The Applications of Machine Vision in Raw Material and Production of Wood Products

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Machine vision has been developed nearly for 70 years and been widely applied in electronics, automotive manufacturing, food processing, *etc*. With deepening study of its theory and technology in forestry industry, the industry of wood products is moving steadily toward the goal of automated identification and production to improve the manufacturing intelligence of enterprises. In this study, theoretical and algorithmic research on image acquisition, feature extraction, recognition, and classification involved in machine vision-based wood recognition technology were analyzed on the basis of its global development. The applications of machine vision in the wood materials, such as the identification of tree species, wood inspection and classification, defects detection of wood product, surface analysis of wood color, and quality control of furnishing products were thoroughly analyzed. The development trend of machine vision in the production and management of wood materials was considered in the current development of wood and furnishing enterprises. These results lay a solid foundation for wood science research, and intelligent manufacture of wooden furniture, and efficient development of greener and cleaner production of the furniture industry, which could improve the environmental effect of the wood products and furniture and make a great contribution for the carbon goal of "30-60" in China.

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INTRODUCTION

In the past 20 years, the Internet has changed the world, and robots will reform the world over the next 20 years (Murphy 2019). In industrial intelligent manufacturing, machine vision endows machines with human-like ability, which can help people accomplish various tasks accurately and efficiently. Machine vision automatically receives images in the real scene through the non-contact perception of optical devices (such as lenses, industrial cameras) and analyzes the images in-depth to obtain the scene information, which is used to output corresponding judgments and controls (Fig. 1). The machine functions with human-like vision and understanding through "its own eyes" (Smith *et al*. 2021). While vision begins with the eye, its true meaning is in the brain; seeing is not equal to understanding (Serre 2019). To make machine vision genuinely meaningful, it is necessary to solve the seeing problems by machine and to give machines the ability to understand the information, so as to make the machine more intelligent and universal. Accordingly, machine vision is an interdisciplinary subject that integrates mathematics, physics, engineering, biology, psychology, computer science, and other disciplines. It involves many fields such as operation, optical devices, image processing, neurology, cognition, information retrieval, natural language processing, *etc*. (Szeliski 2021).

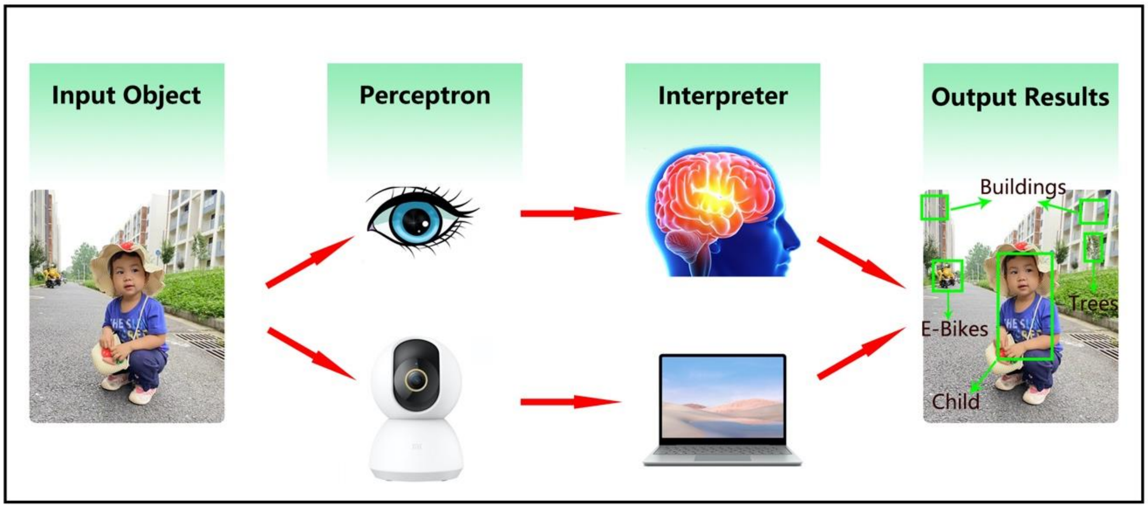

Fig. 1. Basic working principle of machine vision

The Development of Machine Vision

As shown in Fig. 2, the research of machine vision began in the 1950s with statistical pattern recognition of two-dimensional images. Roberts (1961) proposed the "building block world". In the 1970s, simple applications such as edge detection using machine vision were started (Davis 1975; Agin and Binford 1976).

