IMAGE EVALUATION METHOD FOR ROTARY TILLAGE OPERATION QUALITY
/
面向旋耕作业质量的图像评价方法

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ABSTRACT
In the scene of paddy field rotary tillage, a real-time detection method of rotary tillage condition based on machine vision is proposed, and the quality of rotary tillage is evaluated by the index of residual stubble. The residual root stubble is selected as the research object, and the root stubble detection method based on the standard deviation of Y component in YCrCb space is proposed to determine the residual root stubble of soil after rotary tillage, which is divided into three levels: less root stubble, medium root stubble, and more root stubble. Finally, the accuracy of the algorithm is verified by field test and questionnaire survey. On the basis of manual evaluation, the accuracy rate of the working condition is 83.6 %, which provides a more accurate basis for the real-time adjustment of the control strategy for the unmanned operation of agricultural machinery in the field, and realizes the rotary tillage quality from qualitative evaluation to quantitative evaluation, and lays the foundation for the data of rotary tillage quality.

摘要
在面向水田旋耕作业场景中，提出基于机器视觉的旋耕工况实时检测方法，以残余根茬量的指标来评价旋耕质量。选取残余根茬量为研究对象，提出基于 YCrCb 空间 Y 分量的标准差的根茬量检测方法来判断旋耕后土壤的残余根茬量，分为三个等级：根茬量较少、根茬量中等、根茬量较多；最终以现场试验和问卷调查的形式验证算法的准确性。在人工评判的基础上，该工况的准确率为 83.6%，这对大田农机无人化作业的控制策略的实时调整提供较为准确的依据，实现对旋耕质量从定性评价到定量评价的转换，为旋耕质量数据化奠定基础。

INTRODUCTION
In the traditional rotary tillage operation mode, manual observation of the quality of rotary tillage operation is time-consuming and labor-intensive, and there is a certain degree of subjectivity. Therefore, the automatic operation of paddy field agricultural machinery needs to have the function of automatic inspection of the operation quality of rotary tillage operation conditions. Scholars have studied the effects of different soils on crops *(Huifeng Wang et al., 2019; Yong Liu et al., 2016; Giulia Bondiet al., 2018; Bruno Vizioli et al., 2021)*, and there are different studies from the planting stage to the harvesting stage *(Guilherme Adalberto Castioni et al., 2018; Rituparna Saikia et al., 2020; Lotfollah Abdollahi et al., 2015)*. From a qualitative point of view, scholars first proposed the concept of soil surface roughness *(Gerard Govers et al., 2000)*, and then proposed a soil surface roughness index based on the standard deviation of the sampling height measurement describing the vertical component of the roughness *(Bertuzzi, P. et al.,1990; Chi-hua Huang et al.,1992; Grant, C.D. et al.,1992)*. From the perspective of quantitative analysis, scholars improve the measurement quality by using high-precision instruments and technologies, such as using laser sensors to scan the contour of the soil surface *(Yi Qiu et al., 2020; Daniele Pochi et al., 2010)* and using unmanned aerial vehicles to carry cameras and imaging technology to evaluate the quality of cultivation *(Roberto Fanigliulo et al., 2020; Naveed Anwar et al., 2018)*. If the simulation experiment is only conducted in the laboratory, very good results will be obtained whether using laser sensors or cameras. However, in the field operation environment, there are many uncertainties, so the quantitative analysis of rotary tillage quality is more challenging *(Cezary Kaźmierowski et al., 2015)*.

The purpose of this paper is to evaluate the working conditions of rotary tillage in paddy field. By selecting the perception of working conditions of residual stubble as the research object, the automatic detection algorithm of residual stubble of rotary tillage is studied.

