Furniture Panel Processing Positioning Design Based on 3D Measurement and Depth Image Technology

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Abstract-In recent years, furniture panel processing positioning based on computer vision technology has received increasing attention. A 3D measurement imaging technology based on laser scanning technology is proposed to address the significant environmental impact of traditional visual technology. Subsequently, deep image processing techniques are introduced to address the high image noise. In the experiment of measuring panel using 3D measurement technology, 14 measurement lines were taken every 10mm of the measurement length. The maximum measurement value was 204.62mm, the minimum measurement value was 204.37mm, and the manual measurement result was 204.5mm. 14 measurement lines were taken every 14mm of the measurement length. The maximum measurement value was 134.15mm, the minimum measurement value was 133.894mm, and the manual measurement was 134.1mm. 14 measurement lines were taken every 14mm of the measurement thickness. The maximum measurement value was 26.646mm, the minimum measurement value was 26.242mm, and the result of manual measurement was 26.5mm. The 3D imaging technology based on laser scanning is relatively accurate in measuring the 3D data of panels, which can be applied in the positioning and detection system of panel processing. In addition, the experiment compares depth image processing methods, verifying the effectiveness of the designed method. Meanwhile, this research also has certain reference significance for exploring the real-time positioning of other objects.

Keywords—Laser scanning; 3D measurement; deep image processing; positioning; computer vision

I. INTRODUCTION

In the current modern industrial automation and intelligent production, object positioning technology has become a key link. The stability and accuracy of positioning technology are crucial for production efficiency and product quality [1-2]. However, in actual positioning, object positioning systems often encounter anomalies, leading to a decrease in positioning accuracy or even failure. Common positioning faults include hardware failure, software failure, and environmental impact [3]. Among them, environmental factors are an important factor leading to abnormal visual positioning. For example, temperature, humidity, vibration, and other factors at the production site can affect the stability and accuracy of equipment [4-6]. In addition, external light sources, electromagnetic interference, etc. may also cause interference to the visual positioning system, leading to positioning failure. Object positioning technology is of great significance for furniture automation manufacturing. The pursuit of quality of life is also increasing day by day. In the home environment,

furniture, as an important component of life, is increasingly attracting consumer attention in terms of quality, style, personalization, and other aspects. To meet consumer demand, the Chinese furniture market is undergoing profound changes, gradually developing towards high-end, branded, intelligent, and personalized directions [7-8]. In this process, the furniture panel industry plays an important role. Furniture panels are not only the basic materials that make up furniture, but also a key factor affecting the quality, appearance, and safety of furniture. A high-quality board not only gives furniture a beautiful appearance but also ensures its durability, providing consumers with a safe and reliable user experience. With the continuous expansion of the high-end furniture market, the furniture panel industry will also usher in more business opportunities. Meanwhile, this also puts higher requirements on the technical level, innovation ability, and product quality of furniture panel enterprises. In order to strengthen the automation and intelligent production of furniture panels in enterprises, more practitioners have added object positioning technology to the processing of furniture panels.

The scanning imaging and image preprocessing of objects exerts a crucial role in the precise positioning of objects. Yin T et al. seamlessly integrated RGB sensors into lidar-based 3D recognition to address the low resolution of lidar sensors. The proposed framework significantly improved the strong center point baseline and outperformed competitive fusion methods [9]. Jiang W et al. proposed a new high-speed 2D and 3D imaging scheme on the basis of traditional single-pixel imaging, which was difficult to achieve high imaging speed using traditional single-pixel imaging mechanisms. The new scheme performed 2D and 3D imaging on a rotating chopper with a speed of 4800rpm, with an imaging speed of up to two million fps, providing a powerful solution for high-speed imaging [10]. Pan X et al. built a deep generative prior method to address the difficulty in capturing rich image semantics. The results showed that this method helped to preserve the reconstruction information, resulting in more accurate and faithful reconstruction results of real images [11]. To optimize the limits of plug and play image restoration, Zhang K et al. inserted deep denoising priors as module parts into iterative algorithms ground on semi quadratic splitting to solve various image restoration problems. The results showed that the designed strategy with deep denoising prior was not only significantly superior to other model-based methods, but also more competitive [12]. Guo Y et al. proposed a fully variational depth network based on deep learning and high-resolution color images to address the edge misalignment and depth discontinuity in color images used for

