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Intelligent Layout Optimization Algorithm Combining Machine Vision in Tourism Product Design

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Abstract. In today's tourism market, product quality is a key factor in enhancing competitiveness and meeting consumer needs. However, due to limitations in process and mechanical accuracy, many product surfaces often exhibit various defects. Traditional manual inspection methods have many shortcomings in practical industrial applications. This article successfully constructs an intelligent layout optimization algorithm by combining computer-aided design (CAD) technology and machine vision technology, further improving the quality of tourism product design. This algorithm predicts possible surface defects in the product through machine vision technology in the early stages of product design and optimizes them during the design phase to avoid waste in later production. By combining CAD and machine vision, products can be comprehensively optimized during the design phase, improving production efficiency and meeting the growing quality needs of consumers for tourism products. This reflects important significance in promoting technological innovation in the tourism industry and enhancing the international competitiveness of tourism products.

Keywords: Tourism Product Design; Cad; Machine Vision; Defect Detection
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1 INTRODUCTION

In today's tourism market, the quality of products is the key factor to enhance competitiveness and meet consumer demand. With the rapid growth of science and technology, the application of advanced technology in tourism product design has become an important direction of industry innovation. With the rapid development of technology, mobile augmented reality (AR) technology has become a highly focused research field. With the acceleration of urbanization, the characteristics and ecological environment of rural landscapes have been seriously threatened. Therefore, the integration of landscape and ecological engineering, rational planning, and management of rural local landscapes is of great significance for protecting the rural ecological environment, enhancing rural economic development, and promoting rural social harmony. In the process of landscape planning, it is necessary to fully understand and respect the natural environment of rural areas, including terrain, hydrology, vegetation, and other elements. Based on the premise of protecting the natural environment, carry out reasonable development and utilization. Rural local landscape planning should focus on inheriting and promoting regional culture, protecting and excavating historical and cultural heritage and folk customs with local characteristics. Through landscape design, showcase the uniqueness and charm of rural culture. Chang [1] combines ecotourism development to transform rural local landscape resources into economic value. By developing ecotourism industries such as farmhouses and homestays, we aim to increase the income sources of villagers and enhance the level of rural economic development. In the design of tourism products, layout optimization is a complex and key link. Traditional layout optimization methods often rely on designers' experience and intuition and lack scientific and systematic. Especially in tourism landscape design, CAD-assisted intelligence technology provides designers with new tools and methods, making the design process more efficient, accurate, and creative. Du [2] discussed the application of CAD-assisted intelligent technology in tourism landscape design, as well as how to improve design quality and efficiency. During the design process, CAD can help designers choose suitable materials and elements. For example, through the software's built-in material database, it is easy to select suitable stones, wood, or vegetation. CAD software can perform data analysis and optimization, such as lighting analysis and feng shui optimization, to help designers improve design solutions. By utilizing machine learning and deep learning techniques, landscape design schemes can be automatically generated. Designers only need to provide some basic design requirements and constraints, and artificial intelligence can automatically generate multiple design schemes for selection.

Tourism product design is a process that involves multiple factors and complexity, including the planning of tourist attractions, the arrangement of tourist routes, and the organization of tourism services. In this process, how to optimize the layout of tourism products is an important issue. The continuous development of computer-aided design (CAD) and machine vision technology has provided new possibilities for the automation and intelligence of tourism product design. Frutiger et al. [3] explored an intelligent layout optimization strategy based on CAD and machine vision, aimed at achieving automation and optimization in tourism product design. CAD, as a computer-aided design tool, has been widely used in tourism product design. Designers can use CAD software to plan tourist attractions, arrange tourist routes, and organize tourism services. Through CAD technology, designers can design and plan tourism products more accurately, thereby improving the quality and efficiency of tourism products. Machine vision is a technology that simulates human visual functions through computer vision technology. In tourism product design, machine vision can be used to identify and classify the features and attributes of tourism products, such as the type of tourist attractions, the length of tourist routes, and the level of tourism services. In addition, machine vision can also be used to analyze and optimize the layout and design of tourism products, thereby improving the efficiency and user satisfaction of tourism products. With the rapid development of technology, virtual reality (VR) technology has gradually integrated into our daily lives. Especially in the field of education, the application of VR provides new experiences and opportunities for students' learning. George et al. [4] explored the impact of virtual reality on students' design decisions, particularly in evaluating density and proximity. We hope to reveal the advantages of VR technology and its impact on students' design abilities by comparing traditional simulation processes with design decisions in VR. In virtual reality, designers can have a more intuitive view of the entire design, including architecture, landscape, interior design, etc. They can observe the design at different times and under different lighting conditions to better understand the relationship between density and proximity. This real-time and interactive experience allows designers to evaluate and understand the impact of design decisions more accurately. Overall, the impact of virtual reality technology on students' design decisions is mainly reflected in providing a more realistic and intuitive design experience. It has changed the way students evaluate design decisions, enabling them to more accurately understand the relationship between density and proximity, thereby making better design decisions.

