Postprint: A Method for Estimating Tomato Leaf Mold Disease Severity Based on Envelope Removal

Authors: Jia Fangfang, Hong Quanchun, Song Weiyi

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Abstract

Elucidating the spectral characteristics of tomato leaf mold disease (Fulvia fulva) and estimating its disease severity can provide a basis for large-area remote sensing monitoring of tomato leaf mold disease. This study analyzed the leaf spectral variation characteristics under different severity levels of tomato leaf mold disease to screen sensitive bands for disease severity identification. The continuum removal method was used to process spectral reflectance, and a disease severity estimation model based on spectral characteristic absorption parameters was constructed. The research results indicate that: with the deepening of disease severity levels, the original spectral reflectance, spectral sensitivity, and relative reflectance of tomato leaves all showed a gradually decreasing trend; the visible band (550–730 nm) and shortwave infrared band (1,860–2,260 nm) are the optimal bands for identifying tomato leaf mold disease severity; and with the increase of disease severity levels, the absorption band position ( ) shifted toward shorter wavelengths, while both the maximum absorption depth (Dc) and absorption area (A) exhibited an increasing pattern. The stepwise regression model constructed using spectral parameters for predicting tomato leaf mold disease severity levels achieved an R^2 of 0.81, and the model validation results were satisfactory. The research findings hold high practical value for quantitative estimation of tomato leaf mold disease severity using hyperspectral remote sensing technology, as well as for monitoring and controlling crop pests and diseases.

Full Text

Continuum Removal Method for Monitoring Fulvia fulva Morbidity Using Hyperspectral Data

JIA Fangfang[1,2], HONG Quanchun[1], , SONG Weiyi[1] [1]Department of Life Science, Shangqiu Normal University, Shangqiu 476000, China [2]Zhengzhou University, Zhengzhou 450002, China

Abstract

Clarifying the spectral characteristics of tomato leaf mold (Fulvia fulva) and estimating its morbidity degree can provide a theoretical basis for large-scale remote sensing monitoring of this disease. This study analyzed the spectral variation features of tomato leaves under different disease severity levels, identified sensitive bands for disease recognition, and constructed a morbidity estimation model based on spectral absorption parameters derived from continuum removal processing. The results demonstrated that as the disease severity grade increased, the original spectral reflectance, spectral sensitivity, and relative reflectance of tomato leaves all showed a gradual decreasing trend. The visible band (550–730 nm) and shortwave infrared band (1860–2260 nm) were identified as the optimal regions for distinguishing F. fulva severity. With increasing disease severity, the absorption band position ( ) shifted toward shorter wavelengths, while both the maximum absorption depth (Dc) and absorption area (A) exhibited increasing trends. The stepwise regression model constructed using spectral parameters achieved an R^2 of 0.81 for predicting tomato leaf mold severity grades, with satisfactory validation results. These findings hold significant practical value for quantitatively estimating F. fulva morbidity degree using hyperspectral remote sensing technology and for monitoring and controlling crop diseases in general.

Keywords: Tomato; Fulvia fulva; Hyperspectral; Continuum removal; Morbidity degree

Introduction

Tomato leaf mold, caused by Fulvia fulva (Cladosporium fulvum), is a major disease affecting tomato cultivation, typically causing yield losses of 20–30% and up to 50% under severe conditions [1,4,5-8]. Traditional laboratory analysis methods are time-consuming and destructive. In contrast, hyperspectral remote sensing technology offers simple, cost-effective, and non-destructive approaches for diagnosing and quantifying plant health status. However, hyperspectral data present challenges including large data volumes, redundant information, and complex spectral features. The continuum removal method has proven effective for enhancing absorption features and extracting characteristic parameters [9-10], with successful applications in monitoring crop diseases such as cotton verticillium wilt [12] and wheat yellow rust [11]. Previous studies have identified the red edge region (650–700 nm) as sensitive to plant stress [2,3]. This study aims to establish a robust method for estimating tomato leaf mold severity based on spectral absorption characteristics.

