Ambient Cognitive Environments and the Distributed Synthesis of Visual Ambiences

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Abstract. One of the current trends in computer science leads to the design of computing organizations based on the activity of a multitude of tiny cheap decentralized computing entities. Whether these chips are integrated into paintings or disseminated in open environments like dust, the fundamental problem lies in their cooperative operation so that global functions are obtained collectively. In this paper, we address the issue of the creation of visual ambiences based on the coordinated activity of computing entities. These entities are distributed randomly on a 2D canvas and can only change their own color and perceive their immediate neighbors.

1. Introduction

It is a fact that research on *ubiquitous computing*, since Mark Weiser coined the term in 1988, has developed very rapidly [2], [3]. It is especially true for the last two or three years with the explosion of mobile telephony, PDAs, wireless networks, etc. Ubiquitous computing is associated to the disappearance of computers, not because they're not there anymore, but because they become invisible. But it's not because we can't see them anymore that we can't interact with them. The question of interaction with ubiquitous systems has not really been raised as such. What is studied is the interaction with mobile devices such as PDAs but what about the interaction with the "societies" of computing entities that will "live" and develop in our walls, objects, clothes, etc.? This is an almost sociological question and we argue, with others [14], that it could be studied efficiently using the computerized concepts and tools that are interested in the sociological aspects of computing, namely multi-agent systems.

Our approach consists in considering this interaction as a multimodal dialogue between a human user and his(her) physical environment. We develop this approach in a project called *DanCE with (MA)²CHInE*[1], in which we consider the environment as being populated with dozens of physical communicating objects. Each of these communicating objects is characterized by limited capabilities for the treatment of information, the communication with others, and the interaction with their physical environment. The problem can then be reformulated as a problem of building decentralized cognitive systems, which we call *Ambient Cognitive Environments* (ACEs). To build such cognitive environments, one has to address the three main

[1] Dynamic Ambient Cognitive Environments with Multi-Agent Multimodal and Adaptive Computer-Human Interaction Engine

processes that are typical of any situated cognitive system: perception, decision, action. However, each of these processes has to be handled in a decentralized way: we treat perception as a sensor fusion problem, decision as a distributed consensus reaching problem and action as a distributed coordination problem.

In this paper, we develop only the latter problem of action and we focus more precisely on the production of visual ambiences. In the meantime, we explain the abstractions that will allow us to extend the model to other kinds of expression such as music, choreography, etc. This model is based on an analytical approach to different artistic domains. In each of these domains, the analysis must lead to a description of the corresponding expression (visual, musical, choreographic, etc.) in terms of qualitative pairs such as cold/warm, quiet/loud, slow/fast, etc. These pairs form together an ontology that the multimedia production system should know and that it should be able to manipulate so as to express chosen emotions.

The aim is to be able to give instructions to the system using this ontology. The difficulty is then for the system to translate a given order into a coordinated activation of distributed colored cells. These cells are distributed randomly on a 2D canvas in a way which is similar as in the works on amorphous computing [1], [9], [10]. Individual cells can change their color and perceive other cells in their immediate vicinity but they can also move. Specific algorithms have therefore to be proposed so that all the cells in the canvas can collectively express specific colored contrasts or spatial structures. Such graphical composition primitives have finally to be composed in a way that preserves the individual properties of each.

The paper is organized as follows: in the next section, we elaborate some more on Ambient Cognitive Environments. We show in section 3 how the analysis of visual expression allows to propose a grid relating emotions with structural properties of pictures. We then show in section 4 how this can be expressed in a decentralized way by elementary colored cells.

2. Ambient Cognitive Environments

The work presented in this paper is part of a larger project in which the objective is to identify the right concepts and develop the corresponding technical tools to dynamically organize distributed sets of computing entities as cognitive systems. This is what we call ***Ambient Cognitive Environments*** (ACEs). The aim is that these high-tech environments become sensible to the people that live in them. The aim is not to be intrusive and spy the movements of these people, but to become aware of their emotional dispositions and adapt accordingly. The environment adapt by producing visual and sonorous ambiences that are calm when people are calm, or that become calm when children get too excited, or that become suddenly “flashy” and buzzing when people are too calm, etc. But not only the ambience may be adapted: specific actions may be done using motorized objects; specific displays could be produced on the walls, on clothes, either to establish a contact or to convey some information; finally, electronic devices such as mobile phones, PDAs, MP3 players, etc. could be used to send focalized audio or visual messages to one person.