With the application of CAD technology, designers can make use of the powerful computing power of computers to carry out more accurate and efficient layout designs. However, although CAD technology is powerful, it cannot directly perceive and deal with the surface defects of products. Machine vision collects the visual images of products through image sensors, then processes the images by image processing technology to extract the target features, and finally determines whether the products have appearance defects. With the development of technology, the application of augmented reality (AR) and virtual reality (VR) technologies in the construction of ships and offshore structures is becoming increasingly widespread. These technologies can provide more intuitive and precise design and construction methods, thereby improving production efficiency and quality. The extraction and conversion of 3D CAD data plays a crucial role in this process. Han et al. [5] explored how to extract 3D data from existing CAD systems and convert it into formats suitable for AR and VR. In the construction of ships and offshore structures, designers usually use professional CAD software for design. This software can create highly detailed 3D models, including ship structures, mechanical equipment, piping systems, etc. In order to convert these data into AR and VR formats, we need to extract 3D data from CAD models. Due to possible differences between CAD models and the actual environment, we need to calibrate and match the data to ensure the accuracy of AR and VR applications. This may include using image recognition technology to calibrate the model, using sensor data to match the model, and so on. With the introduction of this technology, designers can foresee the possible defects of products in the early stage of product design, so as to optimize them in the design stage and avoid the waste of later production. In this article, an intelligent layout optimization algorithm combining CAD with machine vision is proposed. The algorithm makes full use of the accuracy of CAD technology and the intuition of machine vision technology and realizes the intelligent optimization of product layout through their mutual complement. The algorithm can also predict the possible surface defects of products through machine vision technology in the early stage of product design so as to optimize them in the design stage and avoid the waste of later production.

These research results show the research on the combination of CAD and machine vision in tourism product design, which lays a solid foundation for the growth of this field. Some researchers only focus on the application of CAD technology or machine vision technology but do not fully combine their advantages. The main innovations of this study are as follows:

(1) This article proposes an intelligent layout optimization algorithm that combines CAD and machine vision, fully utilizing the advantages of both to achieve more efficient and accurate product layout optimization.

(2) This article uses convolutional neural networks (CNN) for the detection and recognition of surface defects in tourism products. By training a depth model, it is possible to identify various surface defects more accurately and reduce the impact of factors such as lighting and angle on the detection results.

This article first discusses the application of CAD and machine vision in tourism product design. Then, a tourism product defect detection method combining the CNN model was proposed to achieve intelligent layout optimization. The feasibility of this method was verified by combining examples. Finally, it summarized the research results and analyzed the directions for improvement in tourism product design.

2 RELATED TECHNICAL BASIS

The intelligent layout optimization algorithm based on CAD and machine vision is a combination of CAD technology and machine vision technology. This algorithm first uses CAD technology to design and plan tourism products and then uses machine vision technology to extract and analyze the features and attributes of tourism products. Based on these features and analysis results, the algorithm can automatically optimize and improve the layout of tourism products, thereby improving their efficiency and quality. Jauhar et al. [6] explored the application of an intelligent layout optimization algorithm based on CAD and machine vision in tourism product design. This algorithm combines the advantages of CAD technology and machine vision technology and can achieve automation and intelligence in tourism product design. Through this method, designers can design and plan high-quality tourism products more efficiently, thereby improving production efficiency and market competitiveness. In the future, we will further research and improve this algorithm to better meet the needs of tourism product design. The knowledge graph is a tool for representing knowledge in a graphical manner, which can effectively express and organize complex knowledge structures. In AR, knowledge maps can be used to enhance the knowledge representation and organizational capabilities of AR systems. For example, through knowledge graph technology, AR systems can present complex knowledge structures to users in a graphical manner, enabling users to understand knowledge more intuitively and comprehensively. At the same time, knowledge maps can also be used to improve the adaptive learning ability of AR systems, enabling them to better meet user needs through continuous learning and optimization. Lampropoulos et al. [7] proposed a method that combines deep learning, semantic web, and knowledge graph to enhance the functionality of AR. Deep learning can improve the intelligence and interactivity of AR systems; The semantic web can improve the information processing ability of AR systems; Knowledge maps can enhance the knowledge representation and organizational capabilities of AR systems. By combining these three technologies, we can build a more powerful and intelligent AR system, providing users with a richer and more practical experience. In the future, we will further research and explore the specific implementation and application of this combination method to promote the further development of AR technology.

Tourism landscape design, as an important component of the human living environment, has also begun to shift towards low-carbon and environmental protection. In recent years, the rapid development of virtual reality technology has provided new ideas and methods for landscape design. Lin et al. [8] explored the role of low-carbon vision based on virtual eye movement behavior preferences in tourism landscape design. Virtual eye movement behavior preference refers to people's preferences for eye movements and fixation points when using virtual reality technology. This preference has important guiding significance for tourism landscape design. Low carbon vision refers to the use of low energy consumption, low pollution, and low emission design concepts and materials in tourism landscape design to achieve a visually low-carbon lifestyle. Through virtual reality technology, designers can simulate landscape design schemes in computers and observe user eye movement behavior preferences in real time. This design method can greatly shorten the design cycle and improve design efficiency. By introducing low-carbon visual and virtual reality technologies into tourism landscape design, the environmental quality of cities can be improved, and the image and social benefits of cities can be enhanced. Meanwhile, it can attract more talent and investment, promoting the economic and social development of cities. Low carbon vision based on virtual eye movement behavior preferences plays an important role in tourism landscape design. By introducing virtual reality technology and low-carbon visual concepts, design efficiency and quality can be greatly improved, promoting the popularization and promotion of low-carbon life, and improving social benefits. The key to implementing AR applications on mobile devices lies in tracking registration algorithms, which accurately match and register virtual information with the real environment. The tracking and registration algorithm based on SLAM (Simultaneous Localization and Mapping), which simultaneously locates and builds maps, has become an important technology in mobile AR applications. SLAM technology is mainly used to solve the localization and map construction problems of robots in unknown environments. In mobile AR applications, SLAM technology is equally important. Through the SLAM algorithm, AR applications can achieve self-localization in unknown environments, while constructing a physical environment model around them, accurately matching and registering virtual information with the real environment. Based on the matched feature points, calculate the geometric transformation relationship between the virtual environment and the real environment, such as rotation and translation. Liu et al. [9] transformed objects in the virtual environment to align them with objects in the real environment. To verify the effectiveness of the SLAM-based mobile augmented reality tracking registration algorithm, we conducted experiments in different scenarios. The experimental results show that this algorithm can achieve high-precision virtual object registration and tracking, while also having good robustness and real-time performance. In different scenarios, the algorithm can quickly and accurately match and register virtual objects with the real environment. The BIM model contains rich architectural information, such as geometric shapes, material properties, building equipment, etc. At the same time, augmented reality (AR) technology provides new possibilities for the display and interaction of BIM models. By combining AR technology with BIM models, users can view and manipulate virtual building information in a real environment. However, achieving accurate registration and localization of 3D point clouds in indoor scenes is a major challenge in this process. Mahmood et al. [10] proposed using geometric features of augmented reality to address this issue. The registration and localization of indoor scene 3D point clouds based on BIM mainly involves two steps: establishing a 3D point cloud model of the indoor scene and matching the virtual model with actual point cloud data. Establish a 3D point cloud model for indoor scenes. This step can be achieved through techniques such as laser scanning or structured light scanning. These technologies can obtain detailed geometric information about the indoor environment, including the shape, size, and position of objects. Then, use this information to reconstruct a three-dimensional point cloud model of the indoor scene in the computer.

