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Parametric Design Method of Buildings Based on Convolutional and Deep Neural Networks

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Abstract:

The application of AI technology in architectural software has brought various innovations and changes to the industry. By introducing convolutional neural networks and deep neural networks, architectural design software is expected to automatically identify and generate complex architectural images, optimize the design process, and provide intelligent design assistance. Through literature research, this paper aims to discuss the specific application of CNN and DNN in parametric design and the innovation brought by them, and analyzes the application of these technologies in architectural image recognition, generation, design optimization and other aspects. This paper aims to provide a comprehensive reference for researchers in related fields and promote the innovative application of AI technology in architectural design. The application of AI technology in architectural software has brought numerous innovations and changes to the industry. By introducing convolutional neural networks and deep neural networks, architectural design software is expected to automatically identify and generate complex architectural images, optimize the design process, and provide intelligent design assistance. Through literature research, this paper aims to discuss the specific application of CNN and DNN in parametric design and the innovation brought by them; it also analyzes the application of these technologies in architectural image recognition, generation, design optimization, and other aspects. This paper aims to provide a comprehensive reference for researchers in related fields and promote the innovative application of AI technology in architectural design.

Keywords: Architectural Design, Convolutional Neural Network, Deep Neural Network, Fusion Application, Research Progress

1. Introduction

Convolutional neural network (CNN) is an efficient model for processing image data [1], extracting image features through convolutional layer, pooling layer and fully connected layer. Its advantage lies in its powerful image processing and feature extraction capabilities. The convolution layer is responsible for capturing the local features in the image, capturing the key feature information in the building geometry, such as curves, boundaries and corners, and generating the feature map by sliding the convolution kernel on the image. The pooling layer reduces the dimension of the feature map through maximum pooling or average pooling, thus reducing the computational complexity and the number of parameters. The fully connected layer is used to map extracted features to the output space to achieve tasks such as image classification and recognition. The convolutional layer slides over the input data through the convolutional kernel (filter) to extract local features. These features can be low-level features such as edges and textures, or they can be complex features at higher levels. The formula is expressed as:

$$y_{i,j}=\sum_{m}\sum_{n}x_{i+m,j+n}\times\omega_{m,n}+b$$

Where x is the input data, ω is the convolution kernel, and b is the offset term.

Deep neural network (DNN) realizes complex nonlinear mapping through multi-layer structure and has powerful learning and modeling ability. The basic structure of DNN consists of an input layer, multiple hidden layers, and an output layer. The input layer accepts the raw data and passes it to the hidden layer for processing. Through the combination of multiple neurons and nonlinear activation functions, the hidden layer extracts and transforms the features of the input data layer by layer to form a complex network structure. The output layer makes the final prediction or classification based on the extracted features. DNN achieves complex pattern recognition and prediction by extracting data features layer by layer. The output of each layer is transformed by a nonlinear activation function (such as ReLU) and the input is transferred to the next layer. The formula is expressed as:

$\alpha^{(l)} = f(W^{(l)}\alpha^{(l-1)} + b^{(l)})$

Where $\alpha^{(l)}$ is the activation value of layer, $W^{(l)}$ is the weight matrix, $b^{(l)}$ is the bias vector, and f is the activation function. The activation function in the neural network is shown in Figure 1.

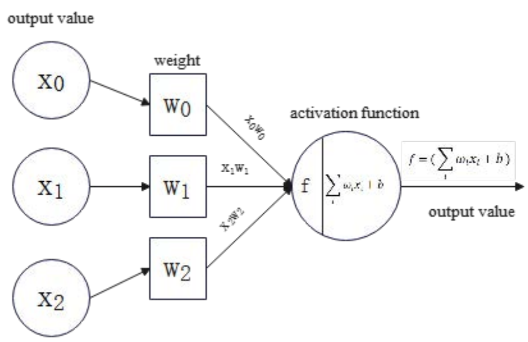

Figure 1 Activation function

In architectural parametric design, the design tasks not only include the optimization of geometric form, but also involve many aspects such as functional layout, material selection, and structural performance, etc. These problems often involve high-dimensional data and complex parameter relationships. These multi-dimensional and multi-level design requirements determine that a single technical method is difficult to comprehensively tackle, which is the advantage of CNN and DNN. CNN is responsible for the preliminary feature extraction of geometric morphology, which simplifies the complex 3D morphology into a low-dimensional feature representation and provides basic data for subsequent optimization. However, DNN further processes these features and combines with other high-dimensional parameters to achieve comprehensive optimization. Architectural design is an iterative process, and designers need to constantly adjust and optimize the scheme to meet changing requirements and constraints. The advantages of CNN in geometric shape feature extraction, combined with the ability of DNN in high-dimensional data modeling and multi-objective optimization, provide a comprehensive solution for architectural design.

