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Full Length Research Paper

Color image segmentation using perceptual spaces through applets for determining and preventing diseases in chili peppers

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Plant pathogens cause disease in plants. Chili peppers are one of the most important crops in the world. There are currently disease detection techniques classified as: biochemical, microscopy, immunology, nucleic acid hybridization, identification by visual inspection *in vitro or in situ* but these have the following disadvantages: they require several days, their implementation is costly and highly trained. This paper proposes a method for knowing and preventing the disease in chili peppers plant through a color image processing, using online system developed in Java applets. This system gets results in real time and remotely (Internet). The images are converted to perceptual spaces [hue, saturation and lightness (HSL), hue, saturation, and intensity (HSI) and hue saturation and value (HSV)]. Sequence was applied to the proposed method. HSI color space was the best detected disease. The percentage of disease in the leaf is of 12.42%. HSL and HSV do not expose the exact area of the disease compared to the HSI color space. Finally, images were analyzed and the disease is known by the expert in plant pathology to take preventive or corrective actions.

Key words: Applets, knowing disease, color image segmentation, perceptual spaces.

INTRODUCTION

Since the beginning of agriculture, there are problems in crop production due to the presence of plant diseases. Chili's production, as with other crops, is affected by pathogens that reduce their quality (Berrocal, 2009; Mondino, 2008; Valadez-Bustos et al., 2009). Chili peppers belong to the genus *Capsicum* of the Solanaceae family of plants (Ochoa-Alejo and Ramírez-Malagón, 2001). *Capsicum annuum* L. is the species most widely grown throughout the world (Mahasuk et al, 2009; Moscone et al, 2007). Some diseases can be diagnosed easily by visual inspection, but others require laboratory tests for diagnosis (González-Pérez et al., 2011). These procedures may require several days or

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weeks, and in some cases have limited sensitivity. Fortunately with the advancement of biotechnology, there are now new techniques and products that are available to supplement or replace the laboratory procedures. Results are obtained faster and diseases are diagnosed earlier.

In general, conventional methods to detect pathogens in plants are classified as: biochemical, microscopy, immunology, nucleic acid hybridization and other traditional methods such as identification by visual inspection *in situ* or *in vitro* pure cultures by microscopic examination (Fox, 1997). Some disadvantages of these methods are described as: high cost of its items, the requirement of specialized equipment and the need of a high level of appropriate training for its execution, because of the possibility of contamination and the consequent production of false positives. Other disadvantages are the strict biosecurity requirements if radiolabeling is used. Biological assays on its part have the disadvantage of being laborious and expensive, due to the requirement of temperature-controlled facilities, extended period for the manifestation of symptoms and the need for specific indicator plants for each disease. It was observed that some pathogens can interfere with the expression of symptoms in materials with mixed infections.

Procedures used in optical and electron microscopy, allow efficient diagnosis of plant pathogens; which are not used in mass programs due to their limited capacity of analysis, high cost and requirement of specialized personnel (Leuven, 2006). Due to the disadvantages of the methods mentioned above, it is required to have automatic methods to detect plant diseases. An area that offers this possibility is the digital processing of color images. Currently, the digital image processing is used in a variety of applications to solve specific problems. Detection of plant disease is not an exception. Some advantages of this field are as follows:

A. Does not require expensive equipment,
B. Is not required to have complex and highly equipped laboratories,
C. Does not need specialized training,
D. Results of processing can be obtained quickly and directly *in situ*,
E. Information may be available in real time via networked systems and
F. Detection techniques are not invasive because they use digital images and, the plan is not affected.

Color image processing, is one of the most interesting topics in recent years in the area of image processing. Color is very important in the detection of plant disease.

For example, *Pepper huasteco Yellow Vein Virus (PHYVV)* is one of the pathogens that affect the cultivation of chili pepper and one of its symptoms is a yellow mosaic in diseased leaves. Color image is specified by its components red, green and blue (RGB). RGB model is recommended for viewing the color, but it is not good for analysis because it has high degree of correlation between the components R, G and B (Angulo, 2007; Angulo and Serra, 2007; Denis et al., 2007). In addition, the distance in RGB perceptual space does not represent color differences as the human visual system perceives them. For that reason in image analysis and processing, these components are often transformed into another perceptual space (Ortiz et al., 2002; Yang et al., 2010). Perceptual spaces are best suited to represent the color because they are more similar to how humans perceive and interpret color. The components of these color models are the attributes of the human perception of color: hue, saturation and luminance (intensity) (Ortiz et al., 2002).

