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DESIGN RICHNESS AND DESIGN REPRESENTATION
or
WHAT'S IN A SQUARE?

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Introduction

The study presented in this paper is based on intuitively appealing idea, which is widely accepted by design practitioners and in design studies. It states that the results of designing depend on the representation used..That is, the same design processes with the same set of goals have the potential to produce different designs if applied to different representations. More specifically our hypothesis is that this potential for designing depends on the complexity of representation. We will formalize this idea and construct a computational model for its simulation. We will then test the hypothesis on a simple illustrative design problem. We will finally interpret the dependence found, deduce some insights about designing from it and provide some recommendations on how to choose and control representations..

Formalization

Model of a design process

We assume that the following simplified computational model of designing is used:

1. The initial design **d** (or a set of designs) is given;
2. It is represented using a given representation ***R***. This yields its description ***r*** in a form of some data structure, which is built using a predefined set of variables. The set of constraints (both implicit and explicit) is imposed on this data structure.
3. The computational process of designing and its goal are given. It operates on the representation of the initial design and produces new designs (that is, new values of variables in design description) $\boldsymbol{r} \rightarrow \boldsymbol{r'}$..By controlling this process one can generate different design descriptions. The set of all designs descriptions, that can be produced by this process from the initial design, is denoted as ***DR***.

When this model of designing is implemented, it usually incorporates some form of randomization within computational design process, which enables different designs to be produced from the same initial design. This feature is used to emulate an action of a human designer who can end up with different results even if he/works on the same initial design. In our simulation the design process is completely deterministic.

The set of potentially constructible designs ***DR*** derived within representation ***R*** conceptually can be viewed as a space (we shall call it the *potential design space*). Clearly the very nature of this model, where everything exists only inside the boundaries, defined by a representation, where all the processes operate within these boundaries, makes the potential design spaces different for different representations..

The schematic structure of this model is shown in Figure 1. It illustrates that representations could be very different and have different fundamental characteristics. In Figure 1 the same initial design **d** is represented using two alternative representations $\boldsymbol{R}_1$ and $\boldsymbol{R}_2$, which have different dimensionalities and which produces different potential design spaces $\boldsymbol{DR}_1$ and $\boldsymbol{DR}_2$ that map onto two overlapping but different design spaces $\boldsymbol{D}_1$ and $\boldsymbol{D}_2$. The implicit assumption here is that some representational frame of reference exists. That is, a canonical general representation $\boldsymbol{R}_c$ can be found which allows us to describe any design represented using any ***R*** uniquely.

