SUPPORTING DESIGN USING SELF-ORGANIZING DESIGN KNOWLEDGE

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Abstract. This paper presents the potential of swarm intelligence models as an alternative to cognitive models in the representation of design knowledge to develop a model of a self-organizing design environment. The presented framework for design knowledge provides the basis for an incremental development of swarm intelligence models for responding to design changes.

1. Introduction

Design can be described as a process of exploratory search through a state space, where the search involves making decisions based on the goals and a set of given requirements and constraints (Simon, 1969; Archer, 1969; Coyne et al., 1990; Carrara et al., 1992). Specifically, the field of Artificial Intelligence (AI) has been pursuing the issue of knowledge representation along with its acquisition, interpretation and application (Carrara et al., 1992), and recent research in design knowledge representation has adopted cognitive agent models. However, the representation of design knowledge as cognitive agents has faced some limitations in developing design behaviours as design systems have become large scale systems which are composed of thousands of agents. It is difficult to model agents' reasoning processes and knowledge explicitly and assign agency to all components of the complex design system to assist in generating new designs.

We propose swarm intelligence models as an alternative to cognitive agent models for multi-agent systems (MASs) in the design domain, in which a group of simple agents can adapt dynamically to changing circumstances with the capacity for self-organization. The self-organizing design knowledge is based on the assumption that intelligent collective behaviours or complex environments result from local interactions using simple rules. It employs agents of comparatively low cognitive abilities using bottom-up modeling rather than attempting to build individual agents that have a huge amount of information and computational abilities (Mataric, 1995). This paper looks at the implications of the swarm intelligence approach to modeling design knowledge and at what kinds of applications of swarm models would be effective.

2. Swarm Intelligence Paradigm

The swarm intelligence paradigm that demonstrates self-organizing mechanisms is based on a social insect metaphor approach for solving problems using the emergent collective intelligence of simple agents. It is largely explained by two notions, self-organization and stigmergy.

2.1. SELF-ORGANIZATION AND STIGMERGY

In general, the definition of self-organization emphasizes the emergence of properties, the distinction of levels within a system and the system boundaries (Parunak et al, 2003). Bonabeau (1999) defines self-organization as a set of dynamical interactions whereby structures appear at the global level of a system from interactions among its lower level components. The rules specifying the interactions are executed on the basis of purely local information, without reference to the global pattern. Many structures built by social insects are the outcome of a process of self-organization, of which the common features are no central planning, indirect interaction through the environment, simple individual rules and complex adaptive behaviour (Parunak, 1997; Bonabeau, 1999; Camazine, 2001). Furthermore, the following four key mechanisms of self-organization (Bonabeau et al., 1999) are derived from these natural multi-agent systems: positive feedback, which amplifies and reinforces popular agent behaviours; negative feedback, which regulates and makes proper distribution over all activities for stabilization; amplification of fluctuations, which can act as seeds from which structures nucleate and grow: and multiple interactions, which are very simple, often rule-based behaviours.

Stigmergy is a major mediating factor to explain task co-ordination and regulation in termites, first introduced by Grasse (1959). He found that the behaviour of termites in the nest construction is influenced by the constructions themselves through the modification of the environment. In his vision, a worker deposits a piece of building material in a particular location; this changes the sensory input subsequently obtained at that location and hence could also change the behaviour at that location in the future until it had completely evaporated (Holland & Melhuish, 1998). This process is called sematectonic communication, a form of indirect communication. While the research with a view of the cognitive models generally focus on building an agent itself and its reasoning process, this mechanism of swarm intelligence models considers the environment as a medium of inscription of past behaviour effects, to influence future ones. Ants' foraging and collective clustering are rooted on stigmergy.

