Expert Systems with Applications 40 (2013) 75–82

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Automatic expert system for weeds/crops identification in images from maize fields

M. Montalvo [a,*], J.M. Guerrero [b], J. Romeo [b], L. Emmi [c], M. Guijarro [b], G. Pajares [b]

[a] Dpto. Arquitectura Computadores y Automática, Facultad Informática, Universidad Complutense, 28040 Madrid, Spain
[b] Dpto. Ingeniería del Software e Inteligencia Artificial, Facultad Informática, Universidad Complutense, 28040 Madrid, Spain
[c] Centre for Automation and Robotics, UPM-CSIC, Arganda del Rey, Madrid, Spain

ARTICLE INFO

Keywords:
Automatic expert system
Image segmentation
Image thresholding
Weeds/crop discrimination
Maize fields

ABSTRACT

Automation for the identification of plants, based on imaging sensors, in agricultural crops represents an important challenge. In maize fields, site-specific treatments, with chemical products or mechanical manipulations, can be applied for weeds elimination. This requires the identification of weeds and crop plants. Sometimes these plants appear impregnated by materials coming from the soil (particularly clays). This appears when the field is irrigated or after rain, particularly when the water falls with some force. This makes traditional approaches based on images greenness identification fail under such situations. Indeed, most pixels belonging to plants, but impregnated, are misidentified as soil pixels because they have lost their natural greenness. This loss of greenness also occurs after treatment when weeds have begun the process of death. To correctly identify all plants, independently of the loss of greenness, we design an automatic expert system based on image segmentation procedures. The performance of this method is verified favorably.

1. Introduction

1.1. Problem statement

Machine vision is an excellent sensor, which is being currently incorporated in autonomous tractors, for treatments over site-specific areas in a larger field (Davies, Casady, & Massey, 1998). Focusing on maize fields, one of the most important treatments is weeds killing, where plants (weeds and crops) must be identified as a previous step. Different methods and strategies for plant identification have been applied in different works (Burgos-Artizzu, Ribeiro, Tellaeche, Pajares, & Fernández-Quintanilla, 2009; Guerrero, Pajares, Montalvo, Romeo, & Guijarro, 2012; Guijarro et al., 2011; Montalvo et al., 2012; Onyango & Marchant, 2003; Tellaeche, Burgos-Artizzu, Pajares, & Ribeiro, 2008b; Tellaeche, Burgos-Artizzu, Pajares, Ribeiro, & Fernández-Quintanilla, 2008a). López-Granados (2011) makes a revision of methods where plant identification is a key step in the process. Most existing strategies address the problem of green identification under the assumption that plants display a high degree of greenness, but they do not consider the fact that plants may have lost their degree of greenness for different reasons.

Indeed, maize is an irrigated crop, which is also unprotected from the rainfall. When the layer of water is abundant or its fall on the ground is relatively strong, soil materials (particularly clays) impregnate the vegetative cover, particularly those parts close or near to the soil. In this case, the green spectral component of pixels belonging to the plants is masked by the dominant red spectral component coming from materials existing in the soil; Fig. 1 displays an image where this appears clearly in the middle central part of the image and also at the ends of the leaves in the maize that are oriented toward the soil. Fig. 2 displays similar occurrences at the bottom part (center and right). This makes methods based exclusively on the greenness identification, i.e. plant coverage based on the computation of vegetation indices, fail under such situations. Indeed, soil and masked plants are both identified as soil.

In Guerrero et al. (2012) we have already addressed this problem by applying a learning approach based on support vector machines. As all learning strategies, this method requires a training phase where samples are conveniently provided for estimating the required parameters (support vectors), and then the posterior decision phase is highly dependent of the samples supplied, i.e. from the images which have been used for training. Moreover, the learning phase requires a certain number of images previously selected.

