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GUEST EDITORIAL

Special Issue: Learning and creativity Part 1

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Special Issue Part 1 (Issue 3) and Part 2 (Issue 4) of *AIEDAM* are based on a workshop on Learning and Creativity held at the 2002 conference on Artificial Intelligence in Design, AID '02 (www.cad.strath.ac.uk/AID02_workshop/Workshop_webpage.html; Gero, 2002). It was the sixth of similar workshops, with the previous five focusing on Machine Learning in Design and being held at AIDs '92, '94, '96, '98, and '00 (Gero, 1992, 2000; Gero & Sudweeks, 1994, 1996, 1998). The first three workshops also resulted in special issues of *AIEDAM* (Maher et al., 1994; Duffy et al., 1996, 1998).

The purpose of the workshop was to explore the subject of learning and creativity. The objective of the workshop was to bring the ideas, experiences, and latest research together and to produce an insightful understanding of the subject of learning and creativity.

The workshop itself focused upon two main topics: the nature of learning and creativity, and learning and creativity in computational-based team design. With respect to the first topic, agreement was reached on defining aspects of creativity. Creativity was considered a judgement, and to involve a product, a process, and a situation. Whether a relationship exists between learning and creativity remained undecided. With respect to the second topic, agreement was reached that an agent-based, mutually learning design system can be developed. Agents (both human and software) can learn from each other. This requires communication, common goals and understanding (e.g., ontologies), and knowledge.

The basic ethos of the workshop was the stimulus for this special issue. A general call was extended to the *AIEDAM* community and workshop participants. The position taken and questions raised for the call was that learning and creativity in design are two related activities, but can the interrelations between the activities be defined? What is the nature of these interrelationships? Does creativity necessarily result in new knowledge and/or learning? Can creativity be supported by computational means? Can learning be supported by computational means? If so, can such computational systems support design practice? Can automated design be considered to be creative? Can learning from past design manipulations be considered to be creative? Authors were invited to submit papers discussing their work in relation to these questions and address:

- the links between learning and creativity in design;
- the nature of creativity and learning;
- creativity and learning in team design; and
- techniques, knowledge, and approaches to computationally supported creativity and learning.

The result is a mixture of papers presented in Issues 3 and 4 as Parts 1 and 2, respectively. In Part 1, the first three papers concentrate on creativity and the fourth on learning and creativity. The first paper by van Langen, Wijngaards, and Brazier focuses on the nature of creativity and artificial systems. The second paper by Weas and Campbell discusses a particular method to support creativity. Koza et al. present an application of a creative technique in the third paper. The link between learning and creativity is discussed by Sim and Duffy in the fourth and last paper in Part 1. Three studies of learning and design are presented in Part 2. Wu and Duffy study the nature and interrelationships between learning and design in teams. By contrast, Nath and Gero focus on reusing experiences of design processes and Alisantoso, Khoo, and Lee synthesize past design concepts.

Van Langen et al. address the basic question of whether artificial systems can be creative and what the requirements are for such creative systems. They give an overview of a number of papers on creativity before giving their definition of a creative system. They define a *result* as creative if

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an assessor deems the result as being new, unexpected, and valuable. They define a *creative system* as one that produces creative results sufficiently often. They go on to state that for a system to be creative it must be able to interact with its environment, learn, and self-organize. A number of pieces of research work are then discussed in relation to those requirements. The paper closes by highlighting areas requiring future research.

The analysis of interconnected decision areas (AIDA) method originated in the mid-1960s but has never been implemented until very recently, according to Weas and Campbell. Their paper introduces the first known implementation of the AIDA process in software for helping decision makers to hypothesize and develop creative solution concepts. The focus of their implementation is to combine the solution principles of various subfunctions within a product in new ways. The method itself does not automatically create solutions, but rather works interactively with the user to identify new potential solutions. The method is described, and its implementation and use in engineering design is discussed. It allows designers to examine the decision space and relate interdependencies among the various choices available. The example of designing a coffee grinder using the method is presented, and the experiences of introducing it into a mechanical engineering design methodology course discussed. Thirty-five percent of the students found that as a technique, AIDA resulted in new and different design solutions. With the exception of patent searches, other more effective techniques were found to be guided brainstorming methods.

