Towards a Co-creative System for Creating, Suggesting, and Assessing Material Textures for 3D Renderings During Design Reviews in Industrial Design

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ABSTRACT

Generative AI co-creative systems have enabled users to create images, videos, and music, and quickly explore alternatives. We propose using this approach in exploring and choosing materials, an important task for creating a product in industrial design. This paper describes a co-creative system that utilizes generative AI to explore and suggest material textures and provide feedback on the materials used in a product that is aimed to be used during design reviews in order to quickly explore alternative materials on a product's 3D rendering. We first interview industrial designers on how they assess material choice in design deliverables during the design session. Based on our findings, we then develop a prototype of the co-creative system for generating and providing feedback on material textures. We believe that using this system can assist designers in not only creating textures for their 3D renderings but also in providing material-aware feedback to feasibly create the product.

CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**; • **Computing methodologies → Texturing**; Natural language generation.

KEYWORDS

generative AI, texture transfer, industrial design

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1 INTRODUCTION

In the early stages of the industrial design life-cycle, 3D renderings are one of the tools commonly used by industrial designers to quickly show a product's visual representation to other stakeholders such as clients and engineers. When assessing 3D renderings during design review sessions, the product's choice of material is a critical aspect evaluated by other stakeholders, and changing the material can be done based on factors such as the product's aesthetic, manufacturability, and material availability. Depending on the reason for changing the material, design review sessions may repeat for several days or weeks, which contributes to the industrial design life-cycle being a complex and iterative process. Meanwhile, generative artificial intelligence (AI) has enabled the creation of novel and indistinguishable data such as images [6, 19], text [2], speech [20], and 3D models [16]. Furthermore, it has paved the way for developing co-creative systems that allow users to explore outputs in domains such as art, music [14], and design [10, 13]. Specifically, in texture transfer, previous studies have demonstrated transferring material textures onto 3D models such as furniture [7, 9, 12, 21, 22] and interior scenes [4, 23, 24]. Recently, CLIP [17], several methods are able to texture 3D models [5, 15, 18] and scenes [11] by simply inputting text prompts. Building on accessible text-to-image models like StableDiffusion, tools like DreamTextures [3] have been developed and embedded into 3D modeling software to create texture maps and apply them to 3D models. However, in the context of industrial design, designers have to ensure that the 3D model is not only visually appealing but they also have to ensure that the product can be feasible to construct in later stages. The choice of materials plays a crucial role in both of these aspects. According to previous research [1, 8], industrial designers and engineers choose materials based on a wide range of aspects including technical properties such as mechanical properties, material cost and availability, and sensory characteristics such as visual aesthetic and tactile feel. With many factors to consider, choosing materials for a product can be a challenging task. How can we utilize texture transfer methods in developing a co-creative system that not only involves texture transfer but also ensures that the materials generated are suitable and feasible for the product being designed?

In this paper, we propose a co-creative system that leverages generative AI to assist industrial designers in changing and suggesting materials for 3D renderings of a product, while also providing feedback on its feasibility based on the materials applied. In order to know the rationales behind changing the material of a product design during design reviews, we first conducted a formative interview study with industrial designers on the aspects they and other stakeholders assess design deliverables, especially those that are affected by material choice. Based on our interview findings, we present an initial prototype of a co-creative system for transferring

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images of material textures to a product's 3D rendering, suggesting materials, and providing recommendations on assembling the product based on the materials currently applied. We envision that using this system can help industrial designers and stakeholders quickly change material textures in 3D product renderings, while also considering the product's feasibility during the early stages of the industrial design life-cycle in order to minimize product flaws.

2 FORMATIVE STUDY AND RESULTS

We first conducted a semi-structured interview study with industrial designers to gain knowledge on the aspects they and other stakeholders evaluate various design deliverables such as sketches, 3D renderings, and physical prototypes during design review sessions throughout the industrial design life-cycle. We recruited industrial designers online using email and social networking sites such as Facebook and LinkedIn. Interested participants were first required to answer a pre-interview questionnaire requesting their demographic details, and read and accept an informed consent form that explains the purpose of the interview study. A total of seven participants (5 males, and 2 females) were recruited. Five of the participants shared their experiences as professionals, and one participant shared his experience as a university student. One participant (P4) shared her experience as both. All participants have worked on various products such as furniture, electronics, and appliances.

