The Curse of Creativity

David C. Brown
Computer Science Department, Worcester Polytechnic Institute, USA

Computational design creativity is hard to study, and until fairly recently it has received very little attention. It has mostly been studied by looking at analogical reasoning and genetic algorithms: almost to the point of fixation. That is, the focus has been on extreme non-routine cases. But there are hard sub-problems and others ways of moving towards creative systems that are worth considering. This paper presents three of the alternatives, discussing one in more depth. The one discussed here is to look at what changes can be made to routine design systems in order to produce more creative outputs. This approach focuses on working "upwards" towards creativity, by examining smaller, ingredient decisions that make a difference to the result. As the amount of creativity displayed by a design is a judgment made by some person or group, it should be possible to investigate the degree of impact of changes to routine design mechanisms. This will contribute to our understanding of less "extreme" reasoning that leads to judgments of increased creativity: i.e., the foundation on which more extreme methods rest.

1. Introduction

It is common wisdom that people should be given tasks that computers can't do well, and computers should be given tasks that people can't do well. So in design computing why are we attempting to study computational design creativity?

The main answer is that the field (like many others) progresses by tackling simpler problems first and moving towards harder ones. Routine parametric design and design checking were starting points, moving gradually to Configuration and most recently to harder problems such as distributed/collaborative design and to creative design: from routine to non-routine [Brown 1996]. One goal has always been to build working systems, while another is to learn more about the knowledge and reasoning used for each type of design activity studied.

Computational design creativity is hard to study, and until fairly recently it has received very little attention, even though it is widely held to be very important both from intellectual and economic points of view. It has mostly been studied by looking at analogical reasoning and genetic algorithms: almost to the point of fixation. That is, the focus has been on extreme non-routine cases. There are hard sub-problems and other ways of moving towards creative systems that are worth considering. This paper presents three of the alternative approaches to computational design creativity research, discussing one in more detail.

2. Theoretical and Perceived Creativity

In Boden's theory of creativity [1994], creative ideas must be *new* and *valuable*. In addition, the theory must be able to "distinguish first-time novelty from radical novelties". The former can be

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generated by a system, perhaps using rule-like knowledge that "underlies the domain and defines a certain range of possibilities". This resulting "conceptual space" defines what *could be* produced by a system, resulting in newness that is in some sense expected: i.e., each "new" design is just mapping out the possibilities defined by the system. However, the conceptual space needs to be changed by transformations in order to allow "radical originality": producing transformational creativity.

However, there is a difference between a formal theory of creativity, which attempts to define what might be called *theoretical* creativity, and how people detect and evaluate creativity: i.e., a performance-based view of computational design creativity, that we might call *perceived* creativity.

First, as creativity is judged, different individuals or groups may vary in their assessment of the product or concept. The scope of that judgment varies at least in the following (not independent) ways: how many people are judging (e.g., one person versus a group)); the depth of knowledge that this represents (e.g., professors or children); and the historical range represented (e.g., designs from this year only or since the beginning of time).

Second, people can judge degrees of creativity [Amabile 1983]. What's not clear is whether everyone judges in the same way. Boden [1994] warns that "In general, one cannot assess creative ideas by a scalar metric". However, Ward et al. [1997] hint at some idealized scale by noting "the possibility that the mundane and the exotic … represent endpoints on a continuum of human creativity".

Besemer [2006] has developed scales based on how people judge the creativity of products. The Creative Product Analysis Model (CPAM) [Besemer & Treffinger 1981] is the basis for a well-validated, practical, product creativity assessment instrument called CPSS [Horn & Salvendy 2006] [O'Quin & Besemer 1989]. The model has three main dimensions (also known as factors): *Novelty*, *Resolution* and *Style*. Each of these factors has between 2-4 characteristics that further refine them: nine in total.

Rather than a simple scale, the scores for the nine characteristics represent a "fingerprint" of the product being evaluated, including, for example, an individual or group's judgment of the degrees of "surprise" or "elegance" the product stimulates or displays.

However, these judgments are dominated by the Novelty dimension. This suggests that people would have little trouble viewing a product that was very novel as creative. In fact, the correlation between novelty and creativity is so widely recognized and strong that some writers actually confuse newness with creativity.