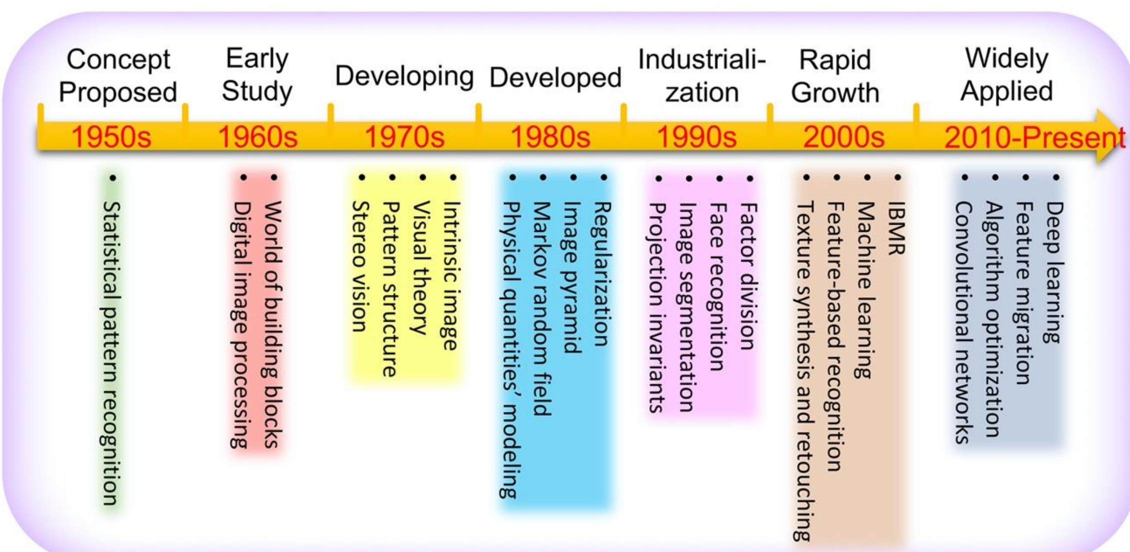

Fig. 2. Overview of the historical development of machine vision

In the 1980s, new concepts, methods, and theories of machine vision emerged continuously, such as image pyramids (Burt and Adelson 1983), modeling based on three-dimensional physical quantities (Kass *et al.* 1988), and the Markov random field model (Bertero *et al.* 1988). A new interdisciplinary field based on image modeling and drawing emerged in the 1990s (Seitz and Dyer 1999). Since then, machine vision has been industrialized, including face recognition, image segmentation, *etc*. (Turk and Pentland 1991; Belongie *et al.* 2002). Entering the 21st century, people have endowed the machine with the ability of autonomous learning through specific algorithms, which further makes machine vision more feasible in object category recognition without human supervision (Debevec and Malik 1997; Freeman *et al.* 2000; Fergus *et al.* 2007). With the use of convolution neural network and other algorithms in machine vision (Rawat and Wang 2017; Voulodimos *et al.* 2018), the performance and application of machine vision have been improved and expanded.

Research on machine vision in China started at the end of the 20th century and is divided into three stages: early stage, middle stage, and high-speed development stage (Song and Peng 2019). In the initial period (1980s to 21st century), domestic machine vision started from agent business. On the basis of absorbing foreign machine vision theory and technology, it gradually explored and researched the aspects of image collection, quality control, image recognition, and application system development (Zhang *et al.* 1994). Machine vision has been pioneered in industries such as special printing, welding, and painting, which has led to significant improvements in product quality and production efficiency in those industries (Wang *et al.* 1989). In the mid-term (2000s), China began to develop the self-contained core technology of machine vision and substituted it for manual production activities in traditional industries such as textiles, agricultural products, and steel (Zhang *et al.* 2008).

At the stage of rapid development (2010-present), after decades of theoretical and technological accumulation, domestic machine vision has made great progress in the theory and technology of image processing, feature extraction, convolution neural network, and in-depth learning (Zhao *et al.* 2019). It is widely used in the fields of electronic devices, food, military industry, automotive manufacturing, and especially in the 3C electronics industry. Currently, China is the third largest machine vision application market after the United States and Japan (Li 2012).

Composition and Function of Machine Vision

A machine vision system is a multi-application system consisting of hardware and software, mainly including light source, lens, industrial camera, image acquisition card, computer, and image processing software (Fig. 3a). The light source should have a reasonable illumination, favorable homogeneity, and stability (Smith *et al.* 2021), so that the measured object can be distinguished from the background as obviously as possible to obtain a high stability, high quality, and high contrast image (He *et al.* 2020a). The camera lens is similar to the crystalline lens in the human eye. Its main function is to modulate the light beam so that the measured object can be imaged on the photosensitive surface of the image sensor and realize image signal transmission. Its resolution, contrast, depth of field, and aberration play a crucial role in image quality. The essential function of industrial cameras is to convert optical signals into electrical signals, which are then transmitted to the image acquisition card for further signal conversion and image processing. Compared with ordinary cameras, industrial cameras have higher transmission ability, anti-interference ability, and image stability.

The image acquisition card converts the video/image signals from industrial cameras into digital signals that can be processed by the computer through analog-to-digital conversion. It enables the acquisition information to be presented and stored in the computer quickly and accurately, while providing signals to control camera parameters (such as trigger time, exposure time, *etc*.) so that the machine vision makes a rapid response to the dynamic image (Zhang 2006). The computer is mainly responsible for the operation of each unit in the control system, as well as the operation and command output of the visual acquisition results. The digital signal output from the image acquisition card is transmitted to the computer. The software in the computer completes the analysis, processing and other operations of the image, and then outputs the corresponding control instructions according to the processing results. Finally, the recognition, positioning, and detection of the object under test are realized.

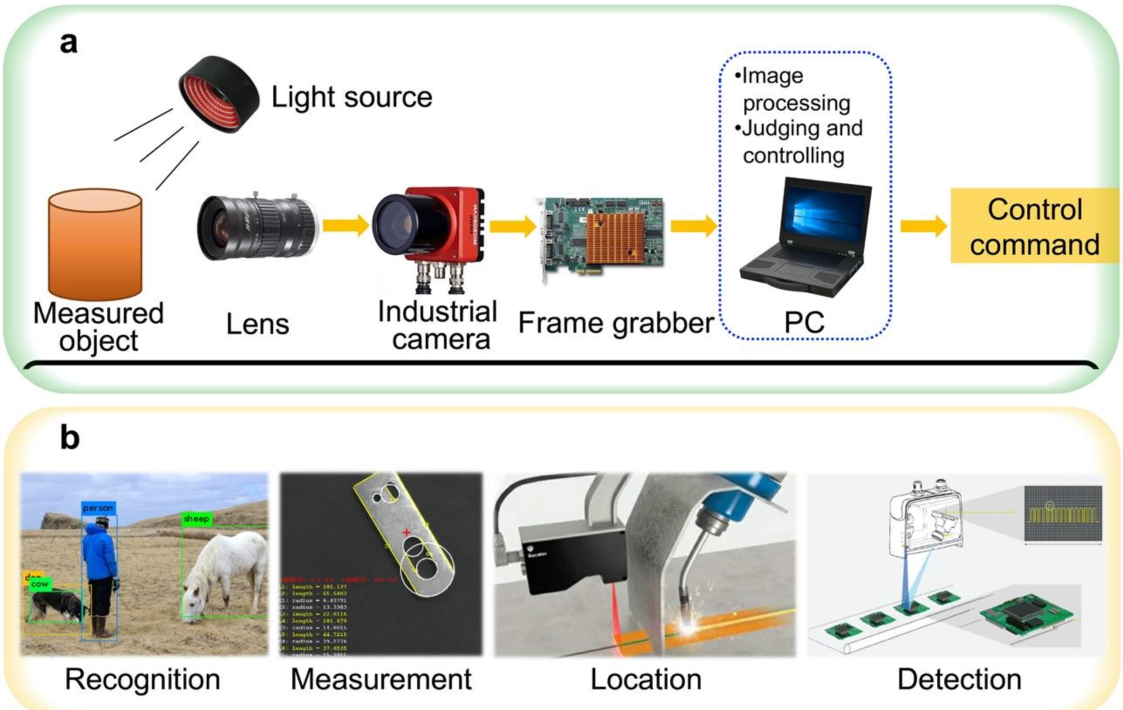

Fig. 3. Basic components and main functions of machine vision (a. basic composition; b. main function)

