

How Designs Differ: Non-linear Embeddings Illuminate Intrinsic Design Complexity

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Motivation

Fully **unsupervised** method to construct low dimensional **semantic spaces** from high dimensional design spaces

Continuous generation of new valid designs by exploring the semantic space

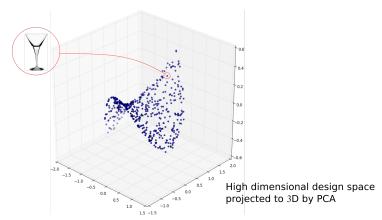
Valid vs Invalid Design

Design representation using Bezier curves: dimensionality / degrees of freedom?



Manifold Assumption

High dimensional design parameters actually lie on a lower-dimensional manifold (semantic space)

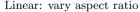


Experiment samples

Synthetic example: superformula

$$(x,y) = superformula(a,b,m_1,m_2,n_1,n_2,n_3)$$





Nonlinear: vary n_2 and n_3



Multiple categories: vary m_1 or m_2

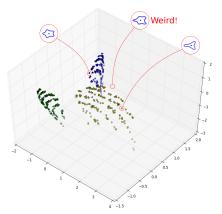
Experiment samples

Real-world example: glassware

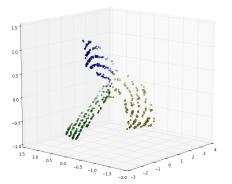


Start by learning the properties of design spaces.

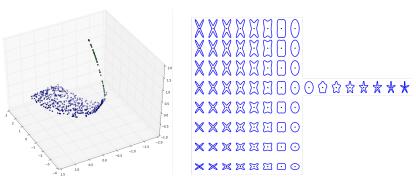
Why?



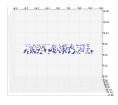
Multiple manifolds



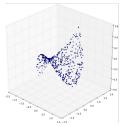
Multiple manifolds with intersection



Multiple manifolds with different intrinsic dimensionality



Linear: PCA

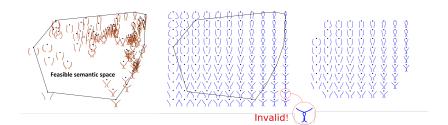


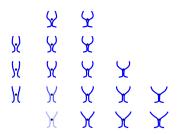
Nonlinear: kernel PCA, autoencoder, ...

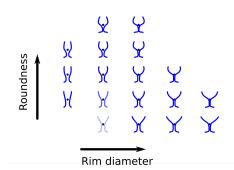
Embedding: $f: \mathcal{X} \to \mathcal{F}$

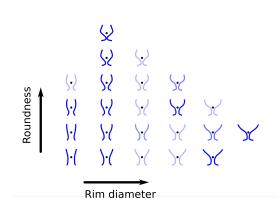
Reconstruction: $g: \mathcal{F} \to \mathcal{X}$

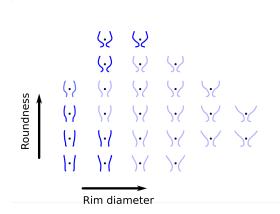
Choose valid designs in a semantic space

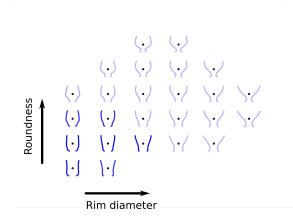


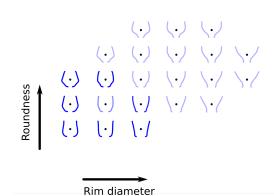


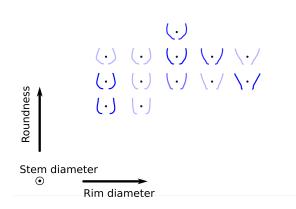












Application Examples

Design optimization: $\mathcal{X} \in \mathbb{R}^D \to \mathcal{F} \in \mathbb{R}^d$, continuous

Semantic-based design automation: $\mathcal{F} \to \mathcal{X}$

Thank you

 $\label{eq:code-data:github.com/IDEALLab/design_embeddings_idetc_2016} Get \ code+data: \\ \ github.com/IDEALLab/design_embeddings_idetc_2016$

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