The negative feedback amplifier is regarded as one of the most outstanding inventions in the control arena. Koza et al. show how negative feedback of electrical circuits can be replicated by the automated design and invention technique of genetic programming. Genetic programming uses the Darwinian principle of natural selection coupled with evolutionary algorithms such as crossover and mutation to create ever improving populations of programs. That is, randomly generated computer programs are generated through transformations or combinations of different available programmatic ingredients. Selection for evolution is based upon a fitness function of the new program's execution. The paper describes the approach and lists previously patented inventions that have been *reinvented* by genetic programming. Examples and comparisons of the reinvention of patented inventions are presented and discussed, and a new patentable general-purpose controller described. The paper outlines the implications of the approach with increasing computer power and methods for extending the approach to more complex circuits.

Knowledge transformers are discussed by Sim and Duffy as a link between learning and creativity. A knowledge transformer is taken as an operator that derives a piece of new knowledge from a given input or an existing piece of knowledge. Seven pairs of knowledge transformers were specified to characterize the learning process: abstracting/detailing, association/disassociate, derivations/randomization, explanation/discovery, rationalization/decomposition, generalization/specialization, and similarity comparison/dissimilarity comparison. These transformers are considered to be linked to the thought process in creativity, and a few examples of where the transformers can be used to explain discoveries in science and invention in technology are given. Discussion of whether cognitive processes exist that are similar to the knowledge transformers, in the formulation of models and theories of creativity, focuses on bisociation in idea generation, the Darwinian model of evolution, the geneplore model of generative and explorative processes, and Li's theory of conceptual intelligence. The paper concludes that the creative process can be explained through knowledge transformers, and that they may provide the basis for linking learning with creativity.

In Part 2, modeling collective learning in design is the focus of Wu and Duffy's paper. Collective learning is understood as to how a group of agents interact and learn from each other. Although considerable work exists in organizational, team, and individual learning, the authors suggest that there is relatively little known about the nature of learning between individuals in design. The authors give an overview of the relevant work in the area before putting forward a number of hypotheses regarding the nature of collective learning and design. The hypotheses address aspects such as the inputs and outputs of a team design activity; the existence, elements, and forms of collective learning; collective memory being interconnected to learning; and the links between team design and collective learning. Protocol analysis experiments are reported, to check the hypotheses, and a model of collective learning in design is presented.

Nath and Gero present a computational system that can learn search strategy rules from its own experience of designing. The design activity is initially taken as an uniformed search during which heuristics are learned to select or reject design decisions. Where appropriate, these heuristics are then used during subsequent searches, or new heuristics are learned to change the computational design generator from a search-based process to a knowledge-based one. The coupling between computational design and learning is discussed and the learning mechanism, built on the SOAR system, explained by an example in architectural layout generation. The strengths of the developed method are reported such as: learning is a dynamic activity driven by the requirements of the design process *in situ* rather than a passive retrospective activity; a unified representation space allows seamless transformation between learning and designing; situated heuristics support reasoning about regions of the search space rather than specific points; inappropriate solutions can be eliminated, enabling rapid exploration; and costly knowledge elicitation can be eliminated. Some weaknesses of the method are presented, as some heuristics are likely to be too general because of its inability to account for the absence of instantiated patterns, and that all new knowledge is within the deductive boundary of the knowledge that was encoded *a priori*.

The focus of the paper by Alisantoso et al. is upon extracting and using past design knowledge for a so-called concept–capability mapping, to assist designers in estimating the capability of a design to meet specified requirements, and synthesizing past design concepts. Two algorithms are presented within the approach: the *dissimilar objects* algorithm and the *attribute decomposition* algorithm. A case study on the design of vacuum cleaners is used to illustrate the approach. They conclude that the design rules extracted from past designs were reasonable and effective in estimating the design, and that the performance is likely to improve if more past design information was made available.

The Guest Editors are truly grateful for the efforts of all the authors in this Special Issue. We particularly thank the reviewers of the workshop and journal papers. They helped to make this Special Issue a reality. We feel that the articles in this Special Issue make a significant contribution to the development of learning and creativity and hope the readers find them as interesting and beneficial as we did.

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