Development of a monitoring system for grain loss of paddy rice based on a decision tree algorithm

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Abstract: China has the world's largest planting area of paddy rice, but large quantities of paddy rice fall to the ground and are lost during harvesting with a combine harvester. Reducing grain loss is an effective way to increase production and revenue. In this study, a monitoring system was developed to monitor the grain loss of the paddy rice and this approach was tested on the test bench for verifying the precision. The development of the monitoring system for grain loss included two stages: the first stage was to collect impact signals using a piezoelectric film, extract the four features of Root Mean Square, Peak number, Frequency and Amplitude (fundamental component), and identify the kernel impact signals using the J48 (C4.5) Decision Tree algorithm. In the second stage, the precision of the monitoring system was tested for the paddy rice at three different moisture contents (10.4%, 19.6%, and 30.4%) and five different grain/impurity ratios (1/0.5, 1/1, 1/1.5, 1/2, and 1/2.5). According to the results, the highest monitoring accuracy was 99.3% (moisture content 30.8% and grain/impurity ratio 1/2.5), the average accuracy of the monitoring tests was 92.6%, and monitoring of grain/impurity ratios between 1/1 and 1/1.5 (>95.4%) had higher accuracy than monitoring the other grain/impurity ratios. Monitoring accuracy decreased as impurities increased. The lowest accuracy for grain loss monitoring was obtained when the grain/impurity ratio was 1/2.5, with monitoring accuracies of 88.2%, 75.7% and 78.8% at moisture contents of 10.4%, 19.6% and 30.4%.

Keywords: monitoring system, combine harvester, paddy rice, grain loss, sensor, data mining, decision tree, development

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1 Introduction

China is the world's most populous country. By the end of 2018, approximately 1.395 billion people populated the country, accounting for approximately 18.5% of the world's total population. However, only 134.86 million hm^2 of arable land exist in China, which makes up approximately 7% of the world's arable land[1]. In other words, China feeds 18.5% of the world's population with 7% of its arable land. This is such a remarkable project that also illustrates the population pressure on the land and food in China. Supposing the grain loss rate per hectare of cultivated land could be reduced by 1% when harvesting and that the average rice output per hectare was 7500 kg, these numbers mean that 75 kg of loss grains per hectare would be saved. That is, approximately 10 billion kg of paddy rice can be saved in 130 million hm^2 of Chinese cultivated land, which can meet the grain demand of 20 million people or so in the city (Beijing, the capital of China), which is equivalent to a country (one, Romania, or two, Portugal). Therefore, after fulfilling the mechanization of harvesting, how to monitor and control the grain loss in the process of rice harvesting has become one of the most significant problems involved in intelligent harvesting in China.

Among the performance parameters, including loss, breakage and impurity, the loss rate is the most important one for the rice combine harvester. When crops are fed into the harvester from the header, the reel bats strike the crop ears, and grain loss can occur. In the threshing progress, the threshing and separator structure and operation parameters directly influence the threshing performance indicators of which grain loss is the most important one. Grains are blown out by airflow during the cleaning progress, and the loss during cleaning is unavoidable. Therefore, grain loss occurs in the three stages—head-feeding, threshing and cleaning—when harvesting. Considering that threshing grain loss accounts for a large proportion of the total loss, while grains are mixed and carried along with the stalks and straw during threshing, monitoring of the threshing rice loss in real-time is especially important and difficult.

At present, the piezoelectric film is often used to collect the electrical impulses generated by grain and MOG (material other than grain) touching the sensor plate[2-5]. However, interference signals generated when harvesting in the field are inevitable because of the complex working environment of the combine harvester, including vibration disturbances, materials of many types impacting the plate, and changeable grain moisture content[6]. Furthermore, the low recognition accuracy of the grain impact signals from abundant MOG impact signals of the various materials results in a decrease in measurement accuracy.

