Modern Craft Product Design Using Digital Technology Combined with Visual Sensing System in Complex Environment

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1. Introduction

Craft production is a term used by archaeologists to refer to the manufacturing of a group of goods that includes pottery, stone tools and decorations, baskets, textiles, and metal objects. However, the word craft has many meanings and the category craft is not altogether unambiguously defined [1]. Crafts are distinguished from two other categories of noncomestible objects: art and industrial products. Art is the work of known individuals whose works are assessed by their originality or genius. The industrial product is a mass-produced item that is manufactured by machine rather than by hand. Craft production is still performed across the world and is a proven and effective approach when it comes to creating furniture, cabinets, and other woodworking skills [2].

With the advancement of the industry, the use of water and steam to mechanize industries has been phased out in favor of electronics and information technology, which has resulted in a considerable increase in automated control [3]. Digital image processing and 3D printing technology have evolved in response to the current trend of personalizing, customizing, and achieving goods by moving away from mass production lines, and has even been called the hallmark of Industry 4.0. The fast advancement of information technology has enabled billions of people to create vast volumes of data via a variety of digital devices, including unstructured, semistructured, and structured data. Image semantic feature extraction extracts multidimensional semantic information from pictures using computer models to help people comprehend them [4].

With the development of digital technology, visual sensing technology, and information technology, visual sensing technology is widely used in designing craft products. Using digital technology the design of arts and crafts can be improved and the efficiency and aesthetics can be
enhanced. Digital technology such as 3D images plays a key role in visual sensing technology, and three-dimensional images have gradually become a common application in designing craft products [5]. Before the interior soft decoration design of the craft products, the layout must be understood to determine the specific decorative scheme of various types of soft decoration. However, different soft decoration items placement schemes must be evaluated from multiple aspects such as function, visual effect, and occupied area, which typically requires a senior technician to spend a significant amount of time to complete, resulting in a lengthy processing time. Digital technology can be used to model the layout, function, and visual effects of different craft products before manufacturing [6].

In recent years, many scholars have also carried out different degrees of exploration and achieved satisfactory research results. At this stage, the most commonly used is the three-dimensional visual simulation system using visual interaction technology [7]. Liu et al. [8] investigated the impact of printer design and printing settings on the quality of 3D printed items and developed a strategy for improving the physical layer surface smoothness of 3D printed products. Zhou [9] used the existing big data and 3D technology to conduct a deep analysis of the optimization of the rapid design system of arts and crafts machine salt baking. An instance-level image retrieval approach based on generative adversarial networks is suggested in [10], which employs adversarial training in the retrieval process. The improved generator and discriminator are used to try to generate retrieved similar images and to identify different images from the retrieved ones. Wilson [11] examined some of the changes that have occurred in several historic and modern Jamaican craft and design processes. Efforts were made to connect Jamaica’s diverse craft design, particularly the country’s traditional skills and materials, with more contemporary designs. Xu et al. [12] employed speeded-up robust features (SURF) algorithm to extract stable features, high matching error rate, and loss of correct matching information in the process of matching and purifying. From feature extraction and feature, matching is improved. Experimental results show that the improved algorithm is better than the original algorithm in terms of the number of feature points, stability, and final matching accuracy. Wang et al. [13] used a rough registration method using the SIFT feature point depth map, using an optimized two-way matching algorithm, and the matched feature point pairs are purified. Experimental results show that the curvature between the front and side of the human body varies greatly. When the overlapping area is small, face registration can be performed more accurately, and complete face modeling can be performed.

Henceforth for better extraction of image features, this study proposes an improved ORB feature matching algorithm by using multiple constraints. The performance of the proposed algorithm is verified through the comparative experiments and the accuracy of target image feature extraction is significantly improved. The proposed improved ORB algorithm has the potential for application in designing modern craft products.

The rest of the manuscript is ordered as follows: Section 2 provides an overview of the application of digital technology and visual sensing in craft design. Section 3 is about the results and discussion and the conclusion is given in Section 4.

2. The Influence of Digital Technology and Visual Sensing System on Product Design

Combining digital technology and visual sensing system to use in modern craft product design is a new direction of current research [14]. Under normal circumstances, the modern craft product design includes three stages, the concept stage, the design stage, and the engineering stage.

