Weed Detection Using Textural Image Analysis

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Abstract

The objective of the work described here was to detect broad-leaved weeds in grassland. We used textural image analysis to detect weeds in grass. In the textural analysis, images were divided in square tiles, which were subjected to a 2-D FFT. The power of the resulting spectrum was found to be a measure of the presence of coarse elements (weeds). Application of a threshold made it possible to classify tiles as containing only grass or as containing a weed. A weed was assumed to be detected when a sufficient number of adjacent tiles were classified as containing weed material. The algorithm has a success rate of 94%.

Key words: Robot system, Machine Vision, Texture Analysis, Fast Fourier Transform, Weed Detection

1 Introduction

The goal of precision farming is to maximize profitability and minimize environmental damage by managing each part of an agricultural field at just the right time, using just the right amount of fertilizer and/or pesticide. This is at odds with the trend to minimize the cost of labour by using ever larger machines. It has been suggested that in the future small, autonomous machines ("robots") will make it possible to precision-farm large areas without incurring large labour costs.

Weed control is often mentioned as a likely area of application of agricultural robots. One of the earliest references is the robot of (Tillett et al., 1998) in cauliflower. In some recent literature, the focus was on weeds in sugarbeet (Åstrand and Baerveldt, 2003) and on volunteer potato in maize (Van Evert et al., 2006)(Fig. 1). While these authors address weed control in arable fields, robotic weed control may have application in grassland as well. A prime example is broad-leaved dock (*Rumex obtusifolius* L.). In organic farming, this troublesome grassland weed is best controlled by manual removal of the plants, possibly combined with grassland renewal and rotation with a grain crop (Van Middelkoop et al., 2005). A motorized tool exists to shred dock plants (WUZI; described by Van Middelkoop et al., 2005) but operating this tool is physically demanding. A robot that detects dock plants and destroys them using this tool would be a logical development. (Ahmad and Kondo, 1997) used uniformity analysis to detect the presence of broad-leaved weeds in lawns. We implemented the algorithm of Ahmad and Kondo and found that it performed reasonably well for docks in grass, but at several seconds per image it was too slow to be usable for real-time detection. (Gebhardt and Kühbauch, 2006) also describe a vision system to detect dock plants; unfortunately, it seems that their system is at present too slow for use in real-time. Thus, the objective of the work described here was to develop a fast vision-based algorithm for detection of broad-leaved weeds in grassland. The overall aim of our work is to develop a robot for the detection and control of broad-leaved weeds in grassland.

Fig. 1. This experimental robot was used in field tests of the detection method for broad-leaved dock.

2 Materials and methods

2.1 Images

We obtained 161 colour images of grass and of grass with dock plants. The images were taken on 1 May 2006 on a farm near Wageningen, The Netherlands; and on 22 August 2006 on a farm near Wilnis, The Netherlands. On both farms several fields were used. The images were taken with an ordinary digital camera (Cybershot DSC-60, Sony), which was hand-held approximately 1.6 m above the ground while aiming straight down. The size of the images is 2304 × 1728 pixels.

For each image, the presence or absence of a dock plant was determined by a weed scientist. The location of each dock plant was determined by clicking on the image and recording the pixel coordinates of the approximate location of the plant’s tap root. If more than one dock plant was visible in an image, the location of the largest plant was recorded.

2.2 Fourier analysis to distinguish between dock plants and grass

The texture of an image of grass is very different from the texture of an image of a dock plant. The leaves of grass have a width of less than a cm. The leaves of broad-leaved dock have a width of at least several cm and can be much larger than that. At the edge of each (grass or dock) leaf, there is a discontinuity in colour and brightness. Thus, an image with only grass will have many more discontinuities in colour and brightness than an image with grass and docks.