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MATERIAL AND METHODS

Experimental equipment

In this experiment, a Kubota M854k tractor with a speed of 2 m/s and a rated power of 85 horsepower is used, and a rotary tiller with a working width of 2.2 m on the rear suspension. On the tractor, Advantech's MIC-7700 industrial computer and Intel Real Sense D435i depth camera are independently built. The camera parameters are shown in Table 1. The camera collects color images and depth images in real time, and the obtained image data is transmitted to the industrial computer; the industrial computer runs a homemade software system to analyze the image data. The specific installation method is shown in Figure 1. The industrial computer is installed under the tractor seat. The camera is installed above the rear of the tractor with a height of 2.45 m, and its optical axis is installed at 35°with the ground, as shown in Figure 2, where AB is the ground, AC is the distance from the camera axis to the ground, BC is the camera installation height of 2.35 m, the angle between AC and AB is the angle between the camera axis and the ground is 35°.

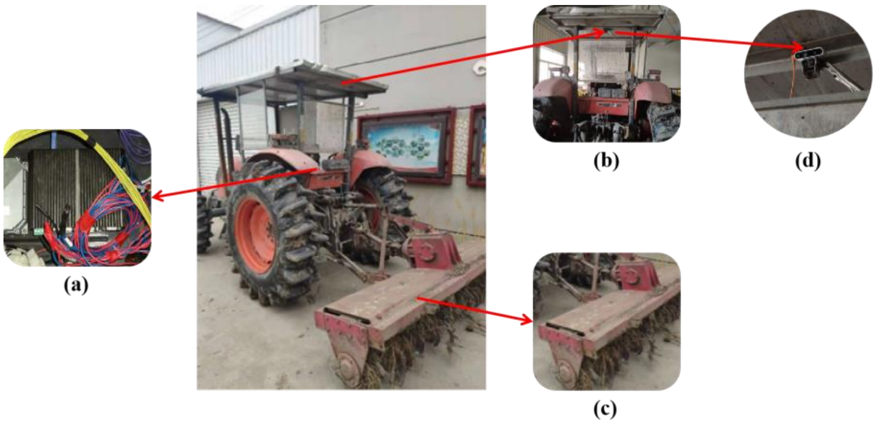


Fig. 1 - Tractor for experiment

(a) Industrial computer; (b) Camera installation location; (c) Rotary tiller; (d) Camera installation location;

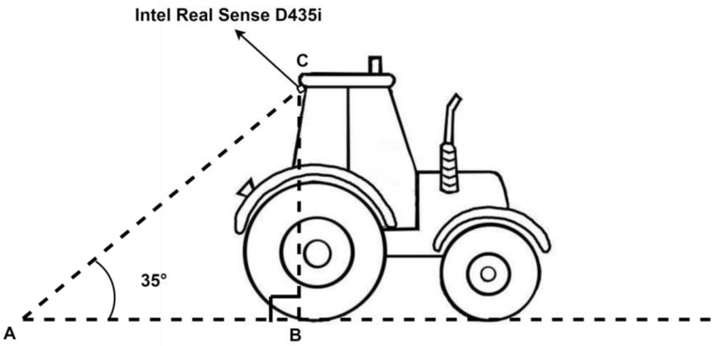


Fig. 2 - The camera is installed on the tractor.

