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*Research Article*

# Product Design Method Based on Data Fusion and Transmission Based on Multimode Sensor

**Jun Hu**

*School of Design, Jiangnan University, Wuxi 214122, Jiangsu, China*

Correspondence should be addressed to Jun Hu; 7190306001@stu.jiangnan.edu.cn

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With the progress of society and the improvement of economic level, the traditional manufacturing industry is gradually transformed and upgraded in the changing times. In addition to the need for innovation in production technology, product design also plays a vital role in the sustainable development of the entire industry. However, the existing design methods have been unable to meet the high-quality requirements of consumers for material life. Therefore, this paper integrates multimodal sensor data fusion and transmission into product design. The multimodal sensor data fusion and transmission technology is developed on the basis of the human organs' ability to comprehensively judge the environmental information. This paper gives a brief overview of product design methods on the basis of this theory. Among them, the generation, development, classification, attribute level, and emotional level of products of product design methods are studied. And through the research on multimodal data fusion algorithm, the design method based on multimodal sensor data fusion and transmission technology is designed and practiced, and compared with the traditional QFD technology design method. The experimental results show that the design method proposed in this paper has the highest market demand adaptability of 86.37%, which proves its effectiveness. Popularizing this technology and method in the current stage of manufacturing industry product design can effectively improve the quality and efficiency of the design process. This has practical significance for enhancing the core competitiveness of products in the market.

## 1. Introduction

Above the new journey of the 21st century, the distance between countries around the world has gradually narrowed, and the social economy begins to develop in diversification. At the same time, the market has higher requirements for the quality of enterprises. How to achieve high-quality product production is the biggest challenge in the sustainable development strategy, which is very important and role in this product design. With the improvement of scientific progress and technology, on the basis of extension of traditional methods, the production of modern industrial products is to introduce emerging technology (such as big data computing, deep learning, and other artificial intelligence technologies). This has higher requirements for the performance, quality, and efficacy of the product. The product performance, quality, and efficacy are mostly determined according to the quality of the product design method. In recent years, the transformation and upgrading of enterprises have increasingly offset the direction of the product update, especially in the field of manufacturing, and are particularly obvious. The production efficiency and quality of the enterprise have been significantly improved. But looking at the entire development market, most companies are not satisfactory in product design methods. Therefore, catering to the development of the times, reforming the product design method is critical to achieving sustainable development of enterprises.

As early as the second half of the 20th century, scholars proposed multimode sensor data fusion and transmission concept. But its application value is the first to play in military fields. Until the continuous update of science and technology, especially after computer control technology and sensor technology, it gradually spread to the civilian field and has been developed in recent years. Multimode data fusion technology is essentially from a simulation of objects. In the entire data fusion large system, there are a variety of sensors, and each sensor provides data characteristics in different scenarios. The basic principles of multimode draw on the object to integrate the peripheral environment and make a comprehensive judgment. The system integrates different data features provided by different sensors according to fixed methods and rules, and makes comprehensive judgments, so as to generate a more in-depth and objective cognition of the problem scene.

In recent years, many scholars have conducted research on multimodal sensor data fusion and transmission technology. Liu et al. proposed a multimode data fusion frame, an depth multimode encoder. This framework is designed on the basis of deep learning technology. It is mainly used for new modal predictions in sensor data compression, missing data interpolation, and multimode scenario [1]. Stanislas and Dunbabin described a novel probabilistic sensor fusion framework to improve the detection accuracy and classification of various target obstacles encountered in the sea RobotX Challenge [2]. Gui et al. have developed a multimode data fusion method that effectively fused different sources of sensor data and process data to assess the quality of the 3D printing part [3]. Mojahed and de la Iglesia proposed an intermediate fusion method to calculate the fusion similarity between the objects. This method uses the appropriate similarity metrics to consider similarity between object composition elements [4]. Kumar proposed a new method based on decision-making methods to resolve errors to acquire human gait data. He used motion sensors and visible cameras to simultaneously record step data [5]. Jayaratne et al. proposed an expandable self-organizing neural architecture. It is used for ambient integration based on multimodal fusion. He used nonsupervised machine learning to handle large numbers and high-speed sensor data [6]. These studies have achieved certain results in practice.

However, other scholars have different views on the further application and research of multimodal sensing technology. Based on multimode and high-dimensional sensor data influx, Nweke et al. f conducted in-depth summary of human activity recognition methods using mobile and wearable sensors [7]. Based on multimode data fusion, Bakalos et al. studied the channel status information of visual monitoring, Wi-Fi signals, and utilities from ICS sensor data [8]. Du and Zare proposed a novel multi-instance multiresolution fusion framework. The frame can fuse the multiresolution and multimode sensor output and learn from automatically generated, inaccurate data [9]. Vakil et al. reviewed the sensor fusion method to achieve the convergence of passive radio frequency and photoelectric sensors. And the EO/RF neural network fusion method was proposed [10]. Kumar et al. proposed a novel multimode frame. It used sensor devices to perform isolated signature identification, which has been tested on 7,500 Indian sign language gestures consisting of 50 different signatures [11]. Asvadi et al. proposed a multimode integrated vehicle detection system from 3D-LIDAR and color camera data. He combined the detector together to improve vehicle detection accuracy [12]. In summary, after recent years, the application of multimode sensor data fusion and transmission technology has been deeply studied by many scholars. However, there is not much study that integrates it with product design.

