LEARNING TO BE CREATIVE AND THE CREATIVE MEMORY

A discussion motivated by a control- based coordination model

T ZAMENOPOULOS, K ALEXIOU
UCL, Bartlett School of Graduate Studies, Centre for Advanced Spatial Analysis (CASA), 1-19 Torrington Place, London WC1E 6BT, UK

Abstract. In this paper we discuss the interplay between learning and creativity, motivated by a control-based model. In particular we adopt control theoretic methodologies as well as complex systems and multi-agent systems abstractions, to consider a set of issues that allude to the formulation of distributed design systems able to support and/or simulate creative and learning behaviour.

1. Introduction

In this paper the interplay between learning and creativity in design systems is discussed. First, a learning control designing model is presented shortly. In the following, learning, creativity, and their interplay are discussed based on the proposed model, and using control theoretic methodologies as well as complex systems and multi-agent systems abstractions. The objective is to consider a set of issues that allude to the formulation of design systems that can support and/or simulate creative and learning behaviour. The motivation is to formalize the interaction between the two processes in a way that is suitable for hybrid distributed design systems like the ones that emerge in human-machine networks.

2. A learning control designing model

In this section, we present a model that generates spatial plans based on knowledge learnt by distributed sources: human or artificial agents. We focus on plan design problems seen in the context of urban development that involve location and physical layout decisions intended to satisfy distributed and time-variant targets. Plans are seen as complex artefacts that contain information about decisions to be implemented (solution space), performance attributes (performance space), requirements (problem space) and interdependencies among those spaces. The information contained in plans is organised using the Structure-Behaviour-Function framework (SBF) as proposed by Gero (2000).

In general, learning is seen as a function used to capture, maintain and restructure SBF interdependencies. In the proposed model we use Neural Network algorithms to discover and represent these interdependencies. The acquired knowledge might be seen as the domain knowledge for the system.

Designing is usually perceived as a purposeful, decision-making process where search (within a set of design variables), exploration (of alternative problem spaces), (co) evolution (of problem and decision spaces) and learning (associations among those spaces) are the critical engines behind the structuring of the problem, performance and solution spaces. Design as co-evolution implies that the focus (target) of the design changes in time and we need to explore simultaneously the problem and solution spaces (Maher 2000). This can be seen as a typical adaptive control assignment. Adaptive control has the aim to explore and adapt problem and decision formulations so that they follow time-variant expectations and performance constrains. In this framework, learning is a mechanism that drives and improves the control abilities.

Moreover, plan designing is usually conceived as a distributed activity. Design knowledge and processes are distributed, not only because plans are collectively formed by communities, interdisciplinary groups or distributed decision makers, but even expert reasoning is fragmented to diverse goals, criteria, evaluations and models. The distribution of decision-making also implies the distribution of the problem and solution spaces across scales (for example from the architectural to the urban scale). In this model, decision-making is distributed to different agents (human or artificial) with individual goals and evaluations. Each agent is self-interested in the sense that each agent controls a partial component of the overall plan description according to individual domain knowledge and individual expectations.

In summary, the design problem is formulated as a coordination problem among self-interested agents and is addressed via a distributed learning control methodology. Coordination is extensively discussed in the context of organisational theory and multi-agent systems and relates to the question of how a distributed system can synchronize its activities. In this model, coordination is not explicitly modelled but is considered as an emergent property supported by the processes of learning and adaptation across scales.

2.1 PLAN DESCRIPTION

We focus on spatial plan designing that involves building layout and facility location-allocation decisions. Plans are composed in a "collective space" by agents (human or artificial) that control parts of the overall description.

Artificial agents are introduced by users on the basis of a purpose or domain problem. The interface among human and artificial agents is built by objects embedded in a Virtual Reality (VR) world (figure 1). The specifications of these objects are dynamically identified and modified by agents. We should note that human actors (and their computational constructs) and the way they manipulate object descriptions, form the knowledge or reasoning sources for the artificial agents. So, agents learn through the modification of the objects in the VR world.