guiding depth image reconstruction. Under the guidance of highresolution colors, the restored depth image was closest to the ground truth on the edge contours [13]. To assess the position and application of lightweight panels in Iranian furniture production. Khojasteh-Khosro S et al. built an analysis method on the basis of consumer behavior and preferences. The main evaluation criteria for purchasing furniture were product quality, design, price, environmental protection, and guaranteed functionality [14]. Thio V et al. proposed a new step detection strategy relying on the sine wave approximation of acceleration signals to address the noise and infinitely increasing position errors in sensors embedded in smart devices. This method could detect step scores and complete steps, thereby achieving continuous and real-time updates. The results demonstrated the feasibility of using the sine wave approximation method for step detection, and the expected benefits of integrating pedestrian prediction positioning with ultrasound systems [15]. To solve the difficulty in accurately identifying various types of defects in glued wood panels, Chen L C et al. adopted computer vision and deep learning to identify low, high, normal, long, and short defects. The new method achieves higher accuracy than other methods with excessive killing and escape rate analysis [16]. To address the enormous demand for low-cost and high-precision positioning and navigation solutions in emerging IoT applications, Feng D et al. built an indoor positioning system that combined inertial measurement units with ultra-wide bands by extending Kalman filters and unscented Kalman filters. The results indicated that the prior information provided by the inertial measurement unit could significantly suppress ultra wide-band observation errors [17]. In response to the problem that the currently released dataset for crowd counting and localization is too small to meet the requirements of supervised convolutional neural network algorithms, Wang Q et al. built a large-scale crowded crowd counting and localization dataset NWPU-Crowd, consisting of 5109 images and 2133375 annotated headers with dots and boxes. The results showed that the new dataset could meet the requirements of supervised convolutional neural network algorithms [18].

In summary, domestic and foreign researchers have put forward many discussions on the positioning of furniture panel processing, including the three-dimensional measurement technology. However, few scholars have combined 3D measurement technology based on laser scanning technology with depth image processing technology. Compared with the methods used in the study, although these methods may be enhanced in certain directions, they are still relatively weak in continuous and large-scale image processing. In response to this issue, a furniture panel processing and positioning design based on 3D measurement and depth image technology is proposed, aiming to apply different technologies to different stages of panel positioning to achieve optimal positioning results. Compared with other works in the same direction, the method proposed in the study has higher processing efficiency for sheet images due to the use of mature methods that have been validated for a long time, thus meeting the requirements for processing a large number of images. The innovation of the research lies in the combination of 3D measurement imaging technology and depth image processing technology, which helps to better locate the position of the panel.

II. METHODS AND MATERIALS

Aiming at the high-precision measurement problem required for furniture panel processing positioning, a 3D measurement imaging technology based on laser scanning is introduced. On this basis, deep image processing technology is applied to process the images scanned by 3D measurement imaging technology, providing a position positioning basis for furniture panel processing.

A. 3D Measurement Imaging Technology Based on Laser Scanning

Currently, 3D measurement technology has been applied in many fields. This study adopts a 3D measurement technology based on laser scanning technology. The basic principle of laser measurement is to use the reflection of light for measurement. After the laser beam is emitted onto the object being measured, a portion of the light is reflected by the object, while another portion of the light is absorbed or scattered by the object. A laser measuring instrument obtains relevant information about the measured object by measuring the reflected light [19-20]. Laser scanning measurement utilizes an external motion platform to continuously scan laser lines through the target surface, thereby obtaining the overall contour of the object. To achieve real-time measurement of moving target objects, the laser triangulation method is used for measurement. The basic principle of laser triangulation is to irradiate a beam of laser at a specific angle onto the surface of the measured object, and then observe the laser spot on the measured object from a different angle. The position of the light spot varies with the height of the measured object [21-22]. The photodetector measures the position of the spot imaging, which can determine the height of the laser irradiation point on the object. The laser triangulation measurement technology utilizes optical reflection laws and the principle of similar triangles. Its vertical measurement is shown in Fig. 1.