All interviews were conducted individually and online using Zoom for 1 to 2 hours per interview. At the start of the interview, we asked the participants for details about their work or university courses such as their job positions, and previous projects worked on. Next, we asked them about the stages of the design process they undergo in developing a product, and the kinds of design deliverables that are created and assessed at each stage before creating the final product. In each stage, we asked the participants how the design deliverable made at that stage is evaluated which includes the stakeholders involved in assessing the deliverable, and the aspects the deliverable is assessed on, especially those that are influenced by material choice.

Based on the interviews with the designers, we found that they and other stakeholders critique the material choice of a product in stages where they are reviewing 3D renderings and physical prototypes of a product. Generally, in these deliverables, stakeholders assess the material choice based on aspects such as ergonomics, aesthetics, market trend, and manufacturing. For instance in manufacturing, P6, a student graduate, mentioned that his classmate "*tried to merge two different types of wood [together]. So visually, through the rendering, it's really pretty. But the critique of the professor is that the particular wood type is very difficult to merge together*". In aesthetics, P5, a professional industrial designer, conducts user testing on refrigerator prototypes of different materials where users choose the one they prefer saying, "*Before, chrome is very popular. It gives a more durable and elegant impression of the product. For the high-end market, that's okay. But for the low-end market, they would prefer just plastic, because they have this old perception that you could get electrocuted or something like that.*"

3 SYSTEM OVERVIEW

Based on how feedback is administered during design review sessions, we develop an initial prototype of a system that is aimed to be used during these sessions on 3D renderings, where designers, clients, and other stakeholders can quickly explore materials for their products, and receive feedback using generative AI. Specifically, the system uses StableDiffusion [19] to generate material image textures and GPT-3 [2] to suggest materials and provide feedback on the materials used in a product's 3D rendering. The system is comprised of three main modules for interaction: the generation module, the suggestion module, and the assembly feedback module. The system also tracks the displayed rendering's material information which comprises the names of the materials applied to each part of the product and also saves renderings. The user interface is shown in Figure 1, which shows a 3D rendering of a bedroom nightstand. The targeted products of this system are furniture and interior scenes, which are products that can have a wide variety of material choices.

3.1 Generation Module

The generation module facilitates creating material texture maps, and semantically applying them to the product's 3D rendering in order to quickly change the material of a product. In creating the texture maps, it uses StableDiffusion, a text-to-image generative model trained on billions of paired images and captions that allows users to arbitrarily create images by inputting textual prompts. In order to use the generation module, the user first types in the material they want to generate, and selects the parts of the product they want to apply the material onto. Next, the inputted material is appended to the following textual prompt, "*<MATERIAL NAME> texture map, 4k*" and fed into StableDiffusion to generate up to four image textures. Each generated texture is then mapped onto the selected parts, after which, candidate renderings with the material applied are shown to the user. The user can choose to select a candidate and update the current rendering accordingly or regenerate material textures.

3.2 Suggestion Module

The suggestion module facilitates recommending materials to the user by leveraging GPT-3. The current implementation suggests materials based on interior design styles such as the Scandinavian and Transitional interior design styles. The user must first specify in the drop-down the type of material they would like the module to suggest, and also the interior design style. Using the inputs, we retrieve suggestions from GPT-3 by using the following text prompt: "*"What examples of <MATERIAL TYPE> materials are of <STYLE> interior design style? For each example, give your reason. Separate the example and reason by a | . Return in bullet points."*" The last sentence in the prompt is added in order for the system to properly parse the text returned by the user when displaying the suggestions. The module then returns a list of suggested materials that are of the selected interior design style, where each material is accompanied by a reason that is also generated by GPT-3 and an image texture generated by StableDiffusion. The user can then use these suggestions when generating materials for the 3D rendering if they have a particular interior design style in mind.

