3D SURFACE DEFECTS RECOGNITION OF LUMBER AND STRAW-BASED PANELS BASED ON STRUCTURE LASER SENSOR SCANNING TECHNOLOGY
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基于结构激光传感器扫描技术的木材和秸秆人造板三维表面缺陷识别

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ABSTRACT
The surface defects, especially the insects holes and dents, seriously affect the quality and value of lumber and agri-crop straw-based panels. In this study, two kinds of surface defects, insects holes and dents, were selected as the object of system detection. A surface defect recognition system based on Gocator 3D (3 Dimensional) structure laser sensor was built. An image processing method based on deep learning was designed using HALCON. While the shape features (6-dimensional) and gray-scale texture features (7-dimensions) of the image are extracted, the principal components analysis method is used to reduce the dimensions of the eigenvector. The SVM (Support Vector Machine), GMM (Gaussian Mixture Model) and KNN (K-Nearest Neighbor) are used to classify and identify the defects on the surface of the lumber and agri-crop straw-based panels, and the final classification accuracy is up to 94.67%. The experimental results show that the system can quickly and accurately identify the insects holes and dents through intelligent algorithm. The research results show that the quality evaluation of agricultural and forestry products based on image processing technology is feasible. Structure laser sensor scanning technology can be used in 3D surface defects detect and recognition of lumber and straw-based panels.

摘要
木材和农作物秸秆人造板表面缺陷，特别是孔洞和凹痕，严重影响产品的质量和价值。在本文研究中，选择孔洞和凹痕这两种表面缺陷作为检测对象。建立了基于三维结构激光传感器的表面缺陷识别系统。使用 HALCON 设计了基于深度学习的图像处理算法。在提取图像的形状特征(6 维)和灰度纹理特征(7 维)的同时，使用主成分分析方法来减小特征向量的维数。应用 SVM，GMM 和 KNN 三种方法来进行木材和农作物秸秆人造板表面的缺陷的分类和识别, 最终分类精度高达 94.67％。实验结果表明，该系统能够通过智能算法快速准确地识别孔洞和凹痕。研究结果表明基于图像处理技术的农林产品质量评价是可行的。结构激光传感器扫描技术可用于木材和农作物秸秆人造板表面三维缺陷的检测和识别。

INTRODUCTION
The low quality of forest resources, deficiency amount, uneven distribution, inadequate utilization and poor management of the status quo for the forestry has brought great challenges. One of the keys to solve the above problems is to improve the level of lumber production and processing. Another one is the strategic shifting of raw material resources supply must he properly solved (*Zhou D., 2016*). Wood has been the major source of raw material particleboards and fibreboards, but recently, rice-wheat straw(RWS) has gained more attention of researchers to be used as an alternative of wood (*Muhammad Y., Abdul W., Aqeel A. et al. 2010; Qian X. 2010*). Efficient use of crop straw resources is an important indicator of a country's agricultural modernization level (*Ying C., 2015*). The utilization of rice straw for the production of high quality biocomposite products, will add economic value, help to reduce the environmental impact of waste disposal and, most importantly, provide a potentially inexpensive alternative to the existing commercial artificial wood - panels (*Altaf H., Houssni E., Vivian F., 2013; Wang H., Wang F., Sun R., 2016*). The detection of surface defects is an important way to improve the level of production and processing (*Liu J., Liang J., Liang X., et al., 2010*).

Lumber and wood-based panel surface defects have various kinds and varied shapes, generally divided into sections, insects holes, dents, cracks and discoloration. Traditional method of surface defect detection is mainly through human identification and screening. However, this method has the problems of low efficiency, low accuracy and high labor cost. With the development of science and technology, the agricultural and forestry manufacturing industry has begun to move toward industrial automation. Surface defects detection can be industrialized through machine vision and image processing. Machine vision is using the machine instead of the human eye to measure and determine *(Zhao P., Zhao Y., Chen G., 2017)*. At present, most of the machine vision systems are based on X-Y 2D (2 Dimensional) plane detection, mainly operating on grayscale of the target object. However, the traditional 2D inspection of machine vision could not meet the demand when information on the Z axis needs to be detected. 3D (3 Dimensional) structure laser sensor scanning technology based on Intelligent algorithm can automatically and accurately scan full range of target, in order to obtain the target's grayscale, height and other information through deep learning.

