Two Complementary Approaches for Weed Detection Given by Spectral and Spatial Information

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Abstract

The aim of this study was to detect and localize weed patches in order to improve the knowledge on weed-crop competition. A remote control aircraft provided with a camera allowed to obtain low cost and repetitive information. Differents stages of image processing were necessary for the detection of weed patches. First a colorimetric base shift allows to separate the soil and plant pixels. Then, a specific algorithm including Gabor filter was able to detecte crop rows on the vegetation image. Weed patches were then deduced from the comparison of vegetation and crop

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images. Ground localization and geometric corrections were realized using georeferenced landmarks. Finally the development of a new acquisition device is introduced and its first results for the discrimination of weeds and crops using the spectral properties are shown.
Keyword : weed detection, spatial analysis, spectral analysis, Gabor filter, neural network, image processing.

1 INTRODUCTION

Weed detection was extensively studied as herbicide application has a relevant impact on economics and environment. Developing a spraying strategy in the context of precision agriculture needs to improve in-field detection of weeds. Weed detection using image analysis was directed through different approaches. First experimental works were based on the spectral signature of weeds and crops. Vrindts *et al.* [1] determined some specific spectral bands to achieve weed identification. Statistical analysis were conducted to find spectral properties of each species. In the same way Pollet *et al.* [2] developed an imaging spectrograph. This device gave an image with the spatial dimension on vertical axis and the spectral dimension on horizontal axis. Another experimental method was based on morphological properties extracted from leaf shape using simple geometric shape factors (elongation, diameter, ...)[3, 4]. In the same way Manh *et al.* used deformable templates to modelize leaf shape[5, 6]. In these two last cases high resolution images was needed. Moreover computation time was very important and limited this application to small areas. In-field detection of weeds was also possible on stubble. For example, Biller *et al.* [7] achieved a sensor to detect plants on bare soil. In this case, two optical bands as red $(650\,nm)$ and infra-red $(850\,nm)$ were used to find vegetation . The difference

between the two wavelengths was determined and controlled online spraying. Finally, last approach concerned remote sensing imaging. For example aerial images taken with four cameras equipped with optical band-pass filters were used by Rew *et al.* [8] to find wild oat in triticale crop . They showed the increase in normalized difference vegetation index (NDVI) with wild oat infestation. All these previous approaches were conducted in order to discriminate weeds and crops from their spectral signature or shape. The objective of this paper is to develop complementary spectral and spatial methods upon aerial photographies in order to improve weed detection and localization.

2 ACQUISITION AND PREPROCESSING

2.1 Image acquisition

A remote control aircraft was customized for this application. A Olympus μII[1] camera was placed in the hold; the shot was manually triggered through the remote control. A miniature video camera and an embedded high frequency (HF) emitter provided online images of the flying-over area on a TV. Different flight altitudes were tested from about ten meters up to few hundred meters. The resulting resolution was found to vary from less than a centimeter per pixel up to some meters per pixel. After developing, films were digitalized using a Canon CanoScan D660U scanner. 1702 by 1136 pixels images on red, green, blue (R,G,B) channels were obtained. Theses images were then saved in BMP format to avoid compression losses. Images analyzed in this paper corresponded to weed/crop competition test fields located in INRA domain in Dijon (France).

[1] aperture of $1:2.8$ and focal of $35\,mm$

2.2 Georectification

In the case of high resolution images, only low altitudes flights were realized. Several shots were then needed to get the whole field. Landmarks (black and white draughtboard) were placed and georeferenced in the field using D-GPS coordinates (Trimble Pro XRS) to locate images and also to give black and white references. A specific algorithm was developped to give the transformation matrix between image coordinates and GPS coordinates.

3 IMAGE PROCESSING

3.1 Soil and plants discrimination

Two methods are generally employed upon color images to solve this problem: texture analysis or color discrimination. In most cases the first method is very efficient but accuracy depends on soil roughness (due to clods, tyres and implements prints) and needs high cost time algorithms. The second method is based on the color properties between soil and vegetation. In this case the R,G,B color base is not adapted to find accurate colorimetric information on images acquired under natural light. Indeed, color levels depend on lightness, that has to be separated from chromatic values. The HSV (hue, saturation, value) color base allows this separation but RGB-HSV transformation appears to be non-linear and unstable for low RGB values. Steward and Tian [9] described another color base which is a linear conbination of RGB values that appeared to be more adapted to vegetation images.

$$\begin{bmatrix} V_1 \\ V_2 \\ I \end{bmatrix} = \begin{bmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 \\ -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & \frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

The equation 1 describes a base rotation. The three vectors $(V_1, V_2, I)$are unitary and perpendicular, so information are fully independent. I corresponds to the luminosity vector including shadows and other lightness defaults such as reflects.

