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Lee, Ju Hyun; Gu, Ning; Ostwald, Michael J. 'Creativity and parametric design?: comparing designer's cognitive approaches with assessed levels of creativity', International Journal of Design Creativity and Innovation Vol. 3, Issue 2, p. 78-94 (2015)

Available from: <http://dx.doi.org/10.1080/21650349.2014.931826>

Accessed from: <http://hdl.handle.net/1959.13/1306879>

Creativity and parametric design? Comparing designer's cognitive approaches with assessed levels of creativity

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Since its inception, computational parametric design has been promoted as a means of supporting heightened creativity. In order to test three common claims about parametric design and creativity, this paper describes the results of a study that compares the cognitive processes of a small set of designers, with the results of an independent assessment of the levels of creativity visible in their work. Specifically, using a combination of protocol analysis (of the design process) and consensual assessment (of the design outcome) the research explores three suggested indicators of a connection between cognitive activities and creativity. The three indicators are: geometry versus algorithm use, problem-driven versus solution-driven processes, and expert versus novice activities. Through this research the paper contributes to a heightened understanding of the actual, rather than theorised, relationship between parametric design and creativity.

Keywords: parametric design; generative design; cognitive activity; creativity; problem-solving

1. Introduction

Parametric design is a computationally-intensive design generation and decision-making paradigm (Blosiu, 1999). It has been praised as heralding a new approach to architecture and it has been repeatedly linked to claims about improved levels of creativity (Schumacher, 2009). Past research in this field (Kolarevic & Malkawi, 2005; Holzer, Hough, & Burry, 2007; Oxman, 2008b; Turrin, von Buelow, & Stouffs, 2011) has focussed on the performance modelling and optimisation capacity of parametric design approaches; two features which have also been linked to the creative potential of

this approach to design (Furjan, 2007; Male-Alemany, 2007). Parametric design environments have also been presented as supporting creativity because they allegedly encourage designers to rapidly explore alternatives at an early stage in the design process (Pasquarelli, 2002; Spiller, 2008).

Despite the suggestion found in much past research, that there is a connection between the generative capability of parametric design and creativity, only a small number of past studies have attempted to examine the actual nature of the relationship between the two (Iordanova, Tidafi, Guité, Paoli, & Lachapelle, 2009; Lee, Gu, Jupp, & Sherratt, 2014). One of the reasons for the existence of a growing number of unsubstantiated claims about the creative potential of parametric design is that it is difficult to obtain evidence of this relationship. For this reason, the present paper describes the results of a small but detailed study that analyses the actual relationship between cognitive approaches to design, and levels of observed creativity, in a parametric design environment. Focussing on three modes of design conceptualisation – thinking geometrically or algorithmically, being problem-driven or solution-driven, and disparities between the practices of expert and novice designers – our method seeks to reveal patterns in the cognitive activities of designs which can be linked to independently assessed levels of creativity.

Before describing how the present research investigates these three facets of the cognitive behaviour of designers, it is first necessary to define what we mean by both design and creativity. The word “design” is used as a verb and a noun in the English language. Design can be thought of as a verb denoting an activity from which creativity *could* emerge (Glanville 1999). In contrast, creativity has been linked by psychological and cognitive researchers to “creative thinking”, “problem solving”, “imagination” and “innovation”. Their use of the concept is seemingly similar to the definition of creativity used in the design domain. In particular, Kryssanov et al. (2001) categorize two notions of creativity associated with novelty and appropriateness; a combination which has since met with widespread acceptance. The two have also proved to be meaningful measures of the creativity implicit in a design. Thus, in the context of this paper, creativity is a measure of value or novelty which is expressed (or made tangible or visible) in a design. Or even more specifically, we accept that, regardless of debates about the actual mechanics or context of creativity, it is possible for a design to be independently ‘judged to be creative’ (Amabile, 1983).

The present paper adopts a three stage experimental method to examine the relationship between a design process and a creative outcome. The stages are: (1) 'cognition', (2) 'confluence' and (3) 'comparison'. The first uses protocol analysis to investigate the precise actions undertaken by designers while they are working on a set task using parametric software. The second, confluence, relies on expert opinion to arrive at a balanced assessment of the creative merits of the designs produced in the previous stage. The final stage looks for correlations between the practices of designers and the levels of creativity observed and assessed in their outcomes.

This paper commences with an overview of arguments connecting parametricism and creativity, before describing the rationale for the tripartite method used to analyse this connection. Thereafter, the paper reports on the results of a small but detailed study of the cognitive behaviours of designers working in parametric environments, the consensual assessment of creativity in their outcomes and any correlations between the results of these two stages. This last stage of the process highlights three different subsets of the results which, it has been theorised, are indicators of creative potential.

