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Cooperation of Nature and Physiologically Inspired Mechanism in Visualisation

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ABSTRACT

A novel approach of integrating two swarm intelligence algorithms is considered, one simulating the behaviour of birds flocking (Particle Swarm Optimisation) and the other one (Stochastic Diffusion Search) mimics the recruitment behaviour of one species of ants – *Leptothorax acervorum*. This hybrid algorithm is assisted by a biological mechanism inspired by the behaviour of blood flow and cells in blood vessels, where the concept of high and low blood pressure is utilised. The performance of the nature-inspired algorithms and the biologically inspired mechanisms in the hybrid algorithm is reflected through a cooperative attempt to make a drawing on the canvas. The scientific value of the marriage between the two swarm intelligence algorithms is currently being investigated thoroughly on many benchmarks and the results reported suggest a promising prospect (al-Rifaie, Bishop & Blackwell, 2011). We also discuss whether or not the 'art works' generated by nature and biologically inspired algorithms can possibly be considered as 'computationally creative'.

Keywords: Stochastic Diffusion Search (SDS), Particle Swarm Optimisation (PSO), Swarm Intelligence, Blood Vessel Remodelling, Visualisation, Optimization, Metaheuristics, Swarm Regulated Freedom, Gaussian Constrained Freedom

INTRODUCTION

In recent years, studies of the behaviour of social insects (e.g. ants and bees) and social animals (e.g. birds and fish) have proposed several new metaheuristics for use in collective intelligence. Natural examples of swarm intelligence (a form of collective intelligence) that exhibit a form of social interaction are fish schooling, birds flocking, ant colonies in nesting and foraging, bacterial growth, animal herding, brood sorting etc.

This chapter explores the artistic side of this collective intelligence, which emerges through the interaction of simple agents (representing the social insects/animals) in two nature-inspired algorithms, namely, Particle Swarm Optimisation (PSO) (J. Kennedy & Eberhart, 1995) and Stochastic Diffusion

Search (SDS) (Bishop, 1989). Additionally, the mechanisms of blood vessel and blood flow are utilised to add another layer of detail to the drawing.

In the presented work, a user-made sketch is used as an input for the system. Then, the swarms of 'birds' and 'ants' explore the digital canvas they are provided with, going through all the lines made in the sketch and reworking them in their own way. The output of the system would be the swarms' 'interpretation' of the original sketch. As mentioned earlier, at a later stage, the physiologically inspired mechanism of blood flow is also used to add more details to the drawings made by the swarms.

A-Life (Artificial Life), where the boundary between biology and artificial intelligence is blurred (Levy, 1993), inspired many artists and researchers in computer graphics to explore this blurred area. Among the direct responses to A-Life are some works by Karl Sims (e.g. Sims, 1991, 1994). In an earlier work, Harold Cohen, an artist who used techniques of artificial intelligence to produce art, developed a computer program called AARON, which produced drawings as well as paintings (McCorduck, 1991).

Following other works in the field of swarm painting (Moura & Ramos, 2007, Aupetit, Bordeau, Monmarche, Slimane, & Venturini, 2004, Urbano, 2005, 2006) and ant colony paintings (Greenfield, 2005, Monmarche, Aupetit, Bordeau, Slimane, & Venturini, 2003), this work, in addition to exhibiting the cooperation of birds and ants as a new way in making a drawing, benefits from the mechanism used in blood vessels.

There are many works where the input of the nature has been utilised, some of which *are* claimed be to art. As for the presented work, despite the novelty of this hybrid approach, it is not the intention of the authors to use the results outlined in this work to make neither strong epistemological claims of computational creativity nor strong aesthetic claims of style.

In this chapter, each of the swarm intelligence algorithms used are introduced, and an approach to their possible integration is highlighted. Subsequently, the simplified mechanisms of blood vessel and blood flow are described, followed by an explanation on how the new hybrid algorithm produces a drawing and the role played by blood vessel remodeling. Lastly, the similar individualistic approach of the swarms in making a drawing is highlighted, followed by a brief section on creativity in general as well as a discussion on whether swarms can be computationally creative. The chapter comes to an end with a conclusion and possible future research.

BACKGROUND

After a brief introduction to communication in social systems, this section introduces two swarm intelligence algorithms as well as their integration strategy, followed by the simplified mechanism of blood vessel and blood flow.

Communication in Social Systems

Communication – social interaction or information exchange – observed in social insects and social animals plays a significant role in all swarm intelligence algorithms, including SDS and PSOs. Although in nature not just the syntactical information is exchanged between the individuals but also semantic rules and beliefs about how to process this information (J. F. Kennedy, Eberhart, & Shi, 2001), in typical swarm intelligence algorithms only the syntactical exchange of information is taken into account.

In the study of the interaction of social insects, two important elements are the individuals and the environment, which result in two integration schemes: the first one is the way in which individuals selfinteract and the second one is the interaction of the individuals with the environment (Bonabeau, Dorigo, & Theraulaz, 2000). Self-interaction between individuals is carried out through recruitment strategies and it has been demonstrated that, typically, various recruitment strategies are used by ants (Holldobler & Wilson, 1990) and honey bees. These recruitment strategies are used to attract other members of the society to gather around one or more desired areas, either for foraging purposes or for moving to a new nest site.

In general, there are many different forms of recruitment strategies used by social insects; these may take the form of global or local strategies, one-to-one or one-to-many communication, and deploy stochastic or deterministic mechanisms. The nature of information sharing varies in different environments and with different types of social insects. Sometimes, the information exchange is quite complex where, for example it might carry data about the direction, suitability of the target and the distance; sometimes, the information sharing is instead simply a stimulation forcing a certain triggered action. What all these recruitment and information exchange strategies have in common is distributing useful information throughout their community (Meyer, Nasuto, & Bishop, 2006).

In many hive-based (flock-based) agents – like the ones used in this chapter – the benefits of memory and communication seem obvious, but as argued in (Schermerhorn & Scheutz, 2009), these abilities are not beneficial in every environment, depending on the way resources are clustered throughout the environment and on whether the quality of the food sources is sufficiently high.

The algorithms used in this chapter rely both on memory and communication and the communication methods deployed are less greedy than the one presented in (Schermerhorn & Scheutz, 2009), thus allowing the agents to explore various parts of the search space. Nevertheless, the effect communication has on the artistic performance of swarm-based algorithms on this work is under further investigation.

The parable of the *blind men and the elephant* suggests how social interactions can lead to more intelligent behaviour. This famous tale, set in verse by John Godfrey Saxe (Saxe, Lathen, & Chief, 1882) in the 19th century, characterises six blind men approaching an elephant. They end up having six different ideas about the elephant, as each person has experienced only one aspect of the elephant's body: wall (elephant's side), spear (tusk), snake (trunk), tree (knee), fan (ear) and rope (tail). The moral of the story is to show how people build their beliefs by drawing them from incomplete information, derived from incomplete knowledge about the world (J. F. Kennedy et al., 2001). If the blind men had been communicating about what they were experiencing, they would have possibly come up with the conclusion that they were exploring the heterogeneous qualities that make up an elephant.

Birds: Particle Swarm Optimisation

Particle Swarm Optimisation (PSO), first developed in 1995 by Kennedy and Eberhart (J. Kennedy & Eberhart, 1995, Eberhart & Kennedy, 1995), is a population-based, optimization technique which came about as a result of an attempt to graphically simulate the choreography of fish schooling or birds flocking (e.g. pigeons, starlings, and shorebirds) flying in coordinated flocks that show strong synchronisation in turning, initiation of flights and landing. Despite the fact that members of the swarm neither have knowledge about the global behaviour of the swarm nor a global information about the environment, the local interactions of the swarms triggers a complex collective behaviour, such as flocking, herding, schooling, exploration and foraging (Reynolds, 1987, Mataric, 1994, Bayazit, Lien, & Amato, 2002, Janson, 1998).