Scholars have studied grain loss monitoring and control with the purpose of reducing the loss rate and improving profits. YT-5 type piezoelectric ceramic and PVDF films have been utilized as

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sensing material to monitor grain sieve losses and grain separation losses in real-time in the working process of the combine harvester[5,7,8]. Relevant models between separation loss and crop throughput have been developed, and experimental studies have been carried out to estimate the grain separation performance utilizing impact-type sensors[9,10]. Craessaerts et al.[11] provided a fuzzy model for the prediction of sieve loss by the data input of fan speed and load on the sieve section. Four pressure sensors were mounted on the cleaning section to monitor the sieve load[11-13]. An artificial neural network was introduced to assess the grain losses in the field condition and the simulation result showed that the ANN method was appropriate and feasible to assess the grain losses[14].

In this study, a monitoring system was developed to determine the grain loss of the paddy rice. KV-UAF42 (universal active filter) was configured for a range of high passage to filter the machine vibration interference signals. Features of the material signals that impact the sensor plate were extracted, including the Root Mean Square, Peak Number, Frequency, and Amplitude, and a training data set was obtained. A decision tree algorithm was used to mine the dataset and establish a kernel recognition model. The model was evaluated by the method of 10-fold cross-validation. In the end, grain loss for the paddy rice, the widely planted grain variety, was determined with the monitoring system, and the accuracy of this method was verified.

2 Materials and methods

2.1 Monitoring system design

2.1.1 Signal acquisition

A piezoelectric film was pasted on the sensitive plate to record the kernel-MOG mixture impact on the sensitive plate. The size of the sensitive plate was 170 mm (length)×120 mm (width)×1 mm (thickness).

When kernels and MOGs impacting the sensor plate, the vibration waves were captured by the piezoelectric film (diameter 50 mm) and converted into voltage signals. The voltage signals were amplified and filtered by the KV-UAF42 active filter module with the traditional high-pass filtering method. The output analog signals were transmitted into the analog input port of the wiring terminal (AI 0, ADAM-3968 SCSI 68P Terminal Board REV.B1) and then transformed into digital signals by A/D conversion in the PCI-1710U Data Acquisition Card. Finally, the captured sampling data were transported to the Industrial Computer. The measuring instruments were connected to the circuit as shown in Figure 1.

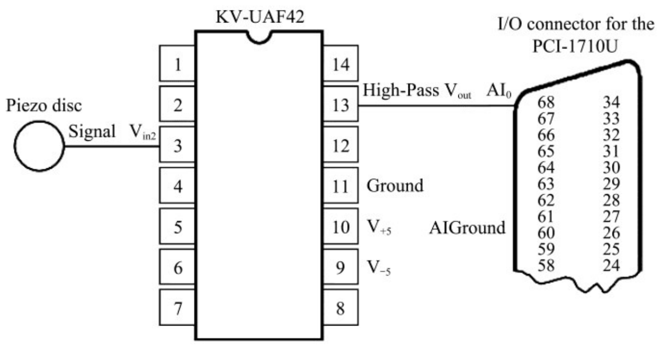


Figure 1 Connection of the measuring instruments to the circuit

The vibration of the combine harvester influences the output voltage signals significantly, and after the fast Fourier transform (FFT), its frequencies are mainly lower than 800 Hz[8]. The piezoelectric film with a Resonance Frequency of 2.9 kHz is used. The KV-UAF42 high-pass filter with a center frequency of 5 kHz, which can filter the low frequency vibration interference of the working machine and let the high frequency collision signal on the sensor plate (5-20 kHz) pass is chosen[2-5]. The PCI-1710U Data Acquisition Card has 12-bit A/D conversion capability, and the sampling rate reaches 100 kS/s.

2.1.2 Software

The software was designed using Labview. The flow diagram of the software is shown in Figure 2. The lower and upper thresholds of the soft trigger voltage were set to −0.2 V and 0.2 V, and the signals exceeding the voltage range of [−0.2, 0.2] V were captured and analyzed. Four features of each captured signal were extracted, including the Root Mean Square (V), the Peak Number, the Frequency (Hz) and the Amplitude (V). The frequency and amplitude were extracted from the fundamental component of the input signal, and the peaks and troughs above the threshold of half amplitude of the input signal were counted. The collision signals of kernels and MOGs were shown in Figure 3. The data set, including extracted four features and the classifications for kernel and MOG, as shown in Table 1, and the data set was machine learned with Decision Tree algorithm.