Table 1

Camera parameters

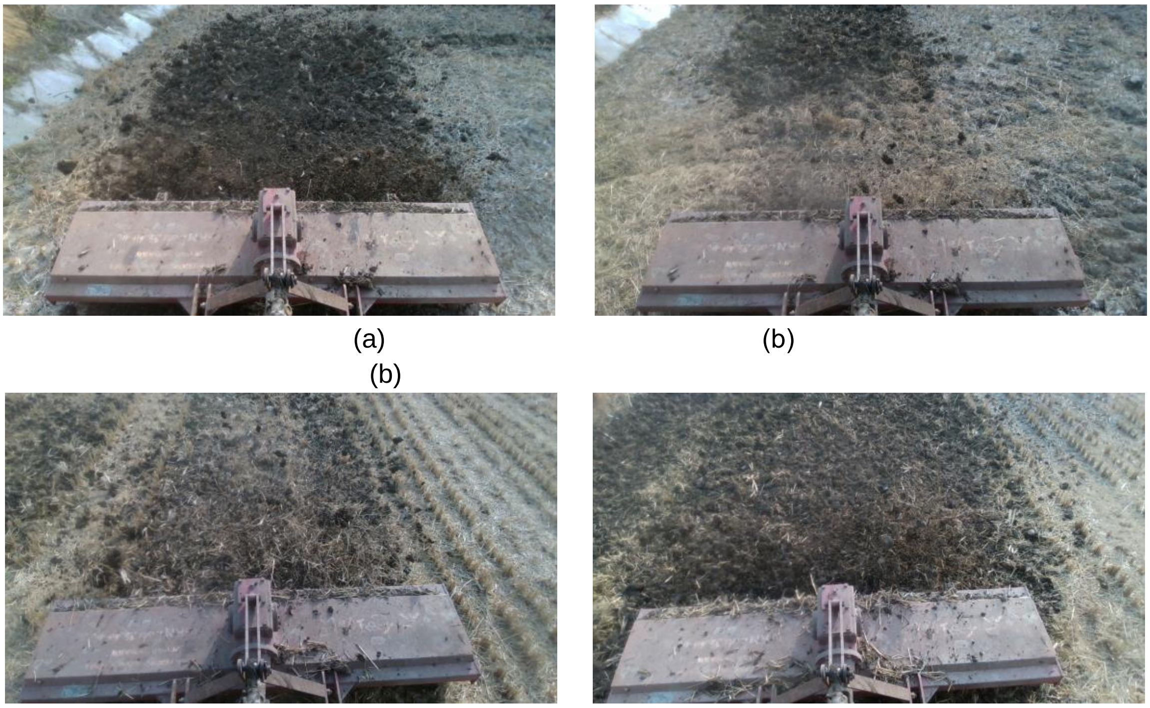
The camera specifications	Parameter index
Use environment	Indoor and outdoor
Depth detection range (m)	0.2 m - 10 m
Color camera resolution (frames)	1920 * 1080 / 90 fps
Depth camera resolution (frames)	1280 * 720 / 30 fps
Shape size (length * width * height)	90 mm * 25 mm * 25 mm

Test scenarios and data collection

This test site is in Changshu Guli town, Wuqiu village, at national modern agriculture (rice and wheat) demonstration base, as shown in Figure 3. The tractor is performing rotary tillage.

A total of 14732 images of normal operation, good quality, uneven tillage depth, and different residual stubble are collected for the operation scene of rotary tillage after rice harvest. The images are divided into different operation conditions for analysis. The image acquisition frequency is 10 frames per second, and the size is 1280 * 720 pixels. As shown in Figure 4, the depth map of the corresponding image is retained for the detection of the depth information of the rotary tiller.

Fig. 3 - Rotary tillage scene



(a) (b)

(b)

(c) (d)

Fig. 4 - Images of different rotary tillage operations

(a) Good quality; (b) More root stubble; (c) Medium root stubble; (d) Less root stubble

Detection of rotary tillage residual stubble based on image understanding

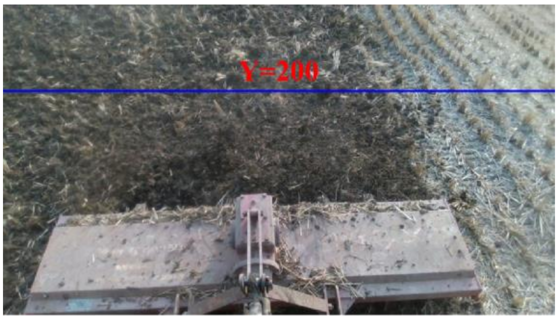
- ROI selection

Figure 5 shows that the upper part of the image is mainly land completed by rotary tillage, and the lower part is mainly the rotary tillage machine. The selection of region of interest (ROI) needs to exclude the rotary tiller part and retain the stubble part of the soil after rotary tillage. In the process of tractor operation, the rotary tiller may oscillate slightly, so the rotary tillage area cannot be accurately determined by the position of rotary tillage machine. It can be seen from the analysis of the rotary tillage image that the position of the newly-cultivated area in the image is basically in the trapezoidal part near the upper end of the image, so the 400 * 400 pixels area in the middle of the top of the original image can be used as ROI.

