DEVELOPMENT OF A MACHINE VISION SYSTEM FOR WEED MAPPING

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ABSTRACT The objective of this work was to develop a machine vision for weed mapping in a field irrigated by a center pivot. The system was composed by two digital cameras and a DGPS. One camera acquired color images and another near-infrared (NIR) images from the same scene, and the DGPS saved the position of that scene. The DGPS position was assumed to be in the center of the image. Sample images of the field were acquired in a specific grid. The images were processed for estimation of weed infestation at each position. The green excess index and the ratio of near-infrared and red bands were used to enhancing the weeds and crops. The crop rows were detected by Hough Transform, and plants between rows were assumed to be weeds. An algorithm was developed with LabView software to do all the image processing and obtain the weed infestation results. Once the weed infestation georeferenced grid was built, it was possible to obtain maps using spatial statistics techniques. The system was tested in a 0.8 hectare center pivot irrigating black beans, half the area being in a tillage seeding system and the other half in a no-tillage. A total of 150 images of each tested spectral band were acquired to produce the maps. The developed algorithm was capable to produce weed spatial variability maps for both seeding systems using both cameras. The color images were more adequate to detect the weed infestation in both seeding areas than the NIR images.

Keywords: digital imaging processing, precision agriculture, spatial statistics.

INTRODUCTION It is important to give especial attention to weeds located near crop lines since they probably consume necessary nutrients for grow and development of the crop, affecting quality and productivity.

One of the most efficient methods to combat weed growth is by applying herbicide to the target. Conventional application performed by sprayers uniformly apply herbicides over
an entire area, causing the deposition of chemical products in places where there are no weeds. As well as generate unnecessary costs, it harms and pollutes the environment. Therefore, it is necessary to use the correct chemical product quantity and apply only where there are weeds. A study conducted by Baio (2001), using a site-specific herbicide application system verified an herbicide economy of 31.6%, when compared to the total area application. Thus, weed mapping has become a useful tool for site-specific herbicide application, based on the precision agriculture philosophy.

Precision agriculture can be defined as a group of technologies and procedures used to optimize agricultural production, where spatial variability management of production and factors related with production are some of the key elements (Stafford, 2000). Therefore, information on spatial variability factors as fertility, moisture, productivity, pests, diseases, weeds, and others must be analyzed with a high level of detail for rationalization and optimization of agriculture management.

According to Christensen et al (1993), weed mapping can be done with the aid of digital images to delimitate weed areas in crops. Cameras can be attached to different platforms such as airplanes, balloons, model airplanes or vehicles that circle the field to be mapped (Antuniassi, 1998).

Senay et al. (1998), report that there are studies demonstrating that remote sensing techniques and digital image processing are intimately related with precision agriculture, but it is necessary to develop techniques for extraction of information from the images. One of the irrigation systems that is growing in Brazilian is the central pivot irrigation, both in traditional and no-till seeding systems. Since the central pivot is a structure that passes over the entire crop area, it can also become useful for weed mapping by attaching digital cameras to its structure and thus forming the artificial vision system.

With this system it is possible to map the entire area by digital images and with these images it is possible to map weed spatial variability and others attributes. However a large challenge to development of machine vision systems is still the implementation of algorithms capable of identifying the objects of interest in the agriculture conditions.

Spectral bands or spectral indices can assistance in the mapping of plants since they minimize external factors and promote the contrast of the objects of interest. With digital image processing techniques by means of RGB color models it is possible extract important image information, favoring crop and weed identification (Sartori et al., 2005).

Implementation of site-specific herbicide management techniques may help farmers achieve optimized production, improving quality and reducing environmental problems in the future.

The goal of this study was therefore to development an artificial vision system to construct weed maps using digital image processing techniques and geostatistics.

**MATERIALS AND METHOD** The present study was conducted in an experimental field belonging to the Universidade Federal de Viçosa (UFV) in the city of Coimbra, Brazil. This field was irrigated by a central pivot system and planted with common beans, for which half of the field was no-tillage seeded and the other half was conventionally seeded (tillage).
The artificial vision system was formed by two STH-DCSG-VAR/-C model cameras, being one monochrome and the other color, and a laptop computer. These cameras simultaneously acquired two images of the same scene.

A high pass filter was connected to the monochrome camera with the wavelength stating at 695 nm and finishing at 1050 nm. This filter was used to restrict the spectral band that reaches the camera sensor only within the near infrared (NIR) range.

NIR and color (RGB) images were obtained, being that RGB refers to the red, green and blue spectral band respectively.

The cameras were connected to a laptop computer using cables of 10 meters in length connected to a framegrabber PCMCIA card IEEE 1394. A 12 Vcc battery connected to the PCMCIA card was used to operate the cameras.

