

# Development of a Machine Vision-Based Monitoring and Evaluation System for Lodged Wheat

**Xiaoyan Liu**

School of Mechanical Engineering, Hunan Mechanical and Electrical Polytechnic, China  
liuxiaoyan0424@163.com (corresponding author)

**ZhongLin Xia**

School of Mechanical Engineering, Hunan Mechanical and Electrical Polytechnic, China  
xiazhonglin2025@163.com

**Bin Li**

School of Mechanical Engineering, Hunan Mechanical and Electrical Polytechnic, China  
273470289@qq.com

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## ABSTRACT

This study develops an intelligent processing system that integrates monitoring, identification, and assessment of lodged wheat to address yield loss during mechanical harvesting caused by lodging in precision agriculture. This system provides decision support for automatic header adjustment and disaster assessment. The system uses Visual C++ as the integrated development platform and comprehensively applies machine vision technology. Features of the lodged straw layer were enhanced through color difference analysis, linear grayscale transformation, and grayscale inversion. Image enhancement was achieved using median filtering. Precise segmentation of the straw layer and wheat ear layer was realized using mathematical morphology methods (erosion and dilation). Combining Roberts operator edge detection and Hough Transform line detection, lodging boundaries were extracted, and the lodging height difference was calculated. A fully functional software system was successfully developed. The system accurately identifies lodging areas, with detected lodging boundaries showing high conformity to actual conditions, and calculated height difference parameters prove reliable. The system achieved automated processing from image input, providing an effective technical solution for reducing harvest losses in precision agriculture.

**Keywords-***precision agriculture; lodged wheat monitoring; machine vision; target segmentation; height difference assessment*

## I. INTRODUCTION

As one of the three major cereal crops worldwide, the stable production of wheat is essential for ensuring national food security. In China, mechanized wheat harvesting has become nearly universal, serving as a crucial safeguard to guarantee that every grain is efficiently collected and stored. However, during the late growth stages, wheat is often prone to lodging due to extreme weather events—such as strong winds and heavy rainfall—or suboptimal agronomic management, including excessive planting density and over-fertilization. Lodging not only disrupts photosynthesis and grain filling, thereby reducing yield, but more importantly, it presents significant challenges for mechanized harvesting. When conventional combine harvesters operate in lodged fields, the header struggles to effectively lift and feed wheat ears that are

pressed close to the soil surface, resulting in substantial missed harvesting and grain losses. In severely lodged conditions, mechanical harvesting losses may exceed 10%, and in extreme cases, can even lead to near-total yield failure [1-4].

China's Ministry of Agriculture and Rural Affairs has prioritized the reduction of mechanical harvest losses in grain crops on par with yield improvement, promoting it as a core objective of national agricultural mechanization [5, 6]. In this context, leveraging technological means to intelligently perceive the operating environment and adjust harvesting strategies in real time has become crucial for reducing harvest losses and unlocking the potential for increased grain yield and loss mitigation.

The main principle of precision agriculture lies in the refined management and optimization of agricultural production processes through information technology. Among these technologies, machine vision—which enables computers to simulate human visual perception—has demonstrated significant potential in agriculture. Its non-contact, rapid, and information-rich characteristics make it highly suitable for various applications. For example, machine vision is essential for crop growth monitoring and automated fruit harvesting [7, 8]. Furthermore, it plays a crucial role in pest and disease detection; research has specifically demonstrated the effectiveness of image processing techniques in identifying pathogens, such as the detection of diseases in apple leaves, which validates the practical utility of this technology in crop farming [9, 10]. Applying machine vision technology to the detection of lodged wheat allows harvesters to observe and interpret crop conditions, enabling intelligent and adaptive adjustments of the header during operation.

Although extensive research has been conducted on image processing applications in agriculture, studies focusing specifically on lodged wheat remain confined to algorithmic exploration and validation within controlled laboratory settings, with limited advancement toward practical field implementation [11, 12]. Most existing studies concentrate on optimizing individual processing components, lacking an integrated, user-oriented system solution. In addition, current methods still face limitations in robustness under complex field conditions, real-time processing capability, and effective linkage between detection results and mechanical actuators—issues that demand further research and engineering validation.