2.1. Concept Stage. The formation of a concept is a synthesis and transformation of information and experience. Information has grown more open and fair as a result of the fast advancement of information technology, and the coverage of information resources has become increasingly comparable. Due to the different cultural backgrounds of the recipients, a new interactive model can be established through digital tools and methods, and changes in thinking and behavior can be explored through online resources. At this stage, product characteristics can be determined in advance, production scale can be adjusted, and the most suitable product concept can be designed. This stage seems very simple this stage helps to determine the nature of the product, the production method, and the scope of application. The application of digital technology can make the work at this stage easier and more feasible. Using the Internet’s information circulation, digital computing, storage, and other resources, the overall situation of the product market can be understood from the design, production, and sales stages for the first time. It has laid a solid foundation for product design and production. This stage also includes the design to improve the image of the product, the design using the demand forecast of the product’s full life cycle design, and so on. Because this technology has the advantages of simple structure, convenient use, and long storage time all design schemes need to rely on digital technology, mainly relying on digital information storage technology [15].

2.2. Design Stage. The design stage is to draw design sketches and make models. Digital technology plays an important role in this stage. The addition of digital technology promotes the choice of form and dependence on the information. Although the tools and methods used in different products are different, it is undeniable that digital technology is particularly important [16], virtual.

Reality (VR) technology has given great support to the development of new products. With the development of VR technology and multimedia techniques, human-computer interaction (HCI) technology is constantly improving the design of virtual products. Designers can directly use them in a virtual environment while designing products, but they need to use some devices, such as three-dimensional position trackers and head-mounted displays. Through these
devices, the visual, auditory, tactile, and virtual conceptual product models are connected, which helps to check and evaluate the designed products.

2.3. Engineering Stage. Using this state, the designer visualizes the virtual product designed to make the commercial design. Virtual assembly design is one of the important factors affecting virtual design in new product development. Virtual assembly will be used at this stage, and the process planning, processing, assembly, and debugging can be realized by simulating the assembly model on the computer [17]. Although no commercialized virtual assembly system is used in the analysis and evaluation of product development, this technology has been recognized in the development of new products. In the past, it often took a lot of time, manpower, and material resources to develop traditional products. Modern design requires designers to consider virtual assembly issues in the early stages of virtual product development, assisting designers to discover assembly defects in the design in time, and optimize solutions in time. This only saves time and effort but also reduces the cost of new product development. Therefore, when designing a new craft product, many investigations are required in the early stage to collect data and grasp the market demand. The application of digital technology and visual sensor system improves efficiency, making the collected information more accurate and more convenient to store and organize. Table 1 provides examples of modern craft designs.

2.4. ORB Algorithm. The Oriented Fast and Rotated Brief (ORB) algorithm detects features and extracts local features in the target image through the FAST Keypoint Orientation (oFAST) method. The FAST feature points can be judged by the function which can be expressed as

$$N = \sum_{x \in \text{circle}(p)} |I(x) - I(p)| > \varepsilon_d,$$

where \(\varepsilon_d\) represents the threshold, \(I(p)\) is the grey value at the current feature point and \(I(x)\) is the grey value of any pixel at the edge of the adjacent area of the feature point. Since the FAST feature operator has no direct information, the ORB algorithm needs to use the grey-scale centroid method when detecting FAST feature points with direction information [18, 19]. The moment of the image in the feature point domain is expressed using

$$m_{pq} = \sum_{x,y} x^p y^q I(x, y).$$

The grey centroid of the image in the field of feature points is expressed as

$$C = \left( \frac{m_{10} m_{01}}{m_{00} m_{10} - m_{01} m_{11}} \right).$$

The ORB algorithm first builds the image scale pyramid and then detects the oFAST scale features. The Gaussian Function \(G(x, y, \sigma)\) and the scaling function \(L(x, y, \sigma)\) can be expressed as (4) and (5), respectively:

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

$$L(x, y, \sigma) = G(x, y, \sigma) * F(x, y),$$

where, \(F(x, y)\) represents the original image, and \(\sigma\) is the scale factor. Through the Gaussian difference function and the original image for convolution calculation, a scale-space pyramid composed of images of different scales can be obtained, and then the oFAST feature points are extracted in the pyramid.