Before progressing any further, there are two key limitations to this research that must be acknowledged. First, the results of the experiment reported in this paper are only about the behaviour of parametric designers. Without an identical study of 'traditional' (non-parametric) designers' cognitive behaviours, also mapped to creativity in the same way, there is no basis for constructing a comparison. Thus, this paper cannot prove or disprove claims about the creative benefits of parametric design. However, the present paper does describe a method for examining this larger issue and then provides the first half of the evidence for constructing such a comparison. This evidence is also tested against three theorised indicators of a creative design process. The second limitation to the research is a practical one associated with the protocol analysis method. Protocol analysis is used for very fine-grained studies of the actions of designers. The method collects a large volume of detailed data; however, it is so time-consuming to undertake that only very small sample sizes are used. Thus, Ho (2001) used only two participants and Ahmed et al.'s study (2003) used only twelve, although both studies are widely quoted in creativity research. In a statistical sense, neither of these group sizes could be considered representative of a larger population. However, in order to investigate individual design strategies or to capture cognitive approaches in

detail within a reasonable timeframe, small sample sizes are an unavoidable limitation in research of this type. Nevertheless, the strength of this method is that it collects many hundreds of indicators that are then methodically derived and coded, leading to a high degree of confidence in the results. The results reported in the present study were derived from an exhaustive study of the actions of four participants. This scale is comparable with the majority of past studies undertaken in design cognition using this method, but its results cannot be directly extrapolated to comment on larger issues.

2. Parametric Design and Creativity

2.1.1. Parametric design

As the name implies, parametric design is the process of generating and testing alternative design propositions using pre-determined parameters (Monedero, 2000). Researchers (Lawson, 2002; Hanna & Turner, 2006; Roberto, 2006) typically describe parametric design as a new algorithmic approach to design generation that is rule and constraint-based. Unlike traditional digital design environments (CAD or BIM), parametric design allegedly supports the creative process by, as Roberto (2006) suggests, automating the production of design variations. Thus, by using parameters to control different variations, designers can explore multiple viable solutions and concepts without being limited by their own drawing and modelling skills (Lawson, 2002). The process of generating design variations, which is effectively automated in parametric design, is also thought to be the key to pursuing creativity as well as to extending the boundaries of design knowledge (Gero, 1996; Liu & Lim, 2006).

In the parametric design process, rules define relations between geometric elements (Lee & Kim, 1996) and configure the parameter attributes. Rules can also address specific design factors such as user needs, functional requirements or structural demands (Park, Elnimeiri, Sharpe, & Krawczyk, 2004). Oxman (2008a) argues that such rules can result in parametric formations which enable topological variations. Fundamentally, parametric design offers increased computational control over design geometry by way of its adaptability and responsiveness for problem-solving (D'INO, 2012). Scripting or coding activities can therefore be regarded as a *potential* channel for creativity because they provide a means of representing design ideas (Salim & Burry, 2010). When understood in this way, parametric design supports idea generation and evolution which can potentially lead to heightened levels of creativity (Lee et al., 2014).

2.1.2. Three cognitive perspectives of parametric design

Three distinct variations in cognitive behaviour during the design process have been theorised as enabling or supporting creativity. The first of these is specific to parametric design environments and it is related to the degree to which designers move between geometric (shape-making) and algorithmic (rule-making) processes. The second factor is pertinent to design practice more generally, and it relates to the particular way in which designers approach problems and solutions. The final variation in cognitive behaviour is about the different behaviours of expert and novice designers. Each of these three factors is described hereafter and they also form the basis for the review of experimental results later in the paper.

Parametric design process is fundamentally reliant on the construction of mathematical algorithms for defining rules, and 3D geometric views for modifying and evaluating design variations. These two ways of working during the design process are regarded as being possible indicators of levels of creativity. A further suggestion is that divergent thinking generates design variations, while convergent thinking identifies and focuses on a selected solution, both adequately supported by scripting and coding activities in parametric design (Lee, Gu, & Sherratt, 2011). However, as Roberto (2006) warns, the danger of parametric design lies in the fact that the outcome may be too abstract and may only make sense virtually. Therefore, evaluating design variations in the 3D geometric view is critical for high quality decision-making. Although it can be time consuming to switch between the different representations while designing, the move between geometric and algorithmic environments may be essential in parametric design for supporting creative outcomes.

Just as designers shift between rule setting and outcome evaluation processes, so too they cycle between problem-defining and solution-finding processes. For example, Maher and Poon (1996) argue that the problem definition process in design is variable and will change in response to the current solution seeking behaviour. Coley et al. (2007) suggest that design problem solving behaviour is a core and measurable cognitive indicator within the design process (Coley, Houseman, & Roy, 2007). Such ideas are implicit in the theory of a co-evolutionary process for explorative design which, arguably, results in creative products or outcomes. Dorst and Cross (2001) develop this model in their proposition that creative design comes from developing and refining both the formulation of a problem and ideas for a solution. Thus, one possible

indicator of the creative potential of a system is found in the degree to which it facilitates the co-evolution of problem and solution ‘spaces’ in the design process (Maher & Poon, 1996; Dorst & Cross, 2001). More specifically, the studies of Kruger and Cross (2006) support the validity of arguments about the combined importance of problem- and solution-driven design strategies. Their findings identify that the use of a solution-driven strategy produces lower quality solutions but with higher levels of creativity. In contrast, they demonstrate that a problem-driven design strategy can result in the best balance between quality and creativity.

