

Research Article

Research on the 3D Virtual Product Network Display Algorithm Based on Digital Drive

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In order to improve the effect of 3D virtual product network display, this paper combines digital drive technology to analyze the virtual simulation algorithm and proposes a digital drive-based Hough transform clustering virtual image processing algorithm. Through the knowledge of clustering and generalized Hough transform, generalized Hough transform is applied to clustering. Moreover, this paper uses cluster analysis to determine the image characteristics of three-dimensional virtual products. In addition, this article combines the methods proposed in this article to construct a three-dimensional virtual product network display system. The research shows that the digital-driven 3D virtual product network display algorithm model proposed in this paper has a good 3D virtual display effect.

1. Introduction

In today's postindustrial society, consumers are not only satisfied with the quantity of warm-saturated material products. They believe that consumption is more a process of experience. When the consumption behavior is over, they will still retain the feeling of "experience" in their minds. Moreover, they are concerned with a feeling, an emotional, intellectual, and even spiritual satisfaction. What they want is products and services that can stimulate the soul, participate in them, and integrate them into their own lifestyles. This is the experiential consumption model [1]. At present, many designers and companies have also realized that design is no longer simply a study of product shape and function but also a study of the psychological and physiological systems of consumer groups. Moreover, it is a study of human emotional attributes, which enables consumers to resonate with design and meet the individual needs of consumers. Therefore, the virtual display experience of the product came into being. It is to create a three-dimensional model of the product on the basis of network computer technology, and display it on a personal computer or Internet

platform to realize the interaction between the user and the product, and produce the same sensory and emotional experience as the real world [2]. The key technology used is virtual display technology. Virtual display technology is an important part of virtual reality technology. Its most prominent feature is that it has changed the way that humans had to experience a certain space or scene in person, otherwise they would not be able to understand it or can only be heard. Now, users can use digital devices to interact with the virtual environment, thereby effectively broadening their horizons and cognitive means. On the other hand, virtual display technology is not only a medium for demonstrating products or spaces but also a brand-new design tool. It displays a multidimensional information transmission space in a visual form and provides technical support for us to build and experience the virtual world [3].

At present, in the industrial product design industry, the main display method is still renderings or flash animation demonstrations. Customers can only watch the fixed pattern and style of the product or product information in a static way, thus lacking an immersive experience. This topic compares and analyzes the user experience concept and product virtual display display methods, design principles, artistic form characteristics and other aspects, and arrives at reasonable design standards, which can enable consumers to choose without leaving their homes. Buy your favorite products to understand product information more conveniently and intuitively; provide product designers with valuable suggestions in design, including simulations of product materials, colors, working principles, and individual creativity, so as to better satisfy the needs of customers also reduce economic costs; companies can better use this high-efficiency and low-cost display method to publish the completed product virtual experience platform on the Internet as a marketing tool to deliver the most authentic product features to users, enhance the competitive advantage of enterprises, and narrow the distance between enterprises and consumers. Although the design and application of virtual display have received more extensive attention, most of them are scattered and isolated, and they are limited to the scope of technical research. There is a lack of more systematic and comprehensive research, especially the discussion of virtual product interaction design from the perspective of user experience, and the research is even more lacking.

This article combines digital drive to design a threedimensional virtual product network display to provide users with a better product experience and improve product design effects.

