Complexity measures as basis for mass customization of novel designs

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Abstract. This paper presents a computational approach to the integration of mass customization into the design of novel solutions. It proposes the use of entropy as a function of the diversity of solutions that can be generated within a design space. This work demonstrates that the potential of design systems to generate novel solutions can be estimated using complexity measures. This principle is implemented in an evolutionary system for the design of automotive instrument panels that display situation-relevant information in configurations that adapt to traffic conditions and driving actions. This sample application shows that applying complexity maximization as a selection criterion in evolutionary design systems yields a large variety of solutions of high fitness. The paper also presents guidelines for future developments.

Keywords. Mass customization, evolutionary design, entropy, creative design

1. Introduction

Mass customization is a relatively recent move towards the individualization of mass-produced artifacts. Economies of scale and market expansion caused convergence in the production line in the early 1900s. In recent decades, however, it has been necessary to transform artifact production along four general dimensions: customer demand, consumption rate and volume, market factors, and technological progress (Broekhuizen and Alsem 2002). Customer factors such as heterogeneity, participation and changing expectations make mass customization necessary. Purchasing frequency, adaptability and commoditization determine the types of products to which mass customization applies. Market factors including saturation, variety and distribution enable mass customization. Lastly, information technology and production flexibility provide the means to carry out mass customization. To date the trend towards mass customization is clear in a number of industries but its impact in the design process remains limited.

One of the main design approaches to mass customization is the design of families of products and component design (Jiao and Tseng 1999). These methods can be defined as routine design since the space of solutions is fixed as a response or set of responses to perceived requirements (Gero 1990). As requirements change, a new design process is initiated with updated goals and a new fixed space is defined within which possible solutions exist. In contrast, mass customization of novel designs requires the synthesis of design spaces within which the selection of a variety of alternative solutions adapts to changing requirements. This paper presents a method to support the automated generation of novel designs.

Mass customization has been categorized in stages between pure standardization and pure customization as depicted in Figure 1. Whilst mass customization has become commonplace in a number of industries, most existing cases are instances of segmented, configured or tailored customization (Svensson and Barford 2002). In pure standardization, all stages from design to production, assembly, and distribution follow a 'Fordian' model. In segmented mass customization distribution channels are customized as in delivery and subscription systems. Assembly is customized in configured mass customization as in the automobile and personal computer industries. Further, in tailored mass customization production is customized –as in the case of prescription spectacles and engravings. In these three primary modes of mass customization, the design stage remains largely unchanged from the model of pure standardization, i.e., the design generator defines one or a set of fixed solutions to be produced, assembled and distributed in customized ways. Creative mass customization integrates the generation of novel solutions into the process by adapting the design process to changing requirements and objectives.

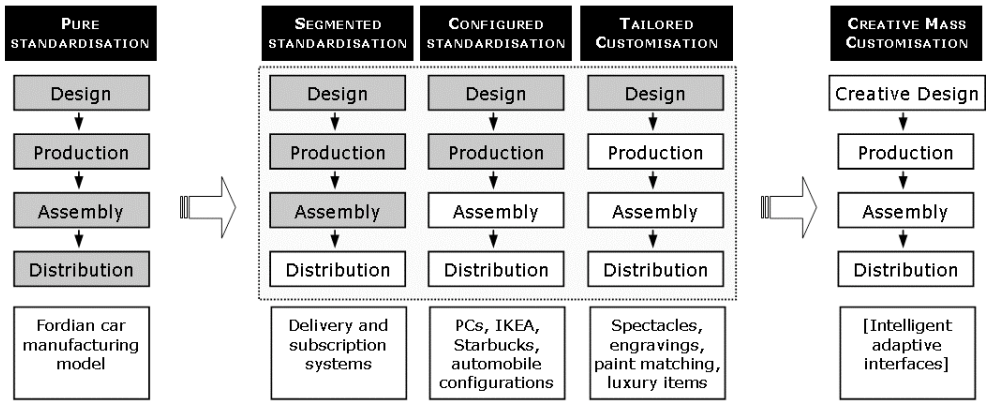


Figure 1 Mass customization types

Stages of mass customization need not be cumulative, so production can be customized for a product but not necessarily its assembly or distribution. To date, design stages are customized only in pure customization where every stage from design to delivery is specific to a unique case –as in the design of some high-rise buildings, racing cars, and spaceships. However, this is expensive and outside the scope of mass production. The extension of mass customization into design represents a key research agenda in design. This paper presents a method that integrates the automated generation of creative or novel solutions into a process of automated reconfiguration.

2. Mass Customization of Novel Designs

Creative design has been defined as a result of generative and evaluative processes (Sosa and Gero 2004). Two levels of evaluation have been identified: personal or individual and historic or collective (Boden 1994). Novelty is a relative value at similar scales: a solution is novel to the individual who has never seen it before, and it is novel for a group who agrees that there has never existed anything like it

before. What defines a novel solution is not contained within its internal characteristics but in the interaction of design and evaluation over time. For this reason the first requirement for an automated design generator of novel solutions is defined as: "a system that generates a number of alternative solutions subject to evaluation by an external process". In this strict sense, such systems generate 'potentially novel solutions'.