Match the virtual model with the actual point cloud data. This step can be achieved by comparing the geometric features of the virtual model with the actual point cloud data. Firstly, key geometric features such as edges, corners, etc., are extracted from the virtual model. Then, match these features with the features in the actual point cloud data. By comparing the similarity between features, the accurate position and posture of the virtual model in the real environment can be determined. With the popularization of mobile devices and the improvement of computing power, mobile augmented reality (AR) technology has been widely applied. In AR applications, object detection is a key task for identifying and tracking objects in the real environment. However, due to the limitations of computing resources and energy on mobile devices, lightweight object detection algorithms have become increasingly important. Nafea et al. [11] provide an overview of lightweight object detection algorithms for mobile augmented reality, introducing the principles, advantages and disadvantages, and application scenarios of various algorithms. Lightweight object detection algorithms are widely used in fields such as mobile augmented reality, intelligent monitoring, and autonomous driving. In mobile augmented reality, lightweight object detection algorithms can be used for real-time recognition and tracking of objects in the real environment, such as faces, gestures, text, etc., providing a more natural and rich interactive experience. In intelligent monitoring, lightweight object detection algorithms can be used to monitor abnormal behavior or events in real-time scenarios, improving security and early warning capabilities. In autonomous driving, lightweight object detection algorithms can be used to perceive and understand the surrounding environment of vehicles in real time, improving the safety and reliability of autonomous driving. With the rapid development of technology, especially the advancement of augmented reality (AR) technology, the education field is undergoing unprecedented innovation. Especially for the engineering field, due to its unique complexity and practicality, designing an interactive learning environment using AR technology is of great significance for improving learning effectiveness and understanding depth. Print et al. [12] explored the design significance of an interactive learning environment based on adaptive augmented reality and how it enhances conceptual understanding in engineering paradigms. The interactive learning environment of adaptive augmented reality is a modern educational platform that combines AR technology, artificial intelligence, and big data. This learning environment can be adaptively adjusted according to students' learning styles, ability levels, and interests, providing a personalized learning experience. By combining virtual information with real environments, it enables students to practice in a simulated, secure, and unrestricted environment, thereby improving their understanding and mastery of engineering concepts. By combining virtual information with real environments, students can better understand engineering concepts and principles. For example, through AR technology, students can see virtual mechanical components or circuits in a real environment, which is more vivid and intuitive than traditional textbooks or slides. Augmented reality is a technology that can bring information from the virtual world into the real world. It identifies specific images or objects and overlays virtual information onto them, enabling users to see and interact with this virtual information. Hybrid image recognition technology is a type of augmented reality technology that combines computer vision and deep learning techniques to accurately recognize and track images or objects. The evaluation of computers and cultural heritage is an important task in outdoor environments. By using augmented reality and hybrid image recognition technology, we can conduct a more comprehensive and accurate assessment of cultural heritage. For example, we can use hybrid image recognition technology to identify and track specific features of cultural heritage and then overlay virtual information on the identified features to provide an in-depth understanding and analysis of cultural heritage. In outdoor environments, the evaluation of augmented reality and hybrid image recognition technologies is mainly conducted by comparing the degree of matching between virtual information and actual cultural heritage. Tzima et al. [13] evaluated the accuracy, real-time performance, and robustness of identification and tracking to determine whether these technologies can be effectively used for the evaluation and display of cultural heritage.