The final sets of cognitive behaviours which are potentially evaluated are concerned with the level of experience of the designer. Comparisons between expert and novice designers’ behaviour in the design process have been a popular research topic (Coley et al., 2007). Kim et al. (2007) found that expert designers use a ‘Limited Commitment Mode control strategy’ more frequently than novice designers in the design problem solving process. Ho (2001), through the application of protocol analysis, identified that the problem decomposition strategy and the strategy of working-forward/backward through design problems can be used to differentiate between expert and novice designers. Similarly Ahmed et al. (2003) indicate that experts use particular design strategies (‘forward reasoning’), whilst novices tend to rely on ‘trial and error’ as a design method (‘backward reasoning’). Ball et al. (2004) revealed that expert designers exhibit more schema-driven analogising, whilst novices show the reverse pattern of analogy. Kavakli and Gero (2002) found that an expert’s cognitive actions are more organised and productive in comparison with the protocols of novices. These studies collectively suggest clear differences between the cognitive activities of expert and novice designer as well as some indicators of behaviours that might correlate to levels of creativity. These will be considered later in the paper in the context of new experimental results.

3. Experimental Design

This section describes the methods used to capture and analyse data about the designers’ behaviour and then assess the creativity implicit in the outcomes of their design process. This paper uses two research methods to achieve this aim. The first of these is drawn from the field of design cognition. In order to capture the cognitive activities of designers during the design process, Coley et al. (2007) identified four viable research

techniques: protocol analysis, observation, ethnography and the diary methodology. This paper applies protocol analysis and structured observation of the behaviour of people working in a parametric design environment. This technique is similar to Suwa et al.'s approach (Suwa, Purcell, & Gero, 1998) using video and audio protocols. The second method used in the present paper is for assessing creativity. The 'confluence approach', using either the Consensual Assessment Technique (CAT) or the Creative Product Semantic Scale (CPSS) is widely accepted by creativity researchers (Amabile, 1983; Besemer & O'Quin, 1987).

By comparing the results of cognitive studies using protocol analysis with expert assessments using the confluence approach, it is possible to correlate, within the limits of the study group, particular kinds of activities with levels of creativity as exhibited in the design product or outcome. The two methods, the cognitive and the consensual, are introduced in the following sub-sections, along with particular variations used for the experiment that is reported in this paper.

3.1. Protocol analysis and coding scheme development

Protocol analysis has become the most widely accepted cognitive research technique in the design domain (Chai & Xiao, 2012; Coley et al., 2007). Protocol studies in architecture and design started with Eastman in the late sixties (Cross, 2001). While acknowledging that this approach tends to understate the significance of social and individual contexts or personalities (Gero & Tang, 2001; Suwa et al., 1998), it remains one of the few methods for developing a detailed understanding of cognitive design processes (Chai & Xiao, 2012).

Traditionally this method asked participants to verbalise their thoughts and actions either while designing (concurrent) or immediately afterwards (retrospective). The debate on the validity of concurrent and retrospective verbalisation is ongoing (Coley et al., 2007). A concurrent verbalisation ('think-aloud') method might interfere with the design process, whilst a retrospective one might result in details being omitted or even recalled incorrectly. A more effective version of the method is found in the work of Suwa et al. (1998) who collected both video and audio data for protocol analysis. The visual data, in particular, supports the clear determination of whether algorithmic or geometric design activities are occurring. This combined technique enables the researcher to rigorously explore cognitive activities in the parametric design

process by comparing words and visual actions (e.g. drawing, scripting, generating, evaluating actions). A post-experiment interview can also enhance the data. The experimental results reported in this paper use video and audio recording, with both think-aloud verbalisations and post experiment interviews.

Once the data (video and audio information in this case) has been collected, then a coding scheme, which follows a defined protocol, must be used to classify and organise the data. There are two accepted coding schemes in the design domain: Suwa et al. (1998) and Gero and McNeill (1998). The former targets the content-oriented aspects of designing, while the latter is focussed on process-oriented aspects. For the present experiment, we selectively borrowed three levels from Suwa et al.'s coding scheme (physical, perceptual and conceptual) and revised them to be more suitable for a parametric design environment. A variation of the coding scheme developed by Gero and McNeill (1998) was then used for characterising the conceptual level of parametric design and for the conceptual level of the coding scheme. Thus, the present research uses the sections of both methods that are most appropriate for the parametric study environment. Designing in parametric environments involves both geometric and algorithmic activities, a factor which was used to inform the physical and perceptual levels in the coding scheme (Table 1).