For a set of novel solutions to be considered potentially creative, they should satisfy the design requirements at hand at an acceptable level, but many may not satisfy all of them or not at the highest level. This is in part because design requirements are often contradictory, thus design can be characterized as a multi-objective problem. The second requirement for an automated generator of novel designs is that "all solutions generated satisfy to some degree the existing requirements and preferably also new and varying requirements". The Pareto-optimal or non-dominated set of solutions generated consists of all those solutions that cannot be further improved without having a detrimental effect on at least one of their objectives.

These alternative solutions need not exclude each other, so the third requirement is "more diverse solutions are preferable". Complete agreement by evaluators cannot be expected, so the system should provide for a range of possible evaluation criteria. When a solution meets the requirements without matching the possible expectations of evaluators, then it can be considered as potentially creative or novel. Under such a view, mass customization of creative designs supports customized evaluations of creativity. Figure 2 shows the change in process by which an automated design generator (gen in Figure 2) produces solutions considered to be creative by groups of evaluators (evals in Figure 2). Whilst in mass production the generator satisfies a set of collective or shared requirements with a solution that is jointly evaluated as creative or novel, a mass customization design generator targets individualized requirements to generate solutions that are considered as creative by smaller evaluation units (i.e., segmentation). A design generator of novel solutions for mass customization should model 'different but related' sets of requirements in order to define a design space and measure its novelty potential.

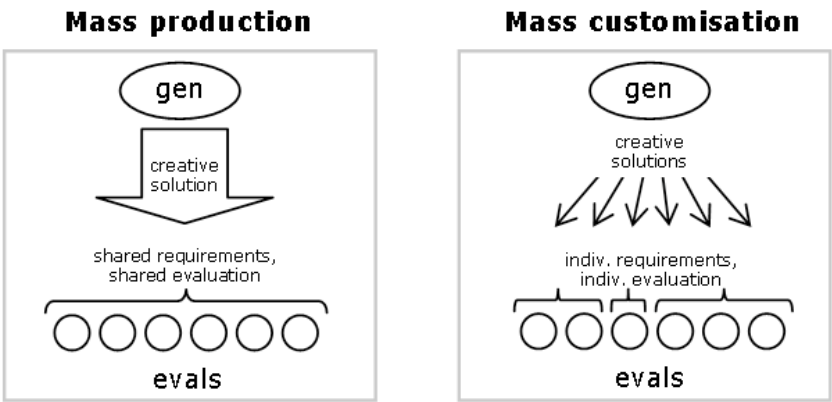


Figure 2. Mass customization of creative designs as customizing solutions for different evaluators

A number of generative systems for the first type of design model shown in Figure 2 exist including evolutionary systems, analogy, and case-based systems (Bentley 1999; Navinchandra 1991; Tseng and Jiao 1997). The underlying principle of these types of generators is to find solutions by searching a design space and converging onto a single solution or more specifically into a single area of the search space where a solution or a family of solutions exists. However, mass customization of novel designs may require a complementary process of divergence causing the system to find a number of alternative points in the design space, some of which may contain solutions considered as novel and even creative by evaluators.

This is not a new requirement for such systems: niching strategies in evolutionary systems are a good example of seeking sets of multiple optima (Sareni and Laurent 1998). One such strategy makes use of entropic measures to guide search based on an analogy with the thermodynamic behavior of an ideal gas undergoing expansion in an enclosure (Farhang-Mehr and Azarm 2002). In that case entropy is used to sample a population that evolves as it approaches the Pareto frontier in order to achieve maximum coverage of the solutions. In this paper we present an alternative approach to mass customization of novel designs using entropy measures and present guidelines for future developments.

3. Complexity Measures

The potential of a design space can be estimated as a function of the diversity of designs that can be generated within it. Diversity of a design space is a function of its complexity which can be measured by its information content. Increasing the complexity of the design space explicitly increases the diversity and divergence and this is likely to result in the production of design novelty. Decreasing the complexity of the design space explicitly results in convergence and the production of routine designs by restricting design variation. Complexity can be estimated using the notion of Shannon entropy (Shannon 1948) as a measure of the information content of a variable with a given probability distribution. More technical definitions of entropy and complexity in design have been discussed elsewhere (Gero and Kazakov 2001). In addition, other complexity measures apart from those based on entropy (Edmonds 1999) could be applied in a similar approach in the future.

Perplexity can be used to compare the entropy between two groups of designs within a design space. Perplexity is defined as entropy to the power of 2. The higher the perplexity, the further apart are individual solutions from each other and the less similar are the designs being compared and the higher their diversity and potential novelty.

This paper presents a computational approach to sampling based on the Monte Carlo Markov Chain (MCMC) method shown to converge well and to produce accurate sample distributions (Gilks et al. 1996). Without accurate sample distributions, any resulting measure may be biased. With an accurate distribution of samples, the design space can be repopulated in order to maximize its complexity. The resulting design space is more likely to contain a number of alternative yet

adequate solutions. This is demonstrated in a design example using an evolutionary system in the next section.

4. Example of Mass Customization of Novel Designs

To demonstrate the use of complexity measures in generating novel designs, we implement an evolutionary design system (Bentley 1999). Genetic algorithms (GAs) use Darwinian principles of natural selection to search a design space. These algorithms are based on a number of evolutionary metaphors. An initial population is normally defined as a set of possible solutions drawn at random. Every generation is evaluated by a function that assigns each individual solution a fitness score. Based on this score, individuals are selected to contribute to the next generation of solutions. Applying genetic operators based on their biological counterparts, the algorithm combines different genes from the selected individuals to form the new generation and introduces mutation as random genetic variations. A number of possible strategies have been developed for every step of the process: populations can be seeded with known solutions and different reproduction and selection operators can be combined (Goldberg 2002; Vose 1999). In this paper we first use complexity measures based on entropy to initialize design spaces with high genetic diversity and then apply the same principle to selection.