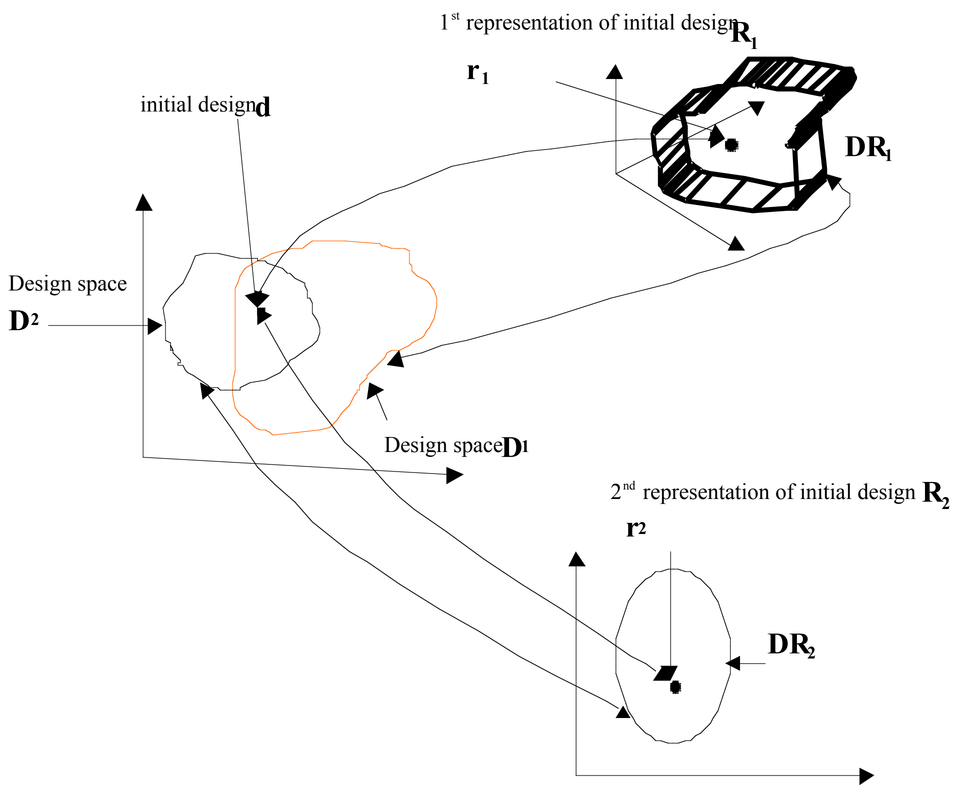

Figure 1. The schematic structure of the computational model of design and the role of representation in it.

The hypothesis that will be formalized and tested in this paper is that the "richness" of representation determines the "richness" of the corresponding potential design space. In other words the richer the representation is – the more can be done by a designer (or by a computational design process),.who utilizes it. The implicit assumption behind this research is that "richness" is a beneficial property and that it is desirable to have a rich potential design space..

Design space richness

We define the richness of a design space, as a degree variability of design descriptions from this space..Since our aim is to be able to compare different potential design spaces (derived from different representation) we will operate with the design description using canonical representation $\boldsymbol{R}_c$.

Note, that we are interested not in a "ordinary" variety among designs but in an "interesting" variety at a qualitative, rather than quantitative level. In order to be reveal this qualitative landscape, which corresponds to $\boldsymbol{D}$, the measure **M** should include the use of mapping from the space $\boldsymbol{D}$ onto a space of qualitatively different designs $\boldsymbol{DQ}$: $\boldsymbol{D} \rightarrow \boldsymbol{DQ}$. The rules that are used to construct this mapping is given by the theory of qualitative representation (de Kleer and Brown, 1984). Basically this amounts to classification of the clusters of states in $\boldsymbol{D}$ into classes with labels in $\boldsymbol{DQ}$.

Thus, we have two given subsets $\boldsymbol{DQ}_1$ and $\boldsymbol{DQ}_2$ within the canonical super space of qualitatively unique designs $\boldsymbol{DQ}_c$, $\boldsymbol{DQ}_1 \subset \boldsymbol{DQ}_c$, $\boldsymbol{DQ}_2 \subset \boldsymbol{DQ}_c$, $\boldsymbol{DQ}_1 \neq \boldsymbol{DQ}_c$,. .Our goal is to construct a measure $\mathbf{M}(\boldsymbol{DQ})$ which allows us to compare two potential design spaces, so if $\mathbf{M}(\boldsymbol{DQ}_1) > \mathbf{M}(\boldsymbol{DQ}_2)$ then $\boldsymbol{D}_1$ is richer than $\boldsymbol{D}_2$.

Because intuitively the notions of variability of a space and its complexity, seems closely related, we postulate their equivalence. Then, we define the space complexity as its information content – Shannon entropy, which is customary in engineering. The same approach was also used in design studies (Arnheim, 1971; Stiny and Gips, 1978). Note that because the space of interest $\boldsymbol{DQ}$ here is a space of unique instances of given data structure, the discrete version of Shannon entropy should be applied.

To summarize, we define the complexity of a design space as and information content of its mapping onto the space of qualitatively different designs.

$$\text{Design Richness (D)} = \text{Complexity (DQ)} = \sum_{dq_i \in DQ} \text{Entropy}(dq_i)$$

where the entropy of the design description dq_i is calculated by designing a probability distribution of the elements within dq_i and then by applying a standard Shannon formula to it.

The space $\boldsymbol{D}$ is normally very large, often infinite. Therefore counting all its states is, in most cases, impractical or impossible. So we use a Monte-Carlo sampling of this space instead to obtain statistical estimate of $\boldsymbol{D}$'s richness.

Illustrative Example

Design representation R

In our example the initial design **d** is a closed 2D shape, whose boundary is composed of polylines..Design is represented as a set of polylines $\boldsymbol{r}$={[(**x0,y0**), (**x1,y1**)],[…],..}.

Two simulation settings were used to represent an initial shape as a set of polylines to be transformed by a design process.

In the first setting the initial shape was randomly cut into n polylines. The number of polylines was treated as a quasi dimensionality of design representation.

In the second setting a new vertex was placed on the envelope singled out by the initial shape and then two additional polylines that connect this new vertex with two randomly chosen vertices were added..