2.1.1 Object definition

Objects are represented as cuboids in the VR world and as aforementioned are built on three classes of information: Structural, Behavioural and Functional. Formally, each object is specified as a row matrix: $A_i = [S_i, B_i, F_i]$. The overall plan description is the column matrix $P = [Ai]$ of all these objects. Structural information depicts the physical components of the objects and their topological relations. So, for instance, for an object A_h (housing), structural information includes location $[x, y]$, volume dimensions $[z_x, z_y, z_z]$ and relations with other objects such as: distance to other facilities -like retail and open space- $[dr, do]$ and adjacency to north, south, east and west, with other buildings. Behavioural information specifies the way each object reacts to changes of its state and its environment. Behaviour is a description of change of the design objects in order to reach their intended requirements. For instance new land uses tend to be developed close or far from other existing land uses in order to fulfil their functional requirements. Finally, we consider that functional information represents the teleology and purpose of the proposed objects expressed as land use and illustrated by different colours in the VR world.

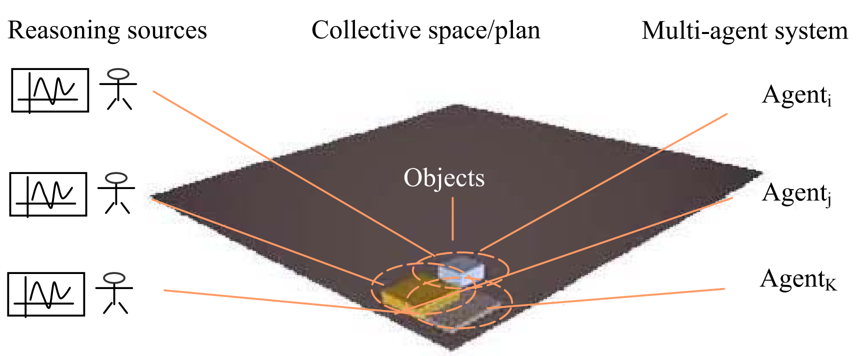

Figure 1: Plan descriptions are built by objects embedded in a virtual reality world

2.2 AGENT ARCHITECTURE

Each self-interested agent carries out two combined control-based activities that correspond to a synthesis-analysis-evaluation route and an evaluation-formulation-reformulation route as proposed by Gero (2000).

The synthesis-analysis route is implemented as a control activity where the objective is to find a suitable path of structures S that, given a function F, can lead the behaviours B_s to follow a reference (expected) behaviour B_e, despite uncertainties and despite exogenous disturbances *Sd* produced by other agents' decisions. The expected behaviour B_e is defined by the formulation-reformulation design activity (also called reference model in the control terminology), which is developed following a similar control process. The objective in this case is to find the appropriate Functions *F* that lead the Expected Behaviour B_e to follow a reference Structural Behaviour B_s, despite uncertainties and despite exogenous disturbances *Bd* (figure 2). The first control activity alludes to the solution generation process and the second alludes to the problem reformulation process. The two processes co-evolve in time. We need to note that the evaluation activity (denoted by E in the figure) is connected to a process of reviewing the performance of the synthesis-analysis system through the reference model (formulation-reformulation route) and vice versa. In terms of learning this means that the formulation of expectations (expected behaviours or design targets) guides the training process of the synthesis activity. Likewise the analysis process guides the training process for the reformulation activity.