Therefore, in order to further promote the diversified development of product design, this paper fuses the analysis and practice of product design in multimode sensor data fusion and transmission technology. It puts forward a novel product design research direction, which not only provides an improvement and strengthening recommendation for the product design industry, but also provides new ideas for multimodal sensor data fusion and transmission.

## 2. Product Design Method and Multimode Sensor Data Fusion and Transmission

*2.1. Product Design Methods.* The product design method theory is gradually explored in practice activities. Its theoretical inquiry is also evolving and improved. The earliest scholar in 1875 proposed a process planning model, as shown in Figure 1. This is also the first attempt to systematically analyze it as a theory. The principle of method analysis in all product design is similar to the principle of analysis in mechanical technology. It mainly summarizes the general rules of all product design.

In the 20th century, many scholars have launched a warm discussion on the product design method. In addition to research on stylized product design, product design evaluation rules and basic principles of product design also have many different definitions and opinions. Product design method theory research is initially carried out. Until the mid-20th century, the industrial revolution accelerated the development process of socio-economic, and the competition in the market was more intense. Head of developed countries, some countries have gradually recognized the feasibility of product design method research and began to invest financial human resources into the research work of product design methods. At this stage, the theory of product design methods has been improved unprecedented.

The design is a critical value and significance of the overall construction of the technical system. In academia, the definition of design methods can generally summarize the ways and means of achieving preset design objectives. In the process of social informationization and intelligent development, various types of product design methods have emerged in the market. This paper is mainly introduced for the most representative five design methods.

Affective design: In the axiological design method, the entire concept is composed of four fields. They are customer domain, functional domain, physical domain, and process domain, as shown in Figure 2. The design process is based on interacting interactions between these areas. The design process phase is divided into three steps, namely, the definition of product properties, product design, and process design. In addition, the axiological design method also includes independent axiom and information axiom. Independent axioms demand that each function is independent of each other. If there is several design to solve the independence principle, it is necessary to solve the preferred according to the information axiom.

Robust design: The steady design method is presented in the middle of the last century. Its basic idea comes from three designs, and it also draws on the statistical analysis

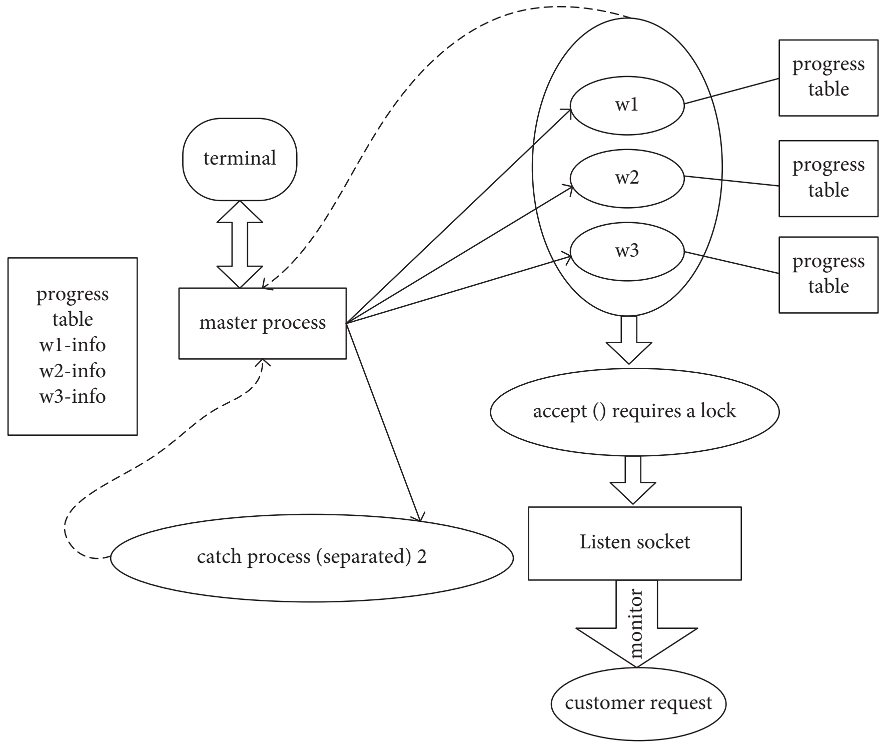


Figure 1: Process planning model.

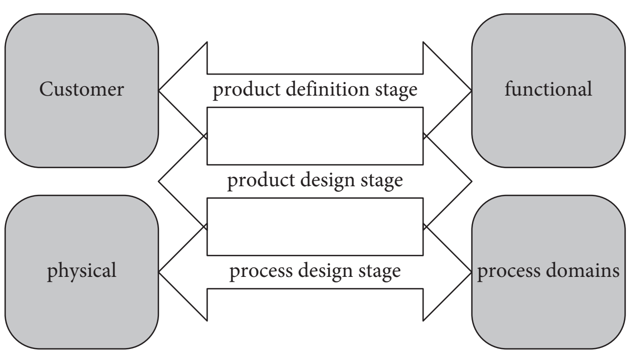


Figure 2: Axiomatic design method legend.

principle in mathematical theory. Robustness can also be called invariance. It refers to the adaptability of an element to changes in the scene. If the adaptability is strong, then the robustness is strong. Such design methods are also divided into three phases, but different from the axiological design. Its three stages are the system design phase, parameter design phase, and tolerance design phase. The disadvantage of the robust product design method is that it cannot present the full face of the product well, especially in the initial stage of the design without the corresponding control and planning.