The design process was constructed as a set of transformation $\boldsymbol{r} \rightarrow \boldsymbol{r'}$, during which the end points of polyline segments are moved. The number of segments in a design description does not change when this design process is run. Only these transformations that leave the transformed shape closed and untangled (without intersections) are applied. The design process does not have a goal and all designs are equally good.

The computational setting are illustrated in Figure 2.

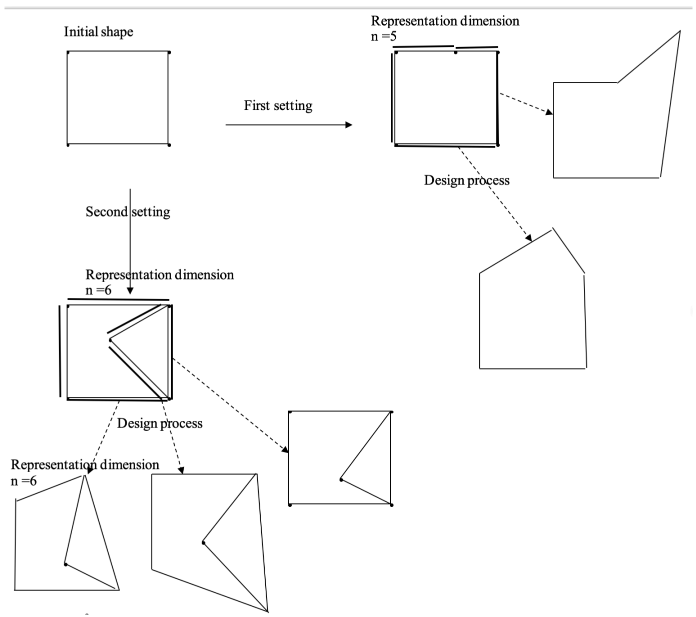

Figure 2. The two settings for design representation and one iteration of design process applied to it.

Simulations

We use Monte-Carlo sampling of the space **D** by applying random transformation of **r** $\rightarrow$ ***r'***,.by shifting the end points of polylines

1. Uniformly within the inscribing circle around the current shape;
2. By drawing the movements of these end points from some normal distribution.

Our motivation here is loosely based on the results of study of human visual perception..

Space of qualitatively different designs DQ

The space of qualitatively distinct designs DQ here is the space of so-called Q-codes. The Q-code encoding is a the published qualitative representation (Gero and Park, 1997), where each internal angle ϕ is coded as a symbol

$$
\begin{aligned}
&a, if, 0 \le \phi < \pi/4;\\
&b, if, \pi/4 \le \phi < \pi/2;\\
&c, if, \pi/2 \le \phi < 3\pi/4;\\
&d, if, 3\pi/4 \le \phi < \pi,\\
&e, if, \pi \le \phi < 5\pi/4,\\
&f, if, 5\pi/4 \le \phi < 3\pi/2,\\
&g, if, 3\pi/2 \le \phi < 7\pi/4,\\
&e, if, 7\pi/4 \le \phi < 2\pi.
\end{aligned}
$$

Each internal angle in the shape was counted. Each design is represented as a symbol string, drawn from this 8-letter alphabet. Clearly, this is many-to-one mapping, which assigns the same single label to a class of shapes. The entropy of each design and of a given design space is then defined as Shannon entropy of this symbolic string.

The Q-codes with different granularities are created similarly by using different set of angle ranges to encode a shape symbolically..One can interpret these different encoding as a separate representations or as a family of representations. We will use here a low granularity Q-code encoding where each angle is classified as one of four symbols depending on which of four quadrants in belongs it.

Since we are only interested in properties of qualitatively different designs, we calculate statistics only using designs that have different Q-codes. In another words, our mapping **M** here is the mapping classes of.polylines (closed 2D shapes) onto unique sequences of.Q-codes..

Different representations

This polyline representation is a family of representation. We derive particular representations from it by choosing the number of segments in shape description..This number gives a natural measure of complexity of representation – its "dimensionality" **N**.

Numerical results

First setting – no extra vertices added

Three different initial shapes have been tried – square, triangle and t-shape. The triangle and square gave virtually undistinguishable dependencies. The dependence of the richness of design space as a function of its dimensionality is shown in Figure 3 for these three initial shapes.