As shown in Fig. 3b, the main functions of machine vision are recognition, measurement, positioning, and detection (Connolly 2009; Han *et al.* 2013; He *et al.* 2021a). Recognition identifies the physical characteristics of the object being measured, including shape, color, surface properties, *etc*. Common recognition application scenarios include face recognition in dense crowds and bar code recognition on parts to obtain processing operations (Guo *et al.* 2016). Measurement is the conversion between the image pixel information obtained by machine vision and the commonly used units of measure to calibrate information such as the geometric dimensions of the detected object on the visual image. Location is to gain the two-dimensional or three-dimensional position information of the surveyed object, and then assist the machine in subsequent operations. As shown in Fig. 3b, by machine vision to locate the seam position of two plates, the robot can quickly and accurately complete the welding work (Pérez *et al.* 2016). Inspection is the examination of the surface appearance of a product in order to determine whether the product has been processed properly, whether there are any defects, whether process adjustments need to be made, *etc*., during processing.

Prospect of Machine Vision Technology in the Field of Furniture and Wood Products

The forest products industry, especially in the field of wood processing, is undoubtedly an important part of today's industry (Kryl *et al.* 2020; Wu 2021). Among them, wood identification is the key technology in furniture manufacturing. The traditional wood identification is based on wood anatomy, which requires comprehensive judgment of wood macroscopic characteristics and microstructure. The task is arduous due to the diversity of tree species and the need for professional wood knowledge reserve, while classification capacity is often limited to the “genera” or “classes” of wood (He *et al.* 2020b; Hwang and Sugiyama 2021). In addition, the characteristics exhibited by different species of wood need to be extracted accurately for subsequent classification. The different characteristics of wood determine the final quality of products, so the material inspection in the production process is also crucial. The method based on artificial vision inspection has the problems of low recognition rate and less accuracy, which leads to high-cost investment, uneven quality, and waste of resources in processing. Therefore, the efficient and accurate identification of large quantities of wood within a limited time frame in actual production is a cutting-edge technology problem that needs to be solved in the furniture and wood products industry.

With the gradual application of computer-based machine vision technology in the field of wood processing, the machine is endowed with human-like vision and understanding functions through optical devices and algorithms to identify information and extract important features from images. This accurate and efficient automatic detection and recognition technology greatly reduces the error of manual operation and provides a new way for fast and accurate identification of wood. Currently, the application of machine vision technology in the field of wood processing has shown a better development trend and plays an irreplaceable role, but there are still many shortcomings in the actual process. In order to solve the existing problems in exploitation, various algorithmic models based on machine vision technology are still constantly being ameliorated and consummated, such as various technical methods for the inspection of wood surface defects that still have limitations in their scope of application (Li *et al.* 2021). The identification technology with stability, efficiency and a wide range of application is still the focus of future machine vision research in the field of furniture and wood products.

ALGORITHM BASED ON MACHINE VISION

With the application of machine vision technology, digital image technology is used to extract macro and micro structural features of wood and then to recognize and classify them. At present, in the foundation of establishing image database, the machine vision technology based on deep learning, such as the construction of deep convolutional neural network, has more distinguished advantages in image processing (Voulodimos *et al.* 2018).

Pre-processing

Machine vision technology acquires macro or micro structural images of wood in wood detection and recognition, and it uses digital image technology for wood feature extraction, so as to identify and classify it (He *et al.* 2021b). Pre-processing is an initial step in wood feature extraction, consisting of noise reduction and enhancement of images, etc. Pre-processing can reduce the computational complexity and effectively improve the image quality. Common pre-processing methods include mean filtering, median filtering, homomorphic filtering, wavelet transformation (Donoho 1995) and gray scale transformation (Sun *et al.* 2005). Advantages and shortcomings are shown in Table 1.

Table 1. Comparative Analysis of Preprocessing Algorithms

Method	Algorithm Usage	Advantages	Shortcomings
Mean Filtering	Gaussian noise reduction	Simple method, fast calculation speed, smooth processing of images, and high definition	Can only reduce noise and damage details
Median Filtering	Salt and pepper noise reduction	Fast data transmission, real-time and adaptive, and wide range of applications	Difficult to completely eliminate noise, easy to change the true value of pixels, loss of ' corner ' and other details
Homomorphic Filtering	Enhance image contrast	Simple principle, small calculation and wide application	Many parameters and parameter values are hard to control
Wavelet Transformation	Transient nonstationary signal	Good noise reduction performance, multi-resolution and energy concentration, high flexibility	Low speed and weak directivity
Gray Scale Transformation	Change pixel gray value to enhance image		

Mean filtering, median filtering, and other methods can efficiently eliminate image noise or artifacts caused by inevitable factors such as noise. As an example, Chen (2016) used median filtering to process the wood surface defects (worm eyes, live/dead knot), which remarkably improved the defect detection effect and proved the effectiveness of this class of denoising algorithm. New algorithmic models such as wavelet transform and bilateral filtering have been incrementally developed to meet the actual demand, so that the images can better retain details as well as authenticity (Wang *et al.* 2017). Gray scale transformation is a common technology of traditional machine learning (ML) model. It converts RGB color image to gray image, which reduces the calculation cost while enhancing the image. In addition, homomorphic filtering is frequently used in image correction of non-uniform illumination to effectively enhance the contrast of wood recognition (Chen *et al.* 2022). Abang *et al.* (2017) proposed an iterative image restoration technology-the Lucy-Richardson (LR) algorithm-which can be used to perform deconvolution to effectively eliminate blur for motion blurred images.