MATERIALS AND METHODS

Through the 3D structure laser sensor scanning technology to automatically and accurately scan the target image, which including grayscale, height and other information. The highly restored height map and grayscale images using otus method and dynamic threshold method for image segmentation. After extracting defects of the lumber shape and texture eigenvectors, three pattern recognition methods were used to classify the lumber surface defects.

Hardware platform

The system consists of Gocator 3D (3 Dimensional) smart sensor, Gocator data cable, I / O cable, HF150W-S-48 converter, host computer and DH-POL-PY300 experimental platform. System physical map is shown in the Figure 1. The Gocator 3D smart sensor is LMI company’s 3D megapixel sensor that combines a line scan camera with a laser emitter. The Gocator 3D smart sensor is manufactured on an industrial design basis, based on the harsh production demanding of the workshop. It has the advantages of high precision, stable performance, good real-time. Therefore, the Gocator 3D smart sensor is suitable for non-contact online real-time detection. The system uses a Gocator2330. Laser Emitter emits structured light for laser molding. Camera observes laser reflected on the target surface, I/O (Input / Out) put Connector accepts incoming and outgoing digital signals, Power / LAN (Local Area Network) Connector turns on power and laser safety signals, and connects to Gigabit Ethernet *(Thies M., Pfeifer N., Winterhalder D., et al., 2004)*. In addition Gocator also includes Camera measurement status indicator, laser status indicator and power status indicator. The principle of Gocator2330 collection of target height data is the triangulation method. The intervals of laser line direction (X axis) and height (Z axis) are calibrated at the factory shipment, and the motion acquisition direction (Y axis) needs to be adjusted to correspond to the actual physical distance. Sensor movement acquisition has two ways: First, the time interval motion acquisition; Second, the encoder motion acquisition, the pulse trigger acquisition. The system uses the encoder motion acquisition, because in the acquisition frequency the acquisition effect will not be distorted for movement speed.

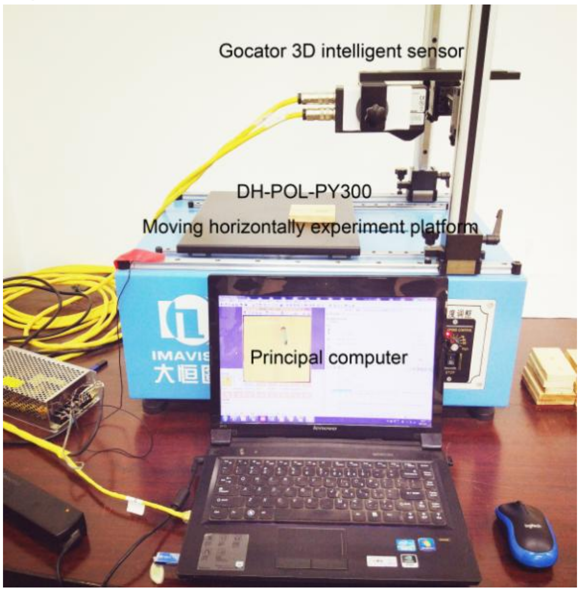


Fig. 1 - Hardware platform physical map

The essence of Gocator2330 is a line scan camera which needs to cooperate with the sports platform to achieve the purpose of acquiring the height information of the target object. DH-POL-PY300 experimental platform includes a rotary encoder to capture images with the Gocator2330. When the target object on the DH-POL-PY300's translation platform starts to reciprocate, the built-in rotary encoder sends a pulse signal synchronized with the platform motion to the Gocator2330. Gocator2330 emits laser beams at the same time capturing imagery multiple messages.

