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USING AI TO GENERATE SHORT VIDEOS AS STIMULI FOR SUPPORTING DESIGN CREATIVITY

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ABSTRACT
Current computational idea generation support tools, especially Artificial Intelligence (AI)-driven ones, mainly produce textual and/or pictorial stimuli to support design creativity at the early stages of design. However, the impact of using AI-generated videos as creative design stimuli remains underexplored. With the advancement in computational power and AI models, generating videos to support design creativity is possible. This paper explores using state-of-the-art AI models to generate short videos as stimuli for supporting creative idea generation. A qualitative case study is conducted, involving design experts comparing the effects of textual, pictorial and video stimuli to support the generation of a flying car concept. The case study indicates that design experts prefer video stimuli generated using AI models as they offer dynamic motion and mechanism information that provides more inspiration. Although the current AI-generated video stimuli have limitations, such as lacking technical details, this paper highlights the great potential of using video to prompt design creativity.

Keywords: Design Creativity, Idea Generation, AI in Design, Design Stimuli, AI-generated Video

1 INTRODUCTION

Creativity, which is defined as "the process by which something so judged (to be creative) is produced" [1], is an integral part of product design and development. It is a significant process during the early stages of design that underpins the generation of innovative ideas for breakthrough products [2, 3]. Although consumers and end-users might not explicitly indicate creativity as a design requirement, creativity is considered a fundamental element for product innovation ultimately leading to product success [2, 4]. Studies have revealed that creative products are more likely to succeed in crowdfunding campaigns [5] and design competition awards [6]. Therefore, it is often a requirement for designers to come up with creative design ideas for informing the development of innovative products. However, coming up with ideas, especially creative ones, is a challenging task.

Generic tools such as Brainstorming [7], mind mapping [8], and Six Thinking Hats [9], were often employed by designers to support the generation of creative design ideas. To better support idea generation in the design context, design-focused tools and methods were developed, including TRIZ [10], design-by-analogy and WordTree [11], the Creativity Diamond Framework [12], the three-driven combinational creativity approach [13], and the 77 design heuristics [14]. These tools or methods help users remove mental blocks and expand design search spaces, but require the users to possess sufficient knowledge and experience to master. In recent years, computational means have been increasingly explored to support designers in generating creative ideas. These new computational approaches or tools often generate stimuli in textual and/or pictorial forms as sources of inspiration or information to support designers in creative idea generation [15]. With the advancement of computational power and Artificial Intelligence (AI) algorithms, AI-generated videos are becoming possible and affordable. However, few studies have explored employing AI algorithms for generating videos to prompt designers in creative idea generation. It also remains unclear whether videos could be used as an effective means to trigger designers' creative minds.

This paper is aimed at exploring the use of state-of-the-art AI models and algorithms to generate short videos as stimuli to support designers in generating creative design ideas. An AI tool, the IdeaMotion, is developed capable of generating short videos based on textual design descriptions. A qualitative case study is conducted to gain insights into using AI-generated videos as stimuli from the perspectives of designers. The following section reviews the related studies on computational and AI tools for supporting design creativity. Section 3 presents the details of the proposed AI video generation tool, and Section 4 showcases a case study with designers. The discussion and conclusions of the paper are presented in Sections 5 and 6, respectively.

2 RELATED WORKS

Employing computational means for supporting design creativity could be traced back to the 1990s. For example, Qian and Gero [16] developed one of the earliest computational systems for supporting design creativity finding analogical mappings through structure and behavior. Bhatta and Goel [17] proposed an autonomous design system IDeAL to support analogical designs by employing the structure–behavior–function model. Chakrabarti *et al.* [18] explored the use of text databases hierarchically by topic to aid design. Bryant *et al.* [19] presented a computational conceptual generation tool utilizingFunctional Basis and existing design knowledge to produce viable design variants. These pioneer studies laid the foundation for subsequent research and development in supporting design creativity utilising computational techniques.