Guided by the practical demands of precision agriculture, the present study develops a comprehensive machine vision-based monitoring and evaluation system for lodged wheat. The system integrates advanced image processing algorithms to enable precise identification and quantitative evaluation of lodged wheat while being implemented as a practical software platform. By establishing a seamless information flow from visual perception to control decision-making, it provides significant technological and equipment support for realizing the intelligent operation of combine harvesters.

## II. THEORETICAL FOUNDATION

### A. Machine Vision Technology in Precision Agriculture

The application of machine vision in precision agriculture has formed a relatively complete technical system. Its workflow typically includes image acquisition, preprocessing, target detection and segmentation, feature extraction, and decision output [8, 13]. Crop status monitoring has been widely explored. Authors in [14] used UAV remote sensing images combined with color indices to monitor large-area rice lodging. Authors in [15] achieved precise identification and counting of maize plants based on deep learning models. These studies demonstrate the feasibility of using visual information to perceive crop status. However, the real-time processing of lodged wheat on ground-based mobile platforms such as harvesters imposes higher demands on algorithmic speed, robustness, and adaptability to varying lighting conditions.

### B. Image Preprocessing and Enhancement Techniques

Image preprocessing is the foundation for subsequent analysis, as it improves image quality and highlights regions of interest. Converting color images to grayscale is a common first step, transforming RGB three-channel information into single-channel grayscale information through a weighted average method, significantly reducing data volume:

$$Gray = 0.299R + 0.587G + 0.114B \quad (1)$$

Grayscale transformation is used to enhance contrast. Linear stretching, which maps the original grayscale range  $[a, b]$  to a new range  $[c, d]$ , improving images with insufficient contrast, is expressed as:

$$g(x, y) = \left( \frac{f(x, y) - a}{b - a} \right) (d - c) + c \quad (2)$$

Grayscale inversion is another effective method, particularly suitable for inverting foreground and background, making dark targets more prominent against a bright background. It is defined as:

$$g(x, y) = 255 - f(x, y) \quad (3)$$

Noise removal is a crucial step in preprocessing. Median filtering, a nonlinear technique, can effectively reduce noise while better preserving image edges. This method works by sorting the grayscale values within a pixel neighborhood and assigning the median value as the output [16].

### C. Image Segmentation and Morphological Processing

Image segmentation partitions an image into regions exhibiting similar properties. For lodged wheat, segmentation commonly relies on color and texture features. Mathematical morphology offers robust tools for segmentation based on shape and structural information [17]. The erosion operation eliminates boundary points, causing the target to shrink, which is useful for removing small noise points and separating fine connections:

$$A \ominus B = \{z \mid (B)z \subseteq A\} \quad (4)$$

The dilation operation is the opposite of erosion, merging background points in contact with the target, thereby filling holes and connecting broken points. It is defined as:

$$A \oplus B = \{z \mid (B)z \cap A \neq \emptyset\} \quad (5)$$

By alternately applying erosion and dilation (opening: erosion followed by dilation; closing: dilation followed by erosion), target contours can be smoothed, thin connections disrupted, and small holes filled, enabling effective separation of the wheat ear layer from the straw layer.

### D. Edge Detection and Feature Extraction

Edges are regions in an image where grayscale values change sharply, containing rich shape information. Edge detection relies on differential operators. The Roberts operator uses local cross-differences to identify edges, offering precise localization and computational simplicity, though it is highly sensitive to noise. It is defined as:

$$g(x, y) = |f(x + 1, y + 1) - f(x, y)| + |f(x + 1, y) - f(x, y + 1)| \quad (6)$$

The Sobel and Prewitt operators introduce smoothing, offering stronger noise resistance, but with slightly inferior edge localization accuracy. The Hough Transform is a classical feature extraction technique that can map edge pixels in image space to parameter space. By detecting cumulative peaks in parameter space, it connects discontinuous edge points in the image into meaningful geometric shapes such as lines and circles [18, 19]. For large areas of lodged wheat, the lodging boundary often approximates a straight line. Therefore, Hough line detection is well-suited for accurately extracting boundary positions and subsequently calculating the height difference.