2. Related Work

Virtual display is an application of virtual reality. Virtual reality is involved in all walks of life, such as military, education, scientific research, and construction. In many fields, people have already experienced the convenience brought by virtual reality products, especially medicine, commerce, and film and television [4]. Virtual reality technology originated in the United States, the literature [5] research on virtual environment. Countries in the world, especially developed countries, have conducted in-depth research on virtual reality technology. At present, research on virtual product display has been carried out in the United States, Europe, Japan, and other countries and regions [6]. Literature [7] developed a virtual product that can provide visitors with close viewing. Literature [8] used virtual reality technology to simulate reality products very realistically. Japan is in a leading position in the study of virtual reality, and it has achieved impressive results in building a large-scale VR knowledge base and VR games. A virtual kitchen display system in Japan [9] provides users with kitchenware and small furniture. Among them, the system can specify the type, color, size, and placement of kitchenware and furniture. Literature [10] designed a virtual system to help users design the interior decoration of the office. You can use equipment such as a three-dimensional mouse and data gloves to add a variety of appliances to the office. There are about 50 institutions researching virtual reality in Germany, focusing on how to apply image processing, visual simulation, and virtual reality technology to industrial production [11]; some virtualization technologies have been maturely used in business, such as many automobile brands in virtual and digital display technology was applied to its product display activities. Mercedes-Benz used virtual display technology to showcase their new cars. Consumers observe the "virtual car" through the display screen and can freely choose the color they like. The Miralab laboratory of the University of Geneva in Switzerland has accumulated a lot of research experience and scientific research results in virtual clothing and animation [12].

As a three-dimensional online virtual shopping environment installation demonstration, VR-Shop is constructed based on multiuser technology, and it can provide an advanced visual interface [13]. The virtual mall enables companies to provide their customers with a complete and efficient service solution, and customers can communicate and enter the market for commercial transactions in the fastest and best way [14]. Active Worlds is different from other similar systems in that it can provide a toolkit for building virtual environments. Active Worlds is a typical virtual world. Through the use of this virtual world, one can learn how to use the toolkit to build a three-dimensional virtual mall: at the same time, users can also click on objects to get their two-dimensional information [15].

The development of emerging science and technology has caused constant changes in the traditional product production market, and the product sale model has also been affected to a certain extent. This is because consumers' awareness of product consumption, product consumer psychology, and product sales models is constantly affected by emerging information technology, and the ways and means for consumers to receive information have also changed [16]. Product design and development will also undergo changes, especially in the context of the current experience economy era, and domestic and foreign markets will also adjust and reorganize the industrial chain and business model in order to adapt to this change. As a result, consumption patterns have become diversified and diversified, and consumer needs have become diversified and individualized. This has triggered a revolution in the traditional product display industry, promoted the diversification and diversification of the manifestations of product display design, and made breakthroughs and developments in the combination of technology and art [17]. Product display design has developed rapidly with the development of digital virtualization technology. Compared with traditional product display, the rise of virtual display technology with interactive and animated presentations has given product display design more room for development. Consumers provide more interesting and brand-new experience in virtual display design [18].

3. Virtual Image Processing Based on Digital-Driven Hough Transform Clustering

As a typical module in data mining, clustering has received more and more attention and applications. As a commonly used data analysis tool, clustering is the process of dividing the target object into multiple similar subcategories based on its characteristics. For example, there is a bunch of fruits, which can be divided into three categories: apples, bananas, and watermelons according to their respective characteristics. Moreover, different from the traditional classification, the classification is to take out a new fruit and divide it into three categories: apple, banana, and watermelon according to its characteristics. The similarity between objects in the class generated by clustering is high, and the similarity with objects in other classes is low. Each class formed by clustering can be regarded as an object class, from which class rules can be derived and similar things can be gathered together. Cluster analysis belongs to unsupervised learning. There is no prior knowledge as the basis for judgment, and it only relies on the similarity between things as the classification criterion.

Through the definition of clustering, it is understood that if you want to complete the task of dividing the data set through clustering, you need to select the data features in the data set, select the appropriate measurement method, and then complete the classification through the judgment criterion function. The specific clustering process can be roughly described as shown in Figure 1.

Among them, the feature selection is represented by the data structure, the similarity measurement is completed by various measurement methods, and the clustering result evaluation is completed by the evaluation criterion function. Most clustering algorithms include these three modules.

3.1. Data Structure. In the process of clustering, the characteristics of the data need to be represented by the data structure. The more typical data structures are the data matrix and the difference degree matrix.