The rise of rural tourism in China not only drives the development of the local economy but also provides more people with the opportunity to experience the customs and traditions of the traditional Chinese countryside. In the landscape design of rural tourism, the visualization method of buildings is a very important part. Wang et al. [14] explored the visualization methods of buildings in rural tourism landscape design in China. Buildings are an important component of rural tourism landscape design in China. They not only provide a place for tourists to rest and stay but are also an important carrier of local culture and history. Through the design of buildings, the historical culture, regional characteristics, and social style of Chinese rural areas can be displayed. In rural tourism landscape design, buildings should maintain the traditional style and reflect the characteristics and customs of Chinese rural areas. For example, traditional building materials, colors, and patterns can be used. Buildings should be integrated with the surrounding environment, reflecting the concept of harmonious coexistence with nature. This can be achieved through the use of natural building materials, emphasis on greening, and the utilization of natural landscapes. Although buildings are part of the landscape, their practicality is also very important. Buildings should meet the accommodation, catering, and other service needs of tourists while also emphasizing energy conservation and environmental protection. With the rapid development of technology, the combination of artificial intelligence and virtual reality technology is changing our travel lifestyle. Among them, the multi-person virtual intelligence system based on distributed virtual reality has attracted widespread attention. You et al. [15] provided a detailed introduction to the concept, structure, working principle, and application scenarios of the system in tourism. A multi-person virtual intelligence system based on distributed virtual reality is a new type of system that integrates various technologies such as artificial intelligence, virtual reality, and distributed computing. It mainly creates a virtual environment shared by multiple people and utilizes intelligent algorithms and data analysis to achieve functions such as user behavior simulation and environmental interaction. Users enter a virtual tourism environment shared by multiple people through virtual reality devices. Simulate and analyze user actions and behaviors through intelligent algorithm modules and then provide feedback to the virtual tourism environment. The virtual environment is updated in real-time based on user feedback and interacts with virtual images of other users. The system collects user data through data storage and analysis modules and utilizes machine learning and deep learning algorithms for learning and optimization to provide more accurate behavior simulation and richer interactive functions in the tourism environment. Color effect is an important aspect of tourism landscape architecture design, which can enhance the visual effect of the design and improve the overall quality of the design. Zhang and Deng [16] discussed the color effects of tourism landscape architecture design in computer-aided collaborative design systems, as well as related issues in computer-aided design and application. The computer-aided collaborative design system is a design tool based on computer technology that can help designers carry out design work more effectively. In landscape architecture design, color effect is an important aspect that can enhance the visual effect of the design and improve the overall quality of the design. Through computer-aided collaborative design systems, designers can better manage and control color information, thereby achieving better color effects. In tourism landscape architecture design, computer-aided design can be used to achieve color effects. By using computer-aided design software, designers can better manage and control color information, thereby achieving better color effects. In order to illustrate the computer-aided design of color effects and its application in landscape design under the computer-aided collaborative design system, this article selects a specific case to illustrate. This case is the tourism landscape design of a park, which uses multiple colors and materials to create unique tourism landscape effects. With the help of computer-aided collaborative design systems and computer-aided design software, designers can better manage and control color information, thereby achieving better color effects [17].

3 INTELLIGENT LAYOUT OPTIMIZATION ALGORITHM COMBINING CAD WITH MACHINE VISION

With the rapid growth of technology, CAD technology has become the core tool for tourism product design, widely used in various stages of tourism product design. The application of CAD technology can not only improve the work efficiency of designers but also provide more accurate and detailed design solutions for products. In tourism product design, CAD technology can first be used to create 3D models. Designers can use CAD software to draw detailed product design drawings and conduct 3D modeling through the software. This can help designers better visualize products and check the consistency and feasibility of the design. CAD technology can be used to design the internal structure of products. Through CAD software, designers can easily design complex parts and conduct assembly simulations to ensure the accuracy and feasibility of the design. This application can greatly reduce the time and cost of the product development process. In addition, CAD technology also supports collaboration among designers. By sharing CAD files, team members can work on the same platform, thereby improving work efficiency and promoting team collaboration.

Machine vision technology utilizes advanced technologies such as image sensors and computer vision algorithms to achieve the collection, processing, and analysis of product images. In tourism product design, machine vision technology can be used for surface defect detection. Traditionally, these detection tasks require manual completion, which is not only time-consuming and laborious but may also have subjective errors. Through machine vision technology, automatic detection and analysis of product surface defects can be achieved. Machine vision technology can also achieve precise measurement of product dimensions through image processing algorithms, ensuring the accuracy and consistency of design. Moreover, machine vision technology can also be used to assist in the assembly process. By identifying the position and posture of products, machine vision systems can guide robots or operators in inaccurate assembly operations, improving assembly efficiency. The goal of this study is to combine CAD and machine vision technology to construct an intelligent layout optimization algorithm to improve the efficiency of tourism product design. This section will provide a detailed introduction to the model construction and implementation process of the algorithm. The intelligent layout optimization algorithm is based on a deep learning model, integrating the accuracy of CAD technology and the intuitiveness of machine vision technology. The construction of the model is divided into the following steps:

⊖ Data collection and processing: Firstly, collect a large amount of tourism product design data, including CAD design drawings and corresponding machine vision images. These data are preprocessed, such as normalization and denoising, to ensure the stability of the model input.

⊜ Feature extraction: For CAD design drawings, use the API interface provided by CAD software to extract key design features, such as layout coordinates, dimensions, etc. For machine vision images, CNN is used for feature extraction to obtain texture, shape, and other features of the image.

⊛ Fusion model construction: A fully connected neural network (FCNN) was constructed by fusing the extracted CAD design features with machine vision features. This network accepts joint inputs of two features and outputs them as layout optimization parameters for the product.

Let the gray value range of the original tourism product image $f\ x,y$ be $g_{\min},g_{\max}$, choose a suitable threshold T, and:

$$g_{\min} \le T \le g_{\max} \tag{1}$$

Image segmentation with a single threshold can be expressed as:

$$g(x,y)=\begin{cases}1, & f(x,y)\geq T\\ 0, & f(x,y)<T\end{cases} \tag{2}$$

$g(x,y)$ is a binarized image.

The algorithm accepts CAD drawings and machine vision images from tourism product design as inputs. Using CAD APIs to extract design features, while using preprocessing techniques to enhance and denoise machine vision images. The extracted CAD design features and machine vision features are fed into the fusion model for joint learning. Through the fully connected layer, the two features are fused in the hidden layer, and layout optimization parameters are generated. Adjust and optimize the layout of tourism products based on the layout optimization parameters generated by the fusion model. Through CAD technology, the layout of products can be accurately modified, achieving efficient space utilization and design optimization. Gaussian smoothing function is:

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}\exp\left(\frac{x^2+y^2}{2\sigma^2}\right) \tag{3}$$

In order to get a better photo group $V(p)$, it is filtered by the following formula:

$$\left|V^*(p')\right|(1-g^*(p))<\sum_{p\in U(p)}(1-g^*(p)) \tag{4}$$

Where $U(p)$ represents all patches that do not meet the required visible information.

