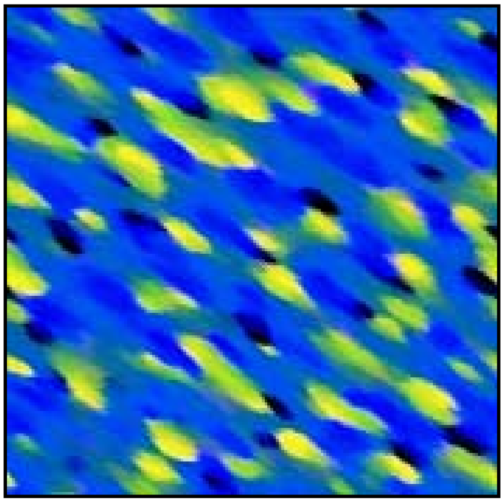

Figure 4. Pherogenic drawing of $p05$ sleeping period.

In this paper, these triptychs were extended to colored pherogenic drawings of sleep. For that purpose, the same values are used as a source for creating an image in the RGB format. The *activity* related values are used to model the R values, while G and B are defined by complexity and mobility, respectively. The resulting image, when applying this strategy to the environmental vectors used for creating the triptych in Figure 3, is shown in Figure 4.

Figure 5 shows the pherogenic drawings of patients $p01$, $p02$, $p03$ and $p04$. It is clear that each night's sleep data set generates unique drawings, even if there are common features to all of them. However, each one shows a different pattern and some major differences are also observed, namely in the dominant color of the drawings. Pherogenic drawing $p01$, for instance, has a strong presence of a *pinkish* color, that is almost absent from the other pictures (except $p04$, where light patches of rose are present).

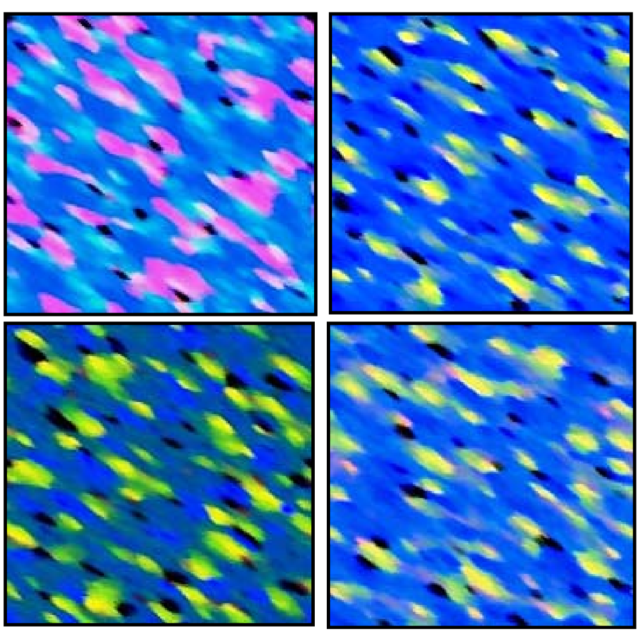

Figure 5. Pherographic drawings of patients $p01$ (top-left), $p02$ (top-right), $p03$ (bottom-left) and p04 (bottom-right).

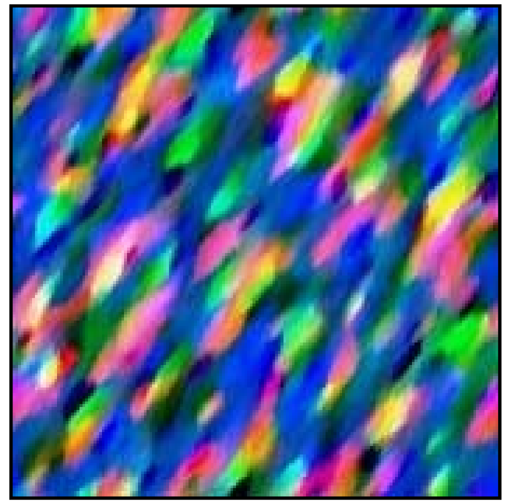

Figure 6. Pherogenic drawing mixing the pheromone maps generated by $p01$, $p02$ and $p03$.