3.1.1. Data Matrix. The data matrix is the object attribute structure, which represents *n* objects according to *m* variables (attributes and characteristics). For example, attributes such as weight, variety, and coat color can be used to represent "products." The data structure of this relational table can be regarded as a matrix of $n \times m$ such as the matrix represented by formula (1)[19].

$$\begin{pmatrix} x_{11} & \cdots & x_{1f} & \cdots & x_{1m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & \cdots & x_{if} & \cdots & x_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x_{nf} & \cdots & x_{nm} \end{pmatrix}.$$
 (1)

3.1.2. Dissimilarity Matrix. The dissimilarity matrix is the object. The object structure is to store the difference formed between n objects. The expression is as shown in formula (2) as the $n \times n$ – dimensional matrix

$$\begin{pmatrix} 0 & & & \\ d(2,1) & 0 & & \\ d(3,1) & d(3,2) & 0 & \\ \dots & \dots & \dots & \dots \\ d(n,1) & d(n,2) & d(n,3) & \dots & 0 \end{pmatrix}.$$
 (2)

FIGURE 1: General steps of clustering.

26

db

Clustering results

estimation

Result output

Data input

Priori

knowledge

verification

In formula (2), d(i, j) represents the degree of difference between the two objects, generally $d(i, j) \ge 0$ and d(i, j) = d(j, i). The smaller the value of d(i, j), the higher the similarity between the two objects [20].

3.2. Measurement Method. In the process of cluster analysis, there are different measurement methods for different types of variables. The commonly used are the interval scaled variables, binary variables, nominal variables, ordinal variables, etc.

3.2.1. Interval Scaling Variable. It is a rough, linear way to scale continuous variables, such as weight. In the process of clustering, each attribute of the object has a different scale unit, which will have a significant impact on the final clustering result. Therefore, in view of this situation, it is necessary to standardize and normalize the data to convert the original unit-free value, as shown in formula (3).

$$Z_{i} = \frac{x_{i} - \bar{x}}{s} (i = 1, 2, 3, \dots n),$$
(3)

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i,\tag{4}$$

$$s_{MD} = \frac{1}{n} \sum_{i=1}^{n} |x_i - \bar{x}|.$$
(5)

In formula (3), $x_1, x_2, \dots x_n$ are the measurement values of *n* data, \bar{x} is the mean value, and the calculation formula is shown in (4). *s* can select the standard deviation of these *n* data, average difference, and extreme difference. Considering that the standard deviation will be amplified by the squared deviation, the average difference is selected as *s* in the standardization process of cluster analysis. In this way, the isolated points in the data have better robustness, and the calculation formula of the average difference is shown in (5).

After standardization, the similarity between objects is generally measured by two methods: distance and similarity coefficient. The distance method includes Euclidean

TABLE 1: Contingency table of binary variables.

distance, Chebyshev distance, and Makowski distance, etc., as shown in formulas (6), (7), and (9). The similarity coefficient method has angle cosine and Pearson similarity coefficient, as shown in formulas (10) and (11) [21].

The Euclidean distance is

$$ED(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}.$$
 (6)

The Chebyshev distance is

$$CD(x, y) = \max_{1 \le i \le n} |x_i - y_i|.$$

$$\tag{7}$$

Alternatively, it can be expressed as

$$CD(x, y) = \max_{1 \le i \le n} |x_i - y_i|.$$
(8)

The Makowski distance is

$$MD(x, y) = \sqrt[k]{\sum_{i=1}^{n} |x_i - y_i|^k}.$$
 (9)

Among them, k is a variable parameter. The angle cosine is

$$\operatorname{Cosine}(x, y) = \frac{\sum_{i=1}^{n} (x_i y_i)^2}{\sqrt{\left(\sum_{i=1}^{n} x_i^2\right) \left(\sum_{i=1}^{n} y_i^2\right)}}.$$
 (10)

