Field phenotyping system for the assessment of potato late blight resistance using RGB imagery from an unmanned aerial vehicle

Ryo Sugiura a,*, Shogo Tsuda a, Seiji Tamiya a, Atsushi Itoh a, Kentaro Nishiwaki a, Noriyuki Murakami a, Yukinori Shibuya a, Masayuki Hirafuji a,b, Stephen Nuske c

a Hokkaido Agricultural Research Center, National Agriculture and Food Research Organization, 9-4 Shinseiminami, Memuro, Kasai, Hokkaido 082-0081, Japan
b Graduate School of Life and Environmental Sciences, University of Tsukuba, 1-1-1 Tennodai, Tsukuba, Ibaraki 305-8577, Japan
c Robotics Institute, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213-3890, USA

In tests for field resistance of potato (Solanum tuberosum L.) to late blight, crop scientists rate the disease severity exclusively using visual examinations of infections on the leaves. However, this visual assessment is generally time-consuming and quite subjective. The objective of this study was to develop a new estimation technique for disease severity in a field using RGB imagery from an unmanned aerial vehicle (UAV). For the assessment of disease resistance of potatoes a test field was designed that consisted of 262 experimental plots on which various cultivars and lines were planted. From mid-July to mid-August in 2012, conventional visual assessment of disease severity was conducted while 11 aerial images of the field were obtained. The disease severity was estimated using an image processing protocol developed in this study. This estimation method was established so that the error of the severity estimated by image processing was minimal when compared with the visual assessment. Comparing the area under the disease progress curves (AUDPCs) calculated from the visual assessment and time series of images, the coefficient of determination was 0.77. A further experiment was conducted to validate the developed method. Eleven images of a field planted the following year were taken, and the resulting coefficient of determination was 0.73. The breeders concluded that these correlations were acceptable and that the UAV image acquisition and the disease severity estimation from the image were more efficient than the conventional visual assessments. Therefore, the developed technique based on aerial imagery allows high throughput, objective, and precise phenotyping with regard to field resistance to potato late blight.

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1. Introduction

Potato (Solanum tuberosum L.) late blight, caused by Phytophthora infestans (Mont.) de Bary, is one of the most serious diseases affecting potato production in Japan. The disease rapidly destroys leaves, and it consequently leads to yield losses and tuber quality deterioration (Mitani, 2007). Currently, potato farmers in Japan take precautionary measures to control the disease by spraying fungicide before crops are infected. However, host resistance is an alternative control measure that is more economically and environmentally sustainable (Kuhl, Zarka, Coombs, Kirk, & Douches, 2007). In addition to both, the improvement of yield potential and enrichment of nutritious ingredients, the consolidation of host resistance to the disease is one of the most important considerations of potato breeding. In potato breeding programs, screening for resistance to diseases, particularly late blight, has generally been based on surveys conducted under field conditions (Forbes, Perez, & Andrade-Piedra, 2014; Gopal & Singh, 2003). Quantitative field resistance to potato late blight is evaluated by observing and recording disease infection. In general, the severity of potato late blight is assessed according to the percentage of damaged leaf area, so crop scientists evaluate the disease severity almost exclusively by visual assessment at field level. This assessment method is time-consuming and laborious if many cultivars and lines of interest are planted in a field, and it is quite subjective. Therefore, an alternative method that provides a prompt and objective evaluation of disease severity as a plant phenotypic data is desired in plant breeding and crop science. The goal of this study was to develop a high throughput phenotyping system that can assess field resistance to potato late blight.

Comprehensive reviews on the detection of plant diseases by using spectroscopy and imaging at leaf level are available (Bock, Poole, Parker, & Gottwald, 2010; Lee et al., 2010; Mahlein, Oerke, Steiner, & Dehne, 2012; Sankaran, Mishra, Ehsani, & Davis, 2010). Bock, Parker, Cook, and Gottwald (2007) concluded that there was a linear relationship between the severity of citrus canker on grapefruit leaves assessed by an image analysis and that which was visually rated. The image analysis appeared to provide a highly reproducible way to assess infected leaves of tomato by bacterial spot (Sun, Wei, Zhang, & Yang, 2014). Moreover, Cui, Zhang, Li, Hartman, and Zhao (2010) developed a multispectral image processing algorithm for the automatic detection of soybean rust. Although these image-based studies were leaf-by-leaf approaches under laboratory conditions, the results suggest that image-based techniques can facilitate the development of high-throughput estimation of disease severity as phenotypic data of in-field plants.