As a case example for mass customization of novel designs, an evolutionary system is built to generate adaptive instrument panels for new automobiles. Car manufacturers offer a range of configurable options of their product lines but only minor alternatives to dashboard design. There are hundreds of potential combinations of exterior and interior colors, trims, engines and extra options, but often only one type of instrument panel or minimum variations for each model line. Ongoing instrument panel research is aimed at increasing the information content available to the driver whilst keeping distraction to a minimum (Campbell et al. 1998). The trend in design of vehicle instrument panel design is to include navigation systems, vehicle diagnostics, and road information in a configurable interface that responds to user requests and to variable vehicle and road conditions.

Given the dynamic nature of driving in different situations, the design of these information displays is a non-trivial task. Figure 3 shows recent examples of digital instrument panel design in which adaptive interfaces could be applied (Siemens VDO 2002). Rather than present all information in a cluttered analogue display, this type of design problem calls for the use of adaptive digital interfaces that present relevant information for a given situation in real-time including state of vehicle systems, road signage, road work, weather conditions, navigation assistance, and communication messaging.

The example system is implemented in Java2 and extends the JGap library (Rotstan 2004) to include our customized sampling and selection operators. Chromosome structures are represented by integer and boolean arrays as shown in Figure 4(a). Boolean genes define group elements such as layout, arrangement, text labels, audio feedback, animations, and design templates. Integer genes represent characteristics of individual elements including their location and size, foreground, background and auxiliary colors, font properties, icons, and decorative elements. Figure 4(a) shows in detail the genetic representation used in this example. Some

genes are represented as Booleans and others as integers which represent different units such as two-dimensional coordinates, pixel and line size, color percentages, or catalog number. Figures 4(b) and 4(c) show two exemplary phenotypic expressions that illustrate visual values such as layout and array type, sizes, direction, color, and outline thickness.

Figure 3 Recent instrument panels by Siemens VDO Automotive (Siemens VDO 2002).

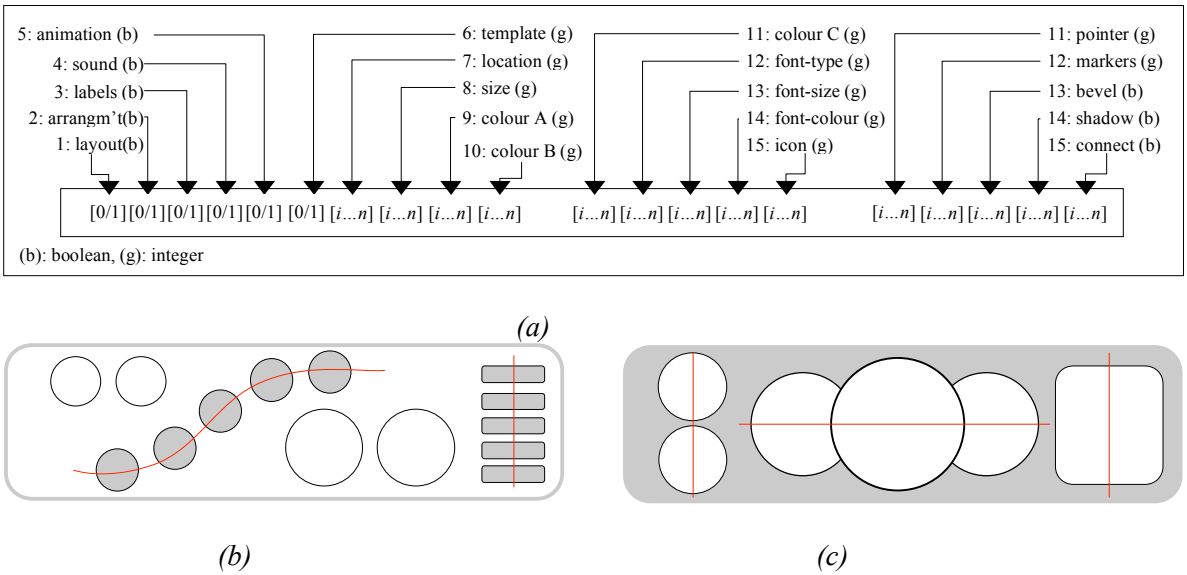


Figure 4 (a) Chromosome representation of instrument panel designs. Two sample solutions with (b) 14 and (c) 6 information elements.

These adaptive instrument panels display situation-relevant information in configurations that adapt to road and traffic conditions and driving actions

including explicit driver requests. The fitness function used in this design generator includes a general heuristic for 'good design' principles that evaluates compatibility between chromosomes (i.e., layout and media, use of text and animations, etc). On top of this, two different fitness functions are tested that generate different types of designs: the first function can be used in emergency situations when a few important 'chunks' of information are prioritized. This function yields hierarchical arrangements of information elements and maximizes variation between elements' locations, sizes, colors, labels, and icons. The second function applies to familiar driving situations where no single 'chunk' of information is a priority but rather a number of complementary instructions and system states are offered. This latter function minimizes variation between elements and favors simple layouts with more homogeneous sizes, colors, icons, and fonts. Whilst the first type of function can be associated to driving situations with high information load such as urban contexts, novice driving skills, rental vehicles, and unfamiliar driving locations, the second applies to situations with less frequent information updates such as highway environments, experienced drivers, and well-known areas. In the following subsections the different genetic operators used in the system are described.