Fig. 1. Schematic diagram of laser vertical measurement.

In Fig. 1, A represents the contact point between the laser and the upper surface of the object, and O represents the contact point between the laser and the lower surface of the object. AP and AD represent the reflected light rays formed by a lens after being reflected by an object. Assuming the initial position of the object surface is in a certain plane, when the distance $\triangle y$ moves to the lower surface, the incident point changes from position A to point O, and the corresponding image point changes from point D to position P. From the changes in the optical path structure, it can be inferred that the incidence points at different heights correspond to different imaging point positions. Based on this relationship, the spatial position information of any point on the surface of an object can be obtained by analyzing the geometric relationship between the image point and the incident point. Eq. (1) can be obtained from the similarity between triangle $\triangle AFB$ and $\triangle BDE$.

$$\frac{AF}{DE} = \frac{FB}{BE} \tag{1}$$

In Eq. (1), A is the projection point of the laser axis on the object. D is the corresponding pixel. F, E are perpendicular feet of the vertical line that reflects light at point A and point D. B is the location of the intersection point between two lasers, that is, the intersection point between the laser and the optical lens. Eq. (2) can be obtained by transforming Eq. (1).

$$\frac{AO \cdot \sin \alpha}{DP \cdot \sin \beta} = \frac{OB - AO \cdot \cos \alpha}{BP + DP \cdot \cos \beta}$$
(2)

In Eq. (2), O signifies the intersection point between the vertical injection of the laser and the lower surface of the object. P is the image point position of the laser reflected light on the laser sensor. α is the angle between AO and OP. β is the angle formed between OP and the linear CCD after passing through the lens. Eq. (2) can be transformed to obtain Eq. (3).

$$AO = \frac{OB \times DP \times \sin \alpha}{BP \times \sin \alpha + DP \times \sin(\alpha + \beta)}$$
(3)

In oblique measurement, Eq. (4) can be obtained according to the ray projection relationship and the principle of similar triangles.

$$\frac{AF}{\sin\alpha} \times \frac{1}{DP \times \sin\beta} = \frac{OB}{BP + DP \times \cos\beta}$$
(4)

In Eq. (4), AF is the height of the incident point on the object. DP is the displacement between pixels. D and F are the image points corresponding to the positions of point A and point O. OB is the imaging objective distance of point O. BP is the image distance. Eq. (4) can be transformed to obtain Eq. (5).

$$AF = \frac{DP \times \sin \beta \times OB \times \sin \alpha}{BP + DP \times \cos \beta}$$
(5)

Laser triangulation scanning imaging technology is widely used in automated production. However, in actual factory operations, there are often problems that cannot detect and recognize objects. There are many reasons for such problems, as shown in Fig. 2.



Fig. 2. System influencing factors.

Fig. 2 shows the factors that the system cannot detect and recognize objects, mainly including external noise, sensor working parameter settings, board position and texture, etc. In addition, the board position detection system may also fail to effectively scan and recognize objects, as shown in Fig. 3.



Fig. 3. The system logic.

Fig. 3 shows the factors that affect the effective identification of the board detection system. Among them, the board position detection system needs to integrate several functional requirements in the software composition structure, including hardware communication, visual processing, robot control, sensor data exchange, etc.

B. Design of Furniture Panel Positioning and Detection System Based on Depth Image Technology

Due to the interference of external environment during image collection, the collected board images often contain some noise and have poor image quality. Therefore, after the panel is scanned into images through three-dimensional measurement, it is necessary to preprocess the images [23]. Several processing algorithms for image enhancement and filtering denoising are studied, and suitable depth image preprocessing algorithms are selected based on their processing effects, effectively improving the plate recognition accuracy, as displayed in Fig. 4.



