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MASS CUSTOMISATION OF CREATIVE DESIGNS

John S. Gero

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1 Introduction

Among a nation's goals are competitive leadership in the international marketplace and excellence in industrial productivity. Superior design, a fundamental prerequisite for superior products and systems, is one of the keys for achieving these goals. Computer aids to design (computer-aided design) have the potential to unlock this key. Whilst the early work on computer-aided design concentrated largely on drafting and then geometric modelling, more recent research has focussed on the development of concepts and tools for design decision making [1]. Where all the design variables take numeric values the processes of simulation can be used during design analysis and evaluation. In some cases simulation can be used with symbolic valued variables. When, in addition, a set of goals or objectives or fitnesses can be expressed in terms of those variables, the processes of optimisation can be used and we have a design optimisation or optimal design problems [2]. Evolutionary systems have proven to be particularly useful in design optimisation [3]]. When the variables are symbolic rather than numeric, artificial intelligence methods have proven to be useful [4].

Whilst much of what we use and consume is designed for mass production, there is an increasing demand for individual products. Some of these we are familiar with, such as purpose-designed buildings; however, there is the potential today to direct design individualised artefacts based on direct marketing [5]. Thus, instead of buying a product that has already been designed and manufactured, it may increasingly become possible to specify individual requirements that result in individualised artefacts. This brings with it the need to be able to design such products. Whilst the current demand is for variations of existing designs there is expected to be a demand for innovative or creative designs that are not simple variations of existing designs. As a consequence there will be an increasing need to produce such designs on demand.

This paper presents a strategy, with appropriate techniques, to develop the capacity to mass produce creative designs – mass customisation of creative designs.

2 Mass customisation of design

2.1 Mass production

The concept of mass customisation of design is analogous to the concept of unit production within the framework of mass production. In mass production, the cost of the infrastructure for production is spread over increasingly larger runs of the same or very similar products. The components can be shared between families of artefacts in order to increase the size of production runs. Mass production has a history going back to the nineteenth century but is epitomised by the early twentieth century production of the Ford motor car. The same concept of the benefits of scale of production continue to underlie not only the motor car industry but many other industries including the computer chip and computer memory industries.

With the investment in infrastructure for mass production it becomes possible to move to a variant of mass production: batch production where the same production line is used for large batches of a single product within a family of products that draw components from the same set of components as all members of that family.

2.2 Mass customisation

It is possible to extend batch production down to the production of a single unit, hence unit production still using the same mass production facilities. Unit production offers the capacity for mass customisation [6], [7]. Each product is a variant from a family of products produced from the same components. Currently, a number of computer hardware suppliers offer the opportunity to “customise and build” to order.

2.3 Mass customisation of design

Mass customisation of design requires an analogous infrastructure in designing as exists in mass production – a production line for designs. Such an infrastructure exists in the form of design processes for parametric or variant design [8]. A variety of such processes exist ranging from design optimisation [2], through designing using knowledge-based systems [4]. More recently, robust search techniques have been introduced into the engineering design process [3].

In all of these approaches the design space is fixed at the outset. The design space can be thought of as being comprised of three subspaces: Function, behaviour and structure subspaces [9]. A description represents the product’s elements and their relationships, which are labelled *structure*. In designing, behaviour may be viewed in two ways. There is the behaviour of the structure, which is directly derivable from structure; it is how a structure performs in its environment in a measurable way. Transforming function to expected behaviours, provides the second view of behaviour. This provides the expectations that the product has to meet. Function has been defined in another context as “the relation between the goal of a human user and the behaviour of a system” [10]. Figure 1 shows the relationship between these three subspaces. These three subspaces constitute the state space of design.

Thus, we are able to produce mass customised designs on demand once we have specified the requirements, turned them into expected behaviours and decided on the variables that will be used to define the structure. From this point on the problem is one of finding values for the structure variables that optimise or satisfice the behaviours. In general, this form of mass customisation of designs produces families of products [11]. The design process searches the space of possible structures. Whilst the space of possible structures is defined by the decisions about what are the structure variables and any constraints on the ranges of those variables, whether those constraints are explicit or implicit.

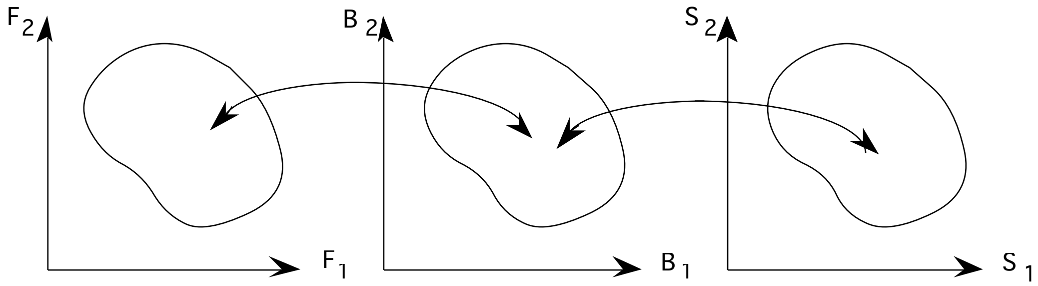

Figure 1. The three subspaces of function (F), behavior (B) and structure (S) which constitute the state space of designs, plus the locus of the transformations between them.