4.1 Sampling

The sampling algorithm used is an instance of the more general Metropolis-Hastings algorithm (Martinez and Martinez 2002). It starts by building a random design space (i.e., a 'population' in GA terms) of the specified size and by setting a target rate threshold to evaluate for stationary distribution. Until such threshold, or a given iteration limit, is reached, the algorithm repeatedly replaces a random individual at a time and estimates the entropy of the modified population. If complexity increases with the replaced individual, then the increase rate represents the updated distribution state. When this rate is less than the given threshold, the algorithm stops and yields a new population with high complexity that further cycles would be likely to increase only marginally. In pseudo-code the algorithm is described as:

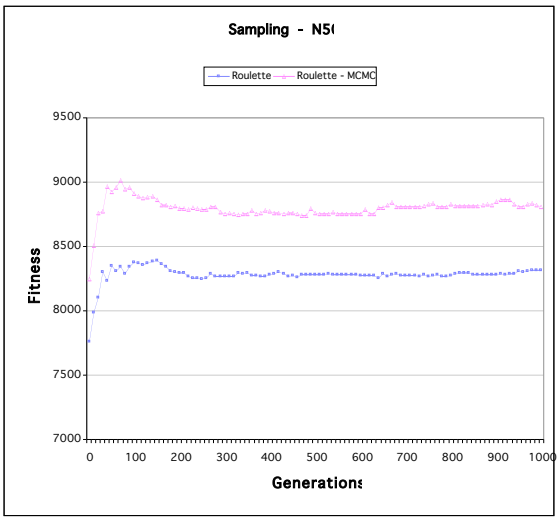
```
generate random population
while (rate > threshold)
   replace random individual
   estimate complexity of population
   if (complexity increases) rate = complexity(t) -
complexity(t-1)
   else restore individual
end while
```

The resulting design space is used in the evolutionary system using standard genetic operators including single-point crossover, mutation rates of 0.01, natural reproduction, and roulette-wheel selection (Vose 1999).

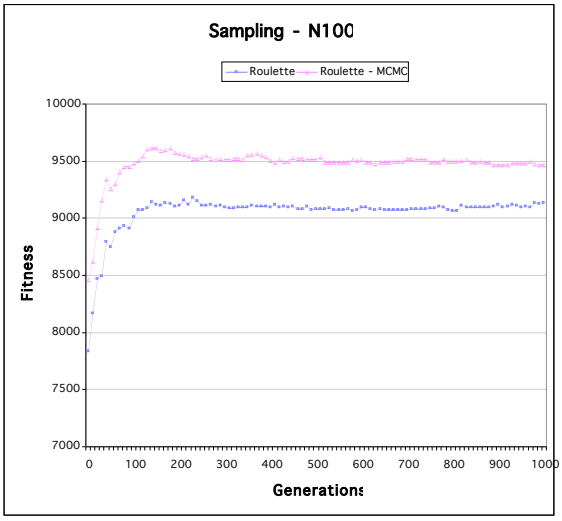
Sampling is tested in experiments of 30 system runs with control pseudo-random seed generators. This allows for the comparison of the effects of entropy sampling against random sampling in the same set of cases. Two experiments are conducted where the size of the design space or population (N) is varied from N =

50 to N = 100. Smaller populations yield solutions with low fitness due to the lack of sufficient genetic material. Larger populations do not produce qualitatively different results and rapidly become computationally expensive. The system is run over 1,000 generations because trials showed that this GA tends to convergence after this limit. The system uses an implementation of the Mersenne-Twister random number generator (Hoschek 2002) and uses the JSci library to calculate population entropy (Hale 2004).

Results demonstrate the significant effects of sampling using complexity measures especially related to fitness. When entropy sampling is used, the evolutionary system generates solutions of consistently higher fitness. Figure 5(a) plots fitness development over time in populations of size 50 (N = 50) and Figure 5(b) in populations of size 100 (N=100). Initial fitness is higher when the complexity of the design space is maximized, and fitness continues to increase until the GA converges. After this point only the effects of occasional mutation can be seen in both curves.



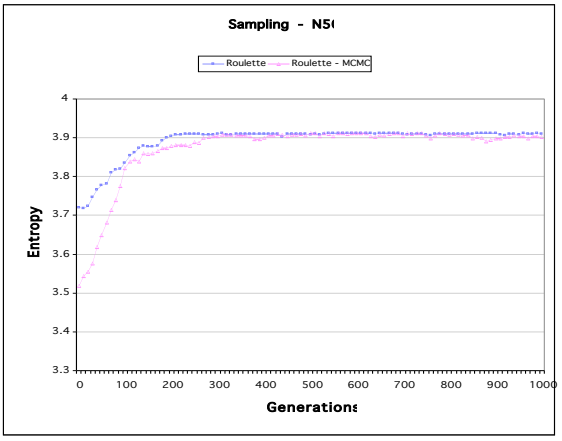
(a)



