Pherogenic Drawings
Generating Colored 2-dimensional Abstract Representations of Sleep EEG with the KANTS Algorithm

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Abstract: Social insects and stigmergy have been inspiring several significant artworks and artistic concepts that question the borders and nature of creativity. Such artworks, which are usually based on emergent properties of autonomous systems and go beyond a centralized human authorship, are a part of a contemporary trend known as *generative art*. This paper addresses generative art and presents a set of images generated by an ant-based clustering algorithm that uses data samples as artificial ants. These ants interact via the environment and generate abstract 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 and classification. In this paper, KANTS is used outside a purely scientific framework and it is applied to data extracted from sleep-Electroencephalogram (EEG) signals. With such data sets, the lattice vectors have three variables, which are used for generating the RGB values of a colored image. Therefore, from the actions 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 the images are actually the pheromone maps of the ant algorithm. As a creative tool, the method is contextualized within the swarm art field.

1 INTRODUCTION

Generative art is a contemporary trend that uses autonomous systems for generating artworks or ornamental objects. There may be more or less human interaction with the process, but, in general, the core of a generative artwork is the result of a computational and sometimes emergent procedure. Swarm Intelligence (SI) (Bonabeau et al., 1999) is one of the techniques used in this field, 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 (robots, for instance) that act directly (i.e., physically) on a canvas. Within SI, social insects and the concept of stigmergy have inspired significant artworks that question the borders and nature of creativity. This paper focuses on a digital approach and describes a SI algorithm called KohonAnts (or simply KANTS), used here for generating 2-dimensional non-figurative images of correlated data sets of human sleep.

KANTS is an ant-based algorithm proposed by Mora et al. (2008) for data clustering and classification. The method is loosely inspired by Chialvo and Millonas' Ant System (AS) (Chialvo and Millonas, 1995), which is modeled by a set equations and parameters that, when properly tuned, guide the swarm to a self-organized state in which complex patterns of global behavior emerge. Instead of the 2-dimensional homogeneous lattice used in (Chialvo and Milonas, 1995) as a *habitat* for the swarm, KANTS evolve on a 2-dimensional lattice with one vector of real-valued variables mapped to each cell. The *agents* also differ from Chialvo and

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Millonas model, since KANTS uses data samples (with the same size as the environmental vectors) of different classes as artificial ants. 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 (Grassé, 1959): communication via the environment, with modification of that same environment. The model's simple set of rules leads to a global behavior in which clusters of ants/samples belonging to the same class tend to emerge.

As stated above, the ants act upon the environmental lattice, changing the vectors' values. Therefore, this array of vectors acts as a kind of *pheromone map* that is shaped by the ants. The maps are used in this paper for generating 2-dimensional RGB colored images. The vectors' values are directly translated into the R, G, and B values (three-variable sleep data set with is used here). 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 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. We believe that these *pherogenic drawings* not only represent an interesting imagery related to human sleep, but could also be a basis for a conceptual framework for artists and scientists to work with.

The paper is organized as follows. Section 2 discusses generative art and swarm art. Section 3 describes the KANTS algorithm used for generating the EEG sleep images. In Section 4 the signals and the sleep staging problem is introduced. Section 5 shows the images generated by the algorithm with a set of sleep data recorded from sane adults. Finally, Section 6 concludes the paper and outlines future lines of work.

2 SWARM ART

Generative art is a term used to classify artistic creations that, with more or less human intervention, are mainly generated by artificial intelligence systems or other computational 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 (Moura, 2001) 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 (Chialvo and Millonas, 1995). 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 (Moura, 2009).

Like Moura, Monmarché et al. (2007) 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's swarm paintings may be categorized as abstract, while the proposal by Collomosse (2007), for instance, which uses Evolutionary Computation to evolve aesthetically appealing techniques for photo rendering, is more related to figurative art. Semet et al. (2004) 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 (2001) proposed a modification of the Chialvo and Millonas ant systems in which the ants evolve on a grayscale image (i.e., the 2-dimensional lattice stores the pixels' 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. (2005) described an evolutionary extension to the model that radically changes the aspect of the pheromone maps. In 2010, Fernandes (2010) 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. These artworks have been exhibited to an heterogeneous audience — see (Moura, 2009) and

(Courchesne et al., 2009). In a sense, the pherogenic drawings described in this paper are also pherographs, since KANTS comes from the same base-system, and the images are actually the pheromone maps of the algorithm. However, we use here the term pherogenic drawings in order to differentiate from the images in (Ramos &Almeida, 2001) and (Fernandes et al., 2005), which are closely related to *photographia*, the inspiration of the term pherographia.

