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Improved Hybrid Preprocessing Technique for Effective Segmentation of Wheat Canopies in Chlorophyll Fluorescence Images

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Abstract

Precision agriculture heavily relies on accurately segmenting wheat canopies from chlorophyll fluorescence (CHF) images. However, these images often face challenges due to inherent noise and illumination variations, primarily induced by the thermal activity of photons emitting a fluorescence effect. The unique nature of fluorescence introduces variations in illumination, especially during the crop's dark adaptation before experimentation. This adaptation aims to capture the full fluorescence effect, starting from minimum fluorescence and progressing to maximum fluorescence. In the initial stages of fluorescence, images tend to appear darker compared to those progressing towards maximum fluorescence. This variability necessitates the development of a sophisticated hybrid approach to eliminate noise and enhance contrast collaboratively, maximizing the benefits derived from CHF images. This paper introduces a novel hybrid preprocessing approach designed to address these challenges. The proposed method integrates five denoising techniques, namely Discrete Cosine Transform, Block Matching-3D, Low-Rank Matrix Approximation, Wiener Filtering, and Median Filtering, to mitigate the impact of noise in CHF images. Simultaneously, two enhancement techniques, Adaptive Histogram Specification and Gamma Correction, are employed to accentuate critical features, compensating for inherent variations in illumination during the fluorescence process. The hybrid preprocessing technique was proposed after analysing different combinations of denoising and enhancement techniques. Through qualitative and quantitative analysis of the results, it was observed that Block Matching-3D denoising with Gamma Correction produced the best output, with an Average PSNR of 0.54 and Average MSE of 0.07. This cascaded approach not only emphasizes noise reduction but also prioritizes the enhancement of crucial information within CHF images. By synergistically combining denoising and enhancement methods, the proposed approach optimizes the overall quality of the images, laying a foundation for improved wheat canopy segmentation. This research contributes a comprehensive and innovative solution to the challenges associated with CHF images in precision agriculture. The proposed hybrid approach holds promise for advancing the accuracy and reliability of wheat canopy segmentation, thereby enhancing the efficacy of precision agricultural practices.

Keywords: Wheat Canopy, Chlorophyll Fluorescence, Denoising, Enhancement, and Segmentation

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1. Introduction

This is the body text with no indent. Precision agriculture has emerged as a transformative paradigm, leveraging advanced technologies to enhance the efficiency and sustainability of farming practices. Central to precision agriculture is the accurate segmentation of crop canopies from imaging data, providing valuable insights for optimized crop management. In this context, chlorophyll fluorescence (CHF) imaging has become a pivotal tool [1], allowing researchers to assess the physiological state of crops by capturing their fluorescence emissions.

However, the utility of CHF images for precise crop segmentation is often hindered by challenges such as inherent noise and illumination variations. These challenges stem from the thermal activity of photons during the fluorescence process, where the crop undergoes dark adaptation before experimentation to capture the complete spectrum of fluorescence, ranging from minimum to maximum [2]. Consequently, images captured at the initial stages of fluorescence exhibit a darker appearance compared to those acquired during the progression toward maximum fluorescence.

To unlock the full potential of CHF images in precision agriculture, it is imperative to employ advanced preprocessing techniques that address these challenges collaboratively. Traditional preprocessing methods often focus on either denoising or enhancement in isolation, neglecting the synergies that can be achieved through a holistic hybrid approach.

This research introduces a novel hybrid preprocessing technique designed to tackle the specific challenges associated with CHF images. The proposed approach seamlessly integrates sophisticated denoising and enhancement techniques, aiming to improve the robustness and accuracy of wheat canopy segmentation. By addressing noise reduction and contrast enhancement collaboratively, the preprocessing technique seeks to optimize the information extracted from CHF images, thereby laying a foundation for more accurate and reliable segmentation results [3].

2. Literature Survey

In the landscape of wheat crop image preprocessing for precision agriculture, diverse studies have addressed the challenges associated with denoising and enhancement techniques. For instance, delved into Discrete Wavelet Transform (DWT) as a denoising method [4], showcasing its effectiveness in preserving essential features while reducing various types of noise in wheat crop images. On a different note, [5] explored the application of Non-Local Means (NLM) denoising, highlighting its adaptability to handle diverse noise patterns, thereby contributing to an improved signal-to-noise [6].

Enhancement methodologies have also been a focal point in the literature. Histogram Equalization-based enhancement method emphasized its efficacy in improving the overall contrast and visibility of crucial details in wheat crop images, particularly in regions with varying illumination [7].