2.1.3 Recognition using decision tree

Decision trees are methodologies used to classify data into discrete form using structured tree algorithms. A standard tree is represented by the J48 algorithm, which consists of a root node, a number of leaf nodes, and a number of branches. Each branch of a tree represents a chain of nodes from the root to a leaf, and each node represents an attribute (or feature)[15-17]. Decision trees are one of the most effective and widely used techniques in many areas of Data Mining, such as pattern recognition, machine learning, image processing and information retrieval[18-20].

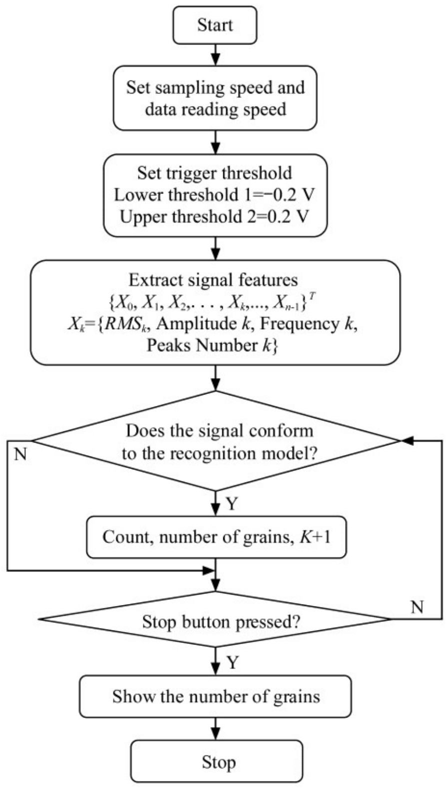


Figure 2 Flow diagram of the software for classification of kernels and MOGs

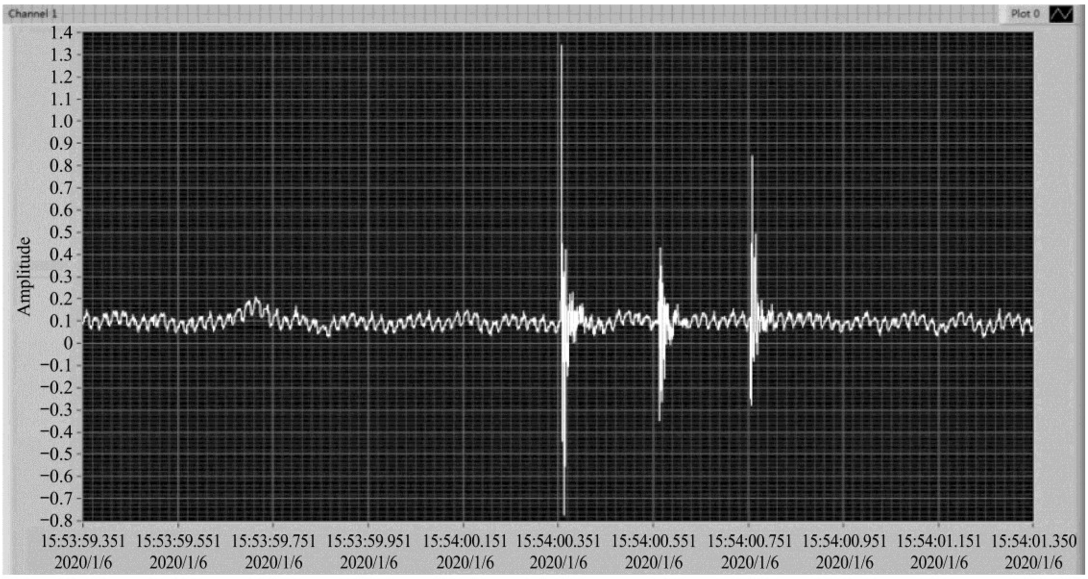


Figure 3 Collision signals coming from kernels and MOGs' impacting on the sensor plate

