Swarmic Autopoiesis: Decoding de Kooning

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Abstract. This paper introduces a novel approach deploying the mechanism of 'attention' by adapting a swarm intelligence algorithm (Stochastic Diffusion Search) to selectively attend to areas of a digital canvas (with line drawings) that has more details (e.g. lines or points). Once the attention of the swarm is drawn to a certain line within the canvas, the capability of another swarm intelligence algorithm (Particle Swarm Optimisation) is used to produce a 'swarmic sketch' of the attended line.

Throughout the process of sketching, the swarms leave traces of themselves on the digital canvas which they would then revisit over and over again in an attempt to re-sketch themselves. This process is introduced in the context of autopoiesis.

Having associated the rendering process with the concepts of attention and autopoiesis, the performance of the participating swarms creates a unique, non-identical sketch each time the 'artist' swarms embark on interpreting the input line drawings. The complexity of the initial drawing reduces after each cycle and the *Swarmic Autopoietic System* continues this process until the digital canvas reaches its simplest form: emptiness. Additionally, a brief discussion is provided on the philosophical aspects of the autopoietic artist.

1 Introduction

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 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.

Although producing artistic works through the use of swarm intelligence techniques have been previously explored, this work explores the concepts of attention and autopoiesis through this type of collective intelligence, which emerges through the interaction of simple agents (representing the social insects and animals) in nature-inspired algorithms, namely Stochastic Diffusion Search (SDS) [8, 3] and Particle Swarm Optimisation (PSO) [20].

In this work, SDS is deployed to enforce the idea of attention to area of the search space (digital canvas with line drawings) where there are more details (i.e. more lines or points); once the area of attention is identified, PSO through its particles, traces the points of the lines selected and its particles' movement are visualised on the canvas. As attention moves from one area of the original line drawing to another, a sketch is produced which is the collective result of the SDS-led attention and millions of simple interactions facilitated by PSO algorithm.

In the last couple of years, there has been several research work utilising the two aforementioned swarm intelligence algorithms; while scientific merits of integrating these algorithms are investigated in detailed (e.g. [6, 4]), their artistic capabilities have been detailed in several publications along with some philosophical arguments on the computational creativity of such systems (e.g. [1, 5, 2]).

In the next section a brief overview of some of the work in generative art and swarm intelligence is provided. Afterwards, the swarm intelligence algorithms used are explained. Subsequently, a historical perspective of attention is presented, followed by explanation on the attention and tracing mechanisms associated with the two swarm intelligence algorithms introduced in the paper, providing details on the performance of the computer-generated nature-inspired attentive swarms in re-interpreting the original line drawings. Subsequently, the concept of autopoietic swarmic artist is explained in the philosophical context of autopoiesis. Finally the paper is concluded and possible future research and suggested.

2 Generative Art and Swarm Intelligence

Among the many works in the field of generative art are research on swarm painting (e.g. [26, 7, 35, 36]), ant colony paintings (e.g. [15, 25, 30]) and other multi-agent systems (e.g. RenderBots [29] and the particle-based non-evolutionary approach of Loose and Sketchy Animation [13]).

In most of the swarm-based work mentioned above (e.g. [26, 7, 35, 36, 15]), the painting process does not re-work an initial drawing, but rather focuses on presenting "random artistic patterns", somewhere between order and chaos [36]. Other classes of research (e.g. by Schlechtweg et al. [29] and Curtis [13]) are based on reworking an initial drawing. There is a significant number of related papers in the area of non-photorealistic rendering; particularly, many papers approach drawing and painting using the optimisation framework (where optimisation and generative techniques are utilised an artistic context). Furthermore, particles have been used for stippling and other aesthetic styles in numerous papers. Turk and Bank's work [34] is an early example of optimising particle positions to control a stroke-based rendering. Hertzmann [16] optimised a global function over all strokes using a relaxation approach. In one of his works, Collomosse [12] used a global genetic algorithm to define a rendering algorithm. More recently, Zhao et al. [40] deployed an optimisation-

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based approach to study the stroke placement problem in painterly rendering, and presented a solution named stroke processes, which enables intuitive and interactive customisation of painting styles.

