Intelligent Control of Threshing and Cleaning System Based on Big Data

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Abstract. When the combine harvester works under different environmental conditions, its threshing and cleaning is a complicated process. To deal with changes in soil, climate, and crop conditions, it is extremely important to adjust and optimize the internal parameters of these machines. It is because the experience of agricultural machinery operators is different to cause uneven harvest quality, which cannot guarantee that all harvesters reach the best harvest state. Now, RS images of sensors and satellites are quite clear, and the error is controlled within the acceptable range. With the advent of the era of big data and AI, many fields have successfully applied them. In the agricultural field, innovation and transformation led by AI are also taking place. The article takes the intelligent control of the threshing and cleaning system as the object of study, which is specifically reflected in the impurity rate, crushing rate, and loss rate of cereals. The goal is to minimize the loss rate during harvest, and the lowest impurity rate and crushing rate in the grain after harvest. This subversive movement will completely rewrite the development status of China's agricultural machinery.

1. Introduction

During grain harvest, many factors such as the lodging level and maturity of the crop, the temperature and humidity of the environment, the speed of the harvester, the speed of the threshing drums, and the opening angle of the screen will affect the quality of the harvest [1]. When many influencing factors are intertwined, experienced agricultural machinery operators often make appropriate adjustments to the harvester according to different operating environments. The best harvesting effect is manifested by lower impurity rate, broken rate and loss rate.

As the process of urbanization accelerates, more and more rural labor forces flock to the cities in search of more stable and high-paying jobs. Due to the shortage of surplus labor in bucolic areas, it has caused an uneven operating experience for agricultural machinery operators. They cannot all achieve high-quality harvests. From an economic perspective, there is an urgent need for the emergence of intelligent harvesting machines to solve the problem of diverse operators affecting the harvesting effect due to different operating proficiency. Agricultural intelligence will help to solve this problem. It can enable farmers to get more output with less input, and continuously improves the quality of products [2].

With the development of big data and the Internet of Things technology, humans try to combine normal brain and artificial brains. This continuous exploration has spawned a whole new field-Artificial Intelligence (AI) [3]. Like a large number of sensors used in cars to help people achieve automatic
driving and obstacle avoidance, after installing sensors on harvesting machinery, intelligent operations can also be achieved. All this is caused by AI. The core is a deep artificial neural network model built by simulating the calculation of the human brain. It can continuously learn knowledge and reason from gigantic data. This is like letting machines and humans have the perception, understanding, decision-making, and the ability to learn and evolve constantly. These techniques or algorithms can learn from huge amounts of data and make judgments without human intervention [4]. It is distinct from a simple feedback mechanism, but the result after deep learning [5]. AI expands our ability to perceive and change our surroundings. It is changing the world. Today, it has swept the world and is employed in many fields such as medicine, education, finance, industry, and security. In the agricultural field, innovation and transformation led by AI are also taking place.

Agricultural intelligence is a far-reaching goal in the development of agriculture. The Internet of Things and cloud computing and other new technologies rely on it to introduce more robots and AI in the agricultural field. Depending on the modular division, the intelligentization of harvesting machinery mainly includes the intelligentization of the header, the intelligentization of the threshing and cleaning system, the intelligentization of the granary, and the intelligentization of the operating parameters of the whole machine [6]. Well-known agricultural machinery companies in the United States and Europe have installed remote real-time monitoring systems on the latest products, and vehicle-mounted terminals transmit real-time information such as operating location and working status to the pastoral machinery information service center through a wireless communication network [7]. This technology is based on the Internet of Things technology in the context of big data. It allows people to take a data-driven approach and collect a lot of information about the environment of crops from the end of the sensor. Big data is increasingly valued by people for its huge data volume and complexity and is widely used in various industries.

As one of the sources of big data, remote sensing (RS) generates observation data and analysis results from satellites, drones, and ground platforms every day. Agricultural RS technology is a part of the core technologies of agricultural intelligence. The acquisition, storage, and analysis of RS big data are the key to the success of it [8]. The generation of RS data originates from image recognition technology. It is distinct from simply taking pictures, but the image-processing system analyzes the images characterized by color, shape, and particles through an artificial neural network, and then obtains RS big data [9]. The advent of the era of high-resolution observation has completely changed the generation, processing, and analysis of RS data [10]. Now, RS images of sensors and satellites are quite clear, and the error is controlled within the acceptable range. This has made big data and the Internet of Things technologies quite mature, and the application of AI in the agricultural field has become natural.