Table 1 Data set of collision signals features for kernels and MOGs

RMS	A	F	P	Class	RMS	A	F	P	Class
0.076	0.004	0.050	223	Kernel	0.061	0.003	0.457	247	MOG
0.079	0.003	0.050	86	Kernel	0.061	0.003	0.038	64	MOG
0.151	0.032	0.027	9	Kernel	0.061	0.003	0.100	83	MOG
0.091	0.004	0.009	35	Kernel	0.062	0.004	0.206	57	MOG
0.093	0.006	0.010	26	Kernel	0.063	0.006	0.032	27	MOG
0.077	0.003	0.050	121	Kernel	0.063	0.005	0.484	82	MOG
0.069	0.009	0.015	22	Kernel	0.059	0.004	0.443	42	MOG
0.074	0.007	0.054	20	Kernel	0.061	0.001	0.037	294	MOG
0.083	0.008	0.131	10	Kernel	0.063	0.002	0.038	173	MOG
0.048	0.015	0.244	12	Kernel	0.058	0.005	0.038	17	MOG
0.075	0.011	0.279	6	Kernel	0.061	0.001	0.050	329	MOG
0.066	0.005	0.065	50	Kernel	0.126	0.02	0.357	6	MOG
0.067	0.004	0.040	64	Kernel	0.073	0.002	0.032	24	MOG
0.123	0.003	0.396	32	Kernel	0.063	0.002	0.037	101	MOG
0.161	0.006	0.356	17	Kernel	0.075	0.014	0.207	11	MOG
0.068	0.002	0.386	89	Kernel	0.058	0.002	0.025	88	MOG
0.078	0.003	0.059	30	Kernel	0.074	0.001	0.021	147	MOG
0.068	0.003	0.065	44	Kernel	0.067	0.001	0.047	217	MOG
0.083	0.002	0.056	36	Kernel	0.065	0.002	0.280	183	MOG
0.187	0.085	0.211	4	Kernel	0.066	0.003	0.023	140	MOG

Note: A-Amplitude; F-Frequency; P-Peak number.

Decision Tree algorithm J48 (C4.5) was used to mine the data of collision signal features and develop the tree-like recognition model, as shown in Figure 4. The model tree was embedded in MathScript module of Labview to recognize kernel signals from the data.

As shown in Figure 4, 19 nodes (10 leaf nodes, each represented by a rectangular box, and 9 internal nodes, each represented by a circle box) are included in the model tree. The letters in the rectangles of the leaf nodes are related to the class kernel and MOG, and the numbers in the bracket represent classified cases/errors. The estimate of the tree's classification performance was obtained using stratified cross-validation of 10-fold. For kernel impact signals, the correctly identified TP number was 261, and the TPR of kernel classification was 96.3%. For MOG impact signals, the correctly identified TP number was 36, and the TPR of MOG classification was 61.0%. The weighted average TPR was 90.0%, which means that approximately 90.0% of the instances have been classified correctly. This indicates that the results obtained from the training data are optimistic with what might be obtained from an independent test set from the same source.