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1. Materials and Methods

1.1 Experimental Design Experiments were conducted during July–August 2016 in a tomato leaf mold disease nursery in Shangqiu, Henan Province (34°29 4.76 N, 115°38 47.15 E). The tomato variety "Baoluo" was cultivated in a 150 m² plot. Disease severity was graded into five levels: 0 (healthy), 1, 2, 3, and 4, according to the percentage of diseased leaf area. For each severity level, 30 representative leaves were selected, with 10 spectral measurements taken per leaf after discarding the maximum and minimum values to obtain average reflectance spectra.

1.2 Spectral Data Measurement Leaf spectral reflectance was measured using an ASD FieldSpec 3 spectrometer (350–2500 nm) equipped with a leaf clip. The instrument provided a spectral resolution of 1.4 nm for the 350–1000 nm range and 2 nm for the 1000–2500 nm range, with a sampling interval of 1 nm. Measurements were taken under clear sky conditions between 10:00 and 14:00 local time. A 1000 W halogen lamp served as the light source, with the probe positioned 15 cm from the leaf surface at a 45° angle. White reference calibration was performed using a standard white panel every 10 minutes. A total of 250 spectral curves were acquired, with 150 used for model development and 100 reserved for validation.

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2. Methodology

2.1 Continuum Removal Method Continuum removal is a spectral analysis technique that normalizes reflectance spectra to enhance absorption features. The method involves fitting a convex hull (continuum line) connecting local spectral maxima across the wavelength range. The continuum-removed reflectance (R) is calculated as:

$$R' = \frac{R}{R_c}$$

where R is the original reflectance and R_c is the continuum line reflectance at each wavelength. This transformation isolates absorption features by removing the baseline effects of overall reflectance shape, making it easier to compare absorption characteristics among spectra with different absolute reflectance values [Figure 1: see original paper].

2.2 Spectral Absorption Characteristic Parameters From the continuum-removed spectra, three key absorption parameters were extracted for each characteristic absorption feature: - **Maximum absorption depth (Dc):** The maximum depth of the absorption feature relative to the continuum line - **Absorption area (A):** The integrated area of the absorption feature - **Absorption position ( ):** The wavelength at which maximum absorption depth occurs

These parameters were calculated for two primary absorption regions: the visible band (550–730 nm) and the shortwave infrared band (1860–2260 nm).

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3. Results and Analysis

3.1 Spectral Reflectance Variation at Different Disease Severity Levels The original spectral reflectance of healthy tomato plants was consistently higher than that of diseased plants across the entire 350–2500 nm range [Figure 2: see original paper]. As disease severity increased from level 0 to level 4, spectral reflectance decreased progressively. The most pronounced differences occurred in two distinct wavelength regions: the visible region (550–730 nm) and the shortwave infrared region (1860–2260 nm). In these bands, the reflectance difference between severity levels exceeded 10%, making them optimal for disease discrimination.

3.2 Sensitive Band Selection

3.2.1 Spectral Sensitivity Analysis Spectral sensitivity (S) was calculated to quantify the discrimination capability between disease levels:

$$S = \frac{R_{healthy} - R_{diseased}}{R_{healthy}} \times 100\%$$

The sensitivity analysis revealed strong correlations between spectral sensitivity and disease severity in the 550–730 nm and 1860–2260 nm bands [FIGURE:3, FIGURE:4]. Sensitivity values ranged from 0.4 to 0.8 in the visible region and showed consistent increasing trends with disease severity.

3.2.2 Characteristic Band Selection Based on correlation analysis between relative reflectance and disease severity, the following characteristic bands were selected: - **Visible region:** 550–730 nm (correlation coefficient |r| > 0.7) - **Shortwave infrared region:** 1860–2260 nm (correlation coefficient |r| > 0.65)

Relative reflectance analysis confirmed that these bands provided the strongest discrimination among disease severity levels [Figure 5: see original paper].

3.3 Spectral Absorption Features

3.3.1 Variation of Absorption Characteristics with Disease Severity Continuum-removed spectra revealed distinct absorption features in both the visible and shortwave infrared regions. As disease severity increased: - The absorption position ( ) shifted toward shorter wavelengths (blue shift) - The maximum absorption depth (Dc) increased progressively - The absorption area (A) expanded systematically

[Figure 5: see original paper] illustrates these trends, showing deepening and widening absorption features with advancing disease progression. The visible band absorption (centered around 670 nm) is associated with chlorophyll degradation, while the SWIR band absorption (centered around 2100 nm) relates to changes in leaf water content and cellular structure.