Importance of using color image processing is because it is a powerful descriptor that in most cases simplifies the identification and removal of objects in scene (Sharma and Trussell, 1997; Youngbae et al., 2008). Besides the fact that humans are able to distinguish approximately 10 million colors under optimal conditions (Sharma and Trussell, 1997). However, one of the difficulties in color image processing is that the color of an object depends not only on the reflective properties of its surfaces but also on the light illuminations and on the properties of the imaging devices (Zhang and Georganas, 2004). It is important to select an appropriate perceptual space to represent the color of an image because the application of different perceptual spaces can significantly change the results of processing (Yang et al., 2010; Youngbae et al., 2008). For this reason, some authors have compared the performance of several perceptual spaces. Stokman and Gevers (2005), proposed a selection framework for a color model using the principles of diversification for image segmentation and edge detection. By formulating statistical and learning systems, researchers found the optimal color channels and their weights. A comparison of edge detectors in color image in multiple perceptual spaces has also been presented (Wesolkowski at al., 2000). Edge detectors such as Sobel operator were evaluated using multiple perceptual spaces (Youngbae et al., 2008).

Machine vision technology has been employed in many agricultural applications involving color grading. Machine vision systems for real-time color classification (Lee and Anbalagan, 1995; Lee, 2000; Zhang et al., 1998) have been commercialized to grade food products based on color. Other agricultural applications include the color grading of fresh market peaches (Miller and Delwiche, 1989a, b; Nimesh et al., 1993; Singh et al., 1992), apples (Hung, 1995; Varghese et al., 1991), potatoes (Tao et al., 1995), peppers (Shearer and Payne, 1990), cucumbers (Lin et al., 1993), tomatoes (Choi et al., 1995), and dates (Janobi, 1998). Many of these systems have shown very promising results (Lee et al., 2008). Although, in México there is no machine vision with applets applied to Chili's production; this is a big concern because Mexico ranks second as producer of chili in the world after China (Valadez-Bustos et al., 2009).

In general some works that can be mentioned are: ImageJ which is a Java application public domain, analysis and digital image processing (Collins, 2007). It offers two working modes: as an applet embedded in a web browser and a desktop application using the Java virtual machine (Rueden and Eliceiri, 2007). It supports images with 8, 16 or 32-bit and recognize TIFF, GIF, JPEG, BMP, DICOM, FITS and RAW. It has a plug-in-based architecture, allowing progressively extended applications. Among its core functions include: calculations with the values of the pixels; measuring distances, angles and areas, after edge detection; implementation of geometric transformations (rotate, scale, etc.) and zoom; simultaneous operations with an unlimited number of images. ImageJ can be used for biological image analysis and remote sensing. Its applications cover many fields including colorimetry, area calculations, angles and distances between pixels, histograms of density, contrast manipulation, or the application of filters for image enhancement (edge detection, median filter, sharpening or smoothing effects, etc.).

Another tool developed by UPIICSA image processing (color and gray). This program allows you to make filtered off operations on pixels, vary the intensity of the image components, histogram display and others. ActiveX control also includes Digital Image Processing (ActiveX control is a generic piece of software that can be included in web pages and applications on the platform Windows is a Dynamic Link Library (DLL), but developed in Visual Basic, generating a file with OCX). The "Image Composite Editor" is a free Java application distribution, designed for the "Earth Observatory" of NASA. This applet allows teachers to create interactive activities for Remote Sensing. Thus, this work proposed a method of segmentation of color images for knowing and preventive disease in chili peppers considering perceptual spaces and Prewitt algorithm for segmentation with a computational system of Java applets to perform image processing in remote or real-time via Internet.