Over the last decade, a number of sophisticated computational tools and approaches, leveraging AI, machine learning, natural language processing, and image processing techniques, have been developed to better support design creativity. Some of these tools provide or produce textual stimuli only to support designers. For example, Georgiev *et al.* [20] proposed a computational approach to produce new scenes through synthesizing existing scenes by thematic relations, for example, “microwave, bake, chestnut” is produced by synthesizing “fireside, roast, chestnut” and “microwave, bake, fish” as “roast” and “bake” are similar thematic relations. B-Link [21, 22] is a data-driven design support tool that helps designers discover and associate textual knowledge, which is underpinned by a large knowledge base created using academic publications. InnoGPS [23, 24] provides a text-based interactive map, which contains a technology space knowledge base created based on the US patent database, to allow designers to explore new design opportunities and directions. TechNet [25], which is a technology semantic network based on paten data, has been used to facilitate the generation of ideas [26] and representation of designs [27]. Pro-Exlpora [28] employs the Markovian model and machine learning to explore new design problems in text forms to inspire designers. Recently, with the rapid advancement of Large Language Models (LLMs), several LLM-based approaches have been proposed to support generating creative design ideas [29]. Zhu *et al.* [30] proposed a generative design approach to automatically generate bio-inspired design in the form of natural language by retrieving and mapping biological analogies using LLM. For instance, generating a piece of natural language text describing a new flying car design inspired by pterosaurs. Chen *et al.* [31] proposed an LLM-based tool to retrieve textual knowledge from a bio-inspired knowledge base and map the knowledge to support divergent thinking. Chen *et al.* [32] leveraged the Function–Behavior–Structure ontology to decompose conceptual design tasks and guide LLMs to generate high-quality textual concepts to stimulate designers.

In addition to textual stimuli, several tools and approaches have also employed images and pictures as stimuli to stimulate designers. For example, the Combinator [33, 34] simulates human combinational creativity and produces combinations of design phrases, such as “kettle cup” and “spider silk violin”, with corresponding merged or overlapped images, to prompt designers. The Retriever [35] employs aspects of analogical reasoning to produce new ontologies of a desired design accompanied by an image mood board to support creative design idea generation. Generative Adversarial Network (GAN), a generative AI framework, has been investigated to produce synthesized images of two items to prompt design creativity [36]. GAN has also been used to learn a specific design style and apply the style to a target product such as producing an image of a streamlining style chair [37], as well as fusing the design features of two objects such as a horse and a bike [38], to stimulate humans in creative idea generation which has gained positive impacts. DALL·E, an AI system for creating images from natural language descriptions, has been employed to generate pictorial ideas based on textual descriptions of combinational designs such as “an avocado chair”, which achieved a similar creativity level to novice designers [39]. Chen *et al.* [40] leveraged the reasoning capability of LLMs to generate design concepts employing the 5W1H method, Function–Behavior–Structure model and Kansei Engineering, and convert the textual concepts into images using text-to-image models for supporting human designers.

Producing textual (such as texts, keywords and phrases) and/or pictorial (such as images and pictures) stimuli to inspire and trigger designers’ creative minds is one of the most often used methods. Such conventional formats of stimuli have been proven to have positive effects on enhancing designers' creativity. While recent advancements in computational power and AI algorithms enabled the generation of videos, explorations on AI-generated video stimuli for supporting design creativity are needed.

3 USING AI FOR GENERATING VIDEO STIMULI

An AI tool, the IdeaMotion, is thereby developed to produce short videos based on the descriptions of designs in natural language to support designers in creative idea generation. An overview of the tool is depicted in Figure 1. The designer would need to generate a piece of design description in text forms or utilize an existing design description as the input of the IdeaMotion. The tool will then extract text features from the input design description. Bidirectional Encoder Representations from Transformers (BERT), a pre-trained machine-learning model for natural language processing, is employed to capture the semantic information from the input. An attention mechanism is introduced to help the tool focus on the key semantic information relevant to video generation.

