Detecting Bare Spots in Wild Blueberry Fields Using Digital Color Photography

F. Zhang, Q. U. Zaman, D. C. Percival, A. W. Schumann

Abstract. *Wild blueberry fields are developed from native stands on deforested land by removing competing vegetation. The majority of fields are situated in naturally acidic and non-fertile soils that have high proportions of bare spots, weed patches, and gentle to severe topography. Producers presently apply agrochemicals uniformly without considering bare spots. The unnecessary or over-application of agrochemicals in bare spots may increase cost of production and environmental pollution. An automated cost-effective machine vision system using digital color photography was developed and tested to detect and map bare spots for site-specific application of agrochemicals within wild blueberry fields. The experiment was conducted at a 4-ha wild blueberry field in central Nova Scotia. The machine vision system consisting of a digital color camera, differential global positioning system, and notebook computer was mounted on a specialized farm vehicle. Custom software for grabbing and processing color images was developed in Delphi 5.0 and C++ programming languages. The images taken by the digital camera were stored in the notebook computer automatically and then processed in red, green, and blue (RGB), and hue, saturation, and value (HSV) color spaces to detect bare spots in real-time within blueberry fields. The best results were achieved in hue image color space with 99% accuracy and a processing speed of 661 ms per image. The results indicated that bare spots could be identified and mapped with this cost-effective digital photography technique in wild blueberry fields. This information is useful for site-specific application, and has the potential to reduce agrochemical usage and associated environmental impacts in the wild blueberry production system.*

Keywords. *Bare spots, Wild blueberry, Machine vision, Color space, RGB, HSV, DGPS, GIS.*

Wild blueberry (*Vaccinium angustifolium* Ait.) production is based on the management of native indigenous stands that are predominantly located in northeastern North America. Fields are developed in areas where pre-existing wild blueberry coverage is sufficient to warrant commercial field development. Fields suitable for commercial development are typically abandoned farmland or recently deforested areas. Field development is reliant upon the removal of competing vegetation and may also include the removal of trees, stumps, and rocks. Therefore, newly developed fields can have a significant proportion of bare spots (varies from 30% to 50% of the total field area) (Zaman et al., 2008).

Canopy expansion in wild blueberry fields is reliant upon a massive rhizome system which consists of approximately 70% to 85% of the weight (d.w. basis) of the plant (Jeliazkova and Percival, 2003). Vegetative expansion of a clone (i.e., each distinct phenotype found within a field) occurs via the rhizome and is typically a slow process with rates of 5- to 10-cm elongation per year being observed. Although the plant is perennial, it is managed on a two year production cycle with plants being typically mowed to ground level prior to the start of the first growing season; new upright shoot growth occurring the first year along with floral bud development, and the second year consisting of bloom, pollination, fruit set, and berry harvest (Eaton, 1988).

Blanket applications of agrochemicals to wild blueberry fields typically occur without considering significant bare spots within fields. Needless application of agrochemicals in bare spot areas may increase cost of production and increase environmental pollution. The unique features of the wild blueberry cropping system emphasizes the need to develop precision application systems to detect and map bare spots for precise site-specific application of agrochemicals.

Several techniques have been developed and evaluated for weed detection and mapping in different cropping systems. To date, very little attention has been paid to map bare spots in wild blueberry fields. Billard and Stewart (2004) calculated normalized difference vegetation index using aircraft-derived CASI imagery images to differentiate weeds from wild blueberry plants. However, obtaining up-to-date aerial photography is expensive, the quality is quite variable, and data processing is also intensive and difficult. Klotz et al. (2003) used a fiber-optic system consisting of 16 aligned lenses that enable the perpendicular recording of hyper-spectral reflectance of the surface under observation for vegetation parameters detection in sugarbeet fields. Gerhards and Oebel (2005) used real-time differential images (NIR-VIS) obtained with a set of three digital