3 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 it is not only the syntactical information that is exchanged between the individuals but also semantic rules and beliefs about how to process this information [21], 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 is the way in which individuals self-interact (interact with each other) and the second is the interaction of the individuals with the environment [9]. Self-interaction between individuals is carried out through recruitment strategies and it has been demonstrated that, typically, various recruitment strategies are used by ants [17] 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 the deployment 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; or sometimes the information sharing is 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 [14].

However, in many hive-based (flock-based) agents – similar to the ones deployed in this work – the benefits of memory and communication seem obvious, but as argued in [28], these abilities are not beneficial in every environment, depending on the way resources are clustered throughout the environment and whether the quality of the food sources is sufficiently high.

The algorithms reported in this paper both rely on memory and communication to enable the agents explore various parts of the search space; albeit the communication methods outlined herein are less greedy than the one presented in [28]. Furthermore, the particular effect communication has on the "creative" act of the swarm-based algorithms used in 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 [27] 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 [21]. 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.

4 Attention & Creativity in the Swarms

In this section, the attention mechanism, which is controlled by the SDS algorithm is detailed. This is followed by the process through which the PSO algorithm utilises the output of the SDS-led attention to visualise the particles movements on the digital canvas which produces the final sketch rendered by the swarms. Details of the aforementioned swarm intelligence techniques are provided in the Appendices A and B; further details about attention along with some definitions are provided in Appendix C.

4.1 Attention Mechanism

The input digital image consists of line drawings (Fig. 1) where each line is formed up of a series of points (the image on the left is after one of Matisse sketches).

The swarms's attention in this work is controlled by the level of intensity of drawings within a specific radius, ra of an agent. In other words, the intensity or fitness of an agent, $f_{i,(x,y)}$, where i is the agent number and (x, y) is the coordinate of the agent in the search space (input image), is calculated by the number of points constituting the drawing within the radius ra (see Fig. 2a).

As mentioned earlier in Section A, each agent has two components: status, which is a boolean value and hypothesis. The hypothesis of each agent in this work is the (x, y) coordinate which is used to calculate the fitness, $f_{i,(x,y)}$, of the agents located at any particular pixel within the input image.

After the agents are randomly initialised throughout the search space (Fig. 3a), in order to determine the status of an agent, i, within the swarm (test phase), its fitness, f_i, is calculated as explained above and another agent, r, is randomly selected; if $f_i > f_r$ (i.e. the agent i is located in a more line intense area), agent i is set active, otherwise inactive (Fig. 3b illustrates active agents in red and inactive ones in black).

In the diffusion phase, as in standard SDS, each inactive agent randomly picks another one. If the randomly selected agent is active, the inactive agent adopts the hypothesis of the active one. However, if the selected agent is inactive, the selecting agent generates a random hypothesis (x, y) from the search space.

After n number of test-diffusion phases cycles, the biggest cluster of the agents is identified and the closest point (p_c) to the cluster is calculated. Once the (x, y) coordinate of the point is retrieved, the starting and end points of the line is extracted and a string of (x, y) coordinates from starting to end point of the line is passed on to the PSO particles to trace one by one. Fig. 2b shows that when a point is selected, the two ends of the line (i.e. starting and end points) are identified.

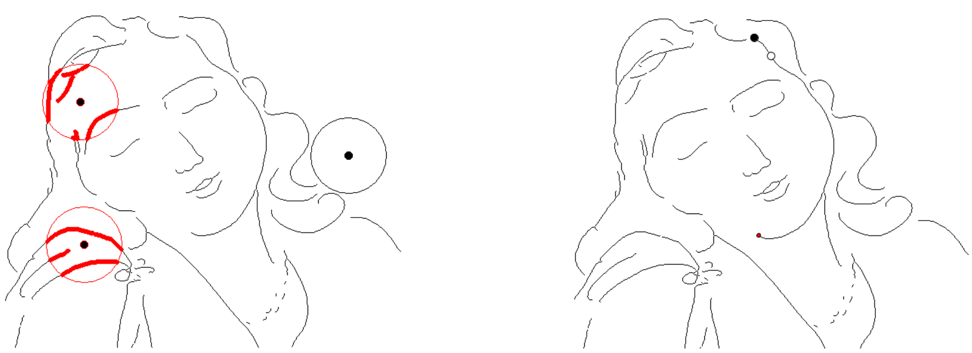
4.2 Tracing Mechanism

The points constituting the lines of the line drawing are treated as targets by the PSO algorithm. Thus, the particles aim to trace these points one at a time until reaching the end of the line (the algorithm tries to minimise the distance between the particles' positions and the points it aim to track).