We propose a new automatic method based on several sequential stages, where the linking of these stages and the image segmentation processes, applied at each stage, are based on the application of the human expert knowledge. This leads to the design of the proposed expert system, gaining an important advantage with regard to the one described in Guerrero et al. (2012) because no training is required and it can be directly applied to the unique image under processing becoming independent from

* Corresponding author. Tel.: +34 1 3 94 75 46; fax: +34 1 3 94 75 47.
E-mail address: mmontalvo@fdi.ucm.es (M. Montalvo).

0957-4174/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2012.07.034

Fig. 1. Original image where weeds in the middle central part appear masked.

Fig. 2. Original image where weeds in the bottom central and right part appear masked.

other images, which are to be selected. One of the processes involved into two different stages is image thresholding, based on the Otsu's method, which is self-adjustable, dealing well with images captured under different conditions such as sunny or cloudy days, affecting illumination variability, (Tian & Slaughter, 1998); they are typical situations in agricultural images coming from outdoor environments. The design of this automatic expert system makes the main contribution of this paper.

Additionally, because this system is designed to identify plants that have lost the greenness, it can be applied to evaluate the treatment effectiveness. Indeed, as mentioned before, some site-specific treatments are intended to kill weeds in maize crops, when weeds are in the dying process, before reaching dry completely; they also have lost their greenness, compared to their healthy state. The proposed expert system can be used for identifying such plants and hence the treatment effectiveness.

Fig. 3. Original image captured after the application of herbicide two days ago (weeds in the central inter crop rows are evolving to a dry stage). The field has also received direct rainfall.

Fig. 3 displays at its central inter-row crop, weeds evolving toward a dry stage after the chemical treatment with herbicide applied two days ago. This image has also received direct rainfall and some parts are impregnated with materials coming from the soil as before.

1.2. Revision of methods

Several strategies have been proposed for segmenting crop canopy images, specifically oriented towards green segmentation:

(1) Visible spectral-index based, including the excess green index (ExG, Ribeiro A., Barroso J., & M. C., 2005; Woebbecke, Meyer, von Bargen, & Mortensen, 1995), the excess red index (ExR, Meyer, Hindman, & Lakshmi, 1998), the color index of vegetation extraction (CIVE, Kataoka, Kaneko, Okamoto, & Hata, 2003), the excess green minus excess red index (ExGR, Neto, 2004) and the vegetative index (VEG) described in Hague, Tillet, and Wheeler (2006), which is designed to cope with the variability of natural daylight illumination. ExG, ExGR, CIVE and VEG have been applied under a combined form in Guijarro et al. (2011) gaining in performance with respect to their individual application. All these approaches need to fix a threshold for final segmentation, i.e. to discriminate between plants and other parts (soil, sky).

(2) Specific threshold-based approaches, including dynamic thresholding. Generally, these techniques assume a two-class problem where plants and soil are to be identified. Reid and Searcy (1987) estimate a decision function under the assumption that the classes follow Gaussian distributions. The Otsu's method (Otsu, 1979) is also applied considering a bi-class problem (Ling & Ruzhitsky, 1996; Shrestha, Steward, & Birrell, 2004). These algorithms are applied to gray images. Gebhardt, Schellberg, Lock, and Kaühbauch (2006) apply also thresholding for segmentation transforming the images from RGB to gray scale intensity. This algorithm was later improved using local homogeneity and morphological operations in Gebhardt and Kaühbauch (2007). Kirk, Andersen, Thomsen, and Jørgensen (2009) apply a combination of greenness and intensity derived from the red and green spectral bands and compute an automatic threshold for a two-class problem assuming two Gaussian probability density functions associated to soil and vegetation respectively; this procedure requires the previous estimation of an angle to rotate the hypothetical greenness axis. Meyer and Camargo-Neto (2008) have applied the automatic Otsu's thresholding method for binarizing ExG and the normalized difference index (NDI), where a comparison is established against the segmentation obtained from ExGR determining that in this last case, a value of zero suffices for the threshold, therefore the Otsu's method is not required. Guijarro et al. (2011) and Burgos-Artizzu, Ribeiro, Guijarro, and Pajares (2011) have applied the statistical mean value of the transformed image obtained with the vegetation indices instead of automatic thresholding such as Otsu. They justify its choice because Otsu's method gives a threshold value higher than the mean and produces infra-segmentation, i.e. some plants are not conveniently identified.

