Optimization of Virtual Reality in Brand Identity Design and Visual Recognition based on Image Fusion and Text Assistance

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Abstract. In traditional brand logo design, the brand design is usually displayed in a floor plan. This display method has a certain visual confusion problem, making it difficult to present the brand design as a whole. To solve this problem, computer-aided design (CAD) virtual reality technology is applied to visual optimization of design. In this article, we use a network image classification technique that combines image fusion and text assistance. The probability of each category of the image obtained by fusion of visual feature extraction and support vector machine (SVM) classification decision fusion through artificial decision algorithms. And calculate the weight of the corresponding text category on the page to which the image belongs based on keyword correlation, in order to improve the accuracy of network image classification. Combining cross compilation methods for visual information simulation of print advertisements, creating various real-time interactive 3D visual environments for print advertisements, and achieving visual optimization design of print advertisements in a CAD virtual reality simulation environment. The results indicate that this method can effectively achieve visual optimization design of print advertisements. Improving the visual feature expression effect of print advertising has great application value in print advertising design.

Keywords: Computer Aided Design (CAD); Image classification; Brand design; Virtual reality technology; Print advertising
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1 INTRODUCTION

Brand design is gradually extending from brand logo design to the creation of a more systematic brand visual identification system. Consumers' perception of brand image is gradually shifting from brand logos to other brand visual assets. The aging of a brand often starts with its vision, and the redesign and optimization of the brand logo and visual assistance system is an important part of brand strategy. CAD human-machine interfaces have evolved from visual perception as the main approach to various channels of perception such as audiovisual, olfactory, and tactile. From manual input as the main approach, it has evolved to include multiple performance channels for voice and posture input. Users can experience real experiences in the CAD virtual reality world. With the development of technology, the popularization of devices, and the increasing recognition of virtual reality technology, the demand for virtual reality in various industries is becoming stronger, and the brand design industry is no exception.

CAD virtual reality brand design platform can realize remote multi person interaction design. Designers, production personnel, and others can collaborate on clothing in a virtual space simultaneously. Participants can gain control at any time and carry out design, modification, and other operations on the brand. Redefining the communication mode of remote meetings in the brand design industry, eliminating distance restrictions, and improving design communication efficiency. Through this CAD virtual reality technology, the design and production process can be deployed to the store terminal, making the entire process transparent. The cleanliness of the brand's design and production area and the progressiveness of the brand's auxiliary facilities and equipment in the process. It reflects the economic strength and design management level of the brand. These are all aspects of a brand that can showcase itself to the public, have strong persuasiveness towards the public, and thus increase brand communication rate. On this basis, personalized sales services can even be generated to achieve personalized design for a small number of key customers, providing targeted services, emerging new consumption highlights, and stimulating consumption. CAD virtual reality technology provides more convenience for themed and stylized store terminals, while also being more environmentally friendly and economical. It also narrows the distance between the front-end of the brand industry and customers, enhances brand image, and enhances user loyalty. In addition to the brand's environmental image, employee image also affects the overall brand image. Employees have always been an uncontrollable factor, and their image greatly affects customers' purchasing desires and also affects the brand's image. CAD virtual reality technology can control these uncontrollable factors. The vast majority of purchasing behavior is liberalized, which also optimizes the buyer's experience. When problems arise, timely feedback and accurate resolution are provided to avoid the problem from expanding in a short period of time and collecting data from the backend public. The user data includes elements such as material styles of fabrics used by customer groups in different regions. Accurately portraying customer profiles, adjusting production strategies, and continuously improving the brand's offline image will also be achieved.