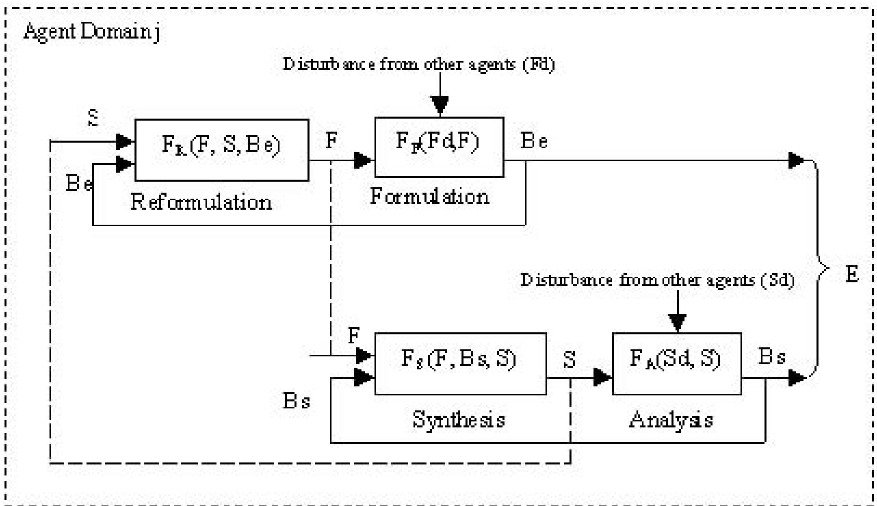

Figure 2. Agent architecture

2.3 MODEL SIMULATION

The model is simulated in Matlab-Simulink (inc). The control architecture adopted (adaptive backthrough control) typically employs two neural networks: the controller (the system that controls) and the plant model (a model of the system to be controlled, namely a neural network that identifies-learns associations among SBF attributes produced by the reasoning sources). First the plant model is trained to capture and learn SBF associations and then this knowledge is used backwards as a guideline for the controller. In effect, we have two types of learning: learning domain knowledge coming from the distributed reasoning sources and learning how to control. In this sense control can be perceived as a self-regulatory process towards time-variant goals.

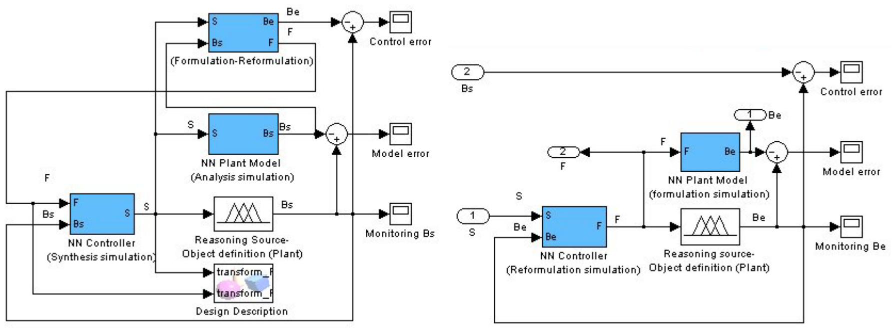

Figure 3. The control model in Simulink

3. Issues of learning and creativity modelling in distributed design systems

In this section the interplay between learning and creativity in design systems is discussed. Learning, creativity, and their interplay, are described and modelled based on complex systems abstractions, control theoretic methodologies and the proposed coordination model.

3.1 THE COMPLEX INTERPLAY BETWEEN MEMORY, LEARNING AND CREATIVITY

The adaptive control architecture we have adopted implies a dual function for the design system. On the one hand, the control signals produced are used to generate structural or functional formulations and hence steer the design system towards its temporal targets. But on the other hand, in order for this steering mechanism to be able to adapt to the changing conditions in time, the control signal is also used as a training signal that enhances the knowledge of the system and its understanding of the domain problem and its environment. The (synthesis and reformulation) control signal first stimulates the reaction of the reasoning sources and then both the signal and the reaction are used as a new source of knowledge. The memory of the system that conveys knowledge expressed as interdependencies among problem, solution and performance spaces guides the generation process. In order for this process to be creative the memory of the system should be restructured to include and retrieve new SBF interdependencies. Using the learning control formalism, we can say that learning is the process that forms the memory of the system and hence facilitates its creative potential, while creativity is the process that produces new sources for learning.

3.2 GENERATION, SCALABILITY AND COEVOLUTION

Starting from the recognition that learning plays an important role to improve the quality of design knowledge through time, several models have been developed that suggest different ways to interpret the function and scope of learning within a design system (e.g. Gero 1998; Grecu and Brown 2000; Liu, Tang and Frazer 2001). Likewise, a wide range of interpretations regarding creativity in design can be found, such as the ability to explore alternative search spaces, to go beyond the bounds of a representation, or to generate better structures despite partial information (see Bentley and Corne 2002: 59). In our model learning seems to have a creative ability when it is focused on discovering associations among design variables as opposed to discovering associations among decision values. This corresponds to the ability of agents to extend their search space and hence modify the definition and complexity of the objects that they manipulate. In effect, the decision and solution spaces can be extended. In this case, creative memory supports the representation and retrieval of new design variables. Currently, scaling and generation of design variables is not an automatic function incorporated in the model, but is defined by human operators.

The control model adopted suggests another interesting way to see the interplay between learning and creativity. The composite control mechanism that corresponds to the synthesis-analysis and the formulation-reformulation design activities correspondingly, facilitates the co-exploration and co-evolution of the problem and decision space. As the two control systems co-evolve in time, so are their learning targets: each control system (acting iteratively as reference model) generates the learning targets for the other.