The Pearson similarity coefficient is

$$r(x,y) = \frac{\sum_{i=1}^{n} (x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x}_i)^2 \sum_{i=1}^{n} (y_i - \bar{y}_i)^2}}.$$
 (11)

3.2.2. The Binary Variables. The so-called binary only contains 0 and 1, where 0 means that the variable does not exist, and 1 means that the variable does exist. We assume that the m variables of an object are binary variables, then the measurement between the objects will be based on the contingency table shown in Table 1, which reflects the possible occurrence of the variables between the objects

As shown in the above table, a + b + c + d is equal to the total number of variables m, a is the number of variables whose values are both x and y, b represents the number of variables whose value x is 1 and y is 0, c represents the number of variables whose value x value is 0 and y is 1, and d is the number of variables whose value is 0 for both x and y. a + d reflects the similarity of two objects, and b + c reflects the difference.

When the status 1 and 0 of the binary variable are equal weights, the simple matching coefficient is used to evaluate the difference between the objects x and y as shown in

$$d(x, y) = \frac{b+c}{a+b+c+d}.$$
 (12)

		Object y	
		1	0
Object x	1	a	b
	0	с	d

When the weights of the two states 1 and 0 are not equal, as shown in

$$d(x, y) = \frac{b+c}{a+b+c},$$
(13)

nominal variables and proportional variables are the deformation and promotion of the above two measures, so that they have a wider scope of application and will not be introduced in detail.

3.2.3. Criterion Function. After the data structure and measurement method are available in the clustering process, the corresponding criteria are needed to further accurately group similar objects into sets. The choice of clustering criteria is very important. At present, there are typical error sum of squares, weighted average square distance sum, and inter-class distance and these three criterion functions.

(1) Error Sum of Squares. The error sum of squares is a commonly used clustering criterion function, which can be described as a hypothetical object set as $X = \{x_1, x_2, \dots, x_n\}$, on the basis of using a certain similarity measurement method, the set is divided into *C* subsets X_1, X_2, \dots, X_c through clustering, and each subset corresponds to a type. Then, the definition of the error sum of squares is shown in equation (14):

$$G_{c} = \sum_{j=1}^{c} \sum_{k=1}^{n_{j}} \left\| x_{k}^{(j)} - \bar{x}_{j} \right\|^{2},$$
(14)

$$\bar{x}_j = \frac{1}{n} \sum_{j=1}^{n_j} x_j \quad (j = 1, 2, \dots, c).$$
 (15)

 \bar{x}_j in formula (15) is the mean value of objects in type w_j , which can represent the cluster centers of these *C* subsets. Therefore, it can be seen from the formula definition that when the object set *X* is given, the cluster centers of *C* subsets determine the value of G_c . G_c means the sum of the squares of the total errors that occur when *n* objects are clustered by a certain measurement method and divided into *C* categories. Obviously, the smaller the G_c , the better the display effect of the clusters. When the number of various objects is not much different, the effect of using G_c can be the best.

(2) The Weighted Average Squared Distance Sum. This criterion function is mainly used when the number of objects in

each class has a large gap, which can prevent the separation of most types of objects. Its definition is as follows:

$$G_l = \sum P_j S_j. \tag{16}$$

In formula (16), P_j is the corresponding prior probability, S_j is the average squared distance of samples within the class, and the definitions of P_j and S_j are as shown in formulas

$$P_j = \frac{n_j}{n}, j = 1, 2, \cdots, c,$$
 (17)

$$S_{j} = \frac{2}{n_{j}(n_{j}-1)} \sum_{X \in x_{j}} \sum_{X \in x_{j}} \left\| x - x' \right\|^{2}.$$
 (18)

In formula (17), P_j is the number of various types of objects, and n is the total number of objects. In formula (18), $2/n_j(n_j - 1)$ is the reciprocal of the number of combinations of two random objects in subset x_j of type w_j , and $\sum_{X \in x_j} \sum_{X \in x_j} ||x - x'||^2$ is the sum of the squared distances of samples in subset x_j .