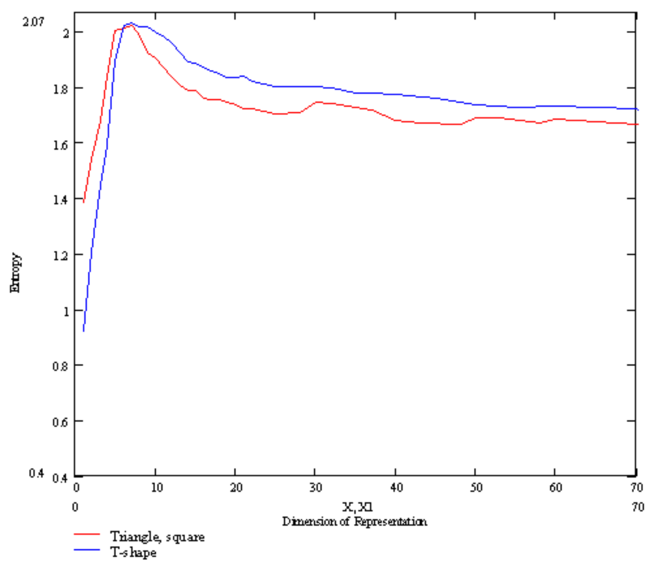

Figure 3. The dependence of the entropy of the qualitative potential design space on the dimensionality of representation (number of segments in shape description) for the 8 letter Q-code for different initial shapes.

The averaged dependencies (when each one of these shapes was equally probably to be used as initial) for the 8 and 4 letter Q-codes are shown in Figure 4. 1000 runs have been performed for each curve. The standard deviation was less than 5%.

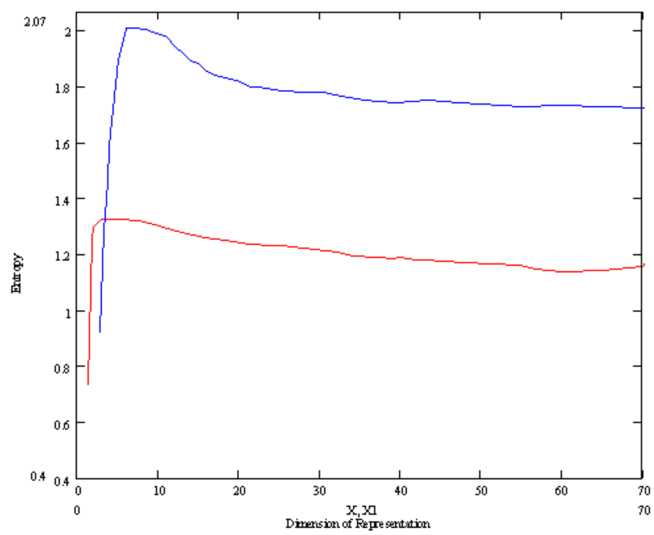

Figure 4. The dependences of the entropy of the qualitative potential design space on the dimensionality of representation (number of segments in shape description) averaged over 3 initial shapes. The upper shape corresponds to the 8 letter Q-code and the lower one to the 4-letter Q-code.

Second setting – extra vertices added

The simulations for the second setting with the same parameters yielded qualitatively different dependence of the complexity (entropy) on representations dimensionality, shown in Figure 5.

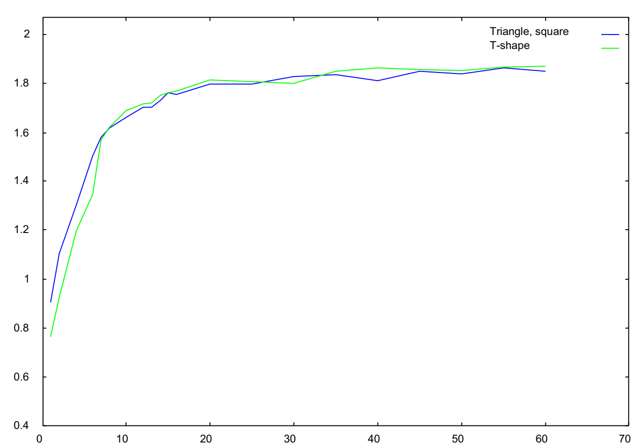

Figure 5. The dependence of the entropy of the qualitative potential design space on the dimensionality of representation (number of segments in shape description) for the 8 letter Q-code for different initial shapes

The following interpretation can be offered ….

CONCLUSIONS

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Acknowledgments
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