### III. SYSTEM MODULE DESIGN AND IMPLEMENTATION

#### A. Overall System Design

The system design follows modular principles to achieve a complete workflow from image acquisition to result output. The overall system architecture is shown in Figure 1, mainly including the image acquisition module, image preprocessing module, target segmentation module, feature extraction and assessment module, and control output module.

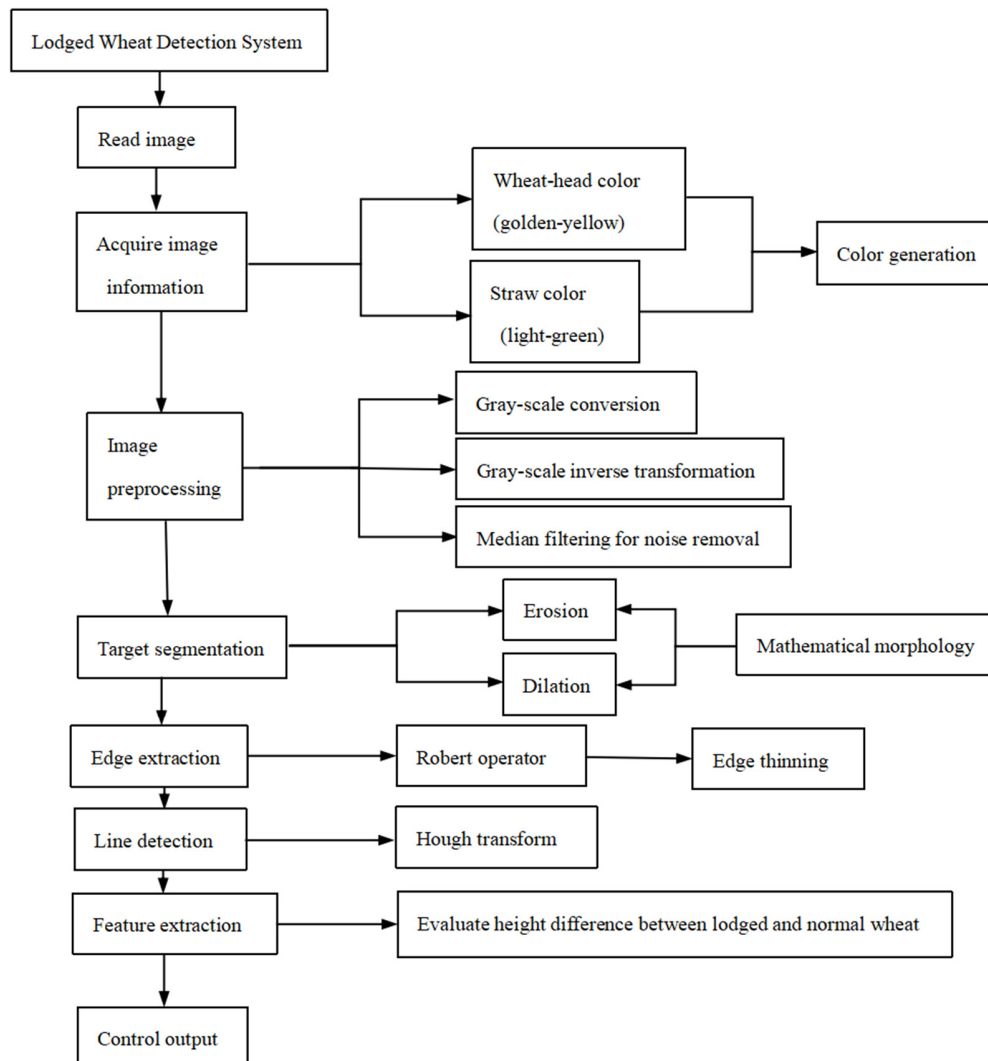


Fig. 1. System design.

During operation, the system first acquires real-time images of the wheat field via a camera mounted on the harvester. Upon detecting a large area of lodging, it automatically captures a valid image and initiates the processing pipeline. The core processing step involves using color differences and grayscale transformation to enhance the target, applying median filtering for noise suppression, performing morphological operations for target segmentation, detecting edges and lines to extract

boundaries, and ultimately calculating the lodging height difference. This height difference signal can be transmitted directly to the harvester's control unit to actuate the hydraulic system and adjust the header height accordingly.