The process of image acquisition will be more or less affected by the equipment and environment, resulting in gray deviation, geometric deformation, inclusion noise, and other issues. Hence, the corresponding pre-processing of images from various sources can clean up and standardize the image data, reduce the data complexity, and enhance the processing accuracy of the algorithm technology while improving the image quality. In brief, pre-processing is essential for image processing of machine vision (Chen 2019).

Edge Detection and Image Segmentation

After preliminary preprocessing, it is necessary to detect the edge to obtain a clear edge contour, in order to facilitate subsequent image segmentation and feature extraction. The principle of edge detection is to detect and extract edges according to the difference of gray values of pixels on both sides of the image edge (Wu 2020). The commonly used edge detection methods are mainly on the basis of wavelet transform, morphology, deep learning and the Canny operator (Canny 1986) algorithms, which provide technical support for wood scientific detection. For instance, Hou and Wang (2011) used mathematical morphology and the Canny operator to process rotten wood images and extract features. The experiment showed that the algorithm has good anti-interference and edge detection accuracy, which can be effectively applied to feature extraction of corroded wood image. Yang (2015) proposed the wood image processing and edge detection based on Markov random field theory, which can significantly intensify wood image and improve edge detection effect, bringing more possibilities for the edge detection of images in the field of wood science.

Among them, corner points, as the maximum point of local curvature on the edge contour or the sharp change point in the contour direction (Teh and Chin 1989), are vital local features of the image. The existing algorithms for corner detection are mainly based on three types of corner detection algorithms: template (Smith and Brady 1997; Rosten *et al.* 2010), edge contour (Mokhtarian and Suomela 1998), and gray intensity change (Harris and Stephens 1988; Lowe 2004). Nevertheless, these algorithms also have their shortcomings, such as the fact that template-based and edge contour-based algorithms are sensitive to gray variation and noise (Zhang *et al.* 2012), which can easily lead to missed and false detection. Meanwhile, the intensity-based corner detection algorithm is vulnerable to interference from other proximity features. Hence, Wang *et al.* (2021a) proposed a corner point detection algorithm based on nonlinear directional derivative (NDD), which can effectively overcome the problem of inaccurate feature extraction and easy generation of pseudo corner points under mixed noise and improve the accuracy of corner detection.

Image segmentation is the foundation of digital image technology identification, separating the target from the background to facilitate subsequent identification and classification work. According to the principle and characteristics of image segmentation, the maximum between-cluster variance method (OTSU algorithm) (Otsu 1979), iterative threshold segmentation method (Perez and Gonzalez 1987), maximum entropy threshold segmentation (Pun 1981), and other threshold segmentation methods as well as algorithmic models such as C-V model (Chan and Vese 2001) and LBF model (Ojala *et al.* 2002) have been established.

Threshold segmentation is a segmentation technique to find the optimal threshold value, which can accurately recognize the target and has the advantages of convenient operation and superior stability performance. Xie and Chen (2014) used three thresholding algorithms (iterative thresholding, maximum entropy thresholding, and OTSU segmentation) to segment wood images, and the experiments showed that the OTSU algorithm had the finest segmentation results. The application effect of a single model is ultimately limited, and the OTSU algorithm has its boundedness, such as sensitivity to noise. The C-V model has high image stability but is computationally difficult and only applicable to images with uniform target gray values. To obtain preferable image processing results, it is often combined with other models to complement each other (Li *et al.* 2021). For example, Dai and Wu (2014) combined the OTSU algorithm with mathematical morphology to segment the image, avoiding the influence of noise on the image, making the image clearer and improving the detection accuracy.

Furthermore, Luo and Sun (2019) proposed an image binarization optimization algorithm based on local thresholding algorithm in order to solve the case of non-uniform background of wood images with high segmentation accuracy, which can effectively segment complex background images. Wang *et al.* (2022) and others put forward a fast fuzzy C-means algorithm for image segmentation in non-destructive testing, which significantly reduces the complexity of the algorithm. The effectiveness and robustness of the algorithm are proved to be relatively high, which provides more possibilities for fine segmentation of unbalanced images in the future.

Table 2. Comparative Analysis of Image Edge Detection and Segmentation Algorithms

Algorithmic Model	Advantages	Shortcomings
Canny Arithmetic	Strong anti-interference and accurate edge detection	Some edge data are easily lost
Otsu Algorithm	Simple algorithm, strong visibility and high accuracy	Easy to be affected by noise, difficult to distinguish between target and background, poor robustness
Iterative Thresholding Method	Simple algorithm, high efficiency and accuracy	Difficult to segment complex background image
Maximum Entropy Threshold Segmentation	High accuracy	Complex computation and limited application
Local Threshold Segmentation	Adaptive threshold adjustment for different regions and multi-target segmentation	Many limitations, slow segmentation speed, not up to real-time
C-V Model	Global optimization and high image stability	Computationally difficult to segment grayscale non-uniform images
LBF Model	High efficiency, can segment intensity inhomogeneity image	Weak edge segmentation is not very accurate

In general, the maximum inter-class variance method outperforms other threshold segmentation methods, which can effectively accurately locate the target, especially for wood image recognition where the difference between target and background grayscale is small and the texture features are not clear. However, there are also shortcomings, such as being susceptible to noise and difficult to separate the target and background from some wood defect images. Advantages and shortcomings of various algorithms for edge detection and image segmentation are summarized as shown in Table 2. Under the background of the rapid development of forest industry, the quantity of wood inspection and the information data brought by the improvement of image technology are becoming more and more enormous. Meanwhile, the requirements of industrial demand for image segmentation are becoming more and more sophisticated, which brings challenges to the speed and quality of image information data processed by traditional detection technologies such as edge segmentation and threshold segmentation, but also points out the direction for future technology improvement (Jia *et al.* 2015).

Feature Extraction

After completion of image segmentation, the process of converting it from high-dimensional to low-dimensional space is feature extraction, which has an essential impact on the subsequent image recognition and classification. It is usually divided into texture features, color features, geometric features, and other local features.