After the feature points are obtained, the rotation-aware BRIEF (rBRIEF) descriptor is used to calculate the feature points. The binary test of the feature point \(P\) can be expressed using

$$\tau(p; x, y) = \begin{cases} 1 & p(x) < p(y) \\ 0 & p(x) \geq p(y) \end{cases},$$

where \(p(x)\) represents the grey level of point \(x\) and \(d(p(y)\) shows the grey level of point \(y\). At this time, \(n(x_i, y_i)\) point pairs are selected. Then, the binary feature point descriptor is generated by the binary test criterion, which can be expressed as:

$$f_n(p) = \sum_{1 \leq i \leq n} 2^{i-1} \tau(p; x_i, y_i).$$

Among them, \(n = 128, 256, 512\), at this time, the feature descriptor does not contain direction information, and the BRIEF feature descriptor needs to be rotated by the main direction of the feature point. For the criterion set of any binary tests at position \((x_i, y_i)\), the matrix can be defined using

$$S = \begin{pmatrix} x_1, x_2, \ldots, x_n \\ y_1, y_2, \ldots, y_n \end{pmatrix}.$$  

From the main direction information \(\theta\) of the detected feature points and the rotation matrix \(R_\theta\), the rotated matrix \(S_\theta\) can be obtained, as shown in

$$S_\theta = R_\theta S = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} x_1, x_2, \ldots, x_n \\ y_1, y_2, \ldots, y_n \end{pmatrix}.$$  

Therefore, the rBRIEF descriptor is expressed as

$$g_n(p, \theta) = f_n(p)[(x_i, y_i)] \in S_{\theta}. $$

Using the above equations, the ORB feature with good real-time performance can be obtained.

The next step is to use Hamming distance to match the feature points of the ORB algorithm, and arbitrarily select the feature descriptors of the images \(K_1\) and \(K_2\), respectively, as given in (11) and (12),

$$K_1 = x_0 x_1 \cdots x_n,$$

$$K_2 = y_0 y_1 \cdots y_n.$$

Hamming distance is used to measure the descriptor similarity of the ORB feature algorithm, set as \(D(K_1, K_2)\), as shown in.
Table 1: Introduction to modern technology product design.

| Product                                           | Product description                                                                 |
|---------------------------------------------------|-------------------------------------------------------------------------------------|
| UWB helmet positioning label                      | Triangular appearance and arc chamfer, the shape is both tough and round. The front arc design of the product makes the product appear lighter and thinner. The upper and lower shell design makes the product assembly easy and modern, technical and precise in color and form expression so that the product can be adapted to different helmets. Silicone fits different types of helmets; magnetic charging is more user-friendly and easier to operate. This positioning device has a maximum positioning accuracy of up to 10 cm. The device can realize the real-time tracking of the position and distribution heat map of the statistician. It can grasp personnel dynamics anytime and anywhere, facilitate personnel management, form good working habits through supervision of employee behavior, reduce "violation behaviors," and facilitate the implementation of comprehensive risk management and control. The appearance of the equipment focuses on the characteristics of the operating experiment area. Use the thorough design of the meter reading area to divide the whole into upper and lower areas. Just like ice cubes floating on the Arctic Ocean, it creates an icy psychological feeling while introducing the concept of suspension into the product, adding technological charm. Due to the complex conditions caused by unstable shale, a large amount of time waste and economic loss is caused to drilling work every year. Through the measurement of shale data, the drilling work can be given to reduce unnecessary waste of time and economic losses. It mainly adopts sheet metal stamping and bending processes. Various processing techniques are relatively mature. For this product, such processing is practical and simple. This product adopts a spectral ritual lidar system for detecting biological aerosols, which solves the problem that the existing lidar system has a narrow detection range and the existing lidar system has a single function at this stage. Meanwhile, it can realize real-time, fast, reliable, non-contact continuous monitoring of the properties of atmospheric biological aerosols. This is a product that perfectly combines function and aesthetics. The overall color is white, supplemented by black, to highlight the visual effect. The products are using the concept of green and environmental protection in the materials used and the processing technology adopted. Based on conveying the design concept, it saves costs, simplifies the production and processing process, and protects the environment as much as possible. The product is made of biodegradable plastic material, the whole is processed by CNC, and the part of the product is marked with screen printing on the surface. |
| Microcomputer shale expansion tester               |                                                                                      |
| Smart laser bio detector                          |                                                                                      |

\[ D(K_1, K_2) = \sum_{i=0}^{n} x_i y_i \]  

where the smaller \(D(K_1, K_2)\) the greater the similarity of its feature points. Assuming that there are two points \(P_1\) and \(P_2\) that are closest to the point \(P_0\), if they match \(D(P_0, P_1)/D(P_0, P_2) < t\), it means that \(P_0\) and \(P_1\) are a pair of correct feature matching points. The value of \(t\) can be selected as a compromise on the matching accuracy and the number of matching pairs.