Fig. 4 shows the preprocessing and target area extraction process of the panel image after three-dimensional measurement. In Fig. 4, image preprocessing is mainly aimed at suppressing or eliminating irrelevant signals in the image, enhancing the true information such as edges in the image. The processing methods include filtering denoising, contrast enhancement, etc. The scope of image enhancement processing is divided into spatial and frequency domain processing. The study adopts the spatial enhancement method. The spatial domain refers to the two-dimensional space of the image itself. This processing is performed on the image pixels, as shown in Eq. (6).

$$g(m,n) = T[f(m,n)]$$
(6)

In Eq. (6), (m,n) represents the current operating pixel point. f(m,n) signifies the initial pixel grayscale value. g(m,n) signifies the processed pixel grayscale value. T is the functional model of the processing method. Grayscale transformation is a common spatial domain image enhancement algorithm that can increase the grayscale distribution range of an image and make local details clearer. There are several commonly used enhancement methods. The image inversion method is shown in Eq. (7).

$$g(m,n) = L - T \left[f(m,n) \right] - 1 \tag{7}$$

In Eq. (7), L represents the grayscale value of the original image. The linear transformation method is shown in Eq. (8).

$$g(m,n) = I_1 - k \left[f(m,n) - M_1 \right]$$
(8)

In Eq. (8), k represents the slope of the transformation function. I_1 represents the starting point of the processed pixel grayscale value interval. M_1 represents the starting point of the initial grayscale value interval for pixels. The slope k is shown in Eq. (9).

$$k = \frac{I_2 - I_1}{M_2 - M_1} \tag{9}$$

In Eq. (9), I_2 represents the endpoint of the processed pixel grayscale value interval. M_2 represents the endpoint of the initial grayscale value interval for pixels. To highlight the target of interest or certain regions in the image, segmented linear transformation can be used to expand the grayscale regions at different levels on the image, as shown in Eq. (10).

$$g(m,n) = \begin{cases} \frac{I_2 - I_1}{M_2 - M_1} \Big[f(m,n) - M_1 \Big] + I_1 & M_1 \le f(m,n) \le M_2 \\ \frac{I_1}{M_1} \Big[f(m,n) - M_1 \Big] + I_1 & 0 \le f(m,n) \le M1 \end{cases}$$
(10)

Another method for enhancing depth images of panel is histogram equalization. Histogram equalization is to adjust the probability distribution of pixels at each grayscale level to evenly distribute the overall grayscale range of pixels, in order to expand the dynamic range of pixel grayscale. Its expression is shown in Eq. (11).

$$T(j) = \int_0^j p_j(z) dz \tag{11}$$

In Eq. (11), T(j) represents the probability density distribution function of j. z represents the integral variable. j represents the grayscale value. p_j represents the probability of processed pixels. The probability of pixels in each grayscale interval of the original image is shown in Eq. (12).

$$P(i) = \frac{n_i}{n} \tag{12}$$

In Eq. (12), P(i) represents the probability of pixels in the original image. n_i represents the original image pixels. n represents the total pixels in the image. The grayscale cumulative histogram is shown in Eq. (13).

$$p_{j} = \sum_{i=0}^{L-1} P(i)$$
(13)

In Eq. (13), L signifies the pixel grayscale value . The grayscale value calculation is shown in Eq. (14).

$$j = (L-1)p_j \tag{14}$$

According to Eq. (11) to Eq. (14), the histogram after image processing can be obtained, as shown in Eq. (15).

$$P(j) = \frac{n_j}{n} \tag{15}$$

In Eq. (15), P(j) is the probability density after image processing. n_j is the pixel point after image processing. During image acquisition, due to the low stability of the sampling system, it may be affected by external environmental interference, resulting in a significant amount of noise in the obtained image. To reduce the impact of these noises, the original image needs to be smoothed. In this study, mean filtering is used for denoising. It is a relatively simple and fast processing method in filtering algorithms, as shown in Fig. 5.