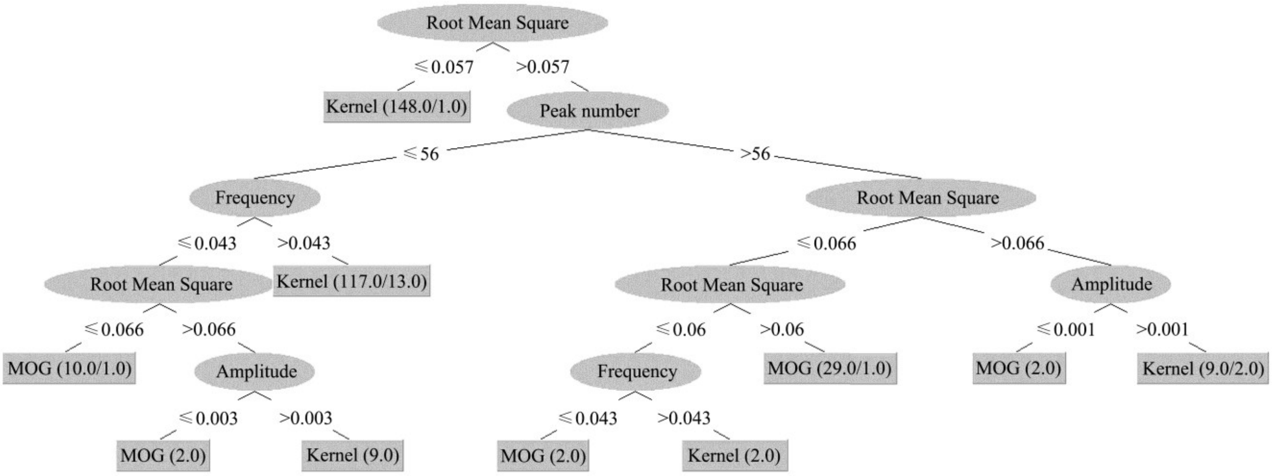


Figure 4 Kernel and MOG recognition model based on Decision tree algorithm

2.2 Experimental method

2.2.1 Test bench

To simulate the effect of material falling down from the concave screen when harvesting, a sensor calibration test bench, which included the frame, the stepping motor, the transmission belt, and the thin flat sensitive plate, was designed as shown in Figure 5.

The sensor plate was installed 30 cm below the transmission belt. The angle between the sensor plate and the falling material was 45 degrees. With the help of the rotation speed adjustment of the stepping motor, the speed of the transmission belt connected with the stepping motor was capable of adjustment in the range of 10-100 mm/s.

Grains, short straw and stalks were mixed and dispersed on the transmission belt, which is driven by the stepping motor. As the transmission belt conveyed the materials, the mixture fell and impacted the sensitive plate of the vibration measuring element.

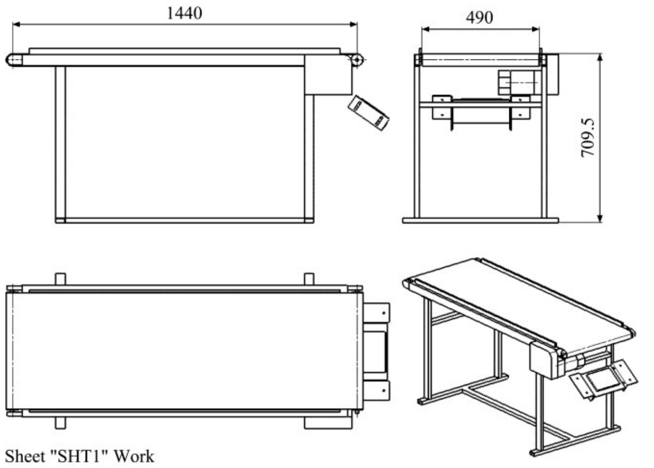


Figure 5 Test bench to simulate materials of grains, short straw and stalks falling down

2.2.2 Test method

The moisture content of the rice crop varies greatly at different times in one day (morning, noon, and afternoon) because of the influence of the environment and weather of paddy fields. When the sunshine is high at noon, the moisture content is as low as 15% or even less. Before sunset, the moisture content of the rice crop can increase up to 25% or even more with a decrease of temperature and the generation of fog in the field. In addition, the proportion of material components (kernels and MOGs) beneath the concave screen changes with the field environment and operation parameters when harvesting. As shown in Figure 6a, the two piles on the left are thick and thin straw, most of which can generate signals by impacting the sensor plate, and the pile on the right are stalks, which can rarely generate signals because of their light weight.

To obtain the kernel-MOG mixture of different moisture and impurity rates, the rice crop was harvested when the expected moisture and impurity rates were reached and then transported to the laboratory[21]. The collected materials were divided into three groups according to the moisture content: 10.4% (L), 19.6% (M), and 30.4% (H), and the 1000-grain weight of each group was measured manually. Similarly, each moisture-group was divided into five groups according to the “grain/impurity mass ratio”: 1/0.5 (R1), 1/1 (R2), 1/1.5 (R3), 1/2 (R4), and 1/2.5 (R5). Finally, 15 groups of different moisture and grain/impurity mass ratio were obtained, and the mixture of each group was weighed and spread on the belt before the test started. As the kernel-MOG mixture fell, the position of the sensor was adjusted to ensure that all of the mixtures fell on the sensor plate, as shown in Figure 6b.

The impact signals of the mixture were counted according to the two different cases—“with recognition model” and “without recognition model”—and the monitoring accuracies of the two methods were calculated and compared to verify the effect of the recognition model.

a. Straw and stalks

b. Kernel-MOG mixture falling onto the sensor

Figure 6 Experimental method

The 1000-grain weight changes with the grain moisture. Through weighing experiments, the 1000-grain weight is recorded in Table 2, corresponding to different grain moisture content. Each group of grain/impurity mixture was 10 g weight and was fall onto the sensor plate in 5 s.

