GENERATING TIRE TREAD DESIGNS USING A SENSORY EVALUATION REGRESSION MODEL OF GENERAL USERS AND TIRE MANUFACTURER EMPLOYEES AND A GENERATIVE MODEL

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ABSTRACT

In this study, a CatBoost regression model was constructed to clarify the relationship between geometric features extracted from tire tread images and sensory evaluations of “quietness” and “grip performance” on DRY and WET surfaces. SHapley Additive exPlanations (SHAP) was then applied to visualize the contribution of each feature, enabling the identification of geometric features that are important for sensory evaluation. Furthermore, by comparing the sensory evaluations of general users and tire manufacturer employees, we identified the geometric features that caused differences in their evaluations. In addition, the evaluation values for CatBoost regression model were used to screen the training data input to StyleGAN, generating tire tread images likely to obtain high sensory evaluations of “quietness” and “grip performance” on DRY and WET surfaces from both general users and tire manufacturer employees.

Keywords: *Generative design, Tire tread, CatBoost, SHAP, StyleGAN*

1 INTRODUCTION

Tire treads affect major tire performances such as “quietness” and “grip performance” (Lee et al., 2022). Their appearance also shapes impressions of performance and influences consumers’ purchase intention (Kii et al., 2023; Creusen & Schoormans, 2005). Although many studies have examined the relationships between “quietness” and “grip performance” and geometric features of tire treads (Bridgestone, 2008; Kim & Jeong, 2010), few have investigated the relationship between tire tread appearance and geometric features. Hayakawa et al. (2025) constructed a regression model to predict general users’ sensory evaluations of “slip resistance” from geometric features extracted from tire tread images and generated tire tread images by screening the training data input to StyleGAN using evaluation values obtained from the regression model. However, their study examined only “slip resistance” and general users. This study constructs

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regression models to predict sensory evaluations of “quietness” and “grip performance” on DRY and WET surfaces for general users and tire manufacturer employees, hereafter referred to as experts, from geometric features extracted from tire tread images. The predicted values obtained from the regression models are also used to screen the training data input to StyleGAN and generate tire tread images likely to receive high sensory evaluations from general users and experts, respectively. This approach may automate part of the traditionally manual tire tread design process and contribute to the advancement of generative design.

2 METHOD FOR GENERATING TIRE TREAD DESIGNS

2.1 Method for calculating feature values

Each power spectrum image obtained from a tire tread image using the 2D discrete Fourier transform was segmented into 180 regions combining 18 angular sections (0°–5°, 5°–10°, …, 85°–90°) and 10 frequency bands (0–2 Hz, 2–4 Hz, 4–6 Hz, 6–8 Hz, 8–10 Hz, 10–15 Hz, 15–20 Hz, 20–25 Hz, 25–30 Hz, and 30–40 Hz). Z-scores of the maximum power spectrum values within each region were used as feature values.

2.2 Method for constructing sensory evaluation regression models

CatBoost, hereafter referred to as CB, LightGBM, Random Forest, and XGBoost were trained using feature values and sensory evaluation values of general users and experts. SHapley Additive exPlanations (SHAP) was applied to interpret the regression model with the highest coefficient of determination.

2.3 Method for image generation based on regression models

The regression model with the highest coefficient of determination was used to screen the training data input to StyleGAN. StyleGAN was trained on the screened data to generate tire tread images likely to obtain high sensory evaluations from general users and experts, respectively.

3 CASE STUDY

3.1 Data collection and pre-processing

A total of 535 line diagrams of SUV tire tread images were collected from the Japanese Patent Office’s Patent Information Platform. An online questionnaire used 95 randomly selected images for general users and 30 for experts. Participants rated “quietness” and “grip performance” on DRY and WET surfaces on a five-point Likert scale from 1 (“low perceived performance”) to 5 (“high perceived performance”). Participants were 227 general users and seven experts engaged in product design at a tire manufacturer. Valid general-user respondents numbered 153, 139, and 143 for “quietness” and “grip performance” on DRY and WET surfaces, respectively; all expert responses were valid. Sensory evaluation values were averaged for each tire tread image.

3.2 Constructing sensory evaluation regression models

Sensory evaluation regression models were constructed using the feature values and sensory evaluation values of 95 tire tread images for general users and 30 images for experts. Table 1 shows the coefficients of determination (R^2) and root mean squared errors (RMSEs). The CB

Table 1. R^2 and RMSEs of regression models constructed using each machine-learning algorithm

Participant Group	Algorithm	Quietness		Grip performance on DRY surfaces		Grip performance on WET surfaces	
		R^2	RMSE	R^2	RMSE	R^2	RMSE
General users	CatBoost	0.72	0.07	0.50	0.05	0.63	0.09
	LightGBM	0.50	0.12	0.22	0.09	0.36	0.13
	Random Forest	0.43	0.13	0.14	0.09	0.27	0.14
	XGBoost	0.51	0.12	0.24	0.09	0.33	0.14
Experts	CatBoost	0.83	0.24	0.42	0.33	0.54	0.26
	LightGBM	0.47	0.65	0.11	0.91	0.31	0.87
	Random Forest	0.40	0.70	0.23	0.85	0.24	0.90
	XGBoost	0.40	0.69	0.04	0.69	0.42	0.80

regression models achieved the highest coefficients of determination for both groups and were interpreted using SHAP. For general users, SHAP identified high-frequency vertical and horizontal lines and low-frequency oblique lines as important for "grip performance" on WET surfaces. More low-frequency stripes may give a rugged impression and lead to higher perceived "grip performance." For experts, SHAP identified high-frequency horizontal lines, low-frequency oblique lines, and vertical lines as important. More vertical and high-frequency stripes may improve drainage performance and "grip performance" on WET surfaces (Bridgestone, 2008; Kim & Jeong, 2010).

3.3 Image generation based on regression models

The CB sensory evaluation regression model for each group computed evaluation values for 535 images, and the top 40% (214 images) were selected as the training data input to StyleGAN. The generated images contained low-frequency oblique stripes that positively affect general users' sensory evaluations of "grip performance" on WET surfaces (Figure 1), and vertical and high-frequency horizontal stripes that positively affect experts' evaluations (Figure 2). These images are therefore likely to obtain high sensory evaluations from each group.



Figure 1. Images generated by StyleGAN based on the training data screened by the constructed CB sensory evaluation regression model for general users (WET grip performance)



Figure 2. Images generated by StyleGAN based on the training data screened by the constructed CB sensory evaluation regression model for experts (WET grip performance)

4 DISCUSSION

These findings suggest potential usefulness in the initial configuration stage of tire tread design, where the number, width, and direction of grooves are determined. The generated images may serve as initial design candidates, while geometric features identified by SHAP may provide references for incorporating features that contribute to higher sensory evaluations by general users or experts.

5 CONCLUSIONS

CB regression models were constructed to predict sensory evaluation values of “quietness” and “grip performance” on DRY and WET surfaces for general users and experts from geometric features extracted from tire tread images. The constructed CB regression models were also used to screen the training data input to StyleGAN and generate tire tread images likely to obtain high sensory evaluation values from general users and experts, respectively. These findings suggest potential usefulness in the initial configuration stage of tire tread design. Two study limitations should be considered. First, the sample size of experts was limited compared with that of general users; experiments with more experts are therefore necessary to achieve greater generalizability. Second, although the generated tire tread images contained features positively correlated with sensory evaluation values, their effectiveness has not been validated. Sensory evaluation experiments and image validation using metrics such as the Fréchet Inception Distance (FID) are therefore necessary.

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