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bi-spectral cameras to detect weeds. Some weed detection methods are based on color difference, such as normalized difference vegetation index (Ei-Faki et al., 2000), HSI (Burks et al., 2000; Tang et al., 2001), excess green (Gliever and Slaughter, 2001) and color indices (Ei-Faki et al., 2000). Obtaining thresholds manually is a widely applied technique in both RGB- and HIS-based agricultural color vision experiments. Cui et al. (2009a, 2009b) detected soybean leaf rust using both RGB and HSI image processing techniques. Sharp (2008) discriminated sheep sorrel from wild blueberry using a Field Spec® 3 hand-held spectral radiometer (Analytical Spectral Devices Inc., Boulder, Colo.). Similar techniques might be used for bare spot mapping in wild blueberry fields but have so far not been realized, probably due to the inherent difficulties of the methods and the relatively high computing and economic costs involved. Zaman et al. (2008) tested and evaluated a cost-effective digital color photography technique to estimate wild blueberry fruit yield by calculating blue pixel ratios. The digital photography technique using a cost-effective, reliable color camera and differential global positioning system (DGPS) might be an option to detect and map bare spots in wild blueberry fields.

In this study, a ground-based automated machine vision system consisting of a digital color camera, notebook computer, custom software, and DGPS was developed and tested for real-time detection and mapping of bare spots. The information obtained from this system can then be used for precise application of agrochemicals in wild blueberry fields to improve farm profitability and reduce environmental impacts.

Methodology

Farm Motorized Vehicle (FMV)

An automated machine vision system (AMVS) was mounted on a specially designed farm motorized vehicle (FMV, fig. 1) to map bare spots in real-time within blueberry fields. The FMV was constructed using locally available materials and parts to minimize the cost. A 190-cc gasoline engine (Honda Inc., Halifax, N.S.) on the FMV was capable of generating 4.47 kW at a maximum speed of 3600 rpm. The engine with a chain-sprocket power transmission system provided the required power to the FMV. The FMV could be driven at 0- to 10-km/h ground speed. The wild blueberry fields had no tramline or rows, therefore, the slim bicycle wheels were used to minimize the crop damage during field operations.

Automated Machine Vision System

Hardware Components

The AMVS consisted of a 10-megapixel, 24-bit digital color camera (Canon Canada Inc., Mississauga, Ont.), Trimble AgGPS332 DGPS (Trimble Navigation Limited, Sunnyvale, Calif.) and a notebook computer (Panasonic Corporation, Secaucus, N.J.) (fig. 1). The camera was mounted on the front of the FMV, pointing downward from a height of 1.5 m with a clear view of the ground. The DGPS antenna was mounted on the FMV to get geographic coordinates of the central pixel in the image. The DGPS receiver was configured for a 1-Hz acquisition rate using Canadian Coast Guard Beacons for differential correction.

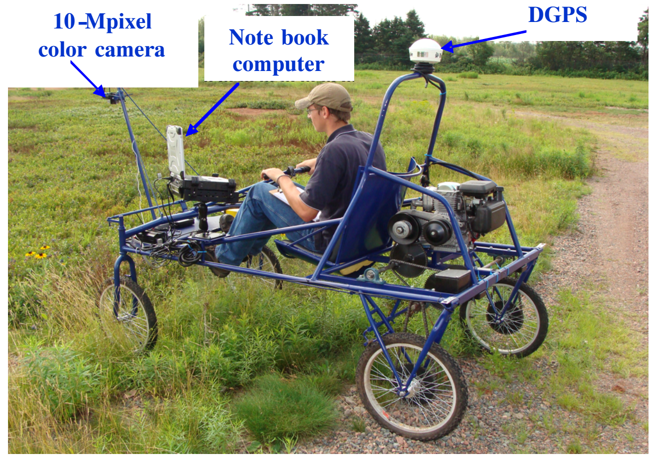


Figure 1. Configuration of the automated machine vision system mounted on a farm motorized vehicle.