In fact, pherographia, as used by Fernandes, results in typical figurative artworks, while the swarm paintings presented in this paper are purely abstract. The pherographs are created using a photograph as a base-image; KANTS uses correlatd data, which interacts in a heterogeneous environment, "shaping" that same environment. Of course, pherographia, since it imitates the base-image, may also be used for creating non-figurative works, as long as such kind of image is chosen as a base-image. That is, pherographia relies much more on the human decision, while the results given by KANTS, as shown in Section 5, are more unpredictable, since they depend on large quantities of data, gathered from natural phenomena.

Pherographia and 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) (Takagi, 2001). 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 (1991), 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 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 (Todd and Latham, 1992). Since then, several researchers and artists have been working on interactive evolutionary art, which has also been used in combination with swarm art.

Aupetit et al. (2003), for instance, use an interactive EA for evolving the parameters of 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 (Aupetit et al., 2003) was modeled in such a way that they are responsive only to the luminance values of the colors.

Greenfield (2005) 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 (Greenfield, 2006).

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 (2007), for instance, edited a book on evolutionary and artificial art that gathers some of the most relevant proposals in the field. Lewis (2007) gives 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 a motivating field that blends art and science by using 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 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 (Kohonen, 2001). However, KANTS is also based on AS and its working mechanisms are very similar to the algorithms in (Chialvo and Millonas, 1995) and (Ramos and Almeida, 2001). The way the concept of pheromone is implemented is the main difference when comparing KANTS with AS.

In this section, a simplified version of KANTS is described. Since performance is not an issue here, the algorithm has been deprived of some parameters that can be useful for fine-tuning its behaviour, but are not fundamental for swarm art. The reader is referred to (Mora et al., 2008) for a detailed description of the original KANTS. Please note that although KANTS is different from traditional Ant Algorithms, it is stigmergic, and directly inspired by AS: its working mechanisms are simple extensions of the model's set of equations. Therefore we use here the metaphor and the terminology associated with this kind of algorithms and models: *ants*, *pheromone*, *reinforcement* and *evaporation*.

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 $[1/3, 1/2]$ provides a good basis for KANTS clustering abbility.

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 $[0, 1.0]$). 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.

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

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

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 (1971) 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, which models the probability of an ant moving to a specific cell in the habitat j belonging to the current cell's Moore neighborhood, is defined after a discretization of time and space: $P_{i \to j}$ 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 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, $\vec{v}_{cij}(t)$:

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

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 are modified by the ants). The ants update the cell's vector where they are currently on, 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 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, 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.

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

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

Finally, the grid vectors are all evaporated in each time step. Evaporation, in KANTS, is done by updating the values according to 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' values towards their initial values.

With this set of equations, 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 outcome of KANTS' *stigmergic* behavior when applied to the iris flower data set (Fischer, 1936). 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. After 50 iterations the ants start to cluster. At $t = 100$, 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 *break* (see $t = 150$). However, these results and others (Mora et al., 2008) validate the algorithm as a non-supervised clustering algorithm.

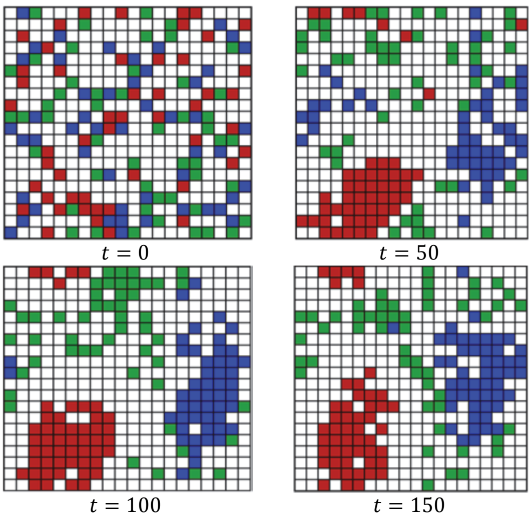

Figure 1: KANTS: Evolution of the position of the ants in the grid. Iris flower data set. Red samples: Setosa; green samples: Versicolor; blue samples: Virginica.

Mora et al. (2008) also describe a classification tool that uses information retrieved by the state of swarm. However, the pheromone maps (i.e., the grid) 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. Section 5 shows how the grid can be visualized as a kind of data's fingerprint. But first, Section 4 introduces the sleep staging problem and the data used for generating the pherogenic drawings.

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 the diagnosis and treatment of sleep disorders. However, sleep classification is not completely standardized. Usually, sleep experts make the classification by visual methods, i.e., they analyze the signal and then, according to its patterns in a specific time period, they decide in which stage the patient was in 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. Then, portable devices may be used for monitoring sleep (Krejcar et al., 2011) or for detecting sleep disorders (Acharya et al., 2010). However, automatic sleep classification is a hard computational problem that requires efficient solutions at different levels of the process.

After extracting the relevant information from the signals associated with sleep — electroencephalography (EEG), electromyography (EMG) and electrooculography (EOG) — competent classification tools are also required for a correct identification of the sleep stages. Even though several attempts have been made to automate the classification, 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.