If we abandon the project of a univocal representation of a night's sleep, the possibilities are endless. It is possible, for instance, to combine the pheromone maps generated by different data sets. Figure 6, for instance, shows the result of mixing the environmental vectors generated by applying KANTS to $p01$, $p02$ and $p03$. The image uses for R the activity-related vectors generated by $p01$ data, G values are set by the complexity values generated by $p02$, and B is defined by the mobility-related values of the environment shaped by the data of patient $p03$. With such an uncorrelated input, the RGB image is much more dynamic and vivid than the images generated by a single night's sleep.

Although the hypnograms are clearly different for each patient, such state-time representations of the sleep do not help to interpret

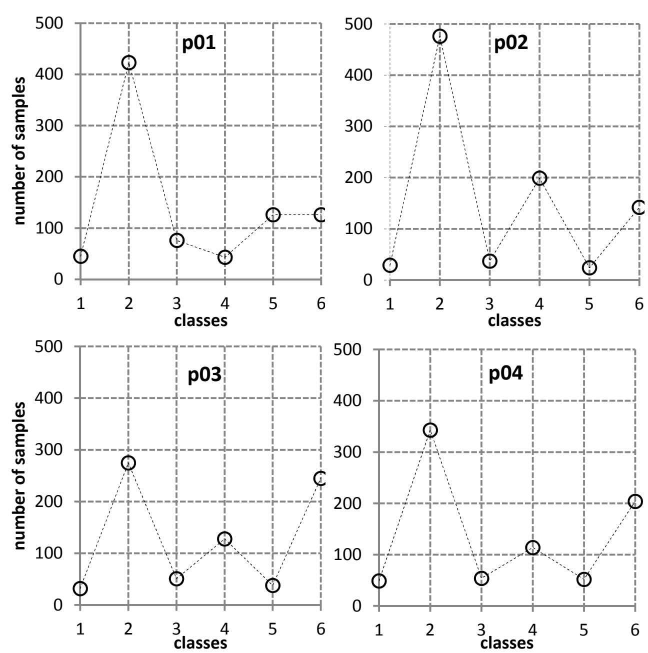

Figure 7. Distribution of the samples over the class-domain (the classes are assigned by medical experts).

the differences observed in the pherogenic drawings of each patient. The main characteristics in the hypnograms, for the untrained eye, are perceived in the time-domain. However, for KANTS, the sequence of events is not relevant. The behavior of the algorithm only depends on the values of the samples, not on their order. Therefore, in order to try to interpret the differences between the drawings, it is better to analyze the distribution of samples in each patient.

Figure 7 shows the distribution of samples of each class in each patient's data set. By comparing the distribution of $p01$ with the other patients, the main observable difference is the reduced number of class 4 (NREM4) samples (when compared to other patients). This fact could explain why the pherographic drawing of $p01$ has a clear distinct palette of dominant colors. As for $p03$, which generates a picture with much darker tones, it has a ratio between class 6 and other classes that is clearly higher than the same ratio in other patients' data. This could explain its unique tone in the set of pherogenic drawings.

These hypotheses are hard to demonstrate, due to the stochastic nature of KANTS and the high number of variables involved in the process. However, it is expected that radically different distributions produce radically different images, since the samples are the "artists" here. The samples act upon the environment, shaping it, and the result of such actions depend on the values of the samples. Therefore, different samples create different patterns in the pheromone maps, thus making it plausible that the main differences observed in the sleep pherogenic drawing are due to the disparity in the ratio between the samples of each class. This conclusion leads to us an even more daring hypothesis.