A high-level description of PSO is presented in form of a social metaphor – The Lost Child in Jungle – demonstrating the procedures through which the information exchange is facilitated between members of the swarm in its simplest possible form. Formal explanation and mathematical equations of standard/basic PSO will be presented in the next section.

The Lost Child in Jungle

> A group of villagers realise that a child is lost in the jungle nearby and set off to find him. Each one of the villagers is given a mobile phone equipped with GPS that can be used to communicate with the head of the village. Each villager is also provided with a diary to record some data, as explained below.
> The villagers should log the location where they find the best information so far about the child in their diaries (Personal Best position) and inform the head of the village about it. Whenever they find something better that might lead to the location of the child (a location with a better fitness than their current Personal Best position), they should provide the head of the village with the update.
> The head of the village is responsible to compare all the Personal Bests he has received so far from all the villagers and pick the best one (Global Best position). The resulting Global Best position is communicated back to the villagers.
> Therefore, each villager should log the following three in his diary throughout the search:
>
> - current position
> - speed in walking
> - Personal Best position (which is also called *memory*)
> - Global Best position
>
> In the next step, when villagers decide about their next move from their current position, they need to consider their two bests (Personal and Global) and their current speed.
> Thus, while each villager does not neglect his personal findings, he has extra knowledge about its neighbourhood through Global Best position (the topology of the metaphor presented here is global neighbourhood); therefore, preserving a balance between exploration of the search space (e.g. jungle, in this case), and exploitation of potentially good areas around each villager's Personal Best.

In this example, villagers are metaphorically analogous to particles in PSO, where optimisation is based on particles' individual experience (Personal Best) and their social interaction with the particle swarms (via Global Best). Algorithm 1 describes the metaphor chronologically:

ALGORITHIM 1

```
Villagers spread in the jungle

While ( the child is not found )
   For all villagers
      Evaluate the fitness of the current location
          (how good the current location is
          to lead to the child)

      If (current location is better than personal best)
         Personal Best = current location
      If (Personal Best is better than Global Best)
         Global Best = Personal Best
      Villager decides about his next move
      (using information logged in the diary)
   End For
End While
```

At the end of the search, villagers will most likely congregate over the area where the child is likely to be found and hopefully, using this algorithm, the child will be brought back to his family in the village!

Standard PSO

A swarm in PSO algorithm is comprised of a number of particles and each particle represents a point in a multi-dimensional problem space. Particles in the swarm explore the problem space searching for the best (optimal) position, which is defined by a fitness function. The position of each particle, x, relies on the particle's own experience and those of its neighbours. Each particle has a memory, containing the best position found so far during the course of the optimisation, which is called personal best (pbest or p); whereas the best found position so far throughout the population, or the local neighbourhood, is called global best (gbest or p_g) and local best (lbest or p_l) respectively.

The standard PSO algorithm defines the next position of each particle by adding a velocity to the current position. Here is the equation for updating the velocity of each particle:

$$v_{id}^{t} = wv_{id}^{t-1} + c_1 r_1 \left(p_{id} - x_{id}^{t-1}\right) + c_2 r_2 \left(p_{gd} - x_{id}^{t-1}\right) \quad \text{(Eq 1)}$$

$$x_{id}^{t} = v_{id}^{t} + x_{id}^{t-1} \quad \text{(Eq 2)}$$

where w is the inertia weight whose optimal value is problem dependent (Shi & Eberhart, 1998) and it is set to 0.5 for the work presented here; $\vec{v}_{id}^{t-1}$ is the velocity vector of particle i in dimension d at time step $t-1$; $c_{1,2}$ are the learning factors (also referred to as acceleration constants) for personal best and neighbourhood best respectively (they are generally constant and are usually set to 2); $r_{1,2}$ are random numbers adding stochasticity to the algorithm and they are drawn from a uniform distribution on the unit interval $U(0,1)$; $\vec{p}_{id}$ is the personal best position of particle x_i in dimension d (initially set to the value of particle x_i in dimension d); and p_{gd} is global best (or neighbourhood best), initially set to a random particle.

Therefore, PSO optimisation is based on the particles' individual experience and their social interaction with the particle swarms. After updating the velocities of the particles, their new positions are determined.

```
ALGORITHM 2
Initialise particles

While ( stopping condition is not met )
   For each particle
      Evaluate fitness of particle

      If (current fitness < pbest)
         pbest = current fitness

      If (pbest < global (or local) best)
         global (or local) best = pbest

      Update particle velocity (Eq 1 or 3)
      Update particle position (Eq 2)
   End For
End While
```

In this chapter, Clerc-Kennedy PSO (PSO-CK) is used:

$$v_{id}^{t}=\chi\left(v_{id}^{t-1}+c_1 r_1\left(p_{id}-x_{id}^{t-1}\right)+c_2 r_2\left(p_{gd}-x_{id}^{t-1}\right)\right) \quad \text{(Eq 3)}$$

where χ=0.72984 is reported to be working well in general (Bratton & Kennedy, 2007). The values of other variables are reported earlier (Equation 1).
Algorithm 2 summarises the behaviour of PSO algorithm for a minimisation problem.

Ants: Stochastic Diffusion Search

This section briefly introduces a multi-agent global search and optimisation algorithm called Stochastic Diffusion Search (SDS) (Bishop, 1989), whose behaviour is based on the simple interaction of agents.

Chemical communication through pheromones forms the primary method of recruitment in ants. However in one species of ants, *Leptothorax acervorum*, where a ‘tandem calling mechanism’ (one-to-one communication) is used, the forager ant that finds the food location recruits a single ant upon its return to the nest, and therefore the location of the food is physically publicised (Moglich, Maschwitz & Holldobler, 1974). In SDS, direct one-to-one communication (which is similar to tandem calling recruitment) is utilised.

SDS presents a new probabilistic approach for solving best-fit pattern recognition and matching problems. SDS, as a population-based multi-agent global search and optimisation algorithm, is a distributed mode of computation utilising interaction between simple agents (Meyer, Bishop, & Nasuto, 2003).

Unlike many nature inspired search algorithms, SDS has a strong mathematical framework, which details the behaviour of the algorithm by investigating its resource allocation (Nasuto, 1999), convergence to global optimum (Nasuto & Bishop, 1999), robustness and minimal convergence criteria (Myatt, Bishop, & Nasuto, 2004) and linear time complexity (Nasuto, Bishop, & Lauria, 1998). A social metaphor, *the Mining Game* (al-Rifaie & Bishop, 2010), is used to explain the mechanism through which SDS allocates resources.

The Mining Game

This metaphor provides a simple high-level description of the behaviour of agents in SDS, where mountain range is divided into hills and each hill is divided into regions:

> A group of miners learn that there is gold to be found on the hills of a mountain range but have no information regarding its distribution. To maximize their collective wealth, the maximum number of miners should dig at the hill which has the richest seams of gold (this information is not available a-priori). In order to solve this problem, the miners decide to employ a simple Stochastic Diffusion Search.
>
> - At the start of the mining process each miner is randomly allocated a hill to mine (his hill hypothesis, *h*).
> - Every day each miner is allocated a randomly selected region of the hill to mine.
>
> At the end of each day, the probability that a miner is happy is proportional to the amount of gold he has found. Every evening, the miners congregate and each miner who is not happy

selects another miner at random for communication. If the chosen miner is happy, he shares the location of his hill and thus both now maintain it as their hypothesis, *h*; if not, the unhappy miner selects a new hill hypothesis to mine at random.

As this process is structurally similar to SDS, miners will naturally self-organise to congregate over hill(s) of the mountain with high concentration of gold.

