Proceedings of the ASME 2020 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference

August 16-19, 2020, St. Louis, MO, USA

IDETC/CIE 2020 – 24736

Part-Aware Product Design Using Deep Generative Network

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We propose a data-driven generative design framework that can facilitate the design exploration of engineering products in support of creative conceptual design and optimization. The framework consists of two modules: 1) a 3D mesh generative design module that can generate part-aware 3D objects using variational auto-encoder (VAE), and 2) an evaluation module that can assess the engineering performance of 3D objects in real-time based on locally linear embedding (LLE) [1]. The novelty of our framework lies in three aspects. First, it generates 3D shapes with the consideration of individual parts' interconnection and constraints (i.e., part-aware) as opposed to generating a holistic 3D shape. Second, it transfers 3D shapes to watertight meshes with the same connectivity (i.e., the same number of vertices and the same way how vertices are connected) so that the surface details (e.g., smoothness, curvature) can be captured by mesh representation and learned by neural networks. Third, the LLE-based solver can quickly assess the engineering performance of the generated 3D shapes to realize real-time evaluation. In this study, we apply our framework to the aerodynamic car design.

In engineering design, on one hand, we want to generate a variety of design concepts to meet the diverse customer needs and preferences. On the other hand, products must meet desired engineering performance, such as the sit-stability of chairs, the aerodynamic performance of automobiles. However, human designers have cognitive limitations, thus cannot create diverse engineeringly-desired 3D shapes without computer-aided design (CAD) and computer-aided engineering (CAE) software. But current CAD software is primarily a drawing and modeling tool that cannot automatically create new designs, and the use of CAE tools is often time-consuming leading to a stretched design cycle that hinders the entire design process and increases the development cost. Even if we would be able to generate a large number of

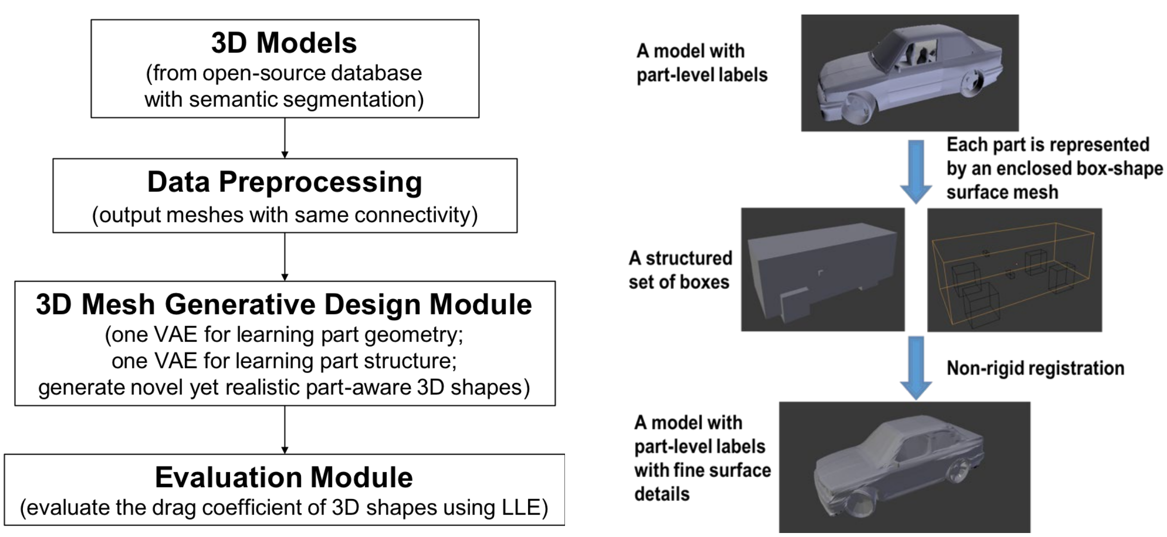

Figure 1 : The part-aware product design framework (left) and the application of the framework in the automobile case study (right)

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different design candidates, the evaluation of every single design using a CAE tool will be expensive both computationally and economically. Our framework aims to tackle these challenges by integrating generative design techniques and a fast solver for 3D shape aerodynamics.

Figure 1 shows the proposed design framework. For the generative design module, we adopt a deep neural network method based on VAE to learn the design concepts and geometries from existing products to generate a variety of designs that may not be seen from the current market. The data-driven generative method can take advantage of existing successful designs instead of designing from scratch. Inspired by SDM-NET [2], we apply two VAEs, one for learning individual part geometries and one for learning the part structure of the system. We use 589 3D car models with semantic segmentation from ShapeNet [3] and ModelNet [4] to train a neural network from which new 3D car structures that are part-aware can be generated by random shape generation and shape interpolation.

For the 3D shape representation, we chose the mesh instead of voxels or point cloud for the sake of capturing surface details of automobile parts (e.g., mirrors and tires). CAD models of cars often contain interior structures and meshes of inconsistent connectivity. The data structure of these meshes is not suitable for neural network model input. So, to ensure that the parts with the same semantic label (e.g., mirrors, tires) have the same mesh connectivity, we use enclosed box-shape meshes with 19.2K triangles to fit the bounding box of each part. This step forms a coarse representation of a 3D car shape. We then apply the non-rigid registration method [5] to transform each bounding box to its corresponding part to get a watertight mesh with fine geometry details.

For the evaluation module, we propose to use LLE – a manifold learning method – to evaluate the drag coefficient of a 3D car model in real-time at the price of accuracy compared to high-fidelity solvers, such as commercial computational fluid dynamics (CFD) software. We select a sample of 60 cars with different types, such as sedans, sports cars, SUVs from those 589 car models to make sure that the sample statistically represents the whole dataset. With these samples, we first use a high-fidelity CFD solver to get their drag coefficients and use a signed distance field to represent each car shape as a vector. LLE algorithm assumes that all the car shapes lie on a manifold space and each shape represented by the vector can be a linear combination of its nearest neighbors in the manifold space. In this study, we assume that the drag coefficient of an automobile can also be a linear combination of the drag coefficients of its nearest neighbors. Therefore, the drag coefficient of a new car design can be quickly calculated, thus significantly reducing the computational time of assessing the aerodynamic performance. The experiment that gauges the accuracy of this fast solver is still ongoing.

In the future study, we plan to add an optimization module in the framework to enable optimal 3D shape generation in support of the design decision-making considering the tradeoff between part-level and system-level constraints and performance. We also plan to develop an interactive design GUI to support human-AI design exploration and optimization.

Acknowledgment

The authors gratefully acknowledge the financial support from the NSF through grant DUE-1918847.

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