The DGPS coordinates from the previous and the current DGPS output were converted to decimal degrees, were averaged, and offset, and automatically estimated the timing for next image acquisition. The distance offset was calculated with Universal Transverse Mercator (UTM) projected coordinates by utilizing the ProLat UTM (Effective Objective, Issaquah, Wash.) program function. The UTM projection was selected due to its ability to produce a flat grid of geometrically correct Cartesian ground coordinates (in meters).

The high resolution images were automatically downloaded from the camera to the notebook computer via a USB port. The DGPS position data were simultaneously logged by the notebook computer via the serial port using the National Marine Electronics Association (NMEA-0183) Recommended Minimum speCific GPS/TRANSIT Data (RMC) sentence.

Software Development

Custom software was developed with the Delphi 5.0 compiler (Borland Software Corp., Scotts Valley, Calif.) and Microsoft Visual C++ programming language (Microsoft Corp., Redmond, Wash.) as two independent programs "RemoteControl" and "WildBlueberry," for grabbing and processing images, and to detect bare spots in real-time, respectively. The "RemoteControl" program was triggered by the DGPS to grab the images and save them as 1.47- × 1.0-m field of view JPEG files in the notebook computer. The "RemoteControl" program controlled the camera remotely then downloaded and named each image file name to text files, "Log.txt" and "NewPic.txt." The "Log.txt" recorded all file names, while the "NewPic.txt" recorded only the recently downloaded image file. The "RemoteControl" program could also monitor the distance moved based on the speed data obtained from DGPS. The "WildBlueberry" program would process the newly captured image by monitoring the content of the "NewPic.txt" file. Processing consisted of reading the new captured image and detecting bare spots. The digital color images taken by the camera were processed in real-time to differentiate bare spots from wild blueberry plants in RGB color space: difference of blue to red (B-R), difference of red to green (R-G), and difference of blue to green (B-G). Manually obtained thresholds for segmenting the image to discriminate bare spots from the remaining pixels in all images were 15, 50, and 20 for (R-G), (B-R), and (B-G), respectively. RGB images were also converted into hue, saturation, and value images to detect bare spots. The thresholds for segmenting hue, saturation, and value images were 0.17, 0.33, and 0.3, respectively. The color difference scale produced by the pre-processing of the RGB and the HSV images (three in each class) were converted into binary images for calculating the ratio of white pixels (ROWP) as a parameter for bare spot detection (fig. 2). The ROWP (0-1) of the images (number of white pixels/total number of pixels in the binary image) was calculated with the "WildBlueberry" program and the ROWP values were saved in the database. The ROWP values ≥ 0.3 and ≥ 0.4 were labeled as bare spots for RGB and HSV, respectively. The ROWP values < 0.3 and < 0.4 were labeled as wild blueberry plants for RGB and HSV, respectively. The binary images were also labeled and saved in the notebook.

Performance Testing

Field experiments were conducted in a 4-ha wild blueberry field verified to have 29% bare spots in Colchester County, Nova Scotia, Canada on 25 and 27 August 2008. The bare spots mapped manually on foot using a ProMark3 mobile mapper GPS (Thales Navigation, Santa Clara, Calif.). The camera was set to a resolution of 1600 × 1200 pixels and the shutter speed at 1/1000 second. The ISO parameters were changed under different lighting conditions: auto mode under sunny conditions, 400 under cloudy conditions, and 800 after 5:00 PM. The camera was controlled remotely by the software in the notebook computer to grab images after moving a preset distance equivalent to one image at a ground speed of 0.4 m/s. The image size captured a field of view of 1.47 × 1.0 m on the ground. Captured images on the notebook computer were processed with an average time of 661 and 512 ms in HSV color space, and in RGB color space, respectively. Seven thousand images were saved and processed in real-time using custom software for bare spot mapping.