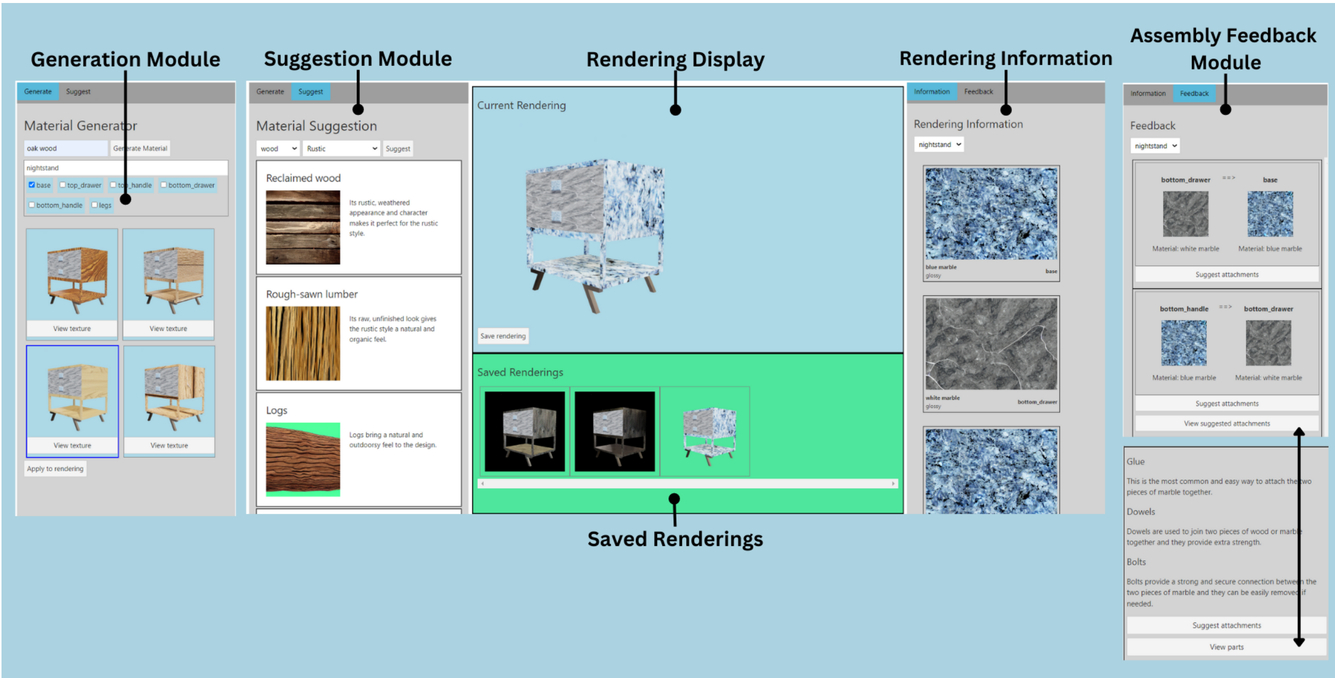

Figure 1: The user interface of the proposed system. Note that the modules and rendering information components are tabbed, so all of them are displayed in the figure.

3.3 Assembly Feedback Module

The goal of the co-creative system is not only to facilitate creating and suggesting materials but also to provide feedback on the 3D rendering based on the materials used. Currently, the module provides feedback on how the parts of the product can be assembled together, considering the materials applied to each part. For each pair of parts that are connected together, the following prompt is sent to GPT-3: " *"What can be used to attach a <PRODUCT NAME> <PART 1> made of <MATERIAL 1> to a <PRODUCT NAME> <PART 2> made of <MATERIAL 2>? Give <N> recommendations. For each recommendation, give your reason. Separate the recommendation and reason by a | . Return in bullet points."*" GPT-3 then returns a list of suggested attachments that can be used to attach the two parts together which are displayed to the user. As the designer generates and applies material textures to the rendering, this module aims to provide material-aware feedback on the attachments that can be used when assembling the product prototype or final product in the later stages of the design life cycle.

4 CONCLUSION AND FUTURE WORK

This paper proposes a co-creative system for exploring, suggesting, and providing feedback on the material choice of products in 3D renderings to be used during design review sessions in the industrial design process. To gain practical insight into how material feedback is provided during design review sessions, we first conducted a formative interview study with industrial designers. We then created an early prototype of a generative AI co-creative system to suggest and provide feedback on materials in 3D renderings during design reviews.

The system is still a work in progress, and it currently suggests materials based on interior design style and provides material-aware feedback on the assembly of the product's parts. In the future, we plan to incorporate other criteria such as cost and environment in suggesting and assessing materials based on the formative study findings. Furthermore, we are also consulting with industrial designers for feedback on the prototype to improve the system's functionality. For example, one of them mentioned that interior design style can be a basis for choosing materials because certain materials can be associated with certain styles (e.g., oak and other light-colored woods are associated with the modern interior design style), which is why we incorporated it as a criterion when suggesting materials. We plan to continue consulting with designers iteratively to ideate more bases in suggesting and assessing materials, and to test the systems' functionality to improve the prototype. Lastly, we plan to conduct a user study on using the system to explore materials for 3D renderings of various interior scenes.

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