Learning visual constraints for constraining Deep Generative Models for Generative Design

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Abstract. Generative design aims to autonomously produce several design alternatives given a set of design specifications. The focus of this research is conceptual design generation in generative design as this is the most flexible and critical phase of the process. We propose a framework to generate 3D images of conceptual designs for products by using a method for learning visual constraints to regulate the training of Deep Generative Models. In doing so the Deep Generative Models should produce diverse conceptual designs while ensuring the functionality and viability of the generated designs. An overview of recent research that uses Deep Generative Models such as Variational Autoencoders and Generative Adversarial Networks for generative design is provided. A method for learning visual constraints by using learnable constraints is discussed as well as techniques for evaluating the validity and novelty of the designs.

Keywords: Generative design, Deep Generative models, Learnable constraints.

1 Introduction

1.1 Background

The design process is complex as architects, engineers and designers must consider factors such as aesthetics, productivity, budget and time when developing a design. This has resulted in the conventional product design process typically producing a single detailed model as a solution. Generative design seeks to autonomously generate several design alternatives given constraints and design criteria [1]. Currently in industry generative design is performed by integrating genetic algorithms and topology optimization (a method to minimize mass and maintain structural integrity) to create design variations in 2D and 3D models [2]. Recently the use of Deep Generative Models in generative design has been explored as these models have the potential to provide more diverse and aesthetic designs [3]. A deep generative model is an algorithm for constructing a generator that learns the probability distribution of training data and generates new data based on the learned probability distribution [4].

The conceptual design stage is usually the second stage of the design process and is considered a crucial stage of the process. It is non-routine and creative in its nature when compared to the other design stages which are more methodical (e.g. calcula-

tions and structural analysis). Creative design is based on reflection, reaction, critique and inspiration being drawn from the process itself [5]. This implies the conceptual design stage is an iterative process thus making it time consuming. Developing the concepts requires knowledge and experience to apply constraints to conceptual designs. If constraints are applied incorrectly then the entire design process is undermined due to human error. The addition of constraints (e.g. predefining the objects geometry and overall size) before conceptual designs are generated restricts the diversity of designs produced. This may be avoided by enabling Deep Generative Models to learn knowledge constraints and visual concepts. The functionality of the 3D conceptual designs can be achieved by maintaining integral design features by utilizing the concept of learning visual constraints. The aforementioned highlights the potential of allowing Deep Generative models to learn visual constraints in order to generate functional and aesthetic 3D conceptual designs.

1.2 Problem Definition

The aim of the paper is to learn visual constraints for constraining Deep Generative Models in order to generate 3D conceptual designs which are diverse, functional and practical; resulting in the minimization of human intervention in the pre-processing phase of the design process. Deep Generative Models are the latest technique used in generative design research. Deep Generative Models have been coupled with techniques such as topology optimization to generate designs. The use of Deep Generative Models solely for design generation has a tendency to reproduce invalid designs according to recent research [3]. In this paper visual constraints refers to restrictions and rules which allow for a product to have its main features to be appropriately positioned thus ensuring that the product can perform its given function. An example of such a constraint is learnable knowledge constraints which were used to generate human images. The image of a target pose was generated by a generative model by learning constraints from front view images of a person [6]. Constraining of Deep Generative Models refers to the regulation of its training to produce a set of desirable outcomes. The focus of this paper is on conceptual design generation. Conceptual designs embody fundamental ideas of a design which can be visual represented in several forms (e.g. sketches). Conceptual design generation is the focus as it can be the most time consuming phase of the design process [2]. 3D conceptual design refers to an image of 3D product designs. This research will assess which Deep Generative Model (mainly variations of Generative Adversarial Networks and Variational Autoendcoder) can accurately generate 3D images. This research will also assess which method of learning visual constraints can be used to generate conceptual designs.

2 Literature review

2.1 Generative Design

The design process is an iterative process consisting of problem definition, conceptual design stage and detailed design stage. The process has incomplete problem specifica-

tions. The conceptual design stage is a creative design process which presents concepts and generalized forms. Creative design is based on reflection, reaction, critique and inspiration being drawn from the process itself, which is referred to as conceptual emergence [5]. Experience and understanding is required to develop solutions to design problems. The design and problem space contains a set of feasible designs which are created to solve a particular design problem. The design space has states with each state representing a conceptual design. The states can be defined by multiple characteristics (e.g. performance, size, weight).

Generative design is usually a capability of CAD (Computer Aided Drawing) applications that autonomously generate a number of design alternatives given a set number of constraints [2]. Engineers or designers can choose which designs they want to explore further. Generative Design utilizes capabilities such as Topology Optimization and Genetic algorithms to explore the design space of a new product. In the engineering domain the typical generative design process begins with an input which is a 2D or 3D model, either a Concept Design or Detailed Design. The engineer/designer specifies the constraints such as geometric constraints (e.g. maintaining a certain geometric shape at a specific relative position) [2].

In the conceptual design phase a range of ideas are developed which satisfy the form, fit, and function requirements. Generative Design is highly applicable to conceptual design as this phase allows for flexibility to explore alternative ideas for products [2]. The concept designs can be represented as 2D sketches, abstract 3D models, or fully detailed designs.