(V_1, V_2) provide a colorimetric plane. V_1 is defined as the difference between red and green channels. Then V_1 is positive for vegetation pixels and negative for soil pixels. In this paper only positive values of V_1 were considered.

3.2 Seed frequency characterization

Previous image treatments led to vegetation images including crops and weeds. With the assumption that crops corresponded to repetitive structures, the Fourier's transform was tested. In this case each pixel was individually analyzed through his spatial distribution and V_1 intensity. The Fourier transform result corresponded to the period and the rotation angle of periodic structures. For further task, the seed frequency was characterized using a specific algorithm.

3.3 Low frequencies enhancement

First trials showed that the seed frequency had often a very low value generally making the filtering difficult. The size of the filter kernel depends on the frequency, a low frequency involves a big kernel, with inaccurate results and very long computation time. To minimize this constrain, a dilation of the lowest frequencies must be achieved. The eas-

iest way is an under-sampling of the image by removing a line and a column from two. This step is recursively repeated to obtain a frequency which allows an accurate filtering. In our case a value of $1/10$ is needed which corresponds to about 10 pixels between two rows.

3.4 Gabor filter

The filter is a directive band-pass filter along the axis[10]. It was centered on ω, σ_x and σ_y set the band width respectively along the R_1 axis and the R_2 axis. Periodic structures with a frequency near ω and a rotation angle close to φ value were unchanged but other strucutres were deeply faded.

$$g(x,y) = \frac{2}{\pi\sigma_x\sigma_y} \exp\left(-\frac{R_1^2}{\sigma_x^2} - \frac{R_2^2}{\sigma_y^2}\right) \cos\left(2\pi\omega R_1\right) \tag{2}$$

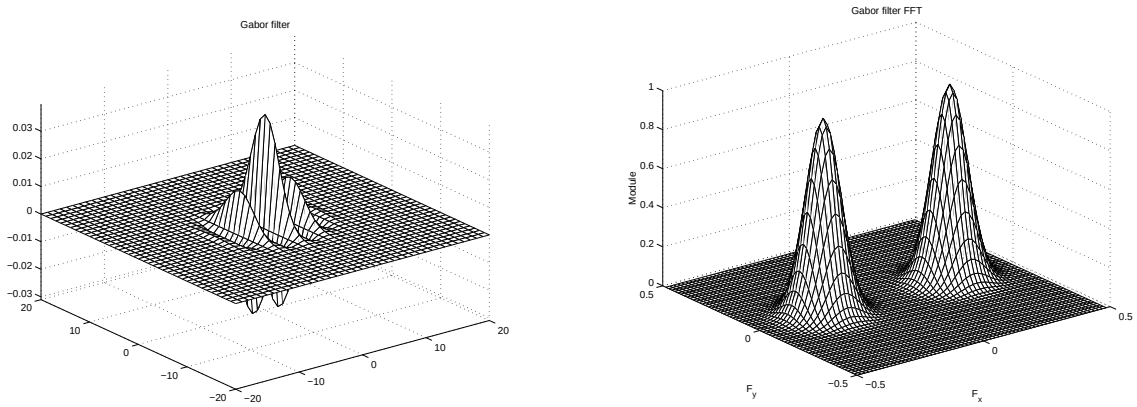
with

$$\begin{cases} R_1 &= x\cos\varphi + y\sin\varphi \\ R_2 &= -x\sin\varphi + y\cos\varphi \end{cases}$$

The spatial representation of $g(x,y)$ is shown in figure 1-a, the FFT in figure 1-b. It is a directive band pass filter centered on ω, and oriented by φ. The width is defined by σ_x and σ_y. After sampling, a mask can be defined. The size of the mask is depending on σ_x and σ_y. We truncate $g(x,y)$ on the interval $[-3\varphi, 3\varphi]$, where φ is the maximum of (σ_x, σ_y). We keep a good approximation with an acceptable filter size.

