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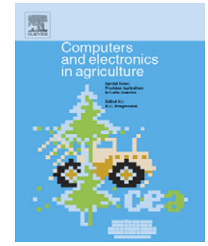

A new vision-based approach to differential spraying in precision agriculture

Alberto Tellaeche[a], *Xavier P. BurgosArtizzu*[b], *Gonzalo Pajares*[c,*], *Angela Ribeiro*[b], *César Fernández-Quintanilla*[d]

[a] *Dpto. Informática y Automática, Escuela Técnica Superior de Informática, UNED, Spain*
[b] *Instituto de Automática Industrial, CSIC, Arganda del Rey, Madrid, Spain*
[c] *Dpto. Ingeniería del Software e Inteligencia Artificial, Facultad Informática, Universidad Complutense, 28040 Madrid, Spain*
[d] *Centro de Ciencias Medioambientales, CSIC, Madrid, Spain*

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ABSTRACT

One of the objectives of precision agriculture is to minimize the volume of herbicides by using site-specific weed management systems. To reach this goal, two major factors need to be considered: (1) the similarity of spectral signatures, shapes, and textures between weeds and crops and (2) irregular distribution of weeds within the crop. This paper outlines an automatic computer vision method for detecting *Avena sterilis*, a noxious weed growing in cereal crops, and differential spraying to control the weed. The proposed method determines the quantity and distribution of weeds in the crop fields and applies a decision-making strategy for selective spraying, which forms the main focus of the paper. The method consists of two stages: image segmentation and decision-making. The image segmentation process extracts cells from the image as the low-level units. The quantity and distribution of weeds in the cell are mapped as area and structural based attributes, respectively. From these attributes, a multicriteria decision-making approach under a fuzzy context allows us to decide whether any given cell needs to be sprayed. The method was compared with other existing strategies.

1. Introduction

Nowadays, there is a clear preference to reducing the use of chemicals in agriculture. Numerous technologies have been developed to make agricultural products safer and to lower their adverse impacts on the environment, and precision agriculture is a valuable component of the framework to achieve this goal (Kropff et al., 1997; Zhang et al., 2002; Stafford, 2006).

Within that general framework, weeds can be managed site-specifically using available geospatial and information technologies (Gerhards and Christensen, 2006). Initial efforts to detect weed seedlings by machine vision focused on geometrical measurements such as shape factor, aspect ratio, and length/area (Pérez et al., 2000). Later, colour images were successfully used to detect weeds and other types of pests (Søgaard and Olsen, 2003). Yang et al. (2003) estimated weed coverage and weed patchiness based on digital images, using a fuzzy algorithm for planning site-specific application of herbicides. Recently, Gerhards and Oebel (2006) used real-time differential images (NIR-VIS) obtained with a set of three digital bispectral cameras to detect small weed seedlings in different crops. Other approaches have used colour indices to distinguish plant material from the

* *Corresponding author*. Tel.: +34 1 3 94 75 46; fax: +34 1 3 94 75 47.
E-mail address: pajares@fdi.ucm.es (G. Pajares).
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background (Thorp and Tian, 2004; Ribeiro et al., 2005). Bacher (2001) estimated weed density in a field of spring barley by image binarization and morphology followed by the identification of crop rows using information on distances between rows within the crop to decide on spraying. This process serves to make weed plants appear isolated from the crop.