Four important aspects, we believe, characterize these ACEs: first, people interacting with ACEs shouldn’t have any technical job to do to make them run, hence the automatic configuration of such environments depending on available sensors, effectors, computing resources, etc.; secondly, people shouldn't wear specific equipment to interact with ACEs, hence the focus on body capture techniques that rely or low-cost cameras, without any constraints on the body of the person; thirdly the interaction should be multimodal, using interaction modalities that people are used to, hence the focus on multimodal languages to analyze the performance of a dancer and the response of the system; finally, ACEs should be able to learn to adapt their responses to specific people, with specific ways of expressing emotions, and with specific sensibilities to visual and sonorous environments, hence the central importance of machine learning techniques in the project.

We may summarize all of this as the fact that the interface should not be more visible than the computers themselves. If computers are disappearing, the interface should also become as discrete and as natural to use as possible. We could finally imagine that these kind of environments may adapt to people with either perceptive or motor disabilities, by choosing dynamically the right modalities to establish a communication with them.

In order to be able to combine multiple modalities, we need to use a level of representation such that these different modalities can be described in a homogeneous way and compared with one another. We distinguish four levels of abstraction in the characterization of the behavior of the user: *raw data* are acquired directly by the various sensors; *primitives* correspond to quantitative measures, obtained by the processing of raw data (e.g. position, speed, etc.) ; *qualities* correspond to a subjective characterization of behavior by a set of pairs of terms (e.g. slow/fast, warm/cold, etc.); *emotions* finally correspond to more general terms used to characterize the global ambience of a situation (e.g. sadness, calm, liveliness, etc.). Although ill-defined, the latter notion of emotions correspond to the intuitive concept, based both on cognitive and physical reactions to some situations [11]. By defining these levels, the objective is twofold: first, to maintain a multilevel representation in order to allow an incremental analysis of the behavior; second, to be able to compare the various methods of capture, and therefore the expressions of the interlocutor, by using a representation that is abstract enough (*qualities* or *emotions*).

3. Analytical study of visual expression

In this paper, we focus more specifically on the automatic generation of visual ambiences. This ambience is not meant to reflect the emotional state of the user [12] but rather to inspire chosen feelings to the spectator. Our approach is based on the hypothesis that these feelings rely, for some part, on the composition of contrasts and graphical structures. To do this, we first need to present some general considerations about the analytical study of visual expression. Any picture, either a photography or a painting, has an emotional content. Depending on the cultural and historical context, we perceive pictures with different codes, that make us feel various emotions such as happiness, sadness, calm, serenity, etc. This also depends on the receptiveness of each individual person but we can consider that the interpretation code is largely shared inside a given culture. A sunset over the sea for example (see figure 1) generally produces a tragic effect and inspires feelings of calm and serenity. This common emotional answer to pictures has been analyzed and codified at the beginning of the XXth century by artists such as W. Kandinsky [6][7] and P. Klee [8]. Kandinsky, in particular, tried to identify the role of shapes, colors, contrasts in the production of emotions. However, he hardly said anything about the interactions between these elementary components because of the complexity of this study.

3.1. Spatial structures and contrasts

A picture can be decomposed into several zones, each of which can be associated to distinct "tensions". While the top of a picture symbolizes lightness, ascension, freedom, the bottom symbolizes heaviness and constraint. In addition, objects in the picture are organized along abstract structuring lines that express the dynamics. While horizontal and vertical lines symbolize calm and rest, diagonals express movements.