2 RELATED WORK

Ben et al. [1] matched the images obtained from the viewpoint with the information in the 3D CAD model, and initiated automatic processing of the images collected from the viewpoint. Campos et al. [2] have developed a new dense visual inertial SLAM system for visual maps. It uses a network image classification technique that combines image fusion and text assistance. This demonstrates excellent visual configuration in the processing of miniaturized image information systems. Recently, the health status of the ecosystem for advertising brand logo design has received increasing attention from advertisers and ordinary internet users. The brand identity is abused, and the privacy and security of internet users are violated. In this article, we extensively studied the threats faced by online advertising and traced the root causes from a systematic perspective. Chua et al. [3] analyzed the design and application issues of internet advertising, and also reviewed and analyzed existing threat mitigation strategies. Kim et al. [4] introduced a new method to find significant viewpoints with deep representation based on the ease of semantic segmentation. By selecting significant viewpoints, it is possible to better understand the fine-grained shape changes of mirror materials. Kwon et al. [5] analyzed the contribution of visual cultural innovation in the state of graphic design. Explored the visual culture and multimodal literacy issues in art education through the design of graphic art signage. Lee et al. [6] proposed a new deep learning model for identifying machining features from 3D CAD models and detecting feature regions using Gradient Weighted Class Activation Mapping (Grad CAM). Logos typically include textual and/or visual design elements that describe the types of products/services marketed by the brand. However, there is limited knowledge on how and when logo descriptiveness affects brand equity [7]. Manavis et al. [8] aim to optimize the design and development process of products. The form of a brand product refers to the design of its appearance, structure, function, and other aspects. Its research adopts computational design methods to study the form of branded products. Manavis et al. [9] used computer simulation and other techniques to optimize and design the form of branded products. These CAD technologies include computer-aided design, computer-aided engineering, computer simulation, etc. Through the application of these technologies, brand product forms that better meet consumer needs and expectations can be designed in the shortest possible time. Finally, the design plan will be evaluated and tested. These evaluations and tests include functional evaluation, appearance evaluation, reliability evaluation, etc. Through these evaluations and tests, we can determine the advantages and disadvantages of the design scheme, and make improvements and optimizations to the design scheme. Merino et al. [10] are a technique used to optimize processor instruction sets, which can reduce the size of instruction sets and improve processor performance. ESP is achieved by dividing the instructions in the program into different subsets and selecting the most effective instructions in each subset. The brand logo design under current computer-aided design is a very important technology. Naranjo et al. [11] analyzed the automated processing tasks of image architecture in deep learning convolutional networks. It identifies different image models and uses a pre designed network image dataset for image result recognition, constructing an image quality detection and tracking system. Descriptor subset selection technology is an important technique for optimizing processor performance, which can help processors achieve higher performance and lower power consumption [12]. Torres et al. [13] investigated and analyzed the commonalities and asymmetries between consumer responses to different computer-aided design (CAD) virtual reality technologies. When analyzing consumer preferences for logo design, this article applies Constrained Dual Scaling (CDS) to explain the reaction style in categorical data. The research results indicate that virtual reality natural logo design in augmented reality has a positive impact on visual recognition elements. Waluya et al. [14] believe that CAD technology can be used for 3D modeling. This can help designers create accurate 3D models of products to better express their appearance and structure. In addition, CAD technology can also be used for engineering analysis and optimization to ensure that the design of product packaging meets customer needs and safety standards. Wan et al. [15] conducted an asset evaluation of the brand's identity recognition ability. In traditional brand logo design, brand design is usually displayed in floor plans. This display method has certain visual confusion issues, making it difficult for brand design to present as a whole. It constructs a framework for dividing brand assets by testing consumers' market performance. Qualitative survey results indicate that brand design logos require structured recognition. Wang [16] analyzed the optimization design of human-machine interface for engineering CNC machine tools in the field of visual communication perception. Due to the many visual expressions involved in the development and design process of engineering equipment, it is particularly important to make good use of these visual optimizations. Its research optimizes human-machine interface design from the field of visual communication perception, and analyzes and tests the intensity levels of visual perception and perception elements in human-machine interaction interfaces. Yu and Sinigh [17] used CAD technology for packaging structure design and optimization. It uses CAD technology to create a 3D model of packaging and uses computer-aided engineering tools for structural analysis and optimization. To ensure that the structural design of the packaging meets the protection and transportation requirements of the product. Zheng et al [18] effectively developed a deep model layout for advertising graphic design. By capturing the model environment in CAD virtual reality, the visual and textual semantics of user input were constructed to synthesize layout design. Compared with other visual information layout methods, the heuristic visual layout rules proposed in this paper have stronger stability. The experimental results show that its model can synthesize high-quality layouts based on the visual semantics of input images and keyword-based abstracts of input text.

3 METHODOLOGY

3.1 Brand Product Design Theory under CAD Virtual Technology

The brand community of CAD virtual reality refers to the community that uses CAD technology to create virtual reality scenes for brand marketing and promotion. These scenes can be three-dimensional virtual reality spaces or two-dimensional CAD drawings. The brand community using CAD virtual reality can bring multiple benefits to the brand. Firstly, it can provide a highly realistic and interactive virtual reality experience, allowing customers or consumers to experience the real effects and usage experience of brand products. Secondly, it can provide a wider range of marketing and promotion opportunities for brands, as customers can better understand the characteristics and advantages of brand products in virtual reality, making it easier to generate purchasing desires. In addition, it can also help brands better understand their target customers and markets, thereby better formulating marketing strategies and marketing promotion plans. It is the collection of these cultural elements that creates culture itself. As shown in Figure 1.

