Modular Generative Adversarial Networks for Support in Product Design

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Abstract

This paper presents a literature review on modularity and creativity in terms of design variants for generative adversarial networks for image creation. The objective is to lay the foundation for providing a suitable tool to support product design, as this area is considered a potential beneficiary of this concept. Based on the literature, a new model will be developed as an IT artifact in future research. Current approaches that allow the user to control certain features of GAN outputs are explored and commonly used metrics are investigated. Finally, limitations and future research directions are reflected upon.

Keywords: Generative adversarial networks, product design, modular networks, design support, novelty integration.

1. Introduction

During the current developments throughout the fourth industrial revolution, the ways in which people collaborate and create new ideas have shifted significantly. Consequently, companies in the manufacturing sector adapted to these changes as well by altering their approaches to creating business value [11]. One of the main advances is called *data-driven product design* (DDPD), which is a paradigm to use huge amounts of data to (partially) automate decision-making processes by modern technologies such as the Internet of Things (IoT), computer-aided design (CAD), and artificial intelligence (AI). The rationale behind the integration of these means into areas that were traditionally dependent on human mental work is to boost the overall efficiency of product design [11]. As DDPD evolves, the need for more dedicated research in this field is necessary for technological adaptation. Generative adversarial networks (GANs), originally developed by Ian Goodfellow et al. [4], have greatly evolved since their introduction in 2014, which lead to the emergence of numerous variants. Fundamentally, GANs consist of two components called *generator* and *discriminator*, which are both artificial neural networks. The former aims to reproduce realistic new instances of given input data with the objective of deceiving the latter. In turn, the prediction of the discriminator is used to improve the quality of the generator's output, thus forming a cycle where both components mutually improve each other. GANs are widely used for image generation, style transfer, image-to-image translation, and other creative applications, thus making the concept an appropriate foundation for DDPD.

In this paper, several advanced GANs for application in the field of product design are discussed. For example, *ModularGAN* [13] addresses the issue of limited scalability and flexibility by proposing an alternative to the usually fixed and streamlined architecture by splitting the GAN into composable feature-specific modules. More focused on innovation, *CreativeGAN* [9] proposes a modification to GANs to cause more novelty in outputs by altering a pre-trained GAN. In manufacturing, *StarGAN* [3] can be used to optimize the prediction accuracy of spot weld positions to reduce wasted resources and improve the overall process. To formalize the research, one research question (RQ) guides the systematic work:

RQ: What is the current state of user control over features in GAN outputs with respect to different levels of granularity, especially for the use case of product design?

The remainder of the paper is structured as follows. In Section 2, the protocol of a systematic literature review is explained. Subsequently in Sections 3 to 5, the theoretical results and answers to the research question are discussed. Section 6 briefly summarizes the main findings and outlines potential future research directions.

2. Systematic Literature Review Protocol

The query investigates the application of GANs in product design, emphasizing how they leverage image datasets for feature-specific modifications to augment the design process. Scopus, ScienceDirect, SpringerLink, and IEEE Xplore are selected as primary databases due to their extensive coverage, and diverse range of scientific and technical literature. The search query is used to extract relevant information from the above-mentioned databases. However, a query that works effectively on one database may not yield the same results on another. This necessity for query modification arises from several database-specific factors, including differences in search algorithms, indexing methods, keyword modification, and subject coverage. The search is further restricted to publication years from 2015 onwards, as the concept of GANs was first proposed the year before, in 2014 [4]. The detailed search query for the particular databases is highlighted in Table 1.

Table 1. Search query for literature review

Database	Search Query	Year
Scopus	Title, abstract, keywords: ((„GAN“ OR „generative adversarial network“ OR „generative AI“) AND „product“ AND „design“) Source type: Conference proceeding or journal Subject area: Computer science or engineering	2015 - 2024
ScienceDirect	Title, abstract, keywords: („GAN“ OR „generative adversarial network“ OR „generative AI“) AND („product“ OR „design feature“) Subject area: Computer science or engineering	
SpringerLink	Title: „GAN“ OR „generative adversarial network“ OR „generative AI“ **AND** Keywords: „product design“ Subject area: All.	
IEEE Xplore	All Metadata: „GAN“ OR „generative adversarial network“ OR „generative AI“ AND „product design“ Subject area: All	

Furthermore, several inclusion and exclusion criteria were applied to the literature. While all inclusion criteria had to be fulfilled, meeting one of the exclusion criteria lead to the rejection of an article from the initial literature set. The criteria are stated in Table 2.

Table 2. Selection criteria for the SLR

Inclusion criteria	Exclusion criteria
Written in English language	Insufficient methodological explanations
Topical focus on GANs / generative AI	Less than six pages / short paper without finalized research
Consideration of architectural concepts, especially modularity in GANs	Application domain not comparable to product design or related fields
Potential for feature-specific adaptations	Insufficient evaluation of results

The final quantitative results of the SLR are illustrated in Fig. 1. The review was divided into an automized part, yielding the articles retrieved from the databases by their respective search mechanisms, and a manual selection process based on the stated selection criteria.