In the context of SDS, agents take the role of miners; active agents being 'happy miners', inactive agents being 'unhappy' miners and the agent's hypothesis being the miner's 'hill-hypothesis'. Algorithm 3 presents the metaphor chronologically:

ALGORITHM 3

```
Initialisation phase
Allocate each miner (agent) to a random
  hill (hypothesis) to pick a region randomly

While (not all/most miners congregate over the highest
   concentration of gold)

   Test phase
      Each miner evaluates the amount of gold
        they have mined (hypotheses evaluation)
      Miners are classified into happy (active)
        and unhappy (inactive) groups

   Diffusion phase
      Unhappy miners consider a new hill by
        either communicating with another miner
        or, if the selected miner is also
        unhappy, there will be no information
        flow between the miners; instead the
        selecting miner must consider another
        hill (new hypothesis) at random
End
```

SDS Architecture

The SDS algorithm commences an optimisation or search by initialising its population, which are the miners, in the mining game metaphor. In any SDS search, each agent maintains a hypothesis, *h*, defining a possible problem solution. In the mining game analogy, the agent hypothesis identifies a hill. After initialisation, the following two phases are iterated (see Algorithm 3 for these phases in the mining game; for high-level SDS description see Algorithm 4):

- Test Phase (e.g. testing gold availability)
- Diffusion Phase (e.g. congregation and exchanging of information)

ALGORITHM 4

```
Initialising agents()
While (stopping condition is not met)
   Testing hypotheses()
   Diffusion hypotheses()
End
```

In the test phase, SDS checks whether the agent hypothesis is successful by performing a partial hypothesis evaluation which returns a boolean value. Later in the iteration, contingent on the precise recruitment strategy employed, successful hypotheses diffuse across the population and in this way information on potentially good solutions spreads throughout the entire population of agents.

In the Test phase, each agent performs *partial function evaluation, pFE*, which is some function of the agent's hypothesis; $pFE=f(h)$. In the mining game, the partial function evaluation entails mining a random selected region on the hill which is defined by the agent's hypothesis, instead of mining all regions on that hill.

A simple example that SDS's partial function evaluation can be illustrated is text search, where the position of the first letter of each word in the text is a hypothesis (hill). In order to use partial function evaluation, one letter within a word (region within a hill) is compared against the letter in the word which is sought; this way, a full comparison of all the letters is not required. An example of text search using SDS is given in (Bishop, 1989).

In the Diffusion phase, each agent recruits another agent for interaction and potential communication of hypothesis. In the mining game metaphor, diffusion is performed by communicating a hill hypothesis.

Standard SDS and Passive Recruitment
In standard SDS (which is used in this chapter), *passive recruitment mode* is employed. In this mode, if the agent is inactive, a second agent is randomly selected for diffusion; if the second agent is active, its hypothesis is communicated (*diffused*) to the inactive one. Otherwise, there would be no flow of information between agents; instead a completely new hypothesis is generated for the first inactive agent at random (see Algorithm 5).

```
ALGORITHIM 5
For ag = 1 to No_of_agents
   If (ag.activity() == false)
      r_ag = pick a random agent()
      If (r_ag.activity() == true)
         ag.setHypothesis(r_ag.getHypothesis())
      Else
         ag.setHypothesis(randomHypothsis())
      End If-Else
   End If
End
```

Cooperation: Birds and Ants

In an ongoing research, an initial set of experiments aimed to investigate whether the information diffusion mechanism deployed in SDS ('ants') on its own improves PSO ('birds') behaviour. Early results show the high potential of this integration. For detailed theoretical work and statistically analysis, refer to (al-Rifaie, Bishop & Blackwell, 2011).

In the hybrid algorithm, each PSO particle (villager, in the Lost Child metaphor) has a current position, a memory (personal best position) and a velocity; each SDS agent (miner, in the Mining Game metaphor), on the other hand, has hypothesis (hill) and status (happy or unhappy).

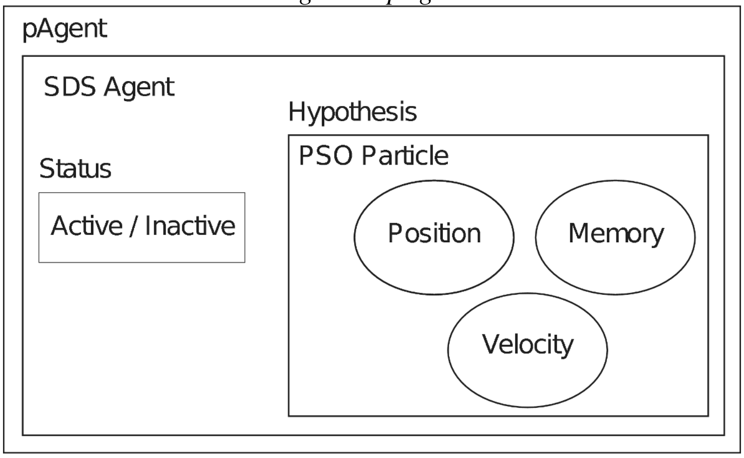
ALGORITHM 6

```
Initialise pAgents

While ( stopping condition is not met )
   For i = 1 to No-of-pAgent
      Evaluate fitness value of each particle

      If ( evaluation_counter MOD n == 0 )*
         // START SDS
         // TEST PHASE
         For pAg = 1 to No-of-pAgents
            r_pAg = pick-random-pAgent()
            If ( pAg.pbestFitness() <= r_pAg.pbestFitness() )
                pAg.setActivity (true)
            Else
                pAg.setActivity (false)
            End If-Else
         End For

         // DIFFUSION PHASE
         For ag = 1 to No_of_pAgents
            If ( pAg.activity() == false )
               r_pAg = pick-random-pAgent()
               If ( r_pAg.activity() == true )
                  pAg.setHypo( r_pAg.getHypo() )
               Else
                  pAg.setHypo( randomHypo() )
               End If-Else
            End If
         End For
      End If
      // END SDS

      If (current fitness < pbest)
         pbest = current fitness

      If (pbest < gbest)
         gbest = pbest

      Update particle position (Eq 1 or 3)
   End For
End While
```

* Each time PSO evaluates the fitness of a particle, `evaluation_counter` is incremented by 1. The value of `n` is problem dependent. If `n` is smaller, SDS is run more often than when the value of `n` is larger.

In the experiment reported here, every particle in PSO is an SDS agent too – together termed *pAgents*. In pAgent, SDS hypotheses are defined by the PSO particle positions, and an additional Boolean variable (status), which determines whether the pAgent is active or inactive (see Figure 1).

Figure 1. pAgent



This figure illustrates the structure of pAgent. (© 2011, al-Rifaie. Used with permission.).

The behaviour of the hybrid algorithm in its simplest form is presented in Algorithm 6.

In Algorithm 6, when the pAgents are initialised, pbest are initially set to the position of the particles and gbest is set to one of the particles randomly; *evaluation counter* counts the number of function evaluations in PSO and *n* is set to 3000 in this work. Therefore, SDS algorithm is run after every 3000 PSO function evaluations.

Test and Diffusion Phases in the Hybrid Algorithms

In the Test Phase of a stochastic diffusion search, each agent has to partially evaluate its hypothesis. The guiding heuristic is that hypotheses that are promising are maintained and those that appear unpromising are discarded. In the context of the hybrid PSO-SDS algorithm, it is clear that there are many different tests that could be performed in order to determine the activity of each pAgent. A very simple test is illustrated in Algorithm 6. Here, the Test Phase is simply conducted by comparing the fitness of each pAgent's particle's personal best against that of a random pAgent; if the selecting pAgent has a better fitness value, it will become active. Otherwise it is flagged inactive. On average, this mechanism will ensure 50% of pAgents remain active from one iteration to another[i].

In the Diffusion Phase, each inactive pAgent picks another pAgent randomly; if the selected pAgent is active, the selected pAgent communicates its hypothesis to the inactive one; if the selected pAgent is inactive too, the selecting pAgent generates a new hypothesis at random from the search space.

As outlined in the pseudo-code of the hybrid algorithm (see Algorithm 6), after each *n* PSO function evaluations, one SDS cycle[ii] is executed. The hybrid algorithm is called *SDSnPSO*, where *n* refers to the number of PSO function evaluations before an SDS cycle should run.

The next section gives a brief introduction of the mechanism of blood vessels.

