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How to Trade off Aesthetics and Performance in Generative Design?

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ABSTRACT

In order for a product to succeed in the market, it needs not only good performance but also aesthetics. However, there is a trade-off between performance and aesthetics. This requires a design process that can balance the two attributes from the initial stage of the product design. This study proposes a framework that allows AI to generate various conceptual designs while analyzing performance and aesthetics. This framework generates wheels through 2D topology optimization, performs design automation to 3D, then proceed wheel stiffness prediction deep-learning and design evaluation for the generated wheels. Finally, the trade-off between performance and aesthetics is analyzed.

1. Introduction

Current wheel design process is subject to repetitive work due to pre-design and post-engineering reviews, inefficient work is carried out. Also, only a small amount of design concepts can be engineered. To improve these problems, this study presents a deep learning-based generative design framework that allows designers and engineers to review the conceptual designs together to proceed with detailed design.

The framework of the study aims to create wheels that satisfies both performance and aesthetics automatically. It contains three main steps.

First step is the wheel design model development. Disk view images are generated through 2D piece wheel topology optimization. Furthermore, Deep Convolutional Generative Adversarial Network (DCGAN) is trained using wheel cross-section data collected from existing wheels to generate new wheel cross-section images.

Second step is the performance prediction. It uses disk view images and wheel

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cross-section images created during the previous step to automate 3D wheel generation. The generated 3D wheel data were used as input data for computer-aided engineering (CAE) automation and deep learning. The stiffness values obtained through CAE automation were used as label data for deep learning. Deep learning to predict each stiffness was conducted by converting 3D wheel CAD data into voxel data and using corresponding rim stiffness and disk stiffness values as label data.

Third step is the design evaluation and trade-off analysis. On-line surveys were conducted on customers and designers, and the preference and performance of the evaluated wheels were compared. Through these tasks, it was possible to create a concept wheels that considered both performance and aesthetics. The entire framework is shown in Fig. 1.

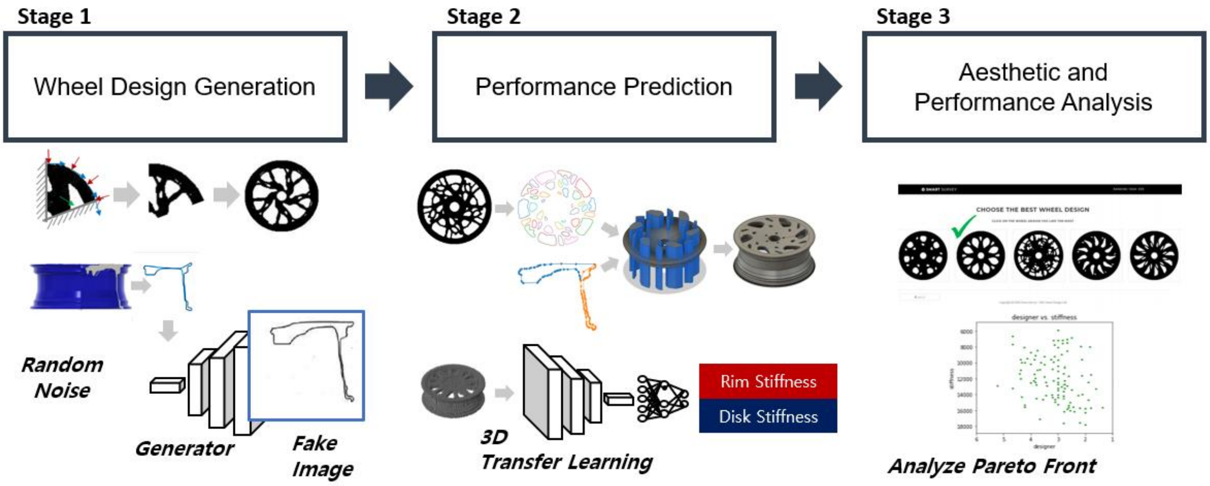


Fig. 1 Research Framework

2. Wheel Design Generation

2.1 Create 2D Disk View Design

SIMP-based 88 lines code (Andreassen, 2011) was modified to optimize multi-objective function for wheel shapes. This was done for each piece, with compliance minimization as the first objective function, and L1 distance with reference data collected from commercial wheels as the second objective function (Oh, 2019). The generated 2D wheel images were filtered and a total of 1448 images were selected.