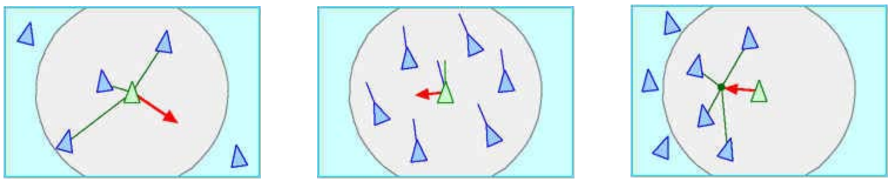
2.2. EMERGENCE AND ADAPTATION

Emergence is the appearance of structures at a higher level that are not explicitly represented in low-level components or external commands (Crutchfield, 1994). In modeling MASs, the emergence of complex unplanned structures could be used to support exploration in the solution space where the cognition of agents cannot understand and predict all the global effects of actions at the collective level. By using the emergence of collective behavior, the group of agents may be able to perform tasks without explicit representations of the environment and of other agents (Kube et al, 1999). Furthermore, the self-organizing emergent structures can maintain themselves either through evolutionary mechanisms or through some form of learning (Castelfranchi, 1998).

According to Carranza et al. (2000), swarm networks where sematectonic communication is implemented can be appreciated in terms of 'learning' or 'adaptation'. The computations of the nodes in the structures of the swarm networks could be composed of the following three functions: diffusion, which is local averaging of the morphogen values, to generalize to neighbor nodes for the agents; evaporation of the morphogen as the capacity to 'forget', which is necessary to be adaptive and therefore to learn; gradient calculation, which explains the way agents move from one node to another node according to the changes in the 'weights' of the connections between nodes. Specifically, Popper (1994) distinguishes between two basic levels of adaptation: genetic adaptation and behavioral adaptation. The swarm models at the behavioral level can learn from previous experience, and each agent is directed towards an end to optimize their positions as slow evolution rather than the unexpected advent of changes. It is different in that sense from the mutations at the genetic level which are completely "blind" and cannot influence the posterior mutations.

2.3. THE FLOCKING ALGORITHM

Among the various behaviour-based approaches, the most simple in principle is the modelling of flocks, which is a particularly evocative example of emergence. On the notion of swarm intelligence, Reynolds (1987) developed a computer model of co-ordinated animal motion, Boids, which is a class of simulation used to capture the global behaviour of a large number of interacting autonomous agents. The basic flocking model consists of three simple steering behaviours based on a collision detection algorithm; separation, cohesion and alignment.



Separation: steer to avoid crowding of a local flockmates

Alignment: steer towards the average heading of local flockmates

Cohesion: steer to move towards the average position of local flockmates

Figure 1. Simple steering behaviours (Craig Reynolds, 1987) www.red3d.com/cwr/boids

According to Reynolds' note, each boid has direct access to the whole scene's geometric description, but reacts only to flockmates within a certain small radius of itself. As a result, the individual agents had a tendency to align with the surfaces of the geometric model of the site, which ended in the emergence of the "smoothest" trajectory on the environment. Similarly Holland and Melhuis (1998) showed a demonstration where robots were able to achieve effective clustering and sorting, showing all the signs of self-organization by using a set of behaviour rules such as avoidance, aggregation, dispersion and wandering. They have specified algorithms for each basic behaviour and evaluated them based on the criteria.

Our research borrows concepts from the features of swarm intelligence to produce a model of a self-organizing design environment. Despite considerable research into self-organizing mechanisms that have already been undertaken in biology, chemistry and sociology, there is relatively little research using swarm models in the design domain. The main reason is that only agents' local activities can be controlled directly, whereas function in architecture at a global level is hard to define. Therefore, understanding how to engineer the process of self-organization at the global level is essential to the development of self-organizing design knowledge, and the recognition of the mechanism comes from analyzing some common principles of self-organization in natural multi-agent systems.

This allows the construction of artificial swarm-intelligent systems, which exhibit the following features: flexibility, robustness, decentralized control, and self-organization (Bonabeau et al., 1999). Flexibility allows adaptation to changes and robustness endows the group of agents with the ability to function as a whole even though some individual agents fail to perform their tasks. In addition, the features of decentralized control and self-organization are exhibited through the local interactions of agents and the environment. These are the reasons why swarm intelligence models are considered for the representation of design knowledge in this research. We expect that design knowledge as swarm intelligent agents could form basic principles for a self-organizing design environment.

