Title:
Customer-Centered Design Sampling for CAD Products Using Spatial Simulated Annealing

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Introduction:
Customer-centered design [3,4] is an emerging field in engineering and industrial product development process. The product that is developed should satisfy the customers' needs not only through its performance but also through its external appearance, thus leading to its low risk of market failure. Therefore, a tool which can automatically generates variety of designs for a product based on the customer preferences can be beneficial for engineers and product designers. The objective of this study is to develop a tool that can produce variety of designs options within the costumers' design preferences, thereby creating customer-centered designs for the customers. For this purpose, sampling of designs for a given CAD product in its predetermined design space can be very beneficial and can let the designers to produce creative design by letting them escape from the traditional time-consuming design process.

A sampling technique is proposed in this paper which is based on spatial simulated annealing [1] algorithm and called SSA Design Sampler (SSA-DS). This technique automatically searches and generates N number of design variations for a CAD model in its predetermined constrained or unconstrained design space. A given CAD model is first parameterized by defining the n number of design parameters and each design parameter represents a coordinate in the design space. The range of each design parameter x_j (where $j = 1,2,\ldots,n$) is specified by defining its upper and lower bounds. The design parameters and their bounds form the $n - dimensional$ design space, and each design parameter defines a dimension in the design space. SSA-DS samples designs based on the space-filling criterion, which is achieved by utilizing Audze-Eglais potential energy [5].

In order to validate the performance of SSA-DS in constrained and unconstrained spaces, a wine glass model is utilized which consists of five design parameters ($n = 5$), and therefore they form a 5-dimensional design space. For the wine glass model, SSA-DS is first utilized to create initial designs in unconstrained design space. On this basis of these initial models, customer preferences in terms of external appearance of the product are learned via one-to-one interviews with selected participants, which are recognized as customers in this study. Initial designs generated by SSA-DS from unconstrained design space were then shown to the participants one by one to learn whether they liked or disliked them. Next, the reasons behind their likes and dislikes of the designs were inquired. In this way, the participants' preferences are quantized and are represented by geometric constraints.

These geometric constraints divide the design space into two sub-spaces. First, one consists of customer-centered designs which satisfy the geometric constraints that are learned via one-to-one interviews. Other one is composed of non-customer-centered designs which violate the geometric constraints. After learning the customer preferences, SSA-DS is utilized once again in the constrained design space to generate N number of customer-centered designs. Fig. 1 shows the flow diagram for the generation of customer-centered designs through the proposed SSA-DS technique.

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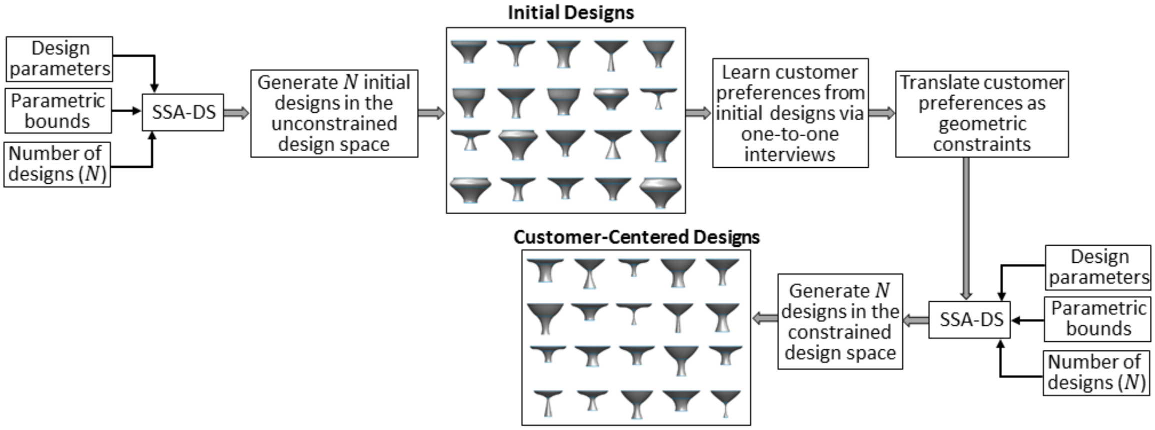

Fig. 1: Flow diagram for the generation of customer-centered designs through SSA-DA technique.

<u>The SSA-DS Technique:</u>

SSA-DS utilizes the Audze-Eglais potential energy U (see Eqn. 1) as a fitness function. The U has to be minimized in order to sample N space-filling designs for a given CAD model.

$$U = \sum_{p=1}^{N} \sum_{q=p+1}^{N} \frac{1}{\sum_{j=1}^{n} (\bar{x}_{p,j} - \bar{x}_{q,j})^2} \tag{1}$$

$\bar{x}_{p,j}$ and $\bar{x}_{q,j}$ are the *scaled* parameter values for the j^{th} dimension of the designs p and q, respectively, which are obtained by scaling design parameter values between 0 (for parameter's lower bound) and 1 (for parameter's upper bound).