(3) The Sum of the Distances between Clusters. This criterion function is generally used to express the distance distribution of the distances between clusters in the results after clustering, which is described as follows:

$$G_{b} = \sum_{j=1}^{c} (m_{j} - m)^{T} (m_{j} - m).$$
(19)

Obviously, the larger the G_b , the larger the distance between the classes, and the higher the quality of the clustering. This judgment can be used to distinguish things.

With the long-term research of scholars at home and abroad, clustering has been widely used. According to different research objects, various types of clustering methods have appeared. According to the scope of application, there are roughly division, level, density, etc.

3.3. Division Method. The main idea of this method can be described as a preset data collection of m objects. According to the principle of minimizing the objective function, these data sets are divided into k categories. The principle of division is usually that objects in the same class are as related as possible, and objects in different classes are as different as possible. The corresponding function is as follows:

$$E = \sum_{j=1}^{k} \sum_{x \in C_j} ||x - \bar{x}_j||.$$
(20)



FIGURE 2: Data classification based on density.

In formula (20), \bar{x}_j is the mean value, and x is the object in the data space. The more commonly used division method is the k mean. The characteristics of this method are simple process and fast calculation, but it cannot achieve good results when dealing with very different classes.

3.4. Hierarchical Method. The main ideas of the hierarchy method are as follows: For a given m data object and $m \times$ m similarity matrix, the algorithm treats each object as a class, there will be m classes, and there is only one object in each class. The interclass distance is the distance between objects. Then, the algorithm merges the two classes with the shortest distance, leaves m-1 class and then recalculates the distance between classes. By analogy, the algorithm completes the merging of m classes. Typical hierarchical methods include BIRCH algorithm and so on. The main advantage of the hierarchy method is that no input parameters are required. The problem with this clustering method is that once it is merged or split, it cannot be returned, and it is easy to cluster into chains. Therefore, the hierarchical method is rarely used alone and needs to be combined with other methods.

3.5. Based on the Density Method. The main idea of this method is to cluster according to the spatial distribution of data objects as a classification principle. This method does not need to preset the number of classes. When the distribution density of a point in a certain area is greater than a preset threshold, the point is classified into the cluster closest to it. For each object in the class, at least the minimum number of objects must be included in the neighborhood of the given radius ε . The size of the density mainly depends on the choice of radius ε . The data in Figure 2 can be divided into two categories from the intuitive density. The main feature of the density-based method is that it is not limited to the shape and noise of the cluster. However, when the distance between the objects is far, the clustering quality cannot meet the needs of the experiment. The typical density method is DBSCAN algorithm and so on.

Hough transform has been widely used in the fields of image boundary recognition, aerial image automatic



FIGURE 3: Hough transform of straight line.



FIGURE 4: Hough transform of circle.

interpretation, and biomedical image processing. Hough transform uses a voting algorithm to identify objects with specific shapes. After the algorithm maps the target contour from the image space to the parameter space, it detects the extreme points in the parameter space to determine the description parameters of the curve, thereby completing the identification and detection of the regular curve.

When the Hough transform is used to detect a straight line, in the image space X - Y, the collinear point (x, y) is described by a straight line as follows:

$$y = \alpha x + m. \tag{21}$$

Among them, α is the slope and *m* is the intercept. Therefore, it is rewritten as

$$m = -x\alpha + y. \tag{22}$$

Equation (21) can be regarded as a straight line in the parameter space of $\alpha - m$, -x is the slope, and y is the intercept. Hough transform detection straight line is to regard equations (21) and (22) as the common limiting conditions



FIGURE 5: The relationship between the round point and the reference point.

of image space and parameter space, which reflects the point-pair relationship between the two spaces. As shown in Figure 3, each point on the straight line passing the point (x_i, y_i) and point (x_j, y_j) in the image coordinate space corresponds to a straight line in the parameter space. Compared with the points (α_0, m_0) and (α_0, m_0) , the two straight lines are the straight line parameters determined by the two points in the image space.