2. Process of parameter monitoring and adjustment
When the combined harvester harvests different crops under different environmental conditions, whose threshing and cleaning is a complicated process, which is influenced by many factors. To deal with changes in soil, climate, and crop conditions, it is extremely important to adjust and optimize the internal parameters of these machines. The grain loss caused by improper threshing and cleaning parameters on the harvester is 3%-5% every year, accounting for about 60% of the total loss during crop harvest. This article will focus on how to reduce the loss caused by threshing and cleaning, and how to achieve a high-quality harvest. The intelligent monitoring and control of the threshing and cleaning system are specifically reflected in three aspects: monitoring and adjustment of impurity rate, monitoring, and adjustment of broken rate and monitoring and adjustment of loss rate. The goal is to minimize the loss rate during harvest, and the lowest impurity rate and crushing rate in the grain after harvest.

2.1. Monitoring and adjustment of impurity rate
Because the speed of the threshing drums is too high, the speed of the fan and the opening angle of the sieve cannot keep up with the pace, which causes the grain particles in the granary to be mixed with other impurities such as broken straw. Excessive impurities can affect the cleanliness of the grain, which in turn influences the quality of the harvest. The specific process of monitoring and adjusting the
The impurity rate is as follows: The elevator camera located above the granary uses image recognition technology to collect images of the delivered grain in real-time (Figure 1a). Unlike granulated grains, impurities such as short straw will show different images. This image will be indicated red on the cab display (Figure 1b); The camera transmits the collected data to the AI controller. After the AI chip processes the data, the impurity rate of the cereal is pushed to the display at the current moment. This is a dynamic process of big data collection, recording, and processing.

![Image of elevator camera and impurities](a) The elevator camera  (b) Impurities of short straw

Figure 1. Collect images above the granary.

When the impurity content of the grain sent by the elevator rises to more than the set value (Figure 2a), after the AI controller calculates and analyzes, the result that the impurity content is higher is reached. Then it issued a system command to achieve the purpose of reducing the impurity rate of cereals. First, a red alarm message with "high impurity content" will be shown on the display to prompt the operator (Figure 2b); On the one hand, the AI controller sends a deceleration signal to the axis of threshing drum power input. A speed sensor (Figure 2c) is mounted on the other end of the drum shaft to detect its speed reduction; On the other hand, the AI controller sends a speed-up signal to the axis of fan power input. A speed sensor (Figure 2d) is installed on the other end of the fan shaft, and its speed is detected to increase; Meanwhile, the AI controller sends a signal to increase the opening angle of the cleaning screen. An angular displacement sensor mounted on the screen detects that its opening angle has increased (Figure 2e). The speed and opening angle changes during this process are indicated on the monitor in real-time. Figures 3a and 3b are the parameter values respectively before and after adjustment.

![Image of parameter adjustment](a) Speed of the threshing drum (b) Speed of the fan

Figure 3. Changes in parameter values.

![Dynamic change curve of the parameters](c) Speed of the threshing drum (d) Speed of the fan

Figure 4. The dynamic change curve of the parameters.

![Impurity rate returns](e) Cleaning screen opening angle

Figure 5. The impurity rate returns.
and Figure 4 is the dynamic change curve of the parameters in the adjustment process. After the AI controller performs the above series of parameter adjustments, the impurity rate returns to a reasonable interval (Figure 5).

![Figure 6. The broken rate is rising.](image)

**Figure 6. The broken rate is rising.**

![Figure 8. The dynamic change curve of the parameters.](image)

**Figure 8. The dynamic change curve of the parameters.**

![Figure 7. Changes in drum speed values.](image)

**Figure 7. Changes in drum speed values.**

![Figure 9. The dynamic change curve of the parameters.](image)

**Figure 9. The dynamic change curve of the parameters.**

### 2.2. Monitoring and adjustment of broken rate

Because the speed of the threshing drums is too high, the grains are crushed by the impact of it and the gravure plate, which affects the quality of the harvest. The specific process of monitoring and adjusting the crushing rate is: the elevator camera located above the granary uses image recognition technology to collect images of the delivered grain in real-time. Because broken kernels are relatively small in shape compared to normal kernels. The collected information will be highlighted in red on the cab display (Figure 6a). After the AI chip processes the data, the broken rate of the cereal is pushed to the display at the current moment. This is a dynamic process of big data collection, recording, and processing.