Fig. 5. Mean filtering denoising method.

Fig. 5 shows the mean filtering denoising method. The pixel value of any point in Fig. 5 is the mean of surrounding N/times M pixels, where the pixel value of the red point is the sum of the pixel values of the surrounding blue background area divided by 25. After image enhancement processing, a high-quality image is obtained. In subsequent processing, the target information is often only a part. For the entire image, only this part of the features need to be extracted and analyzed. The image obtained through image preprocessing can be used for panel detection and recognition. The detection system framework is shown in Fig. 6.



Fig. 6. Framework diagram of panel detection system.

Fig. 6 is the framework diagram of the board detection system. From Fig. 6, the system mainly includes several parts: external data loading, communication control, sensor settings, image acquisition and display, and depth image data processing. The interactive interface written by C#.NET integrates several functional modules of the software system, making the operation simple and efficient.

III. RESULTS

To verify the effectiveness of the plate processing positioning and detection system, simulation analysis is conducted. Firstly, the relationship between laser sensors and imaging images in 3D measurement technology is analyzed. Subsequently, the depth image processing method is validated. Finally, the recognition accuracy of the plate positioning detection system is experimentally analyzed.

A. Analysis of Furniture Panel Processing Positioning Design Based on 3D Measurement Technology

This experiment is developed in the Visual Studio 2022 17.4 development environment, using C# as the programming language. The Halcon machine vision algorithm package processing function library and open graphics library 3D display tool are combined to build the system software framework. Table I displays the experimental parameter settings.

TABLE I. EXPERIMENTAL PARAMETER SETTINGS

Parameter type	Index	Explain
Response time	10ms	/
Measuring range	250-650mm	X-axis
	200-1000mm	Z-axis
Laser wavelength	660nm	/
Laser line length	600×3mm	At a height of 850mm
Resolving power	0.6-1.8mm	X-axis
	1-4mm	Z-axis
Working voltage	20-35v	DC
Communication protocol	UDP	/

The images formed by 3D measurement technology are the basis for subsequent positioning and detection of panel processing. To verify the effectiveness of 3D measurement technology, experiments are conducted on various aspects of the technology, mainly focusing on the quantitative analysis between 3D measurement imaging technology on the basis of laser scanning and image formation. The relationship between the object distance of the sensor and the imaging resolution is shown in Fig. 7.



Fig. 7. The relationship between sensor distance and resolution.

In Fig. 7(a), when the laser sensor was close to the measured object, the resolution was higher. The resolution change speed in the X-direction was smaller than that in the Y and Z-axes. The length of the laser line in the X-direction depended on the distance Z between the measured object and the sensor. When the Z-axis distance was 1000mm, the laser line length reached the maximum value of 600mm, and the corresponding measurement resolution was also the lowest. In Fig. 7(b), the resolution decreased when the laser sensor was far away from the measured object. The resolution change speed in the X-direction was smaller than that in the Y and Z- axes. When the Z-axis distance was 900mm, which was the initial position, the corresponding measurement resolution was the highest. It indicates that when the sensor is further away from the target, it is easier to obtain more accurate images. The resolution is

inversely proportional to the distance from the measurement object during measurement. The coordinate distribution of the measured object on the X and Z-axes is shown in Fig. 8.



Fig. 8. Sensor single measurement test coordinates.

As shown in Fig. 8, the coordinate distribution of Test1, Test2, and Test3 on the Z-axis was relatively stable, with Test1 concentrated around 443.5, Test2 concentrated around 443.2, and Test3 concentrated around 443.7. The coordinate information on the X-axis and Z-axis is relatively complete, which can verify the connection status and good data

measurement of the laser sensor. The actual measurement of panel using 3D measurement technology is shown in Fig. 9.