The Simplified Mechanism of Blood Vessels

In this part, three different features of blood vessels will be explained in physiological and mechanical terms as they occur in the body. These aspects of the blood vessel mechanism have been imitated to collectively cooperate with the swarms in order to draw. In the presented drawings (see the figures in the next sections), each member of the swarm takes the shape of the blood vessels, as if the vessels are cut in order to see their calibre, thickness, etc. The main focus of attention will be on:

- Vessel calibre, which is affected by the blood flow and its shear stress
- Blood vessel thickness
- Geometrical heterogeneity of endothelial cells lining the vessels

Each of these will be explained independently and details on how these mechanisms influence the drawings of the swarms will be provided at the end of this section.

Blood Flow Shear Stress and Vessel Calibre

Hemodynamic forces of the blood flow have been identified as factors regulating blood vessels (Kamiya & Togawa, 1980, Lowell & O'Donnell, 1986) and influencing development of vascular pathologies such as atherosclerosis (Zarins et al., 1983), and aneurysms (Kerber, Hecht, Knox, Buxton, & Meltzer, 1996). The flow of blood on the luminal vessel wall and endothelial surface creates, by virtue of viscosity, a frictional force per unit area known as hemodynamic shear stress (Fung, 1997, LaBarbera, 1990). Shear stress has been shown to be a critical determinant of vessel calibre (Lowell & O'Donnell, 1986, LaBarbera, 1990, Kamiya, Bukhari, & Togawa, 1984), as well as an important factor in vascular remodeling (Zarins, Zatina, Giddens, Ku, & Glagov, 1987, Gibbons & Dzau, 1994) and pathobiology (Zarins et al., 1983, Kerber et al., 1996).

The luminal surface of the blood vessel and its endothelial surface are constantly exposed to hemodynamic shear stress (Fung, 1997). The magnitude of the shear stress can be estimated in most of the vasculature by Poiseuille's law (Fung, 1997), which states that shear stress is directly proportional to blood flow viscosity, and inversely proportional to the third power of the internal radius (LaBarbera, 1990, Kamiya et al., 1984, Zamir, 1976).

In equation Eq 4, Poiseulle's law states that the flow rate Q is also dependent upon fluid viscosity η, pipe length L and the pressure difference between the ends P by:

$$Q = \frac{\pi r^4 P}{8 \eta L} \qquad \text{(Eq 4)}$$

Measurements using different modalities show that shear stress ranges from 1 to 6 dyne/cm^2 in the venous system and between 10 and 70 dyne/cm^2 in the arterial vascular network. Studies have shown that shear stress actively influences vessel wall remodeling (Kamiya & Togawa, 1980, Lowell & O'Donnell, 1986, Kraiss, Kirkman, Kohler, Zierler, & Clowes, 1991). Specifically, chronic increases in blood flow, and consequently shear stress, lead to the expansion of the luminal radius such that mean shear stress is returned to its baseline level (Kamiya & Togawa, 1980, Girerd et al., 1996).

This is clearly demonstrated in the radial artery of dialysis patients proximal to their arteriovenous fistula (Girerd et al., 1996) or in feeder arteries supplying cerebral arteriovenous malformations (Rossitti & Svendsen, 1995), both of which lead to the expansion of the blood vessels calibre as a result of increased shear stress in the vessel lumen. Conversely, decreased shear stress resulting from lower flow or blood viscosity induces a decrease in internal vessel radius (Lowell & O'Donnell, 1986). The net effect of these endothelial-mediated compensatory responses is the maintenance of mean arterial hemodynamic shear stress magnitude at approximately 15 to 20 dyne/cm^2 (Girerd et al., 1996, LaBarbera, 1990). This shear stress– stabilizing process is dependent on intact endothelial function (Lowell & O'Donnell, 1986).

The effect of this mechanism on the drawing is discussed later in the chapter. In simple terms a proportional correspondence between the speed of drawing on a canvas and the size of the discs' diameter in the drawing (which represents the vessel calibre) is demonstrated.

Remodeling of Vessel Wall Structure and Blood Pressure

Various studies have demonstrated that increased blood pressure is one of the major contributing factors to blood vessel remodeling (Baumbach & Heistad, 1989, Short, 1966). A fundamental tool to understand the varying structure of different blood vessels including their wall thickness is the Laplace law. This law, which can be applied to any tubular element with cylindrical geometry, relates intramural stress (σ), wall thickness (W), lumen radius (r), and transmural pressure (P, or the difference between luminal and extraluminal pressures) according to the following equation:

$$\sigma = \frac{Pr}{W} \qquad \text{(Eq 5)}$$

which may be rewritten in terms of the W to lumen diameter (D) ratio as:

$$\sigma = 0.5 \frac{P}{(W/D)} \qquad \text{(Eq 6)}$$

Laplace law dictates vascular structure to maintain σ within a relatively tight domain. Within an individual, there is high plasticity of vascular structure, which continuously adapts to accommodate for the changing conditions.

Blood Pressure and the Concept of Small Vessel Remodeling. Early studies (Baumbach & Heistad, 1989, Short, 1966) have shown that hypertension (or high blood pressure) could be associated with changes in the structure of resistance vessels, such that the vessels had a decreased lumen and increased media:lumen ratio (lumen is the hollow part of the vessel through which the blood passes, and media is the major and the thickest layer of the blood vessel wall), but no change in media cross-sectional area (or volume). (Baumbach & Heistad, 1989) used the term remodeling for the fist time to describe these changes.

Vessel Remodeling Classification. It was proposed that the term remodeling should only be used in situations where there is a structurally determined change in lumen diameter. A detailed classification that categorized the remodeling into the six changes is proposed in (Mulvany, Baumbachand, Aalkjær, & al., 1996). It was suggested that remodeling should be termed:

- Inward remodeling: decrease in the vessel lumen
- Outward remodeling: increase in the vessel lumen

Furthermore, since remodeling can result in either increase, no change, or decrease in the amount of vessel wall, there should be a sub-classification into *hypertrophic*, *eutrophic*, and *hypotrophic* remodeling, respectively:

- Hypertrophic remodeling: increase in the amount of blood vessel wall
- Eutrophic remodeling: no change in the amount of blood vessel wall
- Hypotrophic remodeling: decrease in the amount of blood vessel wall

This classification provided a framework for defining various modes of vascular remodeling in order to discuss the mechanisms involved. It is worth mentioning that only certain remodeling categories are used and imitated in this chapter.

Examples of the Different Types of the Remodeling. In this part, the impact of blood flow on the blood vessel remodeling is discussed by giving examples of different types of remodeling:

Primary Hypertension and Inward Eutrophic Remodeling
Histological studies demonstrated increased media:lumen ratios in the small vessels of patient with primary hypertension[iii] (Suwa & Takahashi, 1971, Furuyama, 1962, Nordborg, Ivarsson, Johansson, & Stage, 1983). In another study, it was shown that the media:lumen ratio of resistance vessels was increased in hypertensive patients, but that this was not associated with any increase in the cross-sectional area of the media (measured normally to the longitudinal axis) (Short, 1966). Thus, the available evidence indicates that in primary hypertension the resistance vessels have experienced inward eutrophic remodeling. Furthermore, the size of the individual smooth muscle cells within the media is also normal (Korsgaard, Aalkjaer, Heagerty, Izzard, & Mulvany, 1993), while the functional responses of the smooth muscle are slightly affected (Aalkjaer, Heagerty, Petersen, Swales, & Mulvany, 1987).

Secondary Hypertension and Inward Hypertrophic Remodelling
In contrast to the above inward eutrophic changes in primary hypertension, in human secondary hypertension[iv] due to renal causes, the reduction in vessel lumen diameter is accompanied by an increase in media cross-sectional area leading to an inward hypertrophic response (Rizzoni et al., 1996).