Parallel design: The parallel design method is to set the product design and systematically. It takes a parallel operation mode to improve the contradiction between the product in production, inspection, and distribution. Parallel design work patterns not only are beneficial to reduce product production cycles, but also improve corporate production efficiency. It also enhances team spirit and cooperation between employees. Although it launches new challenges for most of the operating systems of many companies, this design method is also accepted and used by many companies.

Computer-aided design: Computer-aided design methods as the name suggests mainly take advantage of this tool. This method is the product of social information development. It can speed up the product design cycle and reduce human cost and time cost. But it also has a lot of limitations. Because artificial intelligence technology is still in the stage of development and improvement, computer-aided technology is not mature enough. During the entire product design, there are still many works that can only be done with manual.

Quality function deployment design: Quality function deployment design is also known as QFD design technology. It is the most important difference with the top four types of design methods to be the only way to integrate customer needs during design. In addition to the quality, functions, and development costs of the product, it has a strong role in maximizing customers. This can also greatly enhance the core competitiveness of the product. This method is now applied in product design in many fields. For example, it has its presence in parts manufacturing, clothing production, and software development and other industries.

Products can be seen as a symbol, including aesthetic impression, semantic interpretation, and symbolic contact three-part cognitive reactions. Aesthetic impression focused on the appearance level. It is an impression that is generated by the attractiveness of the product symbol. Semantic explanation is to understand product information from the angle of symbolics. Symbolic connections resonate at the spiritual level of products and users. According to the three-level theory of the product, as shown in Table 1, the product attribute can be divided into sensory level, the performance level, and understand the level.

In the product stimulating the user emotional level, according to the theoretical analysis of the human need hierarchy, it can define three levels of demand for product design, which is functionality, excellence, and pleasure. Pleasant can be divided into physical joy, psychological joy, social pleasure, and conscious pleasure, as shown in Table 2.

Different from other art design forms such as sculptures and paintings, product design is a practical art. In addition to the appearance of visual aesthetics, the emotional experience of product interaction is also closely related to the purpose of product function and therefore has multiple levels, as shown in Table 3.

*2.2. Multimodal Sensor Data Fusion and Transmission.* Generally speaking, in the process of product design, the matrix planning of the product is firstly carried out to collect and input various product concepts and design requirements, and finally the optimal solution is found in the concept and requirement matrix. In this paper, the conventional algorithm of multimodal data fusion is introduced first, and then the multimodal sensor data fusion research is carried out on the basis of the principles of CCA and DCCA algorithms. The product data are mapped from the sample space to the feature space for end-to-end feature extraction. In view of the characteristics of DCCA algorithm that is easy to over-fit, a DCCA algorithm based on random vector functional connection network (R-DCCA) is proposed, which realizes the fusion of deep multimodal product design information and data, and improves the efficiency and analysis quality of product design.

Canonical correlation analysis (CCA) is a linear mathematical model. It is a multivariate statistical analysis method suitable for multiview and multiscale analysis of multisource heterogeneous data. Its main goal is to find the linear projections of data from different data sources that are most relevant to product information. Its purpose is to identify and quantify the link between two sets of product data variables. And it focuses on the correlation between the linear combination of one set of variables and the linear combination of another set of variables [13]. Its ideas are to first solve a pair of linear combinations of the two groups of variables, which have the largest correlation coefficient. Then, from the linear combination pair of linear combinations that were originally selected, the pair with the maximum correlation coefficient was selected, so that it was performed. These selected linear combination parallelisms are typical variables, and their correlation coefficient is called a typical correlation coefficient. The canonical correlation coefficient measures the strength of the link between these two sets of product variables. This maximization technique strives to map the high-dimensional relationship between two sets of product variables to a few pairs of canonical variables.

Assuming that there are two groups of variables, using $(p \times 1)$ random vector $X^{(1)}$ to represent the first set of $p$ random variables. Similarly, the second set of $q$ random variables were coped by $(q \times 1)$ random vector $X^{(2)}$. It is assumed that $X^{(1)}$ is a smaller group, that is, $p \leq q$. For random vector $X^{(1)}X^{(2)}$, let

$$\begin{aligned} E\left(X^{(1)}\right) &= \mu^{(1)}; \mathrm{Cov}\left(X^{(1)}\right) = \Sigma_{11}, \\ E\left(X^{(2)}\right) &= \mu^{(2)}; \mathrm{Cov}\left(X^{(2)}\right) = \Sigma_{22}, \\ \mathrm{Cov}\left(X^{(1)}, X^{(2)}\right) &= \Sigma_{12} = \Sigma_{21}'. \end{aligned} \tag{1}$$

The formal representation of the above two sets of variables is recorded:

$$\begin{aligned} X_{(p+q)\times 1} &= \begin{bmatrix} X^{(1)} \\ X^{(2)} \end{bmatrix}, \\ \mu_{(p+q)\times 1} &= E(X) \\ &= \begin{bmatrix} \mu^{(1)} \\ \mu^{(2)} \end{bmatrix}, \\ \sum (p+q) \times (p+q) &= E(X-\mu)(X-\mu)' \\ &= \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}. \end{aligned} \tag{2}$$

The main task of typical correlation analysis is several selected covariances (or related coefficients) in $\Sigma_{12}$ rather than its all $pq$ covariances to synthesize contacts between $X^{(1)}$ and $X^{(2)}$