According to Fig. 9(a), 14 measurement lines were taken every 10mm interval. The maximum measurement value was 204.62mm, the minimum measurement value was 204.37mm, and the manual measurement result was 204.5mm. As shown in Fig. 9(b), a total of 14 measurement lines were taken every 14mm interval. The maximum measurement value was 134.15mm, the minimum measurement value was 133.894mm, and the manual measurement result was 134.1mm. As shown in Fig. 9(c), 14 measurement lines were taken every 14mm of the measurement thickness. The maximum measurement value was 26.646mm, the minimum measurement value was 26.242mm, and the manual measurement result was 26.5mm. The 3D imaging technology based on laser scanning is relatively accurate in measuring the 3D data of panel, which can be applied in the positioning and detection system of panel processing.

B. Analysis of Furniture Panel Positioning and Detection System Based on Deep Image Technology

Deep image processing technology can highlight the target area, suppress or eliminate irrelevant signals in the image, and enhance the true edge information in the image. Common processing techniques include grayscale transformation and histogram equalization. The latter is displayed in Fig. 10.



Fig. 9. 3D measurement technology for measuring the three-dimensional dimensions of panel.



Fig. 10. Comparison chart of histogram equalization processing.

From Fig. 10(a), for some unclear detail features in the original image, after histogram equalization processing, the grayscale levels of these areas were richer. As shown in Fig. 10 (b), the histogram after equalization was greatly expanded. The original image had a grayscale range of 1720 to 3470, while the balanced image had a grayscale range of 700 to 5100. The grayscale range of areas with similar grayscale and occupying many pixels in the original image was widened, making small grayscale changes in large areas visible and making the image clearer. Experimental data shows that histogram equalization can enhance the visual effect of images and enhance the overall contrast of images. During image acquisition, due to the low stability of the sampling system, it may be affected by external environmental interference, resulting in much noise in the obtained image. This makes the subsequent processing and analysis of the image more complex. To reduce the impact of these noises, the original image needs to be smoothed and filtered. The mean filtering is used to process image noise, as shown in Fig. 11.

As shown in Fig. 11, the upper image is the original image with added noise, and the lower image is the image processed by mean filtering. The noise in the image below was significantly reduced. The experiments show that mean filtering can effectively remove noise. To analyze the positioning accuracy of the plate processing positioning detection system and verify the stability performance, the actual coordinate position under the sensor detection system is indirectly obtained by obtaining the position displayed by the robot at the specified position, and experimental data is measured accordingly. The data and statistical error distribution diagram are shown in Fig. 12.



(a) Adding noise to the original image









In Fig. 12, the maximum error of the experimental group in the X-axis was 2.2mm and the minimum was 0.6mm. The maximum error in the Y-axis was 2.6mm and the minimum was 0.8mm. The maximum error in the Z-axis was 2.8mm and the minimum was 0.8mm. The experimental data shows that the overall coordinate deviation of the experimental group can be controlled within 5mm, which can meet the positioning and detection requirements of the system.

IV. DISCUSSION

In order to accurately locate furniture panels, a furniture panel processing and positioning system based on 3D measurement and depth imaging technology was studied and designed. The results showed that the experimental group of the detection system had a maximum error of 2.2mm and a minimum error of 0.6mm in the X direction. The maximum error in the Y direction is 2.6mm, and the minimum is 0.8mm. The maximum error in the Z direction is 2.8mm, and the minimum is 0.8mm. Similarly, scholars such as Fan J proposed the Chaos Cuckoo Search Algorithm (Ccsa) to solve image segmentation problems in computer vision and improve image accuracy. Unlike ordinary cuckoo search, chaotic mapping combines deterministic search and random verification. The experimental results show that compared with other existing methods, the proposed CCSA model improves accuracy and reduces uncertainty [21]. In contrast, the study uses grayscale transformation for image enhancement and employs mean filtering for denoising. From the perspective of image detection accuracy, the proposed method has slightly poor performance in image processing. The reason is that the method used in the study is greatly affected by image quality factors, and in the process of sheet metal processing, image quality is greatly affected by environmental factors such as surrounding sawdust and dust, resulting in relatively low image detection accuracy. Take a measurement line every 14mm and use 3D measurement technology for measurement. The maximum measurement result is 26.646mm, the minimum measurement value is 26.242mm, and the manual measurement result is 26.5mm. The research of Qian J and other scholars adopted a deep learning based color stripe projection contour technique for single absolute 3D shape measurement. The results show that this method can perform high-precision single frame absolute 3D shape measurement on complex objects [22]. This result is slightly higher than the 3D scanning imaging technology used in the study, indicating that the research can further optimize the scanning accuracy.