Besemer's statistical analysis of her data has led her to isolate *Surprising* and *Original* as characteristics of Novelty. An interesting research question is how much those characteristics correlate with transformational creativity. It is clear that this will vary greatly with the difference between the designer and the group judging, with regard to group size, depth of knowledge and historical range. However, by taking the mostly assumed default group as 'the world's professional designers of that type of product' and the range as 'from the beginning of civilization' the research question becomes more refined, and the standards for high creativity much tougher.

3. Current approaches

It is not the goal of this paper to review current research into computational design creativity. However, this author believes that current creativity research tends to be based on *the goal of transformational creativity*. A lot of it appears to be based on or influenced by larger scale, general reasoning, such as Analogy (for example see [Yaner & Goel 2008]), Genetic/Evolutionary Algorithms (for example see [Koza 2008]), and Conceptual Blending [Turner & Fauconnier 1995] (for example see [Nagai et al. 2009]).

The *consequences* of this goal are that:

1) researchers tackle a very hard problem "head on", making slow progress;
2) these powerful methods don't give a clear idea of what their limits are—knowing what a method *can't* do is as important as knowing what it can do;
3) the computational methods used don't always match what people can do, and therefore don't provide very good hypotheses about human creativity; and
4) detailed psychologically based hypotheses about what people might be doing tend to be ignored.

3. Some Research Alternatives

This section elaborates on three of the alternative approaches to computational design research. The first will be discussed in more detail in future sections.

3.1. New Wine in Old Bottles

The first alternative methodology is to take a well understood but not intentionally creative approach and see how it might be modified in order to produce results that people would be willing to say are creative, due to their novelty and other characteristics [Besemer 2006]. A secondary goal would be to determine whether the post-modification mechanisms could meet the criteria for transformational creativity.

This alternative addresses the four "consequences" given above. Although this too may produce slow progress, #1 is addressed by working on several smaller problems to examine the impact of their solutions. By using a routine design (RD) problem-solving method (PSM), #2 is addressed as we know the limits quite well. By picking a RD PSM which is already based on expert behavior we stand a better chance of addressing #3, and #4 can be addressed by focusing on using modifications based on hypotheses about the ingredients of creative reasoning that can be found in the psychological literature (see [Brown 2008]).

Of course, from this author's point of view, an obvious candidate for this first alternative is to look at what changes can be made to Design Specialists and Plans Language (DSPL) based routine design systems [Brown 1996b] [Brown & Chandrasekaran 1989] in order to produce more creative outputs. However, this isn't the only candidate.

This approach focuses on working "upwards" towards creativity, by examining smaller, ingredient decisions that make a difference to the result. It should be possible to investigate the degree of impact produced by changing the internal reasoning mechanisms in a DSPL system. This will contribute to our understanding of which less extreme reasoning mechanisms impact judgments of increased creativity. This is the foundation on which more extreme methods rest, as many authors agree that creativity is "…an outcome of subsets of … processes acting in concert…" and not just a single reasoning mechanism [Ward et al. 1999].

3.2. Using Cognitive Science and Psychology

The second alternative is to look more carefully at what cognitive science and psychology tells us about creativity. Everyone agrees that "novelty" is a key ingredient of the production and evaluation of creativity in a designed product, while some others add "surprise". Novelty appears to be the principle component of *all* models of creativity, and all creativity metrics. Judging both originality and surprise appears to be quite difficult, and needs much more attention. Srinivasan & Chakrabarti [2010], as well as others, have already made useful contributions to this problem.

Suggestions about the many ingredients of creative reasoning and its evaluation from the literature include:

A. *Novelty:* surprising and original; recognizing, evaluating and seeking it.

B. *Domain Knowledge:* having lots of it; being able to search it; finding relevant knowledge; rich interconnections; different representations; knowledge of its potential; similarities and differences; not just hierarchical representations.

C. *Heuristic knowledge:* having lots of it; for selecting ways to think (such as planning, simplification, analogy, etc.)

D. *Constraints:* being able to drop, weaken or invert them; having meta-knowledge about them to enable their modification.

E. *Combinations:* novel combinations of old ideas; combination of apparently unrelated ideas.

F. *Associative reasoning:* a quality of over inclusiveness; ability to associate the apparently unrelated.

G. *Suppressing inhibitions:* allows less relevant ideas/methods to “intrude” into the problem solving process.

H. *Abstract and imprecise descriptions:* such as for intermediate solutions and goals.

I. *Alternative methods:* for making decisions; for making goals more concrete.

J. *Critical assessment:* as an antidote to inclusiveness; identify misfits; heuristically eliminating very weak ideas and potential mistakes; resist pruning too strongly to just the routine ideas; resist <u>too much</u> novelty.