2.2 Create 2D Wheel Cross Section

Deep learning was used in this stage to create a new wheel cross-section image. The 1218 wheel cross-section images for deep learning were gathered by cutting the wheel cross-sections of the actual wheels by 1 degree. DCGAN learned this image data and 11 images randomly drawn from latent space were obtained by the generator like Fig. 2.

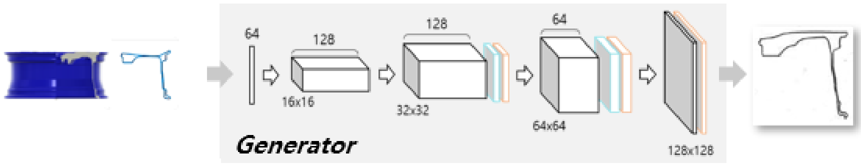


Fig. 2 Process for Creating Wheel Cross-Sections

3. Performance Prediction

3.1 3D CAD Automation

3D wheels were created by combining 1,448 generated 2D disk view images and 11 wheel cross-section images in random matching. It goes through a total of four stages of process (Yoo et al., 2021). First, the edge of the disk view image is extracted and converted into coordinate data. Coordinate data is sorted and grouped to sketch. Second, the edge of the wheel cross-section data is also extracted, converted into coordinate data, and sorted. The wheel cross-section coordinate data were separated with in rim parts and spoke parts. Subsequently, both coordinate data of disk view and wheel cross-section are stored in csv files respectively. Third, 1,448 generated disk view data and 11 wheel cross-section data are randomly matched. There were about 130 spokes per 1 wheel cross-section data. Finally, design automation was carried out using Autodesk Fusion360 API. Sketch and revolve the spoke part of the wheel cross-section first, and then sketch the coordinates of the disk view to subtract them from spoke body for disk patterns. Sketch and revolve the rim part of the wheel cross-section. Combine the rim body with the spoke body. The process is shown in Fig. 3, and a total of 1,432 CAD data generation has been completed.

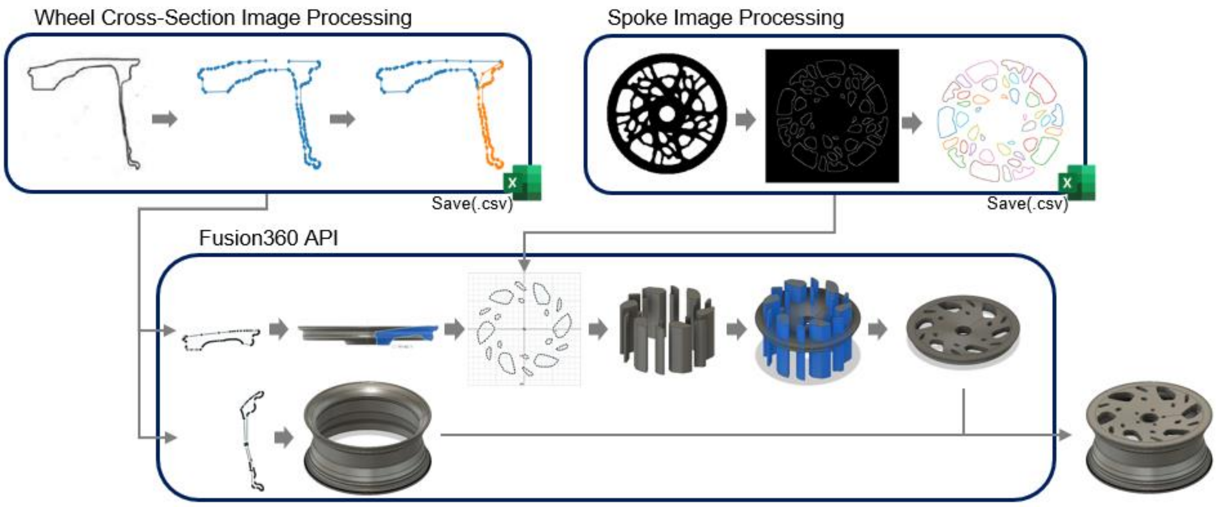
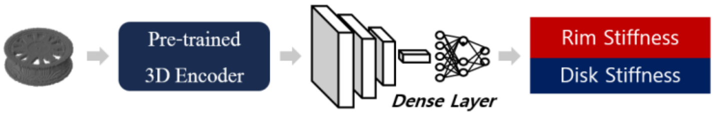


Fig. 3 3D CAD Automation Process

3.2 Deep Learning Models to Predict Wheel Performances

Deep Learning to predict rim stiffness and disk stiffness was conducted on 926 data excluding data that failed to analyze. Label data were generated by extracting rim stiffness and disk stiffness using Altair Hyperworks analysis automation sorfware. The input data were generated by converting 926 CAD data to voxel data. These data were split into 800(for train/validation) and 126(for test). 800 train/validation data were augmented to 8000 by rotation. Transfer learning was conducted using the Encoder and Flatten layers of VAE, which had already been learned about wheel geometry. Each model consists of optimal layers through architecture search. The architecture (Fig. 4(a)) and results (Fig. 4(b)) of the deep learning models are shown in Fig. 4.