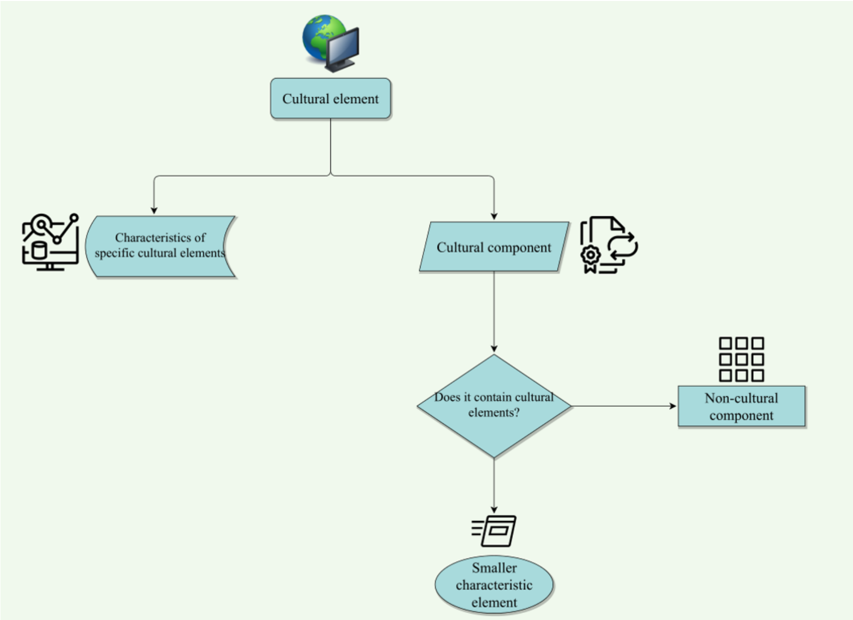

Figure 1: Judge the cultural characteristic elements.

CAD virtual reality technology has high interactivity, strong immersion, and new communication capabilities, providing new ideas for brand image development from both online and offline perspectives. Deeply tap into the potential for brand image development. This technology has a profound impact on the precise adjustment and upgrading of brand image centered on consumers. The innovative application of virtual reality technology in brand image. Not only can it bring economic benefits to brands, but it also makes new attempts for the application of virtual reality technology in other industries. Figure 2 shows the cultural element structure of brand design.

The application of computer-aided VR technology in brand image visualization has achieved spatial transformation between real brand image and virtual visual presentation, enabling the interaction and fusion of virtual information and the real world. The transformation of brand image from design form to communication mode has brought about a richer visual expression of brand image design. Delivering immersive brand image recognition and aesthetic value to users.

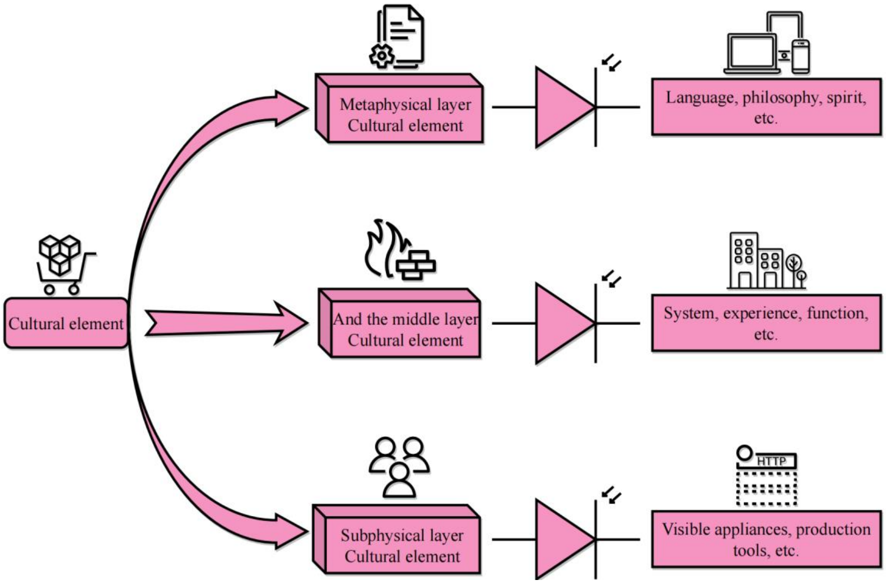

Figure 2: Structure of cultural elements.