Texture features describe the grayscale distribution of the target region, expressing the surface properties and periodic variations of the corresponding object. The frequently-used texture feature methods include wavelet transform, GABOR filtering method (Gabor 1946), gray level co-occurrence matrix (GLCM) (Haralick *et al.* 1973), local binary picture (LBP) (Ojala *et al.* 1996), and other algorithm models. The GLCM model is a statistical method to determine textures by identifying the spatial relationships corresponding to image pixels, and it is abundant in feature parameters to provide a comprehensive portrayal of textures. Kobayashi *et al.* (2015, 2017, 2019) constructed the identification model of GLCM extracted from CT images and stereograms, which demonstrated that this method was promising for wood texture feature identification. However, owing to the high computational cost of this algorithm, Qin *et al.* (2005) proposed the basic gray level aura matrices (BGLAM) to reduce the computational cost and improve the identification performance. Zamri *et al.* (2016) implemented their feature dimensionality reduction and rotational invariance by using the improved BGLAM algorithm, and its classification performance far exceeded that of the GLCM model. The LBP model calculates texture by comparing the pixel values of the gray image center and the surrounding pixels, which has a higher feature vector dimension than GLCM. Besides, it can identify local patterns such as edges, planes and corner points. Thus, comprehensive performance of LBP model is superior to that of GLCM. Local phase quantization (LPQ) is outperforming LBP and GLCM on microscopic images.

Color features are insensitive to image orientation, dimension, *etc*. They are often applied as feature points to analyze images, and commonly used models include HSV (Smith 1978), RGB (Blackmer and Schepers 1996), *etc*. Geometric features are mainly based on the shape features and geometric invariant distance of the target region, and commonly used methods such as scale invariant feature transformation (SIFT) (Lowe 2004), Fourier descriptors (Zahn and Roskies 1972), *etc*.

Unlike texture feature, which is an overall image descriptor, local features are various types of different structural elements in the image such as points, corners, and edges, so the extraction of local features usually includes feature detection and feature description. The edge of an image is the place where the regional attributes mutate and contains a large amount of vital image information, thereby making edge features one of the most essential features for image targets and widely used in the field of machine vision detection (Li and Liu 2020). SIFT is a commonly used algorithm for local feature extraction, and its principle is to detect corners, edges, and other regions as the key points. Especially in the detection of wood cross-section cell corners, SIFT plays an extremely important role. Furthermore, based on the SIFT algorithm, Deng *et al.* (2020) used the speeded-up robust features (SURF) algorithm (Bay *et al.* 2006) to extract wood image features, and their experimental results showed an average recognition rate reaching 94%.

Identification and Classification

In the wood identification classifier based on machine vision, support vector machine (SVM) (Cortes and Vapnik 1995) and neural networks (NNs) are commonly used. SVM is a linear model algorithm that can clearly classify multidimensional spatial data points. Ma *et al.* (2017) used the SVM algorithm to identify wood samples on the basis of the KPCA method to reduce the dimensionality of wood samples. The experiments showed that SVM has high accuracy and minimal error when applied to wood identification.

The conventional neural network models include BP neural network (Rumelhart *et al.* 1986), RBF neural network (Rumelhart *et al.* 1988), and SOM (Kohonen 1990). The principle is to establish a mapping relationship between input data and output data. Wang (2007) combined wood texture features with gray level co-occurrence matrix and used BP neural network to classify them, where the results indicated an accuracy of up to 90.25%. Among these models, the artificial neural network (ANN) (Rosenblatt 1958), which imitates the learning process of biological brain, is the foundation of modern computer deep learning. It is capable of learning complex nonlinear relationships of wood characteristics, and has more advanced performance in wood identification, classification, and other applications. In short, new identification algorithm models emerge in endlessly, the recognition speed and accuracy of neural network remain at a high level (Ming 2019).

Machine Vision Recognition Technology Based on Deep Learning

In recent years, with the increase of computing power and image processor speed, Convolutional Neural Network (CNN) (LeCun *et al.* 1989), a deep learning model that can autonomously learn the features of sample data to analyze and solve problems (Voulodimos *et al.* 2018), has gained outstanding advantages in image detection and recognition. The CNN model has a multilayer network structure, where each layer automatically learns data features, and its results are input down layer by layer. Nowadays, deep convolution network technology is gradually applied to wood identification and positioning, such as RCNN network (Girshick *et al.* 2014), YOLO network (Redmon *et al.* 2016), and SSD network (Liu *et al.* 2016).

Peng *et al.* (2020) proposed a Faster R-CNN based defect detection method, utilizing ZF, VGG16 and ResNet101 as feature extraction models, and the results indicate that this method has special superiorities in wood recognition and detection. Fabijańska *et al.* (2021) suggested that the CNN algorithm model with residual connectivity has an outstanding advantage over other existing CNN architectures in testing tree species and wood core image data.

In summary, with the in-depth application of deep learning algorithms such as CNN in machine vision, the recognition capability is continuously upgraded by constructing deep convolution neural network. On the one hand, the image preprocessing is omitted, and the process tasks such as segmentation, feature extraction and classification are greatly simplified and the error is reduced, thus breaking the technical barriers of feature extraction in traditional machine vision (Bogucki *et al.* 2019). On the other hand, the essential features of the data set can be obtained by learning only a small amount of sample data, which provides a technical basis for automatic recognition and accurate extraction of wood. Futuristically, the establishment of a wide, accurate and reliable wood information database is an indispensable task for the application of machine vision in the field of forest industry, which provides a solid data foundation for machine vision technology based on deep learning (Figueroa-Mata *et al.* 2018; He *et al.* 2021; Hwang and Sugiyama 2021).

APPLICATION OF MACHINE VISION IN HOME RAW MATERIALS AND PRODUCTS MANUFACTURING

In the context of the development of the world's manufacturing industry "Industry 4.0", traditional industries such as wooden furniture are facing important opportunities and challenges. With the in-depth application of computer vision technology in the wood processing industry, many experts and scholars in China and abroad are committed to solving the problems existing in the development process and constantly improving it, so that the algorithm model of machine vision technology in all aspects of image acquisition, preprocessing, segmentation, feature extraction, recognition, and classification are becoming more perfect. It greatly promotes the intelligent process of furniture manufacturing, including a series of processes such as raw material identification and selection, plate sizing and grading, defect detection, color analysis, painting, and decoration.