Table 1 shows a list of commercial application of generative design. Genetic algorithms are currently used in industry to perform topology optimization.

Table 1. Commercial applications of generative design to date

Domain	Product	Technique
Aerospace	Bionic partition for airplane	Genetic algorithms ;slime mold and mammal bones [7]
Furniture	Chair	Genetic algorithms [8]
Architecture	Office space planning	Multi- objective genetic algorithm [9]
Automotive	Seat bracket for seat belt	Genetic algorithms[10]

Recently there have been several papers that explored the use of neural networks in generative design frameworks [4],[11],[12],[3],[13]. Deep Generative Models and Topology Optimization were used in a framework to produce 2D black and white wheels designs [4].

There is a lack of large reliable databases of images or models of products that are required for training neural networks [4]. A method to generate training data was proposed by using a topology optimization algorithm which has a multi-objective

function. The framework consisted of multiple stages. A BEGAN (Auto-encoder used for the discriminator) was used to generate the 2D wheel designs and topology optimization followed. BEGAN was selected as it produced simpler and sharper images fast and stably. Mode collapse of BEGAN was addressed by using topology optimization and manual methods and human intervention. Although the BEGAN was selected, the DCGAN was tested in the framework as well and generated more varied and complex shapes. However the reference designs generated by BEGAN were simpler and sharper and yielded better topology designs than DCGAN. The choice of GAN was based on the specific framework that was developed which was centered on topology optimization. The use of 2D design space and pixel wise designs is seen as undesirable in the field of design as it is an over simplification of a problem hence making it unrealistic.

A novel topology design approach using an integrated Deep Learning Network architecture was developed to generate 2D beam designs [11]. A topology optimization algorithm was used to generate training data in a similar manner as [4]. Wasserstein GAN was used to generate the 2D beam designs. According to [11] mode collapse of WGAN was identified as a concern but this is in contrast to [14]. Unlike other GAN variations which experience mode collapse, WGAN is able to eliminate mode collapse [14]. A sample of the initial dataset generated by using the topology optimization algorithm is not provided. Evaluation of the novelty of the 2D designs are not considered since the main focus of the results were on the quality of image generated by the WGAN. Thus the extent of variation in the designs generated cannot be assessed.

An indirect design representation for topology optimization using Variational Auto-encoder (VAE) was used by [12] in order to produce 2D heat conduction images (black and white). Training data was generated similarly to [4] and [11]. Multi-layer perceptron networks were used for the encoder and decoder of the VAE [12]. The VAE was augmented by the addition of a style loss function for the purpose of style transfer. The VAE augmentation prevents unrealistic scattering of material clusters thus forcing it to follow the topological style from the training images. The VAE augmentation with regards to style indicates the necessity to constrain deep generative models in order to produce more realistic results for certain applications (i.e. in sciences and engineering). The VAE tends to produce blurry images, and not all image details are preserved in the reconstructed or generated images due to the choice of the VAE loss function. More details can be preserved by using modified VAEs such as ones based on adversarial training.

In [3], the use of two deep generative models in generative product design frameworks is explored. VAE with a deep convolutional architecture) and WGAN were used to generate 2D window designs. The VAE approach produces diverse designs with respect to shape, color and style. The WGAN produced designs with window features (mullions and frames) in suitable positions and more asymmetric designs; indicating that unconventional designs were produced by the WGAN. The aim of the 2D window experiments was to create distinctive designs. The problem of the 2D window designs is not as complex as the 2D wheel, beam and heat conduction problems. Hence the 2D window experiment cannot confirm whether WGAN can solely

produce viable and practical designs for more complex problems. All the window designs were blurry. The training of the WGAN and VAE were not progressive and the WGAN was not trained long enough for it to converge which would affected the generated images [3]. The method of evaluating the models was done by visual inspection.

In [13] the focus was on generating 3D (voxel format) beam models using 3D Convolutional Neural Networks (CNNs) in order to reduce overall computational time. A 3D CNN was trained on intermediate results from a conventional topology optimization process produced by the program called TopOpt. The topology optimization program at an intermediate stage is stopped and the current structure is fed to 3D CNN which predicts the final optimized structure. Due to the use of the 3D format the 3D CNN was able to learn the density distribution of the beams in relation to the design criteria for the beam problem. The use of 3D CNN resulted in 40% reduction in overall computational time while achieving structural accuracies of 96% when compared to the ground truth (3D models generated by TopOpt). The novelty of the designs was not an objective. An objective of the 3D beam model experiment is structural performance of the design The experiment shows that the 3D CNN is able to predict final designs in this context. A beam is a simple problem compared to other design problems; the approach to the problem is systematic. Based on the 3D beam experiments, CNNs solely cannot be considered when aiming for innovative designs.