Particle's movement is visualised on the canvas (i.e. trajectory of the particles moving from position (x_0, y_0) to (x_1, y_1) and so forth). The adopted PSO algorithm is briefly presented in Appendix B (more

Figure 1. Input images: series of points forming line drawings.

Figure 2. (a) Agent's fitness: in this figure, the (x, y) coordinates of three exemplar agents are illustrated with black dots in the centre of the circles; the highlighted points of the line drawing within each circle contribute towards the fitness of the agent, $f_{i,(x,y)}$. (b) Selected line: The hollow circle represents the selected point, p_c and the two ends of the line – start and end – where p_c resides, are highlighted in black and red, respectively.



(a) (b)

technical details on the behaviour of particles are reported in a previous publication [1]).

Input to PSO algorithm is a series of points forming up a line (whose starting and end points, as well as the closest point to the agents' biggest cluster, p_c, are extracted as mentioned above). The algorithm is then instructed to trace the line commencing from p_c to the beginning of the line, and them back towards the end of the line drawing. Once the line is traced, it is removed from the search space and the other lines are considered one by one according to the attention mechanism deployed.

This process ensures that in addition to the potential aesthetic of the swarms' final sketches, the process of sketching is enriched with attention to details.

5 Autopoiesis and Autopoietic Artist

In 1972, the Chilean biologists, Humberto Maturana and Francisco Varela, coined the term autopoiesis, referring to the self-maintaining chemistry of living cells [23]. Autopoiesis is composed of two Greek words, 'auto', meaning self, and 'poiesis' meaning production or creation.

There are many ways to think about systems that create products we socially conceive of as art. This paper is inspired by Alfred North Whitehead's *process view of organisation*, viewed though the transformational conceptual-lens of *autopoietic theory* (Maturana and Varela [38]); according to which we view a creative system as a clearly delineated and identifiable network of *continuously operational* component producing processes and concomitant elements, bounded as an autonomous entity *within its own artistic environment*.

The continual *creative swarmic processes* of our autopoietic artists' attention and reconstitution (sketching) mechanisms are detailed sections C, 4 of this paper and are illustrated in accompanying video, which displays her behaviour as she *artistically decodes* a line-sketch of an abstract painting by Willem De Kooning[2].

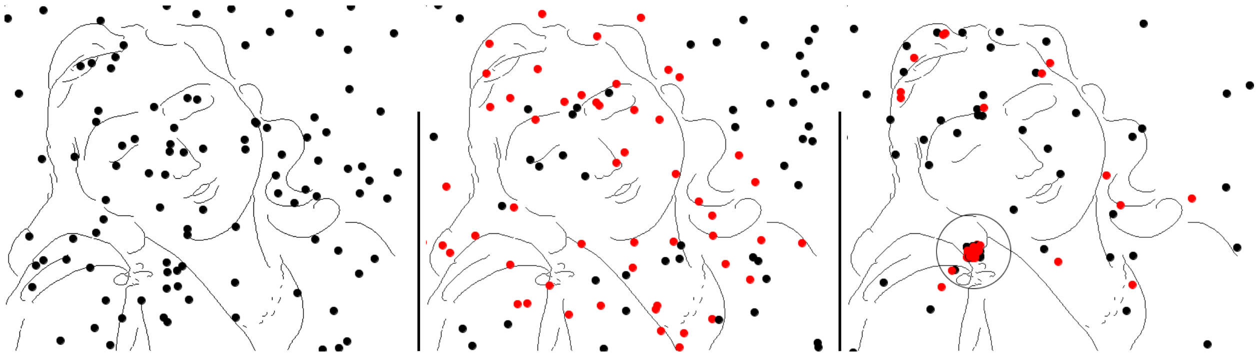
As observed in section 4, the 'autopoietic' artist is composed of two functionally distinct types of agent: (i) a swarm of *attending* agents, akin to ants (and governed by the principles of Stochastic Diffusion Search) and (ii) a swarm of *drawing* agents akin to birds (and governed by the principles of a Particle Swarm Optimiser). The job of the attending agents is to select areas of *meaning*[3] for the drawing agents to 're-interpret'.