Identification of Wood Species

The physical and chemical properties of different species (such as wood color, texture, odor, and mechanical properties, *etc*.) are varied. Choosing appropriate wood raw materials is the first step in the manufacture of wood products furniture, so it is necessary to identify and identify furniture panels. Wood anatomy is one of the most important methods for the identification of wood species. Traditional wood tree species identification and appraisal is that technical personnel or experts observe the color, annual ring, vessel openings, and other characteristics of the wood through microscopes and other equipment to determine the species of the wood. Obviously, this method requires extensive experience and a large reservoir of knowledge base (Yan *et al.* 2013). Whereas machine vision is used to learn autonomously about wood macro/micro features (*e.g*., pore distribution, vessel size, surface color, wood rays and annual rings), the quantitative analysis of these features by algorithms can rapidly achieve the automatic detection and identification of wood species (Hwang and Sugiyama 2021; Sözen and Bardak 2021), as shown in Fig. 4.

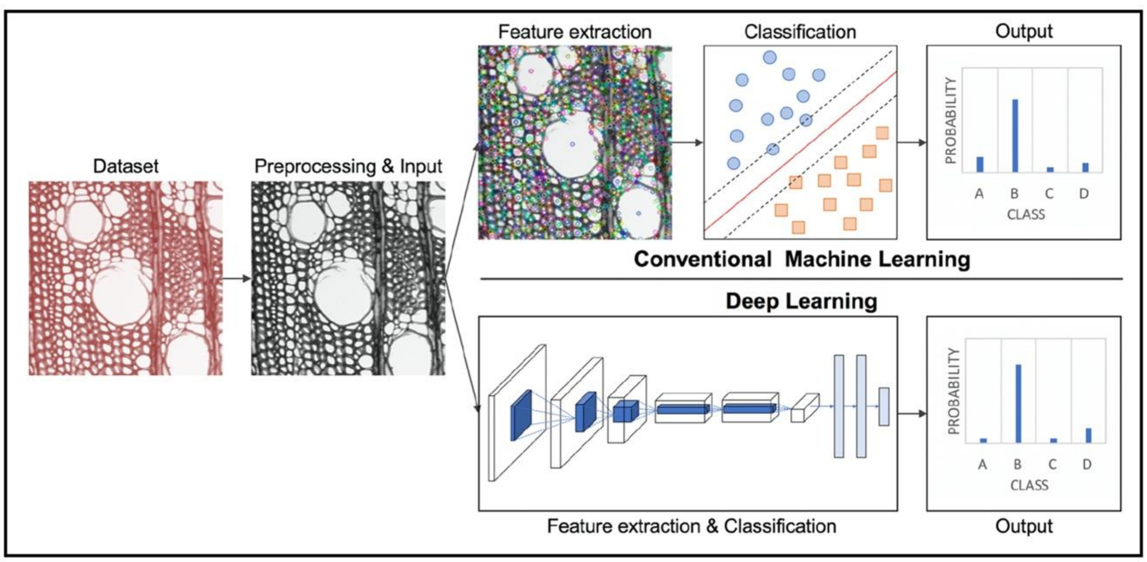

Fig. 4. Identification of wood species based on wood microstructure by machine vision (reprinted from Hwang and Sugiyama 2021 through Creative Commons Attribution 4.0 International License, https://creativecommons.org/licenses/by/4.0/)

Nowadays, wood anatomy based on machine vision is gradually emerging. Kobayashi *et al.* (2017) conducted principal component analysis (PCA) on GLCM features extracted from hardwood stereograms and found that some texture features have an obvious relationship with anatomical structures. In addition, k-means clustering analysis of local features extracted from microscope images showed the possibility of matching feature clusters with anatomical elements (Hwang *et al.* 2018). Lens *et al.* (2020) reported a very high success rate of wood identification with only 112 species of lateral wood profiles. Thus, it can be seen that the primary task of developing wood identification based on machine vision is to establish a large digital database. In the long run, global collaborative efforts in wood anatomy and computer science are an important foundation for the realization of open, cloud-based machine vision recognition and classification systems. At present, many experts and scholars in China and abroad have gradually begun this work. For example, Ravindran *et al.* (2018) constructed a data set of 2303 wood texture images of ten species of Meliaceae based on the wood specimens of the Forest Products Laboratory of the United States Department of Agriculture. He *et al.* (2020) constructed a total of 10237 wood structural images of 26 species of Dalbergia and Pterocarpus from 4 timber museums around the world. These high resolution and low noise images laid the foundation for the construction of deep learning models.

Hwang and Sugiyama (2021) reviewed the current application status of machine vision in wood science, especially in the field of wood anatomy, and summarized the workflow principles of CV-based wood recognition systems from image databases to traditional machine learning with deep learning. In conclusion, under the new ML model of artificial intelligence, the research of deep learning provides a technical basis for accurate wood identification. The in-depth application of machine vision will bring a huge innovation to the identification of wood species. The ability to use machine vision for rapid and accurate identification of wood species, free of subjective will and without excessive professional knowledge, which will drive the development of wood science in general and wood informatics in particular.

Log Scaling and Sawn Timber Classification

The surface quality of sawn timber plays a vital role in wood furniture, which is also an important structural material of wood structure buildings. It needs to be graded to ensure sufficient mechanical properties, and some developed countries in Europe and America have taken it as an important reference for the quality and value of wood products. The analysis and processing of log diameter, sharpness and sawdust size, defects, pitch position and other information of the original wood in the image by machine vision can quickly realize log scaling and sawn timber classification, which not only saves a lot of manpower and material resources, but also helps to increase the efficiency of furniture production (Kurdthongmee and Suwannarat 2019).