Fourier analysis is a method that decomposes a function in terms of a sum of sinusoidal basis functions (vs. their frequencies). We expect the Fourier analysis of an image of grass to show a larger contribution of high-frequency basis functions to the total signal than would be the case for an image of dock plants. Inspection of the relative contribution of the various basis functions to the original signal will then indicate the presence or absence of docks.

For two-dimensional digital images the 2D discrete Fourier Transform is given by (Rosenfeld and Kak, 1982):

$$F(u,v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) \exp\left[-j2\pi \left(\frac{mu}{M} + \frac{nv}{N} \right) \right] \quad (1)$$

Where *m* and *n* are the pixel coordinates of the $M \times N$ digital image. The real and the imaginary parts of,

$\exp\left[-j2\pi\left(\frac{mu}{M}+\frac{nv}{N}\right)\right]$, can be written as: $\cos 2\pi\left(\frac{mu}{M}+\frac{nv}{N}\right)$, and $\sin 2\pi\left(\frac{mu}{M}+\frac{nv}{N}\right)$.

This way $F(u,v)$, is a measure of the contribution of these sinusoidal basis functions to the image, and as such a measure of the texture in the image. Large colour variations over small parts of the image have higher coefficients for high frequency sinusoidal functions, where small colour variations over larger parts in the image have higher coefficients for low frequency functions. Note that the Fourier transform is a transformation; it is always possible to restore the original signal by using the inverse FFT. In that case the – in the exponent of equation 1 is replaced by +.

Since we need to determine the location of the dock plants, we applied the Fourier Transform on small square sections ("tiles") of the image, to get a probability value for the presence of a dock plant in each tile. Several considerations have to be taken into account when determine the size of the tiles. We need to detect the dock plants in real time, therefore the fast FFT is used (Brenner and Rader, 1976). A precondition of this algorithm is that the height and width of the tiles, *M* and *N* are equal and a power of 2. For proper detection M and N needs to be larger than the size of the objects which needs to be detected (grass in our case). When M and N are very large the determination of the position of docks is too coarse. Furthermore when the total image is too large, the number of tiles to be analyzed is too large to perform in real time.

Fig 2. Typical image of grass (left) and dock (right).

In order to find an optimal set of parameters, we analyzed tiles with only grass, and tiles covered with dock leaves and performed Fourier analysis with different settings for M and N. We also experimented with decreasing the resolution of the image before subjecting it to Fourier analysis.

First, five images were selected with only grass, and from the images with one or more dock plants, ten image parts with docks were extracted (Fig. 2) The images were reduced with reduction factor *r* =[1,2,4 and 8]. From the reduced images tiles are taken with size $M = N$ = [32, 64, 128, 256, 512]/r. The RGB colour images needs to be transferred to monochrome before applying the FFT. A number of methods can be used for this conversion. Summing the red (R), green (G) and Blue (B) values and dividing the result by three gives the intensity of the image. Using only the (G) values is another possibility. The so called extensive green image ($2G - R - B$) represents the largest contrast between the green grass or weed and the background. After the monochrome conversion the mean grey value is subtracted, which minimizes the first Fourier coefficient, which corresponds with a frequency of zero (DC level). From each grass and each dock tile the average magnitude of all FFT's is calculated. The difference between the mean grass spectrum and the mean dock spectrum for each *M* is investigated. Based on this results so called window functions which maximizes the separation between the grass and dock spectra, can be defined. Multiplying the window with *F* gives a probability whether a certain tile contains dock leaves.

Based on the results of the previous experiment several window functions were defined. The total power of the spectrum of a tile was found to be the best measure of the presence of dock leaves.

The algorithm for the detection of broad-leaved dock in grass consists of the following steps.

1. Decrease the resolution of the original image to the desired size.
2. Convert the colour image to monochrome.
3. Perform 2-D Fourier analysis and calculate the power in the window on each tile.
4. Form a binary image by thresholding the image resulting from the previous step.
5. Erase the blobs in the binary image that are smaller than a given minimum size.
6. Connect blobs that are close together through a dilation followed by an erosion.
7. Blobs larger than a given minimum size indicate the presence of a dock plant.