The lens pattern used was C-mount with focal length of 2.8 mm and the images were saved in bitmap format with dimensions of 480(V) x 640(H) pixels using the SRI´s Small Vision System (SVS) software that controls the cameras, provided by the manufacturer.

The camera sensor was the CMOS MT9V022 image sensor with 1/3” format. These cameras were positioned on the upper section of the central pivot mobile structure, with the lens turn down, focusing the target. Figure 1 shows the developed system.

In the field covered by the central pivot, reference stages were placed and their coordinates were captured using a DGPS Trimble Pathfinder Pro XRS.

Thus, the cameras moved laterally with the central pivot structure during its movement, acquiring images of the entire field. The irrigation did not function while the central pivot movement.

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**Figure 1: Machine vision system with cameras, laptop computer and an example of the reference point.**

The image was acquired when the reference point appeared in the middle of the area to be captured. The reference points were organized in circular sections and the straight line distance between each point of each section was 6.5 m. The distance between each radius also was 6.5 m. Figure 2 shows the reference points acquired by DGPS represented by...
“x”, and the black line indicates the seeding system field division. A total of 74 points were acquired in the tillage seeding system and 82 points in the no-tillage seeding system.

![Figure 2: The image on the left shows the division of tillage and no-tillage seeding systems in the field and the right-hand image show all the reference points acquired in the field by the DGPS with the black line indicating the seeding system division.](image)

All images were acquired at 25 days after emergency (DAE) of the crop and on a cloudy day.

The LabView software, version 8.6, was used for all images processing to calculate the weed cover percentage.

Firstly, the transformation of RGB images in monochrome index images was performed to increase contrast among plants and soil. For each pixel of the image indices a defined value by the excess green index (ExG) was attributed using the R, G and B spectral bands according to Gée et al. (2008). This index was calculate by equation 1.

\[
ExG = 2g - r - b
\]  

(1)

Where, r, g and b are the normalized digital values of R, G and B, respectively, according to equation 2.

\[
r = \frac{R}{R + G + B} \quad g = \frac{G}{R + G + B} \quad b = \frac{B}{R + G + B}
\]  

(2)

Where R, G and B are the digital values of each pixel on the red, green and blue spectral bands, respectively.

Next, was realized the thresholding process in these index images and also in the near infrared images. Using the histogram of each monochrome image the T threshold was obtained by the automatic iterative thresholding method presented by Yang et al. (2001) that divided the whole image in two classes, plants and soil. Each pixel with value larger than the T threshold was given a value of 255 (white color), which correspond to plants (weeds and crops), while the pixels with values less than T acquired the digital value of 0 (black color), corresponding to the soil class and the rest of the image (stones, straw, etc.).

After attainment of binary images another algorithm was developed in the same software to remove the crops from the image and leave only the weeds. A filter function open and close provided by the same software was used to remove noise from the images.
Consecutive application of these two functions promoted noise elimination without alteration to object size.
The next step was indentifying the crop line angle in images by the Hough transform according to Duda & Hart (1972). Later, the images were rotated to leave crop lines vertical. A 320 x 480 pixel block was cut from the central portion of each image, keeping in the same central point as the original image. These blocks assure that the image area is common in both cameras and crop rows had the same size on the images. From these blocks the crop rows were removed and the weed cover percentage was calculated through a function developed in the system. This function transforms the images into a signal of pixel values of either 1 or 255.
To remove crop rows and calculate the percentage of area occupied by weed coverage, a function of machine vision that transformed images into a signal representing pixels with a value of 1 or 255 (presence of plant) was implemented for each column. When analysing this signal it was found that the peaks indicated the presence of crop rows and the valleys the space between rows, making identification of position and width of the crop rows possible. After locating these rows it was possible to separate them from the space between rows and calculate the weed cover percentage in each image by counting the pixels representing the weeds. All plants in rows were considered crops and between rows were considered weeds. With the values of weed cover percentage of all images associated with a point with known coordinates, four maps were constructed with classes of weed cover percentage, a map for each image type in each seeding system type, using geostatistics of the software GS + version 9.

RESULTS AND DISCUSSION

Figures 3, 4 and 5 illustrate the machine vision system for all image processing and calculation of the weed cover percentage in the software LabView, where Figure 3 illustrates the entire transformation process of the RGB images in an ExG image index from limiarization of the histogram and filtration for noise removal.

Figure 3: Visualization screen of the machine vision system referring to the RGB image transformation process in an ExG image index, from limiarization and noise elimination.
Figure 4 illustrates all stages referring to application of the Hough transform in the binary image with a circular mask, attainment of the angle of inclination of the crop rows, rotation of the image and cropping of the block.

Figure 4: Visualization screen of the machine vision referring to the application process of the circular mask on the binary image with identification of the angle of inclination of the crop rows by the Hough Transformation, rotation and cropping of the images.