Table 2 1000-grain weight of three different grain moisture contents

No.	Moisture/%	1000-grain weight/g
1	10.4	26.0
2	19.6	29.0
3	30.8	33.0

2.2.3 Evaluation of experiment

The monitoring accuracy of the sensor was calculated after the tests. The following formula was used to determine the accuracy of grain monitoring for paddy rice at three different moisture contents and five different impurity rates.

$$P = \frac{MK(R+1)}{1000mR} \times 100\% \qquad (1)$$

where, P is the accuracy of grain monitoring; M is the 1000-grain weight, g; K is the number of monitored grains; m is mixture weight, g; R is the “grain/impurity mass ratio”, hereinafter referred to as “grain/impurity ratio”.

3 Results and discussion

3.1 Calibration test

It is observed from Tables 3-5 that the average detection accuracy of the three different moisture contents—the average detection accuracy of 93%, 94% and 91% correspond to the moisture of 10.4%, 19.6%, and 30.8%, respectively—did not fall below 90% with the recognition model. At the same moisture content, the detection accuracy of the higher impurity rate had higher detection accuracy than that of the lower impurity rate.

Table 3 Monitoring results of moisture 10.4% mixture group

	Grain/impurity ratio	Monitoring kernel number	Actual kernel number	Accuracy
1	1/0.5(6.67 g/3.33 g)	242	256	94.5%
2	1/1(5 g/5 g)	199	192	96.4%
3	1/1.5(4 g/6 g)	150	154	97.4%
4	1/2(3.33 g/6.67 g)	142	128	89.1%
5	1/2.5(2.86 g/7.14 g)	123	110	88.2%

Table 4 Monitoring results of moisture 19.6% mixture group

	Grain/impurity ratio	Monitoring kernel number	Actual kernel number	Accuracy
1	1/0.5(6.67 g/3.33 g)	235	230	97.8%
2	1/1(5 g/5 g)	175	172	99.3%
3	1/1.5(4 g/6 g)	143	138	96.5%
4	1/2(3.33 g/6.67 g)	113	115	98.3%
5	1/2.5(2.86 g/7.14 g)	120	99	78.8%

Table 5 Monitoring results of moisture 30.8% mixture group

	Grain/impurity ratio	Monitoring kernel number	Actual kernel number	Accuracy
1	1/0.5(6.67 g/3.33 g)	224	202	89.1%
2	1/1(5 g/5 g)	159	152	95.4%
3	1/1.5(4 g/6 g)	123	121	98.3%
4	1/2(3.33 g/6.67 g)	105	100	95.0%
5	1/2.5(2.86 g/7.14 g)	109	87	75.7%

The detection accuracy was 99.3% (the highest) at the moisture content of 30.8% and the grain/impurity ratio of 1/1, and it was 75.7% (the lowest) at the moisture content of 19.6% and the grain/impurity ratio of 1/2.5. The detection accuracy was more than 95.4% at the grain/impurity ratio of 1/1 and 1/1.5, as shown in Figure 7.

The grain/impurity ratio had a greater impact on the accuracy of the monitoring device than the moisture content, mainly because the impurity detection accuracy (TPR) was not that high (61.0%), resulting in a considerable portion of impurities that were misidentified as grains.

3.2 Comparison test

To verify the validity of the developed monitoring system, the monitoring accuracy of the system "with recognition model" and "without recognition model" were compared at the grain/impurity ratio levels of 1/0.5 (R1), 1/1 (R2), 1/1.5 (R3), 1/2 (R4) and 1/2.5 (R5) and moisture content levels of 10.4%, 19.6% and 30.8%.

When the impurity rate of the mixture increased, the monitoring accuracy using the recognition model was stable, whereas the monitoring accuracy without the identification model decreased greatly, as shown in Figures 8a-8c.

The increase in the impurity contents made it more difficult to monitor grain impact signals. The impact signals formed by a large amount of impurity of thick straw and heavy stalks on the sensor plate were similar to those of the grain impact signals. If not processed, the monitoring accuracy would be extremely unstable. After distinguishing by the "grain-impurity" recognition model, the monitoring accuracy was steady and improved by approximately 30%, on average.