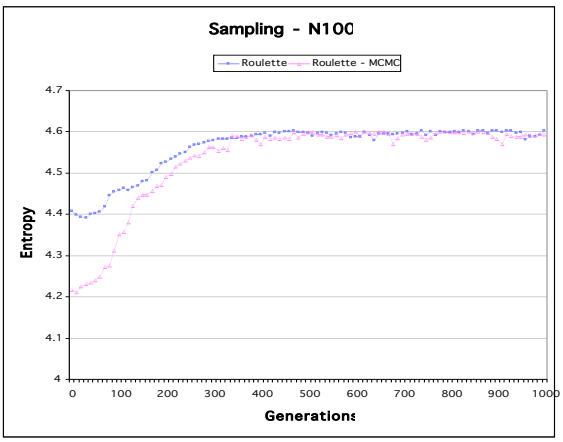
(b)

Figure 5 Comparison of fitness development over 1,000 generations of random sampling and entropy sampling. (a) Design space size N = 50, (b) N = 100

This indicates that entropy sampling is more effective in producing designs of higher quality. However, the number of total solutions is not significantly different when compared to random initial populations. The reason for this becomes apparent when population entropy is plotted over time, Figure 6. The entropy of the initial population (generation = 0) is considerably lower in design spaces where complexity is maximized. However, this advantage is rapidly lost in subsequent generations until both cases reach convergence in a set of solutions. In sum, entropy sampling aids the GA to find better but not more regions in the landscape.



(a)



(b)

Figure 6 Comparison of entropy development over 1,000 generations of random sampling and entropy sampling. (a) Design space size N = 50, (b) N = 100

An apparent reason for the rapid increase of entropy is that the system uses standard GA operators, in particular roulette-wheel selection. Under this selection strategy, the fittest individuals of a generation are more likely to be chosen to transmit their genetic features into the following generation. As a consequence, gene combinations that receive low fitness values tend to be lost. In other words, the key effect of such a selection mechanism is a rapid diversity decrease. As a result, it became necessary to consider an alternative selection operator, which is described in the following subsection.

A final note on entropy sampling is that the algorithm rapidly becomes computationally expensive since it calculates the population entropy at every iteration. This makes the use of entropy sampling impractical in very large design spaces.

4.2 Selection

A selection operator based on entropic measures was first tested based on the following strategy. At every generation, individuals are selected as a function of population complexity. With an iteration limit equal to the size of the population, a random individual is continuously replaced with a random entry. At every iteration, if population complexity increases, the replacement is selected, otherwise the replaced individual is selected. The solutions generated by the system with this selection operator were fewer and of lower fitness. This mechanism seemingly concentrates on dispersing the sample and prevents the GA from converging. In order to guide the process, an elitist strategy is integrated into this process (Thierens 1997). In this case, a small ratio (0.05) of the fittest solutions is selected for the next generation, whilst the rest of the design space (0.95) is populated with individuals that maximize complexity following the strategy described above. The modified entropy selection operator is defined as:

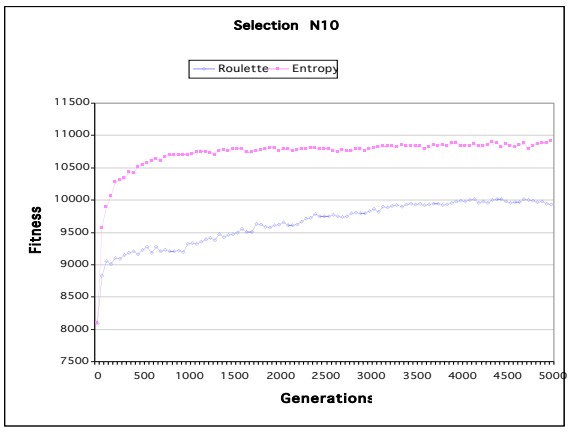
```
sort population by fitness
select top 0.05 individuals
```

```
for (population size * 0.95)
   replace random individual
   estimate complexity of population
   if (complexity increases) select new individual
   else restore individual
end for
```

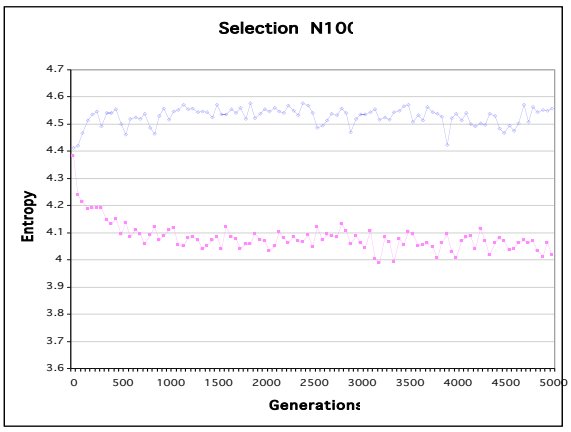
Entropy selection is tested in experiments of 30 system runs with control pseudo-random seed generators. This enables comparison of the effects of entropy selection with roulette-wheel selection in the same set of cases. A range of other selection operators were also compared including Boltzmann and pure elitism (Vose 1999) which produce only marginally better results than roulette-wheel when compared to entropy selection. Experiments were carried in design spaces of size 100 (N =100). The system is run over 5,000 and 50,000 generations. The system uses an implementation of the Mersenne-Twister random number generator (Hoschek 2002) and uses the JSci library to calculate population entropy (Hale 2004).