Linear combination is used to express a simple summary of a set of variables. For coefficient vectors $a, b$, assuming [14]

$$\begin{aligned} U &= a' X^{(1)}, \\ V &= b' X^{(2)}. \end{aligned} \tag{3}$$

It can be obtained

$$\begin{aligned} Var(U) &= a' \sum_{11} a, \\ Var(V) &= b' \sum_{22} b, \\ Cov(U, V) &= a' \sum_{12} b. \end{aligned} \tag{4}$$

The goal of CCA is to find coefficient vectors $a$ and $b$, making:

$$\mathrm{Corr}(U, V) = \frac{a' \sum_{12} b}{\sqrt{a' \sum_{11} a} \sqrt{b' \sum_{22} b}}. \tag{5}$$

As much as possible, namely,

$$\begin{aligned} \left(a^{*}, b^{*}\right) &= \arg\max_{a,b} \mathrm{Corr}\left(a' X^{(1)}, b' X^{(2)}\right) \\ &= \arg\max_{a,b} \frac{a' \sum_{12} b}{\sqrt{a' \sum_{11} a} \sqrt{b' \sum_{22} b}}. \end{aligned} \tag{6}$$

The optimization problem can be equivalent to [15]

Table 1: Three-level theory of products.

| Sequence | Level | Awareness level | Product association |
|---|---|---|---|
| 1 | Instinct level (sensory) | Automatic preset layers | Shape |
| 2 | Behavioral level (efficacy) | Brain activity that governs everyday behavior | Product fun and efficiency |
| 3 | Reflective level (understanding) | Thinking activity | User self-image, personal satisfaction, memory |

Table 2: Four architectures for product delight.

| Sequence | Category | Architecture explained | Contact product |
|---|---|---|---|
| 1 | Physical pleasure | Obtained through bodily sensory channels | Whether it is suitable for personal physiological characteristics |
| 2 | Psychological pleasure | Interact with others | Can express personal image and status |
| 3 | Social pleasure | User is happy | Satisfaction and pleasant experience of completing tasks |
| 4 | Conscious pleasure | Appreciation of art, etc., extends pleasure | Related to product aesthetics, value, or the degree to which it improves life and respects the environment |

Table 3: Perspectives and hierarchical dimensions of product cognition.

| Category | Year of presentation | The main points | Hierarchical dimension |
|---|---|---|---|
| Perceptual level | 1998 | Three-factor perceptual structure | Satisfactory event<br>Commendable conduct<br>Striking object |
| | 1992<br>2000 | Four levels | Physical pleasure and psychological pleasure<br>Social pleasure and conscious pleasure |
| | 2000 | Needs other than technology | Amazement, entertainment, and affinity |
| | 2003 | Interactive products enjoy optimism | Stimulate, belong, and call |
| | 1999 | User needs theory | Functionality, usability, and entertainment |

$$\begin{aligned}(a^*, b^*) &= \arg\max_{a,b} a' \sum b,\\ s.t. a' \sum_{11} a &= 1,\\ b' \sum_{22} b &= 1.\end{aligned} \tag{7}$$

The method of solving the above problem is to construct a Lagrangian equivalent. Similarly, the optimization conditions for the second set of typical variables are

$$\begin{aligned}\arg\max a_2' \sum_{11} b_2 &= 1,\\ s.t. a_2 \sum_{11} a_2 &= 1,\\ b_2 \sum_{22} b_2 &= 1,\\ a_2' \sum_{11} a_1 &= 0,\\ b_2' \sum_{22} b_1 &= 0.\end{aligned} \tag{8}$$

The optimal target function value for the above optimization problem is as follows: define matrix $T \triangleq \sum_{11}^{-1/2} \sum_{12} \sum_{22}^{-1/2}$, assuming $U_k, V_k$ is the front $k$ left quasi-different vectors of the matrix $T$ and matrix with the front $k$ right strange vector, respectively. Then, the optimal objective function value is the sum of the $k$ number of matrix $T$, that is, the $Ky$ Fank– norm of the matrix $T$. Therefore, the optimal solution of the above optimization problem is

$$(a^*, b^*) = \left( \sum_{11}^{-1/2} U_k \sum_{22}^{-1/2} V \right). \tag{9}$$

This solution is based on the assumption that the covariance matrix $\Sigma_{11}, \Sigma_{12}$ is a nonsingular matrix. This condition is easily satisfied in practical applications and can be obtained by data regularization. For example, the input data matrix after a given centering is

$$\begin{aligned}\overline{H}_1 &\in R^{n_1 \times m},\\ \overline{H}_2 &\in R^{n_2 \times m}.\end{aligned} \tag{10}$$

The estimate of the covariance matrix is

$$\widehat{\Sigma}_{11} \frac{1}{m-1} \overline{H}_1 \overline{H}_1' + r_1 I. \tag{11}$$

Among them, $r_1 > 0$ is the regularization coefficient. The advantage of estimating the effectiveness matrix using regularization items is to reduce the pediment.

In the product analysis model, there will be a certain relationship between the characteristics of customer needs. Not all requirements in the customer demand characteristics are equally important, and the relative importance of all customer demand characteristics should be determined on the basis of fully considering the customer's wishes. However, the linear operation of CCA limits the expressive power of the product design analysis model. Aiming at the defect that the feature extraction of traditional schemes relies heavily on prior background knowledge and requires a large amount of computation, we propose a deep canonical correlation analysis (DCCA) algorithm. The basic information of the product is learned by using a deep neural network to perform complex nonlinear transformations between two sets of variables. And make the results highly linearly correlated, making full use of the deep nonlinear mapping of neural networks, transforming product concepts into multimodal data, and mapping from sample space to feature space.