Color image segmentation

It is more complex to process color image segmentation than gray image segmentation, because at the time of processing image, the color and result could be altered. Color image segmentation involves detection of edges or regions by deterministic or stochastic labeling procedure, based on information from intensity and/or spatial information. It requires initially choosing a perceptual space for processing. Recent studies have shown that many of the current color spaces, having been developed for computer graphics applications, are inadequate for the quantitative treatment of the images. A representation should be based on distances or norms for vectors of the points in the space of representation (Hanbury and Serra, 2003). A good way to perform the color images segmentation is using polar coordinates with hue of angular magnitude (with values of 0 to 360°), and with luminance and saturation of linear values (with values from 0 to 1). Hue and saturation components contain all the color information and light have the gray information.

Perceptual spaces

Perceptual spaces (also called color models) are a method by which we can specify, create and visualize color (Bensaali and Amira, 2005). In essence, a color model is the specification of a three-dimensional coordinate system and a subspace of the system in which each color is represented by a single point. Each perceptual space is optimized for a well-defined application area. Due to the nature of the human eye and the trichromatic theory, all colors recognized in an image are a combination of so-called primary colors Red, Green and Blue (RGB) (Bensaali and Amira, 2005; Ortiz et al., 2002). Among the color spaces most frequently used processing images are RGB, YIQ, CMY, YCbCr and HSI. However, for image processing it is more convenient to use HSI, HSV or HLS perceptual spaces. These spaces are more closely related to human interpretation of colors. Components of these color models are the attributes of human color perception: hue, saturation and luminance or intensity (Ortiz et al., 2002).

Luminance is the lightness or darkness of the color and is usually expressed as a percentage from 0% (black) and 100% (white). Hue is the color reflected from or transmitted through an object. It is measured as a polar (angle in degrees) between 0 and 360°. Normally, the hue is identified by the name of the color, like red, orange or green. Saturation, sometimes called chroma, is the strength or purity of color. Saturation represents the amount of white in proportion to the pitch and is measured as a percentage between 0% (gray) and 100% (fully saturated). In the standard color wheel, saturation increases as we approach the edge of it. Coordinates of hue and saturation defines the chromaticity. A color can then be characterized by its luminance and chromaticity.

MATERIALS AND METHODS

We used a bitmap image (bmp) of 24 bits (Figure 2). Its dimensions are 299 pixels wide and 249 pixels high. The system used is a web application using Java applets in NetBeans 6.9.1 and developed with JDK 6.2.1. The tests were run on an HP 630 Notebook PC with a Pentium Processor P6200 2.13 GHz, 300 GB HDD, OS Windows 7 Starter. Threshold and Prewitt were used for segmentation of images. This method is based on perceptual space: hue, luminance and saturation.

+1	+1	+1
-1	-2	+1
-1	-1	+1

Figure 1. Prewitt filter of compass edge detecting templates sensitive to edges at 45°.

Steps to run the segmentation method are described:

1. Convert from RGB to perceptual space [hue, saturation and lightness (HSL), hue, saturation, and intensity (HSI) and hue saturation and value (HSV)]. For the conversion of perceptual spaces (Tables 1 to 3).
2. Pre-processing is performed to remove noise through the opening (or lock) reconstruction.
3. Applies color segmentation method with each perceptual space. This method is applied for each channel (hue, luminance and saturation).
i. Threshold applied to the image.
ii. Prewitt filter applied to the image. Figure 1 shows the Prewitt mask.
4. Invert from perceptual space to RGB
5. Analyzes the results of the segmentation of color images obtained from the computer system of Java applets on a real-time or remote (Internet). System highlights details of the disease and expert in plant disease, the diagnosis right to take action and avoid loss in production.
6. Finally, knowing and preventing the disease of chili pepper by comparing each perceptual space and presenting conclusions.

RESULTS

Table 4 shows the images obtained by applying the methodology described. The original image of the diseased leaf (Figure 2) was transformed to each of the spaces color (HSV, HSL and HSI). Threshold and Prewitt was applied to each of these spaces color. Other filters were tested such as Laplacian and Sobel, Roberts, etc. However, Prewitt gives better results. The comparative table shows the differences of color in areas where there are symptoms of the disease. The color change is what the system detects and then an expert in plant pathology in chili peppers can determine the magnitude of the problem. This comparison chart shows that the HSI color space better detects the disease (Figure 3). The images e) and f) expose the region of the disease. The percentage of progress of the disease in the leaf was 12.42%. The percentage 87.58% represents the healthy region of the leaf.