2.5. Improved ORB Feature Matching Algorithm Using Multiple Constraints. To eliminate the errors caused by the ORB feature operator in feature description and matching, the algorithm needs to be improved [20]. Under normal circumstances, most researchers use the RANSAC algorithm to improve, however when the number of wrong matching point pairs is relatively large, directly using the RANSAC algorithm will produce relatively large errors [21]. Therefore, an improved ORB feature matching algorithm is proposed, and the flow of the algorithm is shown in Figure 1.

2.5.1. Rough Matching Using K Nearest Neighbor. First, the K-nearest neighbour (KNN) algorithm is used for feature matching. Next, the Best Bin First (BBF) algorithm is used to search for the nearest neighbors. This method can organize a lot of calculations into the neighborhood of the test sample set. This greatly improves computational efficiency [22, 23]. Assuming that \(V_r\) is the feature vector of \(r\) in the set of template image feature points, and \(V_s\) and \(V_t\) are the feature vectors corresponding to the nearest neighbor feature point and the next neighbor feature point, respectively, then the \(K\) nearest neighbor rough matching point pair can be expressed as given in.

\[ r_i(V_s, V_t), i = 1, 2, \ldots, n. \]  

2.5.2. Purification of Nearest Neighbour Ratio. The Hamming distance of the two feature points in the matching pair is the closest, however, there are still false matching points. Through the ratio of the distance between the nearest neighbor feature point and the second nearest neighbor feature point, the wrong matching point pair is eliminated [24]. Suppose the Hamming distance between \(V_r\) and \(V_r\) is \(\text{Dist}(V_r, V_r)\), the Hamming distance between \(V_r\) and \(V_t\) is \(\text{Dist}(V_r, V_t)\), \(Q\) is the ratio of \(\text{Dist}(V_s, V_t)\) and \(\text{Dist}(V_r, V_t)\), and \(T_Q\) is fixed threshold. When \(Q > T_Q\), the matching point pair \((r, s)\) is wrong, so the criterion for eliminating incorrect matching points using the Hamming distance can be expressed as equations (15) to (18).
The constraint relationship can be expressed as an algorithm to purify the remaining matching pairs [25]. To improve the accuracy of matching, it is necessary to apply the RANSAC algorithm using multiple improvements, after the rough matching results. The results are shown in Figures 3 and 4, respectively.

Figures 3 and 4 show that the matching pairs of the rough matching of the first group, the second group, and the third group are 455, 397, and 418, respectively, and the corresponding accuracies are 37.5%, 39.1%, and 44.3%, respectively. The matching logarithms of the first group and the third group using the nearest neighbor ratio method for feature purification are 291, 283, and 305, respectively, and the corresponding accuracies are 55.9%, 48.6%, and 56.7%, respectively. Similarly, the matching logarithms of the first group, the second group and the third group using the two-way matching method for feature purification are 327, 304, and 320, respectively, and the corresponding accuracies are 48.8%, 46.9%, and 49.9%, respectively. Likewise, the matching logarithms of the first group, the second group and the third group using the angle constraint method for feature purification are 252, 242, and 258 respectively, and the corresponding accuracies are 52.4%, 54.0%, and 60.4%, respectively. Compared with the accuracy of rough matching, the accuracy of feature matching using these three methods is improved. The accuracy of feature matching using the angle constraint method is relatively high, but there are still many wrong matching point pairs. To further verify the matching effect of the ORB feature matching algorithm using multiple improvements, after the rough matching, the three mentioned methods are used to continuously remove the wrong matching point pairs for the rough matching results. The results are shown in Figure 5.