Usually, the classification of sleep stages is made under the Rechtschaffen and Kales (1968) 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 960 samples of six possible classes.

An automatic tool for classifying sleep data can be constructed under two different principles. In the first approach, the manual classification is mimicked and translated into an automatic process. Another approach extracts relevant information from the signals, quantifies it and then use traditional numerical classification system. In 1975, Hjorth (1975) proposed a method for extracting three parameters from EEG. The first 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 estimates the bandwidth of the signal and represents *complexity*. The main advantage of Hjorth's method is its low computational cost when compared to other methods. Furthermore, the time-domain orientation of this representation may prove suitable for situations where ongoing EEG analysis is required.

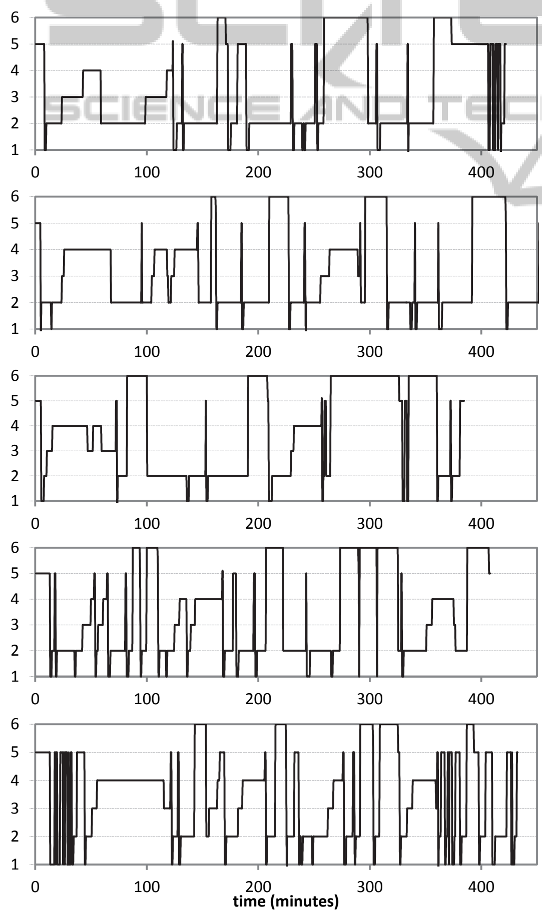

Figure 2: Hypnograms of patients $p1$, $p2$, $p3$, $p4$ and $p5$ (top to bottom). States, y-axis: 1 (NREM1); 2 (NREM2); 3 (NREM3); 4 (NREM4); 5 (Awake); 6 (REM).

However, our choice of the Hjorth parameters is merely practical: the three variables may be directly translated into RGB values, generating the desired 2-dimensional representation of sleep. Besides Hjorth parameters, there other feature extraction methods. 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 EXPERIMENTS

For testing KANTS and retrieving its pheromone maps as RGB images, real data from five adult sane patients were used. The patients are labeled $p01$, $p02$, $p03$, $p04$ 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 parameters corresponding to the EEG signals of each patient were created. The files contain 844, 907, 769, 685 and 865 samples, respectively, from $p01$ to $p05$. Each vector is labeled with the class assigned by the experts. 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 shows the hypnograms of some patients. A hypnogram is a graphical representation of the stages of person's sleep in a time-domain that 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.

KANTS habitat size is set to 200×200. With this size, the ratio between the number of ants and the number of environmental vectors is much smaller than the values suggested in (Mora et al., 2008). However, the objective of this work is not to optimize the clustering ability of KANTS, but instead to generate images during the process. Given the size of the data sets, the suggested ratio would generate 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 ($p01$), 9070 ($p02$), 7690 ($p03$), 6850 ($p04$) and 8650 ($p05$).

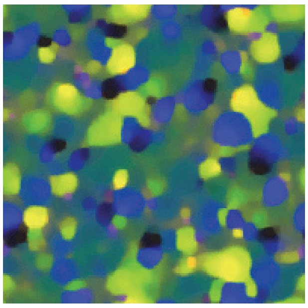

Figure 3: Pherogenic drawing of $p05$ sleeping period.