Matlab (Mathworks Inc., El Segundo, Calif.) code was also programmed and run to process the images in the laboratory to detect bare spot features in both RGB and HSV color space. Two hundred images, representing three different cases: (1) wild blueberry plants, (2) bare spots, and (3) partly wild blueberry plants and partly bare spots, were post-processed in the Matlab environment both in RGB and HSV color space due to the slow processing time of the Matlab program. Although the Matlab software provided a good man-machine interface to process the images, it was inefficient and inadequate to process the images in real-time to detect bare spots within a field. The bare spot detection results of selected images obtained with the Matlab program were compared with results of the same images obtained from the custom software in order to examine the accuracy of algorithms of different image processing methods for bare spot detection.

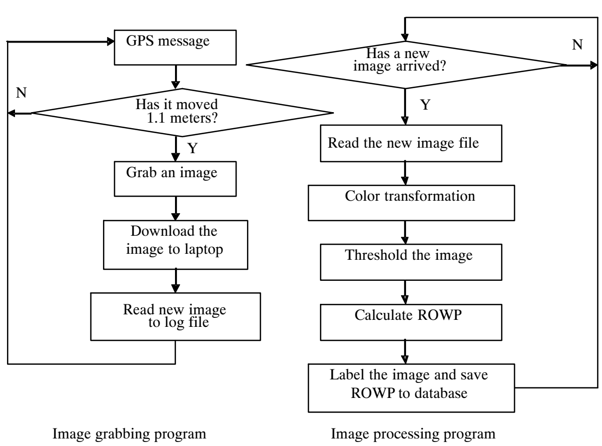


Figure 2. Flowchart of the image grabbing and processing software.

Two hundred color images taken by the camera were selected to compare the bare spot detection results of the same images using different image processing methods. The images taken by the camera were divided into 4 × 4 sub images (400 × 300 pixels) to improve the spatial resolution of bare spot detection. The 16 sub images of each selected image were labeled and processed to calculate ROWP values with different image processing methods. The ROWP values of the sub images (16 ROWP values of each image) were superimposed on the actual selected image to quantify the bare spot detection accuracy of different image processing methods. A small computer program written in C++ was developed to place the calculated ROWP values of the sub images on the actual image to examine whether ROWP values (16 values of each image) were correctly placed on the bare spots and plant areas of the actual image.

The results (bare spots and plants) of the 7000 images, using 16 sub images of each image obtained from the AMVS were mapped in ArcView 3.2 GIS software (ESRI, Redlands, Calif.). The bare spots and plant areas of the selected field were also mapped manually on foot using a ProMark3 mobile mapper GPS (Thales Navigation, Santa Clara, Calif.) for comparison. The polygons (bare spot areas, BSA) were drawn for both AMVS and ProMark3 mobile mapper GPS bare spot maps using ArcView 3.2 GIS software. The area of each polygon in both maps was calculated. The accuracy of AMVS for bare spot mapping was calculated as follows:

$$\text{Accuracy (\%)} = \frac{\text{BSA with GPS} - \text{BSA with AMVS}}{\text{BSA with GPS}} \times 100$$

Results and Discussion

Image Segmentation in RGB Color Space

The color difference of (R-G) and (B-G) could detect bare spots with an accuracy of 80% and 92.5%, respectively (figs. 3d, e, f and g, h, i). The color difference of (B-R) could not detect bare spots in most situations. The white blobs in the processed images indicate the bare spot areas. There were also some white blobs in wild blueberry plant areas. The reason for white blobs in plant areas may have been due to non-green color of leaves on some wild blueberry plants. The visual observations revealed that some blueberry plants have a few light red or pink color leaves.

Image Segmentation in HSV Color Space

The hue images could discriminate bare spots from wild blueberry plants with 99% accuracy (fig. 4). The saturation images detected bare spots with 70.5% accuracy. The reason for a few persistent errors in bare spot detection might be because of non-green color of some wild blueberry leaves as previously mentioned. Based on these results the hue image is a robust measurement for bare spot detection, but it requires 30% more time for processing the image than the RGB color difference method.