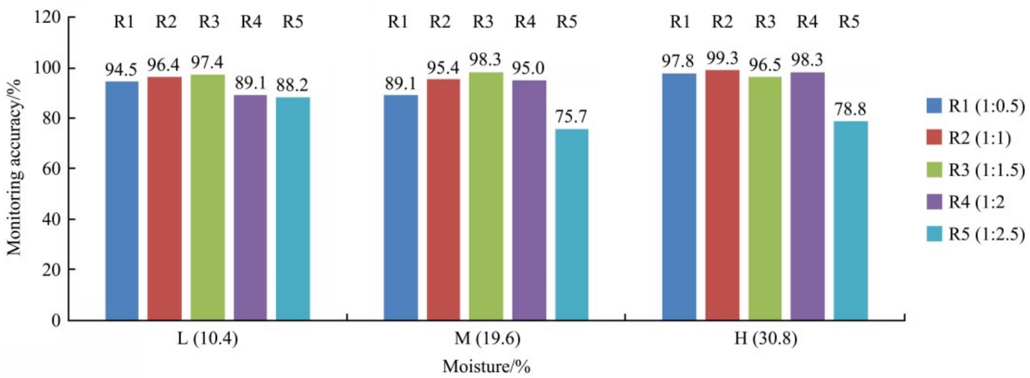
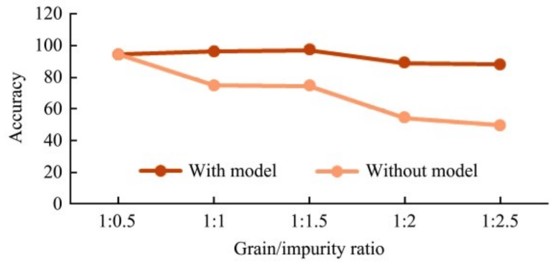
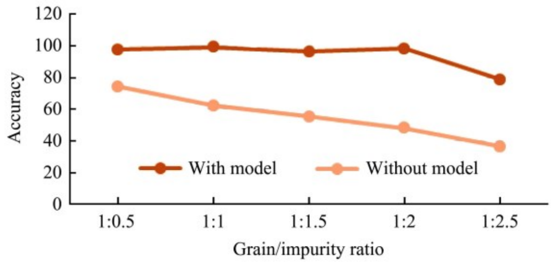


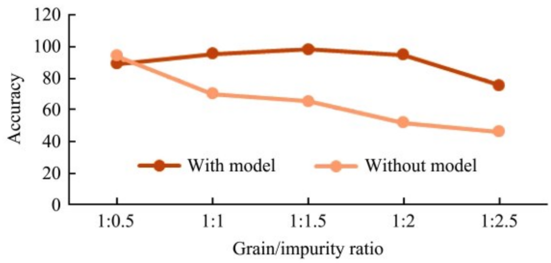
Figure 7 Detection accuracy based on the moisture and impurity rate of paddy rice



a. Moisture 10.4%



b. Moisture 19.6%



c. Moisture 30.8%

Figure 8 Comparison tests results of different moisture

4 Conclusions

The monitoring system for grain loss of paddy rice was developed to determine the grain loss based on the different moisture contents and grain/impurity ratios of materials beneath the concave screen. The moisture contents between 10% and 30% and the grain/impurity ratios between 1/0.5 and 1/2.5, which were involved in almost all of the grain-MOG mixture during combine harvesting, were taken into consideration in the development of the monitoring system.

The results showed that the piezoelectric film was capable of acquiring the impact signals of grains and MOGs. Four features were extracted from the signals: Root Mean Square (RMS), peak number, Frequency and Amplitude. A Kernel/MOG recognition model based on the Decision Tree J48 (C4.5) algorithm achieved a certain precision of classification. The validation experiments showed that the average accuracy of the monitoring system did not fall below 90.7% at moisture contents between 10% and 30% and grain/impurity ratios between 1/0.5 and 1/2.5, and the monitoring accuracy was improved by approximately 30%, on average.

Acknowledgements

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