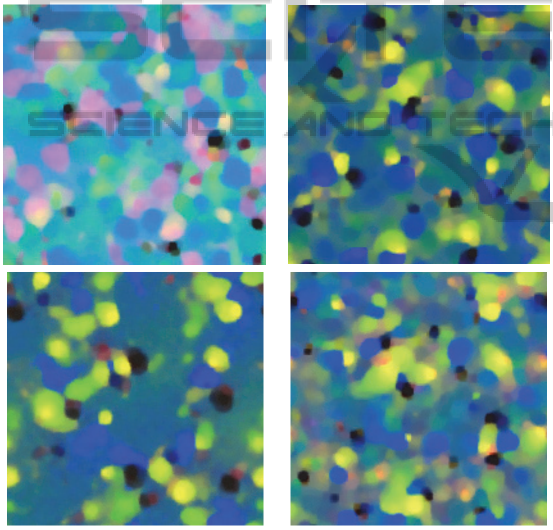

Figure 4: Perographic drawing of patients $p01$ (top-left), $p02$ (top-right), $p03$ (bottom-left) and $p04$ (bottom-right).

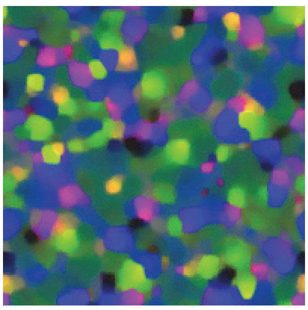

Figure 5: Pherogenic drawing mixing the pheromone maps generated by $p01$, $p02$ and $p03$.

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 (Mora et al., 2008) puts the system in the self-organized state. Learning rate α is set to 0.2 and evaporation rate k is set to 0.0025. The algorithm stops after 50 iterations and the environmental lattice at $t = 50$ is used to generate the images in the RGB format. Each set of values was stored in 200×200 arrays, each one being the source for creating an RGB image: activity related values are used to model R values, while G and B are defined by complexity and mobility, respectively. The resulting image of patient $p05$ is shown in Figure 3 while Figure 4 shows the drawings of patients $p01$to $p04$. It is clear that each night's data set generates unique drawings, even if there are common features to all of them. However, each one shows different patterns and major differences are also observed, namely in the dominant color of the drawings: $p01$, 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).

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 maps generated by different data sets. Figure 5 shows the result of mixing the environmental vectors. 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 values of the environment shaped by patient $p03$. With such an uncorrelated input, the picture is more dynamic and vivid than the images generated by a single night's sleep.

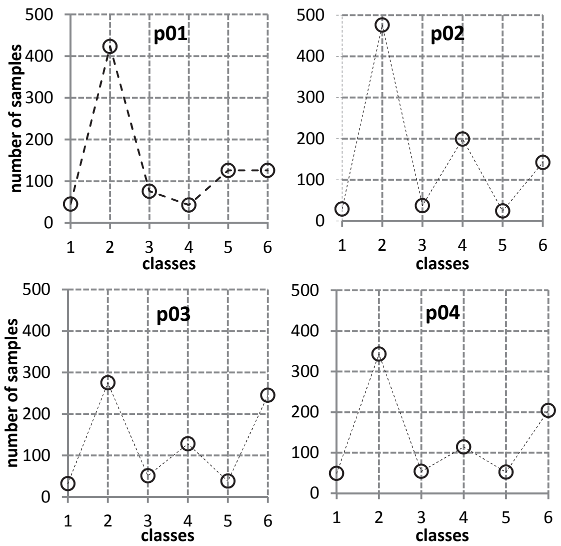

Figure 6: Distribution of the samples over the class-domain (the classes are assigned by the medical experts).

Although the hypnograms are clearly different for each patient, such state-time representations of the sleep do not help to interpret the differences observed in the pherogenic drawings of each patient. The main characteristics of the hypnograms are perceived in the time-domain. However, for KANTS, the sequence of events is not relevant. The behaviour of the algorithm only depends on the values of the samples, not on their order. Therefore, for interpreting the differences between the drawings, it is better to analyze the distribution of samples in each patient, as in Figure 6.

By comparing the distribution of $p01$ with other patients, the main difference is its reduced number of class 4 (NREM4) samples. 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 darker tones, its ratio between class 6 and other classes is clearly higher than in other patients. 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 different images, since the samples are the *artists* here: they act upon the environment, shaping it, and the result of such actions depend on the values of the samples. Therefore, different samples may create different patterns.

Being a art project, there is an unavoidable (and desired) subjectivity in this work. However, for the authors, the results are motivating, not only creatively, 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, dreams, an inseparable feature of human sleep, added a mystic aura to this physiological state. Having the opportunity of generating representations of sleep with a 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 patient, since the data samples shape the environment, and in part created by the swarm and its local rules, from which global and complex behaviour emerges.

6 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 trough 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 parameter set, which describe the EEG signal in the time-domain. The resulting images are aesthetically interesting, 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 a person's night sleep. Furthermore, they are the result of a distributed creativity, in part generated by the person/patient (or by the data generated by the patient during the sleep period), and in part created by the swarm and its local rules, from which global and complex behavior emerges.

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 2000×2000 size image requires a computational cost that is 100 times the cost of creating a 200×200 sized image. Since creating 200×200 pheromone maps takes 10-15 minutes, 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 sets 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.

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