Many studies of plant phenomics have developed useful diagnostic tools regarding plant information (Dhondt, Vuys, & Inze, 2013; Golzaraini et al., 2011; Granier et al., 2006; Jansen et al., 2009; Rajendran, Tester, & Roy, 2009; Walter et al., 2007). These studies achieved high-throughput measurements of plant biomass, growth rate, yield potential, and environmental tolerance as well as basic traits such as canopy area, shoot height, and leaf colour variation using a laboratory-scale imaging system. On the other hand, field-based challenges for the collection of phenotyping measurements have recently been reported (Chapman et al., 2014; Fiorani & Schurr, 2013; White et al., 2012). For instance, Montes, Technow, Dhillon, Mauch, and Melchinger (2011) developed a high-throughput phenotyping platform employing light curtains and spectral reflectance sensors, which were installed onto an agricultural vehicle to determine the aboveground biomass of maize under field conditions. Furthermore, structural traits such as the shoot height and leaf inclination of sugar beets were measured using stereo-imaging, while the plant function denoted by vegetation indices was obtained from hyperspectral images in the field (Fiorani, Rascher, Jahnke, & Schurr, 2012).

In studies of precision agriculture and remote sensing, field monitoring and imaging methodologies have been improved and refined, providing relevant information on plant phenotypes in the field (Montes, Melchinger, & Reif, 2007; Walter, Studer, & Kollikler, 2012). Satellite and airborne imagery have often been used for remote sensing in precision agriculture. Although these remote sensing methods provide spatial