TV-L1 denoising with a PDA with min-max contrast stretching has also been utilised by authors to enhance the overall quality of wheat crop images [8]. Meanwhile, Gamma Correction based enhancement approach has also been utilised to compensate for illumination variations, demonstrating its potential to enhance image features [9]. Hybrid approaches have gained attention as well, with the integrating Principal Component Analysis (PCA)-based denoising with Adaptive Histogram Equalization for simultaneous noise reduction and contrast enhancement in wheat crop images [10]. These studies collectively contribute to the evolving landscape of wheat crop image preprocessing, showcasing innovative strategies to enhance image quality for precise analysis in precision agriculture applications.

3. Identified Gaps in the Literature

After the comprehensive analysis of literature in context preprocessing of wheat crop images various research gaps have been identified. This examination highlights crucial areas where further investigation is warranted to advance the field and develop more effective methodologies for detecting and mitigating stress in wheat crops. The gaps are as follows:

- The existing literature lacks comprehensive preprocessing techniques tailored specifically for Chlorophyll Fluorescence (CHF) images of wheat crops.
- There is a scarcity of research exploring preprocessing methods that effectively enhance the spectral signatures in CHF images of wheat crops.
- Current preprocessing approaches may not adequately address the challenges posed by environmental variability, such as changes in lighting conditions and field heterogeneity.
- There is a lack of dedicated preprocessing techniques optimized for the early detection of drought stress in CHF images of wheat crops.
- Limited research explores the integration of spatial and temporal information in the preprocessing of CHF images for wheat crop stress detection.
- The absence of open-access CHF datasets for wheat crops hinders the development and validation of preprocessing techniques.

Addressing these gaps can significantly advance the field of wheat crop stress detection using CHF images by focusing on tailored preprocessing techniques that enhance the quality and informativeness of the data. After identifying gaps in the preprocessing of wheat crop images, particularly CHF images, it is crucial to understand their significance in stress detection, specifically in the context of drought stress. The detailed information regarding the selection of a specific modality for stress detection and its research importance is provided in the next section (Section 4)

4. Significance of Using CHF Images for Precision Agriculture

Precision agriculture, propelled by technological advancements, aims to optimize farming practices through the utilization of real-time data and advanced analytics. An integral component of precision agriculture involves the timely detection and mitigation of environmental stressors that impact crop health. In this context, chlorophyll fluorescence (CHF) imaging emerges as a potent tool with substantial implications, particularly in identifying various stressors such as heat, frost, drought, and salinity. Our research endeavors to enhance CHF images through various preprocessing operations, facilitating the extraction of the photosynthetically active area of interest. This extracted area can then be further utilized to identify key features related to drought, aiding in the detection of drought stress. Recognizing the significance of CHF images in this regard is crucial for unlocking their potential within the realm of precision agriculture. CHF images prove powerful due to their ability to provide insights into plant stressors, enabling more informed and targeted agricultural interventions. The CHF images are potent enough due to following reasons:

- Photosynthetic Indicator: Chlorophyll fluorescence is a direct indicator of the photosynthetic activity of plants. As plants experience drought stress, their physiological processes, including photosynthesis, are affected. CHF images capture the fluorescence emitted by chlorophyll molecules during photosynthesis, providing a non-invasive means to assess the impact of drought on the plant's vital processes [11].
- Early Detection of Stress Responses: Drought stress often manifests as a gradual process, impacting the plant's physiology over time [12]. CHF imaging allows for the observation of temporal dynamics in fluorescence emissions. Early detection of changes in chlorophyll fluorescence patterns enables farmers and researchers to identify drought stress at its incipient stages, facilitating proactive intervention.
- Quantitative Assessment of Stress Severity: CHF images provide quantitative metrics related to fluorescence parameters, such as the quantum yield of photosystem II (PSII) and the non-photochemical quenching coefficient. These metrics offer insights into the severity of drought stress, allowing for a nuanced understanding of how different levels of stress influence the plant's photosynthetic efficiency [13].
- Spatial Resolution for Site-Specific Management: Drought stress often exhibits spatial variability within a field. CHF imaging, when integrated into precision agriculture systems, enables the capture of spatial patterns in chlorophyll fluorescence [14]. This spatial resolution facilitates site-specific management strategies, allowing farmers to tailor interventions based on the localized impact of drought stress [15].
- Integration with Precision Agriculture: CHF images can guide precision irrigation practices by identifying areas of the field experiencing drought stress. This information empowers farmers to optimize water usage by targeting irrigation where it is most needed. Precision irrigation, informed by CHF imaging, contributes to resource efficiency and sustainable water management [16].
- CHF imaging serves as an early warning system: As they offer a proactive approach to managing crop health. By detecting drought stress early on, farmers can implement timely interventions, such as adjusting irrigation schedules or applying targeted treatments, minimizing yield losses and ensuring crop resilience [17].