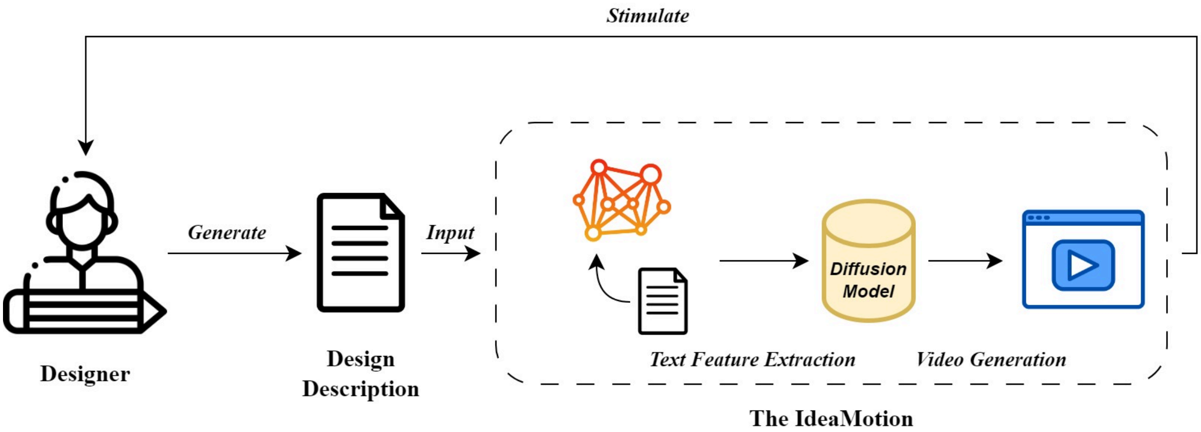


Figure 1. An Overview of the IdeaMotion

Once the key semantic features are obtained, the features are mapped to the video latent space. A readily available diffusion model based on the Unet3D structure [41] is employed to ensure the diversity and complexity of texts in the latent space are captured. The representation of the video latent space is then mapped to the video visual space to produce a video interpreting the input design description. Unet3D is a three-dimensional convolutional neural network-based structure for processing video data that can capture the spatiotemporal relationship in the video. It has an encoder for extracting high-level features and a decoder for restoring these features, which are used for video denoising and generating respectively. The IdeaMotion is packed as a web-based tool with simple user interfaces, as shown in Figure 2 and Figure 3, of which Figure 2 shows the user input interface asking the user to describe the desired design in text and Figure 3 shows the output interface playing the video generated. Due to the limitations of the models used and computational power, the generated video length has been limited to 2 seconds.