Figure 5 shows the machine image screen referring to the process of removing the crop rows to obtain the weed coverage percentage.

Figure 5: Visualization screen of the machine vision referring to the identification process of crop row position and width, separation of these rows from the image and calculation of the weed coverage percentage.

To construct the maps, the most suitable semivariogram models were first adjusted for each situation, based on the model parameters. The types of models with their respective coefficient of determination values ($R^2$) and spatial dependence indices (SDI) utilizing the ($C/Co+C$) relationship are presented in Table 1.
Table 1. Model characteristics of both cameras and seeding system.

<table>
<thead>
<tr>
<th>Seeding system</th>
<th>Conventional (Tillage)</th>
<th>No-tillage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Camera type</td>
<td>RGB</td>
<td>NIR</td>
</tr>
<tr>
<td>Model type</td>
<td>spherical</td>
<td>spherical</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.98</td>
<td>0.95</td>
</tr>
<tr>
<td>SDI (C/Co+C)</td>
<td>0.78</td>
<td>0.63</td>
</tr>
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According to Zimback (2001), the spatial dependence interval (SDI < 25 %) is considered weak, (25 % ≤ SDI < 75 %) is moderate and (IDE ≥ 75 %) is strong. Thus, from Table 1 it can be observed that the models generated by the RGB camera in both planting systems were strongly dependent and the others only moderately dependent.

The \( R^2 \) values indicate that the adjusted models illustrate the data greater than 75%, especially in the case of conventional planting systems.

The spherical model presents a characteristic of linear tendency for small distance intervals, while the exponential model has a tendency for greater semivariance values for small distance intervals. The Gaussian model is characterized by mitigation of the graph for small values of \( h \) and is used when encountering large continuity between data pairs at proximal points (Isaaks and Srivastava, 1989).

Cross validation was used to confirm the potential of the models to estimate values not sampled manually. The regression coefficients together with the standard error of each camera and planting system can be seen in Table 2.

Table 2. Cross-validation parameters of both cameras and seeding system.

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>Camera type</td>
<td>RGB</td>
<td>NIR</td>
</tr>
<tr>
<td>Regression coefficient</td>
<td>1.1</td>
<td>0.98</td>
</tr>
<tr>
<td>Standard Error (SE)</td>
<td>0.17</td>
<td>0.20</td>
</tr>
</tbody>
</table>

The regression coefficients indicate the proximity to the straight line, whose value is 1, where the estimated values are equal to the real values. In relation to the standard error (SE), the closer to zero the better the estimation of the non-sampled values. In general, these values were low, which promoted credibility of the interpolated values in the maps. Figures 6, 7, 8 and 9 illustrate, respectively, the maps constructed with the RGB and NIR images in the area referring to the conventional and no-tillage planting systems. These maps were constructed with classes which varied by 5% from 0 to 15% in both planting systems and camera types.
Figure 6: Map of weed percent coverage obtained by the RGB camera of the conventionally planted area.

Figure 7: Map of weed percent coverage obtained by the NIR camera of the conventionally planted area.

Figure 8: Map of weed percent coverage obtained by the RGB camera of the no-tillage planted area.
Figure 9: Map of weed percent coverage obtained by the NIR camera of the no-tillage planted area.

When analyzing the maps referring to the conventional planting system (figures 6 e 7), it is possible to observe tendencies of the greater values, 10 to 15% class, located on the right side, and the smallest values, 0 to 5% class, in the lower left corner. These maps presented similarity and predominance of the intermediate class (5 to 10%). Despite this, the processed RGB images generally present less noise than the NIR images and a greater level of detail between the objects. In a study using aerial images in the visible and NIR ranges to measure weed infestation and nitrogen deficiency, Goel et al., (2002) found that weed infestation had no significant effect on detection by NIR images.

In the no-tillage planting system the maps were also predominantly composed of the 5 to 10% class, where lower values were encountered in the upper left corner.

The layer of straw present on no-tillage planted fields makes growth of weeds difficult, minimizing infestation (Mateus et al., 2004; Jakelaitis et al., 2003). This fact was proven in the field, where greater weed infestation was verified in the conventionally planted system than for no-tillage. A greater infestation uniformity of weeds was also verified in the no-tillage planting system than in the conventional system. Therefore, the region of high infestation (10 to 15%) present in the map of the NIR camera in the no-tillage system is probably due to the presence of noise occurring during image processing.

CONCLUSION The tools used for construction of these machine vision systems were capable of constructing weed coverage maps for both planting systems and camera types. Improvements in the operation of image processing must be done to diminish errors associated with separation of crop rows in the machine vision systems. The RGB images showed better detail for distinction between plants and soil and lower production of noise than the NIR images in both of the planting systems studied.

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