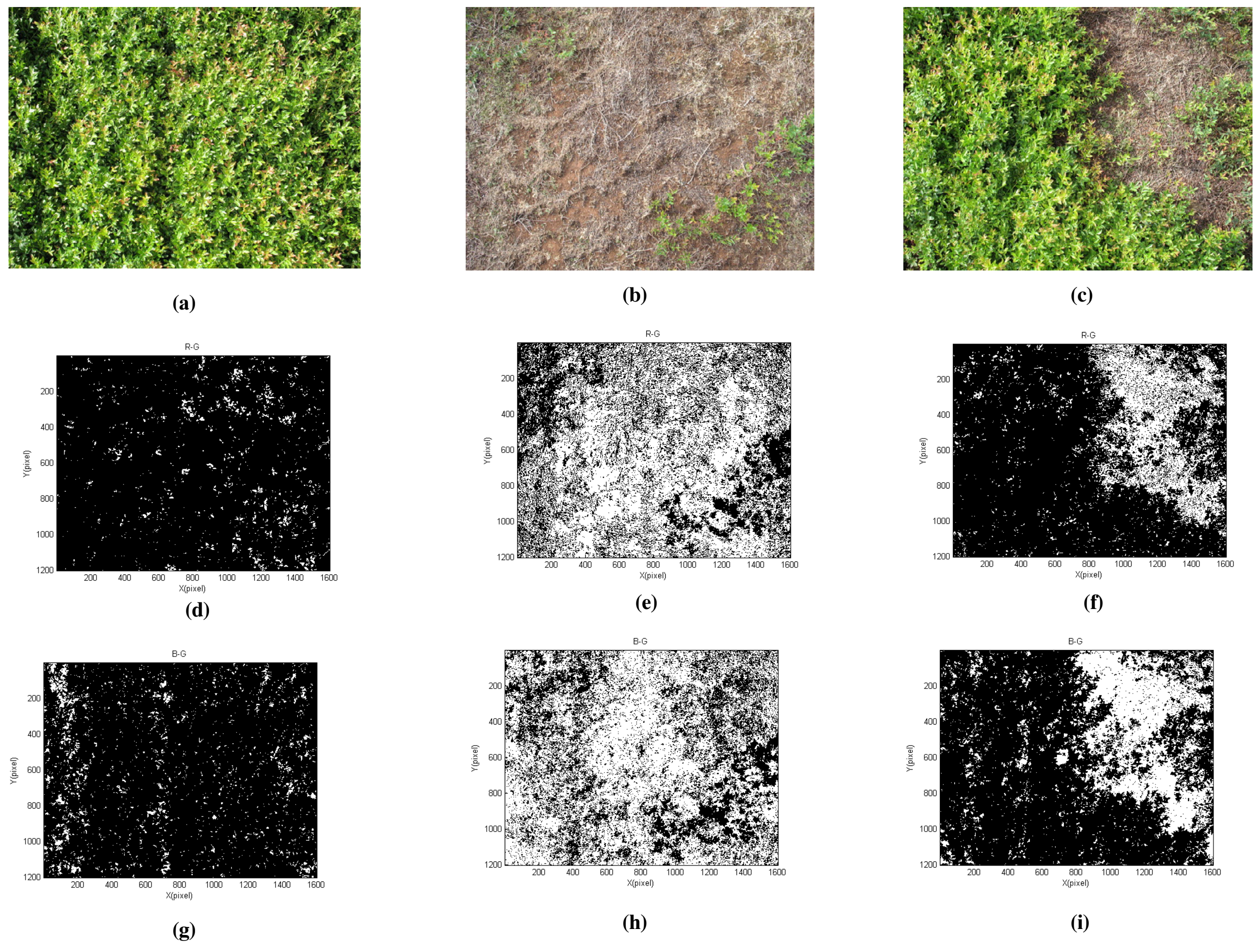


Figure 3. Image segmentation in R-G-B color space, (a,b,c) original color images, (d,e,f) binary image of R-G, (g,h,i) binary image of B-G.