**Nomenclature**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
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<tbody>
<tr>
<td>AUDPC</td>
<td>Area under disease progress curve</td>
</tr>
<tr>
<td>C(b)</td>
<td>Cost function to find the optimum value of ( \beta, %^2 ) day</td>
</tr>
<tr>
<td>( D_k^i (u, v) )</td>
<td>Boolean expression of damaged part for the pixel ((u,v)) in (i)-th plot on (k)-th day</td>
</tr>
<tr>
<td>( E_k^i (u, v) )</td>
<td>Boolean expression of shade part for the pixel ((u,v)) in (i)-th plot on (k)-th day</td>
</tr>
<tr>
<td>( e(t) )</td>
<td>Error of the estimated disease severity of (i)-th plot, %</td>
</tr>
<tr>
<td>( f(t) )</td>
<td>Disease progress curve of (i)-th plot in the time series obtained by the visual assessment, %</td>
</tr>
<tr>
<td>( F_c^i )</td>
<td>AUDPC of (i)-th plot obtained by the visual assessment, %</td>
</tr>
<tr>
<td>( g_k^i )</td>
<td>Disease severity computed from the images of (i)-th plot on (k)-th day, %</td>
</tr>
<tr>
<td>( g(t) )</td>
<td>Disease progress curve connecting (g_k^i) in the time series, %</td>
</tr>
<tr>
<td>( G_c^i )</td>
<td>AUDPC of (i)-th plot obtained by the image processing, %</td>
</tr>
<tr>
<td>( H_k^i (u, v) )</td>
<td>Hue value in the image coordinate ((u, v)) of (i)-th plot on (k)-th day</td>
</tr>
<tr>
<td>( i )</td>
<td>Index of experimental plot</td>
</tr>
<tr>
<td>( k )</td>
<td>Index of the day when the image was taken</td>
</tr>
<tr>
<td>( I_k^i (u, v) )</td>
<td>Boolean expression of healthy part for the pixel ((u,v)) in (i)-th plot on (k)-th day</td>
</tr>
<tr>
<td>( N )</td>
<td>Number of the experimental plots</td>
</tr>
<tr>
<td>RMS</td>
<td>Root mean square error of disease severity estimated by the image processing, %</td>
</tr>
<tr>
<td>( t )</td>
<td>Time, day</td>
</tr>
<tr>
<td>( T )</td>
<td>Time period of interest for the AUDPC calculation, day</td>
</tr>
<tr>
<td>( V_k^i (u, v) )</td>
<td>Brightness value in the image coordinate ((u, v)) of (i)-th plot on (k)-th day</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>Threshold to identify shade parts</td>
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<tr>
<td>( \beta, \gamma )</td>
<td>Thresholds to identify healthy parts</td>
</tr>
<tr>
<td>( \beta )</td>
<td>Optimum value of ( \beta )</td>
</tr>
</tbody>
</table>
information for a large area, they are unsuitable for the high spatiotemporal resolution imaging that is desirable for plant phenotyping. However, unmanned aerial vehicles (UAVs) are a promising platform for agricultural field surveillance (Eisenbeiß, 2009) because the images taken by UAVs have the capacity to provide both high spatial resolution and quick turnaround times (Berne, Zarco-Tejada, Suárez, & Fereres, 2009; Zhang, Walters, & Kovacs, 2014). UAV imagery has recently been applied to crop growth monitoring (Lelong et al., 2008; Torres-Sánchez, Peña, Castro, & López-Granados, 2014), disease detection (García-Ruiz et al., 2013) and weed detection (Peña, Torres-Sánchez, Castro, Kelly, & López-Granados, 2013; Torres-Sánchez, López-Granados, Castro, & Peña-Barragán, 2013). Currently, low cost UAVs and corresponding navigation systems for automatic flight using a global positioning system (GPS) and an inertial measurement unit (IMU) are readily available. This technology makes aerial imaging easier and allows frequent field observations to capture the variation of plant traits over time. Furthermore, much higher resolution images can be obtained compared to satellite and airborne methods because they are taken at quite low altitudes. In this study, a UAV with an installed digital camera was applied as a phenotyping platform for the evaluation of potato late blight resistance.

2. Materials and methods

2.1. Test field

The potato field used in this experiment in 2012 was located in Hokkaido, Japan, at 42°53′30″N, 143°4′16″E. The field was designed to examine resistance against late blight in potato cultivars and lines used in breeding research, and it consisted of an array of diverse sets of breeding cultivars and lines as shown in Fig. 1. The 36 rows were laid out along the long side of the field in an area that was 53.8 m × 27.0 m, and the space between rows was 75 cm. The area of 42.2 m × 22.5 m, located in the centre of the field, was partitioned into 360 experimental plots. These plots consisted of single 3.0 m row, containing 10 seed tubers of single cultivar or line with 30 cm spacing. A total of 270 cultivars and lines were planted in the 360 plots in this experiment. Of the cultivars and lines, 90 were assigned to two plots for replication, and the remaining 180 cultivars and lines were each assigned to a single plot. The 360 experimental plots were surrounded by a single cultivar that was relatively sensitive to late blight. All of the potato cultivars and lines were planted on May 3 2012. Usually, the outbreak of the disease occurs spontaneously if no chemicals are applied in the field in which the study was conducted. Late blight is caused by P. infestans, a member of Stramenopiles, which may be tuber-borne, or inoculum that may be produced by oospores on the ground or on infected plant material (potato, tomato) in the neighbourhood. Therefore, there was no need to deliberately inoculate the plants in the field with the pathogen. The entire field was maintained without any chemical applications throughout the growing season in order to make the late blight pathogen vigorous enough to test field resistance.