Avena sterilis L. ("winter wild oat") is one of the most widely distributed and abundant weeds of cereals in Spain and other regions with Mediterranean climate, causing substantial losses in these crops (Barroso et al., 2004a; Radics et al., 2004). Although some *A. sterilis* plants may be found growing singly or in small patches, the majority of them are aggregated in relatively large patches (Ruiz et al., 2006), and those in early spring, after broad-leaved weeds have been controlled by early postemergence treatments, are practically pure stands (Fernandez-Quintanilla, personal observation). Due to these two features, it is relatively easy for an experienced farmer or a technical consultant to detect patches of *A. sterilis* visually in the early stages of crop growth. In fields of cereals (barley or wheat), the cereal plants grow along the furrows: the plants growing between furrows can only be weeds. But weeds may also grow mixed with the cereal. We sought to detect weeds by differences in appearances: isolated plants, small or large patches, or mixed with the crop. Three main problems arise during detection, namely (1) irregular shapes and different sizes of the patches, (2) spectral signature and texture similar to those of the cereal plants, and (3) irregular distribution of the weeds in the field. This means that methods using only absolute sizes, shapes, textures, or spectral signatures are not applicable to our experiments (Aitkenhead et al., 2003; Onyango and Marchant, 2003; Granitto et al., 2005). The total proportion of weeds in the field is important because it indicates the extent of competition between weeds and the crop (Tian et al., 1999; Ribeiro et al., 2005), but distribution has not been considered in vision-based systems to our knowledge. Barroso et al. (2004b) studied the economic benefits of using site-specific weed management systems for large patches and numerous small patches of weeds. The damage from large patches to the crops is clear; they lower the yield substantially in the current year. When numerous small weeds patches appear during the cereal's growth phase, they tend to compete with the crop aggressively. Moreover, because weeds are more prolific in producing seeds and the seeds persist longer in soil, a failure to control weeds creates serious problems not only in the current year but also for the following 2–3 years (see Appendix A for details of weed density).

Hence, we propose a new method with two objectives: (1) to determine the quantity and distribution of weeds present in the crop and (2) to decide, based on that knowledge, whether to undertake selective spraying to control the weeds. The method consists of an image segmentation process and a decision-making approach. The segmentation process extracts cells from the image as the low-level units. The quantity and distribution of weeds in the cell are mapped as area and structural based attributes, respectively. From these attributes, a multicriteria decision-making approach under a fuzzy context allows us to decide whether any given cell needs to be sprayed.

2. Materials and methods

2.1. Images

The images used for this study were those of a 1.7-ha experimental field of barley on La Poveda Research Station, Arganda del Rey, Madrid. The most common weed in the field was *A. sterilis*, with densities ranging from 10 to 400 plants m^{-2}. Although other weed species (*Papaver rhoeas*, *Veronica hedaerefolia*, *Lamium amplexicaule*) were also present in the field, at the time of image acquisition most of them had been killed by an early treatment with bromoxinil and mecocrop. Images were taken on two dates in April 2003, when the plants were at the early tillering stage (3–5 leaves). Row spacing was 0.36 m. Although the standard row width in the area is 0.17 m, much wider rows are common in other semi-arid areas of North America and Australia. Wider rows simplify weed detection. Digital images were captured with a Sony DCR PC110E camera. The area of each image to be processed was approximately 2.1 m × 19 m and the resolution was 1152 × 864 pixels.

The images were captured under the perspective projection, which means that areas of identical size in the field appear under different sizes in the image, depending on their distance from the camera. Hence, we must compute those attributes that are independent of the perspective projection. This is achieved by establishing relative measurements between crops and weeds instead of using absolute measurements, as described in the next sections.

2.2. The proposed method

The proposed method involves two sub-processes: image segmentation and decision-making. The image segmentation process divides the image into cells and extracts those features and attributes from each cell that make it possible to distinguish between weeds and the crop; based on that information, the decision-making process determines whether a cell is to be sprayed. Such decision-making requires a set of samples for the cells of which the decision to spray – or not – was made in the past. Hence, we must build a knowledge base (KB) containing sets of such samples, a stage called the *off-line* process. The decision-making is carried out by computing similarity measures between the samples stored in the KB and the cell being processed; we call this process of decision-making the *on-line* process. The image segmentation is identical for both processes (Fig. 1).

2.3. Image segmentation: weed detection

The steps involved in the proposed image segmentation process are acquiring and binarizing images, detecting crop rows, partition the image into a grid of cells, and extracting attributes from the cells.

2.3.1. Acquiring and binarizing images

As mentioned before, the images were acquired under the perspective projection, which implies that the crop rows tend to converge at the vanishing point out of the field of view. The goal of this first step was to convert the input red–green–blue