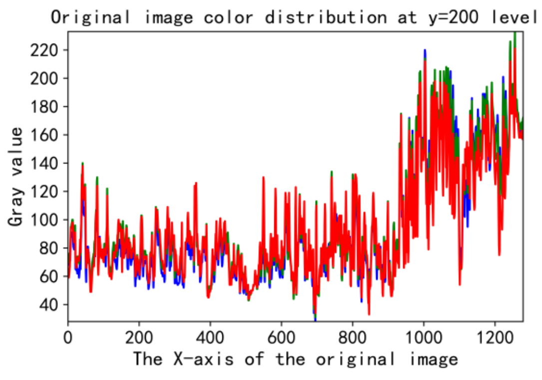
Fig. 5 - ROI region diagram of rotary tillage image

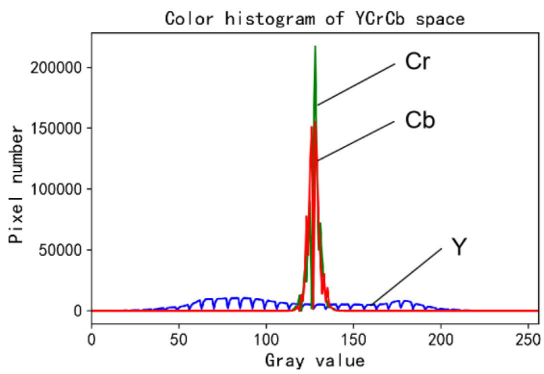
- Image analysis of rotary tillage based on YCrCb color space

The typical image of rotary tillage working condition is shown in Figure 6(a). The left area is the cultivated land, and the right area is the uncultivated land (full of stubble). The horizontal line y = 200 (satisfying the condition of color difference) is extracted from the original image (taking the right upper corner of the image as the coordinate origin, the transverse x axis and the longitudinal y axis), and the line profile method is used to analyze the RGB values of all pixels on the horizontal line. The histogram of the color distribution of the line section is shown in Figure 6(b), and the values of the three components are close in both cultivated and uncultivated areas, so the RGB color space is not applicable. However, there are great differences in brightness characteristics, and the color space separated by brightness and color can be used. As shown in Figure 6(c), the brightness component Y has a wide distribution and approximate bimodal characteristics, which is conducive to the threshold segmentation of different semantic regions. Therefore, the Y component in YCrCb space is suitable for the study of the difference between soil and root stubble characteristics.



(a)





(b) (c)

Fig. 6 - Typical images of rotary tillage and their horizontal distribution histograms

(a) Original image; (b) The original map in the y = 200 horizontal line color distribution (red, green and blue three color curves respectively represent the value of R, G, B three components); (c) YCrCb color space color histogram

Taking the image of rotary tillage after harvesting in machine-transplanted paddy field as the research object, 40 rotary tillage images with less residual stubble, medium number of stubble and more stubble judged by human eyes are selected respectively. Mean m and standard deviation σ are used to describe the characteristics of the image at this time, as shown in Equation 1 and Equation 2. The mean and standard deviation of ROI in Y-component gray image are analyzed, and the statistical results are shown in Table 2.

$$m = \sum_{i=0}^{N-1} K_i \, P(K_i) \tag{1}$$

$$\sigma = \sqrt{\sigma^2} = \sum_{i=0}^{N-1} (K_i - m)^2 \, P(K_i) \tag{2}$$

where:

Ki -- a possible gray value in the image

P(Ki) -- the frequency of the gray value in the image

N -- the number of possible gray values

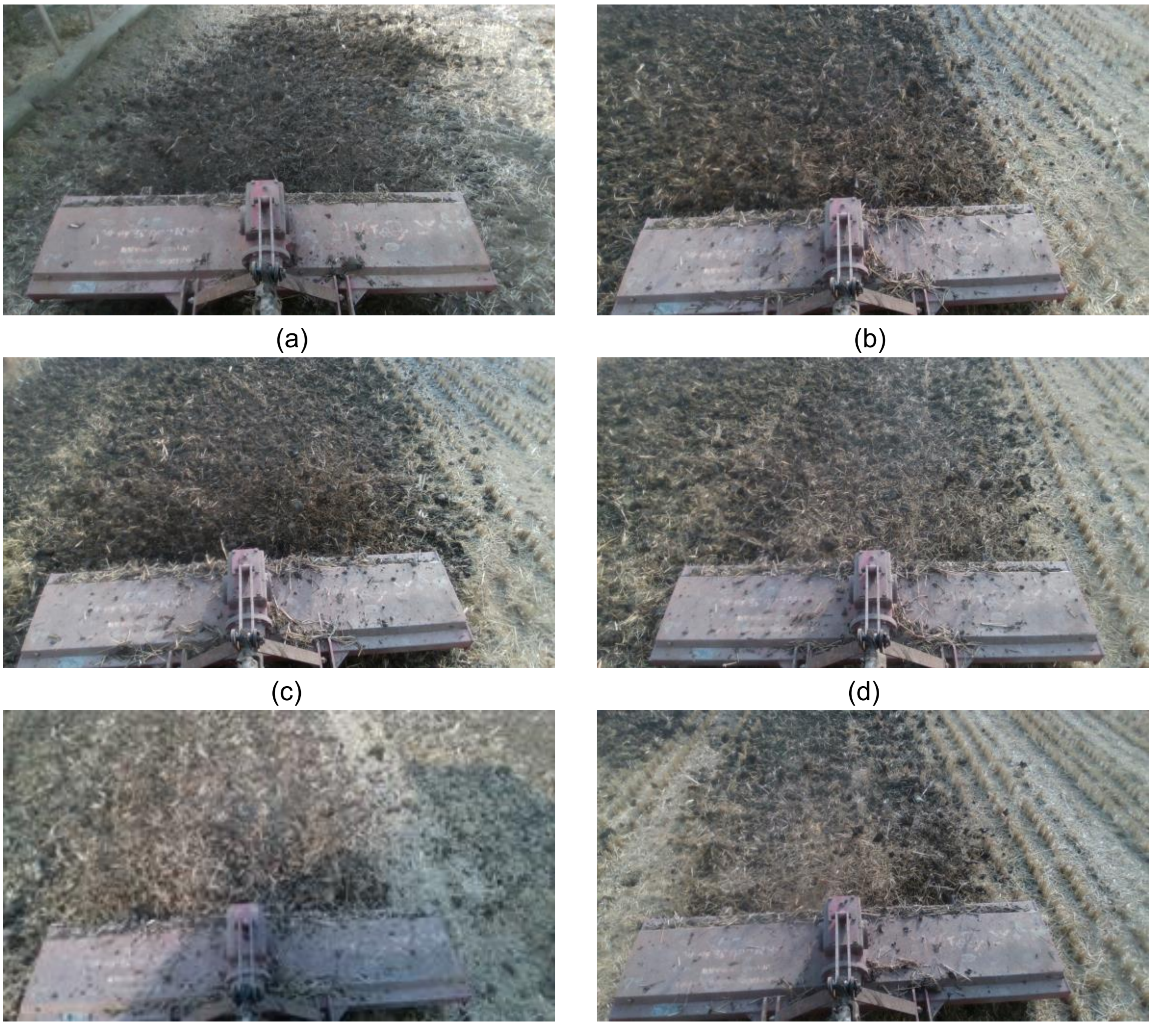
m -- the mean value in Equation (1).