As we shall see later in this paper, the concept of a fixed space of possible structures plays an important role in our conception of creative designs. The space of possible structures is fixed by a human designer outside the formal design process in this form of mass customisation of designs.

3 The problem of mass design customisation of creative designs

It is convenient to characterise designing as routine or non-routine, although there are other ways of categorizing designing processes. *Routine designing*, in computational terms, can be defined as that designing activity which occurs when all the necessary knowledge is available. It may be more formally expressed as being that designing activity which occurs when all the knowledge about the variables, objectives expressed in terms of those variables, constraints expressed in terms of those variables and the processes needed to find values for those variables, are all known *a priori*. In addition, routine designing operates within a context that constrains the available ranges of the values for the variables through good design practice. Figure 2 show graphically the notion of the state space of routine designs being bounded by a set of a priori decisions and constraints.

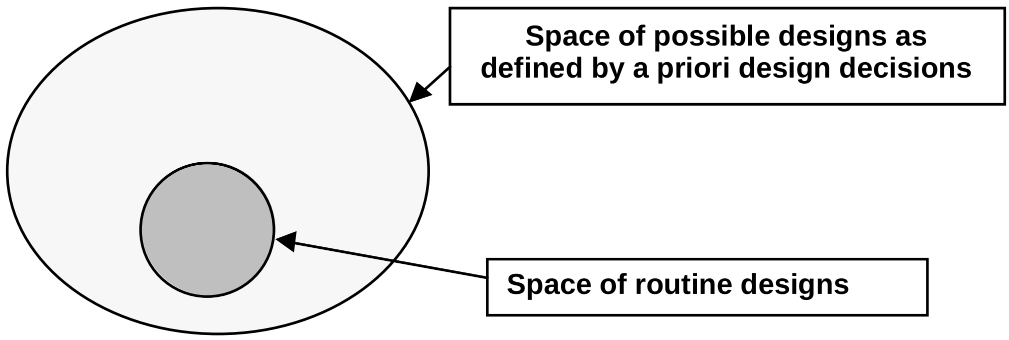

Figure 2. The space of possible designs is defined by the set of *a priori* decisions. The space of routine designs is a subset of those possible designs.

Non-routine designing can be subdivided into two further groups: innovative designing and creative designing. *Innovative designing*, in computational terms, can be defined as that designing activity that occurs when the constraints on the available ranges of the values for the variables are relaxed so that unexpected values become possible, Figure 3. This produces two effects, one for the design process and the other for the product or artifact.

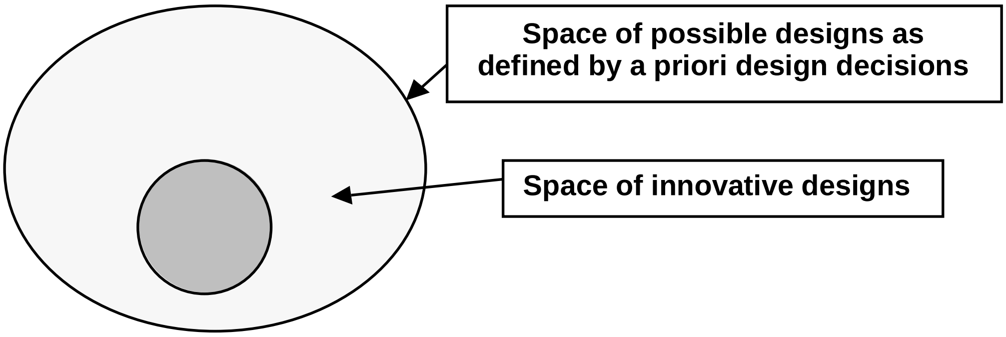

Figure 3. The space of innovative designs is a subset of the possible designs.

In terms of the design process, variable values outside the usual ranges have the potential to introduce unexpected as well as unintended behaviours that can only be brought into formal existence if additional knowledge capable of describing them can be introduced. For example, in designing a structural beam to carry a load across a gap there are standard depth-to-span ratios for different materials. If the depth of the beam is made much larger than these then there is the likelihood that the beam will buckle. However, if no buckling knowledge is applied to its design (and buckling is not normally considered in the design of such beams) then no buckling behaviour will be found. In terms of the artifact, innovative designing processes produce designs that recognizably belong to the same class as their routine progenitors but are also ‘new’.