Finally, contrasts express oppositions between graphical objects that make them reinforce each other. Each individual characteristics of the objects, such as color, shape, size, etc., may give rise to a corresponding contrast. For color only, there are seven identified contrasts, which are based on the properties of colors: contrast of pure hue, value contrast, intensity contrast, complementary contrast, temperature contrast, size contrast and finally simultaneous contrasts. Properties of the shapes can also be used to produce size contrasts (small objects vs. large objects) or shape contrasts (symmetrical vs. unsymmetrical objects). Finally, if pictures are animated, contrasts can be built using the properties of movement such as direction, speed or rhythm.

3.2. Composition of elementary properties

Only through the composition of chosen elementary spatial structures and contrasts can more complex emotions be expressed. Table 1 is an attempt to summarize basic correspondences that we may establish, in western culture, between the composition of pictures, expressed in terms of graphical structural and contrasts, and the emotional content of the picture.

Table 1. Correspondences between the composition of pictures (in terms of spatial structure and contrasts) and their emotional content

Contrasts	dynamic	static	value	temperature	complementary	pure hue	size	intensity	simultaneous	top-bottom position	left-right position	shape	size
			Colors										
Emotions	Structure		Graphical objects										
happy	o					o						o	
calm		o						o					
serene				o						o			
sad			o					o					
restless	o	o				o						o	
tragic			o				o			o			o

If we come back to the example of a sunset over the sea (see figure 1), we can analyze it in the following way:

- the picture shows an horizontal structure, separating the clouds, the sky, the sea;
- several contrasts can be identified
  - a value contrast between the dark sea and lighter clouds and sky
  - a temperature contrast between the sun and surrounding sky, which are very warm (yellow orange), and other regions of the picture, with colder colors
  - a size contrast between the small sun and the large regions around (sea, clouds)
  - an intensity contrast centered on the sun.

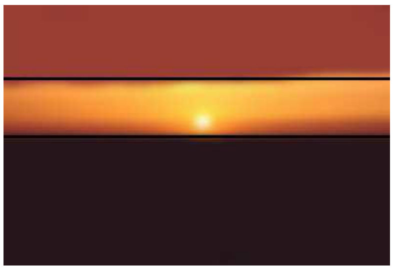

Fig. 1. Sunset over the sea. The picture can be analyzed in terms of contrasts and a graphical structure

Consultation of table 1 thus tells us that the emotional qualities of this picture are the following:

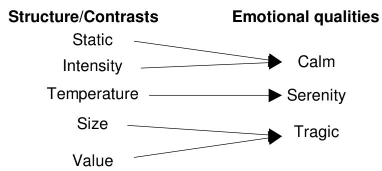

Fig. 2. Correspondence between structural properties, contrasts and emotional qualities for the picture shown in figure 1

3.3. Generic modeling of contrasts

Although contrasts can produce very different visual results, most of them are based on the same principles. This is why we propose a generic model of the way a contrast can be built by the association of graphical objects.

1. a given contrast is built upon an opposition of graphical objects with respect to a specific graphical property (color, shape, size, etc.);
2. objects in the picture are divided into distinct groups (generally two); each of them has its own value for the considered property: in a value contrast for example, some of the objects are characterized by a light value, others by a dark value;

3. there's a quantitative imbalance between the groups: the objects of one group are more numerous than the others;
4. for some contrasts, there's also a spatial imbalance between the groups: objects of the preponderant group are distributed on the whole surface while the objects of other groups are distributed along the main structuring lines of the picture.

4. A multi-agent composition

We have defined the theoretical background of the work from a graphical point of view. We can now explain how it can be implemented as a multi-agent system in which emotional qualities of pictures will be obtained by the coordinated activation of elementary autonomous colored cells. By choosing such a decentralized approach, the aim is to provide methods and algorithms that may be used on decentralized displays. Today's displays rely on LCD or plasma technology. Tomorrow's ones may perfectly well rely on tiny processors integrated in paintings that may change the color of the painting in their vicinity, thus composing together displays as big as entire walls 0. In addition, the proposed approach can be seen more generally as a way of spatially structuring entire networks of processors, which may be very valuable in contexts such as smart dust or sensor networks.