2.3 Software

The software was written in Delphi (Borland Inc., Scotts Valley, CA, USA) and C++, using the VXL image processing library (VXL, 2006) and the FFTW Fourier transform library (FFTW, 2006).

3 Results and Discussion

3.1 Image Processing

Fig. 3 shows a three dimensional image of the mean Fourier magnitude (power) of a large number of grass and dock images for r = 4 and M = 8. From this image we learn that the total power for the grass tiles is larger than for docks. The images for other r and M values have more or less the same form, but have different slope and peak values. For reasons of speed the input images needs to be small, for precise location of the docks, the size of the tiles (M) might not be too big. We tested all possible combinations; r = 4 and M = 8 gave good results, while the speed and precision constraints are achieved.

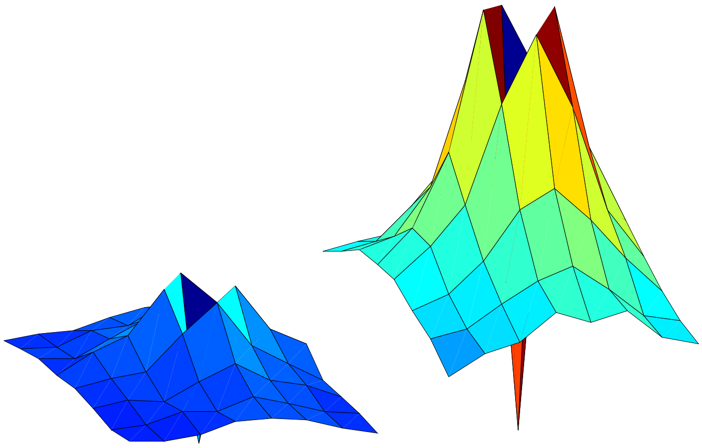

Fig. 3 Three dimensional representation of the mean power spectrum of dock tiles (left) and grass tiles (right), for r = 4 and M = 8.

3.2 Laboratory test

All 161 images were processed with the dock detection algorithm. Fig. 4 shows some typical results. Even small dock plants as in the second image can be detected. The position of the root is estimated by calculating the centre of mass of the dock. In the third image the root is not properly detected, but taking the mass of all blobs in stead of the mass of the largest blob will improve the results. The overall success rate for dock detection was 93% (Table 1). The number of false negatives was equal to the number of false positives. Several of the false positives were caused by shading and by trampled grass. The false negatives were caused primarily by docks that had recently been grazed, so that only a few, small leaves were present.