In order to make the overall correlation function, the transform parameters of the two sets of variables are obtained by joint learning. Therefore, DCCA can be considered as nonlinear extension of linear CCA, which can be used to replace core-based CCAs. Existing work shows that DCCA has learned results, its correlation is significantly higher than CCA and KCCA, and its algorithm is shown in Figure 3.

However, a major defect of the DCCA algorithm is that in the early stage of product design, it is easy to over-fit the product requirements and various basic information data. This will affect the final effect of product design, which can be solved by introducing random vector function links in deep networks. The random vector functional link neural network is a simple single-layer feedforward neural network, and its network architecture is shown in Figure 4.

The network's generalization ability can be enhanced by introducing a random vector connection in the DCCA network architecture. The network structure is shown in Figure 5. The solid line represents a matrix connection in the figure, and the broken line indicates a random connection.

DCCA uses a depth neural network combined with the CCA algorithm for nonlinear transformation of input data. The representation of the view is calculated by a nonlinear variable change of the two views. That is, the output layer of the network is the most relevant through learning. In Figure 5, the lower row nodes represent input data. Intermediate nodes represent hidden layers. The upper node represents the output layer.

In Figure 5, the R-DCCA network consists of a input layer, several hidden layers, and an output layer, wherein the input layer is used to map different modal data, and the original data are entered into the network. The hidden layer maps the data to the feature space through a series of affine transformations and nonlinear mapping functions. The output layer is intended to determine the correlation coefficient between the output feature vectors of different modalities. It tries to find a mapping method to maximize the correlation between different modes and extract depth features of raw data.

The CCA operation is performed between the output feature vectors of the top layer, and the mapping of the deep neural network RVFL is linked from the input to the output through the random vector function, which plays a role in enhancing the generalization performance of the network. The product transmission framework based on R-DCCA is shown in Figure 6.

In Figure 6, the data of different modalities are first extracted. Among them, text modality uses the GloVe model to extract words. Video modality uses CNN extraction characteristics. Audio modal uses LSTM for feature extraction, resulting in three modal corresponding feature vectors. After the three types of feature vectors enter the

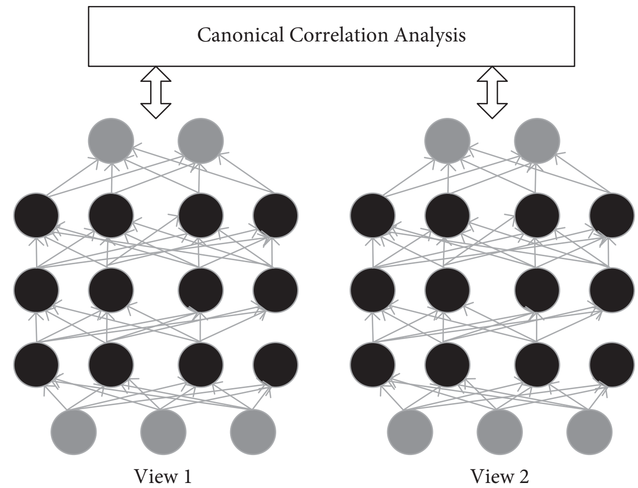


Figure 3: Schematic diagram of DCCA algorithm.

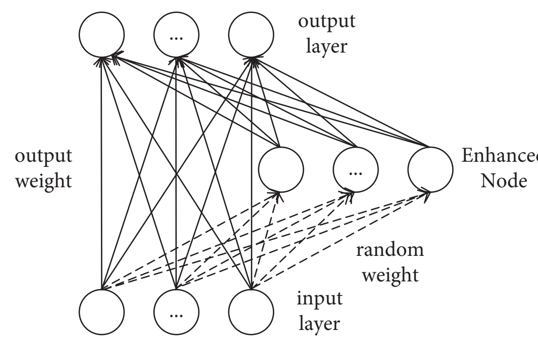


Figure 4: RVFL network architecture.

depth RVFL network, the two or two are typically analyzed at the output.

Aiming at the characteristics of DCCA being prone to over-fitting, this paper proposes to use random vector functional link network instead of fully connected network for feature extraction, so as to achieve the purpose of learning multiple models for Ensemble. New network training optimization target function turns into output layer loss function $L_{out}$ and the weighting and the regularization penalty. This facilitates a clear integration of the various functions and features of the product and provides an opportunity to cross-check the correctness of the design process. If a product feature item is found to be unrelated to any customer requirement feature, then the engineering feature may be redundant, or the product may have been designed without a customer requirement feature. If a customer demand characteristic is not related to any of the technical characteristics listed, then it is possible to increase the technical requirements of the product, which should be technically satisfied.