2. Application of Convolutional Neural Network in Parametric Design

In parametric design, image recognition is an essential link [2]. The application of CNN in parametric design is mainly embodied in image feature extraction, shape generation, and optimization design. Parametric design is a method to generate and optimize design schemes based on parameter changes, and CNN provides a new technical means for parametric design through its powerful feature extraction capability and nonlinear mapping function.

2.1 Image feature recognition and extraction

Image feature recognition technology extracts features such as edges, corners and textures from images and converts these feature information into geometric shapes. Common methods include Canny edge detection, Hough Transform, and Scale-Invariant Feature Transform (SIFT). CNN uses the sliding operation of convolution kernel on the input image to extract the local and global features of the image through multi-layer convolution. Specifically, the convolution kernel is equivalent to a filter that moves across the image, capturing a portion of the image with each move. The superposition of multiple convolutional layers enables the network to extract additional complex feature patterns, such as edges, textures, and shapes, layer by layer. This feature extraction capability considerably improves the understanding and processing power of image information in parametric design. Francesco Lomio [3] et al. proposed the application of image recognition to artificial images, showing that it is possible to successfully identify building types from images extracted from virtual models. The process of model structure training is shown in Figure 2.

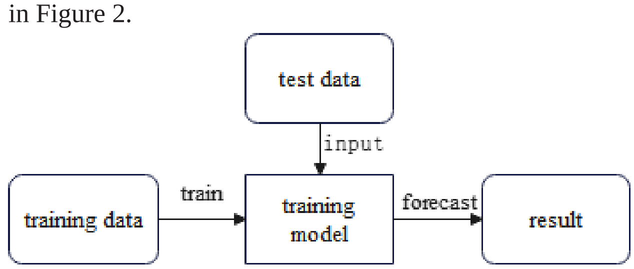

Figure 2 Model training structure

In architectural design, designers frequently need to analyze and extract the features of buildings in order to generate modern designs. For example, designers can use CNN to extract stylistic features from a large number of architectural images, such as spires and arches in Gothic buildings, straight lines and large glass Windows in modern buildings. These extracted features can be used to classify existing architectural styles or as a reference for designing new buildings. In this way, designers are able to better understand the characteristics of different styles and use these characteristics to create modern works.

2.2 Building image generation

In terms of generation, CNN can generate design schemes with specific style and structure by extracting image features and performing feature mapping, which can realize various tasks from sketch generation, image style transfer to 3D building model generation. For example, in architectural design, designers can use trained generative adversarial networks (Gans) to generate novel architectural forms. GAN consists of two parts: generator, which is responsible for generating realistic design images based on input parameters, and discriminator, which is responsible for distinguishing these generated images from real images. Through continuous training and optimization, the generator is able to create extremely realistic architectural designs, and the designer only needs to adjust the input parameters to generate different architectural forms.

With Gans, designers can generate futuristic architectural forms that may have a streamlined appearance and complex geometry. Alawadhi M and Yan W [4] created methods to train deep learning models using rendering, used these methods to train generative adversarial network models, and tested the output models on real-world photos, showing that neural networks trained with synthetic data can be used without using photos in the training data. Identify building objects from photos. Designers only need to enter a few simple parameters, such as the height, width and shape of the building, and GAN can generate a building design that matches these parameters. This approach can not only greatly improve design efficiency, but also provide designers with more creative inspiration, helping them to break the limitations of traditional design and create unprecedented architectural forms.

2.3 Reinforcement Learning

Reinforcement Learning (RL) is a machine learning method that learns how to take actions to maximize the cumulative reward by interacting with the environment, gradually optimizing the design process by continuously trying different design alternatives. Vahid Asghari et al. [5] showed that RL is widely used in the field of construction project management, which can help engineers achieve reinforcement strategies in multi-or single-objective sequential decision making under various sources of uncertainty. The design system adjusts and optimizes the design scheme continuously to find the best solution through multiple experiments and feedback mechanisms.

Through its trial-and-error mechanism, reinforcement learning continuously improves the design scheme in many design experiments. The RL algorithm sets a Reward and Punishment mechanism, evaluates the results of each design and adjusts the strategy based on the feedback. RL gradually learns which features are most important to design goals and which design decisions lead to optimal results. For example, when optimizing the layout of a building, RL can evaluate parameters such as space utilization, light conditions, and ventilation, and adjust these parameters to produce a design that meets both functional and esthetic needs.

Using reinforcement learning combined with the features extracted by CNN, the design system is able to find the optimal design solution over multiple trials and feedback. Reinforcement learning is suitable for solving complex design problems, especially those design tasks with multiple objectives and multiple constraints. Through the exploration of the agent in the high-dimensional design space, reinforcement learning can find the optimal solution that satisfies all the design constraints. In addition, in emergency building design, reinforcement learning can dynamically adjust the design strategy according to real-time disaster data, and quickly generate emergency building schemes that adapt to emergencies.