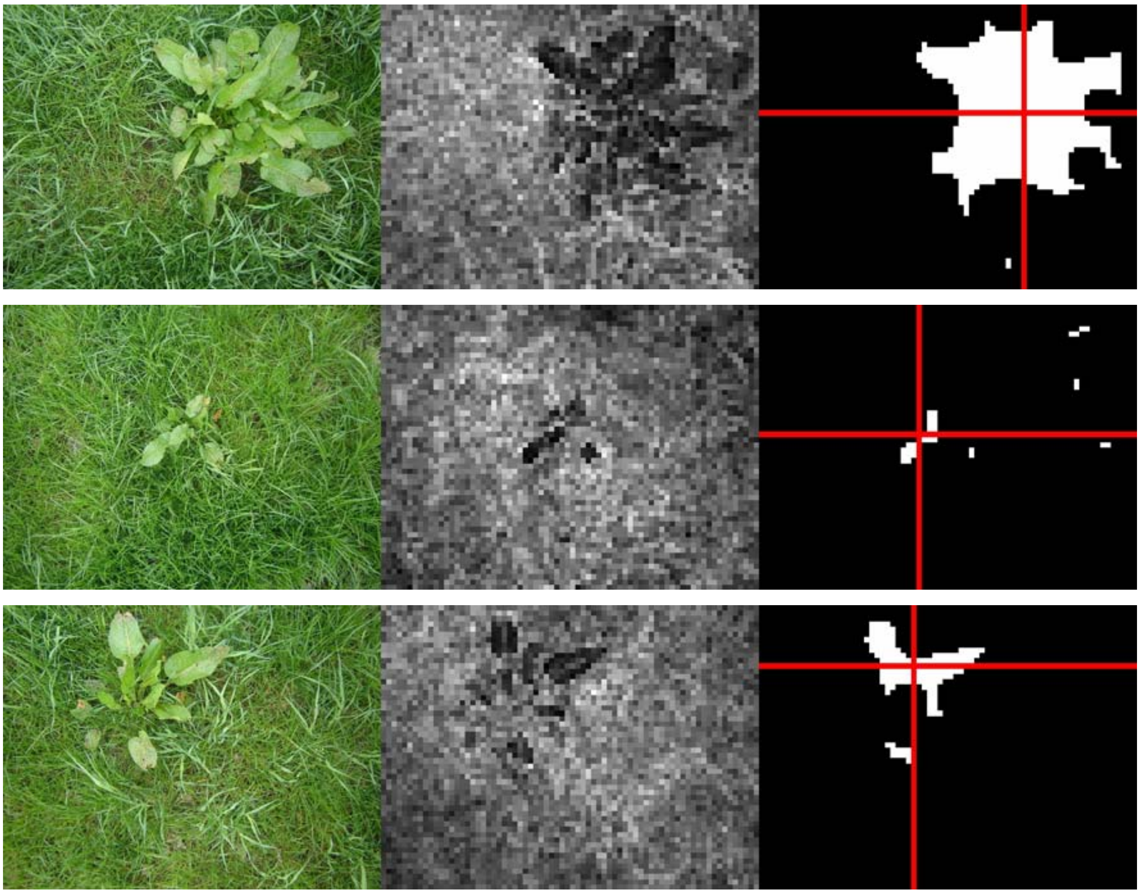

Fig. 4 Typical results of dock detection, left the RGB image, in the middle the total FFT power of tiles (M=8). Right the detected plant in white, and the detected root (red cross lines).

Table 1. Results of the dock detection algorithm.

	Weed (78 images)	No weed (83 images)
Weed found	73	5
No weed found	5	78
% correct	**93**	**94**

3.3 Speed of execution of the algorithm

The algorithm described executes at a rate of 22 frames per second on an ordinary laptop computer with a 1.73 GHz Pentium Mobile processor. It is thus fast enough for real-time application.

3.4 Field test

The real-time usefulness of our detection method was demonstrated at the June 2006 Field Robot Event in Hohenheim, Germany (www.fieldrobot.com). We equipped our small, experimental robot “Sietse” (Fig. 1) with a webcam and an early version of the dock detection algorithm. In front of an audience of about one hundred spectators, the robot was able to detect broad-leaved weeds on a lawn.

3 Discussion and conclusion

From a theoretical point of view, wavelets are a more elegant method than Fourier analysis. Wavelet might also be easier to parameterize for different weeds and/or backgrounds. However, there is no reason to believe that for our specific objective, wavelet analysis would be faster or detect more reliably than Fourier analysis does.

Discussion with dairy farmers in The Netherlands has indicated that a success rate of 93% is more than sufficient for practical use. This is because a robot can be used several times per year and will eventually control all weeds. Also, the damage done to the grass by the robot when it actuates the dock control where there is no dock plant, will be no worse than the damage caused by the hoofs of a playful cow.

We based our robot on an electric toy truck (Fig. 1). This robot was already successfully used for detection of volunteer potato plants in cornfields. Technical details can be found in van Evert et al, (2006). For detection of docks, the camera was moved to the front of the robot and to emphasize that mechanical control of docks is possible, a drill fashioned from a kitchen mixer was attached to the back.

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