2.2. Visual assessment of late blight

Of the 360 plots mentioned above, disease severity was assessed by visual observation of foliar symptoms on 262 plots. Biomass of potato leaves peaked by the middle of July, and late blight infection was highest from late July to early August. Therefore, the severity of late blight was consecutively recorded by visual assessment on July 16, 18, 20, 23, 25, 27, and 30, and on August 1, 3, 5, 8, 11, 14, and 16 in 2012. The severity was defined as the percentage of foliage with symptoms on a scale from 0% to 100%. This follows the severity characteristics utilized by Bock et al. (2010). For example, a disease severity of 0% indicates that disease is not seen in the field, and that of 25% denotes that there are lesions on nearly every leaflet, but plants retain their normal form. A disease severity of 50% shows that every plant is affected, and about one-half of the leaf area is destroyed. A value of 75% signifies that about three-fourths of the leaf area is destroyed, while 100% indicates that all the leaves and stems are dead. Although the assessment was a subjective method using on-site observation by human eyes, one crop scientist quantified the severity during this period in order to remove bias caused by individual differences. The area under the disease progress curve (AUDPC) was calculated for each plot as follows:

\[
F_i(t) = \int_{t_1}^{t_2} f_i(t) \, dt
\]

where \(F_i(t)\) is the AUDPC of \(i\)-th plot, and \(T\) is the time period of interest for the AUDPC calculation. \(f_i(t)\) is the disease progress curve of \(i\)-th plot in the time series and \(t\) is the time in days. This curve is a line graph connecting the disease severity obtained by the consecutive visual assessment. The AUDPC, which is an integrated form of the severity curve, is widely used to summarise quantitative crop disease resistance (Jeger & Viljanen-Rollinson, 2001; Olany, Ojiambo, & Nyankanga, 2006). In this study, the severity obtained by the visual assessment was considered the ground truth reference to evaluate the image processing method described below.
2.3 Aerial image acquisition

Images of the potato field were taken by a UAV (HiSystems GmbH Mikrokopter, Germany). The UAV was a multi-rotor helicopter with four counter rotating propeller pairs and eight brushless motors as shown in Fig. 2. The dimensions were 80 cm in both length and width and 30 cm in height. Without payload the weight was 1.6 kg. A lithium polymer battery (14.8 V; 6200 mAh) drove the motors, and payloads of up to 1.5 kg could be lifted. The UAV was equipped with a navigation system with an installed GPS, IMU, magnetic compass, and altimeter to ensure flight stabilization. This research used a commercially available digital camera (Sony NEX-5N, Japan), which took RGB images. Late blight causes a pigment degradation that is observed as chlorotic and necrotic spots on leaves, turning the leaf brown, and destroying the entire plant. Therefore, images in the visible range would be suitable enough for disease detection. The digital camera was installed onto the UAV, and the camera faced almost vertically downward during flight. The camera weighed 330 g, including a battery and a 16-mm fixed focal lens. The shutter was released via a shutter release interface which was an infrared receiver built into the camera. The shutter controller, composed of a microcontroller and infrared LED, was attached immediately in front of the infrared receiver on the camera. It was programmed so that the infrared light signal needed to take an image was emitted to the camera every 2 s. In this study, field images were taken from approximately 80 m above the ground, and were then used to estimate the disease severity. The vertical and horizontal view angles of the camera were 52.4° and 73.1°, respectively, and the image size was 3264 × 4912 in pixel dimension. Therefore, images taken from an 80.0 m altitude, for example, capture a 78.8 m × 118.5 m area with a spatial resolution of 2.4 cm pixel⁻¹. A radiometric calibration of the camera was not conducted since radiometric distortions of an image due to the sensor response, filter characteristics, and on-board colour processing were too complicated to be identified. The camera functions of automatic exposure control and white balance were applied, and the automatic correction of intrinsic distortion caused by lens geometry was also applied. All of the images were saved in JPEG format on a SDXC card installed in the camera. Images were obtained on July 17, 18, 23, 25, 26, 27, and 30, and on August 2, 3, 7, and 15.