The application of VR technology will become an important means of visualizing the CAD virtual brand image, exploring new development directions for brand image design in the digital era, and has positive practical significance.

3.2 Analysis of CAD Image Classification Algorithms Combined with Cultural and Creative Brands

Build a visual optimization model for brand design based on virtual reality technology. During the construction process, virtual reality technology is utilized to simplify the model structure. Firstly, prepare a brand design scene file based on virtual reality technology, clarifying the background information, textures, and animation requirements of the brand design. Ensure the observation needs of brand design dimensions in three-dimensional scenes, and reduce the running load of computers. Determine the output format of the model scene and the output of industrial design, and obtain a 3D scene that matches the actual brand design specifications. Obtain relevant information about the model in the final EHF file to optimize the visual design of the brand. Utilize virtual reality technology to construct a visual optimization model for brand design. Due to the inability of the entire model to meet the complete design requirements, brand design image models with different differences will be formed. Therefore, simplify it and ensure the image quality of brand design based on the visual image quality of the entire model, reducing model design errors. Train the obtained image features and corresponding class labels into the classifier to obtain the classifier model. At the end of the prediction, extract the same features as the training set images from the images to be classified and input them into the classifier to obtain the prediction results. The entire process is shown in Figure 3.

The basic idea of brand design image classification is to first construct image description features based on training samples. Then, according to the brand characteristics, a classification model is constructed using the generative model or discriminative model. Finally, the test brand images are classified using a classification model. A series of components used to solve specific product design goals are called "design elements", which are micro expressions of product attributes. The design element is the smallest substance in the product composition.

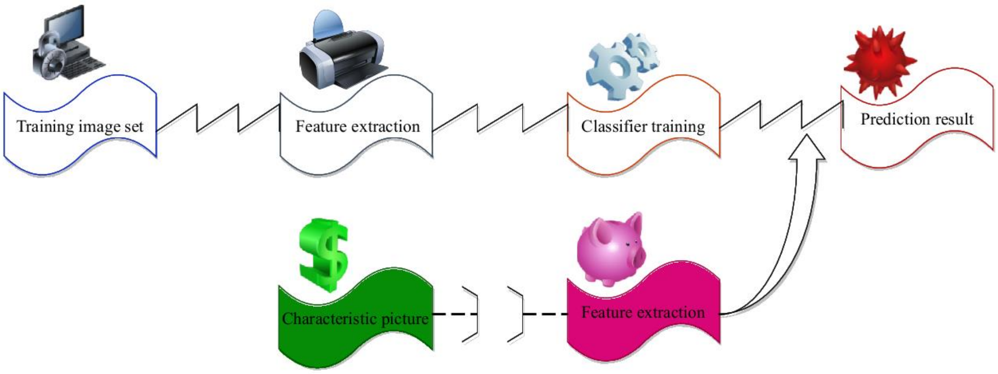

Figure 3: Content-based image classification model.

In the product design process, guided by user needs, different design elements are integrated to achieve specific design objectives. By combining certain methods and systems to form products that meet specific needs. When selecting a product image database for experimentation, in addition to considering the number of images, it is more important to consider whether the classification algorithm can effectively classify product images in various e-commerce environments.

Color moment feature is a simple and effective method to describe color distribution. The low order moments of color moments contain most of the color information. Therefore, the commonly used low order moments are first order color moments, second order and third order color moments. The mathematical definitions are as follows:

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} P_{i,j} \tag{1}$$

$$\sigma_i = \left[\frac{1}{N}\sum_{j=1}^{N}(p_{i,j}-\mu_i)^2\right]^{\frac{1}{2}} \tag{2}$$

$$S_i = \left[\frac{1}{N}\sum_{j=1}^{N}(p_{i,j}-\mu_i)^3\right]^{\frac{1}{3}} \tag{3}$$

Where μ_i is the first moment, σ_i is the second moment, and S_i is the third moment. $p_{i,j}$ represents the probability value of pixels with gray scale of j in the 11111 color channel classification of color images, and N represents the number of pixels in the image.

The color moments do not need to vectorize the features, and they are directly accumulated and counted on each channel, and then only three values are needed to describe the feature information. Generally, a pair of images only need to calculate three color moment values on each of the three-color channels, a total of nine components, to describe the image. However, the recognition accuracy of this method is low, and it needs to be combined with other methods to characterize the image.

Texture features are also commonly used in image classification. Texture, as an important visual cue, is a very vague concept that exists widely in images. There is no formal definition in the image field. Texture features are based on the gray level statistical information of an image.