Results demonstrate the effect of selection based on complexity measures. Figure 7(a) plots fitness development over 5,000 generations. It shows that in both cases populations start at an equivalent fitness level, but entropy selection rapidly increases fitness levels. Figure 7(b) plots population entropy over the same period showing that entropy not only does not increase as in the experiments with sampling, but keeps decreasing over generations. The complexity of the design space keeps increasing as the GA combines exploration of promising regions with exhaustion of fit regions in the landscape.

This combination of elitism and complexity maximization causes a type of 'dispersion with direction' selection in which the fittest solutions serve as 'anchors' whilst other alternative regions of the design space are continuously explored. The overall effect is one of protecting good genetic material and combining it with constant genetic diversity.



(a)



(b)

Figure 7 Comparison of (a) fitness and (b) entropy development of entropy selection and roulette-wheel selection. Design space size N = 100 run over 5,000 generations.

In these experiments trends stabilize after 5,000 generations as shown in Figure 8 in a design space of size 100 (N = 100) run with roulette-wheel selection over 50,000 generations.

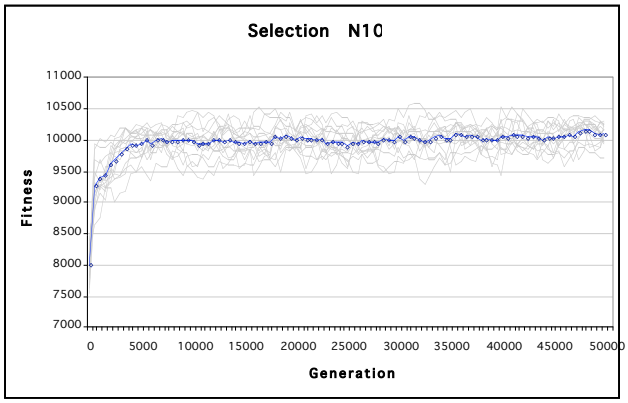
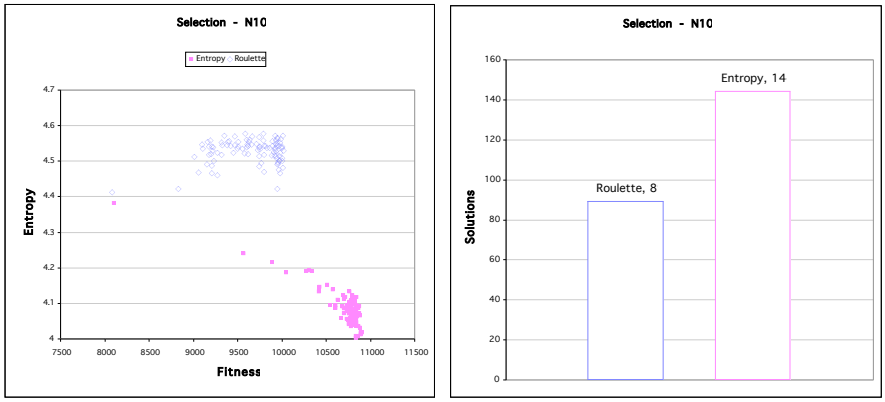


Figure 8 Fitness development over 50,000 generations showing GA convergence

To better understand the relationship between fitness and entropy Figure 9(a) plots entropy over fitness for both selection operators: roulette-wheel and entropy selection. The former shows a positive correlation between entropy and fitness: as fitness increases so does entropy, up to a limit at which fitness stops increasing. In contrast, there is an inverse correlation in entropy selection between entropy and fitness. As fitness increases, entropy tends to decrease until both vary only marginally. Figure 9(b) plots the mean number of solutions generated by the two selection operators. Roulette-wheel selection yields a mean of 89 solutions per case whilst entropy selection yields a mean of 144, a 62% increase. These experiments show that complexity measures are an appropriate basis for design generators where a diverse set of alternative and appropriate solutions is required. The effect of complexity measures on sampling is mainly qualitative. When used to guide a

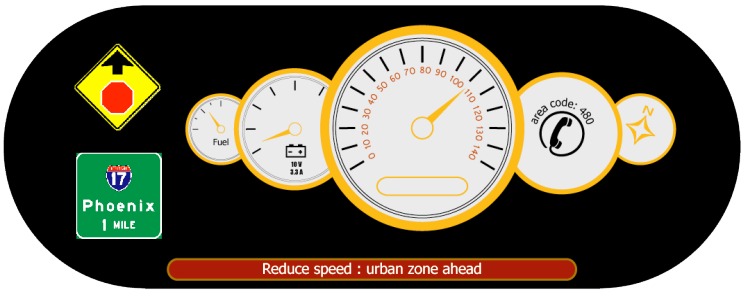
design system, their effects are both quantitative and qualitative, i.e., a larger variety of better alternative solutions is generated. These results are consistent between the two variations of fitness functions described earlier demonstrating that the principle of maximizing complexity is domain independent and is likely to be of relevance in a range of multi-objective design problems.