HSL and HSV do not expose the exact area of the disease compared to the HSI color space. Images a) and b) detect the area and contour of the leaf, but do not hold the diseased area. HSV did not detect the diseased region properly. Images c) and d) detect regions that do not correspond to the leaf disease. These images do not detect regions that do have the disease. HSL indicates that the 14.23% of the leaf exposes the disease. There is a difference of 1.81% between HSI and HSL. Comparing the results presented in applying threshold and Prewitt,

Table 1. Conversion from RGB to HSL and HSL to RGB.

RGB to HSL	HSL to RGB
min = minimun (R,G,B)	L = L/255
max = maximun (R,G,B)	
	If L <= 0.5
R = R – min	min = L•(1 - S)
G = G - min	max = L•(1 + S)
B = B - min	
	If L > 0.5
L = (max + min)/2	min = L – S•(1 - L)
	max = L + S•(1 - L)
If max = min	
S = 0	If min = max
	R = min
If L <= 127	G = min
S = (max – min)/ (max + min)	B = min
If L > 127	If min <> max; H >= 0; H < 120
S = (max – min)/ [510 – (max + min)]	B = min
If B = 0	If min <> max; H >= 0; H < 60
H = 120•G/(R + G)	R = max
	G = min + [H•(max - min)/(120 - H)]
If R = 0	
H = 120 + [120•B/(B + G)]	If min <> max; H >= 60; H < 120
	G = max
If G = 0	R = min + [(120 - H)•(max - min)/H]
H = 240 + [120•R/(R + B)]	
	If min <> max; H >=120; H < 240
	R = min
	If min <> max; H >=120; H < 180
	G = max
	B = min + [(H - 120)•(max - min)/(240 - H)]
	If min <> max; H >=180; H < 240
	B = max
	G = min + [(240 - H)•(max - min)/(H - 120)]
	If min <> max; H >=240; H < 360
	G = min
	If min <> max; H >=240; H < 300
	B = max
	R = min + [(H - 240)•(max - min)/(360 - H)]
	If min <> max; H >=300; H < 360
	R = max
	B = min + [(360 - H)•(max - min)/(H - 240)]
	R = R•255
	G = G•255
	B = B•255

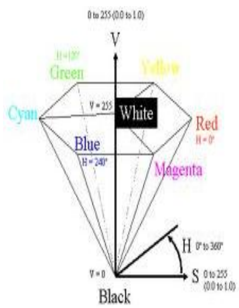
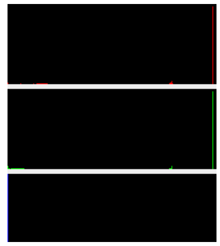
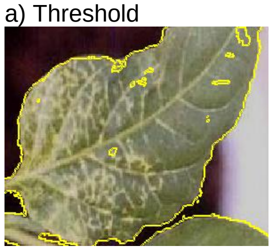
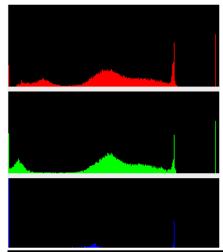
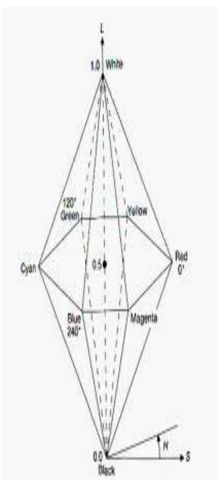
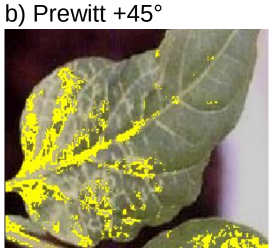
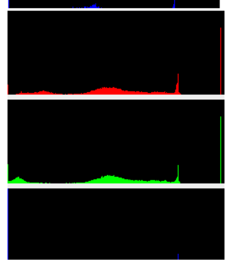
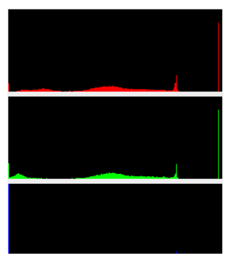
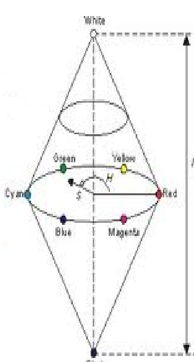
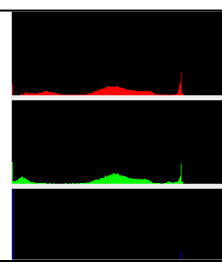
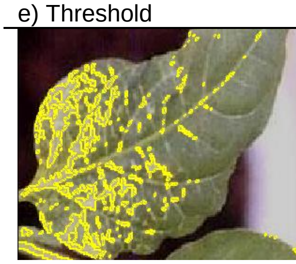
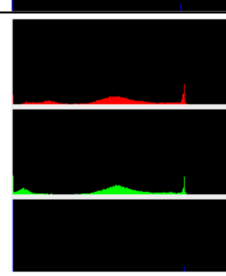
Table 2. Conversion from RGB to HSl and HSI to RGB.