Although it is surely a difficult project, it is not impossible that these (or similar) representations of the KANTS's pheromone maps could help medical experts to detect sleep patterns with a previous inspection of such type of maps, before engaging in the daunting task of classifying each 30 seconds epoch of a night's sleep[2]. Just like an EEG signal, the pherogenic drawings are unique fingerprints of a person's night sleep, gathering information of that sensory period, even if this information may be hard to decode. In addition, KANTS was based on the Kohonen Maps, of which the resulting maps are used for the analysis of variables and data; therefore, it is possible that KANTS maps can be also used for the same purpose. On the other hand, the fact that the time-domain features are not reflected in the pheromone maps may limit such a hypothetical system sleep disorders' fast screening.

Being a swarm art project, there is an unavoidable (and desired) subjectivity in this work. However, for the authors, the results are motivating and appealing, not only in aesthetical terms, but also as a science-art experience. For long, sleep was a mysterious state that science and philosophy tried to study and interpret. In addition, the dreams, an inseparable feature of the human sleep, always added a mystic aura to this physiological state. Having the opportunity of generating 2-dimensional representations of whole 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, that is, 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.

[2] This hypothesis has been discussed with a medical expert.

A final note on the term *pherogenic drawings*. Like pherographia [8], the term pherogenic drawings is also inspired by photography, or at least by the History of Photography. When William Henry Fox Talbot announced that he discovered a photographic process (which later became the major photo-process for more than a century: the negative-positive process), he coined those images with the term photogenic drawings, meaning that the origin (*genesis)* of those drawings was light (*photos*, in Greek). Later, the term was gradually replaced by photography, which means drawing with light. The expression pherogenic drawings is therefore a tribute to Talbot's invaluable contribution to art and science. In addition, it perfectly describes the images generated by KANTS: the origin (*genesis*) of these images is the *pheromone*.

6. SUMMARY AND CONCLUSIONS

This paper describes a swarm art experiment conducted with an ant-based clustering algorithm called KANTS. The algorithm is able to create clusters of data samples by letting those samples (ants) travel through a heterogeneous environment. The ants communicate via the environment and modify it. This work uses the resulting environment (pheromone maps) to create 2-dimensional color representation of data sets. In this case, sleep data is used. The input of the algorithm is the well known Hjorth parameters, which describe the EEG signal in the time-domain. The resulting images are aesthetically appealing, with dynamic patterns and colors that spread through the canvas in a balanced way. They also have the interesting characteristic of being unique representations of a night's sleep: the pherogenic drawings of human sleep are fingerprints of that person's night sleep.

Relationships between the samples distribution and the general aspect of the drawings are hypothesized, as well the possibility of a medical usage of these pictures. Since the resulting image is unique and depends on the data samples, it is possible that major patterns or anomalies in the data samples can be detected by a fast-screening of the pherogenic drawings.

There are still some technical issues that limit the size of the environment, and therefore the size of the images. The computational time of the KANTS algorithm grows at least linearly with the number of vectors in the habitat, which means that a 1750×1750 size image requires a computational cost that is 100 times the cost of creating a175×175 sized image. Since creating 175×175 pheromone maps takes 5-10 minutes, it is easy to conclude that experiments with much larger sizes may be impractical at the moment.

Sleep data with Hjorth parameters was chosen because the three parameters are suited for a direct translation into the RGB format. However, other feature extraction methods of the EEG signal could be used, providing that strategies for translating the values into the RGB image are devised. In addition, other type of data can also be tested. There are many benchmark problems and real-world data set and it would be interesting to observe the resulting pherogenic drawings after different types of data. Another possibility is to create 3-dimensional objects, in which a fourth parameter shapes the object in a third axis.

Acknowledgements

The first author wishes to thank FCT (Ministério da Ciência e Tecnologia) Fellowship SFRH/BPD/66876/2009. The work was also supported by FCT (ISR/IST plurianual funding) through the PIDDAC Program funds and projects TIN2011-28627-C04-02, by

Spanish Ministry of Science an Innovation and P08-TIC-03903, by the Andalusian Regional Government.

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