Detection of effects of three different plant pests for chrysanthemum flowers by using image processing and spectral imaging

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Abstract. Ornamental floriculture is one of the main economic activities in different regions of Colombia. Different flowers have a great success, but its industry faces some challenges on phytosanitary controls caused mainly by the dependence on human monitors and the expertise in the detection of diseases throughout the crop fields. This paper focuses on the detection of the affection patterns caused by tomato spotted wilt virus, puncture leaf miner, and leaf miner larvae on chrysanthemum flowers (Dendrathema grandiflorum). A spectral imaging system was with 11 spectral channels was implemented which were generated by the same number of light emitting diodes groups. By using these images, there were carried out different image processing techniques and the combination of different linear relations among the spectral images were tested to enhance, isolate and quantify the affected area on the leaves. The results show that our system has more selective spectral width than common artificial vision systems and the effects of the diseases can be effectively detected.

1. Introduction
Commercial floriculture has had a growing business in the last decade, boomed with the appearance of small and medium-sized producers, mostly in countries with developing economies and high biodiversity, where it has been established as an important employer. Either so, this industry still faces different difficulties, one of those is the presence of pests that cause damage to the final product, and in the worst scenario, a complete loss of significant areas of cultivated flowers.

Flower leaves manifest the presence of a pest mostly through visible patterns, each one dependent on the main cause of the infection (insect larva, spiders, flies, fungi, etc.). Due to the spectral response to light of leaf tissues, which absorbs most of the received energy and reflects green and infrared spectra, some of patterns become more visible and distinguishable if systems with more spectral discrimination can be used, in contrast to the typical three chromatic vision systems. Such spectral imaging systems can even be used to detect infections in early stages.

In the last five years, these problems have been of keen interest to researchers around the world, proposing multiple techniques for detection of pests and diseases in multiple kinds of crops like vegetables, fruits and commercial flowers [1–7]. Some researchers used red-green-blue (RGB) images color transformations [1–3,8], other authors used a different approach, employing multi and hyperspectral imaging systems to capture a wide range of information that may be hidden inside the leaf biochemical behavior [4–7].
In this manner, this paper focuses on the detection of the patterns of disease-affected regions in chrysanthemum flowers (*Dendrathema grandiflorum*) over spectral images. The images were captured in laboratory conditions using a custom spectral imaging system with 11 light sources with different wavelengths. These spectral images were combined to determine the most relevant ones for the detection of three disease patterns produced by puncture leaf miner, virus, and larva leaf miner.

2. Methodology

Chrysanthemum leaves were collected in national production farms in La Ceja, Colombia. The samples were transported to a research laboratory, following a transportation protocol determined by the Colombian Agricultural Institute to ensure the preservation of biological samples. Then, using a spectral capture vision system developed at the Technological Metropolitan Institute in the artificial vision and photonics laboratory, images of each sample were saved for its posterior processing and analysis.

2.1. Image acquisition

The spectral imaging system used was composed by a spectral illumination lamp and a monochromatic digital camera (Figure 1). The spectral illumination source was a customized lamp and it comprised 11 different light-emitting diode (LED) based sources covering the visible (VIS) and part of the near-infrared (NIR) of the electromagnetic spectrum. The spectral emissions of the 11 LED sources, i.e., the spectral channels of the system, were centered in the following wavelengths: 400 nm, 434 nm, 460 nm, 495 nm, 515 nm, 545 nm, 595 nm, 623 nm, 640 nm, 725 nm, and 850 nm.

The digital camera used for the system was a Basler acA2040-55um camera with a Sony IMX265 CMOS sensor of $2048 \times 1536$ pixels of resolution ($H \times V$ pixels), 55 frames per second (FPS) and 3.45 $\mu$m $\times$ 3.45 $\mu$m pixel size. Images of the leaf samples were acquired at every LED wavelength, where 10 images per each wavelength were averaged to reduce random noise, resulting in 11 averaged spectral images per sample. To correct any spatial non-uniformity of the illumination, spectral images of a White/Background reference (a uniform sample with known reflectance) and dark field images were also taken. All data was saved in 12 bits RAW format and processed in python and OpenCV image processing library.