## 3. Product Design Practice

This article will apply the product design method based on multimode sensor data fusion and transmission in the design of six types of industrial manufacturing products and

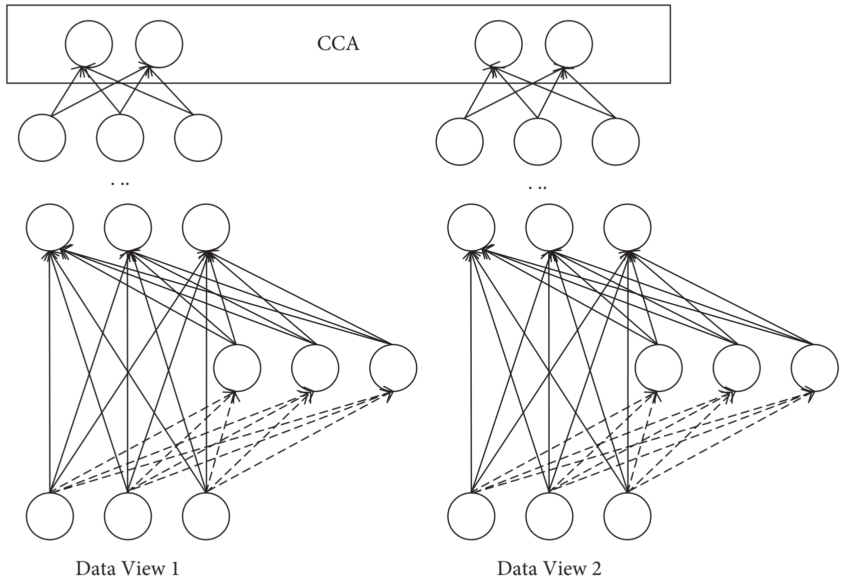


Figure 5: Schematic diagram of R-DCCA algorithm.

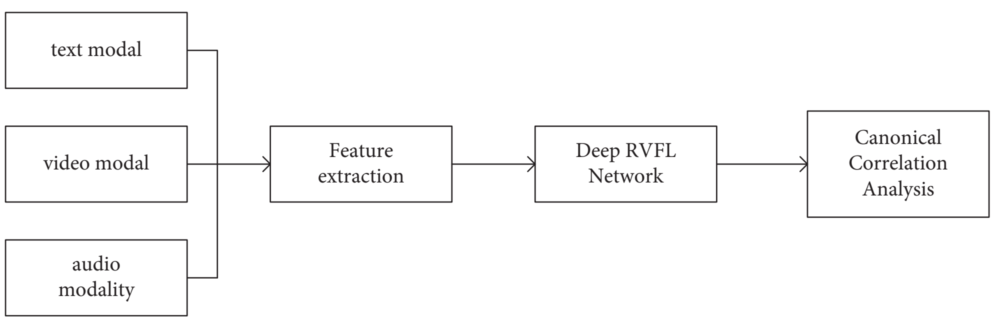


Figure 6: Product transmission framework based on R-DCCA.

use this practice. It is compared to the quality function of the traditional design method, which tests the effectiveness of design methods from the market demand, customer satisfaction, technical characteristics, and design costs.

Market demand adaptation test: Market demand adapter test considers the opportunities of various products in the market and future development. The greater the percentage of the test value of demand-appropriate, the more ideal of the future development trend of the product in the market. The test results are shown in Figure 7.

As can be seen from Figure 7, under the product design method proposed in this paper, the comprehensive test value of the six product market demands is 85.78%; the product market demand for product market based on QFD technology product design is 81.46%. Based on these data, it can be seen that the product design method proposed in this paper can adapt to the changes in the market's trend of product development. Moreover, it has a favorable position in this change of wind direction and has strong market competitiveness.

Customer satisfaction test: Customer satisfaction evaluation mechanism adopts a score system. The full score is 10 points. A higher customer review score indicates higher satisfaction with the product. This test randomly draws 100 customers for investigation, all customers have used 6 products, and the comprehensive score results are shown in Figure 8.

As can be seen from Figure 8, the customer satisfaction integrated test value of six products is approximately 8.16 points under the product design method proposed in this paper. Under the design method based on QFD technology, the comprehensive test value of customers with six types of products is 7.93 points. A product's audience will vary based on the differences between the product's functions and features. In business competition, a good product not only needs to be changed in the design process, but also needs to analyze consumer needs. Multimodal sensors enable optimal analysis in powerful data fusion calculations based on market variables. Accurately solve the expected needs of consumers, and find the optimal solution to meet the individual needs of customers for products to the greatest extent.

Technical characteristic test: Technical characteristic testing and customer satisfaction tests are the same, using fractional systems to detect the advantages and disadvantages of technical characteristics. The test items are shown in Table 4, and the comprehensive test score of four items is shown in Figure 9.