K. *Problem recognition:* error detection; recognition of product inadequacies; recognition leads to formulation of new goals.

L. *Concept expansion:* constructing, stretching, extending, modifying and refining concepts.

M. *Analogical reasoning:* far (cross domain) and near (same domain); depends on intentions and goals.

N. *Visualization:* mental simulation to examine existing things in new situations.

O. *Meta-reasoning:* breaking away from functional fixedness; abandoning old, unsuccessful problem-solving strategies; using meta-knowledge.

P. *Least commitment:* keeping options open as long as possible; suspending judgment; producing multiple partial solutions.

Q. *Forgetting:* productive forgetting; good mental management.

3.3. Products as Art

The third alternative is to focus on the role of artistic creativity evaluation [Boden et al. 2009] [Brown 2009] in assessing the creativity of a product. Besemer [2006] has detected "style" as one of the dimensions by which products are judged to be creative. The ingredient characteristics are "organic", "well-crafted" and "elegant". It is clear that many products with distinct style are close to works of art, and share many characteristics, such as attempting to manipulate the emotions of the viewer/user, for example. In addition, products that are highly related to established crafts (e.g., pottery) tend to be decorative, and some have "applied decorative design" [Jirousek 1995] which move them closer to art.

As we have previously discussed [2009] this is a very challenging area, as it isn't clear whether every ingredient of the evaluation of an artistic artifact for creativity can even be done reliably by a human. For example, product evaluation would include evaluating its intended function, and one would expect to be told it. From an artistic point of view, there might be a contribution to function, but more likely to the style dimension: there might also be intended (but undeclared) contributions to such purposes as "creating beauty", "entertainment", "healing", etc.

While studying this type of evaluation does avoid addressing the goal of transformational creativity, and does avoid tackling that very hard problem "head on", it may be substituting one very hard problem for another. However, considering product creativity with emphasis on the Style dimension is research that still needs to be done.

4. Ingredients of Routine Design Reasoning

From this point on we will concentrate on the first alternative: taking a well understood but not intentionally creative approach to see how it might be modified in order to produce results that people would be willing to say are creative.

Routine design means that everything about the design process is known in advance, including the knowledge needed. However, neither the resulting design nor the trace of use of the knowledge is known in advance. Typically, routine design knowledge is highly compiled: in the "knowledge compilation" sense of the term [Goel et al. 1991]. The DSPL language allows such routine design knowledge to be written down.

As previously presented [Brown 1992], the ingredient types of reasoning supported by DSPL are:

1. Basic Synthesis;
2. Criticism;
3. Decomposition;
4. Evaluation;
5. Execution;
6. Ordering;
7. Patching;
8. Planning;
9. Recomposition;
10. Retraction;
11. Selection;
12. Situation Recognition;
13. Suggestion Making.

Note that they are not independent, as some of these items involve other items, and are therefore at a different level of abstraction. The connection between this list and the mechanisms of DSPL are summarized in Table 1 below.

In DSPL, each Specialist contains Plans and plan selection knowledge. They each represent a subproblem, solving it by plan selection and execution. Plans are precompiled, ordered sequences of actions intended to provide the design for a subproblem. Each Plan provides a decomposition as well as sub-solution recomposition. Sponsors evaluate the suitability of a Specialist's plans for use in a particular situation, while a Selector picks the most suitable Plan.

Steps are the building blocks of the design process, providing a value for an attribute of the design by calculation, or by selection using pattern matching. Tasks group Steps, and therefore define additional problem decomposition. Constraints test values and, on failure, make suggestions about patches. Redesigners attempt to patch the design, guided by suggestions, in order to correct a constraint failure. Failure Handlers (FHs) recognize failing situations that might be patchable, or can trigger suggestion-guided backtracking.