M is a solid model. The spatial indicator function used in surface reconstruction is:

$$\Phi(p)=\begin{cases}1, & p\in M\\ 0, & p\notin M\end{cases} \tag{5}$$

Statistics are performed by assigning thresholds to gray pixels:

$$p(\alpha_i)=\begin{cases}\dfrac{p}{h} & h_i>p\\ \dfrac{h_i}{h} & h_i<p\end{cases} \tag{6}$$

Where $p(\alpha_i)$ is the occurrence probability of the i th gray value, and h represents the total quantity of pixels. α_i is the background gray level.

The algorithm adopts an iterative approach for layout optimization. In each iteration, based on feedback from machine vision, the layout is fine-tuned and features are fused again for optimization. Through multiple iterations, the algorithm can gradually approach the optimal layout plan. Through parallel processing, algorithms can simultaneously handle multiple design tasks, improving computational efficiency; GPU acceleration provides powerful computing power, allowing algorithms to complete complex layout optimization tasks in a short period of time.

In neural network algorithms, each type of network contains three core structures: convolutional layer, activation function, and pooling layer. Convolutional layers are responsible for learning and extracting features from input data. In a CNN network, the input data is usually an image, while the output of the convolutional layer represents a specific feature space in the image. These feature spaces are actually the feature point spaces in the input image, which is also the high-level understanding of the image by CNN networks. The function of the activation function is to introduce nonlinear factors into the network, enabling it to learn and perform more complex tasks. The pooling layer is used to reduce the dimensionality of the data, effectively reducing computational complexity while also preventing overfitting. The pooling operation can be seen as a feature selection that selects the most important features while discarding other secondary features.

After the image is fed into the CNN network, it undergoes feature extraction through convolutional layers, nonlinear mapping of activation functions, and feature selection through pooling layers to obtain the output feature space, which will be used as the input for fully connected layers or fully connected neural networks. The function of the fully connected layer is to map the learned distributed feature representations to the sample label space, completing the mapping process from the input image to the label set, as shown in Figure 1. This process actually involves integrating the weights of features to obtain the final classification or regression results.

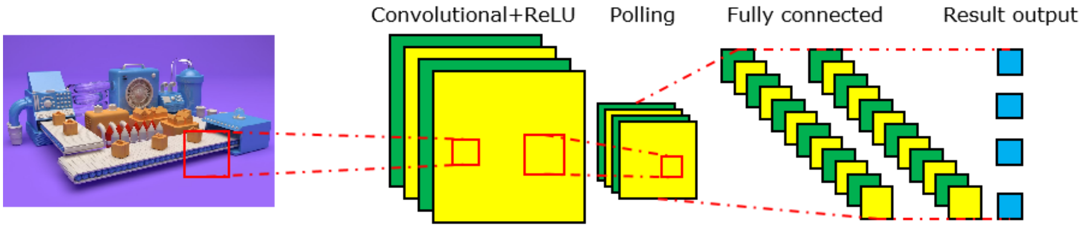

Figure 1: CNN infrastructure.

Different deep CNNs are composed of these basic structures connected before and after, and layer parameters are adjusted. According to the different functions of each infrastructure, these connected structures are usually referred to as different stages. These stages constitute the overall architecture of CNN. At different stages, the size of convolutional kernels, activation function types, pooling sizes, etc. may not be exactly the same. This design is designed to better adapt to different task requirements, while also enabling the network to learn and extract features more effectively.

The pooling layer mainly adopts pooling operations, with the aim of reducing the size of the feature space. Pooling operations can reduce the resolution of feature space images. In practical applications, the resolution of input images is usually high, and without pooling, it will result in a significant increase in computational complexity. When the feature space is large, it means that the image details are too rich. Although detailed information may be helpful for certain tasks, in deep networks, excessive details may actually interfere with feature extraction. This is because deep networks typically focus on higher-level features, which may not be directly related to the local details of the image. By pooling operations, unnecessary details can be filtered out, making it easier for deep networks to extract key features related to tasks. The pooling operation is shown in Figure 2.

From the pixel size retention method in the above figure, it can be seen that this operation adopts maximum pooling and average pooling. Maximum pooling is to retain the maximum pixel value in the 2 * 2 size matrix to the corresponding matrix position, while average pooling is to preserve the average pixel value obtained from the 2 * 2 size matrix to the corresponding matrix position. After the pooling operation, the image resolution will be reduced exponentially, so it is inevitable that there will be parameter loss. When the computing power is sufficient, it can be considered not to use the pooling operation to reduce parameter loss.

There are significant differences in convolutional sliding operations between fully connected networks and CNN. In a fully connected network, each unit in the upper layer network is connected to each unit in the lower layer network, and this connection method is called "fully connected". This fully connected approach ensures the complete transmission of information, with each unit receiving information from all units in the upper layer network and integrating it to transmit to the lower layer network. In the structure of a fully connected network, in addition to the input and output layers, the intermediate layer is called the fully connected hidden layer. These hidden layers play a role in feature extraction and decision-making in fully connected networks. Through multi-layer full connectivity, the network can learn more abstract and advanced feature representations, thereby enhancing its ability to handle complex pattern recognition and classification tasks.

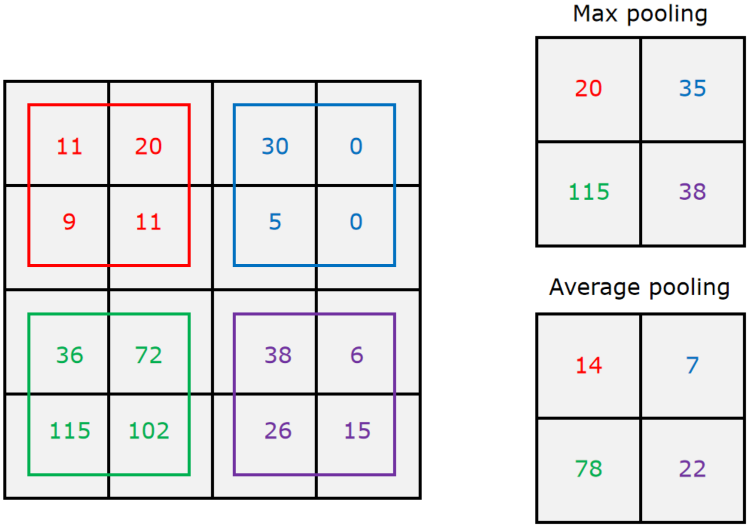

Figure 2: Principle of maximum pool and average pool.