(3) Learning-based, Meyer, Camargo-Neto, Jones, and Hindman (2004) have applied unsupervised approaches, including fuzzy clustering, for segmenting regions of interest from

ExR and ExG. Tian and Slaughter (1998) proposed the environmentally adaptive segmentation algorithm (EASA) for detecting plants through a supervised learning process. Ruiz-Ruiz, Gómez-Gil, and Navas-Gracia (2009) applied the EASA under the HSI (hue-saturation-intensity) color space to deal with the illumination variability. Zheng, Zhang, and Wang (2009) and Zheng, Shi, and Zhang (2010) use a supervised mean-shift algorithm under the assumption that the segmentation of green vegetation from a background can be treated as a two-class segmentation problem; the class separability is validated through a neural network and the Fisher linear discriminant respectively, the color spaces used were RGB, LUV and HSI. Guerrero et al. (2012) apply Support vector machines as the learning strategy applied with identical purpose that the one proposed in this paper.

1.3. Motivational research of the proposed strategy

The above methods are intended for plant identification through their greenness, based on the accentuation of the green color (Meyer & Camargo-Neto, 2008), but their effectiveness drops when the green spectral component becomes less important in favor of the red one as occurs in our case. Based on the images we call *unmasked* plants to the ones where the green spectral component is dominant and *masked* plants to these that have lost greenness in favor of the red spectral component.

Based on the above and considering a gray image containing information about the greenness, we could view the problem as a three-clustering approach, where the goal is to identify three classes, from the histogram of the gray image, by computing two thresholds. Demirkaya, Asyali, and Sahoo (2008) have proposed an iterative method for this pourpose. The histogram is divided into three regions with two pseudo-random thresholds and both thresholds are dinamically adjusted based on the inter-class mean values until no more adjustements are required. The main drawback of this approach is that in this kind of images, the histogram does not display three well separated classes and this method provides two thresholds which are not valid for solving satisfactorily our problem, as we will see later.

Thus, the idea is to apply an automatic strategy for image segmentation similar to that a human expert would apply to a similar problematic situation where the images contain classes which identify masked and unmasked plants due to different facts. This reasoning or knowledge, based on several stages, is the kernel of the proposed expert system. Each stage is designed for a given purpose and specific image segmentation approaches are applied for achieving the goal at each stage.

1.4. Paper organization

This paper is organized as follows. In Section 2 we explain the design of the proposed automatic expert system with its stages and the corresponding image procedures associated. In Section 3 the performance of the proposed strategy is evaluated and finally in Section 4, the most relevant conclusions are extracted.

2. Expert system design

2.1. Reasoning for knowledge extraction

Based on a logical expert reasoning, the proposed expert system is designed according to the modular architecture displayed in Fig. 4. It contains three stages, which are sequentially linked to form the expert system as a whole. Each stage contains the required automatic image processing modules.

(1) *Stage* 1: Unmasked plants do not offer any difficulty in their distinction, they are to be extracted at this first stage.
(2) *Stage* 2: Masked plants and soil remain together, the next step consists in their separation, this is carried out by identifying those pixels, with a certain degree of greenness, which are associated to masked plants. The remainder ones are considered as belonging to the soil.
(3) *Stage* 3: Based on the assumption that pixels belonging to plants are grouped together forming patches and they rarely appear isolated, a procedure to remove small patches and isolated pixels is to be applied.

2.2. Automatic image processing modules

Following the three previous stages, at each stage a sequence of image processing techniques are applied for automatic purposes, they are outlined in the graphic displayed in Fig. 4, being grouped and linked conveniently.