3. Application of Deep Neural Network in Parametric Design

The application of DNN in parametric design covers various aspects from complex pattern recognition, intelligent generation to optimal design. Parametric design is a method to generate and optimize design schemes based on parameter changes, and DNN provides a new technical means for parametric design through its powerful learning and reasoning ability.

3.1 Pattern Recognition

Pattern recognition technology can identify and extract repetitive or similar structures in design, and then automate the design process. DNNS use their multi-layer structure and nonlinear activation functions to identify complex patterns and features from large amounts of data. For example, in architectural design, DNN can analyze and identify the characteristics of different architectural styles, such as the symmetry and decorative details of classical buildings, the clean lines and open spaces of modern buildings. This ability allows designers to better understand and classify different design styles and draw inspiration from them.

In specific applications, designers can use DNN to train a large number of architectural pictures and learn the characteristics of various architectural styles. Designers can then enter new building images, which are automatically identified and classified by DNN, helping designers more quickly find design references that meet the project’s needs. Through the application of pattern recognition in parametric design, such as feature extraction, pattern classification and automatic optimization, designers can identify and optimize design patterns more efficiently and generate high-quality design schemes by using principal component analysis, support vector machine, genetic algorithm and particle swarm optimization.

3.2 Data-driven design decisions

Data-driven design decisions are based on scientific analysis and validation, making design decisions more reliable and scientific. DNN provides decision support to designers by learning and analyzing large amounts of design data. DNN can extract commonalities and rules from historical building data to help designers develop more scientific and reasonable design schemes. Designers can input a large amount of architectural design data into DNN and use its analysis results to formulate original design plans. Through deep learning models, designers can extract valuable information from complex design data, make scientific design decisions, and generate and optimize high-quality design plans.

Through data mining and analysis, DNN can extract valuable information, such as architectural style trends and popular design elements in the market, to help designers better grasp the market demand. Designers can use DNN to analyze existing project data and identify key factors for successful design to optimize the quality and reliability of current projects. DNN can not only analyze existing data, but also predict future design trends and market demand, helping designers to lay out ahead of time. It can also simulate the actual performance of different design solutions, such as the building's energy consumption in different climate conditions, optimize energy efficient designs, and anticipate and solve potential problems. However, DNN models are normally computationally complex and resource-consuming, and load balancing can be achieved by distributing computing tasks across multiple edge devices to avoid overload of a single device. This distributed computing method not only improves the overall efficiency of the system, but also enhances the robustness and scalability of the system [6].

DNN-based decision support system provides intelligent tools for designers. By inputting design parameters, DNN automatically analyzes and provides design suggestions, generates multiple design schemes and analyzes their advantages and disadvantages. Secondly, DNN can identify and classify different design patterns, and using methods such as Softmax classifier, different design patterns can be classified to help designers understand and utilize these patterns. DNN can also predict improved design parameters and estimate design performance and results through methods such as regression models. Using this prediction function, designers can evaluate the performance of various design alternatives at the beginning of the design, so as to select the best one and avoid the cost and time waste caused by later modification.

3.3 User personalized customization

In terms of user customization, deep neural networks provide strong support for designers. By learning from users' preferences and needs, DNN can generate deeply personalized design solutions that meet the particular needs of different users. In interior design, DNN can generate personalized interior design schemes that meet user needs according to user preferences, living habits, and other parameters.

Designers can use DNN to analyze the historical data of users, understand the preferences and needs of users, and then generate personalized design solutions based on these analysis results. Users only need to provide some basic information, and DNN can generate a variety of designs that meet their needs for users to choose from. This approach not only improves user satisfaction, but also provides designers with more design direction.

4. Conclusion

The application of deep neural networks and convolutional neural networks in parametric design provides designers with powerful technical support and creative tools, which not only improves the design efficiency and quality, but also promotes the development of the design industry to the direction of intelligence and innovation. Through these technologies, designers can more easily tackle complex design challenges and achieve more innovative and sustainable design solutions.

In the future, CNN and DNN will make the design process more efficient and precise by providing intelligent tools for data analysis and design generation. Designers can use these tools for rapid design iteration and optimization, thereby reducing design cycles and costs. By combining augmented reality (AR) and virtual reality (VR) technologies, designers can also view and modify design schemes in real time in a virtual environment to improve design experience [7]. In addition, these technologies facilitate interdisciplinary collaboration, allowing designers to collaborate with experts in different fields to leverage data-driven decision making, solve more complex design problems, and achieve additional efficient design processes and better design outcomes.

As DNN and CNN technologies continue to evolve, designers will be able to understand and apply design data more comprehensively, thereby creating design products that are more in line with market needs and user expectations. These technologies will continue to promote the innovation and progress of the design industry, provide designers with endless creative inspiration and technical support, and ultimately create greater value for society.

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