When identifying a round target, the basic parameters of a circle are the center and radius. The use of Hough

Num	Three-dimensional digital effect	Num	Three-dimensional digital effect	Num	Three-dimensional digital effect
1	94.99	21	92.86	41	95.86
2	93.04	22	90.29	42	94.38
3	94.82	23	95.95	43	93.39
4	92.38	24	92.80	44	90.49
5	92.26	25	93.27	45	96.41
6	93.03	26	93.12	46	95.70
7	90.99	27	94.20	47	94.38
8	91.60	28	94.24	48	94.95
9	92.88	29	96.46	49	92.87
10	93.95	30	96.90	50	94.95
11	96.89	31	90.33	51	93.99
12	95.12	32	96.25	52	91.87
13	94.60	33	90.59	53	94.33
14	94.87	34	95.20	54	90.58
15	95.63	35	90.74	55	90.29
16	91.72	36	94.61	56	92.41
17	94.20	37	90.97	57	93.40
18	95.21	38	96.43	58	95.92
19	91.10	39	90.36	59	93.25
20	94.08	40	91.37	60	92.19

TABLE 2: The 3D digital effect of the product.

transform to identify a circle is to use the accumulation of three-dimensional space parameters to extract its parameters. The equation of the circle in the image space is shown in

$$(x-a)^{2} + (y-b)^{2} = r^{2}.$$
 (23)

In formula (23), (a, b) is the center of the circle, and r is its radius. The schematic diagram is shown in Figure 4 (a). Correspondingly, the equation in the parameter coordinate system (a, b, r) is shown in (24), and the parameter space is shown in Figure 4(b).

$$(a-x)^{2} + (b-y)^{2} = r^{2}.$$
 (24)

The traditional Hough transform needs a clear analytical equation to be realized, and its practicability is limited. This method is called Generalized Hough Transform. The generalized Hough transform process usually has two steps. The first step is to establish a parameter table for the target boundary, and the second step is to perform Hough transform according to the parameter table to complete the recognition and detection of any shape target.

As shown in Figure 5, (a, b) is a selected reference point in the target. When the centroid of the target is selected as the reference point, the calculation formula is as shown in formula (25):

$$\begin{cases} a = \frac{1}{K} \sum_{x_{ieo}} x_i, \\ b = \frac{1}{K} \sum_{y_{ieo}} y_i. \end{cases}$$
(25)

In formula (25), *O* represents the point set of the target, and *K* represents the number of points in the point concentration. We assume that (x, y) is any point on the target boundary, the distance between (a, b) and (x, y) is represented by r, φ is the angle between r and coordinate axis X, and θ is the boundary direction angle of (x, y), and then, the relationship between (a, b) and (x, y) can be derived from

$$\begin{cases} a = x + r(\theta) \cos (\varphi(\theta)), \\ b = y + r(\theta) \sin (\varphi(\theta)). \end{cases}$$
(26)

Obviously, any point (x, y) on the boundary has an θ angle corresponding to it. Therefore, the target boundary can be set to the corresponding reference table, and the corresponding φ and *r* values can be calculated through each boundary point, as shown in Table 2 in the target boundary reference table. Then, the algorithm parameterizes the two-dimensional accumulator A(a, b), and the initial value is set to **0**. According to



FIGURE 7: Schematic diagram of the data processing process.

Table 2, the algorithm calculates each possible (a, b) and adds 1 to the corresponding accumulator. The reference point is determined according to the peak value of the accumulator, thereby completing the determination of the boundary of the target to be measured.

After decades of development, the generalized Hough transform has been further generalized and evolved, such as hierarchical generalized Hough and random generalized Hough, and considering that the generalized Hough transform has the same principle as the Hough transform, they are collectively referred to as the generalized Hough transform.