Our 'autopoietic' artist is thus continually engaged in a process of sensing her environment and reconstituting it (by iteratively first

[2] In our case the artistic environment is initially a sketch of Kooning's abstract canvas, displayed initially in the right-hand panel of the video; with the creative output, initially a tabula-rasa, displayed on the left.

[3] For example, in our system we have defined such an area of interest (or 'meaning distinction') to be a line situated in a *complex* region of the image; an area that is rich/dense in comparison with other lines. Thus, by suitably redefining the distinction deployed by the population of Stochastic Diffusion agents (as described in Section V), we can modify what constitutes 'meaning' for the autopoietic artist as she interacts with her creative context/environment.

Figure 3. SDS stages: (a) Initialisation; (b) Test Phase; (c) Diffusion



(a) (b) (c)

choosing a line in the scene and re-rendering it). The bounds of the autopoietic artist are defined by the shifting movements of the swarms that comprise her; the elements of the autopoietic artist are the agents of the swarms; the behaviour of each swarm is fully defined by the behaviour of its agents (SDS and PSO); the bounds of the swarms are defined by the hypotheses (positions) of all the SDS agents, whose behaviour changes and in turn modifies the bounds; the components of the boundaries are produced by the interactions of the components of the unity, by transformation of previously produced hypotheses; and because the iterative re-initialisation of the SDS agent-hypotheses are produced by the interactions of the SDS swarm (and all other PSO agents participate as necessary permanent constitutive components in the production of other components), Varela et al's criteria [37] for an autopoietic entity are appropriately instantiated in the organisation of our 'autopoietic' artist *in the creative space in which her creative unity exists*.

Thus, following Luhmann's conception of *information processing* [22], we view the working autopoietic artist as entailing a reduction in complexity, ravenously consuming 'meaning-distinctions' within her environment; in this way the autopoietic artist iteratively decodes her environment (the De Kooning abstract) by continuously first selecting, then processing, areas of *meaning*

Over time, with her artistic 'interest' drawn to areas of rich complexity, the autopoietic artist, so construed, iteratively erases meaningful-distinctions (lines) in her current artistic context, so gradually simplifying the structure of the work. By iteratively focussing on meaning-distinctions *as-areas-of-rich-complexity*, as the decoding process unfolds it sometimes leads to a less complex (line) structure and ultimately may result in an empty canvas; therein reifying the artwork's 'death' and the tabula rasa (see Fig. 4a)[4].

Alternatively, by refocussing the autopoietic artist's reflections on 'meaning' (as explored by the Stochastic Diffusion swarm) onto different constitutive elements, and modifying her reconstitution (of the resulting artistic structure), different behaviours of autopoietic creativity can be induced. E.g. By insisting that the reconstitutive processes must generate as many elements of 'meaning-distinction' as they consume, the induced autopoietic processes becomes less likely to fade away and more open-ended in their creative endeavour (see Fig. 4 b)[5].

[4] Link to the video of Gluttonous Swarms: `http://doc.gold.ac.uk/~map01mm/Swarmic_Sketches/deKooning_GluttonousSwarms.mov`

[5] Link to the video of Contented Swarms: `http://doc.gold.ac.uk/~map01mm/Swarmic_Sketches/deKooning_ContentedSwarms.mov`

6 Conclusion

This works deploys two swarm intelligence algorithms: Stochastic Diffusion Search (mimicking the behaviour of ants foraging) and Particle Swarm Optimisation (mimicking the behaviour of birds flocking). The former is utilised for facilitating the attention mechanism and the latter is used for regulating the swarmic sketching process. In other words, swarms of ants and birds set off to decode a complex painting by Willem De Kooning in their own swarmic way. The step-by-step behaviour of the swarms, through the attention and tracing mechanisms is detailed.

The concept of attention is discussed in the context of the creativity and then the paper focuses on encapsulating the concept of autopoiesis in the behaviour of the the autopoietic artist described.