They describe the smoothness, roughness, occurrence rules and other characteristics of the image, and reflect the structure information and gray level spatial distribution of the image.

LBP texture features build binary sequence patterns around pixels, and the obtained binary sequence pattern distribution is used as image features to describe. The local binary pattern of pixel point $c(x_c,y_c)$ of the gray scale can be calculated by formula (4).

$$LBP(x_c,y_c)=\sum_{p=0}^{7}2^P s(g_p \geq g_c) \tag{4}$$

Among them,

$$s(g_p-g_c)=\begin{cases}1 & g_p \geq g_c \\ 0 & g_p \leq g_c\end{cases} \tag{5}$$

The basic coding process is shown in Figure 4.

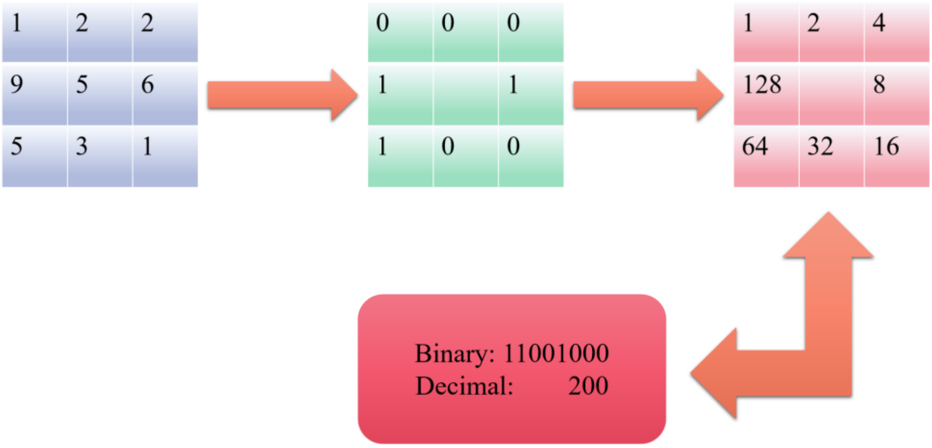

Figure 4: Schematic diagram of basic LBP coding mode.

LBP method is insensitive to illumination changes, fast in operation and strong in local representation, so it is widely used in digital image recognition, analysis and classification.

The method of extracting image texture information based on co-occurrence matrix (GLCM) has been developed for more than 40 years, and it is a widely used texture analysis method. Co-occurrence matrix is the second-order statistical measure of image gray, which describes the smoothness, roughness, appearance regularity and other characteristics of the image. Its essence is the second-order joint conditional probability density $p(i,j,d,q)$ between image gray levels, which constitutes a symmetric matrix, and its order is determined by its gray level N. It describes the probability that a pair of pixels with a distance of θ in the direction of 111111 have gray levels d and j, respectively, which is obtained from formula (6).

$$P(i,j|d,\theta)=\frac{P(i,j,d,\theta)}{\sum_i\sum_j P(i,j|d,\theta)} \tag{6}$$

The gray level co-occurrence matrix can calculate 14 features reflecting the matrix status. In practical applications, the following features are generally used to describe the image texture.

The extraction of local features plays an important role in the classification of commodity images. Local feature descriptors can effectively detect the prominent details in commodity images, such as whether women's leather shoes are pointed or round, and whether sports shoes are nylon buckles or laces. This information is exactly what customers care about, but it is difficult to accurately and fully describe through text features or color and texture features.

First, scale space should be constructed. The scale space of the image is smoothed by the Gaussian kernel of different scale factors. The two-dimensional Gaussian kernel with scale factors is defined by Formula (7). Then, image information at different scales is obtained through continuously changing scale parameters and down sampling.

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{\frac{x^2+y^2}{2\sigma^2}} \tag{7}$$

There is a scale space $L(x,y)$ for the image $L(x,y,\sigma)$.

$$L(x,y,\sigma)=G(x,y,\sigma)*I(x,y) \tag{8}$$

According to different feature point detection methods, Horster and Lienhart classified them into sparse SIFT (sparse) and dense SIFT. In practical use, sparse SIFT mainly uses DOG operator to detect feature points in multi-scale space, and accurately locate feature points after removing unstable points to further describe image local features. Using the dense method to detect feature points can extract the local features of the whole image more completely. Even in some regions where the texture and gray level change are relatively gentle, a sufficient number of feature points can be obtained. Dense methods greatly increase the number of feature points, and are widely used in scene classification.