3.5 Gain computing

After filtering, crops would have high value. A thresholding can be considered, but the results are not satisfying. On vector V_1, crops and weeds have spread values. So after



(a) Spatial representation of Gabor filter

(b) Fourrier transform of Gabor filter

Figure 1: Spatial and spectral representation of Gabor filter

filtering a low value obtained can be due to a weed pixel with high value, or a crop pixel with a low value. Then we decided to compute the gain of each pixel for an accurate thresholding (table 1). The gain is defined for each vegetation pixel as :

$$G(x,y) = \frac{p_g(x,y)}{p_{v_1}(x,y)} \tag{3}$$

In this equation, $p_g(x,y)$ is the module of the point after filtering, and $p_{v_1}(x,y)$ the value of this point on the vector V_1. If the gain is near 1, the point belongs to a periodic structure defined by the coefficients of Gabor filter. For thresholding, a level of $-3\,\text{dB}\,(0.707)$ is generally chosen. A lowest threshold increases the band width, a higher threshold diminishes it.

Table 1: Exemple of gain computation for crop and a weed pixels

	Before filtering : p_{V_1}	After filtering : p_g	Gain : G
Crop	0.5	0.45	0.9
Weed	0.5	0.05	0.1

3.6 Results

We first decided to test this algorithm on synthesis images to confirm the validity of the method. After this step, we tried it on images of various crops. Results depended on species and vegetation stages. Crops with an important spreading out as rape and barley gave bad results. Indeed the space between two rows was rapidly hidden by foliage during the vegetation growth. So the discrimination was impossible with only this method. The FFT did not give the seedling frequency, so the Gabor filter can not be tuned. On other species the identification gave better results, and weeds can be found at early stage.

3.6.1 Low altitude image

The figure 2-a shows an image of a corn field (6 per 3 meters with a resolution of around 5 mm per pixel). Some weeds can be noticed between two rows. After the processing, crops are shown in red and weeds appear in blue (figure 2-b). The end of some crop foils are detected as weeds. This default is probably due to the foil shape elongation which corresponds to high frequency signal.

3.6.2 High altitude image

Using some test field of INRA, we also aquiered high altitude images of weed patches. The picture have a size was about 20 per 16 meters with a resolution close to 10 cm per pixel. The crop was corn (*zea maïs*) volontary infested with green foxtail (*setaria viridis*) patches at various densities. The main weed patches were well recognised, but some corn foils were still detected as weeds.

3.6.3 Partial conclusion

The algorithm for crop row detection was efficient from a quantitative point of view. Crops were well recognized, only some foil extremities were misclassified. Weeds were also globaly well classified. But, weeds located in crop rows were still detected as crops. This result led us to complete this previous spatial analysis using a spectral approach.

4 FIRST WORKS ON SPECTRAL PROPERTIES

4.1 Development of a new acquisition device

Previous works have shown possibilities of spectral information for the crop/weed discrimination [1, 11, 12]. In most studies, the visible band (red, green, blue) is completed with one or several infra-red wavelengths. In the same way, we built a new acquisition device based on a CCD sensor equipped whith a rotating disc holding four filter. Two filters are band pass, one in blue (bandwidth : $50\,nm$, central wavelength : $500\,nm$) and the other in the green (bandwidth : $75\,nm$, central wavelength : $550\,nm$). The two other filters are high-pass at $675\,nm$ (red) and $750\,nm$ (infra-red) as described elsewhere ([13]).The exposure time can be set at different values depending on the filter bandwidth. First trials of this device were realized in laboratory with onion crops and various weeds.

4.2 Crops and weeds separation using PCA

Statistical tools are usually applied with multicomponent images. The principal component analysis (PCA) is often used to find the base which gives the best decorrelation between data. In our case, we can consider each pixel as a 4 component vec-

tor : $p_{i,j} = \begin{pmatrix} V_1 \\ V_2 \\ V_3 \\ V_4 \end{pmatrix}$ with i, j the coordinates of the pixel and $V_1 \cdots V_4$ the values of this pixel on the four wavelengths. We can define the covariance matrix of this image as :

$$C = \frac{1}{N} \sum_{i,j} (P_{i,j} - \overline{P}).(P_{i,j} - \overline{P})^T \tag{4}$$

where N is the number of pixel in the image and $\overline{P}$ the mean vector of $P_{i,j}$. The eigenvectors of the matrix C give the base where the decorrelation is maximum. The principal component analysis was evaluated to find some difference between crops and weeds. It was computed only on the vegetation pixel to improve the discrimination. As a result some slight variations were found but these variations can not be detected by a thresholding. We decided to test another classifier with non-linear capabilities.