#### B. Image Information Acquisition and Preprocessing Module

This module is the starting point of system processing, responsible for image input and initial enhancement. The

system reads 24-bit true-color BMP format images of lodged wheat captured by the camera using VC++, as illustrated in Figure 2(a). In the original image, the golden-yellow wheat ear layer and the light green lodged straw layer form a noticeable color difference, which is the basis for subsequent identification.

### 1) Grayscale Conversion and Transformation

First, the color image is converted to grayscale (Figure 2(b)) according to the weighting coefficients in (1). Subsequently, to strengthen the straw layer (typically darker in the grayscale image) as the target for separation, grayscale inversion, as expressed in (3), is applied, turning it into a bright area, significantly enhancing the contrast with the background (Figure 2(c)).

### 2) Median Filtering for Noise Reduction

Noise is introduced during image acquisition and transmission. This study employs a 3×3 circular template for median filtering (Figure 2(d)). The filtered image shows effectively suppressed noise, and the contours of the straw area become smoother and clearer, laying a good foundation for subsequent morphological processing. Compared to mean filtering, median filtering better protects edge details while removing noise, avoiding blurring of target edges.

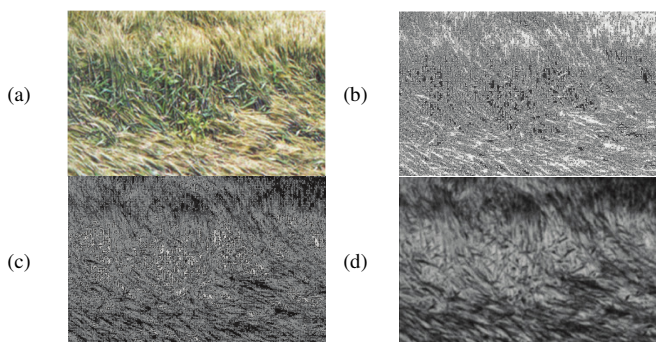


Fig. 2. Image preprocessing module effects: (a) original color image, (b) grayscale image, (c) grayscale inversion image, (d) image after median filtering.

## C. Target Segmentation Module

This module precisely separates the lodged straw layer from the image, generating a binary image.

### 1) Binarization

On the preprocessed grayscale image, a global threshold method or adaptive threshold method, such as Otsu's algorithm, is used to convert the image into a binary image. The target (straw layer) is set to white (255), and the background (wheat ear layer and others) is set to black (0).

### 2) Mathematical Morphology Processing

The initial binary image often contains noise points, holes, and fine connections between straw and wheat ears. In this study, a 3×3 omnidirectional structuring element was employed for alternating erosion and dilation operations.

### 3) Erosion Operation

The binary image is first eroded to remove burs along the straw edges, scattered small noise points, and to disconnect some fine connections. The result after the first erosion (Figure 3(a)) demonstrates that isolated white points are removed and the target area is slightly reduced.

### 4) Dilation Operation

The eroded image is subsequently dilated to fill holes within the straw area caused by erosion or initial segmentation and to expand the region for improved connectivity. The effect after a single dilation is displayed in Figure 3(b).

### 5) Alternating Operations

Due to the complexity of field scenes, multiple iterations of erosion and dilation (i.e., repeated opening and closing operations) are typically required. Through iterative processing, a clear-contoured, well-connected binary mask of the lodged straw layer is ultimately obtained (Figure 3(c)), with the wheat ear layer and straw layer completely separated at this stage.

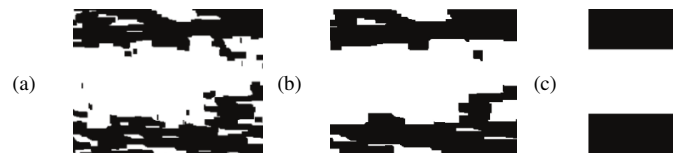


Fig. 3. Target segmentation process: (a) after first erosion, (b) after first dilation, (c) final segmentation.

## D. Edge Detection and Feature Extraction Module

This module is responsible for extracting geometric features—the lodging boundary lines—from the segmented binary target for quantitative calculation.