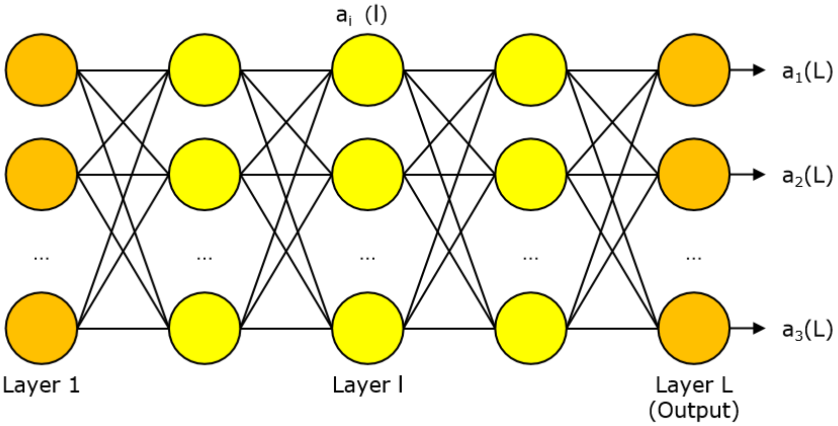

Figure 3: Principle of a fully connected layer.

As shown in Figure 3, the connection mode of the fully connected network presents a hierarchical structure, and each layer is fully connected with the adjacent upper and lower layers. This connection mode makes the network relatively high in parameter scale and computational complexity, but it can also bring better learning ability and performance. For the i neuron in l the layer, its output calculation formula is:

$$z_i \; l = \sum_{j=i}^{n_l} w_{ij} \; l \; a_j \; l-1 + b_i \; l \tag{7}$$

After the calculation, the activation operation will also be carried out. After obtaining the value of each neuron in the l layer, each value will be input to the $l+1$ layer.

Let A and B be two sets on Z, and B be the structural element to inflate A. The expansion result is recorded as:

$$A \oplus B = \{z \mid (b')_z \cap A \neq \varnothing\} \tag{8}$$

Where B' it's a reflection of its origin. The expansion result consists of displacement elements z, and at least one element of B''s displacement to these elements overlaps with A. Generally, the expansion operation is used to connect adjacent parts in an image.

B acts as a structural element to corrode A, and the corrosion result is recorded as:

$$A \Theta B = \{z \mid (B)_z \subseteq A\} \tag{9}$$

On the contrary, the dilation operation is mostly used to disconnect the adjacent parts in the image and to filter out too small parts, such as isolated points.

B as a structural element to open and close A is defined as:

$$A \circ B = (A \oplus B) \Theta B \tag{10}$$

$$A \cdot B = (A \Theta B) \oplus B \tag{11}$$

Open operation and close operation can filter out the connection between small discrete points and discrete areas of the image while keeping the image shape basically unchanged.

4 APPLICATION EXAMPLE ANALYSIS

In the production process of tourism products, the quality inspection of printed patterns is an important link. In order to ensure the stability and consistency of product quality, this study adopts machine vision-based technology to detect printed patterns. Firstly, the image acquisition module is used to capture the pattern area on the product. Next, segment the area to be detected from the original image. In order to better detect patterns, a series of processing is carried out on the segmented images. The first step is grayscale, which converts color images into grayscale images to simplify subsequent calculations. Next is binarization, which converts a grayscale image into a black-and-white binary image by setting a threshold, making the pattern more distinct from the background. After binarization, two morphological operations, corrosion, and dilation, are also used to process the image further. Corrosion can eliminate noise in images, while dilation can expand the contour of the pattern, making it more prominent.

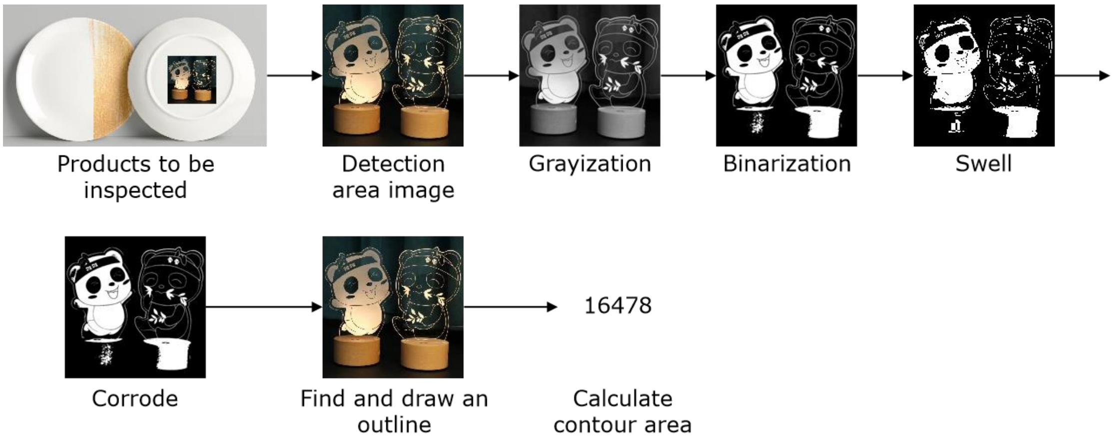

Figure 4: Processing effect diagram when the pattern is intact.