V. CONCLUSION

Traditional computer vision technology has a significant impact on furniture panel positioning due to environmental factors. Based on this, this study introduced furniture panel positioning based on 3D measurement and depth image processing technology. The results indicated that the resolution change rate of the image on the X-axis was smaller than that in the Y and Z-axes. When the Z-axis distance was 1000mm, the laser line length reached the maximum value of 600mm, and the corresponding measurement resolution was also the lowest. When the laser sensor moved away from the measured object, the resolution decreased, and the resolution change rate in the Xaxis was slower than that in the Y and Z-axes. When the Z-axis distance was 900mm, which was the initial position, the corresponding measurement resolution was the highest. In addition, two sets of measurement tests were conducted on the object to observe its coordinate distribution. The coordinate distribution of Test1, Test2, and Test3 on the Z-axis was relatively stable, and the maximum error of the detection system in the X-axis was 2.2mm, and the minimum was 0.6mm. The

maximum error in the Y-axis was 2.6mm and the minimum was 0.8mm. The maximum error in the Z-axis was 2.8mm and the minimum was 0.8mm. Experimental data showed that when the sensor was closer to the target, it was easier to obtain more accurate images. The resolution was inversely proportional to the distance from the measured object during measurement. The overall coordinate deviation of the experimental group was controlled within 5mm, which verified the effectiveness of the positioning detection system. Through the verification and analysis of the results, the design of furniture board processing positioning has been achieved, and the detection system can effectively identify and detect the board, which provides important technical support for the automation processing of the board. However, through the analysis of existing research results, it was found that although the image recognition detection error meets the requirements, there is still significant room for improvement. The proposed work aims to further address the factors that affect measurement accuracy in actual measurement operations, not only limited to environmental factors such as sawdust and dust, but also including scanning imaging hardware, system errors, and more advanced image processing technologies. In addition to upgrading hardware facilities, the most important aspect of the proposed work is to increase the universality of research. A detailed exploration was conducted on the positioning of furniture boards based on the processing environment, taking into account factors such as fiber optics and dust in the processing environment. However, there was insufficient exploration of object positioning in other environments. The future direction of work will further investigate the universality of the proposed method, such as verifying its localization ability under the influence of different factors such as temperature, humidity, light, and object shape.

REFERENCES

- [1] Tang Z, Jia S, Zhou C, Li B. 3D printing of highly sensitive and largemeasurement-range flexible pressure sensors with a positive piezoresistive effect. ACS applied materials & interfaces, 2020, 12(25): 28669-28680.
- [2] Jiahuan Wang, Haixiao Jia, Peifen Pan, et al. Research on The Technology of Man-Machine Collision Early Warning System In Tunnels Based On Bds High-Precision Positioning In Tunnel. Applied Computer Letters, 2023, 7(1)
- [3] She X, Hongwei Z, Wang Z, Yan J. Feasibility study of asphalt pavement pothole properties measurement using 3D line laser technology. International Journal of Transportation Science and Technology, 2021, 10(1): 83-92.
- [4] Bai L, Lundström O, Johansson H, Meybodi F, Arver B, Sandelin K, Brandberg Y. Clinical assessment of breast symmetry and aesthetic outcome: can 3D imaging be the gold standard. Journal of Plastic Surgery and Hand Surgery, 2023, 57(1-6): 145-152.
- [5] Wang G, Ye J C, De Man B. Deep learning for tomographic image reconstruction. Nature machine intelligence, 2020, 2(12): 737-748.
- [6] Jiahuan Wang, Haixiao Jia, Xuejiao Bai, et al. Research on The Location of Railway Train in Tunnel Based on Factor Graph Optimization. Applied Computer Letters, 2023, 7(1)
- [7] Cui Y, Chen R, Chu W, Chen L., Tian D, Li, Y, Cao D. Deep learning for image and point cloud fusion in autonomous driving: A review. IEEE Transactions on Intelligent Transportation Systems, 2021, 23(2): 722-739.
- [8] Zengting Mu. Research on the Design of Wearable Life-Saving Furniture on Water Based on UCD. Applied Computer Letters, 2023, 7(2).
- [9] Li P, Zhao H. Monocular 3d detection with geometric constraint embedding and semi-supervised training. IEEE Robotics and Automation Letters, 2021, 6(3): 5565-5572.