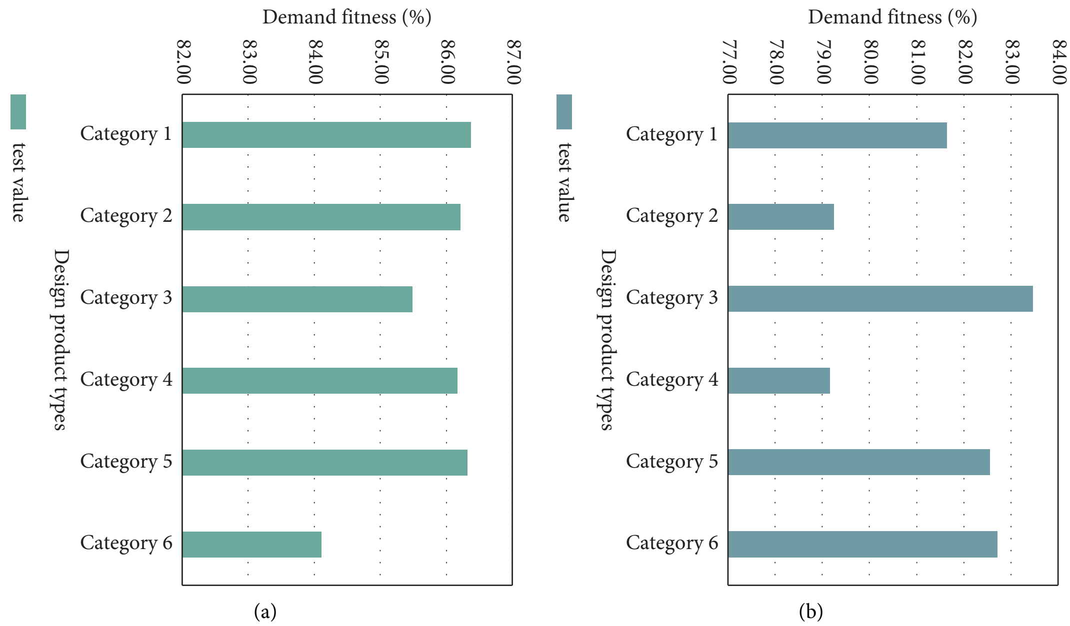


Figure 7: Product market demand fitness test. (a) is a market demand suitable for market demand for product design methods in this paper. (b) is a market demand suitable for market demand based on QFD technology product design method.

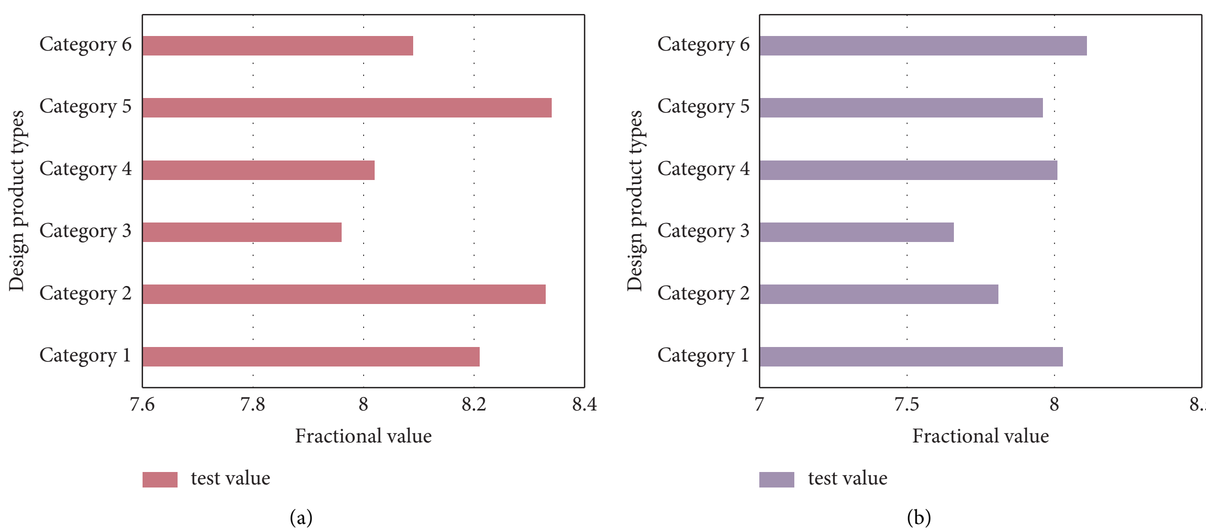


Figure 8: Customer satisfaction test. (a) is a customer satisfaction test of the product design method in this article. (b) is customer satisfaction test based on QFD technology product design method.

Table 4: Technical characteristic test project.

| Sequence | Test belongs | Test items |
|---|---|---|
| 1 | | Product quality |
| 2 | Product technical characteristic test | Product performance |
| 3 | | Product appearance |
| 4 | | Product material |

As can be seen from Figure 9, under the product design method proposed in this paper, the product quality test is 8.04 points, the product performance test is 8.06 points, the product test mean is 8.05 points, and the product material test is 8.13 points. Under the design method based on QFD technology, the product quality test is 7.78 points, the product performance test is 7.61 points, the product surface test mean is 7.86 points, and the product material test is 7.71 points. We can see that the traditional QFD technology product design method is far inferior to the method proposed in this paper in terms of technical characteristics. Whether the quality, performance, appearance, and material of the product can stand out among many choices determines whether the enterprise can survive in the market. The multimodal sensor can effectively analyze and extract the product features, perform optimal fitting, and achieve a high level of practical application to improve the technical characteristics of the product.