4. Network Display Algorithm Model of 3D Virtual Products Based on Digital Drive

The real-time data drive architecture implemented in this article mainly includes five parts: data acquisition system, data server, application cloud server, local area network,



FIGURE 8: System development module.



FIGURE 9: Statistical diagram of the three-dimensional digitization effect of product.

and Unity3D model. The structure diagram is as follows Figure 6.

The core problem of the real-time data-driven model is how to transmit data to the model and realize the synchronization of the 3D digital product network display model with the actual product status under the condition of controllable delay. The communication method adopted between the equipment, server, and model application in this paper is the internal LAN communication of the enterprise, and the data is returned through the coroutine mechanism after obtaining the response from the server. As shown in Figure 7(a), when the server processes the data from the data acquisition system, two types of data will appear-instant data and nonimmediate data. Real-time data will be requested by the client in a very short period of time, while nonreal-time data will not. Therefore, these two types of data are stored on the server side in two ways: memory and disk storage. The instant data stored in the memory helps the server to quickly process the data request from the client and feed the data back to the client. This eliminates the process of reading from the disk storage, improves the efficiency of client-side real-time data acquisition, and reduces delays. The data storage mechanism is shown in Figure 7(b).

Based on the above analysis, it is determined that the modules to be developed for the product network display system are shown in Figure 8.

After constructing the digital product network display system of this article, the system is constructed through the simulation platform, and the effect of the system of this article is verified. First, the three-dimensional digital effect of the products of the system in this paper is verified through experimental research, digital simulation is performed on

Num	Virtual product network display	Num	Virtual product network display	Num	Virtual product network display
1	80.01	21	87.58	41	86.91
2	81.56	22	90.80	42	89.34
3	80.37	23	85.64	43	81.62
4	85.48	24	81.97	44	91.36
5	89.04	25	87.73	45	80.73
6	89.35	26	87.55	46	88.06
7	90.87	27	80.72	47	83.19
8	82.63	28	83.56	48	84.17
9	89.30	29	84.31	49	85.96
10	89.77	30	91.26	50	84.82
11	83.99	31	81.39	51	80.16
12	88.04	32	83.70	52	80.70
13	82.94	33	91.62	53	86.87
14	90.83	34	90.15	54	80.25
15	89.54	35	87.88	55	90.39
16	80.42	36	81.60	56	83.01
17	83.11	37	82.04	57	81.75
18	80.01	38	89.61	58	84.20
19	84.25	39	80.95	59	83.46
20	80.43	40	81.65	60	81.10

TABLE 3: Network display effect of 3D virtual products.



FIGURE 10: Network display test data of 3D virtual products.

multiple real products, and the digital simulation effect is evaluated, and the results shown in Table 2 and Figure 9 are obtained.

From the above research, it can be seen that the system proposed in this paper has a good 3D digital processing effect and has a good performance in product 3D simulation. Afterwards, the 3D virtual product network display of the system in this paper is evaluated, and the results shown in Table 3 and Figure 10 are obtained.

It can be seen from the above research that the 3D virtual product network display algorithm based on digital drive

proposed in this article has a good three-dimensional virtual display effect.

5. Conclusion

User-centered design can bring a market for companies to produce products that better meet user needs. Secondly, the virtual display of products allows users to experience new products first and provides useful feedback information for the development of new products for enterprises, so that new products can be improved to meet user needs and bring more profits to enterprises. By combining the advantages of the two, the three-dimensional virtual display of products based on user experience will bring a win-win situation for enterprises and consumers. This article combines digital drive to design 3D virtual product network display, to provide users with better product experience and improve product design effect. The research shows that the 3D virtual product network display algorithm based on digital drive proposed in this paper has a good 3D virtual display effect.

Data Availability

The labeled data set used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no competing interests.

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