2.2. Image pre-processing

As for the random noise reduction, were an averaging of 10 images per channel was carried out, also a field uniformity correction was performed. After the averaging of the sets of 10 images for the leaf sample, the white reference, and the dark field images, a reflectance image with spatial non-uniformity correction was generated. For this procedure the sample image, white reference image, and the dark field image of each channel were combined following the linear equation (Equation (1)) given by [9] and [10].
\[ I_{R\theta}(i,j) = r_{\lambda} \frac{I_W(i,j) - I_{\text{dark}}(i,j)}{I_W(i,j) - I_{\text{dark}}(i,j)} \]

where \( I_{R\theta}(i,j) \) is the corrected spectral reflectance image of the sample for a specific wavelength, the \( I_W(i,j) \) factor represents the reflectance of the white reference for that wavelength, \( I_{\text{dark}}(i,j) \) is the dark field image, and \( I(i,j) \) is the sample image under correction, for that specific wavelength.

Due to the spatial distribution of LED sources forming the spectral illumination system, some shadows were formed over the leaf contour (Figure 2(a)), considering that in some cases the pixel values could be interpreted as equal to those of a lesion on the leaf, it was necessary to get rid of them. To achieve this, white reference and 434 nm reflectance images were combined, due that leaf tissue absorbs most of the energy present in 434 nm radiation, it serves as a reference for determining leaf area. First, the reflectance leaf image at 434 nm is subtracted from the white reference at the same wavelength, resulting in a gray-level contour image where the background, leaf area, and shadows can be discriminated against. Then, a threshold operator is applied to create a binary mask where non-leaf areas are assigned a value of 1. To reduce possible leftovers at the contours we apply a morphological erode operator with a circular structuring element over the resulting mask.

This mask is multiplied by the current reflectance image, and a new mask is created to eliminate high-intensity pixels left in the process, this final binary mask is multiplied for the masked reflectance image, to recover any possible missing pixels inside the leaf area, a flood fill is applied (Figure 2(b)).

**Figure 2.** Chrysanthemum leaf: (a) original image with background and shadows, (b) processed image with background and shadows removed.

3. Disease detection

To determine the most relevant wavelengths for the detection of the three pests of interest, a trail-error procedure was carried out were thorough observation assisted by an Agronomist whose years of expertise working with the “Instituto Colombiano Agropecuario (ICA)” served as ground truth for the process. Spectral signatures of all diseases were captured with a spectrometer to determine the regions of interest and were compared against healthy samples. This representation allowed us to determine those spectral regions where there is a difference in the sample behavior and construct linear relationships that better describe each one of the disease manifestations.

3.1. Virus

The manifestation of this affection is a discoloration of the leaves (Figure 3) in the zones where insects attach itself and starts feeding. It is visually presented as a light green discoloration at early stages, varying from yellow into dark damaged regions in most advanced stages. The levels of damage can be viewed by subtraction of two spectral regions (434 nm, 725 nm). This operation yields an image where all affected area across the leaf surface is represented by low-intensity levels, whereas healthy regions are represented by mid-high intensity levels.
Figure 3. Sample of chrysanthemum leaf with presence of virus.

This behavior is because the 434 nm spectral region is absorbed by the leaf tissue, contrary to the 725 nm band that is part of the near-infrared region that is greatly reflected, as a result, combining this two bands maximizes the zones where the leaf has changed this typical behavior (Figure 4(a)). Finally, by using a binary threshold operator, the affected leaf regions can be extracted, and a total damaged leaf area can be determined, 30% of the total leaf area in Figure 4(b).

Figure 4. Chrysanthemum leaf infected by virus: (a) result of spectral bands subtraction, (b) segmentation of damaged leaf area.