Creative designing, in computational terms, can be defined as the designing activity that occurs when one or more new variables is introduced into the design. Processes that carry out this introduction are called “creative designing processes”. Such processes do not guarantee that the artifact is judged to be creative, rather these processes have the potential to aid in the design of creative artifacts. Thus, creative designing, by introducing new variables, has the capacity to produce novel designs and as a result extends or moves the state space of potential designs, Figure 4. In the extreme case a new and disjoint state space is produced that results in a new type of design. Creative designing has the capacity to produce such a paradigm shift.

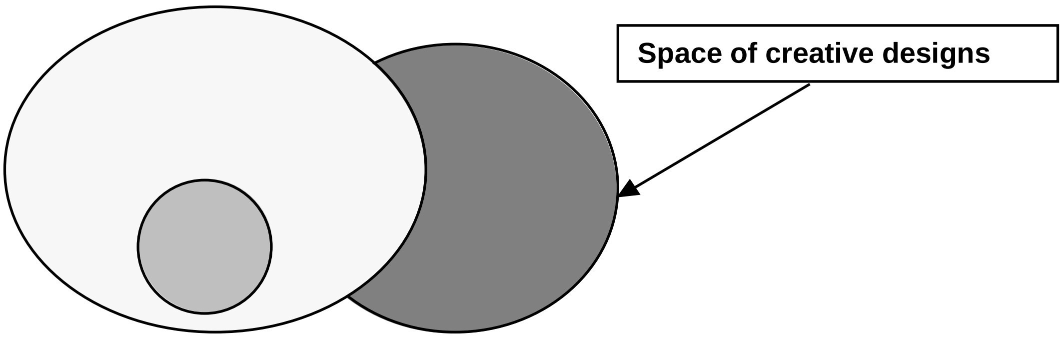

Figure 4. The space of creative designs is a superset of the possible designs, as defined by the set of *a priori* decisions.

The problem remains how is it possible to develop the infrastructure for the generation of creative designs so that it can be used for the mass customisation of creative designs. The mass customisation of routine designs is possible because we have such an infrastructure in the generic processes of design optimisation. Even though we might use different optimisation techniques we are using the same fundamental approach: searching a space of possible designs defined at the outset by the variables. In creative designing, since we aim to change the variables that are used to define the space of possible designs we cannot use such an approach. Further, in routine designing we know the performance of the techniques we apply. The performance is in terms of computational complexity of the search processes. In creative designing we need to be able to determine both the computational complexity of searching a novel state space and more importantly, the potential of a state space of possible designs in terms of the range of designs that can be generated within it.

4 Complexity measures for mass customisation of creative designs

Conceptually, modern design theory views the design process as a search in a predefined space of possible designs. This design space is implicitly fixed by defining its generator (a process that can generate any design in this space). Many choices for such a generic design generators are available – shape grammars [12], rule-based systems [4], and evolutionary systems [3] are examples. Thus, designing with a CAD system is then understood as running a search method coupled with this generator with decisions governed by a behaviour function.

This raises a fundamental question: how can design generators be compared? If the design generator is not fixed a priori but can be modified as part of the design process then a further question arises: how can two modifications of the generator be compared? Currently there are no adequate methods for this. Thus a test is needed which evaluates either the generator or the design space produced by that generator. This evaluation can produce a measure of the design potential of the corresponding space as well as a measure of the hardness of the typical search in this space. The higher the potential the more likely it is that creative designs will be generated (mass customisation of creative designs). The hardness of the search is the measure that describes the computational scalability of any search process. Once these measures are constructed then we are able to compare different design generators, to modify them so that they produces better design spaces, etc. A design space is typically a very large space (often unbounded) and the cost of constructing and evaluating any individual design in it can be high. A design space typically is also an ill-defined space, with no analytical models, no "good" properties available. This makes a direct evaluation of the space very difficult.

The approach we have adopted it to measure the complexity of a typical sample of designs in a state space produced by a creative designing process so as to use that as the basis for determination of the computational hardness and design potential of that state space of possible designs.

4.1 Complexity measures for designs

We take concepts from information theory [13] as the basis for a general approach to the development of measures of computational hardness and design potential both for individual designs and populations of designs. Design complexity measures have been used in axiomatic design [14], which postulates that the best design has the lowest information content. The structural design complexity measures, which were developed by the practitioners of axiomatic design [15], [16], are based on the application of the simplest tool of information theory - Shannon entropy - within a linear symbolic representation. This restriction to linear representations makes it inapplicable for a large majority of design problems, which have non-linear representations, where design descriptions are short, etc. As a consequence we will utilise some more modern tools of information theory (Lempel-Ziv complexity, approximate entropy) as estimators of design hardness and potential. Unlike Shannon entropy they are readily computable and meaningful even for fairly short descriptions.