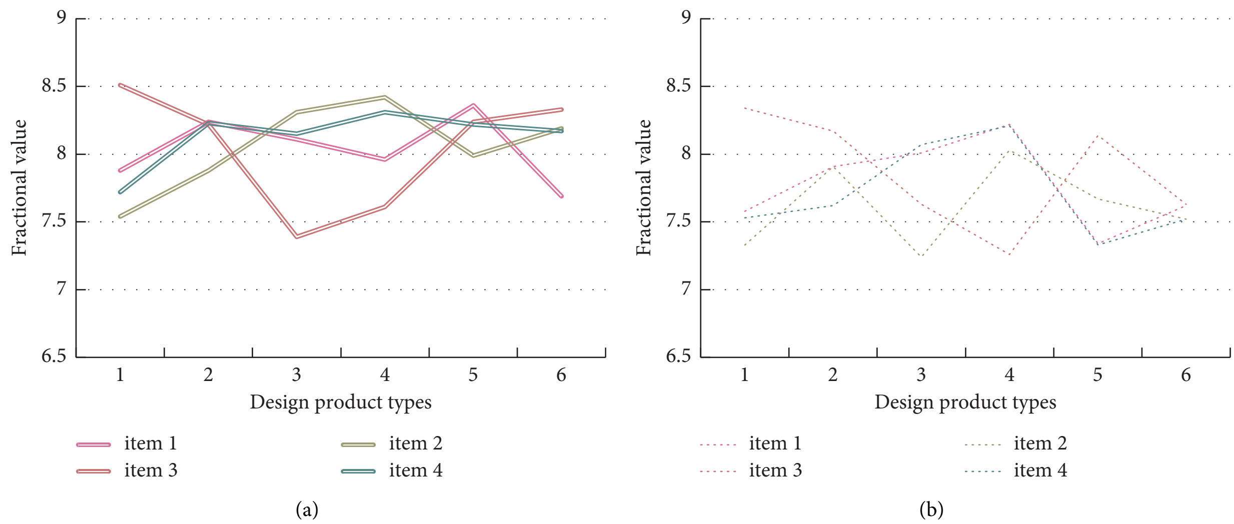


Figure 9: Technical characteristic test. (a) is a technical characteristic test of the product design method in this article. (b) is a technical characteristic test based on QFD technology product design method.

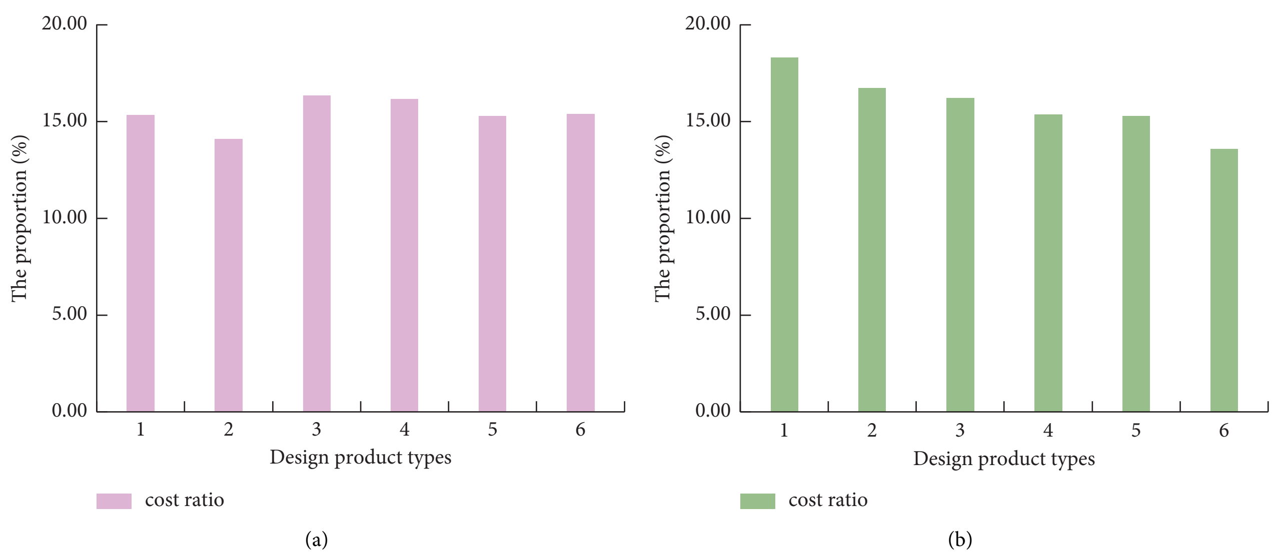


Figure 10: Design cost test. (a) is a design cost test of the product design method in this article. (b) is a design cost test based on QFD technology product design method.

Design cost test: The design cost test is mainly due to the statistics of time costs, human costs, and material costs accounted for the entire production cost during the design of the six product designs. The statistics are shown in Figure 10.

As can be seen from Figure 10, the product design cost is approximately 15.45% under the product design method proposed in this paper. Under the design method based on QFD technology, the product design cost is approximately 15.92% of the overall production cost. QFD technology must go through multiple preparations in the early stage of product design, such as product planning and concept evaluation. These steps require a lot of operating costs, which will increase the proportion of product design costs in the overall manufacturing costs. However, the data fusion technology in the multimodal sensor can integrate these steps, so that it can realize multiple functions in one link, which greatly reduces the time cost and improves the product efficiency.

## 4. Conclusion

Product design plays a vital role in the development of manufacturing enterprises. Mastering a cost-effective design method can strengthen the core competitiveness of the enterprise and make it occupy a favorable position in the new era of rapid development and fierce competition. The design method based on multimodal sensor data fusion technology and transmission technology can integrate various important steps such as planning, evaluation, and transformation in the product design process through data fusion and transmission technology. It solves the problems of high cost and low competitiveness caused by problems such as design efficiency or inaccurate wind direction positioning in the market. Although this paper has carried out a deep research on product design using multimodal sensor data fusion and transmission technology, there are still many deficiencies. There are still many challenges in the integration of multimodal sensors and product design, and the development and impact of product design on the entire market are extremely complex. The depth and breadth of product design method research in this paper are not enough. In the course of this research, the selection and acquisition of experimental data were carried out under absolutely ideal conditions. Completeness and validity are not enough. In the future work, we will study appropriate design methods and means from more perspectives based on the existing technology and level, and continuously improve product quality.

## Data Availability

The data used to support the findings of this study are available from the author upon request.

## Conflicts of Interest

The author declares no conflicts of interest.

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