4 RESULT ANALYSIS AND DISCUSSION

The application of CAD virtual technology in brand image visualization communication has broken the static design expression form in visual communication. In the current era of rapid technological development, the combination of virtual and real worlds has been added to the visual dissemination of brand image. This CAD augmented reality technology fully demonstrates the diversity of brand image presented to the public visually in communication, enhancing people's sensory perception. Virtual reality technology has expanded and enhanced the brand image, providing a new functional perspective for interaction between virtual and real worlds. The use of various forms such as 3D and animated videos to express brand image has brought new infinite possibilities. The application of augmented reality technology not only brings new visual impact and image memory points to the audience. It also enables the brand image to express its ideas more concisely and clearly in visual communication, achieving visual balance and cognitive psychological satisfaction. So, in this rapidly changing era of technology, CAD virtual reality technology will be a new direction and means to enhance the visual dissemination of brand image.

The existing public brand image database lacks temporal information and consumer identity, making it impossible to construct contextual neighbors. The BUPT database is built based on consumer access logs, which includes the timestamp and visitor information of each visited brand image. Therefore, this article conducted an experiment on the BUPT brand image database. It has a large number of well-trained deep learning models. Support the design of complex convolutional neural networks and user-defined loss function and gradient descent methods. Provide a large number of data processing related libraries, including Fourier transform, linear algebra, etc., to make the implementation of neural networks easier. Compared to the TensorFlow framework, its source code size is only one tenth of its size, making the design more intuitive and understandable.

Therefore, the training and testing of MAML, RN, GNN, EGNN, FMix-EGNN, and AugFMix-EGNN models in this chapter were conducted under the framework of Python in the Ubuntu system. The specific parameters of the experimental platform are shown in Table 1.

CPU	*4 2nuclear Inter(R)Xeon CPU E5-2637 3.5GHZ*
Memory	16G
Video card	4 个 GTX YITAN
Video storage	16G
System	Ubuntu

Table 1: Basic parameters of the experimental platform.

The training image samples were 5, 25, 50, 75, and the final classification results were the average of five experimental results, with the highest classification accuracy of 95.49%. The experimental results are shown in Figure 5.

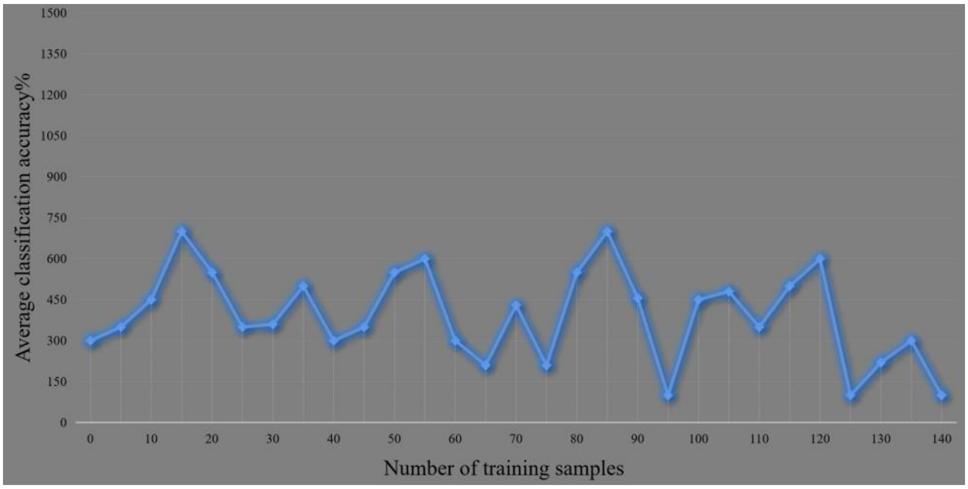

Figure 5: Analysis chart of unclassified results.

To compare the training acceleration effect of synchronous CSC-SC and asynchronous CSC-SC parallel optimization algorithms and the classification accuracy of the final model, this paper uses Mnist data set and Image Net2012 data set to test the benchmark performance of Caffe On Spark's synchronous CSC-SC parallel algorithm. Before training, the data set is converted into lmdb format data of Caffe's input data format, and one, two and four executors are respectively started to train this data set. Each executor starts a Caffe process to bind a CPU core, and the average of all executors' test results is taken as the final result each time. The final results are shown in Figure 6 and Figure 7.