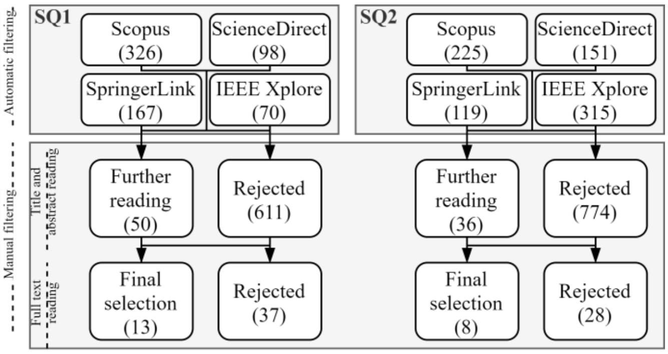

Fig. 1. Visualization of quantitative SLR results

3. Potentials of GANs for Product Design

Product design is usually linked to innovation in any product development or engineering life cycle and is highly correlated with the product's success. In some cases, engineering and product design are bound by certain restrictions due to their functionality, and therefore it is necessary to obtain a balance between *utility* and *novelty* [10]. In product design, novelty is correlated with creativity and is a key component in evaluating the evolution of designs and designers in the field of engineering [5], [1], [6]. Utility, on the other hand, relates to the core functionality of any product. For example, the core components of bicycles include frames, tires, handlebars, and saddles. Without any of these components, the overall functional aspect of the bicycle is diminished. Therefore, it is necessary to put functional constraints on product design to maintain its utility. In addition, as presented by [6], the novelty of the design can be evaluated mainly with novel functions or components, and by studying the structurally differentiating aspects of a design. In product and engineering design, designers can explore novel design concepts with manual and iterative design options. This iterative process can be complemented by a data-driven strategy with GANs, helping designers explore a wider range of designs by reducing manual overhead.

4. Current State of GANs in Product Design

ModularGAN [13] is a novel GAN-based approach introduced in 2018 for GANs to increase flexibility and scalability. The literature highlights the composable and reusable modular architecture to handle image-to-image translation of data with the help of images of facial expressions as the input data. Image-to-image translation of data is defined as the ability to alter the domain of input data while preserving the core structure of the image. Some examples of the image-specific domain based on the case study highlighted in the paper are hair color (black, brown, red), facial expression (smile, no smile), or a combination of multiple features. Unlike the traditional approach where a separate model is required for each domain, ModularGAN utilizes multiple composable modules, which can be used in a non-linear setup. The main goal of the model is to increase efficiency, scalability, and overall flexibility. The model consists of five core components: encoders, generators, transformers, reconstruction modules, and discriminators. Just like in other GANs, the generator creates new data based on a random noise vector, which incorporates condition features into latent space. This latent space is used to encode potential features or attributes during the processing of data. An encoder is used to convert the given image data into a latent representation of essential features of the data. This data is sequentially worked upon by the subsequent modules. The transformers work on the latent space by changing the features based on desired changes, while keeping the non-relevant areas as they are. The reconstruction modules work on the rebuilding the images based on the transformed latent representation. Finally, the discriminators evaluate the images and differentiate between fake and real data, helping the generators with a feedback loop to increase the authenticity and accuracy of the data. For product design as in the present paper, this structure can have the advantage to control individual features of a product design separately, thus giving designers more fine-grained control.

CreativeGAN [9], introduced in 2021, is an approach to specifically enhance the creative synthesis of image data. Usually, the main objective for GANs in productive use is to maximize the quality of outputs in terms of realism to trick the discriminator. In turn, novelty in design is rather a secondary objective. CreativeGAN proposes a method to integrate innovation and unique design techniques by adding novelty detection, localization, and segmentation, which is a suitable addition to GANs with respect to the core application area of product design support studied in this paper. CreativeGAN comprises multiple generators that learn to create new image data based on patterns and statistical distributions and rewrite parts of the images in the later process with a focus on areas with novelty. For this purpose, the model employs a novelty detection system to localize the new design components, which can be used to generate unique designs and enhance creativity. The novel feature map generated with the help of novelty detection and localization is then given to the rewriting module, which integrates generators to create novel data. These should differ from the original data in areas previously found to be the most novel, based on randomly generated images by a GAN during the first steps.

5. Overview of Major Advancements of GANs in Design and Image Synthesis

This section covers additional pivotal studies that leverage GANs in the creative field and the broader applicability of GANs in different application spaces to provide a more comprehensive answer to the RQ. Unlike traditional GANs, where the objective is to replicate the distribution of data, *Creative Adversarial Networks* (CAN) [2] learn the styles and patterns in the data and deliberately deviate from these styles. By maximizing this deviation, CANs aim to add more novelty to the data. The core concept of CAN is more suitable for image data with ambiguous style. The application area explained in the study [2] is focused on generating artistic images by keeping the broader distribution of artwork minimal and instead maximizing the style deviation.