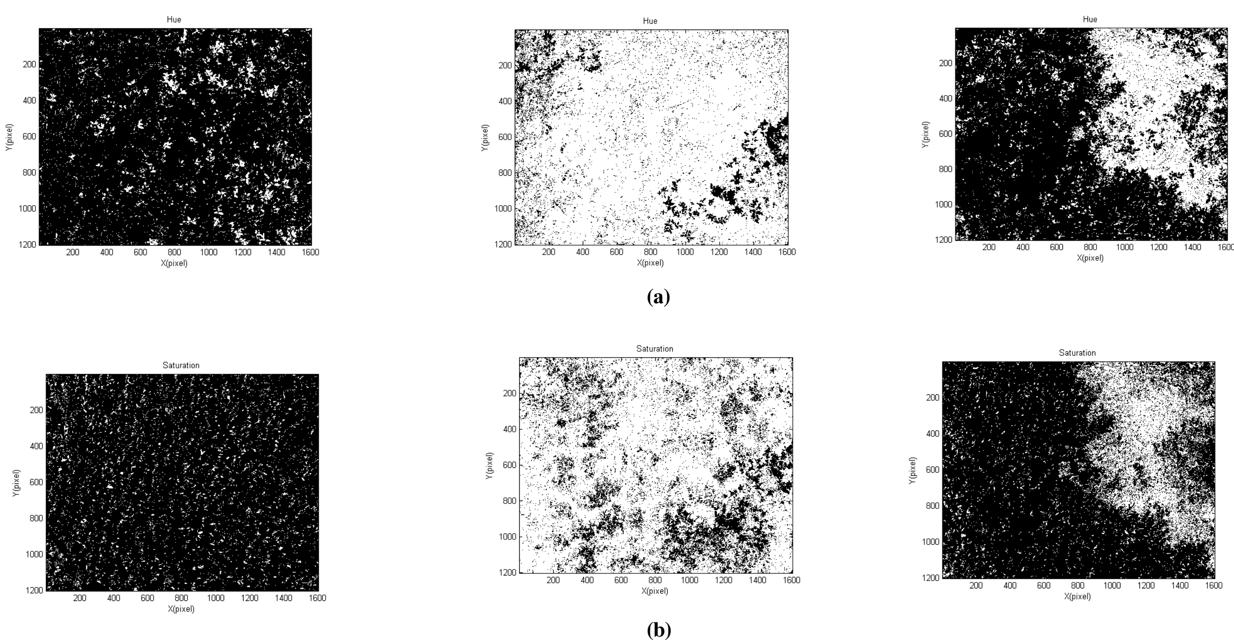


Figure 4. Image segmentation in HSV space, (a) binary Hue image, (b) binary Saturation image.

Based on experience, it is proposed that the segmentation threshold should be adjusted in different weather regimes to increase the accuracy of bare spot detection. It was observed that shadowing was the main factor affecting the accuracy of bare spot detection in sunny days. Error caused by shadow was minimized using the method described by Pilarski et al. (2002) by compensating color of Red-Green-Blue with coefficients of 3.6, 2.8, and 1.8, respectively.