The SSA-DS starts the generation of space-filling designs by sampling N initial random designs in the design space. A restricted distance Hdecreases with the decay of simulated temperature T. The temperature T decreases with the rate S after every Markov chain. Each initial design is perturbed continuously in order to generate new candidate design. The perturbation operates as follows: First, a random design from the initial N designs is selected and it moves over a vector $\vec{h}$ along a random direction. The length of $\vec{h}$ is set according to the following equation: $|\vec{h}| = H * rand(0,1)$. However, for high dimensional problems such perturbation technique often makes the design flee out the defined design space. Therefore, $\vec{h}$ is taken as one-directional and only one dimension of the design is perturbed. After generating the candidate design through perturbation, the potential energy U is calculated for both candidate and current designs. Next, SSA-DS determines if the candidate design should replace the current design according to the Metropolis rule. In SSA-DS, H is initially set equal to the length of design space [2].

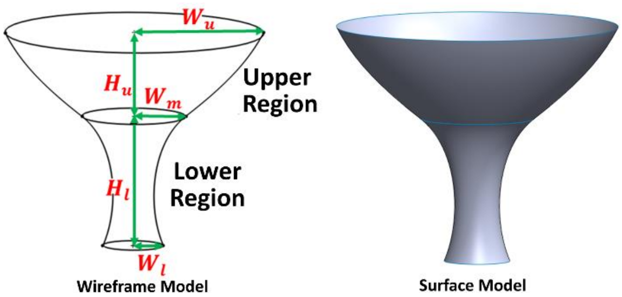

Fig. 2: CAD model for a wine glass (without base) with its design parameters.

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The designs move to the optimal positions in order to be space-filling designs as H and T decrease. In case of the constrained design spaces, initially N feasible designs are generated using the random perturbation. After perturbation of a design, if it does not satisfy the geometric constraints, perturbation is rejected. Another perturbation is performed until a candidate satisfying the geometric constraints is generated.

Parametric Bounds (in millimeters)		
$40 \leq H_u \leq 120$	$90 \leq H_l \leq 170$	$130 \leq W_u \leq 170$
$15 \leq W_m \leq 160$	$15 \leq W_l \leq 65$	
Geometric Constraints		
$H_l \geq H_u$	$W_u/2 \geq W_m$	$W_l \geq W_l$

Tab. 1: Parametric bounds and geometric constraints for the wine glass model.

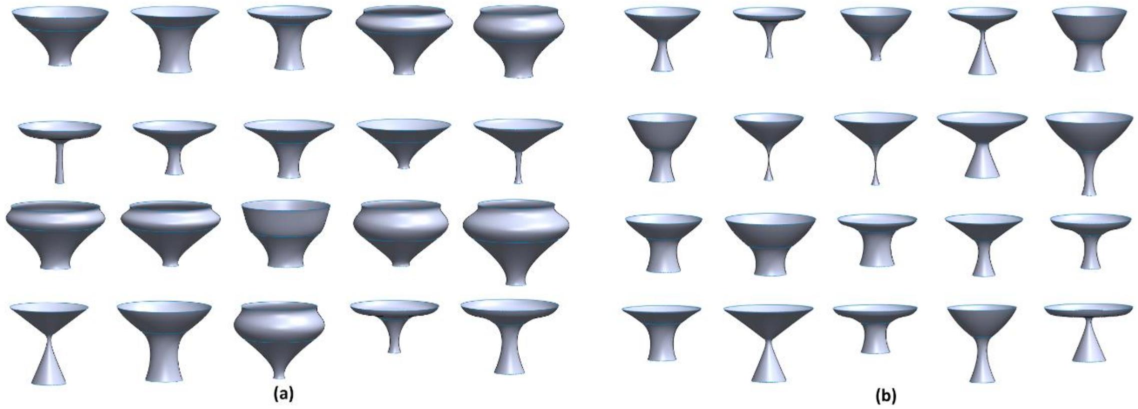

Fig. 3: Wine glass designs obtained using SSA-DS without (a) and with (b) the geometric constraints.

Results and Discussion:

To validate the performance of SSA-DS, a wine glass (without base part) CAD model is utilized (see Fig. 2). To obtain higher design variations, we divided the model into two regions: upper and lower region. $3D$ surface model is generated by performing lofting operation between Bezier curves and surface modification is performed using Khan et al.'s technique [6]. The heights of upper and lower region are denoted by H_u and H_l, respectively. W_u and W_l denote the widths of upper and lower regions, respectively. W_m denotes the width at the connection between upper and lower regions. These design parameters form the 5-dimensional design space. 20 (i.e., $N = 20$) designs are generated first in the unconstrained space for the following parameter settings: of $T = 80$, $H = 1$ and length of Markov chain $L = 10 \times N$ (which is recommended by Chen et al. [2]). Participant preferences are learned using these designs, which are recognized as geometric constraints in this study. As previously mentioned, one-to-one interviews are conducted for this. The geometric constraints and parametric bounds are provided in Table 1. Geometric constrained SSA-DS is utilized once again under the same parameter settings to generate customer-centered designs. Fig. 3(a) and (b) show the designs generated by the SSA-DS approach in the constrained and unconstrained design spaces, respectively. The potential energy U for the initial generated designs in Fig. 3(a) is 245.391. It is 310.817 for the customer-centered designs shown in Fig. 3(b). Due to low potential energy, the designs in Fig. 3(a) has better space-filling then the designs in Fig. (b). This is because the designs in Fig. 3(b) are sampled from the constrained space and the presence of these constrains narrow downs the design space. Computational time taken to generate designs in Fig. 3(a) and Fig. 3(b) are 25.612 and 32.498 seconds, respectively.

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