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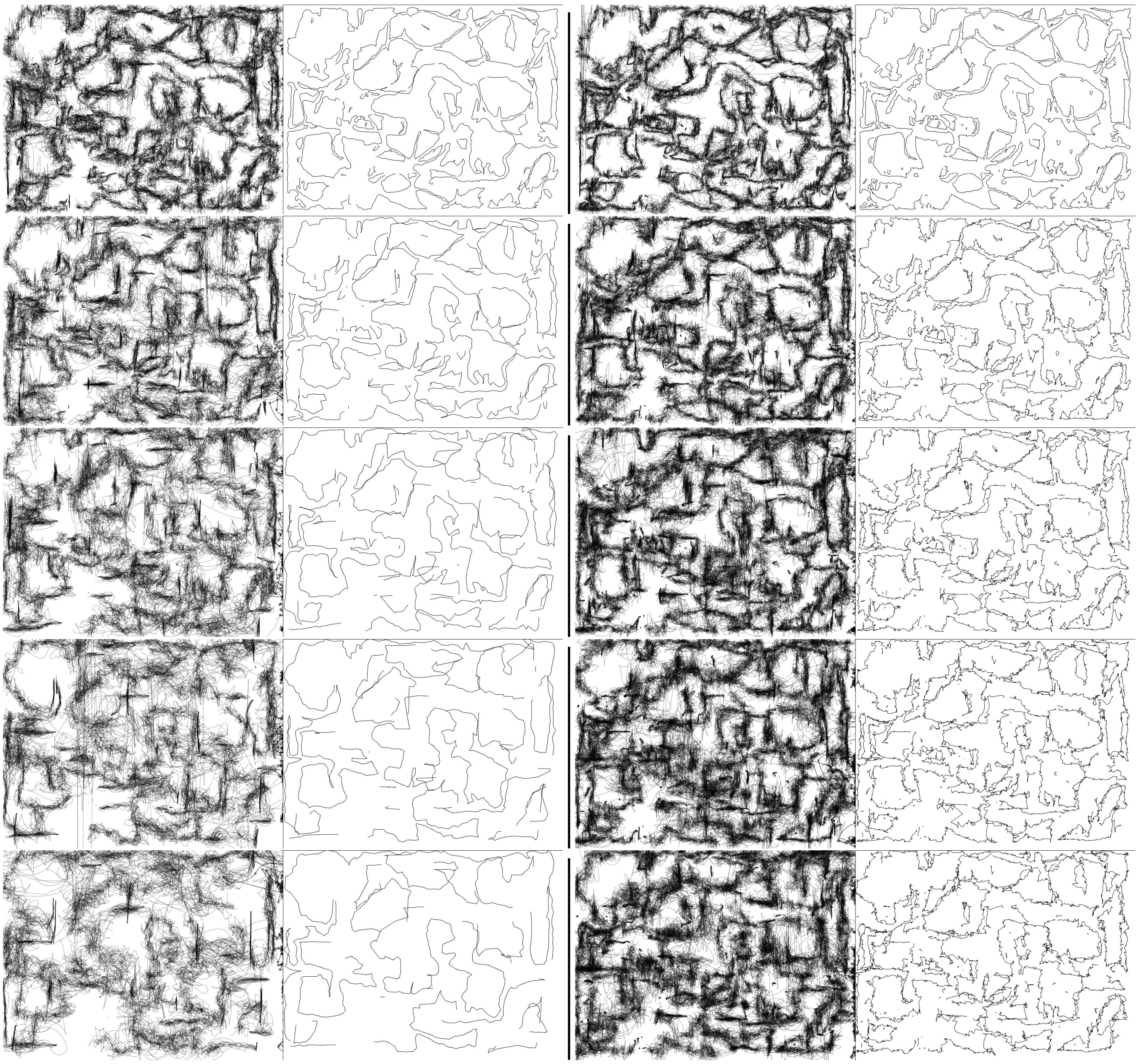
Figure 4. Contented and Gluttonous Autopoietic Artist



(a) Gluttonous swarms (b) Contented swarms

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Appendices

A Stochastic Diffusion Search

This section introduces Stochastic Diffusion Search (SDS) [8] – a swarm intelligence algorithm – whose performance is based on simple interaction of agents. This algorithm is inspired by 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; therefore the location of the food is physically publicised [24].

The SDS algorithm commences a search or optimisation by initialising its population and then iterating through two phases (see Algorithm 1)

Algorithm 1 SDS Algorithm

```
Initialise agents
While (stopping condition is not met)
   For each agent
       Test hypothesis and determine activity
   For each agent
       Diffuse hypothesis
End While
```

In the test phase, SDS checks whether the agent hypothesis is successful or not by performing a hypothesis evaluation which returns a boolean value. Later in the iteration, contingent on the precise recruitment strategy employed (in the diffusion phase), successful hypotheses diffuse across the population and in this way information on potentially good solutions spreads throughout the entire population of agents. In other words, each agent recruits another agent for interaction and potential communication of hypothesis.