Our objective is definitely not to reproduce specific pictures or patterns, but to provide the cells with the capability to manipulate contrasts and spatial structuring as a mean to produce chosen emotional qualities. We based our work on the following assumptions:

- algorithms should function with irregular 2D distribution of computing cells, either static or dynamical (somewhat similar to the distribution that is used in the works on amorphous computing);
- convergence of the algorithms should be fast so that the generation of pictures is also fast;
- since the very notion of contrast is very general and can be instantiated in different ways, the generation of contrasts by the system should be as generic as possible (see paragraph 3.3 above)
- finally, although the perception of emotional qualities is quite general inside a given culture, individual variations evidently exist and the algorithms must allow the integration of machine learning techniques.

4.1. Composition of elementary behaviors

The challenge is now to implement the model presented in paragraph 3.3. with a multi-agent approach. To do this, we chose to rely on a modular approach, decomposing the overall problem into separate concerns. Step 2 in the model (allocation into groups) can be realized quite easily since it doesn't involve any coordination between the agents. The agents will thus realize it independently of each other. Step 3 (quantitative imbalance), on the contrary will need the coordination of all the agents in the picture, with no possible centralization. This will require the following sub-steps:

3.1. collective choice of the dominant group;
3.2. collective count of each group's population;
3.3. migrations of agents between the groups so as to obtain a given ratio;

Similarly, step 4 (spatial imbalance) will require the following sub-steps:

4.1. collective choice of the dominant group;

4.2. homogeneous distribution of agents of the dominant group across the picture and distribution of agents of the other groups along the structuring lines of the picture.

Steps 3.1 and 4.1 are identical, which finally produces the composition schema shown in figure 3.

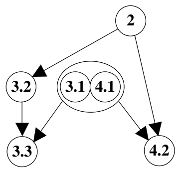

Fig. 3. Composition schema of sub-steps for the construction of contrasts: arrows correspond to functional dependences between the modules

4.2. Step 2: concentration into value intervals

For a given contrast, the opposition between the graphical objects is based on different values for a specific graphical property, for example hue. For a temperature contrast, some of the agents will adopt a warm hue (yellow, orange, red) while others will adopt a colder hue (blue, green). This doesn't mean that all the agents of a group will adopt a given value and that all the agents of the other group will have another fixed value. This rather mean that the agents of one group will have their hue distributed in a given interval of values (340-20 in the chromatic circle) and that the agents of the other group will choose their hue in another interval (210-260 in the chromatic circle). We made the choice to represent all possible properties as intervals of numerical values, inside which we can choose 2 opposing intervals and have the agents distribute themselves into these intervals. The intervals of values can be in direct correlation with the modeled properties (as it is the case with hue) but they can also be abstract descriptions of some properties (as it is the case with a symmetry parameter, which is not directly quantifiable but which can be measured and associated to an abstract scale ranging from 0 to 100). Some of the intervals can also be cyclic as is shown in figure 4.

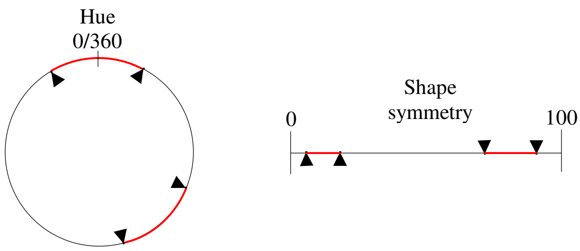

Fig. 4. Value intervals representation, compatible with circular or linear scales

Each of the agents being initially in a random state with respect to the property chosen for the contrast, the agents must evolve to come closer to the specified intervals. They do so at each simulation step with the algorithm shown below.

```
# Activation
∀ interval i, compute d_i = distance to i
choose interval j so that d_j = Min_i d_i
change property x towards interval j
```

Figure 5 shows the result of the concentration algorithm for the temperature contrast. Each colored square corresponds to an agent. At the beginning of the simulation, each agent is in an undetermined state. Agents rapidly change their hue towards the two intervals (340-20 and 210-260).