2.4 Image processing

2.4.1 Rectification of image

Raw images taken from the UAV contained geometric distortions due to variations in the camera pose and rotation. However, transforming the raw image into the rectified image coordinate system removes the distortion. The rectified image coordinate system defined in this study had its horizontal axis parallel to a long side direction of the field, while the vertical axis was parallel to a short side direction. Moreover, the centre of the rectified image corresponded to the centre of the field. In the rectified image, the pixel dimensions were 2000 × 3740, which covered the 40.0 m × 74.8 m area. Therefore, the size of a rectified image pixel was actually 2 cm. The raw image coordinates were transformed based on the perspective into the rectified image coordinates using a homography matrix. The homography matrix for each image was estimated by matching ground control points (GCPs) in the raw image coordinate system to those in the rectified image coordinate system. The 20 GCPs were laid out on both ends of 10 ridges, and the positions of all GCPs were measured by a total station (APL1A, Topcon Co., Ltd.). Although the field had a slight difference in elevation up to 39 cm according to GCP positions, the elevation within the field was assumed to be uniform. The GCP coordinates in each raw image were manually detected on the computer screen. After acquiring a homography matrix using the 20 pairs of GPCs in each of the 11 raw images, the perspective transformation was performed on the image. This image processing yielded 11 rectified images of the field with an identical coordinate system.

2.4.2 Pixel sampling

The RGB colour space of the JPEG formatted image was converted to the HSV colour space (Smith, 1978), which is composed of hue (H), saturation (S), and value (or brightness) (V). H represents a colour type by its value ranging from 0.0° to 360.0°. For example, the H values of 0.0°, 120.0°, and 240.0° indicate pure red, green, and blue, respectively. The S and V are given by values ranging from 0.0 to 255.0.

To understand the colour characteristics in the five categories of healthy leaf, diseased leaf, soil, petal, and shadow, 10 pixels were manually sampled in each category from each image. However, no pixels of diseased leaves were identified in the first or second images. Furthermore, five images that were taken on July 18 and August 2, 3, 7, and 15 did not have any pixels of shade because the images were taken in cloudy conditions and the five images taken on July 30 and August 2, 3, 7, and 15 did not have any petal pixels. Therefore, the number of healthy leaf, diseased leaf, soil, petal, and shade samples were 110, 90, 110, 60, and 60, respectively. Figure 3 shows the probability distribution functions derived from means and standard deviations (S.D.) for the sampled pixels.

In general, a potato leaf infected with late blight turns brown and wilts. As a result, the soil surface, which was previously obscured by leaves, appears in aerial images. Therefore, the basic idea of the disease severity estimation was to detect pixels that changed from the group of healthy

![Fig. 2 – Unmanned aerial vehicle used in this study.](image-url)
leaves and petals into that of diseased leaves and soil. Although severe drought conditions cause leaf wilting, which would reveal the soil surface, this study assumed that the experimental field was not under such conditions.

First of all, the shade pixels could be clearly distinguished from the others based on the fact that the shade pixels sampled for V had the mean value ± S.D. of 29.4 ± 7.7 while healthy leaf, diseased leaf, soil, and petal pixels were 154.0 ± 34.6, 179.4 ± 36.0, 150.6 ± 49.4, and 231.2 ± 18.0, respectively (Fig. 3(c)). Figure 3(a) helped to distinguish a group of healthy leaves and petals from that of diseased leaves and soil. The H values of the healthy leaf and petal pixels were 85.3 ± 13.4 and 104.8 ± 25.9, respectively, while those of diseased leaf and soil pixels were 50.2 ± 8.2 and 38.0 ± 6.6, respectively. The healthy leaves could be separated from the petals using S values as shown in Fig. 3(b) because the S value of healthy leaves was 138.8 ± 20.9, whereas that of the petals was 36.1 ± 15.6. However, there was no need to separate them in this study, and both were considered healthy parts. The distribution functions of diseased leaf and soil largely overlapped in every element, which means it is difficult to separate the two categories. Accordingly, this sampling analysis concluded that image data could be classified into shade, a group of healthy leaves and petals, and a group of diseased leaves and soil. In this study, the healthy leaf and petal group was a healthy part, and the diseased leaf and soil group was a damaged part.