Figure 5 shows that the accuracies of the rough matching of the first group, the second group, and the third group are 37.5%, 39.1%, and 44.3%, respectively. When the close-to-nearest ratio method is adopted, then the corresponding accuracies for continuous purification are 55.9%, 48.6%, and 56.7%, respectively. The corresponding accuracies of continuous purification using the two-way matching method are 79.4%, 77.5%, and 81.3%, respectively. When the angle constraint method was used the corresponding accuracies after continuous purification was achieved are 99.6%, 99.3%, and 99.7%, respectively. The accuracy of the three purification algorithms after continuous action is significantly improved, the wrong matching point pairs that appear are removed, and the image target is well recognized.

2.5.3. Two-Way Matching and Purification. When the nearest neighbor ratio is used for purification, there is no guarantee that all wrong matching pairs can be eliminated. In this case, further purification is required and therefore the two-way matching method is proposed. That is, the feature matching is performed in two directions from the template image to the target image’s forward matching set and reverse matching set. If it exists in both matching sets, it can be determined that the matching is correct.

2.5.4. Directional Included Angle Constraint Purification. Although the mentioned three matching point purification algorithms can purify matching point pairs, when performing feature matching, some changes will occur between the template image and the target image, such as lighting or rotation. Therefore, the direction and angle information of the matching feature points are used to constrain and purify the feature points of the rough matching. To improve the accuracy of matching, it is necessary to apply the RANSAC algorithm to purify the remaining matching pairs [25]. There is a constraint between two correct matching feature points, and the constraint relationship can be expressed as

\[
\theta_1 - \theta_2 < \lambda_d, \quad (19)
\]

where, \(\lambda_d\) represents the main direction angle difference threshold, and the computation process is shown in Figure 2. \(\theta_1\) represents the main direction angle between two matching points in the template image and \(\theta_2\) is the main direction between two matching points in the scene image angle.

3. Results and Discussion

3.1. Purification Effect Experiment. For the four images taken from different angles of the same item, the feature points are roughly matched using the KNN algorithm. Then, the neighboring ratio method, the two-way matching method, and the included angle constraint method are used to purify the rough matching results. The results are shown in Figures 3 and 4, respectively.

When the judgment threshold \(T_Q\) is 0.8, the number of matching point pairs retained will be relatively large and the requirements for purification can also be met.

\[
V_s = \min\{\text{Dist}(V, V_k) | V_k \in \text{B}, k = 1, 2, \cdots, m\}, \quad (15)
\]

\[
V_t = \min\{\text{Dist}(V, V_k) | V_k \in \text{B}, k = 1, 2, \cdots, m; V_k \neq V_s\}, \quad (16)
\]

\[
Q = \frac{\text{Dist}(V_s, V_t)}{\text{Dist}(V_r, V_t)}, \quad (17)
\]

\[
\left\{ \begin{array}{ll}
r \rightarrow s & \text{if } Q < T_Q \\
r \rightarrow s & \text{otherwise} \end{array} \right. \quad (18)
\]

When the judgment threshold \(T_Q\) is 0.8, the number of matching point pairs retained will be relatively large and the requirements for purification can also be met.
3.2. Scale Invariance Experiment. Eight images taken at different distances of the same item are tested for size invariance. Among them, the image with the largest scale multiple is the template image, and the rest is the target image. The improved ORB feature matching and the results are shown in Figure 6.

Figure 6 shows that the improved ORB feature matching algorithm has a matching accuracy of 87.5% when the scale is 0.65. When the scale is increased to 0.7, the corresponding matching accuracy is 90%. When the scale is 0.75, the corresponding matching accuracy is 93.2%. When the scale is raised to 0.8, the corresponding matching accuracy achieved is 93.5%. When the scale is 0.85, the corresponding matching accuracy is 95.8%. Similarly, when the scale is 0.9, the corresponding matching accuracy obtained is 95.4%. Likewise, when the scale is 0.95, the corresponding matching accuracy is as high as 97%. As the scale increases, the matching accuracy of the improved ORB feature matching algorithm is gradually increasing. By comparing the matching accuracy of the four algorithms, the accuracy of the improved ORB feature matching algorithm is significantly higher. This validates that the improved ORB feature matching algorithm has high superiority in scale invariance.