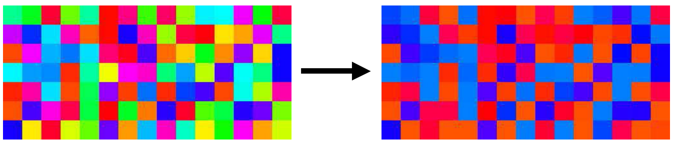

Fig. 5. Concentration into separate intervals of hue for temperature contrast

4.3. Step 3.1: choice of the dominant group

This step is meant to choose the group that will become dominant. This collective choice has to be random and equiprobable. The problem of the choice, or voting, has been studied by D. Schreiber [13] and G. Weiss [15]. In the model of Schreiber, agents spatially organize according to affinities and move to form coalitions. Since the position of the agents is taken into account in some of the contrasts that we want to realize, this was not satisfactory. In the protocols proposed by Weiss, agents order possible solutions depending on their individual preferences. However, this implies a lot of communications since individual votes have to be collected, compared, and diffused back to all the agents.

In our problem, the final choice isn’t important as such. We don’t care about satisfying the initial choices of agents, we only care about obtaining a single final choice. The solution that we propose consists in aggregating incrementally the votes of closest neighbors. After making a random initial choice, the behavior for each agent at each simulation step is the following:

```
# Initialization
choice = random (1..groups_nb)
weight = 1

# Activation
for c = 1 to groups_nb do
  neighbors_weight[c] = sum neighbors with (choice = c)
done
choice = i so that neighbors_weight[i] == max_i(neighbors_weight[i])
weight = neighbors_weight[choice]
```

Evaluation
This evaluation is not a formal proof of convergence of the algorithm but gives indications about its quality. The two criteria were the quality of the random distribution and the speed of convergence. To this end, agents were ask to make their choice between four different colors (red, blue, green, yellow). The simulation has been done with 100 moving agents in a 550x550 pixels space with a 100 pixels perception distance. 100 runs of the simulation have been done.

Table 2 shows the distribution of the 4 possible choices. We can see that the number of occurrences for each choice is very close to the mean value.

Table 2. Distribution of choices for 100 runs

Choice	Red	Blue	Green	Yellow	Total	Mean	Mean deviation
Results	22	30	26	22	100	25	3

Figure 6 below shows, for each convergence time expressed in number of simulation cycles, the number of runs that have converged in that time. One can see that for all the runs, the convergence time is comprised between 2 and 17 cycles, with a mean of 9,1 cycles.

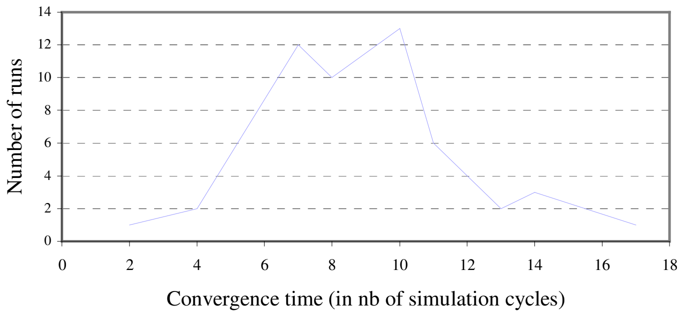

Fig. 6. Number of runs vs. convergence time

4.4. Step 3.2: Count of groups population

Quantitative imbalance requires that we assess the relative size of the different groups. To this end, we chose to count the number of agents in each group.

Our solution is inspired by the BFS algorithm that computes the diameter of a network (the distance between the most distant nodes) by building a covering tree. The difference is that we don't have any predetermined topology (the connectivity between the agents isn't static because they can move across the environment). The solution is also adaptive because the count is updated when agents change from one group to another. The algorithm is shown next page.

```
# Initialization
each agent gets a token
each agent propagates a "presence" stimulus

# Activation
1. Aggregation of agents into associations; the "leader" gets all the
   tokens of the other agents in the association
2. Fusion of associations with one another
3. Diffusion of the result (total number of tokens) to all the agents
```

The algorithm proceeds in three steps:

1. The agents form associations, each of which has got a "leader". The latter centralizes all the tokens of the association. This step is inspired by the Clubs algorithm described in [9].
2. Once the associations are formed, they try to merge:
   - ▷ agents at the border between two associations propagate a gradient towards the leader. The gradient contains the information of the distance to the border, incremented at each agent jump. The gradient diffusion method is described in [10].
   - ▷ when the leader perceives the gradient, it transfers its tokens to its neighbors that is closest to the border (the one that diffused the gradient with the smallest distance). This agent becomes the new leader of the association. The tokens and the leadership thus move from agent to agent towards one of the border of the association.
   - ▷ when two leaders are close enough, they can merge. One of them collects the tokens of both and the corresponding associations become merged.
3. When all the associations have merged, only one leader remains that has collected all the tokens of all the agents of the simulation. He can then diffuse the result to the other agents using gradient diffusion.

Figure 7 shows successive steps in the merging of associations. The first picture corresponds to the state of the system after the constitution of associations. Each subsequent picture corresponds to the fusion of two associations.

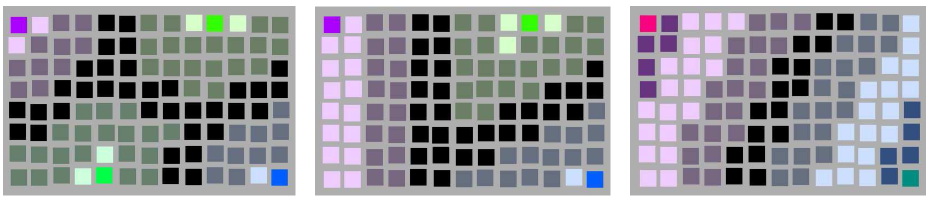

Fig. 7. Steps in the merging of associations: black agents corresponds to borders; leaders are lighter

Since the leader of the last association has collected the tokens of all the agents, he's got as many tokens as the number of agents in the simulation. The algorithm thus counts the agents. When constructing contrasts, we can thus evaluate the number of agents inside each of the different groups. When agents are distributed inside several groups (two for a temperature contrast), the algorithm has to be executed in each group. Furthermore, we will explain in the next paragraph that agents will be able to change group. When this arrives, the count must be dynamically updated. To this end, the migrating agent gets a negative token (-1) for the group that it leaves, and a positive token (+1) for the group it joins. As the algorithm is continuously executed, it converges very rapidly towards a new result.

Evaluation

We evaluated the algorithm in the same conditions as the choice algorithm in order to assess the time necessary to converge towards a global results. Each run is stopped when all the agents have received the correct count.

Table 3. Time to converge towards a global count, diffused to all the agents of the simulation

Duration	Arithmetic mean	Min	Max	Standard deviation
Results	18,8	14	27	3,08

Although adaptive, the algorithm still presents some weaknesses:

- if a leader fails, the tokens that it was responsible for are lost. This may be a problem for amorphous computing in which agents correspond to chips and are thus exposed to potential failures;
- convergence is slower when agents move (associations are less stable) or when they frequently change groups.

4.5. Step 3.3: Quantitative imbalance

Once the agents have chosen the group that will be dominant and they have evaluated the respective size of all the groups, we can adjust the ratio between the groups. This is done by having agents migrate from one group to the other. It is necessary to specify beforehand the desired ratio between the different groups (e.g. 10%-90%). The algorithm, for each agent at each simulation cycle is the following:

```
# Activation
if total[my_group]/sum(total[]) > percentage[my_group]
  token[my_group] -= 1;
  my_group = another_group
  token[my_group] += 1;
end_if
```

Figure 8 shows the quantitative imbalance for the temperature contrast. The desired ratio is 20% for warm-colored agents and 80% for cold-colored agents.

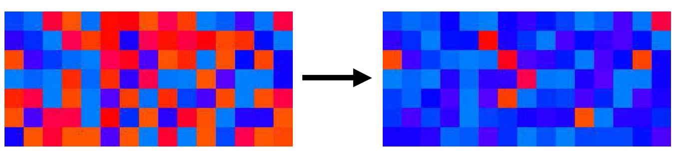

Fig. 8. Quantitative imbalance for temperature contrast. Desired ratio of 20%-80%

4.6. Step 4.2: Qualitative imbalance

The role of this final step is to organize the graphical elements spatially. Our approach consists in positioning attracting agents that propagate gradients in their vicinity. These gradients are meant to structure the distribution of agents from the non-dominant groups. If we have only one attracting agent, the result is a spot of agents that contrast with a homogeneous background (see figure 9).