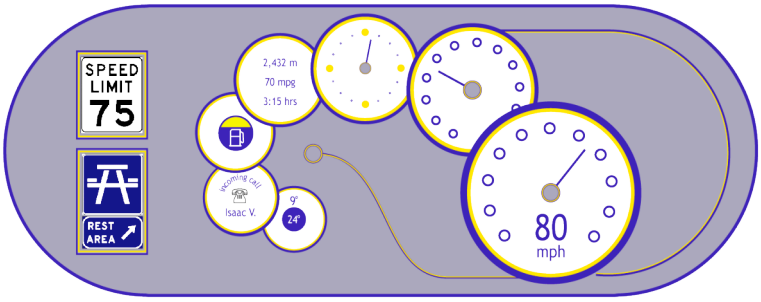
(a) *(b)*

Figure 9 Comparison of (a) entropy over fitness and (b) mean number of solutions generated by roulette-wheel and entropy selection operators.

Figure 10 shows two sample instrument panel designs generated by the system based on the type and amount of information selected by the experimenter. The actual phenotypic representation is determined as explained in the first paragraphs of section 4. The sample in Figure 10(a) gives high priority to information related to speed, selects a linear layout and contrasting colors and a text message to suggest the driver to reduce speed as road signage indicates a zone of slow speed ahead. In contrast, the sample panel in Figure 10(b) displays additional information in a circular layout and extra decorative elements. The transition from the resulting Pareto set to any customized unique solution like those shown here is determined by factors such as user's preference, driving conditions and practices. For instance, based on GPS readings, the vehicle display can adapt to local traffic laws that often change between neighboring countries or states.



(a)



(b)

Figure 10 Sample instrument panel designs.

The design of adaptive interfaces is a complex problem that can be applied to other types of monitoring displays including online information delivery and library indexing (Gavrilova and Voinov 1998). Adaptive information displays represent a potential solution to the type of accidents ascribed to unrecognized or improperly interpreted instrument readouts. Adaptive displays can adapt in a timely manner to the relevant information and the corresponding driving conditions. For these types of problems, the use of complexity measures for mass customization of designs is relevant because several regions of the design space defined at design time can provide appropriate customized solutions at use time under a large range of driving situations.

5. Discussion and Future Work

Mass customization has focused on the individualization of distribution, assembly and production of mass-produced artifacts. In comparison, the design process has remained largely unchanged from the days of pure standardization. In existing cases of mass customization, designers generate a fixed set of solution components to be combined for the final product. Mass customization of novel designs requires the automated generation of qualitatively different products. This paper has demonstrated that the potential of a design system to generate novel solutions can be measured by the complexity of the design space. This idea has been implemented in an evolutionary system for the design of adaptive automotive instrument panels. It is shown that applying complexity maximization as a selection criterion in evolutionary algorithms yields a large variety of solutions of high fitness.

The combination of elitism and complexity maximization implemented in this system causes a type of 'dispersion with direction' selection in which the fittest solutions serve as anchors whilst other alternative regions of the design space are continuously explored. The overall effect is one of protecting good genetic material and combining it with constant genetic diversity. The main conclusions of the work presented in this paper are:

a) complexity measures are useful to guide sampling techniques of automated design generators that seek to increase quality of solutions, and

b) complexity measures present advantages for selection criteria of automated design generators that seek to increase variety and quality of solutions

Future work will be directed at transforming the design space by using the resulting set of solutions to further generate novel designs. Interpolation between these solutions is a feasible way to produce more designs that are "between" the good designs generated (Gero and Kazakov 2001). This work could be further validated by applying other complexity measures than those based on entropy (Edmonds 1999).

Modern design theory views the design process as a search in a predefined space of possible designs (Gero 2000). This design space is implicitly fixed by defining its generator (a process that can generate any design in this space). This notion of design space has played an important role in formalizing designing and the processes that can be computationally implemented (Braha and Maimon 1997; Kalay and Carrara 1994). Many choices for design generators are available – shape grammars (Stiny 1993), rule-based systems (Coyne et al. 1990), and evolutionary systems (Bentley 1999) are some well-known examples that are used in practice. Less well known are generators that modify or change an existing design space; these include analogy (Gero and Kazakov 1999; Navinchandra 1991; Qian and Gero 1995; Zhao and Maher 1992), adaptive evolutionary systems (Gero and Kazakov 2001), first principles (Williams 1990), emergence (Saunders and Gero 2002; Stiny 1993) and variable expansion (Aelion et al. 1992). The importance of these less common generators is that unlike the well-known generators, they have the capacity to produce novel designs, designs that are not simple variants of each other.

This research lays the foundation for the determination of generators with the capacity to mass produce customized designs that are not simple variants of existing designs, i.e., the potential to produce novel designs. Using these concepts it will be possible to select and use generators that are capable of expanding the range of individually designed products in an automated manner, i.e., to mass customize novel designs.

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References

Aelion V, Cagan J and Powers G, 1992, "Input variable expansion - an algorithmic design generation technique", *Research in Engineering Design*, **4**(2), 101-114.

Bentley P, 1999, *Evolutionary Design by Computers*, Morgan Kaufman, San Francisco.

Boden MA, 1994, *Dimensions of Creativity*, MIT Press, Cambridge.

Braha D and Maimon O, 1997, "The design process: Properties, paradigms, and structure", *IEEE Transactions on Systems, Man & Cybernetics: Part A*, **27**(2), 146.

Broekhuizen T and Alsem K, 2002, "Success factors for mass customization: a conceptual model", *Journal of Market-Focused Management*, **5**(3), 309-330.