Table 2

Statistical parameter distribution

Type of parameters	Less root stubble	Medium root stubble	More root stubble
Mean value	62.06	86.10	85.33
Standard deviation	16.36	27.44	34.07

According to the Table 2, soil and stubble have significant differences in the value of Y component. It can be seen from Figure 7 that the greater the standard difference, there is more stubble. Therefore, a root stubble detection method based on the standard deviation of Y component in YCrCb space is proposed for real-time detection of rotary tillage residual root stubble. Through the standard deviation data in Table 2, the residual stubble of rotary tillage can be divided into three grades, less, medium and more, as shown in Table 3.



(a) (b) (c) (d) (e) (f)

Fig. 7 - Typical pictures and standard deviation of different stubble after tillage

(a) σ = 16.486. (b) σ = 18.076. (c) σ = 25.424. (d) σ = 26.548. (e) σ = 36.498. (f) σ = 34.191;

Table 3

Classification Criteria of Stubble Quantity Based on Standard Deviation

Root stubble amount	Less	Medium	More
Standard deviation	Less than 20	20-30	Greater than 30

RESULTS

In order to verify the accuracy of the algorithm, this paper has double verification. In this paper, a field test was carried out. The test site was located at the national demonstration base of modern agriculture in Guli Town, ChangShu, on 30 January 2021. By analyzing the image data of rotary tillage collected by camera, the algorithm is used to determine the stubble quantity. As shown in Figure 8, Figure 8(a) is the paddy field before rotary tillage, and Figure 8(b) is the paddy field after rotary tillage. In order to make the artificial evaluation representative, the staff of Suzhou Agricultural Machinery Extension Station were invited to carry out artificial evaluation on the root stubble amount of field operation. In order to reduce the subjectivity of manual evaluation, 40 agricultural machinery extension station technicians with rich experience in rotary tillage were invited to evaluate the stubble quantity and tillage depth uniformity of field operation. The 40 technicians are distributed as follows, as shown in Table 4.

(a) (b)

Fig. 8 - Paddy fields before and after tillage

(a) Before tillage; (b) After farming;

Table 4

Distribution law of 40 technicians in agricultural machinery extension stations

Subordinate institutions	**All personnel are located in agricultural extension stations in Suzhou**			
Professional title	Senior engineers	Engineers	Assistant engineers	No
	9	18	6	7
Direction of engagement	Agricultural machinery promotion	Agricultural machinery management	Agricultural machinery education	Agricultural mechanization
	35	3	1	1
Work experience	0 year - 5 years	6 years -10 years	10 years – 15 years	Over 15 years
	14	8	3	15
Degree of understanding rotary tillage	Don't understood	Far understood	Understood	Very well understood
	12	19	6	3

Assessment results of rotary tillage residual stubble

A total of 500 images were randomly selected from the collected images, and the results of the algorithm detection were compared with those of the manual evaluation to calculate the proportion of the images with the same judgment in the total. As shown in Table 5, the results are divided into three levels: less, medium and more. The number of manual evaluation results, the number of algorithm evaluation results and the number of consistent judgment results are counted respectively. The results of each evaluation are averaged, and the accuracy rate is the number of images with consistent results divided by the number of images obtained by manual evaluation. The proportion of the quantitative evaluation results based on standard deviation consistent with the manual evaluation is 83.6%.