4.2 Complexity measures for design spaces

Overall, we intend to use the notion of a family of design space generators. That is, a meta-generator exists, which has parameters that can be set to produce different generators. This comes from the work on families and individuals. A typical example of two families in say mechanical energy transmission design might be hydraulic systems and gear systems with spaces of individual designs within each family.

Once we have developed the means to measure the potential of design space and the hardness of designing in this space then we are in a position to control the modification of the generator so that it generates better design spaces. Thus a control strategy needs to be designed for generator modification that balances the increase in the hardness of design process against the gains due to increasing the potential of design space. Design processes are often modelled as randomised algorithms [17]. This gives rise to additional performance variability (beyond the performance variability caused by varying the design space) even when the design space they operate on is fixed and repeated trials are run on a single design space. This implies that there is an inherent risk associated with such design processes. This risk can be quantified, through an analogy with economic risk, as the standard deviation of its performance distribution. Hence, it is possible to interpret this situation as the estimation of the risk of getting a lower average performance in exchange for increasing certainty in obtaining a reasonable design.

4.3 Complexity measures as a basis for mass customisation of creative designs

We can work with individual designs and explore multiple representations of that design. Each different representation of a design produces a different complexity measure and hence a different potential. This notion of re-representation plays an important role in the production of novel designs [18]. Or we can work with a design space and sample designs within that design space. The complexity of individual designs can be measured from their qualitative (symbolic) representation [19]. The complexity can be calculated from both re-represented individual designs and from populations of designs. The results of these calculations can be used to measure both the hardness of future computations (ie how difficult it will be to search the space of possible designs) and the potential of the space of those designs (ie the variability that can be produced).

Then, based on either these measures we can carry out a statistical sampling of a range of representational spaces derived from individual designs or from a sampling of design spaces to determine which of them has more potential or we can use symbolic reasoning [4]. These measures can be used as one of the objectives or fitnesses for any generator that is a synthesis process capable of generating creative designs [20]. Once we have this we are capable of mass customising creative designs. Figure 5 shows an outline architecture of such a system where the complexity of the available designs in measured and used to control the generation of mass customised designs with individual requirements.

For example, the complexity of beam cross-sections generated using a rule-based system can be measured and that complexity used as a fitness in a genetic algorithm as the design generator. The complexity measure can be analysed to determine both the hardness and potential of the design space produced. If the fitness is set to maximise complexity then an increase in variability will result. As variability increases so does the potential for creative designs.

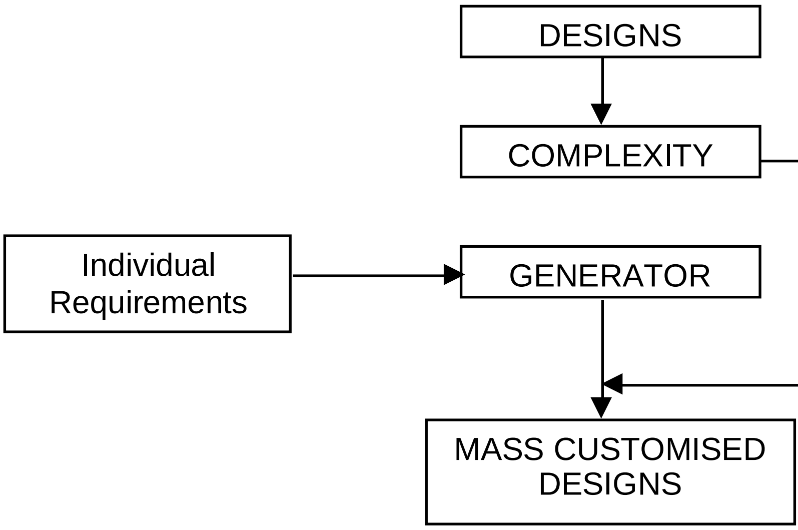

Figure 5. Outline architecture of a system for mass design customisation of creative designs

4.4 Discussion

Mass customising designs involves having the infrastructure for the mass production of designs so that individual designs can be produced on demand. In order to mass customise creative designs we need a richer infrastructure since we need to be able to determine the computational hardness and design potential of any design generator. This is too difficult a task, so we determine the hardness and potential of a space of designs by sampling individuals in that space and use measures of complexity as the basis of our results. We then use the results to control synthesis processes. As a consequence it becomes possible to produce creative designs on demand – mass customisation of creative designs.

4.5 References

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John S. Gero
Key Centre of Design Computing and Cognition, Department of Architectural and Design Science, University of Sydney, NSW, 2006 Australia, Tel: +61-2-9351 2328, Fax: +61-2-9351 3031, E-mail: john@arch.usyd.edu.au, URL: http://www.arch.usyd.edu.au/~john/

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