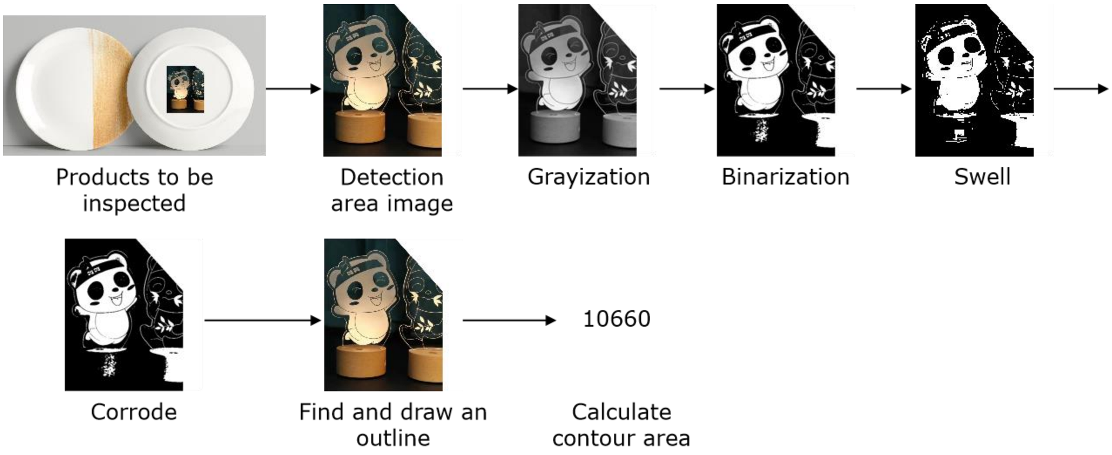

Figure 5: Processing effect diagram when the pattern is defective.

Figure 4 shows the processing effect when the pattern is intact. It can be seen that the contour is clear and the area calculation is accurate. Figure 5 shows the treatment effect when the pattern is missing. In this case, the contour will break and the area calculation will be correspondingly reduced. By processing and calculating the quantity of pixels in the pattern area, the degree of pattern defects can be accurately determined. If the degree of defect exceeds the benchmark value set by the user, the product is judged as unqualified. At this point, the controller can send a rejection signal to other equipment or directly control the rejection mechanism to eliminate it, ensuring that only qualified products can continue to flow to the next production process.

In specific network settings, when the batch size is 6, the iteration cycle is 50, and the initial learning rate is 0.1, the learning performance of the network is excellent. By observing Figures 6 and 7, it can be clearly seen that the accuracy of the network training set rapidly improves with the increase of iteration times, while the loss error rate of the training set gradually decreases.

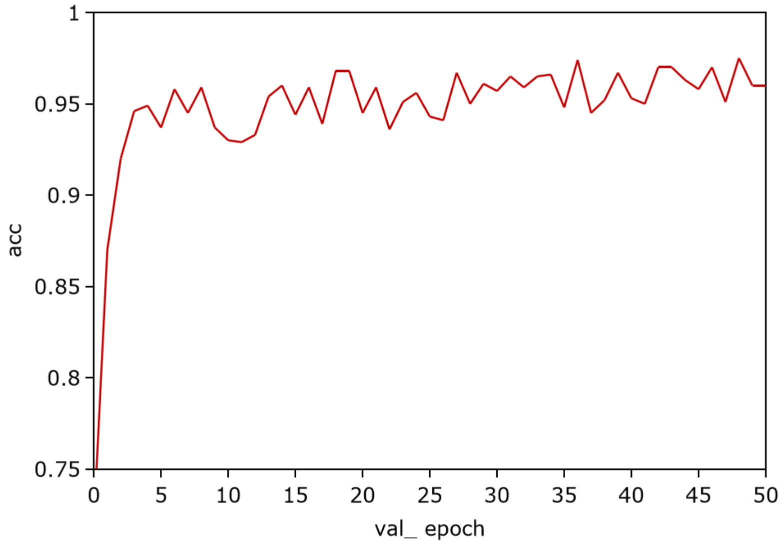

Figure 6: Relationship between the accuracy of training set and iteration times.

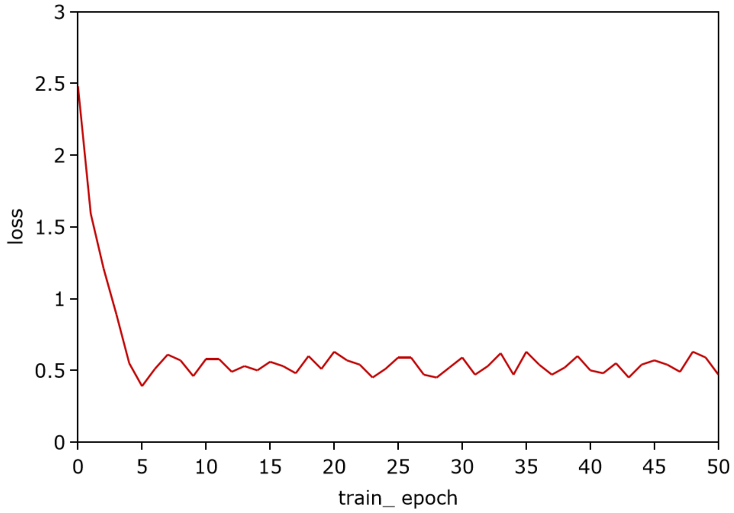

Figure 7: Relationship between training set error rate and iteration times.

