



## Review

# An instance-based learning approach for thresholding in crop images under different outdoor conditions



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## ABSTRACT

We propose an instance-based learning approach for segmentation of crop images. The method proposed is able to automatically discriminate the green textures (crop and weeds) from the rest of the ground under different outdoor conditions, namely light conditions and stages of crop growth. For this purpose a set of images that reflects all the possible conditions to be faced is required and each images should have assigned its optimum threshold by an expert.

The instance-based method proposed is a k-Nearest Neighbors (k-NN) algorithm. Our k-NN is borrowed from the field of symbolic data analysis that is a paradigm for data representation where instances can be described by variables that account for observed variability, such as, in our case histogram variables.

Our method is compared with the well-known automatic thresholding methods, such as the mean value and Otsu's. The method proposed provides good results for all the different conditions analyzed, including burned and saturated images.

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## 1. Introduction

### 1.1. Problem statement

Precision agriculture aims to optimize the performance of farms using both technology and the farming knowledge to accurately execute farm-management decisions. Information and communications technologies, ICT's, have made available to the agricultural sector a set of new tools that enable this optimization, among which are artificial vision systems. Precision agriculture also uses decision support systems, which may be based on artificial intelligent methods.

The setting of the present work is an artificial vision system onboard a robotic vehicle, specifically an autonomous tractor, that in real-time has to identify the weeds in a crop field for both its chemical and physical –mechanical and thermal– management. Our aim in this setting is the task to automatically discriminate the green textures (crop and weeds) from the rest of the ground.

Even in such a restricted setting, where images are always from the same area and type of crop, the task is challenging due to the changing lighting conditions in the agricultural outdoor environments and the growth states of plants (crops and weeds). This paper addresses the automatic image segmentation of textures in images maize fields captured under different conditions (illumination, movement in the tractor, uneven terrain) by means of an intelligent method.

We propose an instance-based learning method capable of providing a greenness threshold for different types of environmental situations that we can find working for a given crop field, maize in our case. For that purpose, we adapt a machine learning algorithm, such as the k-Nearest Neighbor (k-NN) algorithm to the symbolic data analysis paradigm (Bock and Diday, 2000; Billard and Diday, 2006; Brito, 2014), where data units are called symbolic because they can represent the observed variability. In symbolic data analysis, interval or histogram variables are able to summarize and represent a set of observed values. In our case, we will use histogram data which arises in a natural way in computer vision, where histograms are used to summarize the properties of images. Histograms will be the input of the k-NN algorithm that will set the threshold. Thresholding is an important issue, still open, in agricultural images requiring an important effort, where this paper is focused making the main contribution.

Our method takes advantage to correctly thresholded images to provide a satisfactory threshold in real time, separating the green parts from the ground and satisfying the problems caused by variations both lighting and the condition of the plants. Before explaining our approach in detail we will review the segmentation in agronomical images existing in the literature and based on thresholding.

### 1.2. Revision of image segmentation methods and thresholding

A typical setting would be a robot-driven vehicle equipped with computer vision sensors that acts over a site-specific area of a larger farm (Davis et al., 1998). This vehicle automatically applies pesticide only when weeds appear reducing its use. This typical setting raises important issues in image segmentation, because it is required to automatically discriminate between soil and vegetation and, once vegetation is identified, between weed and crop lines (Onyango and Marchant, 2003; Tellaache et al. 2008a,b; Burgos-Artizzu et al. 2009). There is no general solution to this problem, because automatic segmentation is difficult when the conditions of the image widely vary due to factors such as illumination, for example, a day with a high density of clouds that block the sun or tractor moving continuously faces the sun or back (Tian

and Slaughter, 1998). For this reason (Persson and Åstrand, 2008; Guijarro et al., 2011; Joycy and Prabavathy, 2012; Guijarro et al. 2015) offer different solutions taking account the shape or texture in order to avoid the impact of illumination variations.

An automatic and efficient segmentation of vegetation (or greenness) of agricultural images is the first step for many applications such as weed detection for site-specific treatment (Onyango and Marchant, 2003; Sainz-Costa et al., 2011; Tellaache et al., 2008a,b; Burgos-Artizzu et al., 2009; Guerrero et al., 2012; Montalvo et al., 2013; Romeo et al., 2013a,b), even in images containing high weed density (Montalvo et al., 2012). After the image segmentation process, it is common to proceed with the identification of crop rows and weeds are identified as the presence of greenness between the inter-crop row spaces (Guerrero et al., 2013; Romeo et al., 2013a,b). Failures in greenness detection also cause failures in the subsequent processes, such as crop-row identification or weed-crop discrimination, hence the importance of this first step. In this work we provide improved detection of greenness in order to avoid propagating errors in later stages.

There are several strategies proposed for segmenting crop and ground in images, specifically oriented towards green segmentation. In order to obtain an enhanced gray image, where the green parts are outstanding, in literature we found the visible spectral-index, including the excess green index (ExG, Woebbecke et al., 1995; Ribeiro et al., 2005), the excess red index (ExR, Meyer et al., 1998), the color index of vegetation extraction (CIVE, Kataoka et al., 2003), and the excess green minus excess red index (ExGR, Neto, 2004). Also the vegetative index (VEG, Hague et al. 2006) which was designed to cope with the variability of natural daylight illumination. All these approaches need to fix a threshold for final segmentation.

Various techniques for image segmentation have been developed so far (Fu and Mui, 1981; Lim and Lee, 1990; Shareef et al., 1999). Among them, automatic threshold selection is the most popular technique applied in image segmentation field. Thresholding can be roughly categorized into six groups based on the information used: histogram shape-based methods, clustering-based methods, entropy based methods, object attribute-based methods, the spatial methods and local characteristics-based methods. A survey of thresholding methods and their applications exists in literature (Chi et al., 1996). There is no single method that can be considered good for all images, not all methods are equally good for a particular image (Pal and Pal, 1993). Image thresholding, which extracts the object from the background in an image, is one of the most common applications in image analysis (Young et al., 1998).

In our approach we obtain the threshold value through the study of histograms. In general, the threshold is located at the obvious and deep valley in the histogram of frequencies (Sonka et al., 1993). The valley can be detected directly (Prewitt and Mendelsohn, 1966; Weszka and Rosenfeld, 1978; Rosenfeld and Torre, 1983; Wu and Manmatha, 1988). More often, it is formulated as an optimization problem and the valley is identified indirectly. The minimum error thresholding (Chow and Kaneko, 1972; Nakagawa and Rosenfeld, 1979; Cho et al., 1989; Ye and Danielsson, 1988) establishes the threshold by minimizing the Bayes error since it assumes as Gaussian the intensity distribution of an object. By optimizing the average pixel classification error rate (Kittler and Illingworth, 1986) finds a method for the minimum error thresholding, using the exhaustive search or an iterative algorithm. This method assumes that an image is characterized by a mixture distribution where the object and background classes are normally distributed. The histogram of the image estimates the probability density function of the mixture distribution. Other work where the histogram is used to establish a threshold is Bazi et al. (2006) who proposes a novel parametric

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