Blood Pressure Treatment and Outward Remodeling
Outward remodelling of resistance vessel structure is in general seen during anti-hypertensive treatment and in situations with increased flow. Thus, with a certain class of anti-hypertensive medication called ACE-inhibitor[v], the abnormalities indicated in the previous paragraph (inward eutrophic and inward hypertrophic) are reversed (Thybo et al., 1995, Skov, Fenger-Gron, & Mulvany, 1996) and the remodeling will take the following shape: outward eutrophic and outward hypertrophic remodelling.

The way in which remodeling in blood vessels shapes the drawings are discussed later in the chapter.

Blood Flow and the Heterogenic Geometry of Endothelial Cells

It has been proposed that an important determinant of arterial disease is the local geometry of arteries, which in turn regulates the hemodynamic force distribution that acts on the endothelial cells covering the inner surface of blood vessels (Davies, 1995, 2008). In regions with unstable flow such as curvatures, branches and bifurcations in the arterial circulation, steep temporal and spatial gradients of shear stress are associated with an oscillatory flow that act on the endothelial cells. In these regions of disturbed oscillatory flow, multidirectional forces act on the cells, and as a result, the endothelium, unlike elsewhere in the arterial circulation, lacks preferential cell alignment and often expresses a polygonal morphology (Davies et al., 2010). Disturbed flow regions correlate closely with susceptibility to pathological change such as atherosclerosis in arteries and calcific sclerosis in heart valves.

The action of the oscillatory blood flow that causes a polygonal alignment of the endothelial cells has been imitated in regions of the canvas where the speed of drawing is higher than others; in these regions the discs exhibit a wave-like feature unlike other areas where the lines are unidirectional (see Figure 7).

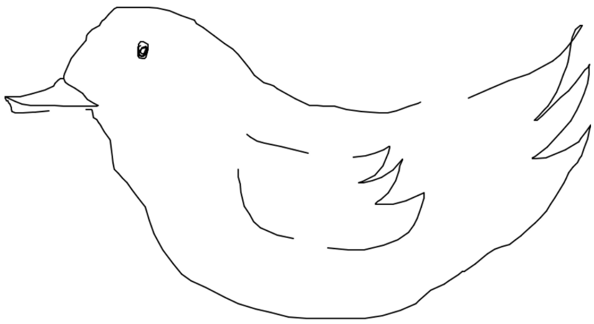
THE DRAWING MECHANISM

To begin with, this section explains how a sketch is provided to the hybrid swarm algorithm (PSO-SDS) and how the hybrid swarms make a drawing based on the original sketch. Afterwards, the influence of the blood flow and blood vessels mechanisms is explored in this context.

Birds and Ants Set off to Draw

In the experiment setup of this work, a sketch is made on a screen with a mouse. Once the swarm (birds and ants) are presented with this sketch, which is a vector of (*x,y*) coordinates corresponding to the points constituting the sketch (see Figure 2), they use it as an 'inspiration' and start making a drawing, which is based on the sketch, but utilises the swarms 'style'.

Figure 2: Sketch



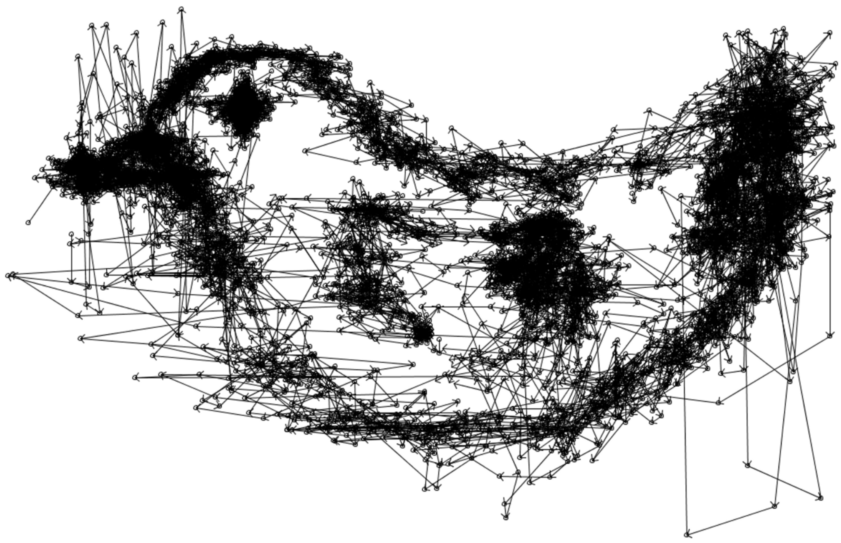
The sketch whose constituting points are used as input to the hybrid swarms. (© 2011, al-Rifaie. Used with permission.).

Each one of the points (constituting the sketch and representing the lost child and the richest hill) is traced by the swarms (e.g. of villagers and miners, or birds and ants) as described in Algorithm 6. When the mouse pointer moves on the digital canvas to make a sketch, it is equal to the moving of the child (in the Lost Child metaphor) and to the change of the position of the richest hill (in the Mining Game metaphor). Each member of the swarms has the shape of a disc (with the centre representing the position of the particle) and as they move, their former position is connected to the current one with an arrow. It can be said that 'the trace of the birds' / 'the footprint of the ants' stay on the canvas, creating a drawing inspired by the initial sketch (see Figure 3).

Therefore, the search space of the swarms is the canvas (a two dimensional array corresponding to the width and height of the canvas in pixels), where they are initialised, and the goal of their performance is to trace the constituting points of the sketch. The swarms search on the canvas is terminated when they reach the end of the sketch (in other words, when there are no more points to consider).

In this context, gbest is the closest (fittest) particle to the point (of the sketch) being considered at any time. The hypotheses are the positions of each disc. The method used to determine whether an agent is active or inactive, and whether there should be information exchange, can be found in the test phase and diffusion phase of Algorithm 6 respectively. SDS cycle is carried out after each *n* PSO function evaluations. Thus, each disc on the canvas represents a pAgent, which is a PSO particle (i.e villager, or bird) and an SDS agent (i.e. miner or ant) at the same time. Twenty pAgents were used in all the drawings of this chapter.

Figure 3: Drawing of the Hybrid Swarms



The Drawing of the Hybrid Swarms (PSO + SDS). (© 2011, al-Rifaie. Used with permission.).

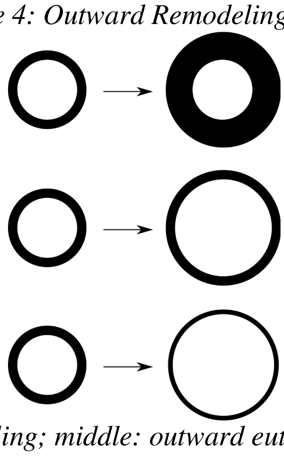
How Blood Flow and Blood Vessels Shape the Drawing

The simplified impact of blood pressure on blood vessels is used in the drawing to reflect the relation between the time spent for drawing each part (e.g. each line) and the form of the discs (e.g. diameter and thickness), which are visible around each member of the swarm.

The size of the discs is affected in either of the following ways (see Figure 4 which shows three types of outward remodeling types, two of which are used for the drawings):

a) Outward Eutrophic Remodeling: Enlarging the lumen (hallow part of the disc) without influencing the media (thickness of its wall)
b) Outward Hypertrophic Remodeling: Enlarging the media while keeping the lumen intact

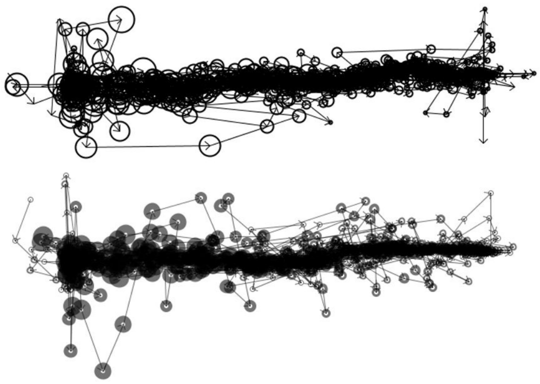
Figure 4: Outward Remodeling Types



Top: Outward hypertrophic remodeling; middle: outward eutrophic remodeling; bottom: outward hypotrophic remodeling. (© 2011, al-Rifaie. Used with permission.).