Figure 6 shows the relationship between the quantity of iterations and the accuracy of the training set. As the quantity of iterations increases, the accuracy of the training set steadily increases, showing a good learning trend. It is noteworthy that after 10 iterations, the accuracy has exceeded 95% and remained stable, which fully proves the excellent performance of the network in the learning process. Figure 7 shows the relationship between the number of iterations and the loss error rate of the training set. From the graph, it can be observed that after 10 iterations, the loss value stabilizes around 0.5 and maintains relatively stable fluctuations during subsequent iterations. This stability indicates the rationality and effectiveness of the network.

In the process of network training, in addition to significantly improving the accuracy of the training set, the accuracy of the test set also shows an ideal trend of improvement. From the observations in Figures 8 and 9, the changes in accuracy and error rates of the test set can be clearly seen as the quantity of training iterations increases.

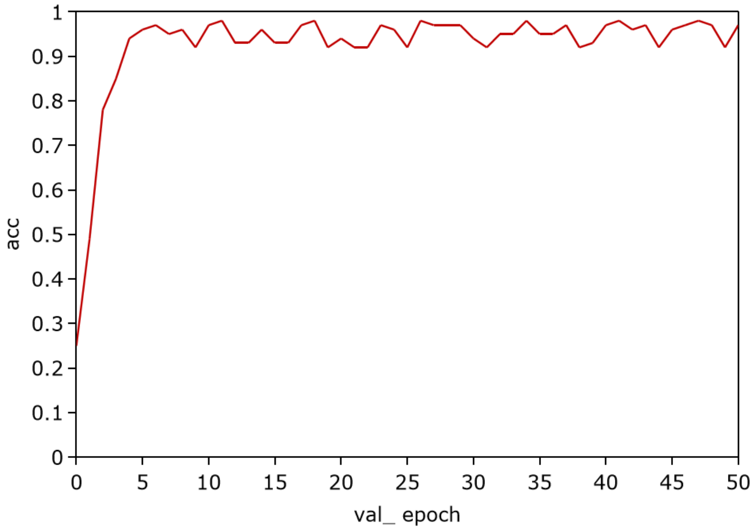

Figure 8: Relationship between test set accuracy and iteration times.

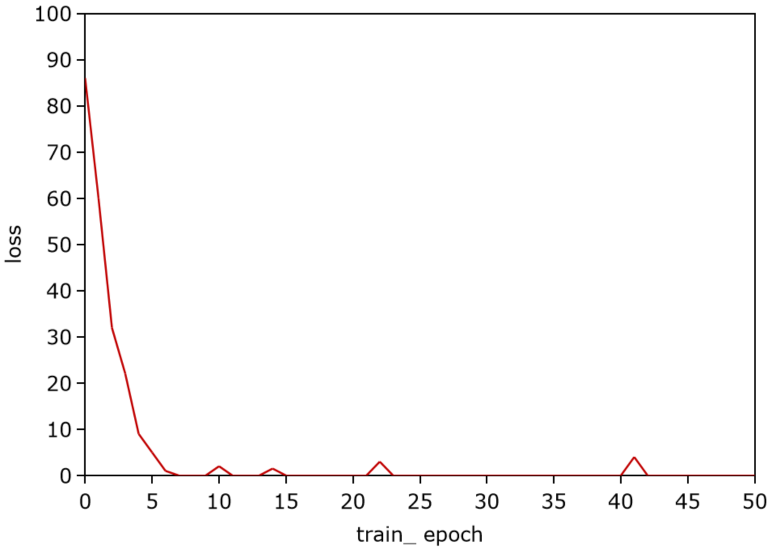

Figure 9: Relationship between test set error rate and iteration times.

Figure 8 shows the relationship between epoch iterations and test set accuracy. This indicates that the network can not only accurately learn the data features of the training set during the training process, but also generalize well to the test set, and has good classification or prediction ability for unseen data. Moreover, in Figure 9, we can see that as the quantity of iterations increases, the error rate of the test set shows a rapid downward trend. The rapid decline rate of loss further validates the high learning ability of the network. This indicates that the network effectively extracts key features from noise and interference during the training process, and gradually optimizes its own parameter configuration to minimize prediction errors.

Under specific network settings, both the training and testing sets showed high accuracy and low error rates, and the learning ability and generalization performance of the network were verified. A highly accurate network can help designers more accurately predict and classify the characteristics of different tourism products, thereby conducting refined designs based on market demand. The sensitivity of the network to images and data helps designers capture more details, thereby improving product quality. The powerful learning ability of the network means that it can identify hidden patterns and trends in a large amount of tourism product data, providing data support for product design. The excellent generalization performance of the network enables it to address unprecedented data and design challenges, which is particularly important for innovation in tourism product design. Designers can utilize this characteristic of the internet to explore new design elements and concepts and promote the diversification and innovation of tourism product design. Through the results of this study, we have seen the enormous potential of CAD and machine vision in tourism product design.

5 CONCLUSION

In tourism product design, layout optimization is a complex and crucial process. Traditional layout optimization methods often rely on the experience and intuition of designers, lacking scientific and systematic approaches. This article proposes an intelligent layout optimization algorithm that combines CAD and machine vision. This algorithm fully utilizes the accuracy of CAD technology and the intuitiveness of machine vision technology and achieves intelligent optimization of product layouts by complementing each other. This article verifies the effectiveness and superiority of CAD and machine vision technology in tourism product design through research and experiments. This algorithm can fully utilize the accuracy of CAD and the intuitiveness of machine vision to achieve automation and intelligence in product design. Moreover, the results show that the algorithm performs well in terms of layout quality and optimization efficiency, significantly improving the design level of tourism products. By analyzing the accuracy and error rate of the test set, it was found that the network has good generalization performance and can adapt well to new data and situations.

The current research mainly focuses on image data, and in the future, more types of data such as text and user behavior data can be considered for integration to achieve more comprehensive and accurate tourism product design. By continuing to study the use of CAD and machine vision in tourism product design, we have the opportunity to further improve design efficiency and product quality, providing every user with tourism products that better meet their needs.

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