As can be seen from Figure 7, the three accuracy rising rate curves almost coincide, indicating that the speed of mnist data set training by multiple executors in parallel is almost not improved compared with that of one executor. On the contrary, as shown in Figure 6, the more the number of executors in parallel with the same number of iterations (such as 10,000), the longer it takes (one executor takes about 900s for 10,000 iterations, and four executors take about 100,000 iterations).

As the training data set is too large and takes a long time, the first 127 categories of Image Net 2012 data set are used in this test, with 163903 training pictures and 6350 test pictures in total. The model adopts the Alexnet 8-tier model structure, including 5 convolution layers and 3 full connection layers. The deepening of the number of layers makes it more accurate than the Le Net 5-tier model. In this experiment, 1, 2, 4, and 8 executors are used for training. In the training phase, a batch of mini batch is 64 pictures in size, and the maximum number of iterations is 100000.

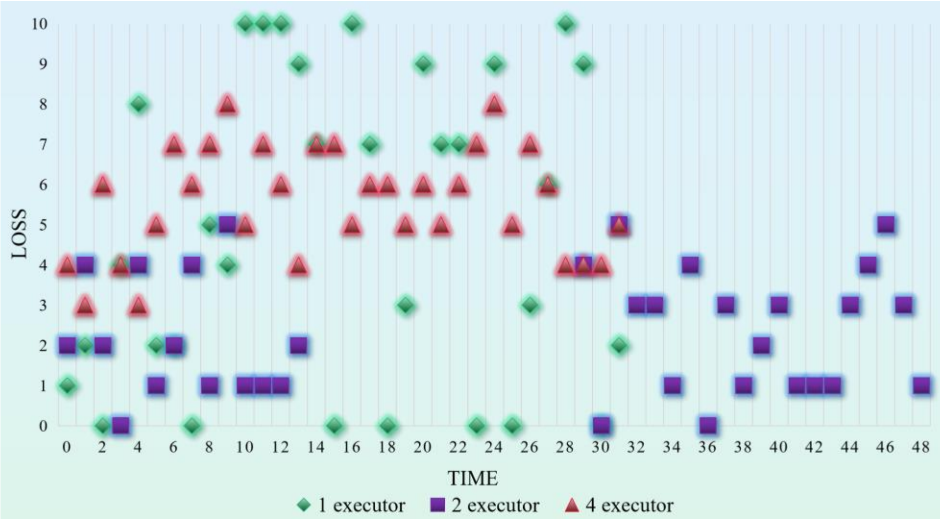

Figure 6: MNIST test loss decline rate.

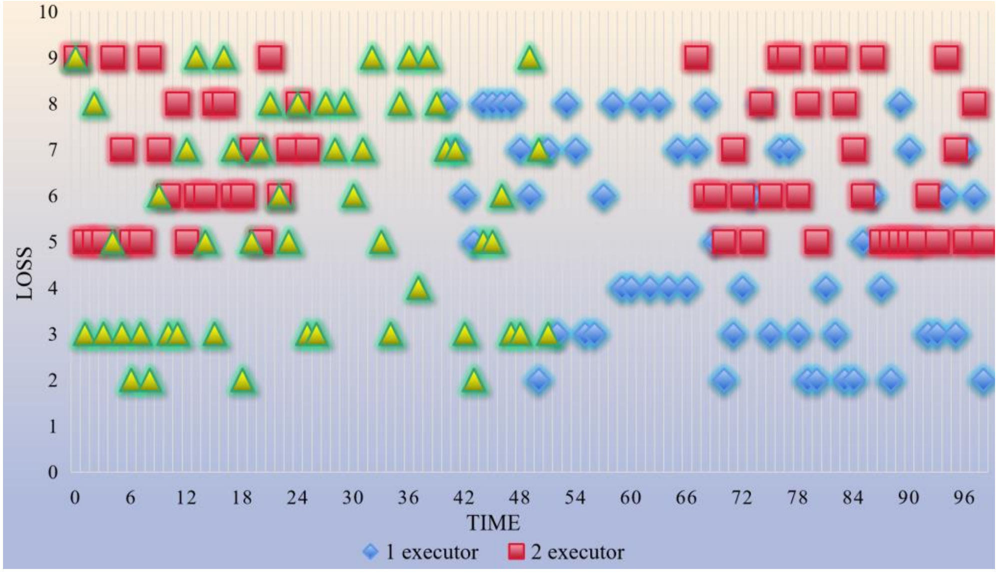

Figure 7: MNIST accuracy rising rate.