(1) *Stage 1, combination of vegetation indices and application a first Otsu thresholding:* given an original input image in the RGB color space, we apply the following normalization scheme, which is usually applied in agronomic image segmentation (Gée, Bossu, Jones, & Truchetet, 2008),

$$r = \frac{R_n}{R_n + G_n + B_n}, \quad g = \frac{G_n}{R_n + G_n + B_n}, \quad b = \frac{B_n}{R_n + G_n + B_n} \tag{1}$$

where R, G and B are the normalized RGB coordinates ranging from 0 to 1 and are obtained as follows:

$$R_n = \frac{R}{R_{\max}}, \quad G_n = \frac{G}{G_{\max}}, \quad B_n = \frac{B}{B_{\max}} \tag{2}$$

where $R_{\max} = G_{\max} = B_{\max} = 255$ for our 24-bit color images.

Vegetation indices to be combined are computed as follows (see references above in Section 1.2),

$$\textit{Excess green}: \quad ExG = 2g - r - b \tag{3}$$

$$\begin{aligned}&\textit{Color index of vegetation extraction}\\ &CIVE = 0.441r - 0.811g + 0.385b + 18.78745\end{aligned} \tag{4}$$

$$\textit{Vegetative} \quad VEG = \frac{g}{r^a b^{1-a}}, \text{with } a \text{ set to } 0.667 \text{ as in Hague et al.} (2006) \tag{5}$$

Based on Guijarro et al. (2011) the above three indices are combined to obtain the resulting value COM as follows,

$$COM = w_{ExG} ExG + w_{CIVE} CIVE + w_{VEG} VEG \tag{6}$$

where w_{ExG}, w_{CIVE} and w_{VEG} are the weights for each index, representing their relative relevance in the combination. Guijarro et al. (2011) provide the four weight values participating in the combination, because in this work we have excluded the ExGR index, the weight values for the three indices are proportionally recalculated, i.e. $w_{G_{ExG}} = 0.36$, $w_{G_{CIVE}} = 0.47$ and $w_{G_{VEG}} = 0.17$.

The resulting combined image COM, is linearly mapped to range into [0,1], after which is thresholded by applying the Otsu's method, obtaining a binary image, where white pixels identify unmasked plants, i.e. plants not contaminated due to materials coming from the soil. The green spectral component of these pixels is dominant with respect the red and blue ones.

(2) *Stage 2, select black pixels and apply a second Otsu thresholding:* once pixels are identified as unmasked plants, the remainder pixels in COM are extracted; they are assumed to belong to soil and masked plants, these last are now our interest. The histogram obtained from pixels belonging to soil and masked plants, is thresholded by applying again Otsu. After this second thresholding two

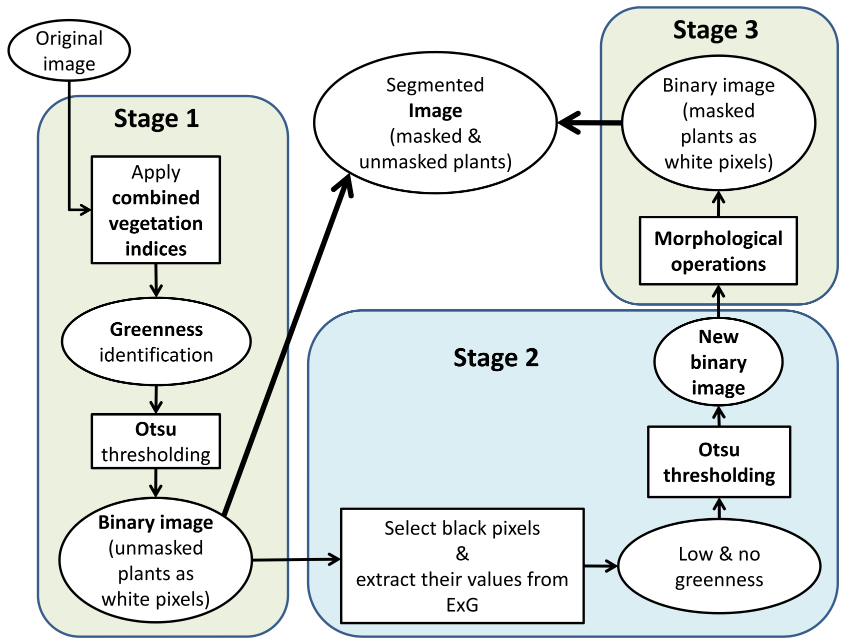


Fig. 4. Expert system architecture.