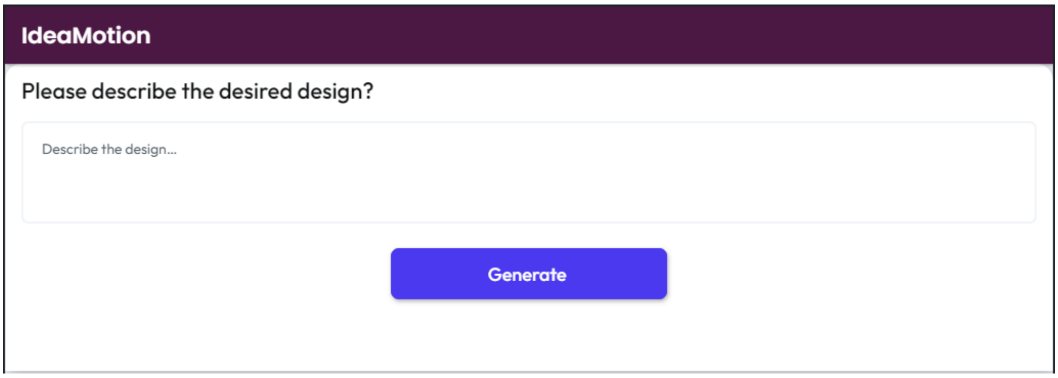


Figure 2. The User Interface of the IdeaMotion – User Input

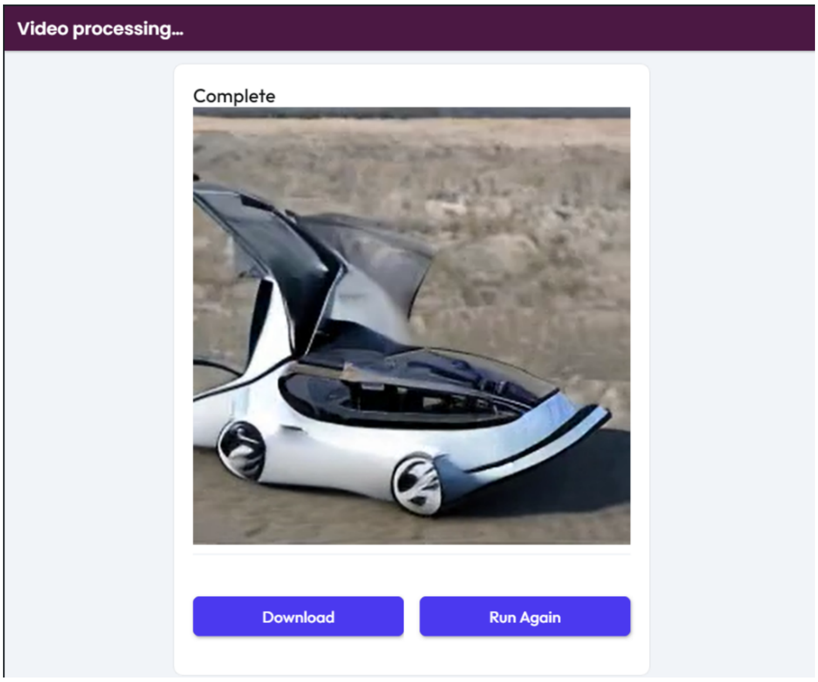
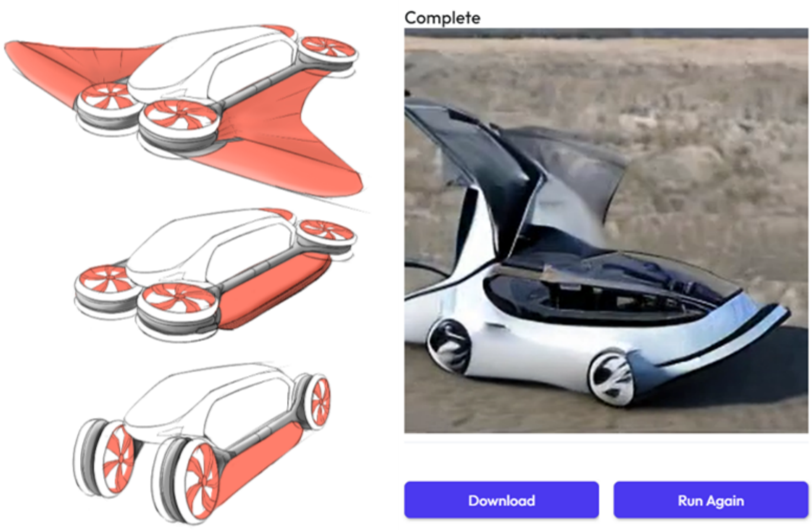


Figure 3. The User Interface of the IdeaMotion – Video Output

4 CASE STUDY

To gain insights into how video stimuli generated by the IdeaMotion support design creativity and compare with conventional textual and pictorial stimuli, a case study has been conducted involving two design engineering experts with over ten years of experience. In the case study, producing a concept of a flying car, which has often been used in design research, is adopted as the design task. Three stimuli of a "flying car" are employed and provided to the design experts, as shown in Figure 4. Figure 4(a) presents a textual stimulus describing a flying car design inspired by pterosaurs (adopted from [30]), Figure 4(b) is a pictorial stimulus created by a human designer that depicts the flying car design according to the textual description in Figure 4(a) (adapted from [30]), and Figure 4(c) is a video stimulus produced by the IdeaMotion using the textual description in Figure 4(a) as the user input.