A top-5 error rate test is conducted every 100 iterations. In the test phase, the size of the input image batch of mini batch is 50, and a test iteration is 127, which can cover all test images. The average value of each executor test is taken as the final result each time. The top-5 error rate decline rate of parallel training of different executors is shown in Figure 8 and Figure 9.

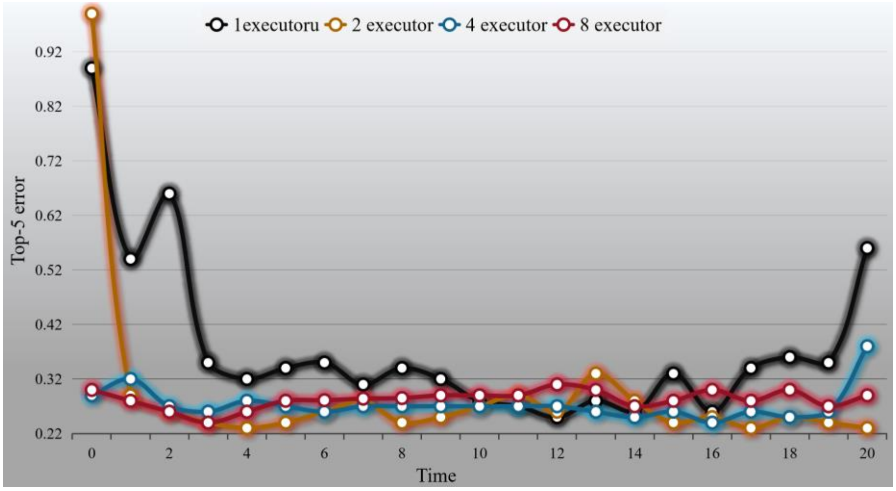

Figure 8: Top 5 Error Reduction Rate.

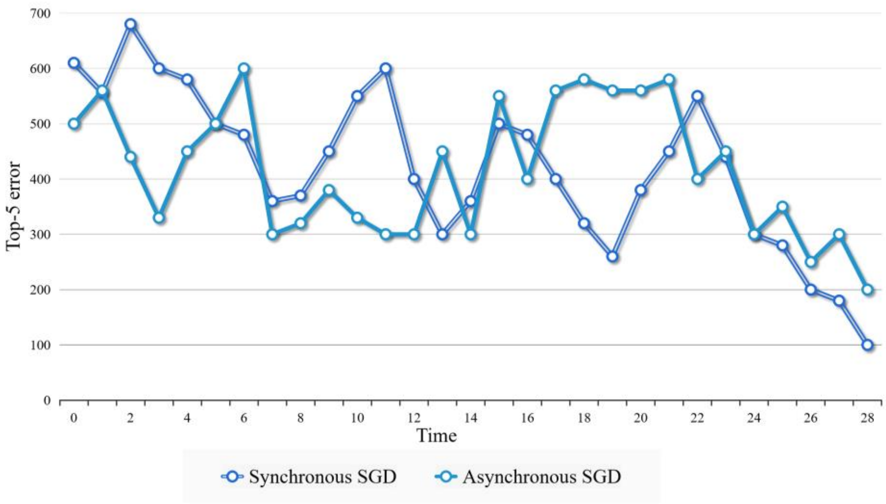

Figure 9: Comparison of asynchronous CSC-SC and synchronous CSC-SC training.

Through experimental verification, we find that asynchronous CSC-SC algorithm can further improve the distributed training efficiency than synchronous CSC-SC algorithm, but because of the asynchronous update of parameters, the classification accuracy of the model finally trained by asynchronous CSC-SC algorithm is lower than that of synchronous CSC-SC parallel algorithm. The asynchronous CSC-SC algorithm can achieve good results when the accuracy can meet the required requirements and the training efficiency is pursued.

5 CONCLUSIONS

The application of CAD augmented reality technology, which combines virtual and reality, in the visual dissemination of brand image. The rich and colorful dynamic vision presents the holographic brand image to everyone's vision, breaking the single expression form of brand image visual dissemination. In order to provide consumers with a good visual experience, attract their attention, and satisfy them from an aesthetic perspective. In the process of CAD design of brand drawings, the local color orientation is fully utilized, and the design is integrated into the local brand image, making the entire design look unified and coordinated. This paper proposes an entropy-based CSC-SC spatial weighting method by extracting and utilizing various brand patterns and color elements. The probability of different visual words appearing in different categories may vary. According to information theory, the concept of entropy can be used to describe the classification ability of different words. Therefore, when calculating word weights, incorporating the classification information of visual words into this area can further improve the discrimination ability of visual words.

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