Table 1: The Ingredients of Routine Design Reasoning

Type	*DSPL*	*Action*
Basic Synthesis	Step	Calculate, or select.
Criticism	Constraint	Values are tested/compared.
Decomposition	Plan Task Step	All three have sequences of actions.
Evaluation	Sponsor	Determine the quality of a plan.
Execution	Plan execution	Carry out the actions in a plan.
Ordering	Plan Task Step	All three have ordered actions.
Patching	Redesigner	Can change an attribute's existing value.
Planning	Plan Plan Sponsor Plan Selector	Hierarchically arranged collections of plans with plan selection produce a dynamically constructed design plan.
Recomposition	Plan	Each plan action adds its subproblem's solution to the overall design.
Retraction	Backtracking	One or more recent design decisions can be retracted and a re-design phase entered.
Selection	Plan Selector Step	The selector selects from amongst suitable plans, while a step selects from amongst suitable values for an attribute.
Situation Recognition	Plan Sponsor Step FHs	All three can make context sensitive decisions, based on recognizing patterns of previous actions or design decisions.
Suggestion Making	Suggestion	If any "agent" (e.g., a Constraint, or a Step) used by another fails, it passes suggestions (about how the failure might be fixed) back to the agent that called it from 'above'.

5. Modifications to Routine Design Reasoning

In this section we will examine some possibilities for modifying the ingredients of routine design systems in order to produce designs that are more likely to be judged to be creative.

5.1. Assumptions and Restrictions

We restrict possibilities by assuming that modifications are made without creating new agents (i.e., no additional reasoners are added), but that new mechanisms are allowed to be ‘called’ or added for exploiting meta-knowledge or meta-reasoning.

We assume that modifications are based on a RD knowledge-base (KB) constructed from DSPL, or something similar. We assume that the base system is doing configuration by selection between alternative pre-determined configurations

As such an RD system is probably highly compiled, values will be constrained early to avoid failure later in the design process. The RD system could be considered to be very *tight* or *loose*, depending on how much earlier constraints restrict later decisions. One would expect tighter systems to be harder to modify to produce more creative results.

Note that the 13 ingredients of RD reasoning listed above allow the construction of not only an RD system, but also systems than can handle other types of tasks. For example, routine configuration, such as assignment or restricted layout, should also be easy to do [Wielinga & Schreiber 1997]. However, as Situation Recognition plays a role at every level of an RD system, then it is possible to build a system that is dominated by that reasoning, where “design” decisions are actually flags that identify complex situations: thus allowing classification, the basis of much diagnosis. It may be possible to use this potential to enhance creativity.

5.2. Matching Creative and Routine Reasoning

In Table 2, the rows show the suggestions (A-Q) about creative reasoning from the literature, while the columns show the ingredients (1-13) of routine design reasoning. The table entries indicate places where relevant modifications might occur: others might be possible.

Table 2: Some possibilities for modifications

	Synth	**Crit**	Decomp	Eval	Exec	Order	Patch	Plan	Recomp	Retr	Sel	Recog	Sugg
Novelty	**y**	**y**		y			y				y	y	y
Domain	**y**	**y**	y	y			y	y			y	y	y
Heuristic		**y**	y	y			y	y			y	y	y
Constr.		**y**		y									
Combin.							y	y	y		y	y	
Assoc.		**y**						y	y		y	y	
Suppress		**y**	y	y				y	y	y	y	y	y
Abstract	**y**	**y**						y			y	y	y
Alt.	**y**		y			y	y	y			y	y	y
Assess		**y**		y				y			y	y	
Recog.		**y**					y				y	y	y
Expand									y				
Analogy	**y**		y			y	y	y					
Visualiz.		**y**											
Meta.	**y**	**y**	y			y	y	y			y	y	y
Least C.	**y**		y		y								
Forget		**y**											

Note that the first two columns (marked in bold) were considered in more detail and will be discussed below. Investigating the other 187 possibilities is more challenging and would require significantly more study. However, it’s important to note how many opportunities there are for potentially interesting research into creative design systems given this ‘humble’ RD basis. The entries made in Table 2 were first done by considering each ingredient of routine reasoning in turn against all 17 of the creative reasoning suggestions, and then by considering it again in the opposite direction (i.e., for each of the suggestions, against all 13 of the ingredients).

5.3. Basic Synthesis & Criticism: Possible Modifications

This section will present some possible modifications to Basic Synthesis and to Criticism that should enhance the perceived creativity of a RD system's output.

5.3.1. Basic Synthesis

A basic synthesis step produces a value for an attribute using calculation or selection: for example, (set x to $p + q$) or (if $a > b$ then set x to 5 else set x to 10).