2.4.3. Algorithm for disease severity estimation

This study assumed that shoot biomass must have peaked by July 17, and there was no damage due to the disease till that day. The foliage area would then decrease slowly because of natural senescence. Consequently, the decrease in foliage area was negligible and thus ignored. Under these assumptions, the image processing method for severity estimation was established.

The developed method processed the rectified image data for each experimental plot. The image data of H and V in an i-th plot were defined as \( H_i^k(u, v) \) and \( V_i^k(u, v) \). The subscript \( k \) in the parameters indicates the sequential index of the day when the image was taken. For example, \( k = 0 \) indicates that the image data was taken on July 17, while \( k = 10 \) means it was taken on August 15. The image coordinate system \((u, v)\) was defined for each experimental plot. This coordinate system is parallel to the rectified image coordinate system, and the origin is the upper left corner of the plot. An area of one experimental plot is the range of \((u, v)\). A shade pixel was denoted by \( E_i^k(u, v) \), and a healthy part pixel was expressed by \( L_i^k(u, v) \). Those are

\[
E_i^k(u, v) = \begin{cases} 1 & \text{if } V_i^k(u, v) < a \\ 0 & \text{otherwise} \end{cases}
\]

\[
L_i^k(u, v) = \begin{cases} 1 & \text{if } H_i^k(u, v) < b \\ 0 & \text{otherwise} \end{cases}
\]

The pixel where \( E_i^k(u, v) \) equals 1 is classified as shade. Similarly, the pixel where \( L_i^k(u, v) \) equals 1 is classified as a healthy part. \( a \) is a threshold used to identify shade pixels, while \( b \) and \( \gamma \) are thresholds between healthy parts and the others. The shade pixels were clearly distinguished from the others using V, and \( a \) was 50.8, which was an intersection between the distribution functions of shade and soil in Fig. 3(c). Although \( b \) was roughly estimated to be around 65.0, which was an intersection of the distribution functions of healthy and diseased leaves in Fig. 3(a), its optimum value could not be specified from this pixel sampling result. The optimal threshold of \( b \) was determined by the method mentioned in Section 2.4.4. The parameter \( \gamma \) was set to be 180.0 since a hue value of 180.0 is the intermediate between pure green and blue.

Subsequently, the pixels of diseased leaves and soil were expressed by \( D_i^k(u, v) \) as the damaged part. That is,

\[
D_i^k(u, v) = L_i^k(u, v)H_i^k(u, v)
\]

where the overline switches the value from 1 to 0 or vice versa as follows:

Fig. 3 — Distribution functions of each element of (a) H value, (b) S value, and (c) V value for healthy leaf (---), diseased leaf (---), soil (---), petal (---), and shade (---) pixels.
The disease severity in the i-th plot on the k-th day was calculated by taking the ratio of the number of pixels of the damaged part on the k-th day to that of the healthy part on the first day (day 0). That is,

\[ g_k^0 = \frac{\sum_x \sum_y D_k^0(u, v)}{\sum_x \sum_y L_k^0(u, v) E_k^0(u, v)} \times 100 \]

where \( g_k^0 \) is the disease severity expressed as a percentage.

This rule means that the severity must not drop because leaves once damaged by disease are assumed not to recover. Disease progress may stop if an epidemic comes to a halt due to unfavourable weather conditions. Furthermore, some leaves might show up even after being damaged by the disease, so that the plants would look as though they were recovering from the damage, especially when viewed from an aerial image. However, the leaf in itself, once damaged, rarely turns into a healthy leaf. This rule was in accordance with the conventional visual assessment measure.

2.4.4. Optimisation of the threshold

The disease progress curve \( g(t) \) was defined as the time series curve connecting \( g_k^0 \) together. The AUDPC, denoted by \( C^0 \), was described by the following equation:

\[ C^0 = \int_T g(t) \, dt \]

where \( T \) is a time period of interest for the AUDPC calculation. This integration interval must be the same as that in Eq. (1), which is the section where \( f^0(t) \) and \( g(t) \) overlapped, in order to compare the AUDPCs using the two measures. Therefore, in this experiment, \( T \) was the section from July 17 to August 15 (\( T = 29 \)).