- [10] Jiang W, Yin Y, Jiao J, Zhao X, Sun B. 2,000,000 fps 2D and 3D imaging of periodic or reproducible scenes with single-pixel detectors. Photonics Research, 2022, 10(9): 2157-2164.
- [11] Pan X, Zhan X, Dai B, Lin D, Loy C C, Luo Pl. Exploiting deep generative prior for versatile image restoration and manipulation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021, 44(11): 7474-7489.
- [12] Zhang K, Li Y, Zuo W, Zhang L, Van Gool L, Timofte R. Plug-and-play image restoration with deep denoiser prior. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021, 44(10): 6360-6376.
- [13] Guo Y, Xie S, Hu Y, Xu X. Color image guided depth image reconstruction based on a total variation network. JOSA A, 2024, 41(1): 19-28.
- [14] Khojasteh-Khosro S, Shalbafan A, Thoemen H. Consumer behavior assessment regarding lightweight furniture as an environmentallyfriendly product. Wood Material Science Engineering, 2022, 17(3): 192-201.
- [15] Thio V, Aparicio J, Anonsen K B,Bekkeng J K, Booij W. Fusing of a continuous output PDR algorithm with an ultrasonic positioning system. IEEE Sensors Journal, 2021, 22(3): 2464-2474.
- [16] Chen L C, Pardeshi M S, Lo W T,Sheu R K, Pai K C, Chen C Y, Tsai Y T. Edge-glued wooden panel defect detection using deep learning. Wood Science and Technology, 2022, 56(2): 477-507.

- [17] Feng D, Wang C, He C, Zhuang Y. Kalman-filter-based integration of IMU and UWB for high-accuracy indoor positioning and navigation. IEEE Internet of Things Journal, 2020, 7(4): 3133-3146.
- [18] Wang Q, Gao J, Lin W, Li X. NWPU-crowd: A large-scale benchmark for crowd counting and localization. IEEE transactions on pattern analysis and machine intelligence, 2020, 43(6): 2141-2149.
- [19] Çam G, Javaheri V, Heidarzadeh A. Advances in FSW and FSSW of dissimilar Al-alloy plates. Journal of Adhesion Science and Technology, 2023, 37(2): 162-194.
- [20] Lai B F L, Lu R X Z, Davenport Huyer L,Kakinoki S, Yazbeck J, Wang E Y, Radisic M. A well plate based multiplexed platform for incorporation of organoids into an organ-on-a-chip system with a perfusable vasculature. Nature protocols, 2021, 16(4): 2158-2189.
- [21] Hao R B, Lu Z Q, Ding H, Chen L Q. A nonlinear vibration isolator supported on a flexible plate: analysis and experiment. Nonlinear Dynamics, 2022, 108(2): 941-958.
- [22] Premier A, GhaffarianHoseini A, GhaffarianHoseini A. Solar-powered smart urban furniture: preliminary investigation on limits and potentials of current designs. Smart and Sustainable Built Environment, 2022, 11(2): 334-345.
- [23] Preethi P, Mamatha H R. Region-based convolutional neural network for segmenting text in epigraphical images Artificial Intelligence and applications. 2023, 1(2): 119-127.