Bare Spot Mapping

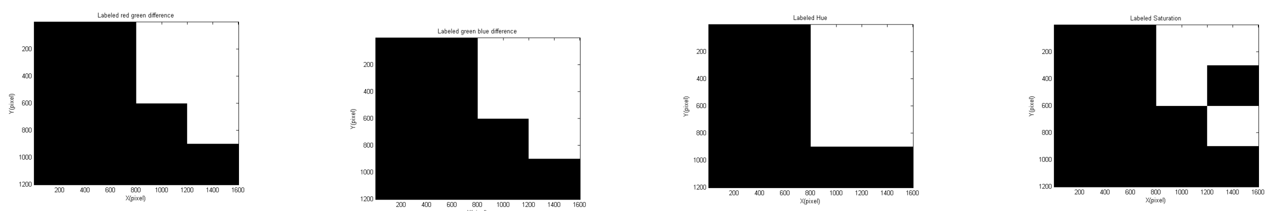
All actual images taken by the camera were divided into 4 × 4 sub-images (16 rectangles) to improve the spatial resolution of bare spots. The size of the sub-image field of view on the ground was 36.75 × 27.5 cm (fig. 5). The ROWP of each sub-image was calculated using different image processing methods saved in the database. Results indicated that bare spots were detected successfully with all image processing methods. The best results were obtained with the hue method in HSV color space. The x, y coordinates (longitude, latitude) of the central pixel in the image was obtained with the machine vision system and x, y coordinates of sub-images were calculated for mapping bare spots. Three sequential images with central pixels, O_{i-1}, O_i, O_{i+1}, and sub-image S_1 and S_{16} in the i^{th} image are presented in figure 6. We deduced that the direction of the i^{th} image parallels the line $O_{i-1}O_i$, while that of the $(i+1)^{th}$ image parallels the line O_iO_{i+1}. Thus each position of sub-images, S_1, S_2, …, S_{16}, was obtained by calculating the intersection of two lines, one was offset from the direction line, and another one was offset from the line perpendicular to the direction line. Due to space constraints, only the map of a part of the field, having more bare spots area, is provided (fig. 7). The bare spots showing in the map were detected by the Hue method. Dark color points represent wild blueberry plants and light grey points represent bare spots. Approximately 29% area in this particular field contained bare spots. Bare spot areas mapped with AMVS were compared with the bare spot areas mapped with the handheld mobile mapper. The manually mapped bare spot areas with the mobile mapper coincided with the areas mapped with the AMVS. The AMVS mapped bare spot areas in wild blueberry fields with 97.4% accuracy. Based on these results, an AMVS consisting of a digital camera, computer, and DGPS is capable of detecting bare spots and could be incorporated into a commercial variable rate fertilizer spreader and sprayer to detect bare spots in real-time and dispense agrochemicals on an as-needed basis within blueberry fields.

Conclusions

Bare spots in wild blueberry fields could be detected using an automated machine system either by color difference in RGB color space, or Hue, Saturation images in HSV color space. However, Hue color space had very high accuracy (99%) for detection of bare spots in the field.

The images were processed efficiently and reliably in real-time to detect bare spots using custom software at a speed of 512 ms per image in RGB space and 661 ms per image in HSV space.

Based on this experience it is proposed that the digital camera should be replaced by an industrial RGB camera to improve the robustness of the system on farm equipment for real-time bare spot detection in the blueberry fields.



(a) (b) (c) (d)

Figure 5. Labeled bare spots of figure 3c by (a) color difference of (R-G), (b) color difference of (G-B), (c) Hue image, (d) Saturation image.

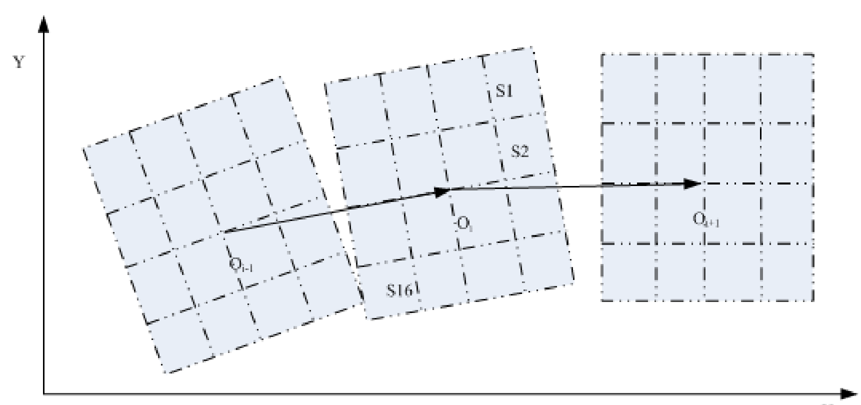


Figure 6. Three sequential images and the method to obtain direction of each image.