3. A Framework for Design Knowledge as Swarm Intelligent Agents

The self-organizing design environment starts from the notion of objects as agents in the design environment. Components of a design, such as doors, windows and rooms in a building design, can be agents playing actively in the design process. Based on this concept we represent design knowledge as swarm intelligent agents. The interactions of object-agents and the environment are initiated by design knowledge.

3.1. OBJECT-AGENT APPROACH

The object-agent approach proposes that each object in the design environment has agency and a 3D model, so it can be an object-agent. The behaviour of the system as a whole is determined by the local interactions between the object-agents and the environment. The change of an object-agent status depends on the response of other agents and the environment, and each change is incremental for the entire design. This approach is derived from research done by Aly (2002) and Maher et al (2002; 2003).

Figure 2 illustrates an object-agent approach as an extension of the society of agents model of Maher & Gero (2002). Object-agents are local nodes as decentralized control points for their coordination, and the organization represents changeable local relationships among agents to support adaptability. The agents interact with neighbour agents in the execution of design tasks. Although the object-agents are relatively simple agents, such a group of agents can form a society, and the society can manage complex design activities.

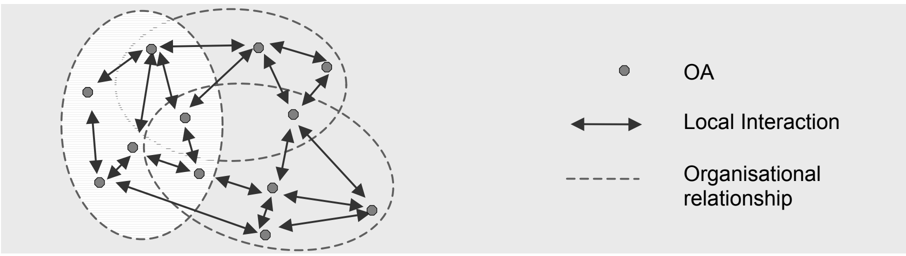


Figure 2. An object-agent approach

3.2. SELF-ORGANIZING DESIGN ENVIRONMENT

By considering the principles of self-organization, we develop a conceptual structure of a self-organizing design environment as shown in Figure 3. The self-organizing design environment is composed of multiple object-agents, a shared environment, and design knowledge including goals. The goals can be a set of tasks given to these agents to support functions as global system behaviours emerging from the interactions of the individual components. Object-agents have their own processes and states, and sense and act through the environment which itself is another active agent.

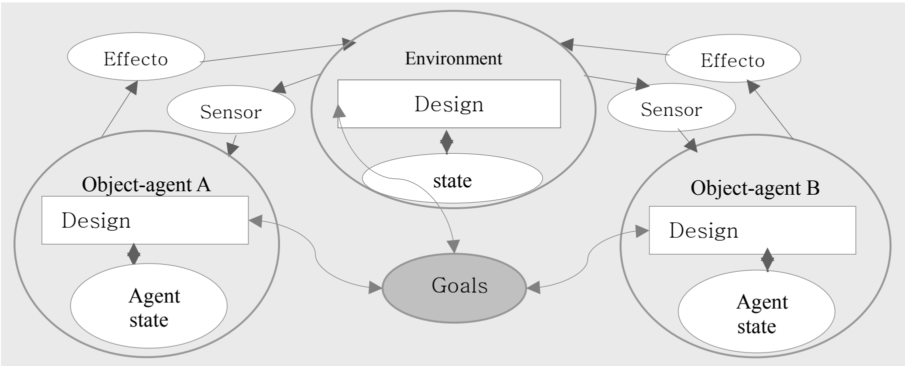


Figure 3. A conceptual structure of a self-organizing design environment

The most essential part of the self-organizing environment is the design knowledge pertaining to a specific object-agent and the environment. It can be utilized as a constraint upon interactive self-organizing processes limiting the manipulation of object-agents. Our ongoing work in this research focuses on modelling design knowledge for a self-organizing design system, specifically, representing design knowledge as swarm intelligent agents.