Here, the concept of speed in drawing a line is analogous to the idea of the blood pressure in the mechanism of blood vessel remodeling. Since blood pressure affects the calibre of the blood vessels (see the earlier sections on blood vessel, blood flow and Eq 4-6), in this context, it implies that the quicker a line is drawn, the bigger the size of the discs around each member of the swarm. In other words, when a line is drawn faster than the other in a drawing, the size of the discs while drawing that line is bigger; but when a line is drawn slower, it will have smaller discs (see Figure 5).

Figure 5: Blood Vessels on High and Low Blood Pressure on Drawing a Line



The speed of drawing the line decreases as it goes towards the right. Top: Demonstrating eutrophic remodeling. Bottom: Demonstrating hypertrophic remodeling. (© 2011, al-Rifaie. Used with permission.).

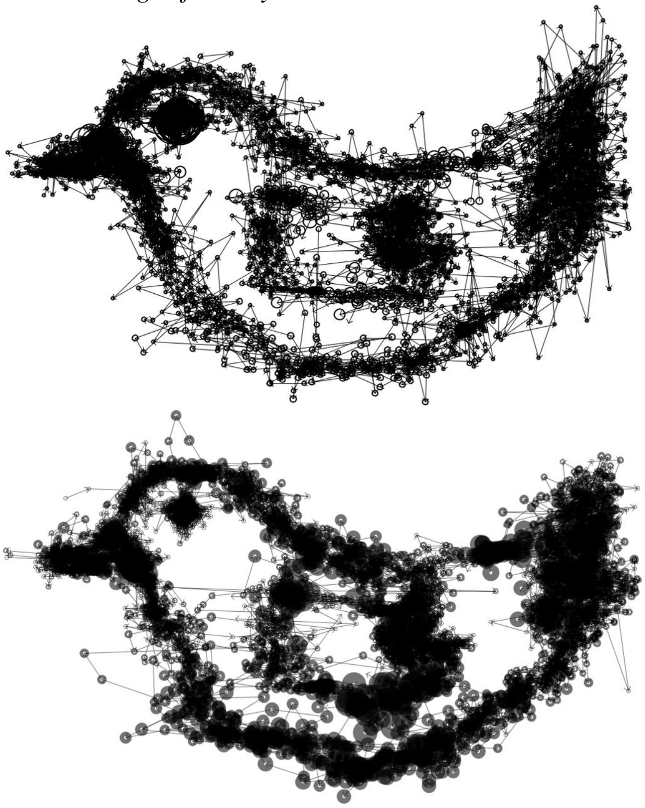
In terms of vessel remodeling, a combination of two concepts are imitated to aid the drawing swarms:

- outward eutrophic remodeling in small blood vessels that are treated with ACE-inhibitors
- blood vessel lumen expansion in areas that experience a constant high blood flow

These mechanisms are used simultaneously so that the speed of the drawing 'pen' (mouse) exhibits both the duration of treatment with ACE inhibitor for high blood pressure and the shear stress of the blood flow. For example when the pen speed is high on the canvas (high blood pressure), the disc becomes wider without any change in the disc thickness (see Figure 6-top).

In another approach, in the swarms' drawings, the outward hypertrophic remodeling is imitated by keeping the diameter of the hollow part (lumen) of the discs constant, whereas the thickness of the wall (media) of the discs is in a linear relationship with the speed of the drawing pen on the canvas. For instance, in areas where the speed of the drawing pen is high, the media is thicker than areas where the pressure is low (see Figure 6-bottom).

Figure 6: The Drawings of the Hybrid Swarms with Blood Vessels Mechanism



This figure shows the effect of the blood pressure on the disk's lumen and its media respectively (top: Eutrophic bird remodeling; bottom: Hypertrophic bird remodeling). (© 2011, al-Rifaie. Used with permission.).

Earlier in the chapter, oscillatory blood flow has been described. In order to implement the oscillatory flow in the drawing, the equation of the simple sine wave or sinusoid is used:

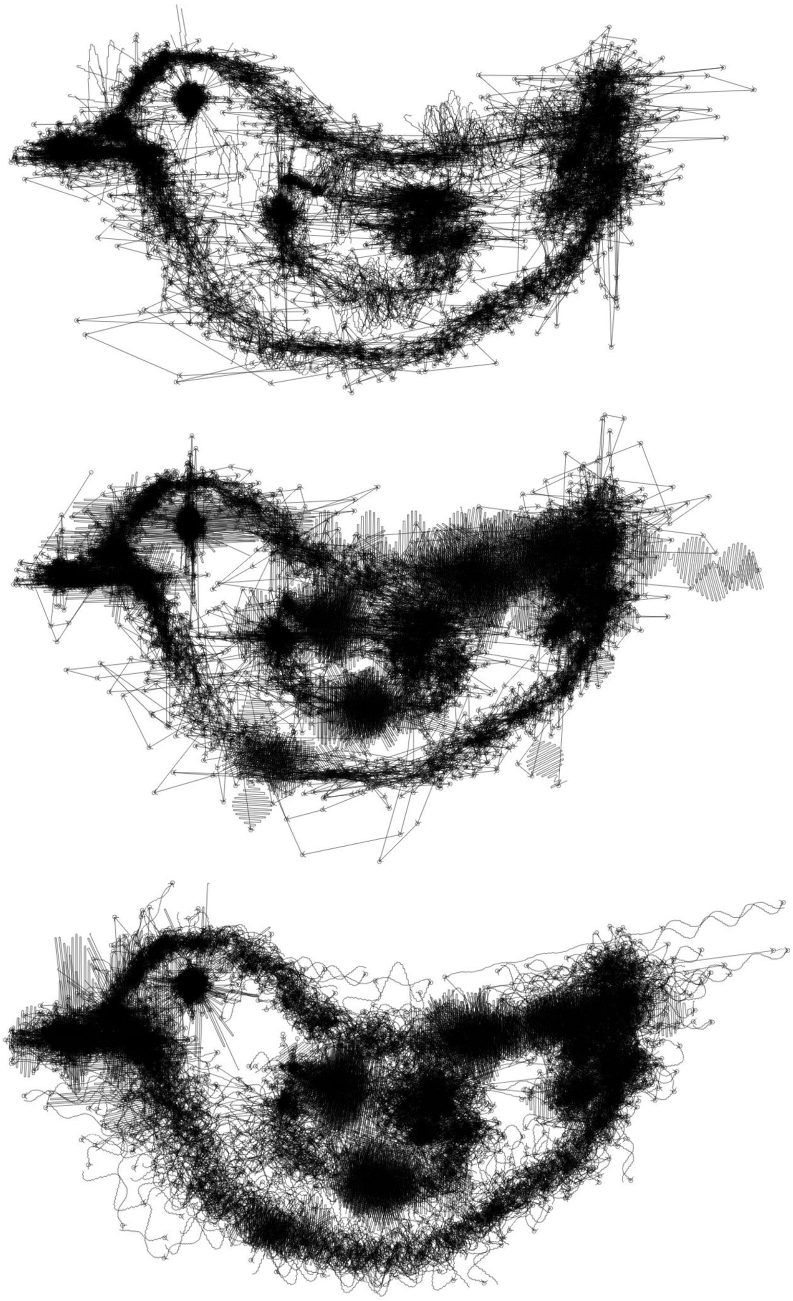
$$y\,(t) = A.\sin\left(\omega t + \alpha\right) \qquad \text{(Eq 7)}$$

where A is the amplitude, ω is the angular frequency, specifying the number of oscillations in a unit time interval in radians per second and α is the phase which determines where the oscillations begin in its cycle at t=0. In this chapter, the main variables are A and ω (α is always set to 0).