Since the disease progress curve \( g(t) \) can be determined once the threshold \( \beta \) in Eq. (3) is given, it is considered as a function of \( \beta \). The optimum value of \( \beta \) was founded so that the cost function \( C(\beta) \) in %2 day was minimal.

\[ C(\beta) = \int_T \left( g(t, \beta) - f^0(t) \right)^2 \, dt \]

\[ \hat{\beta} = \text{argmin}_\beta C(\beta) \]

where argmin provides an argument value that minimizes a given function, and \( \hat{\beta} \) is the optimum threshold. This cost function subtracts two disease severities, the image-based estimation \( g(t) \) and the visual assessment \( f^0(t) \), and integrates the square of the difference. Furthermore, it sums them over all the experimental plots.

2.4.5. Evaluation of the disease severity estimation

To evaluate the method developed in this research, an error of the estimated disease severity for each plot was defined by Eq. (11) as \( e(t) \) as a percentage, and the root mean square error of the estimated severity over all plots, denoted by RMS as a percentage, was calculated using Eq. (12):

\[ e(t) = \sqrt{\frac{\int_T \left( g(t) - f^0(t) \right)^2 \, dt}{T}} \]

\[ \text{RMS} = \sqrt{\frac{\sum_e (e(t))^2}{N}} \]

where \( N \) is the number of the experimental plots (\( N = 262 \)).

Furthermore, this image-based method for the severity estimation was evaluated by examining the correlation between \( F^0 \) and \( G^0 \).

2.5. Test data for validation

Further experimentation was coordinated to validate the developed method the following year, and a similar field for disease assessment was designed. The images from the UAV were taken on July 12, 16, 19, 22, and 25, and on August 2, 5, 7, 12, 16, and 19 2013. The visual assessment was conducted on July 23, 25, 28, and 30, and on August 1, 3, 5, 7, 10, 12, 14, 16, and 19 2013. In the test field, disease severities estimated via image processing and visual assessment were obtained for 321 experimental plots. It was assumed that there were no leaves damaged by the disease on July 12, which was the first day of the image acquisitions. The thresholds calculated from the data in the previous year were applied to the images obtained in this experiment. The period for the AUDPC calculation of \( T \) was from July 23 to August 19 (\( T = 27 \)).

3. Results and discussion

3.1. Optimisation of the threshold

The cost function in Eq. (9) was examined with the threshold \( \beta \) ranging from 55.0 to 80.0. Figure 4 shows the cost function variation, \( C(\beta) \). The cost function decreased gradually as \( \beta \) increased from 55.0, and it reached a minimum of 1.6 × 10^6 %2 day where \( \beta \) is 69.8. Hence, the value of \( \hat{\beta} = 69.8 \) was obtained as an optimum threshold, and \( C(\beta) \) subsequently increased. The images were processed using Eqs. (2)–(7), and the area damaged by the late blight was detected as shown in Fig. 5. A red overlay was applied to illustrate the damaged parts on each image. The image processing captured the gradual spread of the disease over the field. There were no damaged areas in the image taken on July 17 as shown in Fig. 5(a)
because of the assumption mentioned above. The developed method began to detect the disease on July 18 (Fig. 5(b)). Some experimental plots were damaged during early stages such as July 23 and 25 (Fig. 5(c) and (d)). During the course of the disease spread, while the disease damage appeared in most plots July 26–August 7 (Fig. 5(e–j)), a few plots maintained healthy leaves on August 15 (Fig. 5(k)). This variation depended on the disease resistance differences of each cultivar and line although the field arrangement of the cultivars and lines might also influence the disease spread pattern.