Table 1. The coding scheme used for the experiment exploring the parametric design process

Level	Category	Subclasses	Description
Physical	Geometry	G-Geometry G-Change	create geometries without an algorithm change existing geometries
	Algorithm	A-Parameter A-Change Parameter A-Rule A-Change Rule A-Reference	create initial parameters change existing parameters create initial rules change existing rules retrieve or get references
Perceptual	Geometry	P-Geometry	attend to existing geometries
	Algorithm	P-Algorithm	attend to existing algorithms
Conceptual	Problem-finding	F-Initial Goal	introduce new ideas (or goals) based on a given design brief
		F-Geometry Sub Goal F-Algorithm Sub Goal	introduce new geometric ideas introduce new algorithmic ideas
	Solution-generating	G-Generation	make generation (or variation)
	Solution-evaluating	E-Geometry	evaluate primitives or existing geometries
		E-Parameter	evaluate existing parameters
		E-Rule E-Reference	evaluate existing rules evaluate existing references

The *physical* level in the coding scheme represents generative actions and activities in parametric design. Geometry actions represent the modelling activities for generating the digital geometries, while algorithmic actions represent the generative processes, which describe the ‘parameters’ and ‘rules’ as well as the ‘reference’.

The *perception* level represents the activities related to visual imagery in the design process. This level also has the two categories of geometry and algorithm. The perception level is potentially related to the notion of incubation in Wallas’s creative stage model (Wallas, 1926), which might facilitate creativity.

The *conceptual* level consists of three categories of actions: problem-finding, solution-generating and solution-evaluating evaluating (Gero & McNeill, 1998). While cognitive activities of the conceptual level can be largely interpreted as problem-solving processes (Dorst & Dijkhuis, 1995; Ho, 2001), Dacey and Lennon (1998) claim that creative cognition is more than problem solving; selection and evaluation processes are equally important as parts of an integrated process for supporting design creativity. They are reflected in the development of our coding scheme. The solution-generating action is also essential for capturing the generative aspects of parametric design. Making variations in this way is thought to extend the boundaries of the designer’s existing knowledge and expand the realm of possible solutions (Gero 1996, Liu & Lim 2006), both commonly linked to creativity.

3.2. Consensual assessment technique

The consensual assessment technique (Amabile, 1983) is a common approach to measuring the creativity of design products. The combined assessment of experts is widely held to be capable of measuring the creativity implicit in an artefact. A basic requirement of an expert panel assessment is that its members are familiar with the design domain and the techniques for producing the design (Amabile, 1983). The various versions of CAT, many of which can be traced to the work of Amabile, specify the criteria for assessing creativity using multiple criteria such as the creative, technical, and aesthetic dimensions of an object.

Evaluation criteria for design can be selected by reviewing past proposals (Christiaans, 2002; Hennessey & Amabile, 1999). Christiaans (2002) used a number of bipolar subscales, 70 in total come from the CPSS, to validate Amabile’s CAT. A large

number of criteria would be time-consuming and even confusing for assessors. The experiment conducted for the present paper uses four criteria: *novelty*, *usefulness*, *complexity* and *aesthetics*. Novelty, which is often used for measuring creativity in the design domain, represents Amabile's creative dimension whereas 'usefulness' and 'complexity' belong to Amabile's technical dimension. 'Complexity' refers to the degree to which the product shows its level of difficulty (Amabile, 1983). This is specifically relevant to the complex forms that are often produced in parametric design. The final criteria, 'aesthetics', represents Amabile's aesthetic dimension and refers to the degree to which the design is aesthetically appealing (Amabile, 1983).

3.3. Experiment procedure

The design experiment has three stages: the analysis of the behaviour of designers producing a series of concept designs, the assessment of those designs in terms of their creativity, and a comparison between the behaviour of the designers and the level of creativity identified during the assessment process.

For the reporting of results, the participants are identified by number (1-4) and are described using a subscript code to signify each participant's level of experience (Expert or Novice), whether they used graphical (G) or text-based (T) parametric design approaches and whether their designs were rated as more creative (C+) or less (C-).

Stage 1: The design experiment involved four architectural designers who each had experience in parametric design and had successfully completed at least one major design project using this approach. Two of the participants, (1_{EGC+} and 2_{ETC+}), have over five years' experience using these methods and, only for the purpose of analysis, they were regarded as 'expert designers'. The other two participants (3_{NGC-} and 4_{NTC-}), were postgraduate architectural students each possessing one year of experience in parametric design. For the purposes of this study they were classified as 'novice designers'.

Each of the participants was given one hour to undertake a specified design task. The task was the conceptual design of a high-rise building which was required to meet five performance requirements: (a) have two main functional areas being office and hotel; (b) have a maximum floor area of 2,500 square metres per floor; (c) have a height of over 40 stories; (d) reflect the transformation of structural forces using external data, and (e) aim to be a designated regional landmark.

Each design session was video recorded, and after the experiment each designer participated in a post experiment interview, as retrospective protocols, to explain their thoughts and activities in the experiments. Participants were allowed to choose their own parametric modelling tools. Two (1_{EGC+} and 3_{NGC-}) of the four participants chose Grasshopper, a graphical algorithm editor, whilst the other two (2_{ETC+} and 4_{NTC-}) used Python and Maya script editor, a text-based editor. The completed design models were collected. Figure 1 shows the final design models produced by participants and their scripts.