In standard SDS (which is used in this paper), *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 is no flow of information between agents; instead a completely new hypothesis is generated for the first inactive agent at random. Therefore, recruitment is not the responsibility of the active agents.

B Particle Swarm Optimisation

A swarm in Particle Swarm Optimisation (PSO) algorithm comprises 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 optimal position, which is defined by a fitness function.

Each particle has a position x, a velocity v, and a memory, p, containing the best position found so far during the course of the optimisation, and this is called the personal best (pbest). p can also be thought of as a particle 'informer'. Particles participate in a social information sharing network. Each particle is informed by its neighbours within this network, and in particular, the best position so far found in the neighbourhood, is termed the neighbourhood best. The position of each particle is dependent on the particle's own experience and those of its neighbours.

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

$$v_{id}^{t} = wv_{id}^{t-1} + c_1 r_1 \left(p_{id} - x_{id}^{t-1}\right) + c_2 r_2 \left(g_{id} - x_{id}^{t-1}\right) \tag{1}$$

$$x_{id}^{t} = v_{id}^{t} + x_{id}^{t-1} \tag{2}$$

where w is the inertia weight whose optimal value is problem dependent [31]; $\vec{v}_{id}^{t-1}$ is the velocity component 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 constant); $r_{1,2}$ are random numbers adding stochasticity to the algorithm and they are drawn from a uniform distribution on the unit interval $U(0,1)$; p_{id} is the personal best position of particle x_i in dimension d; and g_{id} is the neighbourhood best. Therefore, PSO optimisation is based on particles' individual experience and their social interaction with other particles. After position and velocity updates, the positions of the particles are evaluated and the memories p are updated, if a better position has been found.

In this paper, Clerc and Kennedy's PSO (PSO-CK [11]) or constriction PSO is used:

$$v_{id}^{t} = \chi \left(v_{id}^{t-1} + c_1' r_1 \left(p_{id} - x_{id}^{t-1}\right) + c_2' r_2 \left(g_{id} - x_{id}^{t-1}\right)\right) \tag{3}$$

where $\chi = 0.72984$ [10], which is reported to be working well in general, is used in this work.

C Attention

For centuries, attention has been preoccupying the minds of philosophers and psychologists and scientists. The concept of attention has been studied mostly in psychology and neuroscience (see Table 1.1 in Phuong Vu: Historical Overview of Research on Attention, in [39] for more details) and there has been considerably less notable interest on attention within the field of computational creativity.

In the early 18^{th} century attention was mostly seen as a way of abstraction (see Berkeley's 1710 theory of abstract ideas in [32]):

> "[It] must be acknowledged that a man may consider a figure merely as triangular, without attending to the particular qualities of the angles or relations of the sides. So far he may abstract, but this will never prove that he can frame an abstract general, inconsistent idea of a triangle. "

By 1769, when Henry Home Kames added the appendix of 'Terms Defined or Explained' to his *Elements of Criticism* [19], attention's role as a regulator of cognitive input was regarded as definitive of it:

> "Attention is that state of mind which prepares one to receive impressions. According to the degree of attention objects make a strong or weak impression. Attention is requisite even to the simple act of seeing."

Thus, regulating cognitive and sensory inputs was associated to attention. Later, William James in The Principles of Psychology in 1890 [18] offered a more comprehensive description of attention (i.e. focalisation, etc.):

> "Every one knows what attention is. It is the taking possession by the mind, in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought. Focalization, concentration, of consciousness are of its essence [...]" (p. 403-404)

and few pages further, he continues:

> "Each of us literally chooses, by his ways of attention to things, what sort of a universe he shall appear to himself to inhabit." (p. 424)

Two decades later, in 1908, as emphasised by E.B. Titchener [33], attention was given a greater significance :

> "What I mean by the 'discovery' of attention is the explicit formulation of the problem: the recognition of its separate status and fundamental importance; the realization that the doctrine of attention is the nerve of the whole psychological system, and that as men judge of it, so they shall be judged before the general tribunal of psychology."

and its importance grew over the years in psychology and neuroscience. Although the concept of attention might have been present in the work of some researchers in the field of computational creativity, the focus on attention has not been equally considerable among researchers in this field; perhaps, partly because there has not been a clear definition on attention.