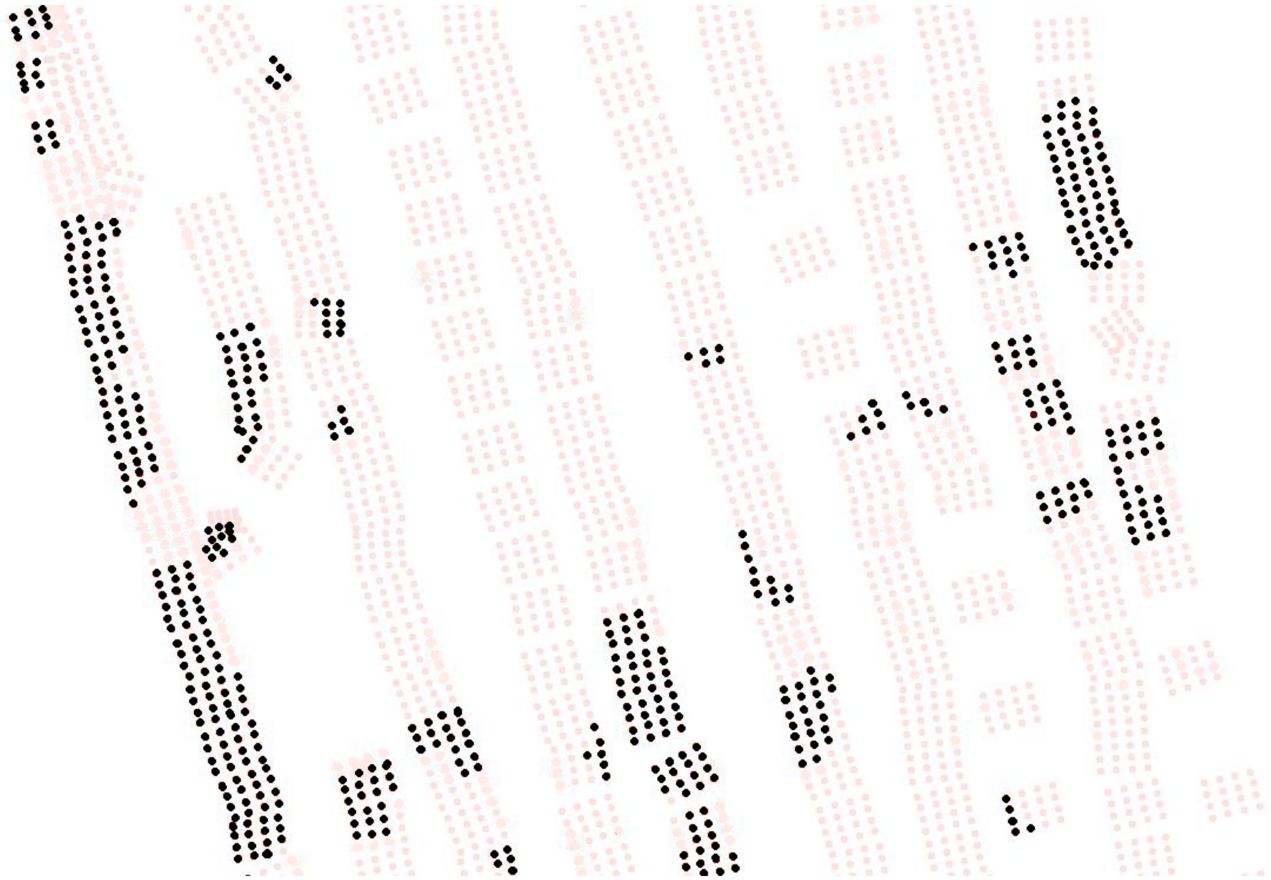


Figure 7. Map of a part of the field having significant bare spots (light color) with less blueberry plants (dark color) using Hue values.

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