4.3 Crops and weeds separation using a neural network

Considering the variability of this kind of natural images, a learning classifier can be an interesting solution [14]. In this case, few pixels are classified by the operator and the system learns the principal characteristics of this train set. For first trials, a very simple neural network was developed. The input vector is the value of the pixel on the four wavelengths. The input layer was composed of 8 cells with a linear activation function. The internal layer had the same number of neurons but with a sigmoid function which allowed a non-linear classification of data. Then, the output layer was composed of 2 neurons for weed and crop (W and C) with also a sigmoid function. The following learning rules were used. The value of 0.1 and 0.9 were prefered than respectively 0 and 1 for a better learn.

Table 2: Learning rule

	Neuron W	Neuron C
Crop	0.1	0.9
Weed	0.9	0.1
Soil	0.1	0.1

With these values a better convergence is obtained. So, the learning phase is faster and more accurate.

Two training sets were tested, both have ten pixels of crops and ten pixels of weeds, but only one set included ten pixels of soil. Only the pixels of vegetation were classified with the network. The results were slightly better when some soil pixels were considered for learning. In this case, the edge pixels were better classified. The figure 4-a shows the infra-red band of the source image. The figure 4-b and 4-c show the result of the two neurons. A simple threshold (equal to 0.5) was applied to obtain theses images. The network is then able to distinguish the two classes even if there are close. For example, on the top right corner (fig 4-a) a field bindweed[2] leaf is covered by an onion leaf. After classification, both plants are well classified.

5 CONCLUSION AND ENHANCEMENT

A specific algorithm was developed in order to discriminate weed directly from an aerial photography. First results showed that weed localization was possible using spatial information given after frequency analysis. The results depended on crops and vegetation stages. Nevertheless, this method appeared to be unefficient when seedlines were no more visible. Moreover, weeds located in crop rows were generally detected as crops.

In order to improve these previous results, species discrimination was tested through

[2] *Convolvus arvensis L.*

spectral information. A specific CCD camera was developed using four optical filters. With the assumption that a correlation can be suggested between spectrometric information and vegetation, various classification tools were tested. Principal component analysis did not allow a classification. This was probably due to a non-linear combination of data (color and specie). The neural network gave better results due to its non-linear function of activation.

At present, the CCD camera is destinated to be embedded in the drone. So, such an equipment will allow to acquire spectral information at a field scale and also combination with spatial information. Other kind of information as image texture, shape analysis would be considered. The combination of all theses information will be achieved using merging tools as fuzzy logic.

6 ACKNOWLEDGMENT

This project is financed with the help of ITCF (French Institute for Cereal and Forage) and the council of Burgundy. Authors also thank INRA (Dijon research center) for field disposal.

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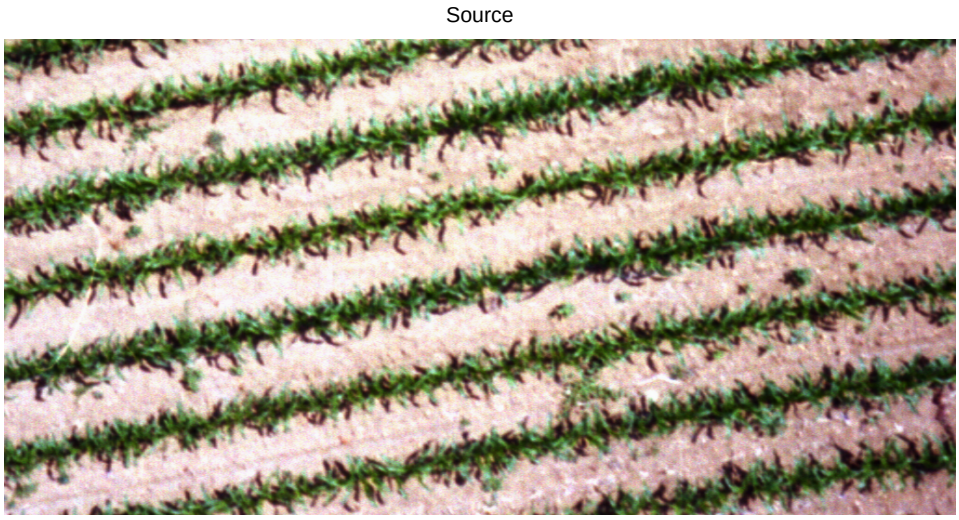
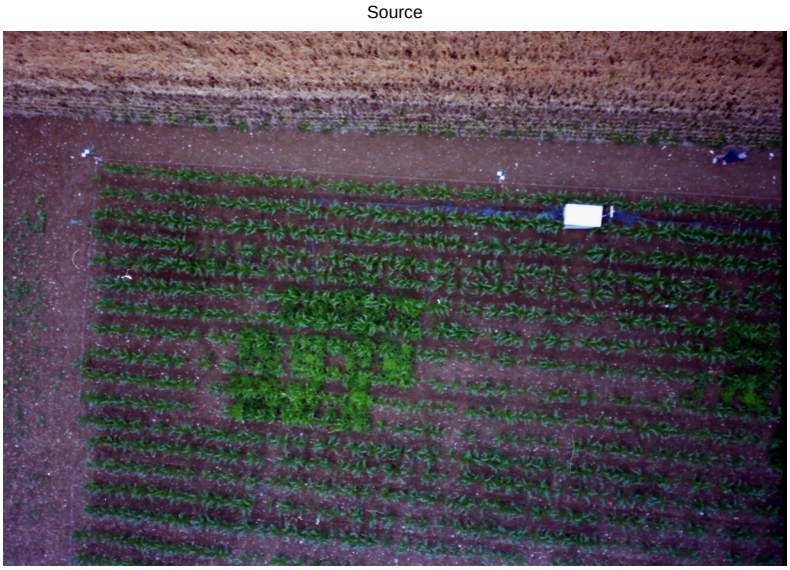