Yang *et al.* (2022) used a mask region convolutional neural network (Mask R-CNN) to segment various sizes of wood in dense stacking scenarios and used Open CV library to fit and count the segmentation mask map. The wood truth rate was as high as 97.89%, which had strong robustness and migration ability. It could be used for in-situ real-time inspection of dense wood, and raw wood could be used for inspection and segmentation without unloading and other scenarios. Thomas (2017) and Hu *et al.* (2019) quickly derive information on the position and size of the plate under the saw by studying the surface characteristics (defects, sizes, *etc.*) of sheet metal through computer classification method based on cutting simulation and ANN neural network, Res Net neural network architecture based on deep learning and transfer learning strategy, respectively, so that the plate can be rapidly sawn in real time. This method not only guarantees the accuracy and quality of the saw, but it also promotes more efficient processing of the sawn material for undercutting and grading. The average time for image classification by laptop with good performance of the latter is only 0.003 s, in which the convolutional neural network is used to replace the traditional image processing algorithm with migration learning, and the classifier efficiency is greatly improved. In the future, the online classification system based on deep learning strategy will be gradually established.

Bhandarkar *et al.* (2008) combined machine vision with computer tomography (CT) to construct an automated system for wood production optimization, using the geometric parameters of the defect profile as tracking variables, detecting, classifying, and locating the size, pith, and defects of logs in a Kalman filter feature tracking algorithm. This information is integrated into 3D modeling to realize automatic, efficient, and optimized production of plates by virtual sawing logs online in a virtual way. Therefore, it can be seen that the application of machine vision in log scaling and sawn timber grading will significantly improve the utilization rate of wood and effectively save forest resources, so as to provide powerful technical support for the realization of China's "carbon emission peaking" and "carbon emission neutrality" goal.

Defect Detection of Wood Products

The detection and location of defects is an important step in the automated production of furniture wood, as they greatly affect the quality grade, processing cost and furniture value. Comparatively speaking, machine vision is widely used in surface defect detection of furniture wood products. From different theoretical algorithm models to defect image segmentation methods and defect classification, machine vision has demonstrated unparalleled superiority over traditional methods, in reducing wood waste at the same time, to improve the quality of furniture products. (Funck *et al.* 2003; Kamal *et al.* 2017; Ding *et al.* 2020; Fan *et al.* 2020; Wang *et al.* 2021b).

Bai *et al.* (2016) used three improved algorithm models (the improved C-V model, the GVF Snake model and the GAC model) to segment the three typical defect images of wormhole, live and dead knots on the wood surface, comparing and analyzing the complexity of the algorithm, the segmentation time, the integrity of the segmentation results and the noise resistance. The results show that different models have different recognition and segmentation efficiency for specific defects, which lays a theoretical foundation for efficient classification of wood surface defects.

Guo *et al.* (2018a,b) used machine vision to conduct image segmentation and defect feature extraction of five typical defects on the surface of wood-based panels (oil pollution, large particle, rubber spots, debris, softness, *etc.*) (Fig. 5). An adaptive fast threshold segmentation algorithm was proposed to adaptively determine the number of segmentation thresholds. Even if the number and type of defects on the surface are not fixed, they are segmented within 15 ms, and the accuracy rate is as high as 97%. In defect extraction, the statistical characteristic parameters of gray level co-occurrence matrix are firstly used to characterize the gray image window, and then the BIRCH hierarchical clustering algorithm is used to cluster the set, so that the accuracy is as high as 92.2% and the recall rate is 91.8%, providing reliable theoretical and technical support for automatic on-line detection of surface defects of wood-based panels. Ren *et al.* (2017) used an automated surface inspection (ASI) method based on deep learning to classify and segment defect images. They achieved 0.0% error escape rate in the segmentation of industrial data set. The deep learning of wood surface defects by computer lays a foundation for realizing the real-time positioning of defects and the automation of size selection process in the future. He *et al.* (2020c) used deep convolution neural network (DCNN) to detect and automatically classify wood surface defects. Through training, learning, and testing of this algorithm, the accuracy of the detection system can reach 99.13%, and it can also maintain high detection efficiency. Thus, the universal application of machine vision in the detection and classification of wood products surface defects, will promote the intelligent transformation and upgrading of home furnishing enterprises, and accelerate the rapid development of enterprises to energy saving and consumption reduction, quality, and efficiency improvement direction.

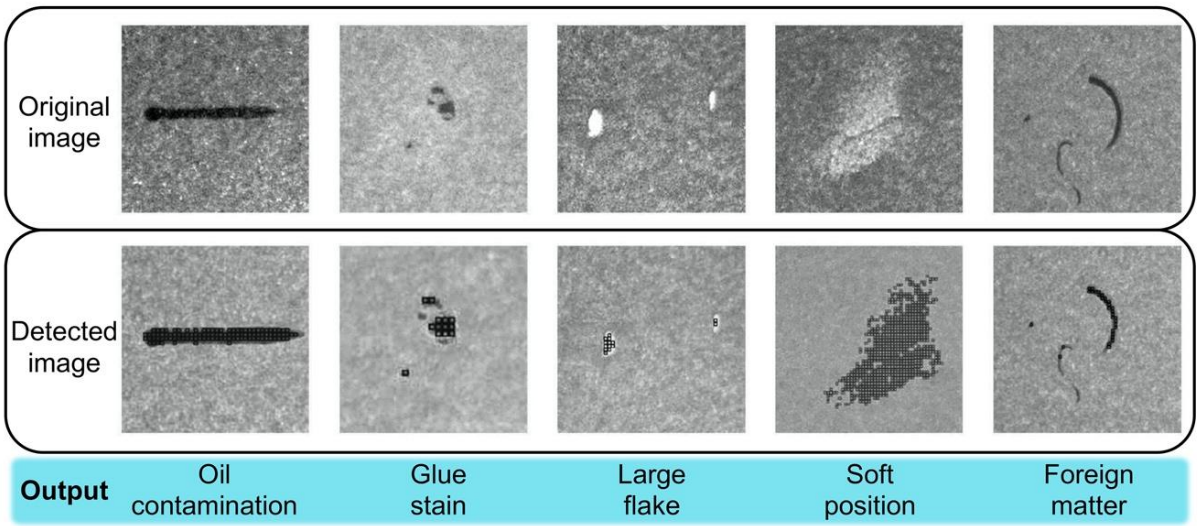

Fig. 5. Inspection of particleboard surface defects by machine vision (Guo *et al*. 2018a, b)