(a) Deep Learning Model Architecture

	Rim Stiffness		
	MAPE(%)	RMSE	R
Valid	0.9644	140.6689	0.9985
Test	1.6636	252.2872	0.9957

	Disk Stiffness		
	MAPE(%)	RMSE	R
Valid	2.1689	352.0844	0.9962
Test	4.5144	734.0551	0.9846

(b) Results of Learning

Fig. 4 Architecture and Results of Deep Learning

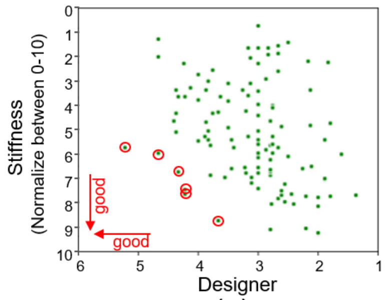
4. Aesthetics and Performance Analysis

4.1 Aesthetics Evaluation

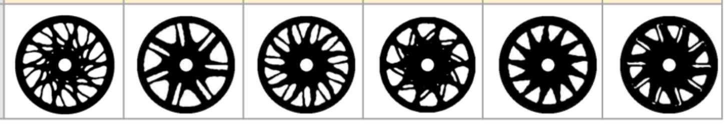
The purpose of the wheel design survey is to evaluate the aesthetics that customers and designers feel about the wheels created by AI. It is also intended to analyze the trade-off of the aesthetics of wheels and engineering performance. First survey was conducted on customers. About 1000 wheels were evaluated by 800 people using the Amazon Mechanical Turk site. 116 wheels were selected with high score through a customer survey. Second survey was conducted on 39 designers. The designers evaluated a nine-point scale rating assessment of the selected wheels through the first survey.

4.2 Trade-off Analysis

Based on the result of the second survey, the relationship between preference and performance for 116 wheels was analyzed. Fig. 5(a) is a plot comparing the designers' preference and the normalized value of average stiffness. The correlation coefficient between designer preference and stiffness was -0.12, which was considered irrelevant. The disk view design of the Pareto Front is shown as Fig. 5(b). Designers prefer relatively neat and clear designs. As the designers' preference increased, the value of stiffness decreased.



(a)

Pareto Front Designs						
Stiffness (Normalized)	5.38	5.61	6.52	7.35	7.60	8.87
Designer Perferences	5.22	4.67	4.33	4.22	4.22	3.67
Disk Shape						

(b)

Fig. 5 Trade-off between Aesthetics and Performance
(a) Pareto Front for Stiffness and Designers' Preference
(b)Wheel Designs at Pareto Front

5. Conclusions

This study focused on developing design tools that can trade off performance and aesthetics to help designers and engineers collaborate. We produced wheels of various designs through topology optimization, built deep learning models predicting wheel stiffness, and went through the process of evaluating the aesthetics of the wheels through surveys. As a result, the trade-off of performance and aesthetics was visually identified. This is significant in that it has provided an efficient framework to reduce repetitive work between designers and engineers and to review the large amount of conceptual design generated by this design tool.

Acknowledgement
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REFERENCES
Andreassen, E., Clausen, A., Schevenels, M., Lazarov, B. S., & Sigmund, O. (2011), "Efficient topology optimization in MATLAB using 88 lines of code," *Structural and Multidisciplinary Optimization*, *43*(1), 1-16.

Oh, S., Jung, Y., Kim, S., Lee, I., & Kang, N. (2019), "Deep generative design: Integration of topology optimization and generative models," *Journal of Mechanical Design*, *141*(11).

Yoo, S., Lee, S., Kim, S., Hwang, K. H., Park, J. H., & Kang, N. (2021). "Integrating deep learning into CAD/CAE system: generative design and evaluation of 3D conceptual wheel," *Structural and Multidisciplinary Optimization*, 1-23.