Figure 1. Design models produced by the participants and their scripts

Stage 2: A panel of seven design expert assessors, each with a minimum of five years of professional experience, assessed the final design models using four evaluation criteria: *novelty*, *usefulness*, *complexity* and *aesthetics*. The four design models were presented to each assessor in isolation, as a collage of images, which were reviewed against a seven-point Likert scale (where 1 is the lowest and 7 is the highest). The assessors were briefed on the design task and constraints in advance and they also participated in an interview to discuss the evaluation criteria. Assessors were asked to analyse each work on its own merits, and not to directly compare them.

4. Results and Analysis

4.1. Protocol analysis results (Stage 1)

Each video session of the four designers were directly transcribed using NVivo 9 software and automatically segmented into smaller episodes. To ensure the consistency and validity of the results, the present researchers segmented and encoded each protocol twice with a three-month interval between the two processes. A final protocol coding was achieved using a process of arbitration. There was little conflict between the first and second coding results. This is because most subclasses in our coding scheme represent only algorithmic or geometric activities that are clear for the coders to make interpretation. There was also a high degree of clarity in activities captured by the video which could be readily interpreted with the assistance of the designer's verbalisations.

The average value of the number of coded segments was 297.8 (1_{EGC+} : 220, 2_{ETC+} : 364, 3_{NGC-} : 319, 4_{NTC-} : 288). Furthermore, over 90% of each protocol was encoded in this way (meaning that less than 10% of the time each designer spent could not be coded using the scheme). While the participants were given only one hour to complete the concept design, three of the sessions took slightly longer than this because of the computer processing delay required to update models. To accommodate this difference, all of the times were normalised to a consistent scale for comparison.

Table 2 shows the results, describing the percentage of the frequency weighted by time duration of each code. On average, 'physical' behaviours account for 45.3% (geometry: 5.5%, algorithm: 39.8%); 'perceptual' account for 6.2%; and 'conceptual' account for 48.5% (problem-finding: 11%, solution-generating: 5.5%, solution-evaluating: 32%). Solution-evaluating processes dominate in the conceptual level while algorithmic activities are dominant in the physical level for each protocol. 'A-Rule' (writing an algorithmic rule) and 'A-Change Rule' (changing an algorithmic rule) are dominant activities in the experiment. This suggests that the algorithmic representation is a preferred medium for progressing design in parametric design.

The second most dominant activity is 'E-Geometry' (visually evaluating the outcome of a rule) and 'E-Rule' (evaluating the rule itself). A large amount of 'E-Geometry' appeared in one participant's (1_{EGC+}) protocol, whereas, 'E-Rule' occurred dominantly in the other protocols for the verification of their parametric design algorithms. Because parametric design often produces solutions that may be

unexpected, the outcomes must be regularly evaluated in the 3D view as well as in the scripting view. There were also some other notable differences between the participants, including the fact that 1_{EGC+}, 2_{ETC+} and 3_{NGC-} often made new rules (A-Rule) rather than changing existing ones (A-Change Rule), while 4_{NTC-} tended to change existing rules. This indicates that there are differences in approaches to undertaking parametric design.

Table 2. The percentage of coding results

Level	Category	Subclass	1 _{EGC+}	2 _{ETC+}	3 _{NGC-}	4 _{NTC-}	Mean	SD
Physical	Geometry	G-Geometry	2.0	0.0	6.4	1.3	2.4	2.8
		G-Change	0.5	0.0	8.8	3.0	3.1	4.0
	Algorithm	A-Parameter	4.9	0.1	3.0	2.9	2.7	2.0
		A-Change Parameter	10.0	4.7	1.6	1.0	4.3	4.1
		A-Rule	24.7	20.0	16.5	19.0	20.0	3.5
		A-Change Rule	6.0	12.2	2.9	26.9	12.0	10.3
		A-Reference	0.0	0.2	0.0	2.8	0.8	1.3
Perceptual	Geometry	P-Geometry	2.8	1.8	1.0	0.4	1.5	1.0
	Algorithm	P-Algorithm	3.2	4.0	2.8	8.6	4.7	2.6
Conceptual	Problem-finding	F-Initial Goal	3.0	0.2	1.4	1.1	1.4	1.2
		F-Geometry Sub Goal	7.0	2.5	10.7	2.3	5.6	4.0
		F-Algorithm Sub goal	4.1	4.4	6.4	1.0	4.0	2.2
	Solution-generating	G-Generation	4.0	13.0	1.9	3.0	5.5	5.1
	Solution-evaluating	E-Geometry	19.4	17.3	18.1	8.8	15.9	4.9
		E-Parameter	0.8	0.0	0.0	0.0	0.2	0.4
		E-Rule	7.6	19.5	18.5	17.9	15.9	5.5
		E-Reference	0.0	0.1	0.0	0.0	0.0	0.1
	Sum		100	100	100	100	100	-