Image acquisition and segmentation

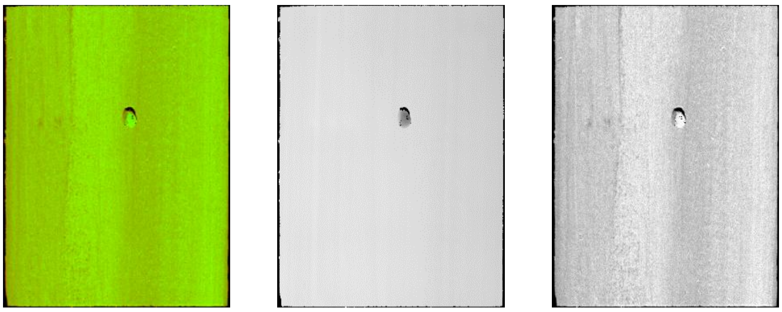
Gocator2330 provides GenTL driver interface, allowing external software to directly control the Gocator2330 to capture the target's 3D point cloud data and grayscale data for processing. The system uses HALCON image processing. HALCON is a software with a widely used machine vision integrated development environment. HALCON provides interfaces to a wide variety of image-captured devices to ensure hardware independence. The system sets GenTL driver to output RGB images of sixteen and input to HALCON for processing, simultaneously sets the acquisition mode for asynchronous loop acquisition. The programming statement of HALCON connecting Gocator2330 and capturing the image is:

```
open_framegrabber ('GenICamTL', 0,0,0,0,0,0,0 'progressive', 16, 'rgb', -1, 'false', 'default', '192.168.1.10', 0, -1, AcqHandle)
grab_image_start (AcqHandle, -1)
grab_image_async (Image, AcqHandle, -1)
```

Among them, 'GenICamTL' represents the name of the 3D sensor, 'rgb' represents a color image, and '192.168.1.99' represents a camera IP address. In the Gocator2330 collected sixteen RGB images, R, G, B three channels were saved image height information, grayscale information and parameters. The image is split using Go2GenTL_ParseData (Image1, HeightMap, Intensity, frameCount, timestamp, encoderPosition, encoderIndex, inputs, xOffset, xResolution, yOffset, yResolution, zOffset, zResolution, width, height, hasIntensity) operators to get the grayscale and height map. HeightMap represents the height map, Intensity represents the grayscale, zOffset represents the Z-axis offset, and zResolution represents the Z-axis resolution. Image split effect is depicted in the Figure 2.

Make use of stretching transformation on the slip height map to obtain the actual height value of the sample. Formula (1) was used to stretch and transform height map.

$$H^{\wedge'} = H^{*} zResolution + zOffset \tag{1}$$

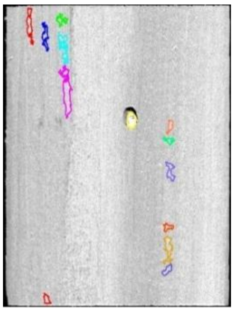


(a). Hole map *(b). Height map* *(c). Grayscale map*

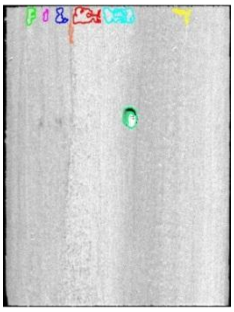
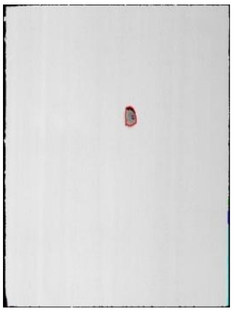
(d). Dent map *(e). Height map* *(f). Grayscale map*

Fig. 2 - Sample image split map

The highly restored height map and grayscale images using otus method and dynamic threshold method for image segmentation, segmentation results are shown in the Figure 3. It can be seen from the comparison chart of the two groups in the Figure 3. That there is no over-segmentation based on the segmentation of the height map of the sample, and the segmentation of the defect obtained by the dynamic threshold method is complete. The image segmentation part of the research is divided into three steps: The height of the image is highly stretched and transformed; Processing the height map to obtain the defect area through the dynamic threshold method; the defect area is superimposed on the grayscale, so as to obtain texture features of defective area.