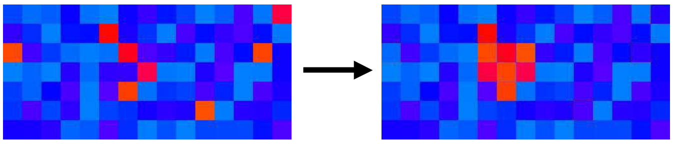

Fig. 9. Single attractive agent

To obtain more complex structures, the approach is inspired by composition rules used by painters. Each Border of the picture is divided into three thirds of four quarters. The points so defined can be joined together, which creates structuring lines. These structuring lines can either be static (horizontals and verticals) or dynamic (diagonals). Such lines will be generated by placing "anchor" agents along the borders at the dividing points and to make them propagate linear gradients. The gradients are characterized by the angle φ that they make with the horizontal. Whether we wish to obtain static or dynamic structures, the probability to generate anchor agents with φ equals to 0° (horizontal line) or 90° (vertical lines) will be more or less high (see figure 10).

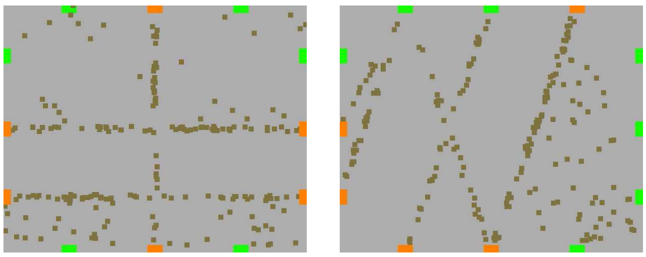

Fig. 10. Static (*left*) and dynamic (*right*) structuring of the picture using either horizontals and verticals or diagonals

Anchor agents can then be distributed along these structuring lines. When they activate, they propagate gradients that attract agents from the non-dominant groups and make them group in localized spots around them. In turn, the spots restitute for the viewer the feeling of "virtual" lines that organize the composition. Figure 11 shows a first attempt to organize the picture according to such principles. In this example, the agents did actually move but the same can be obtained if agents are in a fixed position: a virtual movement can be obtained by exchanging the properties of two neighboring agents.

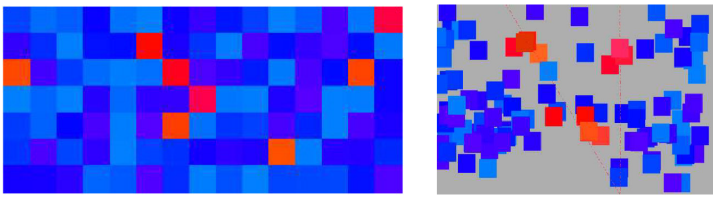

Fig. 11. Dynamical structuring of the picture along composition lines

4.7. Exceptions to the generic model

Two specific color contrasts (simultaneous and intensity contrasts) did not fit well into our generic model. The simultaneous contrast corresponds to the association of a given color to its gray component (i.e. the color we would obtain by changing the picture into grayscale). When viewing such a contrast, we tend to see the complementary color at the boundary between the color and the gray. The intensity contrast corresponds to the association of saturated and unsaturated colors (the latter must prevail) in the picture.

For these two contrasts, the solution we propose relies on the use of a gradient that is propagated around the center of the contrast. This gradient is provided with a *distance* information that is propagated and incremented from one agent to the next. The distance is equal to 0 at the center and is incremented as we move away from it. The distance is then put into correspondence with the characteristics that is involved in the contrast: for the simultaneous contrast, the color of the agents is unsaturated until a given distance from the center; for the intensity contrast, the saturation of the color of the agents decreases as a function of the distance from the center (see figure 12).