Surface Color Analysis of Wood Products

The utilization of machine vision to analyze and evaluate the surface color of furniture wood products can effectively avoid manual errors and contribute to the improvement of wood products grading efficiency and quality control, which further in turn promotes the artistic and cultural value of furniture and the growth of economic benefits of enterprises. (Zhuang *et al.* 2020). Among them, solid wood panels as an indispensable raw material for furniture and wood flooring industry, the introduction of machine vision technology and unsupervised learning methods to meet the customer's personalized interior home art effect, based on the effective promotion of solid wood furniture enterprises intelligent development. For example, Wang *et al.* (2021) established a new data set after preprocessing, selected the first-order color moment, the second-order color moment, and the peak value of color histogram to extract the feature vectors of nine color channels (R, G, B, L, a, b, H, S, and V) of the board image. They realized data dimension reduction. The feature vector set was divided into different clusters by K-means algorithm, and then the classification and sorting of solid wood surface color and texture were completed. This demonstrates the effectiveness of the color classification mechanism (image preprocessing, feature extraction, offline clustering and online classification) and the application value of the clustering algorithm in furniture wood color classification scene.

Li *et al.* (2016) designed a solid wood surface intelligent sorting system using machine vision to sort the surface color of oak wood. By calculating and analyzing the low order moment eigenvalues of the solid wood surface color, the accuracy of the system in classifying the surface color of solid wood can reach 100%. Based on machine vision technology, Wang *et al.* (2021c) carried out extreme learning machine ELM to classify the color of solid wood floor, and used three different algorithms, namely grey wolf optimization (GWO), genetic optimization (GA), and particle swarm optimization (PSO), to optimize and compare their recognition efficiency and accuracy, providing an effective solution for the online intelligent sorting of solid wood floor color in household enterprises. Liu *et al.* (2018) applied the machine vision to the automatic color sorting system of bamboo slice. Through the machine vision to analyze, process and extract the color characteristics of bamboo slices, and combined with the pattern recognition algorithm to design the sorting system, the rapid sorting of bamboo slices was finally achieved.

The surface color and texture of the board are important characteristic parameters. For furniture, it not only can intuitively reflect the surface characteristics, but it also can have a subtle influence on the psychological feelings of users. Therefore, the realization of color analysis and recognition, automatic classification and control of furniture board have dual values for enterprises and individuals.

Application of Machine Vision in Intelligent Manufacturing of Home Furniture Products

In addition to the above several common situations, the application of machine vision in the wood furniture industry is also applied in the fields of precision detection of furniture parts, measurement of bamboo dimensions, intelligent control of household products and automatic painting (Han and Bao 2016; Zhang and Zhao 2017; Shao *et al.* 2021).

As shown in Fig. 6a, machine vision can help users quickly find decoration products that are compatible with the current indoor environment by learning information such as indoor furnishings and furniture shape and size. Furthermore, the machine vision can even recommend colors, styles, and materials to meet the requirements of furniture to the users. In addition, the application of machine vision to furniture painting process not only can avoid the harm of paint to human body, but it also can control the quality of furniture painting and reduce the waste of paint through the precise and repeatable positioning of machine vision (Fig. 6b). Gandhi and Sangeetha (2018) proposed an intelligent numerical control machine tool processing algorithm based on machine vision for automatic painting of furniture manufacturing, so as to solve the operation limitation of traditional woodworking computer numerical control (CNC) machine. It can draw and spray furniture modules without manual interference, and further promote the automation technology innovation of the furniture industry.

Fig. 6. Applications of machine vision in furnishing products

SUMMARY AND FUTURE PROSPECTS

Machine vision has been widely applied in electronic devices, automotive manufacturing, food processing, and other fields. It has brought strong momentum to the national economic development. More significantly, it provides the impetus for China's steady progress toward the "Made in China 2025" manufacturing power. Although the application of machine vision in the field of forestry industry started relatively late, with the development and advance in model algorithms and robotics technology, machine vision is transforming the production, manufacturing and the way furnishing raw materials and their products are used. It endows machines with the ability to efficiently produce and manufacture the materials and products of furnishings, while the entire life cycle of wood-based products becomes cleaner, lower carbon and more environmentally friendly in consequence. More importantly, machine vision provides an opportunity for the development of online, real-time, accurate detection and control of the quality of furniture products, and it has been widely applied in the areas of defects detection, floor classification, *etc*. Moreover, it also brings infinite creation space for intelligent and humanized human-machine interaction design of wood-based products. Overall, the application of machine vision in the wood products in the future will mainly develop rapidly in four aspects: algorithm, technology, processing, and product interaction.

1. Wood-based products are intricate from material to components and then to finished products, and their material properties and product mix are perplexing. Machine vision can accomplish simple manufacturing tasks through common models. Nevertheless, with the improvement of processing accuracy and product structure requirements, the core algorithms of machine vision need to be improved iteratively. It is not only to improve the operation speed, but also to ensure visual accuracy and precision.
2. Combine machine vision with other advanced manufacturing technologies to establish efficient and complete wood processing and quality inspection system. For example, it is possible to improve the speed of thermal imaging of the detection system, so as to speed up the real-time online detection process of wood product defects and other features. Besides, machine vision can be combined with computed tomography technology for making a rapid three-dimensional modeling of the overall characteristics in wood products. The quality inspection and control of wood products are accomplished through online virtual operation, which improves the accuracy and efficiency of machine vision.
3. The furniture product processing industry is a labor-intensive industry. With the increase of labor cost and the growing improvement of machine vision technology, intelligent manufacturing equipment with machine vision as the core will be continuously introduced into the processing, assembly, packaging, quality testing and other processes of wood products, which will provide inexhaustible power for the intelligent, efficient, low-carbon and clean development of furnishing enterprises.
4. As China's aging problem deepens, the needs of the elderly in their daily living and other activities will become an essential social issue. The combination of machine vision and household products endows household products with certain intelligent responsiveness. The elderly can meet their needs through interactive activities with household products, so as to improve the quality of life of the elderly at home.

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