(a). Otsu segmentation grayscale *(b). Otsu segmentation height map*

(c). Dynamic threshold segmentation grayscale (d). Dynamic threshold segmentation height map

Fig. 3 - Segmentation effect comparison chart

Part of the system's image acquisition and segmentation are shown in the Figure 4.

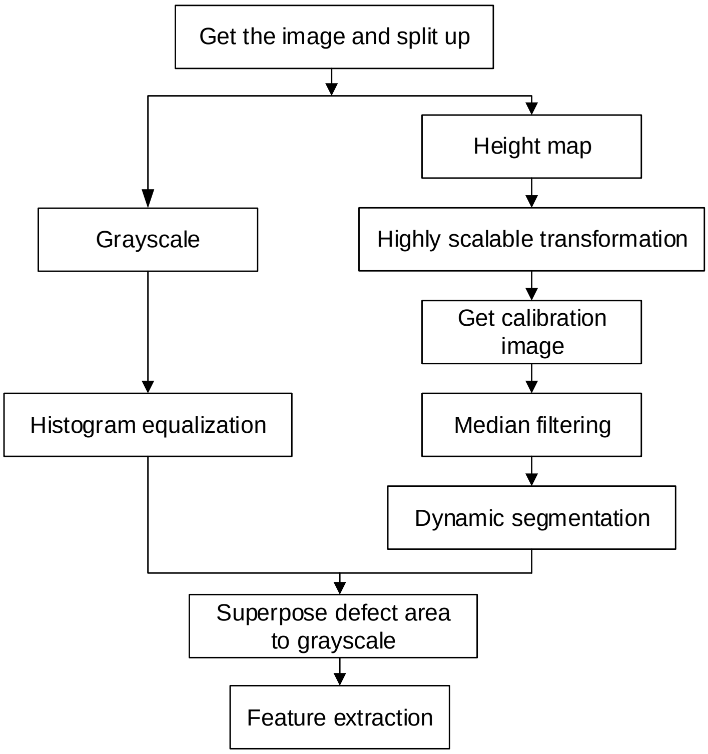


Fig. 4 - Image processing flow chart

RESULTS

Feature extraction

Before recognizing defects, the key step of lumber surface defect recognition system is to recognize and extract the defect eigenvectors. Good eigenvectors should have four characteristics: Reliability: The characteristics of the same category should be as similar as possible; Divisibility: There should be significant differences between features of different categories, and the greater differences, the better. Independence: Eigenvalues should be unrelated to each other and should not interfere with each other. Especially when two eigenvalues are the same, they are not suitable for simultaneous use. Small quantity: In principle the higher the amount of features, the better the recognition and classification, but at the same time it will increase the recognition complexity of the image and the computational complexity of the algorithm and reduce the efficiency and effect of image recognition *(Jiang Q., Liu H., 2004)*.

The system selected a total of six defects of the lumber shape eigenvectors and seven texture eigenvectors. Shape eigenvectors are: circumference, area, circularity, Rectangularity, tightness, eccentricity. The texture eigenvectors are the mean gray-scale value, the variance of gray-scale value and five characteristic parameters selected from the gray-level co-occurrence matrix, which are: Energy, Contrast, Correlation, Entropy, Inverse difference moment *(Bai X., Zou L., 2007)*.

The above thirteen kinds of eigenvectors reflect the differences in the geometric shapes and texture features of the defective areas. Eigenvector information extracted from different defects, such as dents and insects holes, is shown in the Table 1 and Table 2. Because of the high dimension of the eigenvector, the classification speed of the classifier will be slowed down, so it needs to be dimensionally reduced. There are some common feature selection methods: Principal Component Analysis (PCA) (Principal Component Analysis), Linear Discriminant Analysis (LDA) (Linear Discriminant Analysis) and Independent Component Analysis (ICA) (Independent Component Analysis). Because PCA (Principal Component Analysis) has the advantages of simple and no parameter limitation, the system uses PCA (Principal Component Analysis) method to reduce the dimension of the original eigenvectors, and pick out the effective features from it to establish the eigenvector of lumber surface defect recognition *(Zhang X., Zhang C., 2016)*.