Table 5

Statistics of area, perimeter and area-perimeter ratio

Root stubble amount	Artificial evaluation (picture)	Algorithm evaluation (picture)	Consistent results (picture)	Accuracy rate (%)
Less	142	147	127	87.3
Medium	261	248	204	79.3
More	97	105	97	89.7
Grand total	500	500	418	83.6

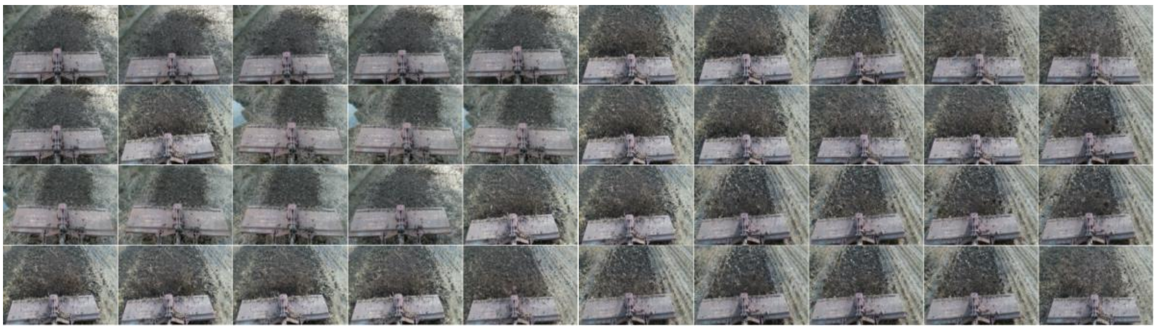
Figure 9 is a typical picture in which the method proposed in this paper is inconsistent with the artificial evaluation. In Figure 9(a), the standard deviation of the Y component is 37.536. The standard deviation of Figure 9(b) is 29.561. According to the method in this paper, the result is that the amount of stubble is medium, but the result of artificial evaluation is that the amount of stubble is more. Figure 9(a) is a typical situation at the boundary of two qualitative factors because it is located at the edge of farmland and is greatly disturbed by external factors.

(a) (b)

Fig. 9 - The Images with inconsistent results obtained by algorithm evaluation and manual evaluation

(a) σ = 37.536; (b) σ = 29.561;

Considering that the artificial evaluation also has certain subjectivity, 20 pictures with different root stubble are extracted according to the algorithm, as shown in Figure 10.



(a) (b)

(c)

Fig. 10 - Randomly selected rotary tillage images

(a) Less stubble; (b) Medium stubble; (c) More root stubble;

The result measured by the algorithm in Figure 10(a) is that the root stubble is less, the result measured by the algorithm in Figure 10(b) is that the root stubble is medium, and the result measured by the algorithm in Figure 10(c) is that the root stubble is more. After the pictures were randomly disrupted and the number of pictures at three levels was not informed, the questionnaire survey results of 40 technicians in agricultural machinery extension stations were obtained through the form of questionnaire survey, as shown in Figure 11. The average results of the three levels of less stubble, medium stubble and more stubble were 18, 21 and 21. The data that obviously deviate from the algorithm results are excluded from the evaluation results of the 40 agricultural extension station technicians, that is, the data that the evaluation results of the 40 agricultural extension station technicians for each grade are satisfied between 10 and 30 are retained. Finally, only 27 agricultural extension station technicians are satisfied with the evaluation results.

The specific results are shown in Figure 12, and the average results of the three grades of less stubble, medium stubble and more stubble are 20, 21 and 19, respectively.

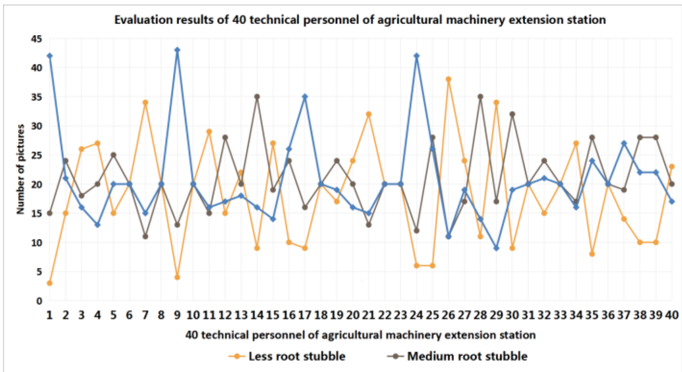


Fig. 11 - 40 agricultural machinery extension station technical personnel evaluation results