3.3. Rotation Invariance Experiment. For images with different rotation angles, using the matching feature point angle values between the template image and the target image, the corresponding rotation angles were calculated. The comparison results for error in angle measurement are shown in Figure 7. The average error comparison result is shown in Figure 8.
Figure 7 shows that when the image is rotated, the error of the rotation angle value measured by the improved ORB feature matching algorithm is significantly lower than that of the original ORB feature matching algorithm. Therefore, the improved ORB feature matching algorithm has good performance in terms of rotation invariance.

Figure 8 shows that the absolute value of the error of the rotation angle measured by the original ORB feature matching algorithm is 1.3° on average. The absolute value of the error of the rotation angle measured by the improved ORB feature matching algorithm is 0.141.3° on average. The comparison of the two experimental results shows that the improved ORB feature matching algorithm has high matching accuracy.

3.4. Algorithm Time-Consuming Comparison. We selected 9 groups of images of the same size for real-time testing experiments. The real-time performance of the improved ORB feature matching algorithm is verified. The comparison results are shown in Figure 9.

Figure 9 shows that the matching speed of the improved ORB feature matching algorithm is significantly higher than...
that of the SURF [12] algorithm and the SIFT [13] algorithm. However, compared with the original ORB feature matching algorithm, the speed of the improved algorithm is slightly slower. The average matching time of the improved ORB feature matching algorithm is 164.72 ms, while the average matching time of the original ORB feature matching algorithm is 133.72 ms. The main reason for this phenomenon is that the improved ORB feature matching algorithm has multiple constraints during the purification process which is why it requires more matching time. The improved ORB feature matching algorithm can still meet the real-time requirements.

4. Conclusion

Recently, big data and digital technology have taken control of many fields and they are developing rapidly which has drastically changed human lives. In this study, digital image processing and visual sensing techniques are combined to analyze modern craft products. An improved ORB feature matching algorithm is designed for target image feature extraction of craft products. To verify the performance of the algorithm, different experiments are designed for purification effect, scale invariance, rotation invariance, and computation time. Results show that the performance of the three three purification algorithms in continuous action is significantly higher than that in a single action, and they have high superiority in terms of scale invariance. The absolute value of the error of the rotation angle measured by the improved ORB feature matching algorithm is 0.14° on average which validates that the improved ORB feature matching algorithm has high matching accuracy. Although, the improved ORB feature matching algorithm takes slightly more time than the original algorithm, however, it can still meet the real-time requirements. The accuracy of target image feature extraction is improved to a certain extent by the proposed algorithm. The proposed algorithm has great significance in image recognition. The proposed algorithm also has a shortcoming that the improved ORB feature matching algorithm is not ideal while recognizing the targets with less texture. Therefore, the later ORB feature matching algorithm needs to be further improved.