Table 1

Eigenvectors of The shape features

Type	Number	Perimeter	Area	Circularity	Rectangularity	Tightness	Eccentricity
Dents	1	473	10675	0.6104	0.7436	1.6379	0.3985
	2	461	14487	0.8621	0.8139	1.1603	1.8275
	3	903	28254	0.4392	0.7573	2.2773	0.9827
Insects holes	1	582	7276	0.1341	0.8538	3.7096	8.4058
	2	789	34779	0.3935	0.8145	2.4438	6.6044
	3	257	2312	0.4127	0.8163	2.2764	3.7724

Table 2

Eigenvectors of the texture features

Type	Number	The mean gray-scale value	the variance of gray-scale value	Energy	Contrast	Inverse different moment	Entropy	Correlation
Dents	1	91.25	37.16	50391	339.207	0.089	12.283	0.00074
	2	121.37	26.34	153125	235.408	0.137	11.780	0.00092
	3	105.63	32.41	5486	700.953	0.059	11.250	0.00067
Insects hole	1	107.55	63.81	249656	268.842	0.312	6.4538	0.00086
	2	110.56	90.57	618996	257.502	0.110	12.018	0.00141
	3	132.39	58.35	320679	272.290	0.103	12.464	0.00095

Principal Component Analysis (PCA) (Principal Component Analysis) is a mathematical analysis method that can transform original data into a set of linearly independent data in every dimension through mathematical transformation. PCA (Principal Component Analysis) can extract the main features of the data to achieve the purpose of data dimension reduction, the essence of which is the optimal orthogonal transform (K-L transform) *(Zhang Y., Zhao Y., Liu Y., et al., 2016)*. The principle of PCA is as follows:

Assuming that the initial eigenvector are $x_1, x_2, ..., x_p$, the linearly independent vector after dimensionality reduction of PCA are $z_1, z_2, \cdots, z_m (m < p)$, the relationship between the two can be expressed as formula (2).

$$\begin{cases} z_1 = l_{11}x_1 + l_{12}x_2 + \cdots + l_{1p}x_p \\ z_2 = l_{21}x_1 + l_{22}x_2 + \cdots + l_{2p}x_p \\ \vdots \\ z_m = l_{m1}x_1 + l_{m2}x_2 + \cdots + l_{mp}x_p \end{cases} \tag{2}$$

In the formula, $z_1, z_2, \cdots, z_m$ which are called the principal components are the linear combination of $x_1, x_2, \cdots, x_p$ called the initial eigenvectors, $l_{11}, l_{12}, \cdots, l_{mp}$ are called the correlation coefficient matrix, which reflects the linear relationship between the principal components and the initial eigenvectors. The dimension of the eigenvector is reduced from the P dimension to the m dimension through the correlation coefficient matrix. Because of the different dimensions and orders of magnitude of the eigenvectors selected by this system, the system first normalizes the eigenvectors by Gauss method and then reduces the dimension. The initial thirteen-dimensional eigenvector is dimensionally reduced by PCA to obtain a nine-dimensional eigenvector.