3.3. DESIGN KNOWLEDGE AS SWARM INTELLIGENT AGENTS

According to Mataric (1995), identifying basic behaviours is proposed as a methodology for structuring simple rules through a principled process of synthesis and evaluation. She postulates that, for each domain, a set of behaviours can be found that are basic because they are required for generating other behaviours, and they constitute a minimal set the agent needs to reach its goals. Therefore, the set of basic behaviours for a design domain can be associated with design objects from the bottom up and a set of design goals can be associated with the environment from the top down.

We have selected a scenario environment of a 3D virtual world, in which a designer can interact with the object-agents by making changes to the design. As the designer makes changes, the swarm models of design knowledge respond by invoking the response of each individual component such as moving, resizing, and changing their properties. The basic behaviour-based rules are developed in three stages, in which the LHS of a behaviour rule expresses conditions for RHS' actions. The following table shows a progression of the specification of behaviour-based rules.

TABLE 1. The specification of behaviour-based rules

	LHS	RHS
STEP 1	Location	Movement
STEP 2	Location/Relationship	Movement/Other actions
STEP 3	Location/Relationship/Function	Movement/Other actions

For example, in the first stage, the LHS deals with only object location, and the RHS shows only a movement responding to the location. In the second stage, LHS expresses the condition of location and relationship, and RHS exhibits a movement or other simple actions such as the change of colours or textures in response to movement. In the third stage, LHS expresses the condition of relationship, location and function, and the response in RHS includes a movement or other actions such as the change of dimension of objects including duplication, growth, and shrinkage.

The above proposed specification can show how we progressively develop the design knowledge. Through the manipulation of information about an object in the design, a designer has the flexibility to change the design. General swarm models are examples of behaviour-based rules, that is, they coordinate the movement of social insects or animals according to their distance, speed and density. However, the rules are not directly relevant for design activities because an agent's behaviour in response to design changes is based on the properties of the other object-agents as well as the environment. Therefore, we have focused on designing novel low-level rules that simulate behaviours of design objects activating self-organizing mechanisms in a design environment, which specify the interactions between object-agents and the environment.

4. Self-organizing 3D Desktop Layout

Modelling flocking behaviour of object-agents would permit the simulation of a self-organizing design environment where complex design tasks can be accomplished by integrating the simple, individual behaviours of object-agents. As an illustration of this idea, the implementation of a dynamic 3D self-organizing computer desktop using BREVE is in progress. Contrary to static 2D desktop layout, the object-agents of the desktop adapt dynamically to changes in the number and locations of the objects on the desktop.

4.1. BREVE

BREVE is a simulation package with rich 3D graphics designed by Klein for the simulation of decentralized systems and artificial life, which defines the state of the environment and the behaviours of agents. Although BREVE is conceptually similar to traditional simulation packages, it is distinguished from those packages by the following features: the ability to simulate continuous 3D worlds, an easy to use object-oriented language and physical simulation capabilities (Klein, 2002). Consequently we chose BREVE as a simulation environment for this demonstration because BREVE is well suited for the simulation of design behaviours of object-agents in the form of 3D models.

4.2. SWARM MODEL

The pilot demonstration is an extension of a classic flocking algorithm, in which a change in the environment sets off a sequence of changes until the agents achieve their goal. In particular, we make a few modifications to a simulation 'SWARM' distributed with BREVE, and adopt some algorithms of SwarmEvolve developed by Spector et al. (2002; 2003). In this application, we model three kinds of agents, each one representing:

1) 3D figures as illustrations on the desktop,
2) 3D application icons, and
3) 3D document icons.