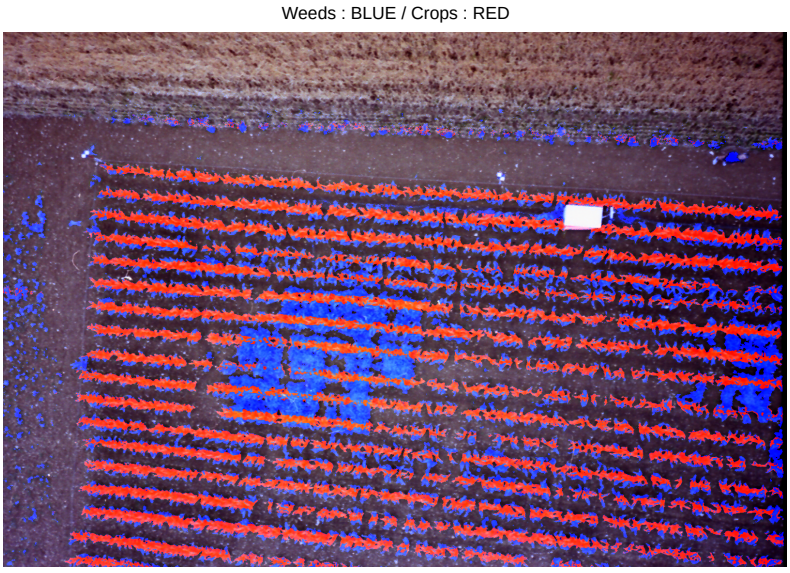
(a) Source image

(b) Result image

Figure 2: Source image

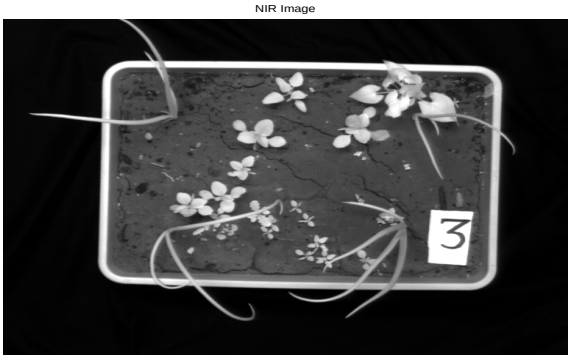


(a) Source Image



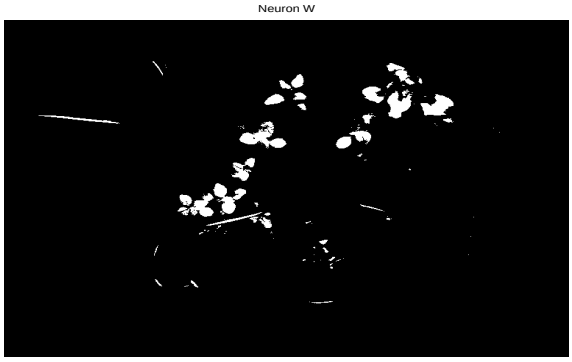
(b) Result image

Figure 3: High altitude image



(a) Source image (IR chanel)

(b) C neuron output (Crops)



(c) W neuron output (Weeds)

Figure 4: Crop/Weed classification using a neural network