Defect recognition

After obtaining a sufficient number of lumber samples and extracting the corresponding eigenvectors of the defects, three pattern recognition methods were used to classify the lumber surface defects. The three methods are SVM (Support Vector Machine), GMM (Gaussian Mixture Model) and KNN (K-Nearest Neighbor) respectively. SVM (Support Vector Machine) is a support vector machine (SVM) (Support Vector Machine), which is a learning algorithm that can transform low-dimensional linear inseparable samples through kernel function transform into high-dimensional space making these samples linearly separable. SVM (Support Vector Machine) is a supervised learning model whose classification effect is superior to the traditional method of pattern recognition in small sample. It is based on the theory of structural risk minimization, which builds the optimal hyperplane in high-dimensional space and makes the global optimization of machine learning *(Jia L., Achuan W., Xinran M., 2014)*. GMM (Gaussian Mixture Model) is a Gaussian mixture model, through establishing the estimation model of the sample probability density distribution (the estimation model is generally a weighted sum of several Gaussian models, each of which represents a class), the sample data are respectively projected on these models, so as to select the type having the largest probability of various types as a result of the decision *(Abolghasemi V., Ahmadyfard A., 2009)*. KNN (K-Nearest Neighbor) algorithm is also called K-nearest neighbor classification algorithm, which can achieve classification by measuring the distance between eigenvectors. The advantage of KNN (K-Nearest Neighbor) is easy to implement, no parameter estimation and suitable for incremental learning. The disadvantage is that once a sample size of a certain type of defect is too large, the sample easily lead to the new input type are misclassified *(Akbari A., Fard A., Chegini A., 2006)*.

A total of 200 lumber images are contained in the sample database of the system, 50 samples are selected as training samples and the remaining 100 samples are used as test samples. After extracting the corresponding eigenvectors of the defects of samples, three pattern recognition methods, SVM (Support Vector Machine), GMM (Gaussian Mixture Model) and KNN (K-Nearest Neighbor), were used to classify experiment of the surface defects.

The algorithm time of SVM (Support Vector Machine) classification under different kernel functions is basically the same, but the highest recognition accuracy was used the kernel function Gaussian radial base.

The recognition accuracy, using GMM (Gaussian Mixture Model) classification under different covariance matrices and KNN (K-Nearest Neighbor) classification at different K values, were not so good, and which need more time. The classification accuracy of the three recognition methods shown in the Tables 3, 4 and 5.

Table 3

SVM (Support Vector Machine) classification under different kernel functions

Kernel function	Recognition accuracy	Algorithm time(ms)
Polynomial	86%	265
Gaussian radial base	94%	256
Sigmoid	92%	243

Table 4

GMM (Gaussian Mixture Model) classification under different covariance matrices

Covariance matrix	Recognition accuracy	Algorithm time(ms)
Spherical	84%	323
Diag	80%	317
Full	88%	295

Table 5

KNN (K-Nearest Neighbor) classification at different K values

K value	Recognition accuracy	Algorithm time (ms)
1	84%	134
3	82%	207
5	88%	288
7	86%	385

From the Table 3, the comparison of the average recognition rate shows that the SVM (Support Vector Machine) classifier based on Gaussian radial basis function has the highest classification accuracy of 94%.

CONCLUSION

In this study, a hardware system of grayscale and height image acquisition based on Gocator 3D structure laser sensor was set up, and a series of image processing algorithms based on HAICON were designed, such as image resolution, height recovery, segmentation and recognition. Through the experimental test of dents and insects holes of the sample, the feasibility of the scheme is verified. After comparing the experimental data of table three, table four, and table five, the SVM classification algorithm based on the Gauss radial basis function is selected to classify the experimental samples. The recognition accuracy of the SVM (Support Vector Machine) classification algorithm based on the Gauss radial basis function is the highest among the ten classification algorithms adopted by this experiment, but its recognition rate is relatively slow. The following research should improve the recognition rate as far as possible while keeping the recognition accuracy unchanged.

The experimental results show that the wood image acquisition system based on 3D structure and the Halcon based wood defect classification and recognition algorithm based on this study can accurately and quickly identify the wormholes and indentations on the wood surface. Therefore, this study can be used to detect the surface defects in the agricultural and forestry processing industry, so as to improve the level of production and processing, improve the utilization of resources, and make the relevant processing industry move towards industrial automation.

The experimental comparison shows that this system can precisely segment the impact dents and insects holes on the surface and recognize them accurately with a recognition rate of 94%. The results show that the Gocator 3D structured laser based surface defect recognition system has good feasibility and high precision, and which may be used for the quality evaluation of agricultural and forestry products, such as straw-based panels, potato, lumber and veneer.

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