kinds of pixels are identified, those belonging exclusively to soil, debris and different materials and those belonging to masked plants. These last ones together with those identified previously as unmasked pixels form the final binary image or segmented image, according to the scheme in Fig. 4. When the method is applied for evaluating the effectiveness in the post-treatment process, all pixels identified after the second thresholding are those belonging to plants affected by the treatment, which have already started their dying process.

(3) *Stage 3, morphological operations and identification of masked and unmasked plants:* once the image has been binarized, the following three morphological operations are applied in the order expressed below:

(a) *Opening*: To remove small patches.
(b) *Majority*: A pixel is set to zero if five or more pixels in its 3*x*3 neighborhood are zeros.
(c) *Cleaning*: To remove isolated pixels resulting from the above two operations, white pixels surrounded by black pixels.

Once the full process is finished, according to the three stages, we obtain the final segmented image, where both unmasked and masked plants are identified. Therefore we have sufficient knowledge about their distribution in the field, which was the objective of this work.

3. Results

The images used for this study were acquired with a HPR817 digital camera device in four different days in April/May 2007. All acquisitions were spaced by five/six days. A set of them were obtained in a pre-treatment phase after the field was artificially watered and also when the field received different amounts of rainfall, Figs. 1 and 2, described in the introduction, are two representative images of this set. A second set of images was acquired in a post-treatment phase after applying a dose of herbicide; in this phase weeds have started its decease process, Fig. 3. Because of the difference of the days, different groups of images were acquired under different illumination conditions. This circumstance does not affect the performance of the proposed process because all image processing methods are independent of this circumstance; particularly the Otsu's method which is relative to each image histogram. Therefore it is not required any further study with regard to lighting conditions. This represents also another advantage with regard learning-based methods (Guijarro et al., 2011). This is an additional justification for the choice of proposed expert system.

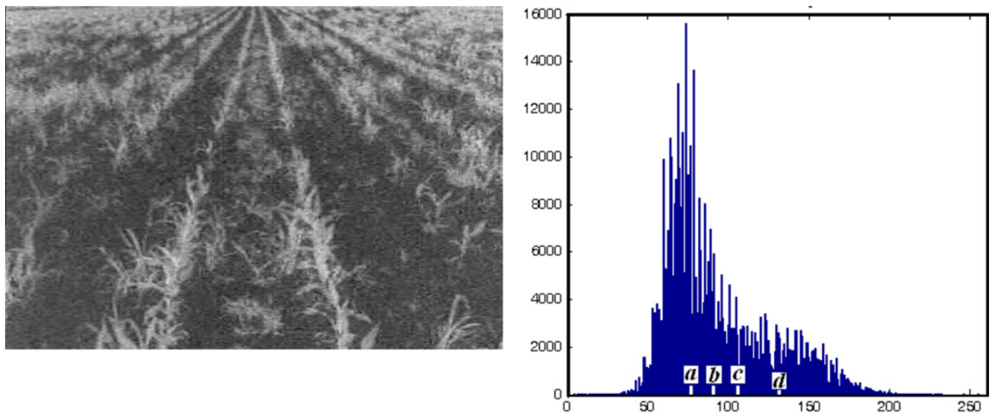
These digital images were captured under perspective projection containing only soil and plants, i.e. without panoramic sky. They were stored as 24-bit color images with resolutions of 800×600 pixels, and saved in RGB (Red, Green and Blue) color space in the JPG format. The expert system was implemented in Matlab R2009*a* (The Mathworks., 2012) and the images were processed with its Image Processing Toolbox.

A set of 230 images were captured and processed, from which 180 contain masked plants (SET-1) and 50 were captured for post-treatment evaluation (SET-2). Of course, all images contain unmasked plants.