Campbell JL, Carney C and Kantowitz BH, 1998, Human Factors Design Guidelines for Advanced Traveler Information Systems (ATIS), Federal Highway Administration, Department of Transportation USA,

Coyne R, Rosenman MA, Radford AD, Balachandran MB and Gero JS, 1990, *Knowledge-Based Design Systems*, Addison-Wesley, Reading.

Edmonds B, 1999, Syntactic Measures of Complexity, PhD Thesis, *University of Manchester*, UK.

Farhang-Mehr A and Azarm S, 2002, "Entropy based multiobjective genetic algorithm for design optimization", *Structural and Multidisciplinary Optimization*, **24**(5), 351-361.

Gavrilova T and Voinov A, 1998, "User-centered design of adaptive interfaces for digital libraries", *in* C Nikolaou and C Stephanidis (eds.), *Research and Advanced Technology for Digital Libraries*, Springer, New York, pp. 693-695.

Gero JS, 1990, "Design prototypes. A knowledge representation schema for design", *AI Magazine*, **11**(4), 26-36.

Gero JS, 2000, "Computational models of innovative and creative design processes", *Technological Forecasting and Social Change*, **64**(2-3), 183-196.

Gero JS and Kazakov VA, 1999, Using analogy to extend the behaviour state space in creative design, *in* JS Gero and ML Maher (eds.) *Computational Models of Creative Design IV, Key Centre of Design Computing and Cognition*, University of Sydney, Australia, pp. 113-143.

Gero JS and Kazakov VA, 2001, "A genetic engineering extension to genetic algorithms", *Evolutionary Systems*, **9**(1), 71-92.

Gilks WR, Richardson S and Spiegelhalter DJ, 1996, *Markov Chain Monte Carlo in Practice*, Chapman & Hall, London.

Goldberg DE, 2002, *The Design of Innovation: Lessons from and for Competent Genetic Algorithms*, Kluwer Academic, Boston.

Hale M 2004, *JSci - A science API for Java*, http://jsci.sourceforge.net/ accessed on 12/2004.

Hoschek W, 2002, *Colt 1.0.3 Distribution: Open Source Libraries for High Performance Scientific and Technical Computing in Java*, http://cern.ch/hoschek/colt accessed on 08/2004.

Jiao J and Tseng MM, 1999, "A methodology of developing product family architecture for mass customization", *Journal of Intelligent Manufacturing*, **10**(1), 3-20.

Kalay YE and Carrara G, 1994, *Knowledge-Based Computer-Aided Architectural Design*, Elsevier, Amsterdam.

Martinez WL and Martinez AR, 2002, *Computational statistics handbook with MATLAB*, Chapman & Hall/CRC, Boca Raton.

Navinchandra D, 1991, *Exploration and Innovation in Design: Towards a Computational Model*, Springer-Verlag, New York.

Qian L and Gero JS, 1995, An approach to design exploration using analogy, *in* JS Gero and ML Maher (eds.) *Computational Models of Creative Design*, University of Sydney, Key Centre of Design Computing, pp. 3-36.

Rotstan N, 2004, *JGAP: A genetic algorithms package in Java*, http://jgap.sourceforge.net/ accessed on 12/2004.

Sareni B and Laurent K, 1998, "Fitness sharing and niching methods revisited", *IEEE Transactions on Evolutionary Computation*, **2**(3), 97-106.

Saunders R and Gero JS, 2002, "How to study artificial creativity", *Proceedings of the Fourth Conference on Creativity and Cognition*, ACM Press, Loughborough, UK, pp. 80-87.

Shannon C, 1948, "A mathematical theory of communications", *Bell Systems Tech*, **27**, 379-423.

Siemens VDO, 2002, *Siemens webzine Future Spring 2002: Personalized cars*, http://w4.siemens.de/FuI/en/archiv/pof/heft1_02/artikel11/index.html accessed on 12/2004.

Sosa R and Gero JS, 2004, "A computational framework for the study of creativity and innovation in design: Effects of social ties", *in* JS Gero (ed.) *Design Computing and Cognition '04*, Kluwer Academic Publishers, Dordrecht, pp. 499-517.

Stiny G, 1993, "Emergence and continuity in shape grammars", *in* S van Wyk and U Flemming (eds.) *CAAD Futures 1993*, Springer, pp. 37-54.

Svensson C and Barford A, 2002, "Limits and opportunities in mass customization for 'build to order' SMEs", *Computers in Industry*, **49**(1), 77-89.

Thierens D, 1997, "Selection schemes, elitist recombination and selection intensity", *in* T Bäck (ed.) *Proceedings of the 7th International Conference on Genetic Algorithms ICGA-97*, Morgan Kaufmann, pp. 152-159.

Tseng MM and Jiao J, 1997, "Case-based evolutionary design for mass cutomization", *Computers & Industrial Engineering*, **33**(3/4), 319.

Vose MD, 1999, *The Simple Genetic Algorithm: Foundations and Theory*, MIT Press, Cambridge.

Williams BC, 1990, Invention from first principles: an overview., *in* PH Winston and S Shelard (eds.), *Artificial Intelligence in MIT: Expanding Frontiers*, MIT press, Cambridge, pp. 430-563.

Zhao F and Maher ML, 1992, "Using network-based prototypes to support creative design by analogy and mutation", *in* JS Gero (ed.) *Artificial Intelligence in Design '92*, Kluwer, pp. 773-793.

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