3.3 DISTRIBUTION, DECENTRALISED CONTROL, AND THE EMERGENCE OF COORDINATION

In complex systems, evolution is a process based on interaction and adaptation across different space-time scales. Evolution implies a multiscalar organization where the different scales co-evolve in time, resulting in structures that were not anticipated before. Emergence is generally associated with this spontaneous formulation of structures through a co-evolutionary process across scales. This definition is consistent with what typically is conceived as emergence in social systems (Clark, Perez-Trejo and Allen 1995: 28), design systems (Poon and Maher 1997) and artificial systems (Ronald and Sipper 2001; Castelfranchi 1998). It follows that actions and decisions are distributed across different scales, which makes coordination one of the main questions in complex systems. In design systems this distribution is typically directed to cooperative networks of designers-stakeholders and machines. In the individual design activity distribution is attributed to the presence of diverse requirements, scenarios and models of action. It is in this context that learning and creativity become desirable properties. Coordination in the macro-scale is an emergent property which can be facilitated by learning in the individual level. Distributed control and multi-agent system methodologies, which have been adopted for our model, seem particularly relevant for simulating and supporting complex emergent behaviour.

In multi-agent systems, emergence is a desirable characteristic that refers to the ability of individual autonomous agents to mutually adapt their behaviour so as to achieve a certain task or goal. In this sense the term emergence insinuates the emergence of coordination. Castelfranchi argues that for "self-organizing emergent structures" to appear there needs to exist some kind of feedback of the collective phenomena to the individual mind. This feedback can be facilitated either through evolutionary/selective mechanisms or through some form of learning (Castelfranchi, 1998: 179). Along these lines we consider that interaction and learning are the keywords to creative complex systems and this has been the focus in the development of the control-based model. Given a collective space of aggregated objects governed by agents, symmetrically informed for each other, coordination can be described as a process towards a Nash-like equilibrium. This equilibrium in the macro scale is critical for the individual agent learning in the local scale exactly as the interactions in the local scale are critical for the global structure.

4. Conclusions

The model presented suggests a view of the relation between learning and creativity through control based and multi-agent theories and methodologies. One of the main points is that the dual function of control as a steering mechanism towards time-variant goals and as a mechanism that stimulates learning, implies that learning and creative exploration are processes that inform one another. A second point is that the composite control architecture adopted can facilitate the co-evolution of problem and decision spaces, through a mutual learning process. Co-evolution seems particularly important for the creative ability of distributed systems, where design and problem formulations are distributed, temporal and often conflicting. Additionally, the creative ability of the system is largely related to the possibility to discover and learn novel interdependencies among SBF variables in order to facilitate the generation and scaling of design objects. Finally, the distribution of the plan designing process in different agents, with individual knowledge and targets, implies the possibility for global phenomena to emergence through the interaction and self-adaptation of agents in the local scale. Creativity in our model is connected to the potential of the distributed control system to coordinate its activities. Coordination is not explicitly modelled but it is an emergent property facilitated by the processes of learning and self-adaptation across scales.

Acknowledgements

The authors wish to thank the reviewers for their helpful comments.

References

Bentley, PJ and Corne, DW: 2002, Creative Evolutionary Systems, Academic Press, London.

Castelfranchi, C: 1998, Modelling social action for AI agents, *Artificial Intelligence* 103: 157-182.

Clark, N, Perez-Trejo, F and Allen, P: 1995, Evolutionary Dynamics and Sustainable Development: A Systems Approach, University Press, Cambridge.

Gero, JS: 1998, Design tools that learn, *Advances in Engineering Software* 29(10): 755-761.

Gero, JS: 2000, Computational models of innovative and creative design processes, *Technological Forecasting and Social Change* 64: 183-196.

Grecu, DL and Brown, DC: 2000, Expectation formation in multi-agent design systems, in J Gero (ed.), *Artificial Intelligence in Design '00*, Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 651-671.

Liu, H, Tang, MX and Frazer, J: 2001, Supporting learning in a shared design environment, *Advances in Engineering Software* 32(4): 285-293.

Maher, ML: 2000, A model of co-evolutionary design, *Engineering with computers* 16: 195-208.

Poon, J and Maher, ML: 1997, Co-evolution and emergence in design, *Artificial Intelligence in Engineering* 11: 319-327.

Ronald, EMA and Sipper, M: 2001, Surprise versus unsurprised: Implications of emergence in robotics, *Robotics and Autonomous Systems* 37: 19-24.