### 1) Edge Detection

The Roberts edge detection operator is applied to the final segmented binary image. The Roberts operator approximates the gradient by calculating differences in diagonal directions, making it sensitive to horizontal and diagonal edges and computationally lightweight, as depicted in Figure 4(a). It can quickly outline the upper and lower boundary contours of the lodged straw layer. Although sensitive to noise, the preceding filtering and morphological processing have significantly improved image quality, allowing the Roberts operator at this stage to obtain precisely located single-pixel edges.

### 2) Edge Thinning

The edges detected by the Roberts operator may still have some width. To accurately locate the centerline and reduce computation for the Hough Transform, thinning is performed on the edge image. The thinning algorithm iteratively removes the outer layer of edge pixels, eventually yielding a skeletonized edge of single-pixel width, as illustrated in Figure 4(b).

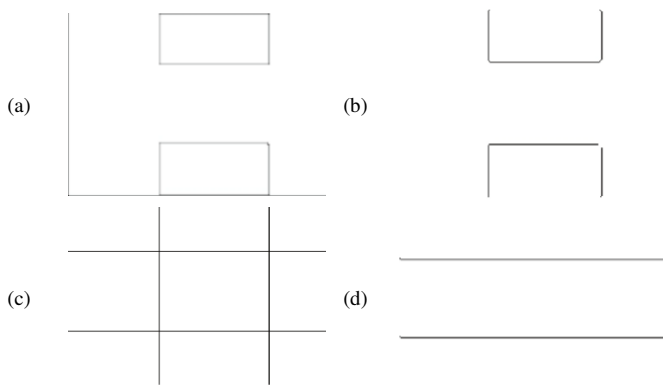


Fig. 4. Edge and feature extraction process: (a) Roberts edge detection result, (b) thinned edges, (c) Hough Transform detecting all lines, (d) final image after edge and feature extractions.

### 3) Hough Line Detection

The thinned edge image is used as input for the Hough Transform. The system identifies peak points in the parameter space  $(\rho, \theta)$  whose cumulative value exceeds a set threshold as lines (Figure 4(c)). The Hough Transform successfully detects the two main horizontal lines representing the upper and lower boundaries of the lodged layer.

### 4) Removing False Lines

In practical processing, some non-target lines, such as vertical edges of straw stems, might be detected. The system filters lines based on their angle parameter  $(\theta)$ , retaining only those close to horizontal (e.g.,  $\theta$  within  $[-10^\circ, 10^\circ]$  or  $[170^\circ, 190^\circ]$ ), thereby obtaining clean lodging boundary lines, as presented in Figure 4(d).

## E. Height Difference Calculation and System Integration

### 1) Height Difference Calculation

In the parameter space of the Hough Transform, each line is represented by  $(\rho, \theta)$ , where  $\rho$  is the perpendicular distance from the origin to the line. Let the parameters for the upper boundary line be  $(\rho_1, \theta_1)$  and for the lower boundary line be  $(\rho_2, \theta_2)$ . Since the two lines are approximately parallel ( $\theta_1 \approx \theta_2$ ), the lodging height difference  $H$  (in pixels) can be simplified as:

$$H = |\rho_1 - \rho_2| \quad (7)$$

This calculation is performed automatically within the software, and the result is displayed in real-time in a specific dialog box of the user interface (Figure 5).

## IV. SYSTEM TESTING AND RESULT ANALYSIS

To verify the effectiveness and reliability of the system, batch testing was conducted in a laboratory environment using pre-collected sets of field wheat images under different lodging severities and lighting conditions. The dataset used in this batch test includes field wheat images pre-collected from actual wheat cultivation fields in China's Hunan Province. These images were captured during the late growth stage of wheat (a critical period for lodging occurrence) using cameras installed on combine harvesters. The field sampling and image

acquisition (dataset collection) methods followed the standard procedures described in [5, 11], which address wheat yield reduction and lodging detection. A test set of 50 images of lodged wheat, annotated with true lodging boundaries, was used. The boundary lines finally detected by the system were overlaid on the original color images, and their conformity to the visually true lodging boundaries was manually evaluated. The stability of the system was assessed by observing the standard deviation of height difference calculation results from processing the same scene 10 consecutive times.