Novelty might be enhanced by avoiding common values for attributes and also common combinations of values. It would be helpful to have knowledge of probabilities of values in successful designs, and be able determine the amount of deviation from a stereotype or from the mode. Pushing away from typical values towards the extreme values should produce novelty.

This sort of modification might be enhanced by having the system learn which attributes impact novelty the most, based on human feedback. A more detailed view might be obtained by an analysis of how the variation in novelty correlates with variation in attribute values.

Other possibilities include using other ways to calculate values—with less or more precision for example—and considering other ways to provide the values for selection process.

Domain Knowledge could be enhanced by adding models of existing designs, both in general and generated by this RD KB (similar to the rule models in Teiresias, for example [Davis & Lenat 1982]). These models might include statistical records of the values of attributes, of configurations, and of complete designs, as well as correlations between each attribute value and others.

Combinations might be produced by selecting similar components to the "normal" one being considered at that point, based on the current partial design. *Abstraction* could be introduced by using less tight tolerances, or by using intervals or qualitative values. *Alternatives methods* in basic synthesis could be added by using alternative calculations or selections.

Analogical reasoning can be approximated by using CBR to determine an attribute's value. It might also be used to provide sets of values; i.e., including related attributes. *Meta-reasoning* can be supported by some of the domain knowledge described above. In addition, "creativity tolerance" might be used by system by keeping track of how many extreme choices have already been made during the design process and limiting the subsequent design actions if it has already gone too far. Lastly, *Least Commitment* in basic synthesis can be enhanced by produce multiple solutions, not just one.

5.3.2. Criticism

Criticism in an RD system is represented by Constraints, where intermediate values or attribute values are tested or compared. Constraint roles include: to detect design failure, to detect incompatible sub-solutions, to constrain in order to prevent design failure, and to check requirements. Forms of constraints might include tests such as ($x > 5$) or comparisons such as ($a < b$).

Novelty might be increased by allowing values that only just fail (i.e., more extremes). *Domain Knowledge* to be added for constraints could include models of typical failure differences, value ranges, etc., as part of the test or comparison: i.e., don't make it a fixed test. It might be useful to keep track of how often and how much the constraint fails, and under what circumstances. Many of the constraints could be *Heuristic*, but it might be useful to know which are heuristic and which not, as this might allow those constraints to be flexed more safely.

Constraints themselves can be manipulated in many ways. It would be interesting to drop a constraint altogether, or move constraint until later in the reasoning (i.e., heuristic "de-compilation"). Constraints could be weakened in a variety of ways: change the test from "<" to "<="; change a constant, allowing ($x > 1$) to become ($x > 0.9$); allow tolerances, so as to change 1 to 1 ± 0.05; change the variable to one that is more inclusive; or "invert" the constraint, using failure handling to fix any negative consequences, if needed.

Associative reasoning might be enabled by using constraints from other similar components, while it is possible to be over inclusive by weakening constraints, as described above. *Suppressing inhibitions* might be equivalent to dropping constraints, or, more radically, by using constraints from other similar components.

Abstraction could be introduced by comparing types of values rather than actual values (e.g., "blue" instead of "navy"), or by converting values to qualitative values (e.g., "medium" instead of 10). It is clear that constraints play a key role in *Critical Assessment,* as they recognize actual and potential problems. They may also play a role in creativity tolerance.

Visualization could be introduced by replacing a compiled test by a simulation (e.g., object interference). This could be activated by *Meta-Reasoning* acting on meta-knowledge about the source/role of the constraint: i.e., a history of, and rationale for, its compilation. Other meta-knowledge might include records of the constraints' activities, such as success and failure counts/details, and when success leads to later failure.

6. Summary & Conclusions

The fine-grained analysis proposed by this paper is almost the antithesis of normal computational creativity research, in which the "blue skies" methodology is adopted: that is, to put it crudely, it isn't any good unless it appears impossible. While that approach has produced some great results in AI—autonomous vehicles for example—it tends to move researchers over and past more "mundane" problems, leaving them to be tackled later, with less prestige, or even left undone.

Creative systems may well be fuelled by important, large scale reasoning methods, such as analogy, that try to address the goal of transformational creativity, but they will be supported and enhanced by smaller scale reasoning such as has been presented here. It's important to note how many opportunities there are for potentially interesting research into creative design systems given this 'humble' Routine Design basis, with a focus on perceived creativity.

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