When the crushing rate of cereal conveyed by the elevator is increased to exceed the set value (Figure 6b), after the AI controller calculates and analyzes, the result of a high crushing rate is obtained. Then it issued a system command to achieve the purpose of reducing the level of grain breakage. The AI controller sends a deceleration signal to the axis of threshing drum power input to reduce the drum speed. Figures 7a and 7b are the drum speed values respectively before and after adjustment, and Figure 8 is the dynamic change curve of the drum speed during the adjustment process. After the AI controller performs the above series of parameter adjustments, the crushing rate returns to a reasonable range (Figure 9).

### 2.3. Monitoring and adjustment of loss rate

Because the fan speed is too high, and the opening angle of the sieve is also large, the grains are blown out of the machine which wrapped in straw and shells, it causing food loss. The specific process of monitoring and adjusting the loss rate is: The camera at the rear of the sieve box uses image recognition technology to collect images (straws, glumes, grain particles) of the discharge in real-time (Figure 10a). After the AI chip processes the data, the loss rate of the cereal is pushed to the display at the current moment. This is a dynamic process of big data collection, recording, and processing.
When the entrainment loss rate in the educts rises above the set value (Fig. 10b), after the AI controller's calculation and analysis, the result of a higher loss rate is achieved. Then it issued a system command to achieve the purpose of reducing the level of grain loss. On the one hand, the AI controller sends a deceleration signal to the axis of fan power input to reduce the speed (Figure 11a); At the same time, the AI controller sends a signal to reduce the opening angle of the cleaning screen (Figure 11b). During this process, the changes in fan speed and the opening angle of the screen are displayed on the monitor in real-time. Figures 12a and 12b are the parameter values respectively before and after adjustment, and Figure 13 is the dynamic change curve of the parameters during the adjustment. After the AI controller performs the above series of parameter adjustments, the loss rate returns to a reasonable range (Figure 14).

3. Experiments and results
The traditional agricultural machinery driven by more than ten years old operator was compared with the AI machinery driven by a new operator for two years. We concluded that: The former need to manually detect the impurity rate and crushing rate, and check the loss rate on the spot. When encountering various conditions, manual control is required, and the operation process is complicated. The latter does not prescribe the above complex operations.

After a short period of training, a new agricultural machinery operator with the help of artificial intelligence technology can reach the level of more than ten years of experience of the previous operator.
This greatly shortens the training period of the operator and liberates a large amount of labor. Moreover, with the support of big data and the Internet of Things, the operating environment and parameters of each harvester can be detected and viewed in real-time from the large screen of the agricultural machinery information service center. After detecting an abnormal parameter, the customer service staff will immediately contact the operator to check and eliminate the fault in time.

4. Conclusion and suggestions for future studies
Through artificial AI, the driver is more convenient to operate, and the labor intensity is greatly reduced. It also improves the performance of agricultural machinery and the degree of intelligence of it. On the one hand, we hope to reduce the difficulty of driving and improve work efficiency through AI; on the other hand, it can liberate the labor force, improve the working environment, and even improve the quality of life.

The intelligentization of agricultural machinery is no longer a one-time thing, but a process. The realization of AI involves the machine learning process. Its sole purpose is to provide the machine with data from experience and statistical data so that it can perform specified tasks and solve specific problems. It is precise because of machine learning that big data has made great progress. AI needs to test the established model and designed algorithm again and again through a large amount of data. The degree of artificial intelligence reaches the level of mature application. In the end, unmanned driving and unmanned operation will be realized, completely freeing people from the agricultural harvest process.

Soon, unmanned harvesters will flexibly harvest crops even on large farms. The user can monitor the working scene of the agricultural machinery in the field at home in real-time. Even when human intervention is required, it can easily, quickly, and accurately intervene in the operation of agricultural machinery.

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