Using this equation, when a line is drawn faster than a threshold, the flow of the lines will be oscillatory (e.g. higher angular frequency in Equation Eq 7). Few approaches to implement the oscillations of blood flow in the drawing are listed below:

a) Lines are straight when the drawing speed is below the threshold, and slightly oscillatory when the threshold is crossed (A is a factor of speed and ω is set to 3). See Figure 7-top.
b) Lines are straight when the drawing speed is below the threshold, and highly oscillatory when the threshold is crossed (A is a factor of speed and ω is set to 0.3). See Figure 7-middle.
c) The flow is slightly oscillatory when the drawing speed is below the threshold (A is a factor of speed and ω is set to 3), and highly oscillatory when the threshold is crossed (A is a factor of speed and ω is set to 0.3). See Figure 7-bottom.

Figure 7: Blood Flow Oscillation in Drawing



This figure shows few implementations of the oscillations of blood flow in the drawings. (© 2011, al Rifaie. Used with permission.).

The next section presents a brief discussion on creativity, followed by a summary on whether swarms can show creativity in the 'artwork' they produce.

Discussion on Creativity

The goal of this section is to discuss whether the hybrid swarm algorithms have the potential to exhibit ‘computational creativity’ in what they draw. In our discussion, we emphasise on the importance of what we later define as ‘Swarm Regulated Freedom’ (SR freedom) – cf. Gaussian Constrained Freedom (GC freedom) – and the combinatorial creativity of the hybrid swarm system. Then we contrast it with examples of potential non-human assessment of aesthetic judgment and suggestions of creativity in natural distributed systems. Our modest conclusion would be that SR freedom (vs. GC freedom) – as for example exhibited in the hybrid bird, ant and blood vessel mechanism presented herein – can be useful in generating interesting and intelligible drawing outputs.

On Freedom and Art

For years, it has been discussed that there is a relationship between art, creativity and freedom, among which is the famous German prose, by Ludwig Hevesi at the entrance of the Secession Building in Vienna:

“Der Zeit ihre Kunst
Der Kunst ihre Freiheit”

That is: *“To Time its Art; To Art its Freedom”.*

Or a quote by Aristotle (384-322 BCE) (Etzioni, Ben-Barak, Peron, & Durandy, 2007), which emphasises on the link between creativity and freedom (here, having “a tincture of madness”):

> *“There was never a genius without a tincture of madness.”*

Boden, in (Boden, 2010), also argues that creativity has an ambiguous relationship with freedom:

> *“A style is a (culturally favoured) space of structural possibilities: not a painting, but a way of painting. Or a way of sculpting, or of composing fugues... and so on. It’s partly because of these thinking styles that creativity has an ambiguous relationship with freedom.”*

Among several definitions that have been given to creativity, around sixty of which (as stated by Taylor (Taylor, 1988)) belong to combinational creativity, which is defined as *“the generation of unfamiliar combinations of familiar ideas”* (Boden, 2007), a category that the presented work might fit in. Considering the existence of many influencing factors in evaluating what is creative, might, among other things, raise the argument about how humans evaluate creativity, their aesthetic capacity and that of other animals (e.g. in mate selection). Galanter (Galanter, 2011) suggests that perhaps computational equivalent of a bird or an insect (e.g. in evaluating mate selection) is “all” that is required for computational aesthetic evaluation:

> *“This provides some hope for those who would follow a psychological path to computational aesthetic evaluation, because creatures with simpler brains than man practice mate selection.”*

In this context, as stated in (Dorin & Korb, 2011), the tastes of the individual in male bowerbirds is visible when they gather collections of bones, glass, pebbles, shells, fruit, plastic and metal scraps from their environment, and arrange them to attract females (Borgia, 1995):

> *"They perform a mating dance within a specially prepared display court. The characteristics of an individual's dance or artefact display are specific to the species, but also to the capabilities and, apparently, the tastes of the individual."*

The question of whether *'mate selection behaviour in animals implies making a judgment analogous to aesthetic judgment in humans'* is perhaps (pace Nagel's famous discussion in Philosophical review (Nagel, 1974) of 'What it is like to be a bat?') a question whose answer will never be clear.

In contrast, the role of education (or training) in recognising 'good' and 'bad', 'creative' and 'non-creative' has been more experimentally probed. A suggestive study investigating this topic, set by (Watanabe, 2009), gathers a set of children's paintings, and then adult humans are asked to label the "good" from the "bad". Pigeons are then trained through operant conditioning to only peck at good paintings. After the training, when pigeons are exposed to a novel set of already judged children's paintings, they show their ability in the correct classification of the paintings.

This stresses out the role of training and raises the question on whether humans are trained (or "biased") to distinguish good and/or creativity work.

Another tightly related topic to swarm intelligence in this context is the creativity of social systems. Bown in (Bown, 2011) indicates that our creative capabilities are contingent on the objects and infrastructure available to us, which help us achieve individual goals, in two ways:

> *"One way to look at this is, as Clark does (Clark, 2003), in terms of the mind being extended to a distributed system with an embodied brain at the centre, and surrounded by various other tools, from digits to digital computers. Another way is to step away from the centrality of human brains altogether and consider social complexes as distributed systems involving more or less cognitive elements."*

Discussion on creativity and the conditions which make a particular work creative have always been among the heated debates for scientists and philosophers (Rothberg & Hausman (eds), 1976). A dated but excellent source on creativity theory is (Sternberg (ed), 1988), where the authors try to answer questions on the conditions of creativity, systems view of creativity, cognitive approaches, etc.

Although this chapter does not aim to tackle any of these issues or suggest that the presented work fits in the category of creative realm, it attempts to investigate the performance of the swarms in this context.

On the "Creativity" of the Swarms

As stated in the introduction of the chapter, there are several relevant attempts to create creative computer generated artwork using Artificial Intelligence, Artificial Life and Swarm Intelligence.

Irrespective of whether the swarms are considered creative or not, their similar individualistic approach is not totally dissimilar to those of the "elephant artists" (Weesatchanam, 2006)):

> *"After I have handed the loaded paintbrush to [the elephants], they proceed to paint in their own distinctive style, with delicate strokes or broad ones, gently dabbing the bristles on the paper or with a sweeping flourish, vertical lines or arcs and loops, ponderously or rapidly and so on. No two artists have the same style."*

Similarly, as it will be discussed next, if the same sketch is given to the swarms several times, the output drawings, made by the swarms, are not the same twice. In other words, even if the hybrid swarm mechanism (of birds, ants and blood vessel) processes the same sketch several times, it will not make two identical drawings; furthermore, the outputs it produces are not merely randomised versions of the input. This can be demonstrated qualitatively by comparing the output of the hybrid swarm system with a simple randomised tracing algorithm, where each point in the sketch is surrounded with discs (similar to the pAgents) at a Gaussian random distance and direction (contrast Figures 8 with Figure 9). The reason why the hybrid swarm drawings are different from using random lines and discs following the points of a sketch, is the underlying algorithms and physiological mechanism [which is used to coordinate the concentrations at any particular point on the canvas] employing proven swarm intelligence techniques; a method which is better (more 'loyal' to the original sketch) than a simple randomisation, but which still has enough 'freedom' to ensure originality in the resulting drawing (i.e. the swarm mechanisms ensure high-level fidelity to the input without making an exact low-level copy of the sketch).

Thus, despite the fact that the swarms are constrained by the rules they follow (rules that were defined earlier in the chapter), the stochastic parts of the algorithms allow them to demonstrate a "regulated difference" rather than a simple "random difference".