Examples of severity comparisons in five plots from the visual assessment and image processing are shown in Fig. 6. The disease progressed from 0.0% to 100.0% along a sigmoid curve in most cases (e.g., Fig. 6(a) and (b)), while the disease progress on some plots was shown to be stagnant in the middle of the period (Fig. 6(c)) or remained at low levels throughout the period (Fig. 6(d)). The estimated severities in these four figures were similar to the visual assessments. The AUDPCs for the estimated and visual assessments were 2020.2 % day and 1987.5 % day, respectively, and the error calculated by Eq. (11) was 6.1% (Fig. 6(a)). The AUDPCs in Fig. 6(b) were 1901.4 % day and 1917.5 % day, and the error was 3.0%, while those in Fig. 6(c) were 891.2 % day and 896.3 % day, and the error was 4.2%. In Fig. 6(d), the AUDPCs were 329.7 % day and 265.0 % day, and the error was 3.0%. On the other hand, some plots showed inaccurate estimates. For instance, Fig. 6(e) indicates that the disease severity curve from the image processing did not fit that from the visual assessment. In Fig. 6(e), the AUDPC estimated by the image processing was 514.0 % day, and it did not match that from the visual assessment that was calculated at 1033.8 % day. The error calculated by Eq. (11) was 22.2%. All pixels in a given plot were of interest for the disease severity estimation. When a plot was invaded by leaves from neighbouring plots, the developed image processing couldn’t separate leaves in the plot from those in its

Fig. 4 – Variation in the cost function with the threshold.

Fig. 5 – Progress of potato damage from late blight development over time. The red overlay shows damaged parts detected by image processing on (a) 7/17, (b) 7/18, (c) 7/23, (d) 7/25, (e) 7/26, (f) 7/27, (g) 7/30, (h) 8/2, (i) 8/3, (j) 8/7 and (k) 8/15.
neighbouring plots, causing an error in the estimation of disease severity.

Accounting all plots, the RMS error calculated was 14.7%. AUDPCs in all plots were compared between the two methods as shown in Fig. 7, and the determination coefficient was 0.77. This result indicated that the image processing method developed in the study could replace the conventional visual assessment for late blight resistance.

3.2. Validation of the estimation method

The disease estimation method developed and the thresholds found in 2012 were applied to the data obtained in 2013. The RMS error of the disease severity estimated by image processing was 17.1%. Furthermore, the determination coefficient between the AUDPCs by the image processing and visual assessment was 0.73 (Fig. 8). The results of the disease severity and AUDPC estimations were slightly worse than those from the previous year. In this experiment, the images were coarsely acquired, and there were no images during the 7 days between July 26 and August 1. However, the breeders concluded that the accuracy was still acceptable for disease severity and AUDPC measurements. Therefore, the developed method based on image processing was validated as an effective late blight resistance phenotyping tool.

4. Conclusions

This research aimed to develop a field phenotyping system that provides an assessment for resistance to potato late blight. Conventional methods for disease assessment at field level generally require a substantial investment in human resources and time. Therefore, the development of an alternative measure that can offer rapid assessment of crops is greatly desired. Currently, aerial images are readily available using a UAV, and these hold tremendous potential for field monitoring and crop status observations. This study showed that aerial images are an effective way to capture the spatial and temporal variation in crop status. RGB images of a potato...
Correlation between AUDPCs from image processing and visual assessment methods in the following year’s validation dataset. The solid line shows the regression line, $y = 0.83x + 217.11$. The coefficient of determination was $R^2 = 0.73$.

...field were acquired to test potato late blight with a UAV. The severity of the disease was estimated using an algorithm applied to image processing and developed in this study. Disease severity was also measured by visual assessment, which was utilised as a comparative reference to the image processing results. The experiment was undertaken twice. The first was conducted to establish the processing method, particularly to determine the thresholds required to detect the damaged parts in the images, and the second validated the developed method. The optimum threshold was successfully found using the image data. The developed method was shown to provide the disease severity and AUDPC values equivalent to that of the visual assessment. The accuracy of the severity estimation was validated by further test conducted the following year. Although the sparse acquisition of images caused a slight decline in correlation between the AUDPCs from the image processing and visual assessment, the validation result was still acceptable.

These results suggest that the aerial RGB image-based method could be a high-throughput phenotyping system to assess disease resistance. It was clear that the severity assessment and the evaluation of disease resistance using imagery are much more efficient than the conventional visual assessment.

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**References**