The decision of generating training data using topology optimisation for some of the aforementioned papers was based on its ability to produce results which are reliable and structurally feasible. The above approaches rely on topology optimization to ensure the designs produced are viable but this approach requires the imposition of constraints (e.g. dimensions are specified as exact values or ranges) before the design process begins. This may inhibit the diversity of designs generated. GANs are capable of producing unconventional designs [3], [4] but experience difficulty when attempting to produce valid (functional) designs for more complex problems. Creation of diversity in the generated designs is a concern.

2.2 Evaluation

The focus of the research is on generating conceptual designs therefore the metrics to be evaluated are validity and novelty (variation) of designs and number of valid designs. Novelty of designs is typically performed by comparing generated designs to reference designs (ground truth). Validity of designs will be based on identification of crucial physical features, relative positioning of features and product dependent characteristics (e.g. width and height).

Development of a loss function (reconstruction error function) employing auto-encoder trained with reference designs was used to evaluate novelty (index similarity) and physical quantities (e.g. volume) in [4]. Reconstruction errors of Auto-encoders are widely used to detect anomalies. If design data is insufficient then a regression model can be used instead of an auto-encoder for evaluating designs [4].

In [11] a CNN is used to evaluate image quality of the designs and it is trained with reference designs.

In [13] Root Mean Square is used as an accuracy metric to evaluate the performance of the CNN to generate the 3D models. Root Mean Square is also used as an accuracy metric to evaluate the performance of the CNN for topology optimization. This helps in understanding the proximity of the actual density distribution values between the predicted and the final structure. Final processing of the structure using TopOpt is used as ground truth. Binary accuracy and spatial gradient of filtered densities were the metrics used to map the progress after each iteration of the CNN.

In [12] a multi objective genetic algorithm was used to identify non-dominated designs (novel designs) that are fundamentally different from the training data designs.

2.3 Learning constraints from images

Learnable knowledge constraints. Posterior regularization (PR) provides a framework for imposing knowledge constraints on probabilistic models [15]. The constraint term encodes the domain knowledge. It is used to regulate the learning of models in different context [15]. The application of PR is limited to a Bayesian formulation or explicit density evaluation models therefore it cannot be applied to Deep Generative Models [6]. It also requires constraints to be fully specified which maybe be impractical as there is uncertainty in some constraints with regard to complex knowledge.

Therefore the use of Posterior Regularization to learn constraints as extrinsic rewards in reinforcement learning was proposed by [6]. The proposed algorithm can be applied to neural models with any type of architecture and thus can be applied to Deep Generative Models. Inverse reinforcement learning is used in the algorithm to learn PR constraints from data. The algorithm is efficient in regularizing large target space with arbitrary constraints and is flexible to learn the constraints and model jointly. The algorithm alternates the optimization of the constraint and the generative model and the constraint is regarded as a reward function to be induced.

Human image generation experiments were conducted using the learnable knowledge constraint method. The domain knowledge learnt in this experiment is the human anatomy (body structure). A front view image of a person and a target pose (defined by key points) were provided. The aim is to generate the person's image within the constraints of the target pose. The constraints force the human body parts (e.g. hands) of the generated image to correspond to those of the true target image (pose). The constraint includes a human parsing module that classifies each pixel of a person image into possible body parts [6]. The images used in the experiment had body self-occlusions and cloth and shape ambiguities. The addition of a body part consistency constraint to the generative model showed improved results over base generative models.

The proposed approach presents a generalizable method to adding knowledge to neural networks by formulating knowledge constraints that prompt the model to learn the desired structure and outcome whereas previous approaches use domain knowledge (i.e. explicitly providing knowledge base) to achieve the same results. The experiments in the paper focused on developing constraints which did not require

explicit knowledge as the constraints were deduced from the images. The learnable knowledge constraint method learnt to classify human body parts and thereafter assigning it to a position for the target pose. The human anatomy was correctly positioned in the generated target poses but the color of the clothing items was incorrectly reproduced in some instances (e.g. the white color of a blouse was used for a pair of shorts). The nature of the constraints was simple when compared to a complex problem such as those in generative design. The proposed method was able to regulate the training of the generative model hence achieving the desired result.

3 Proposed method

A method similar to the target pose input method used in [6] must be devised. This is necessary for allowing the user to input products specifications (requirements) to enable training of the framework to learn desirable outcomes. This must be integrating into the deep generative model and learning visual constraints framework. Deep Generative Models (GANs and VAEs variations) will be implemented in order to assess its accuracy with regards to generation of conceptual product designs. A range of products will be used for this experiment.

Since the aim of the research is to improve conceptual designs generation by using a method to learn visual constraints; a number of products must be evaluated to determine that the functionality is achieved across several product domains. This will prove whether the proposed framework is generalizable with respect to conceptual design. Conceptual designs in the form of images will be produced as the output of the proposed framework.

The methods to evaluate validity of designs and novelty must be decided upon. Evaluation can be performed by either utilizing experts to evaluate designs or an automated process. Specific metrics for each product being generated must be decided upon as each product must satisfy different requirements in order to be functional. The use of specific metrics for each product will be used to measure the validity of the designs. Finally a comparison between the novelty and variation and functionality and validity of the generated 3D conceptual designs by the proposed framework to a base Deep Generative Model must be made.

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