4.2. Expert assessment results (Stage 2)

The results of the expert assessors (Table 3) were averaged for each criterion and for each of the four designs. The first column of the results (non-criteria assessment) shows independent non-criteria based assessment of creativity. These are consistent with the results in the second column (comparative assessment), which are for the comparative

non-criteria based assessment of creativity. These results are also similar with the scores for *novelty* and *complexity* in the final criterion-based assessment of creativity. Overall, the results show that the level of creativity exhibited in 2_{ETC+}'s model was assessed as being the highest and 1_{EGC+}'s model achieved the second highest overall score but had the highest result for *usefulness*. In contrast, 3_{NGC-} and 4_{NTC-}'s models had the lowest creativity overall. *Complexity*, being a straightforward visual property, had a more consistent result (2_{ETC+} highest, 4_{NTC-} lowest). However, whereas scores for *complexity* were consistent across the judges, the scores for *aesthetics* were more scattered. For example, two panel members gave 4_{NTC-}'s model the highest rating (five and six points) because of 'symmetry', 'elegance' and 'simplicity'. In contrast, the other assessors clearly preferred the concept designs of 1_{EGC+} and 2_{ETC+}. This reinforces the known limitations of the expert assessment method and confirms the need for at least seven assessors to achieve a reasonable result, or else a more detailed and explicit assessment criteria might be used.

Table 3. Assessment scores of the parametric design models

	Non-criteria assessment	Comparative assessment	Novelty	Usefulness	Complexity	Aesthetics	Mean
1 _{EGC+}	3.9	Lowest (1)	4.4	4.6	4.7	3.6	4.3
2 _{ETC+}	5.7	Highest (6)	6.6	4.3	6.4	4.6	5.5
3 _{NGC-}	3.9	Lowest (5)*	4.1	4.4	3.9	2.1	3.6
4 _{NTC-}	3.0	Lowest (3)*	2.3	4.0	2.4	3.6	3.1
Mean	4.3	-	4.4	4.3	4.4	3.5	4.1
SD	0.9	-	1.8	0.3	1.7	1.0	1.0

*Two experts selected both 3_{NGC-} and 4_{NTC-} as the least creative ones

4.3. Comparative results (Stage 3)

This section compares the results derived from the protocol with those of the creativity assessment. The comparison is focussed on the three theorised relationships described previously in this paper: geometry versus algorithm use; problem-driven versus

solution-driven processes; expert versus novice activities.

It is noted that one of the conditions for design behavioural patterns to emerge, and to be formally explored and verified, is through patterns of repetition. Due to the small number of participants involved in this study, some of the discussion hereafter is based on observations and analyses of individual behaviours, and sometimes conflicting findings between different data sets are also noted.

4.3.1. Geometry versus Algorithm

Two designers (1_{EGC+} and 3_{NGC-}) used graphical algorithm editors, whilst the others (2_{ETC+} and 4_{NTC-}) used text-based algorithm editors. The graphical editors tended to produce more geometric activities in the physical representation level than the text-based editors. In the conceptual level of the coding, the graphical editor also produced more ‘SP-Initial Goal’ and ‘F-Geometry Sub Goal’ activities for problem-finding compared to the text-based editors. This confirms that the graphical editor is likely to lead designers to conduct more geometry-based activities. In contrast, ‘A-Change Rule’ and ‘P-Algorithm’ behaviours dominated in the text-based algorithm editors. Notably both 2_{ETC+} and 4_{NTC-} struggled with trouble-shooting their scripts (A-Change Rule).

This section looks at our designers’ selections of geometric versus algorithmic approach to parametric design. Participant 1_{EGC+} produced a relatively large amount of ‘F-Geometry Sub Goal’ and ‘E-Geometry’ behaviours, which seem to be the core activities in their geometric approach. 1_{EGC+}’s algorithmic approach was also dominated by ‘A-Change Parameter’ which is one of the significant activities required to produce design variations. In parametric design, this might suggest that ‘A-Change Rule’ behaviour was more concerned with trouble-shooting, whilst ‘A-Change Parameter’ was more related to design generation. In contrast, participant 2_{ETC+}’s protocol produced a relatively large amount of ‘F-Algorithm Sub Goal’ and ‘E-Rule’ behaviours, which seems to be the core activities in their algorithmic approach. 2_{ETC+}’s geometric approach was dominated by ‘E-Geometry’ (evaluating geometries) which has previously been linked to supporting creativity (Lee et al., 2014). This type of switching between geometric and algorithmic modes in parametric design has the potential to support creativity.

4.3.2 Problem-driven versus solution-driven approaches

The coding scheme (in the conceptual level) records cognitive activities in both the problem space (through the ‘Problem-finding’ code) and the solution space (through the ‘Solution-generating’ and ‘Solution-evaluating’ codes). The frequency coverage of ‘Problem-finding’ in the experiment showed that designers who use the graphical algorithm editor adopted a problem-driven process (1_{EGC+} : 14.8% and 3_{NGC-} : 18.5%), in order to progress parametric design. That is, 1_{EGC+} ’s and 3_{NGC-} ’s cognitive activities occurred largely in the problem space. This finding might be significant because it has been argued that design strategies based on a problem-driven process can result in the best balance between quality and innovation (Kruger & Cross, 2006). The results of the expert panel assessment for 1_{EGC+} tend to support this argument. However, whilst also adopting a problem-driven process, 3_{NGC-} ’s model received lower scores for other criteria from the assessors, somewhat undermining the overall score.