Figure 4 shows an image of the self-organizing 3D desktop layout.

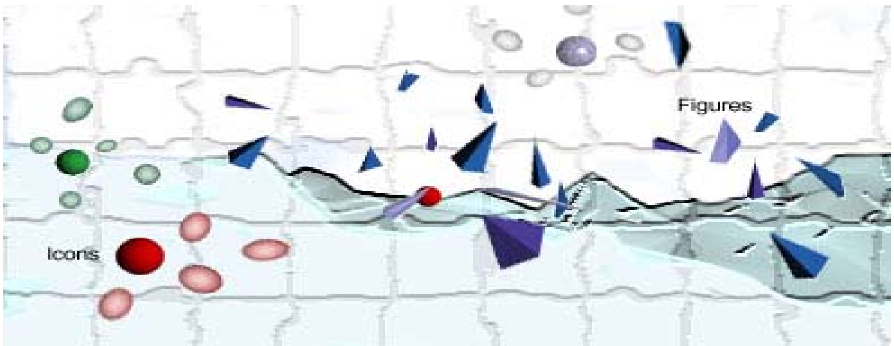


Figure 4. A self-organizing 3D computer desktop

Initially the 3D figure agents adjust themselves arbitrarily by moving randomly, detecting collision areas and avoiding overlapping. We define the goals of these agents to be the preservation of certain distances between each other. A minimum distance between 3D figure agents and 3D icon agents is set up. 3D figure agents are repelled by 3D icon agents when they come within the minimum distance. On the other hand, a maximum distance between 3D document icons and their associated 3D application icon is also defined. 3D document icons are attracted to their associated 3D application icon until they come within the maximum distance. As global behaviours, therefore, 3D icons can stand out in the background, and 3D document icons can flock together around a 3D application icon.

4.3. BASIC BEHAVIOUR-BASED RULES

We define basic local behaviours, consisting of a set of simple rules that fire whenever their conditions are satisfied. The 3D object-agents could direct themselves toward particular goals in response to changes through the local behaviours; overlap avoidance, aggregation or separation, following and wandering randomly. In this demonstration, we deal with the movements of 3D figures and 3D icons according to the location of their neighbour agents, and their change of colours according to their relationship with their neighbour agents. The following simple rules are examples of the first step and second step in the progression of design knowledge specification shown in Table 1.

1) If an agent collides with the other agents of the same kind, it moves back to avoid overlapping.
2) If the location of a 3D icon agent is changed by a user, 3D figure agents move themselves so as to achieve their goal, the preservation of the minimum distance.
3) If the location of a 3D application icon agent is changed by a user, its associated 3D document icon agents move themselves so as to achieve their goal, the preservation of the maximum distance.
4) If the location of a 3D figure agent is changed by a user, the 3D figure agent stops moving randomly and the other agents move themselves so as to achieve their goal.
5) If a 3D document icon agent joins a group around a 3D application icon agent, the colour of the 3D document agent changes into the same colour of its associated 3D application icon agent.

5. Conclusion and Future Research

We propose that modelling design knowledge as swarm intelligent agents is an alternative approach to MASs in design domains because swarm intelligence models may offer a self-organizing algorithm for generating design behaviours. In particular, the framework of design knowledge presented in this paper specifies behaviour-based rules based on the object-agent approach, where each object in the design is also an agent. The example of the self-organizing 3D desktop layout demonstrates the dynamic emergent behaviours of the object-agents as a development of traditional flocking algorithms. We expect that swarm models for design knowledge will produce a self-organizing structure by utilizing collective intelligence that emerges from simple interactions.

Future work on this research involves refining self-organizing design knowledge to produce a range of complex coordinated behaviours. Work is already in progress to specify basic behaviours, where a set of goals and simple rules will be developed by exploiting the influence of the environment in detail. We also plan to incorporate self-organizing design knowledge into a design environment, through which designers explore design alternatives by manipulating design components and observe the impact of those alternatives as swarm intelligence models respond to changes.

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