Table 1 presents the quantitative absorption parameters for each disease severity level. The values demonstrate clear monotonic relationships: Dc1 (visible band) increased from 0.08 in healthy leaves to 0.31 in severely diseased leaves, while Dc2 (SWIR band) increased from 0.12 to 0.35. Concurrently, 1 shifted from 698 nm to 672 nm, and 2 shifted from 2238 nm to 2186 nm.

3.3.2 Modeling Tomato Leaf Mold Severity Correlation analysis revealed that disease severity was significantly correlated with five absorption parameters: Dc1, A2, Dc2, 1, and 2 ($p < 0.01$). A stepwise regression model was developed using these parameters:

$$y = 45.95 - 15.69Dc1 + 0.09A2 - 15.80Dc2 - 0.15\lambda 1 + 0.04\lambda 2$$

where y represents the predicted disease severity grade (0–4).

Table 2 summarizes the model structure and coefficients. The model achieved a coefficient of determination (R^2) of 0.81 ($p < 0.01$) using the calibration dataset ($n = 150$).

Model validation using the independent validation dataset ($n = 100$) demonstrated strong agreement between predicted and observed disease severity levels [Figure 6: see original paper]. The root mean square error (RMSE) was 1.46, indicating satisfactory predictive accuracy for practical applications.

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4. Discussion and Conclusion

This study successfully demonstrated that hyperspectral remote sensing combined with continuum removal analysis can effectively estimate tomato leaf mold severity. The identification of sensitive bands in both visible (550–730 nm) and shortwave infrared (1860–2260 nm) regions provides a robust basis for developing multispectral sensors optimized for disease monitoring.

The continuum removal method proved valuable for isolating absorption features associated with pathological changes in leaf biochemistry and structure. The extracted absorption parameters—particularly maximum absorption depth and position—showed consistent responses to disease progression, enabling quantitative modeling.

The stepwise regression model, incorporating five key absorption parameters, achieved an R^2 of 0.81 and RMSE of 1.46, demonstrating strong predictive capability. This approach offers several advantages over traditional methods: it is non-destructive, rapid, and can potentially be scaled up to airborne or spaceborne platforms for regional disease monitoring.

However, several considerations should be noted. First, the model was developed under specific experimental conditions and requires further validation across different tomato varieties, growth stages, and environmental conditions. Second, the influence of soil background and canopy structure on spectral signals needs to be addressed for field-scale applications. Future research should integrate these spectral methods with spatial analysis and machine learning algorithms to enhance monitoring accuracy and operational feasibility.

In conclusion, this study provides a reliable method for quantifying tomato leaf mold severity using hyperspectral data. The continuum removal technique effectively enhances disease-related spectral features, and the regression model based on absorption parameters offers practical value for precision agriculture and crop protection strategies.

References

[1] Chen Y F. Research advance of tomato leaf mould in China[J]. Journal of Northeast Agricultural University, 2000, 31(4): 411–414

[2] Wang X Y, Wang B L. Progress of infecting and resistant mechanism in tomato leaf mould[J]. Journal of Changjiang Vegetables, 2008, (7B): 1–4

[3] Meng F J, Xu X Y, Li J F. Progress in research on Fulvia fulva (Cook) of tomato caused by Cladosporeum fulvum[J]. Chinese Agricultural Science Bulletin, 2005, 21(6): 297–301

[4] Zhou Y, Yu H X, Jia L H, et al. Effects of different fungicides on colonization efficiency of the leaves of tomato leaf mold[J]. Tianjin Agricultural Sciences, 2016, 22(1): 116–118

[5] An J, Yao G Q, Zhu X C. Study of hyperspectral detection for nitrogen content of apple leaves[J]. Remote Sensing for Land & Resource, 2016, 28(2): 67–71

[6] Jia F F, Zhang L M, Ren T B, et al. Hyperspectral inversion to estimate plastid pigment contents in tobacco leaves based on BP neural network[J]. Tobacco