The flying car has a body that is similar in shape to pterodactyls, with a body designed to control drag, lift, and thrust. It also has a lightweight hull and a propeller to generate thrust. The vehicle's hull is constructed of high-performance carbon fiber, inspired by the lightweight skeletons of pterosaurs. The propeller is mounted on a pivoting arm that is controlled by a joystick. The entire assembly weighs approximately 35 pounds and looks similar to a parasail. The propeller is 16 inches in diameter and is powered by a 930cc marine engine.



(a). Textual (from [30]) ***(b). Pictorial (Adapted from [30])*** ***(c). Video***

Figure 4. Textual, Pictorial, and Video Stimuli of "Flying Car"

To better showcase the video stimulus of the flying car in this paper, six time frames of images of the video with 0.4 seconds apart are presented in Figure 5. As shown in the figure, the flying car has the shape of a pterosaur with a pair of wings at the rear of the car. From 0.0 seconds to 2.0 seconds of the time frames, the fast-running car is gradually opening and extending its wings outward preparing for takeoff, which shows the progress of transforming from ground mode into flight mode.

Figure 5. The Short Video of "Flying Car" in Time Frames

Semi-structured interviews have been conducted with the two experts (Expert 1 and Expert 2) to investigate their viewpoints towards using the three types of design stimuli provided for supporting them in completing the concept generation task, as well as their perspectives on using AI-generated videos for supporting design creativity. The first question asked was "Do you use design stimuli for supporting idea generation? Which type of stimuli do you use?" Both Experts 1 and 2 indicated that they often employ stimuli to support them in idea generation. Expert 1 said "*I give priority to video, but also go for pictures sometimes. Video is kind of dynamic and shifts my attention to make me think differently rather than looking at a static image.*" Expert 2 mentioned that "*I mainly use images, sometimes use videos, but I rarely use texts*". The second question asked was "Have you used AI-generated stimuli for helping you with idea generation?" Expert 1 indicated that "*I have recently used AI-generated images, but have not used AI-generated videos.*" However, Expert 2 said that "*I rarely use AI-generated stimuli, as the quality of generated contents is not very good and sometimes might not be relevant to what I want to see*."

The design task "to produce a concept of a flying car" was then given to the experts. The three stimuli, as shown in Figure 4, were provided to the experts following the sequence of textual, pictorial, and then video stimuli to explore their views if they use such stimuli to support them in the design task. The third question "What are your thoughts on the three stimuli in helping you with the concept generation task?" For the textual stimulus, Expert 1 indicated that "*The textual stimuli will make me think but not really in a particular direction. It would take time to read the text again and again to make me think or inspire me.*" Expert 2 said "*I already have some ideas or images of a flying car in my mind by reading the text. It is good to see 'quantification' in the text such as the weight, size, material and engine model. However, I would need to spend time to generate a visualisation to showcase the design concept.*" Regarding the pictorial stimulus, Expert 1 said "*The image provides a direction. It is not really that I am going to produce something like this, but provides me with a clue or guide.*" Expert 2 said "*This is definitely better than the text, which is more tangible and inspiring. It is almost identical to what I had in mind. But, in a way, it limits imagination, such as the shape is already fixed, and lacks technical details.*" For the video stimulus, Expert 1 said "*This is the most inspiring one for me, as it involves a lot of things which I can interpret, such as the motion, the look and appearance, the loop and the mechanics, and even the environment. There is more divergent thinking looking at this, making me think in different directions.*" Expert 2 said "*It helps me visualise the motion of the design and move on to the engineering side, thinking how each component moves and joined together. But it misses the details of propellers.*" The experts were then asked "Which stimulus do you prefer?" Expert 1 indicated that the video stimulus is the first choice, followed by the pictorial and then textual stimuli. Expert 2 mentioned that the video and pictorial stimuli are the first choices rather than the textual stimulus.