3.2. Puncture leaf miner
This pest is the early manifestation of the leaf miner, here a fly deposit its eggs inside the leaf tissue, which, at a final stage, are visually identifiable as yellow spots, but at early stages are not easily recognizable at simple sight, not even by the trained human monitors at farms. Usually, only removing the leaf and testing it at backlight conditions, some dots are visible, where the fly has laid its eggs (Figure 5).

Figure 5. Sample of chrysanthemum leaf with presence of puncture leaf miner.

Since this disease acts in the internal tissue of the leaf, we obtained better results by using the 640 nm spectral image divided by the 434 nm spectral image, we created an image where this sub-dermal spot became visible (Figure 6(a)). To isolate these spots and determine the severity of the infection in the resulting image, we used a binary threshold operator combined with an erosion operation to reduce leftover noise. Finally, we applied a mean filter to isolate and enhance the affected leaf regions (Figure 6(b)).
3.3. Larva leaf miner

This pest is the final manifestation of the leaf miner fly, where the deposited eggs hatch and the larvae start to feed on the fleshy internal leaf tissue, leaving a trail behind them (Figure 7). The disease manifestation is marked by two stages, in the first one, the larva is only visible at the backside of the leaf; in the second, when it has grown, it starts to feed on the surface of the leaf and its effects become more visible.

The path marked by the larvae leaf miner in the first stage, that is considered as a pre-symptomatic manifestation of this pest, becomes visible in the near infrared of 725 nm. This spectral channel as a near-infrared wavelength, is greatly reflected by the leaf tissue but, as the larvae seek the best source of nutrition and fleshy tissue, the zone of feeding seems to lack the components responsible for near-infrared reflection, resulting in low-intensity levels in this spectral image. Creating a division between 400 nm and 725 nm, spectral images results in an image where the damaged areas are detected (Figure 8(a)) and separated by a binary threshold. From this point the damage of the disease can be quantified (Figure 8(b)), representing 11% of the total leaf area in Figure 8(b).
Finally, in the literature there are not reported researches that focus on the detection of diseases in chrysanthemum flowers by means of image processing but, through molecular and chemical analysis of infected leaf tissue [11,12]. On the other hand, there are implementations in crops of cucumber [1,3,4,13], soybean [14] and brinjal [15], where methods such as histogram analysis, k-means clustering and color based segmentations are commonly used, each one offering good results on its own but sometimes requiring more process for disease region of interest extraction when compared with our proposed method, where through linear operations between the spectral images and a simple thresholding can be obtained similar results.

4. Conclusions
The understanding of leaves biochemical processes is extremely important in the implementation of artificial systems that allow detecting the presence of pests in industrial crops, even more, to effectively prevent the loss of raw material and economic investment.

The combination of different spectral information shows to be useful for the visual enhancement of multiple pests symptoms, the regions of damage varieate depending on the source of infection and how it manifests itself in the leaves. In this work, we show that by somehow simple combinations of spectral images even difficult tasks for human monitors could be facilitated like in the case of the puncture leaf miner. This fact is even more relevant considering the possibility of early detection to stop the disease spreading, efficiently reducing possible economic losses and sanctions from sanitary control agencies.

In this work, we show that the virus is the most easily recognizable pest from the ones selected in this investigation, but while gathering leaf samples, we noticed that in a more uncontrolled setting, its manifestations can be confused with other factors such as when the excessive use of pesticides, which ends up intoxicating the plant. We will continue to search for more discriminant procedures to avoid this problem.

The leaf miner is one of the hardest pests to visually asses in its earlier manifestations, this problem gives great value to tools that allow detecting its presence while it is not visible in the leaf surface. In this case, it makes the method proposed in this work a useful tool for field monitors and pest spreading control. This work shows that including scientific and technical tools in these industries could facilitate the labor of the human monitors and reduce the possible bad consequences coming from the lack of good enough pest detection schemes.

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