Swarm Regulated Freedom versus Gaussian Constrained Freedom

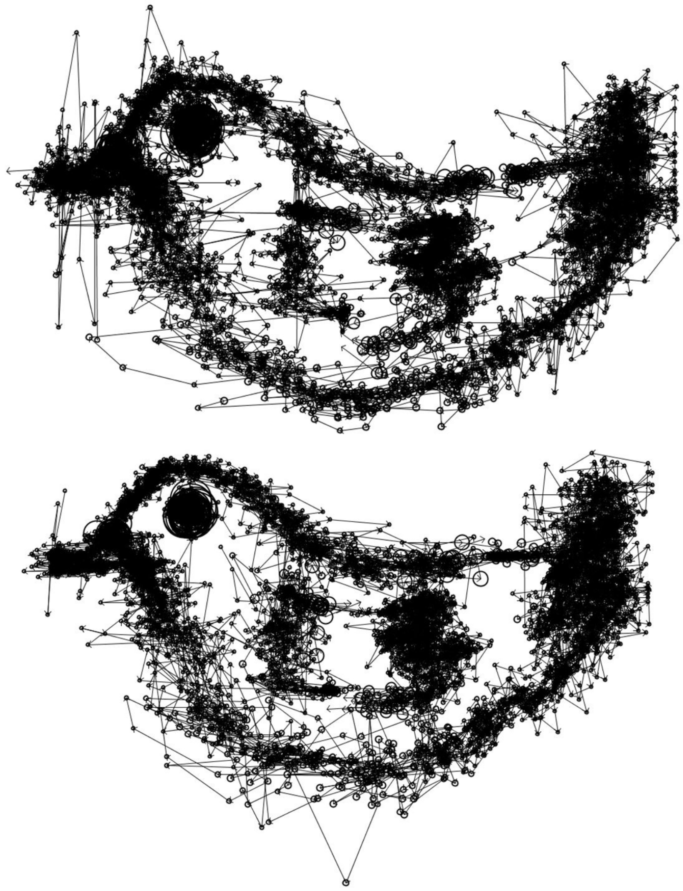
The drawings in Figure 8 (top and middle) show two outputs from the simple randomised algorithm when configured with limited 'artistic' freedom (i.e. there is only small Gaussian random distance and direction from the points of the original sketch – Gaussian Constrained Freedom or *GC freedom*); comparing the two drawings, we note a lack of any significant difference between them. Furthermore, when more 'artistic freedom' is granted to the randomised algorithm (by further increasing the variance in the underlying Gaussian, which allows the technique to explore a wider areas of the canvas), the algorithm begins to deviate excessively from the original sketch. For example excessive randomisation results in a poor - low fidelity - interpretation of the original sketch (Figure 8-bottom). In contrast, although the agents in the hybrid 'birds, ants and blood vessel swarms' are free to access any part of the canvas, they naturally maintain recognisable fidelity to the original input. Thus, it can be seen that simply extending a basic swarm mechanism by giving it more randomised behaviour (giving it more 'artistic freedom') fails to demonstrate that more creative drawings would be produced.

The Swarm Regulated freedom (SR freedom) or 'controlled freedom' (or the *'tincture of madness'*) exhibited by the hybrid swarm algorithm (induced by the stochastic side of the algorithms) is crucial to the resultant work and is the reason why having the same sketch does not result in the system producing identical drawings. This freedom emerges, among other things, from the stochasticity of SDS algorithm in picking agents for communication, as well as choosing agents to diffuse information (see Algorithm 3); the tincture of madness in PSO algorithm is induced via its strategy of spreading villagers in the jungle as well as the stochastic elements in deciding the next move of each villager (see Algorithm 1). Although the algorithms (PSO and SDS) and the mechanism (blood flow) are nature- and physiologically-inspired, we do not claim that the presented work is an accurate model of natural systems. Furthermore, whilst designing the algorithm there was no explicit 'Hundertwasser-like' attempt – by which we mean the stress on using curves instead of straight lines, as Hundertwasser considered straight lines not nature-like and 'godless' and tried not to use straight lines in his works – to bias the style of the system's drawings.

Figure 8: The Drawings of the Swarms with Random Behaviour

This figure shows the drawings made with a simple randomized tracing algorithm, using Gaussian random distance and direction from the points of the original sketch. The variance of the figures on top and in the middle is the same. When variance ('freedom') is increased (in the bottom figure), the drawing gradually loses its original 'identity'. (© 2011, al Rifaie. Used with permission.).

Figure 9: Different Drawings of the Hybrid Swarms (and eutrophic remodeling) off a Single Sketch



This figure shows the drawings generated off the same initial sketch. (© 2011, al Rifaie. Used with permission.).

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This specific work is the artistic outcome of the marriage between the two swarm intelligence algorithms (PSO and SDS) – whose scientific value is currently being investigated on many benchmarks (al-Rifaie, Bishop & Blackwell, 2011) – and the simplified mechanisms of the blood vessel and blood flow. Nevertheless, the difference between using Gaussian Constrained Freedom (GC freedom) and Swarm Regulated Freedom (SR freedom), which uses known swarm intelligence techniques, is highlighted by emphasising on *regulated difference* versus *random difference*.

This chapter discusses the possible inputs of physiologically-inspired mechanisms in computer-generated artwork. Following this theme, we aim to specifically investigate other physiological mechanisms (e.g. eye lens, bones, HIV virus, etc) and the role they can potentially play herein. We raise the question on whether integrating swarm intelligence algorithms (inspired by social systems in nature) and physiologically inspired mechanisms could possibly lead to a different way of producing ‘artworks’. Additionally, the application of the presented nature and physiologically inspired algorithm in producing music is currently being investigated in an ongoing research.

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ADDITIONAL READING SECTION

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KEY TERMS & DEFINITIONS

Stochastic Diffusion Search (SDS): A multi-agent global search and optimisation algorithm, which is based on the simple interaction of agents

Particle Swarm Optimisation (PSO): A population based optimisation technique, which came about as a result of an attempt to graphically simulate the choreography of fish schooling or birds flying

Swarm Intelligence (SI): A decentralised, collective approach to solve problems, where intelligence emerges through the simple interactions of the members of the swarm

Blood Vessel Remodelling: A process referring to the reshaping of the blood vessel that is caused by blood pressure

Visualisation: A technique deployed in different scientific fields to better understand the behaviour of certain mechanisms by visualising their performance

Optimisation: A simple example of optimisation is when a car is about to be parked; in this case, different parameters should be considered and the best (optimal) choice should be made with regard to the following: the distance of the parking location from the current place, the suitability of the place and probably the duration in which the car be kept parked. In optimisation, these cases are compared against each other and the goal is to balance the trade-off between these parameters. Swarm intelligence algorithms have shown to be of significance in solving optimisation problems.

Metaheuristics: They are computational methods used to optimise problems by iterative attempts to improve the quality of a candidate solution considering a performance measure.

Swarm Regulated Freedom (SR freedom): A method used to constrain the freedom of the swarm or their movements by using swarm intelligence algorithms

Gaussian Constrained Freedom (GC freedom): A process used to generate new points by applying Gaussian random distance and direction from the already existing points of an original sketch

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[i] NB. In standard SDS such high average activity would not be useful as it entails most agents will continue to exploit their current hypothesis rather than explore the search space, however in the hybrid algorithm the randomised subsequent behaviour of each pAgent offsets this effect.

[ii] A full SDS cycle includes:

- one Test Phase which decides about the status of each pAgent, one after another
- one Diffusion Phase which shares information according to the algorithm presented

[iii] Primary hypertension is the major type of high blood pressure in humans and accounts for almost 95% of the hypertension cases in the human population and it is of unknown cause.

[iv] Secondary hypertension is the type of hypertension where a cause for the high blood pressure is identifiable, this type accounts for about 5% of high blood pressure in the population.

[v] Angiotensin-converting enzyme inhibitor (ACE-inhibitor) is a class of medications used for the treatment of raised blood pressure. ACE inhibitors act by interfering with the action of the enzyme responsible for converting the inactive angiotensin 1 protein into the active Angiotensin 2, this active form causes increased blood pressure. Angiotensin converting enzyme (ACE) is present in the lung, whereas the Angiotensin type 1 is produced in the liver by the action of rennin. (Renin is an enzyme produced by the kidney in response to stress that might be caused by various stimuli). Angiotensin1 is transported in the blood when it passes through the vessels in the lung the ACE convert it into Angiotensin 2. ACE inhibitors interfere with this process and help treat raised blood pressure.