RGB to HSI	HSI to RGB
min = minimun (R,G,B)	I = I/255
$Hi = \cos^{-1}\{ 0.5\cdot[(R-G) + (R-B)] /[(R-G)^2 + (R-B)\cdot(G-B)]^{1/2}\}$ If B > G H = 2•PI - Hi S = 1 - [3•min/(R+G+B)] I = (R+G+B)/3	If Hi < 2•PI/3 x = I•(1 - S) y = I•[1 + S•cos(Hi)/cos(PI/3-Hi)] z = 3•I - (x + y) b = x r = y g = z
	If 2•PI/3 <= Hi; Hi < 4•PI/3 Hi = Hi - (2•PI/3) x = I•(1 - S) y = I•[1 + S•cos(Hi)/cos(PI/3-Hi)] z = 3•I - (x + y) r = x g = z b = y
	If 4•PI/3 <= Hi; Hi < 2•PI Hi = Hi – (4•PI/3) x = I•(1 - S) y = I•[1 + S•cos(Hi)/cos(PI/3-Hi)] z = 3•I - (x + y) g = x b = y r = z
	R = r•255 G = g•255 B = b•255

Table 3. Conversion from RGB to HSV and HSV to RGB.

RGB to HSV	HSV to RGB
min = minimun (R,G,B) max = maximun (R,G,B)	Hi = H/60 f = H/60-Hi p = V• (1-S) q = V• (1-f•S) t = V• [1-(1-f) •S]
If max = min H = 0	If Hi = 0 R = V; G = t; B = p
If max <> min; R = max; G >= B H = 60•(G - B)/(max - min)	If Hi = 1 R = q; G = V; B = p
If max <> min; R = max; G < B H = 60•(G - B)/(max - min) + 360	If Hi = 2 R = p; G = V; B = t
If max <> min; G = max H = 60•(B - R)/(max - min) + 120	If Hi = 3 R = p; G = q; B = V
If max <> min; B = max H = 60•(R - G)/(max - min) + 240	If Hi = 4 R = t; G = p; B = V
V = max/255•100	If Hi = 5 R = V; G = p; B = q
If max <> 0 S = 1 - min/max If max = 0 S = 0	R = R•255/100 G = G•255/100 B = B•255/100

Table 4. Comparison chart of disease exposure segmentation result.

Color space	Resulting image	Histogram RGB	Description
 HSV	 a) Threshold		Image a) shows in yellow the region of the leaf (70.05% of the image), but does not detect the diseased area. The histograms show the loss of information.
	 b) Prewitt +45°		Image b) shows contour of the leaf, but not detect the disease area. The histograms show the leaf colors more yellow edge (lines (255) of green and red).
 HSL	 c) Threshold		Image c) shows in yellow the diseased area of the sheet (14.23%), but there are regions of the disease are not detected. The heterogeneous areas are observed in histograms.
	 d) Prewitt +45°		Image d) shows contours of the image c), but detection of the disease is not complete. The histograms are shown better than the HSV color space.
 HSI	 e) Threshold		The region of the image e) with yellow representing 12.42% of diseased leaf area. HSI color space is best for detecting areas of the disease. The histograms show clear information.
	 f) Prewitt +45°		Image f) shows that the detection of contours in diseased regions is clear in the HSI color space*. This result makes it possible to understand and correct disease.