5. Data Collection and Characteristics

In total, this research work incorporates (1440 x 2) images, representing the entire fluorescence cycle from its minimum to progressing towards maximum fluorescence. The experiment utilizing this dataset spanned 135 days, with 60 days dedicated to the analysis. During this period, 24 images for each drought and control experiment were captured, encompassing the entire fluorescence cycle and including images from both vegetative and reproductive stages of wheat. The objective was to develop an early drought stress detection system that combines images from both Control and Drought categories. Each image captures the chlorophyll fluorescence characteristics of the Indian wheat variety Raj 3765 under varying environmental conditions, contributing to the dataset's richness and diversity [18]

6. Preprocessing of Wheat Canopy Images

The preprocessing of wheat canopy images is a critical phase in enhancing the quality and suitability of the data for subsequent analysis and segmentation tasks. This section outlines the series of preprocessing steps applied to the Chlorophyll Fluorescence (CHF) images of wheat canopies, with a focus on preparing the data for efficient segmentation and, ultimately, drought stress detection.

6.1. Noise Reduction of CHF Images

In this section, we conduct an experimental evaluation of five denoising techniques applied to Chlorophyll Fluorescence (CHF) images. The primary objective is to assess the denoising efficiency of these techniques in a simulated noise environment with a specified noise level of 0.5. The introduced noise is random, with a mean of 0, replicating conditions encountered in real-world scenarios. The selected denoising techniques are described below:

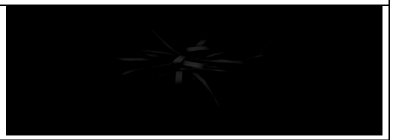
- Discrete Cosine Transform (DCT) Denoising: Utilizes the Discrete Cosine Transform to selectively remove noise from CHF images based on frequency domain thresholding [19] [20].
- Block Matching-3D (BM3D) Denoising: Applies Block Matching-3D collaborative filtering to exploit similarities in 3D groups of blocks for effective noise reduction [21].
- Low-Rank Matrix Approximation: Aims to approximate CHF images as low-rank matrices, effectively separating noise from the underlying image structure [22].
- Wiener Filtering: Applies Wiener filtering, a statistical method, to minimize mean square error between the original and filtered CHF images, especially effective when noise statistics are known [23].
- Median Filtering: Employs a median filter to smooth CHF images and mitigate the impact of random noise, particularly effective against impulse noise [23].

In this section, we present the results of applying various denoising techniques to the entire simulated dataset, initially contaminated with random noise with standard deviation 0.5 and mean =0.

Figure 1. Wheat image simulated with random noise

Fig. 1 illustrates an instance of a noisy image from the dataset, which serves as a representative example. After the denoising phase, the qualitative evaluation of denoised Chlorophyll Fluorescence (CHF) images reveals that the BM3D and Median Filtering techniques have demonstrated superior results as shown in Table 1.

Table 1. Qualitative Comparison of Denoising Techniques

Denoising Technique	Denoised Image
DCT Denoising	
BM3D Denoising	
Low-Rank Matrix Approximation (LRMA)	
Wiener Filtering (WF)	
Median Filtering (MF)	

It can be clearly visualized that the results generated by BM3D denoising and the Median Denoising filter are qualitatively superior compared to other applied denoising filters. Consequently, the outcomes obtained from these two filters are selected for further experimentation with different enhancement procedures to improve the quality of preprocessing. To further enhance the quality of the segmentation process, the denoised images produced by these two filters are undergone by two contrast enhancement procedures detailed in next section 6.2.

6.2. Enhancement of Denoised CHF Images

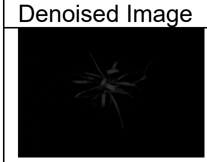
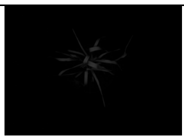
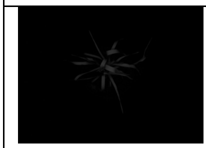
After the successful application of denoising techniques, two enhancement techniques, Adaptive Histogram Specification (AHS) and Gamma Correction (GC) has been applied sequentially after denoising to optimize the visual quality of Chlorophyll Fluorescence (CHF) images. The detailed description of the utilised techniques are given below:

- Adaptive Histogram Specification: It is technique which is employed to enhance the contrast of denoised CHF images. This technique tailors the contrast enhancement to local characteristics within the images, adapting to the specific features of different regions [24]. The goal is to improve visibility and emphasize relevant details for more effective segmentation.