Science & Technology, 2016, 49(7): 8-13

[7] Moshou D, Bravo C, West J, et al. Automatic detection of 'yellow rust' in wheat using reflectance measurements and neural networks[J]. Computers and Electronics in Agriculture, 2004, 44(3): 173-188

[8] Belasque J, Gasparoto M C G, Marcassa L G. Detection of mechanical and disease stresses in citrus plants by fluorescence spectroscopy[J]. Applied Optics, 2008, 47(11): 1923-1929

[9] Kokaly R F, Clark R N. Spectroscopic determination of leaf biochemistry using band-depth analysis of absorption features and stepwise multiple linear regression[J]. Remote Sensing of Environment, 1999, 67(3): 267-287

[10] Zhang X H, Tian Q J. Hyperspectral evaluation of nitrogen accumulation in winter wheat leaves based on continuum-removed method[J]. Chinese Journal of Ecology, 2010, 29(1): 181-186

[11] Zhang J H. Rice nitrogen nutrition diagnosis using continuum-removed reflectance[J]. Journal of Plant Ecology, 2006, 30(1): 78-82

[12] Jing X, Wang J H, Song X Y, et al. Continuum removal method for cotton verticillium wilt severity monitoring with hyperspectral data[J]. Transactions of the CSAE, 2010, 26(1): 193-198

[13] Han Z Y, Zhu X C, Wang L, et al. Hyperspectral evaluation of SPAD value of apple tree canopy based on continuum-removed method[J]. Laser & Optoelectronics Progress, 2016, 53(2): 214-223

[14] Li Y H, Wang Q, Huang J Z, et al. Principle and Method of Ground Remote Sensing Experiment[M]. Beijing: Science Press, 2011: 45

[15] Xie B C, Xue X Z, Liu W D, et al. Hull-curve-method-based extraction and analysis of soil spectral characteristics[J]. Acta Pedologica Sinica, 2005, 42(1): 171-175

[16] Jiang J B, Li Y F, Guo H Q, et al. Spectral characteristics and identification research of soybean under different disease stressed[J]. Spectroscopy and Spectral Analysis, 2012, 32(10): 2787-2791

[17] Zhang Y H, Chen W H, Guo Q Y, et al. Hyperspectral estimation models for photosynthetic pigment contents in leaves of Eucalyptus[J]. Acta Ecologica Sinica, 2013, 33(3): 876-887

[18] Jia F F, Ma X M, Li C M, et al. Effect of water condition on hyperspectral and red-edge characteristics of tobacco leaf[J]. Chinese Journal of Eco-Agriculture, 2011, 19(6): 1330-1335

[19] Liu L Y. Principle and Application of Vegetation Quantitative Remote Sensing[M]. Beijing: Science Press, 2014: 32-33

[20] Kobayashi T, Kanda E, Kitada K, et al. Detection of rice panicle blast with multispectral radiometer and the potential of using airborne multispectral

scanners[J]. Phytopathology, 2001, 91(3): 316-323

[21] Feng W, Wang X Y, Song X, et al. Hyperspectral estimation of canopy chlorophyll density in winter wheat under stress of powdery mildew[J]. Transactions of the Chinese Society of Agricultural Engineering, 2013, 29(13): 114-123

[22] Chen B, Wang K R, Li S K, et al. The effects of disease stress on spectra reflectance and chlorophyll fluorescence characteristics of cotton leaves[J]. Transactions of the CSAE, 2011, 27(9): 86-93

[23] Yuan L, Zhang J C, Zhao J L, et al. Differentiation of yellow rust and powdery mildew in winter wheat and retrieving of disease severity based on leaf level spectral analysis[J]. Spectroscopy and Spectral Analysis, 2013, 33(6): 1608-1614

[24] Cai X Z, Takken F L W, Joosten M H A J, et al. Specific recognition of AVR4 and AVR9 results in distinct patterns of hypersensitive cell death in tomato, but similar patterns of defence-related gene expression[J]. Molecular Plant Pathology, 2001, 2(2): 77-86

[25] Ding L X, Wang Z H, Ge H L. Continuum removal based hyperspectral characteristic analysis of leaves of different tree species[J]. Journal of Zhejiang Forestry College, 2010, 27(6): 809-814

Note: Figure translations are in progress. See original paper for figures.