Participant 2_{ETC+} is regarded as adopting a solution-driven process for progressing design, as 2_{ETC+} ’s protocol had the highest frequency coverage of ‘Solution-generating’ and ‘Solution-evaluating’ behaviours (combination of 36.9%). The frequency coverage of ‘G-Generation’ for 2_{ETC+} was also the highest (13%). 2_{ETC+} ’s protocol had the second highest frequency coverage of ‘A-Change Parameter’ (4.7%). Complementing the solution-driven process, ‘G-Generation’ and ‘A-Change Parameter’ may have enabled 2_{ETC+} to generate more design variations. 2_{ETC+} ’s model had the highest creativity score as assessed by the expert panel. This is consistent with Kruger and Cross’s results (Kruger & Cross, 2006), indicating design strategies adopting a solution-driven process can lead to outcomes with higher creativity scores.

During the experiments, it was observed that participant 1_{EGC+} notably produced ‘F-Initial Goal’ behaviours at the beginning, middle and end of the process. 1_{EGC+} also sequentially decomposed the problem into geometric sub-problems and then algorithmic sub-problems. This is similar to ‘the explicit problem-decomposing strategy (Ho, 2001)’. In contrast, 2_{ETC+} ’s sub-problems were often implicitly followed generating solutions. Figure 2 shows the normalized coverage of 1_{EGC+} and 2_{ETC+} ’s conceptual activities over time. The summed coverage data in each 20-segement interval was visualized using the normalized coverage value (normalized $A = (A - \text{mean})/\text{SD}$) (Bilda & Gero, 2007) to facilitate the exploration of cognitive activities over time. There is a marked difference between the two approaches for ‘solution-generation’, with 1_{ECT+}

producing solutions only at the end and 2_{ECT+} doing so throughout the whole process. The latter highlighting the solution-driven process would be the more promising strategy in terms of creativity, particularly with respect to the reflective processes (e.g. Schön, 1984), therefore it is unsurprising that this would be judged as the better solution.

Figure 2. The normalized coverage of 1_{EGC+} (left) and 2_{ETC+} 's (right) conceptual activities over time

4.3.3 Expert versus novice

As discussed above, 1_{EGC+} and 2_{ETC+} qualify as expert designers whereas 3_{NGC-} and 4_{NTC-} are classified as novices. Novice designers generally had significantly lower frequency coverage of 'G-Generation' and 'A-Change Parameter' than the experts (see Figure 3). These results imply that novices are at a clear disadvantage when engaged in the generative aspects of parametric design.

4_{NTC-} 's protocol had the most frequent coverage in the physical level, while 'Problem-finding' and 'E-Geometry' had a relatively lower frequency coverage. 4_{NTC-} also had a tendency to solve the problem firstly by goal searching; possibly a characteristic of novice's problem-solving. Conversely, 3_{NGC-} , the other novice designer, had the highest frequency coverage of 'Problem-finding' (18.5%) suggesting that problem-finding activities alone may not necessarily have a positive effect on creativity in parametric design. Creativity in parametric design may not only depend on 'Problem-finding', but generative activities including 'G-Generation' and 'A-Change Parameter'.

Both novice designers used 'trial and error' or 'backward reasoning' when progressing design, whereas an expert (1_{EGC+}) adopted a strategy to progress design by developing and applying rules from the initial states of the problem; a behaviour which

is recognised as a ‘working-forward’ strategy and one which potentially supports creativity in parametric design.

Figure 3. The coverage of ‘problem-finding’ (left) and two generative activities (right)

Of the expert designers, 1_EGC+, focused more on geometric sub goals (F-Geometry Sub Goal) and geometric evaluation (E-Geometry), whilst 2_ETC+, focused on algorithmic sub goals (F-Algorithmic Sub Goal) and algorithmic evaluation (E-Rule). These results show that parametric design processes can vary when adopting the geometric versus algorithmic approaches as well as the problem-driven versus solution-driven processes. Overall, expert designers tended to achieve much higher rating scores in the assessment of creativity (Table 3), regardless of the particular approach and process they adopted.

5. Conclusion

While acknowledging the limited scope of the study and the definitions of key terms outlined at the start of the paper, some of the results of this research do correlate with past propositions regarding the relationship between cognitive approaches observed in the design process and the creativity implicit in the resultant product. As a result, the paper has contributed to capturing and understanding potential cognitive approaches to supporting creativity in parametric design, focussing on three conceptual comparisons: geometry versus algorithm, problem-driven versus solution-driven, and expert versus novice.

It is also notable that the expert designers had higher overall results for creativity and the novice designers’ had lower creativity scores overall. However, this does not necessarily mean that being an expert, or having behavioural patterns that are similar to

those of experts, is the only cause of the heightened levels of creativity in parametric design but it does raise several further questions. Can a novice be trained to behave more like an expert and would this make them more creative in parametric design? Conversely, is being a more experienced designer a stronger indicator of creativity in parametric design? These questions cannot be directly answered with the results of our study. Nevertheless, the present results suggest two different and equally viable cognitive approaches for supporting creativity in parametric design. Expert designer 1_{EGC+} adopted a largely geometric approach focusing more on 'F-Geometry Sub Goal' and 'E-Geometry'. Expert 2_{ETC+} focused more on 'F-Algorithm Sub Goal' and 'E-Rule' and therefore adopted a more algorithmic approach. It was also significant to note that 2_{ETC+} undertook a solution-driven process to progressing parametric design largely in the solution space. The design generation was dominated by 'G-Generation' and 'A-Change Parameter'. These different cognitive activities (as observed in 1_{EGC+}'s and 2_{ETC+}'s behaviours) may have facilitated or enhanced creativity in their final outcomes.