- Gamma Correction: It is a non-linear contrast enhancement technique applied to the denoised CHF images [25]. By adjusting the gamma parameter, this procedure fine-tunes the brightness and contrast, aiming to enhance specific visual characteristics and further optimize the images for segmentation.

Qualitative evaluation of results after applying enhancement after denoised images is given in Table 2. below.

Table. 2.Qualitative Comparison of Enhancement Techniques

Denoised Image	AHS	GC
 Technique Used: BM3D denoising	 BM3D Denoising cascaded with AHS	 BM3D Denoising cascaded with GC
 Technique Used: Median denoising	 Median Denoising cascaded with AHS	 Median Denoising cascaded with GC.

The experimental outcomes indicate that both enhancement approaches demonstrated improved results when applied in a cascaded manner after BM3D. However, the combination of BM3D with Gamma Correction exhibited the highest image quality compared to the other three cascaded combinations: BM3D with Adaptive Histogram Specification (AHS), Median Filtering with AHS, and Median Filtering with Gamma Correction (GC). These results are also verified in terms two quantitative metrics also to be double sure about the results detailed below:

Peak Signal-to-Noise Ratio (PSNR): It is employed as the primary evaluation metric to quantitatively measure the denoising efficiency of each technique [26]. PSNR is calculated using the formula given in equation (1):

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\text{Max intensity of a pixel}^2}{\text{MSE}}\right) \qquad (1)$$

where,
Max intensity of a pixel is the maximum possible pixel intensity value.

MSE (Mean Squared Error) is computed between the original and denoised CHF images. It is a metric commonly used to measure the similarity between two images. The MSE between two images is calculated by taking the average of the squared differences between corresponding pixel values in the images. MSE is computed using the formula given in equation (2).

$$\mathrm{MSE} = \frac{1}{n\times m}\sum_{i=1}^{n}\sum_{j=1}^{m}(Iij - Kij)^2 \qquad (2)$$

Where,
n and m are the dimensions (height and width) of the images. Iij is the intensity of the pixel at position (i,j) in the first image. Kij is the intensity of the pixel at position (i,j) in the second image [27].

The MSE gives a measure of the average squared difference between corresponding pixel intensities. A lower MSE indicates a higher similarity between the images, as it means that the pixel values are closer to each other.

Table 3. Quantitative comparison of proposed hybrid preprocessing combinations

Performance Metrics	COMBINATIONS					
	BM3D	MF	BM3D with AHS	MF with AHS	BM3D with GC	MF with GC
Average PSNR	0.49	0.43	0.50	0.44	0.54	0.49
Average MSE	0.37	0.67	0.23	0.53	0.07	0.09

The Table. 3 presents a quantitative comparison of hybrid preprocessing combinations using cascading effect of denoising with enhancement techniques and based on evaluated performance metrics viz. Average PSNR and Average MSE. Among the combinations, "BM3D with GC" stands out with the highest average PSNR (0.54) and the lowest average MSE (0.07), indicating superior image quality and minimal errors. This suggests that the integration of BM3D with Gamma correction (GC) is particularly effective in preprocessing CHF images.

7. Conclusions

In conclusion, this paper addresses the critical challenges associated with accurately segmenting wheat canopies from chlorophyll fluorescence (CHF) images in the context of precision agriculture [28]. The inherent noise and illumination variations, primarily induced by thermal activity during fluorescence, pose significant obstacles in obtaining precise segmentation. Recognizing the unique nature of fluorescence, especially during the crop's dark adaptation, the paper proposes a sophisticated hybrid preprocessing approach to collaboratively eliminate noise and enhance contrast.

The method integrates five denoising techniques—Discrete Cosine Transform, Block Matching-3D, Low-Rank Matrix Approximation, Wiener Filtering, and Median Filtering—aiming to mitigate the impact of noise in CHF images. Simultaneously, two enhancement techniques, Adaptive Histogram Specification and Gamma Correction, are employed to compensate for inherent variations in illumination during the fluorescence process.

Through a comprehensive analysis of various combinations of denoising and enhancement techniques, the study reveals that the Block Matching-3D with Gamma Correction combination produces the best output both qualitatively and quantitatively, achieving an Average PSNR of 0.54 and Average MSE of 0.07. This cascaded approach not only prioritizes noise reduction but also emphasizes the enhancement of crucial information within CHF images.

By synergistically combining denoising and enhancement methods, the proposed hybrid approach optimizes the overall quality of CHF images, providing a solid foundation for improved wheat canopy segmentation. This research contributes an innovative solution to the challenges faced in precision agriculture, holding promise for advancing the accuracy and reliability of wheat canopy segmentation and, consequently, enhancing the efficacy of precision agricultural practices [29][30].

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