* The next step is to use methods of quantification of the disease. Table 5 contains the most used methods. This table corresponds to Table 2 shown in González-Pérez et al. (2011). Severity scale and severity index are two methods that can be applied to these images. Based on the severity scales (severity scale to evaluate-the fungus and ash in chili pepper cultivation (Salaices, Chihuahua Mexico, 1998) and severity scale to evaluate damage by viruses in the chili pepper cultivation (Chihuahua, Mexico, 1998), shown in González-Pérez et al. (2011), the disease progression of the image f is in Category 1.

Figure 2. One leaf disease of chili peppers plant.

Figure 3. Diseased area detected with HSI color space.

allow experts to make an accurate diagnosis of disease severity, using methods of quantification of the disease (Table 5). This table is to be included in González-Pérez et al. (2011) as Table 2. Based on the magnitude of the disease the respective actions must run to ensure maximum plant productivity.

Table 5. Quantitative methods of plant disease.

Method	Advantage	Disadvantage
Pictorial keys assessment. Use diagrams of standard area which are derived from a series of images of the disease´s symptoms that illustrate the steps of a disease´s development.	1. Easy Use.	1. Cannot demonstrate the pattern variations of the disease, caused by the pathogen, causing evaluator´s subjectivity. 2. Variation of the leaf´s size, affects the severity of evaluation because of the evaluator.
Severity scales. Are categorized into different levels of disease severity in convenient intervals, each one of which is assigned a degree (Agrios, 2005).	1. Measurement of the severity is more accurate.	1. Measurement of the severity is slower. 2. Measurement tends to be subjective when carried out visually.
Severity index. They are composed of degrees of severity, related to or not related to the percentage of the diseased areas (Araus, 1998). An example is: 1 = a little 2 = average 3 = high.	1. Easy Use.	1. Variation between the step index of different investigators. 2. Certain indexes do not permit comparisons of their evaluations. An index of 4.5 can represent a lot of disease on a scale of 1 - 5, but relatively little on a scale of 1 – 10. 3. Difficult to interpret, when you do not have the proportion of diseased tissue (Araus, 1998).
Count lesions. More objective than the use of scales.	1. Appropriate as reference method for the development of scales.	1. Slow and costly application. 2. Impractical for routine evaluations.

Conclusion

Here a suitable is presented method which helps to prevent disease. The comparative table (Table 4) shows the leaf disease of chili peppers. Processing an image with any perceptual space is not the most efficient method; each kind of image perceptual space needs to select. In this case, HSI color space was the best to detect the disease. A key step is the transformation between RGB spaces and perceptual spaces mostly used (HSL, HSI and HSV) and the methodology for image segmentation, such as threshold and Prewitt filters. From these results a plant pathology expert can use any method of quantification of the disease (Table 5). The use of severity scales to assess the extent of the disease in the plant is suggested. In González-Pérez et al. (2011), there are some severity scales used in chili peppers. Some scales of severity are:

1. 1st scale: Severity scale to evaluate the fungus and ash in chili pepper cultivation (Salaices, Chihuahua Mexico, 1998).
2. 2nd scale: Severity scale to evaluate damage by viruses in the chili pepper cultivation (Chihuahua, Mexico, 1998).

The percentage of diseased leaf area in the image f of Table 4 is 12.42%. This result is in the category 1 (0 to 30% of diseased leaf area) according to the first scale. The second scale has categories of severity from 1 to 3. This scale is based on qualitative descriptions of disease progression. In this case the leaf disease is in category 1 (yellow mosaic) because it considers the change in color in the image and not the percentage of diseased area. Another method is Severity Index that considers the degree of severity associated with the percentage of diseased area. In the near future it is expected that pathogen diagnosis is made with new technology. These advances will be possible, thanks to the work done in the area of genomics and bioinformatics.

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