While this study has begun to provide an understanding of the relationship between creativity and cognitive activities in parametric design, several challenges remain for future studies. The first is the need for a baseline study, for example, to enable the comparison with design processes using non-parametric modelling environments and even sketching environments. This kind of comparison would be useful to further understand the potential and benefit of adopting parametric design. Secondly, this paper has focused on the conceptual formation of individual cognitive approaches to supporting creativity in parametric design. To better generalise the findings, an increased number of participants could be considered for future research. Finally new techniques can be considered to effectively analyse the volume of data produced and to generalise the findings. For example, graphical analysis techniques such as linkography (Goldschmidt, 1990; Lee, Gu, & Ostwald, 2013), could be considered to clearly identify and explore sequential patterns of cognitive activities in parametric design.

Besides the above methodological refinements, we establish the following three hypotheses, based on the current findings, which should be further explored in future research into this topic. These three are potentially of great significance for understanding creativity in parametric design and for characterising behaviours in parametric design.

- (1) *The combined approach to parametric design provides better support for creativity than either the geometric or algorithmic approaches in isolation.*

Our data indicates that the two experts, whose designs were assessed as having a relatively higher level of creativity, used a combined approach, while the others adopted either the geometric (3_{NGC-}) or algorithmic approach (4_{NTC-}). The importance of the interactions between the two approaches are not only reinforced by the present results, but they have parallels with the argument that parametric design allows rapid progress through algorithmic activities such as scripting or coding (Salim and Burry, 2010), while at the same its evaluation relies on the use of geometric processes. In addition, it is observed in the present study that expert designers used ‘E-Geometry’ (evaluating geometries) as a precursor to making changes to existing rules and/or parameters and vice-versa.

Furthermore, parametric design uses both the geometric and algorithmic level of designing. Thus the combined approach tends to use multiple interactions between the two interfaces as “triggers” for creating and breaking out of “reference frames”. These cross-frames are seen as a foundation to create opportunities for spontaneous ‘A-ha’ (Akin and Akin 1996) responses to design. Even though parametric thinking often highlights the algorithmic approach to design, geometric activities continue to play a significant role in supporting creativity in parametric design. In future studies, these interactions between the two levels of activities should be explored to identify specific patterns of interactions that can support creativity, in order to better learn, practise and teach parametric design.

- (2) *The text-based parametric design approach that produces more algorithmic activities, results in more unexpectedness during design, a quality which can also support creativity.*

Unexpectedness is a major characteristic of design creativity (Gero, 1996). It is also obvious that even experienced designers need to review the outcomes generated by the scripts (when using a text-based algorithm editor) using a graphical algorithm editor. This is because the text-based algorithm editors themselves are more complicated and can obstruct the geometric reasoning. It was observed in the present study that both 2_{ETC+} and 4_{NTC-} struggled with

trouble-shooting their scripts. However, this tortuous process may have an advantage in producing more unexpected outcomes, which in turn may be relevant to design creativity.

On the other hand, algorithms defined in the graphical algorithm editors clearly show the elements and their links graphically (see the “spaghetti links” in Figure 1). This way of designing is similar to Gero’s notion of “routine designing” where the expectation of what follows is defined by a clear schema. In contrast, the introduction of new scripts in the text-based algorithm editors may be closer to “non-routine designing” (Gero, 1996), an approach that supports unexpected discoveries (Akin, 1996) potentially evoking creativity. The different effects of these two types of algorithm editors and their association with the above design theories should be verified in future studies.

(3) In parametric design, the solution-driven approach (rather than the problem-driven approach) is more effective for supporting creative outcomes as well as divergent thinking.

The results of the current study are consistent with the findings of Kruger and Cross (2006) who indicate that the use of a solution-driven strategy produces a higher level of creativity (discussed in the Section 4.3.2). Parametric design solutions evolve through extensive iterations by modifying parameters and rules (algorithms). Parametric design processes also obviously enable the production of large numbers of design variations and are consequently capable of generating multiple design ideas (Iordanova et al., 2009). Thus, the assumption is that solution-driven methods facilitate divergent thinking, which in turn supports creativity.

However, it was observed in the present research that designers generated their schemata and solutions and edited them by creating and changing previous design parameters and rules. That is, they refined and restructured their design solutions by way of the act of editing what they have made before. Contrary to the spirit of this approach to cognitive design, it is difficult to view this activity as a solution-driven. Thus, further investigation, identifying the difference between solution-driven and problem-driven design approaches is necessary,

before the relationship between the two and creativity can be more conclusively examined.

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