Data Availability

The data presented in this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] C. Jiang, F. Zhang, and Z. Wang, "Image processing of aluminum alloy weld pool for robotic VPPAW based on visual sensing," IEEE Access, vol. 5, pp. 21567–21573, 2017.
[2] H. Tian, T. Wang, and Y. Liu, “Computer vision technology in agricultural automation—a review,” Information Processing in Agriculture, vol. 7, no. 1, pp. 1–19, 2020.
[3] G. Chen, H. Cao, J. Conradt, H. Tang, F. Rohrbein, and A. Knoll, "Event-based neuromorphic vision for autonomous driving: a paradigm shift for bio-inspired visual sensing and perception," IEEE Signal Processing Magazine, vol. 37, no. 4, pp. 34–49, 2020.
[4] A. Segura, H. V. Diez, I. Barandiaran, and T. Tommila, "Visual computing technologies to support the Operator 4.0," Computers & Industrial Engineering, vol. 139, Article ID 105550, 2020.
[5] M. Sága, V. Bulej, N. Čuboňova, I. Kuric, I. Virgala, and M. Eberth, "Case study: performance analysis and development of robotized screwing application with integrated vision sensing system for the automotive industry," International Journal of Advanced Robotic Systems, vol. 17, no. 3, Article ID 1729881420923997, 2020.
[6] D. R. Berger, H. S. Seung, and J. W. Lichtman, "VAST (volume annotation and segmentation tool): efficient manual and semi-automatic labeling of large 3D image stacks," Frontiers in Neural Circuits, vol. 12, p. 88, 2018.
[7] A. Sioma, “Automated control of surface defects on ceramic tiles using 3D image analysis,” Materials, vol. 13, no. 5, p. 1250, 2020.
[8] L. Liu, H. Hu, Y. Luo, and Y. Wen, “When wireless video streaming meets AI: a deep learning approach,” IEEE Wireless Communications, vol. 27, no. 2, pp. 127–133, 2019.
[9] H. Zhou, “Optimization of the rapid design system for arts and crafts based on big data and 3D technology,” Complexity, vol. 2021, pp. 1–10, Article ID 906047, 2021.
[10] J.-w. Kang and Q.-x. Ma, “The role and impact of 3D printing technologies in casting,” China Foundry, vol. 14, no. 3, pp. 157–168, 2017.
[11] S. W. Wilson, "Towards sustainable craft production in Jamaica," The Journal of modern crafts, vol. 2, pp. 191–208, 2010.
[12] Y. Xu, C. Yang, J. Zhong, N. Wang, and L. Zhao, "Robot teaching by teleoperation using visual interaction and extreme learning machine," Neurocomputing, vol. 275, pp. 2093–2103, 2018.
[13] Y. Wang, X. Yang, X. Wang, C. Ke, and Q. Wang, "Application of improved SURF algorithm in real scene matching and recognition," in Proceedings of the 2020 International Conference on Computer Vision, Image and Deep Learning (CVIDL), pp. 536–541, Chongqing, China, July 2020.
[14] G. Yang, R. Zeng, A. Dong, X. Yan, Z. Tan, and Y. Liu, "Research and application of 3D face modeling algorithm using ICP accurate alignment," Journal of Physics: Conference Series, IOP Publishing, vol. 1069, Article ID 012419, 2018.
[15] K. Y.-H. Lim, P. Zheng, and C. H. Chen, “A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management, and business innovation perspectives,” Journal of Intelligent Manufacturing, vol. 31, no. 6, pp. 1313–1337, 2020.
[16] D. Mourtzis, “Simulation in the design and operation of manufacturing systems: state of the art and new trends,” International Journal of Production Research, vol. 58, no. 7, pp. 1927–1949, 2020.
[17] Y. Deng, S. Y. Han, J. Li, J. Rong, W. Fan, and T. Sun, “The design of tourism product CAD three-dimensional modeling system using VR technology,” PLoS One, vol. 15, no. 12, Article ID e0244205, 2020.
[18] K. Židek, I. Piel, M. Adámek, P. Lazorić, and A. Hošovský, “Digital twin of experimental smart manufacturing assembly system for industry 4.0 concept,” Sustainability, vol. 12, no. 9, p. 3658, 2020.
[19] G. Yang, Z. Chen, Y. Li, and Z. Su, “Rapid relocation method for mobile robot using improved ORB-SLAM2 algorithm,” Remote Sensing, vol. 11, no. 2, p. 149, 2019.

[20] C. Ma, X. Hu, J. Xiao, H. Du, and G. Zhang, ”Improved ORB algorithm using the three-patch method and local gray difference,” Sensors, vol. 20, no. 4, p. 975, 2020.

[21] C. Luo, W. Yang, P. Huang, and J. Zhou, ”Overview of image matching using ORB algorithm,” Journal of Physics: Conference Series, IOP Publishing, vol. 1237, no. 3, Article ID 032020, 2019.

[22] K. Sasirekha and K. Thangavel, ”Optimization of K-nearest neighbor using particle swarm optimization for face recognition,” Neural Computing & Applications, vol. 31, no. 11, pp. 7935–7944, 2019.

[23] F. Ye, Z. Hong, Y. Lai, Y. Zhao, and X. Xie, ”Multipurification of matching pairs using ORB feature and PCB alignment case study,” Journal of Electronic Imaging, vol. 27, no. 3, Article ID 033029, 2018.

[24] S. Canaz Sevgen and F. Karsli, ”An improved RANSAC algorithm for extracting roof planes from airborne lidar data,” Photogrammetric Record, vol. 35, no. 169, pp. 40–57, 2020.

[25] S. A. Bakar, X. Jiang, X. Gui, L. Guoquan, and L. Zhangyong, ”Image stitching for chest digital radiography using the SIFT and SURF feature extraction by RANSAC algorithm,” Journal of Physics: Conference Series, IOP Publishing, vol. 1624, no. 4, Article ID 042023, 2020.