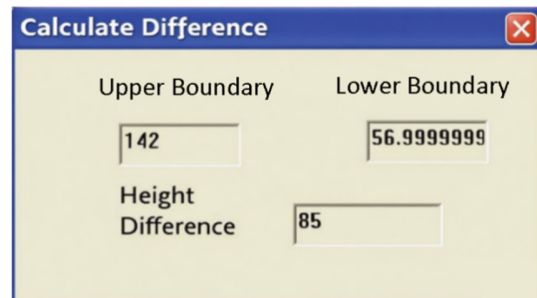


Fig. 5. Schematic of height difference result display.

Among the 50 test images, lodging boundaries were successfully and accurately detected in 47 images, with extremely high visual conformity, as shown in Figure 6. The detection lines output by the system almost completely covered the actual boundary areas where lodging occurred. Only 3 images exhibited slight deviations in boundary detection due to overly complex backgrounds (e.g., heavy weed interference) or extreme lighting unevenness. For a single image processed 10 consecutive times, the calculated height difference values were completely consistent, with a standard deviation of 0, indicating that the system processing pipeline is deterministic and possesses good repeatability and stability.



Fig. 6. Comparison between system detection results and actual boundaries.

The test results demonstrate that the machine vision-based monitoring and evaluation system for lodged wheat developed in this study achieved the expected design goals. The system can effectively identify and segment the lodged wheat straw layer from complex backgrounds, precisely locate lodging boundaries using edge detection and Hough Transform, and calculate a stable height difference.

However, the system also has certain limitations. For example, processing effectiveness might decline under extreme conditions such as severe weed cover or drastic lighting changes. Additionally, the current system calculates the height difference in pixels; conversion to actual physical dimensions (centimeters) requires camera calibration to introduce a scaling factor. These are areas for future improvement and refinement.

## V. CONCLUSION

This study focused on the practical requirement of reducing harvest losses in precision agriculture, successfully designing and developing a machine vision-based monitoring and evaluation system for lodged wheat. The study established an integrated image-processing framework, incorporating color analysis, grayscale conversion, median filtering, mathematical morphology, Roberts edge detection, and Hough line detection. This framework can accurately extract lodging boundary information from field images.

An application with a graphical user interface was developed on the Visual C++ platform, integrating all functions, including image acquisition, preprocessing, segmentation, feature extraction, and result output. The system is user-friendly, offering intuitive and accessible results. Experimental tests confirmed that the system can accurately identify lodging boundaries, with the calculated height difference parameter demonstrating stability and reliability. This provides a direct and effective input for the automatic control of the combine harvester header, laying the groundwork for achieving "see-and-act" intelligent harvesting. The development of this system demonstrates the successful application of machine vision technology in precision agriculture. It offers a practical technical pathway and equipment prototype for advancing the intelligence and informatization of agricultural machinery, with positive implications for the promotion of smart agriculture.

Unlike existing studies on wheat lodging detection that are confined to controlled laboratory environments and focus on optimizing individual processing links, this study develops a user-centered integrated software system, realizing the complete workflow from image acquisition to result output. A composite image processing framework integrating color difference analysis and other methods is proposed to solve the problems of low robustness and poor adaptability to field environments in single-algorithm detection. In addition, the system establishes the connection between detection results and combine harvester control, integrating theoretical principles with practical applications.

Compared with similar studies, the present work offers three key contributions. First, in terms of system integration, existing studies use UAV remote sensing images for detection, which cannot meet the real-time operation needs of combine harvesters, while the ground-based real-time monitoring system in this study is more in line with actual requirements. Second, in terms of algorithm optimization, the proposed integrated framework avoids the limitations of single algorithms and achieves higher boundary detection accuracy and stability. Third, in terms of practical application, the system is developed as software with a graphical user interface, which is easy to

operate and can transmit height difference signals to the harvester control unit. It provides a feasible solution for reducing harvest losses and promotes the intelligent development of agricultural machinery in precision agriculture.

## DECLARATION OF COMPETING INTERESTS

The authors declare no competing interests.

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## DATA AVAILABILITY

Field sampling and image acquisition were performed in accordance with the standard procedures described in [5, 11]. The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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