With a more modular approach, *Attentional Discriminator GAN* (ADGAN) [7], implements an attention mechanism to enhance image generation with multiple combinational attributes. This is highlighted with a study on fashion design images. The attention mechanism is a weightage system, which provides weightage to different regions of an image based on the relevance to the attributes of images. Furthermore, an encoder is used to combine complex attributes more flexibly to produce a diverse set of outputs. Despite the ADGAN model being able to handle multiple combinations of attributes, the complex interaction of contradictory attributes can create challenges while generating data.

Another study [8] from 2022 introduces a text and image fusion technique which the authors call *TxtImg2Img GAN*. A convolutional neural network (CNN) is used to extract the data's dimensional attributes after simultaneously encoding the image and text. In addition, the Hadamard product is utilized to combine image and text data based on novel data pieces generated by transposed CNNs [8]. This method is suitable for designers as a support system to improve efficiency in the design phase, making TxtImg2Img GAN relevant in the design and implementation of modular GANs for product design.

StackGAN [12] is a method divided into two stages. The core concept of StackGAN is to create high-resolution images from text descriptions. The study highlights the limitations and inability of many GANs to generate high-resolution images due to low image and model resolution. The authors propose a two-stage model, consisting of v1 that works to generate low-resolution images from the text description, and v2 that is stacked on the previous output with the help of conditional augmentation to generate high-resolution images. The second stage also refines the images to add details and remove defects.

6. Conclusion

The overall research provides answers to the RQ concerned with the current state of the art in GANs for product design. The question is answered based on the evidence gathered from literature filtering and review. After the introduction of GAN by [4], there have been numerous versions of GAN been introduced over time. Based on the literature filtering, only ModularGAN [13] explores the modular concept of GAN, which subdivides the system into smaller parts. In contrast, CreativeGAN [9] explores the creative design space in a product to overcome GAN limitations to generate novel data. Additionally, ADGAN [7] specializes in multiple complex attribute handling, while TxtImg2Img GAN [8] and StackGAN [12] focus on text-to-image generation. Future research will try to narrow down the search to two core methods, ModularGAN and CreativeGAN and find a balance between utility and novelty.

The current study focuses solely on the theoretical background of product design support with GANs. This creates a great opportunity to explore this model type for multiple attributes and different product groups in the future. The inclusion of complex attributes and different product images can also help to test the model's scalability and flexibility once deployed. Novelty optimization and robust modules can be incorporated into the design to assess the utility of the product and achieve an equilibrium between novelty and utility. The further extension can also incorporate the use of more powerful GPUs to perform more computing-intensive training to obtain better results.

References

1. Cai, A., Rick, S. R., Heyman, J. L., Zhang, Y., Filipowicz, A., Hong, M., Klenk, M., and Malone, T. DesignAID: Using Generative AI and Semantic Diversity for Design Inspiration. In *Proceedings of The ACM Collective Intelligence Conference*. ACM, New York, NY, USA, 1–11 (2023)
2. Elgammal, A., Liu, B., Elhoseiny, M., and Mazzone, M. *CAN: Creative Adversarial Networks, Generating "Art" by Learning About Styles and Deviating from Style Norms* (2017)
3. Gerlach, T. and Eggink, D. H. Generative Adversarial Networks for spot weld design. In *2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*. IEEE, 1–8 (2021)
4. Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. *Generative Adversarial Networks* (2014)
5. Hoggenmueller, M., Lupetti, M. L., van der Maden, W., and Grace, K. Creative AI for HRI Design Explorations. In *Companion of the 2023 ACM/IEEE International Conference on Human-Robot Interaction*. ACM, New York, NY, USA, 40–50 (2023)
6. Jagtap, S. Design creativity: refined method for novelty assessment. *International Journal of Design Creativity and Innovation* 7, 1-2, 99–115 (2019)
7. Lee, H. and Lee, S.-G. Fashion Attributes-to-Image Synthesis Using Attention-Based Generative Adversarial Network. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 462–470 (2019)
8. Liao, W., Huang, Y., Zheng, Z., and Lu, X. Intelligent generative structural design method for shear wall building based on "fused-text-image-to-image" generative adversarial networks. *Expert Systems with Applications* 210, 118530 (2022)
9. Nobari, A. H., Rashad, M. F., and Ahmed, F. *CreativeGAN: Editing Generative Adversarial Networks for Creative Design Synthesis* (2021)
10. Shah, J. J., Smith, S. M., and Vargas-Hernandez, N. Metrics for measuring ideation effectiveness. *Design Studies* 24, 2, 111–134 (2003)
11. Wang, Z., Zheng, P., Li, X., and Chen, C.-H. Implications of data-driven product design: From information age towards intelligence age. *Advanced Engineering Informatics* 54, 101793 (2022)
12. Zhang, H., Xu, T., Li, H., Zhang, S., Wang, X., Huang, X., and Metaxas, D. *StackGAN++: Realistic Image Synthesis with Stacked Generative Adversarial Networks* (2017)
13. Zhao, B., Chang, B., Jie, Z., and Sigal, L. *Modular Generative Adversarial Networks* (2018)