Lastly, the experts were asked to express their views towards AI-generated video stimuli on design creativity in general. Expert 1 said "*Using AI-generated video stimuli is more inspiring which prompts you into different aspects of thinking and see things from different perspectives. Such a project or research in this direction would be of great benefit to design engineers.*" Expert 2 said "*Having something like this to work from at the idea generation stage is useful, especially if the generated video* *is longer. However, I think AI-generated content, like 3D images or animations, should not be considered the final form and designers should always go to further develop or revise. I believe there is a huge potential if AI can generate editable or configurable models or contents. This will further spark creativity.*"

5 DISCUSSION

Prior to showing the experts the stimuli in Figure 4, questions were asked to explore whether the experts use stimuli in idea generation. Both design experts suggested that they often use stimuli in idea generation to help them enhance their design creativity, while they both prefer pictorial and video stimuli rather than textual stimuli. Neither of the designers has previously used AI-generated video as stimuli, while one of them has previously used AI-generated images. To use the design stimuli in Figure 4 to come up with ideas to address the design task, both Experts 1 and 2 agreed that the video stimulus, which was generated by the IdeaMotion, would be their first choice. They both indicated that the video provided allowed them to visualize the motion and the mechanisms of the design. This is something that is very challenging for textual and pictorial stimuli to achieve. Both experts also agreed that the textual stimulus is the least useful one for supporting them in idea generation, and it would be quite time-consuming for them to produce or visualize a concept inspired by the text. Furthermore, Expert 2 pointed out that the video and pictorial stimuli are missing some technical details, while the textual stimulus contains useful quantifications of technical details. Considering the use of AI-generated videos as stimuli for supporting creative idea generation in general, both experts agreed such a format is useful and further research on exploring AI-generated video for supporting design creativity is promising. One of the experts indicated that the generation of editable models by AI would be a potential direction.

Therefore, concerning the case study conducted, video stimuli have significant potential to enhance creativity during idea generation. Although the current AI-generated video produced by IdeaMotion using the diffusion model lacks technical details, the video's dynamic and visual nature can inspire new ways of thinking in comparison to conventional textual and pictorial stimuli. Current AI-driven idea generation support tools mainly generate textual stimuli (e.g. [30], [31], and [32]) and pictorial stimuli (e.g. [34], [36], [37], [38], and [40]), while these textual and pictorial outputs could be potentially converted into videos by adopting AI models for video generation to provide additional inspiration enhancing design creativity. With more powerful AI models, such as Sora [42], becoming available, there is great potential to translate those quantitative technical details from text into videos providing more useful information. There are also some initial works (e.g. Text-to-CAD [43]) on generating simple CAD models, such as a plate or a gear, through text prompts. Most of these tools can only produce OBJ, STEP or STL format CAD files, while such formats only contain information regarding the shape or 3D geometry of a model limiting the capability of using the CAD model for complex tasks such as supporting video or animation. Thereby, further AI research studies are needed to explore the creation of CAD models capable of supporting video generation.

The current research has certain limitations. Firstly, the AI video generation tool, the IdeaMotion, developed in this research uses a diffusion model which limits the length of the videos generated. This limits the amount of information that could be conveyed in the video. Secondly, only a few samples and experts were involved in the study limiting the insights discovered.

6 CONCLUSIONS

This paper explores the use of AI models and algorithms for generating videos based on textual input, and implements this into a tool named the IdeaMotion. The tool uses BERT to capture semantic information from textual input and employs a Unet3D structure-based diffusion model to produce videos. A qualitative case study was conducted by interviewing two design experts to gain insights into using AI-generated videos as stimuli for supporting creative idea generation. The case study shows that video stimuli are preferred by design experts compared with pictorial and especially textual stimuli, as video stimuli provide additional information regarding the motions and mechanisms. This paper has contributed to the body of knowledge in research on design creativity and AI, which provides useful insights on AI-generated videos as stimuli for supporting design creativity. In future studies, more samples of a larger variety of objects including both dynamic and static ones will be explored by interviewing more design experts. A quantitative case study focusing on exploring how the use of AI-generated video stimuli affects the creativity level, including novelty and usefulness, of idea generation outputs in comparison with using pictorial and textual stimuli will be conducted.

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