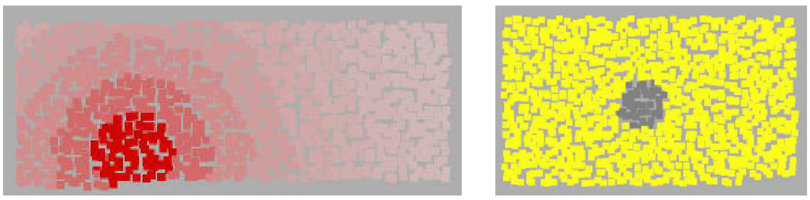

Fig. 12. Intensity contrast (left) and simultaneous contrast (right)

4.8. Composition of several contrasts

Once isolated contrasts can be obtained, we have to address the issue of composing distinct contrasts with one another. When contrasts are orthogonal (they rely on distinct properties), they can be combined either by aligning the two contrasts or by generating them in a disjoint way.

In the case of aligned contrasts, the first contrast (we call it the “master” contrast) is built by using the technique that we described in this paper. The second one (we call it the “slave” contrast) is then built by executing only step 2 (see paragraph 4.2) on a different characteristics of the agents. For example, after building a temperature contrast, we can simply superimpose a value contrast by making warm colors brighter and cold colors darker (see figure 13). In the case of disjoint contrasts, the whole algorithm has to be run twice, once for each contrast (see figure 13).

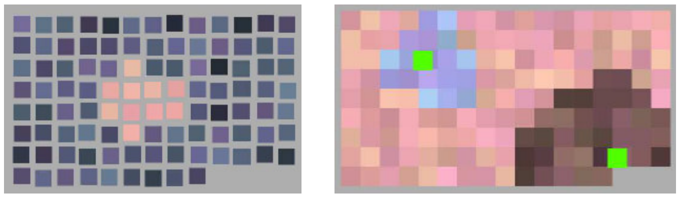

Fig. 13. Aligned contrasts (left) and disjoint contrasts (right)

4.9. Parameterization of the model

In order to be interesting, the result has to be variable and changing, and it has to be adapted to the user. This can be done using several strategies:
- in step 2, the intervals that we choose to define the contrast will greatly influence the result that we obtain. Indeed, the contrast will be stronger when the distance between the intervals is bigger (see for example figure 14);
- a stronger contrast will also be obtained by using a bigger ratio between the different groups;
- finally, a user may change the correspondence shown in table 1 between emotions and pictural means needed to express them.

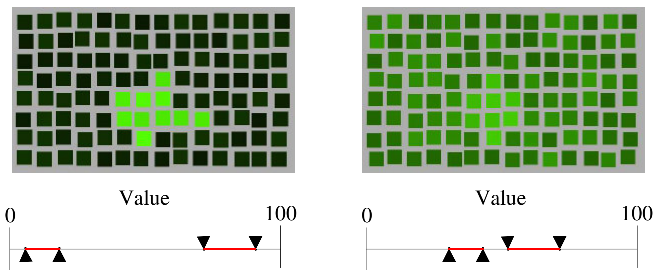

Fig. 14. Different value contrasts obtained by varying the intervals of the 2 groups

5. Conclusion

We presented in this paper a global and coherent approach to the creation of visual ambiences, based on the use of contrasts and spatial structuring of pictures. Inspired on the one hand by the analytical works of painters like Kandinsky and Klee, and on the other hand by researches on amorphous computing, our work demonstrates the feasibility of a decentralized approach. In particular, we presented a generic and modular model for the creation of contrasts. This model relies on decentralized algorithms that implement collective choices and counts, which allows to distribute agents in separate groups and to control the relative abundance of the groups. We showed that these algorithms converged fast towards global solutions, which may lead to new applications for amorphous computing. In particular, we showed how a spatial structuring of processor networks may be obtained by using contrasts and composition structuring rules. In addition, this model can easily be adapted to different users by changing some parameters, either by hand or by using machine learning techniques.

Future research directions will explore this parameterization problem in a more detailed and systematic way. We will use genetic algorithms on the one hand to produce various system behaviors; we will define validation protocols on the other hand in order to be able to assess the efficiency of the system, not in terms of speed of convergence but in terms of emotional qualities expressed by the system.

6. References

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