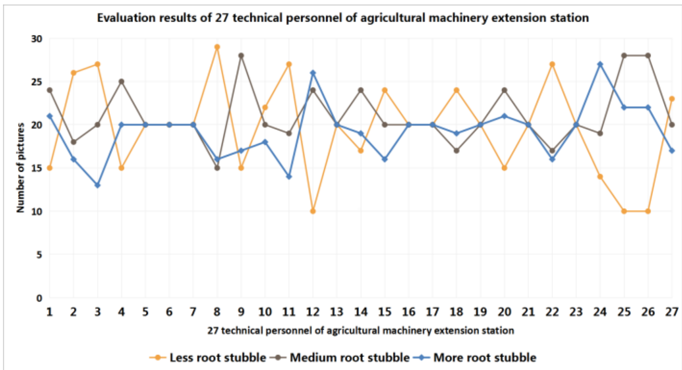


Fig. 12 - 27 agricultural machinery extension station technical personnel evaluation results

After considering the results of artificial evaluation and algorithm evaluation, combined with the results of technical personnel evaluation, it can be seen that the rotary tillage stubble detection method proposed in this paper has high reliability and can replace the artificial to evaluate the rotary tillage stubble in real time. The reasons are as follows. (1) Table 5 calculates the accuracy of algorithm evaluation based on manual evaluation, and the accuracy is 83.6 %. In order to ensure the reliability of the algorithm, this paper uses the form of questionnaire survey to collect the evaluation results of 40 agricultural machinery extension station technicians. The images evaluated by them are all different levels of images obtained by the algorithm, such as the average values of the evaluation results of Figure 11 and Figure 12 are basically consistent with the results obtained by the algorithm, and the error is within the acceptable range. (2) From Figure 11 and Figure 12, it can be seen that on the basis of algorithm evaluation, in the broken line diagram of three different situations of rotary tillage stubble obtained by manual evaluation, the data of three different situations fluctuate greatly, which is the disadvantage of manual evaluation, and the algorithm in this paper will reduce the disadvantages of manual evaluation, and the evaluation of rotary tillage operation conditions is relatively fair. (3) Whether the results obtained by the algorithm or the results obtained by manual evaluation, there will be an unhandled critical value, as shown in Figure 9. Therefore, for the critical value, both cannot be accurately judged, so it can be ignored, and the error is within an acceptable range.

CONCLUSIONS

In this paper, a real-time detection method of rotary tillage condition based on machine vision is proposed for paddy field rotary tillage operation condition, and the accuracy of the algorithm is verified by analyzing the index of rotary tillage residue. The root stubble amount detection method based on standard deviation in the Y component gray image of YCrCb space was used to determine the residual root stubble amount of soil after rotary tillage. After experimental analysis, the root stubble amount was divided into three grades by using two standard deviation thresholds. Finally, the accuracy of the algorithm is verified by field experiments and questionnaires. The results showed that on the basis of artificial evaluation, the accuracy rate of rotary tillage residue was 83.6 %. Based on the actual situation, the method proposed in this paper can replace manual automatic detection of working conditions. The deficiency is that the accuracy of the algorithm will decrease when the tractor is performing rotary tillage at the edge of the farmland or at the intersection of two different stubble quantities (such as the number of stubbles between a small amount and a medium amount), which is a problem to be solved in the later stage. In the detection of residual stubble in rotary tillage, the interference caused by possible shadows was not considered, and this situation needs to be taken into account in order to improve the environmental adaptability of the algorithm. To solve the above two problems, the accuracy of the algorithm will be improved. Scholars have also done little research on the quality evaluation of rotary tillage, so this paper has not been compared with the research done by other scholars.

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