The kernel of the proposed Automatic Expert System (AES) consists in the identification of masked and unmasked plants based on the histogram separation into three classes and two thresholds; hence we focus our analysis on the study of the two thresholds obtained in stages 1 and 2 through the Otsu's method to the COM image. The performance of AES is compared with the double thresholding approach proposed in Demirkaya et al. (2008) (DEM).

With respect images in SET-1, we base the analysis on the image displayed in Fig. 1, which is a representative element of this set. This is because all the images on this set behave similarly with respect to the AES. Fig. 5(*a*) displays the COM gray image obtained from image in Fig. 1; Fig. 5(*b*) displays its corresponding histogram ranging in [0,255], i.e. the original values in COM are multiplied by 255. In the basis of the histogram appear four identifiers, *a*, *b*, *c* and *d*, indicating four thresholds; *a* and *c* are the ones obtained by AES in stages 2 and 1, respectively; *b* and *d* are the ones obtained by DEM. Table 1 displays the four values for each approach (SET-1).

Fig. 6(*a*) displays the binary image obtained with threshold *c*, see histogram in Fig. 5(*b*) and Table 1 for SET-1. White pixels are identified as unmasked pixels at the first stage of the AES and



(a) (b)

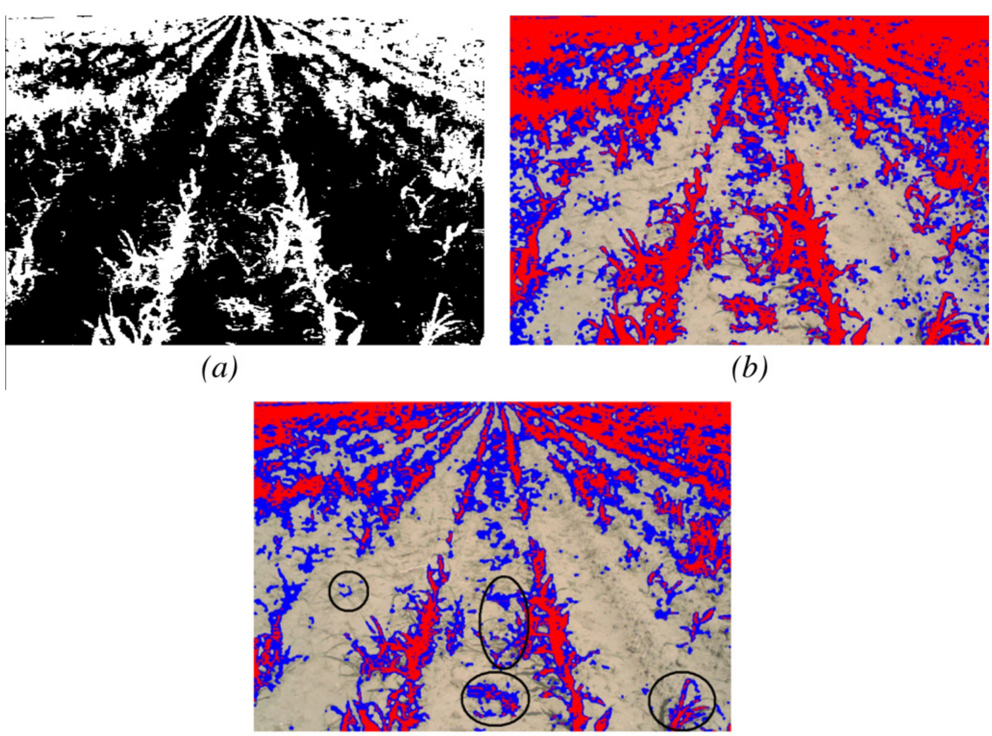
Fig. 5. (*a*) Image obtained from Fig. 1 by applying the COM vegetation index; (*b*) histogram for the image in (*a*) with four thresholds.

labeled in red, Fig. 6(*b*). Now, considering black pixels in the binary image, they are processed according to the image processing procedures defined in stages 2 and 3 in the AES; the threshold *a* is obtained at stage 2, which allows the identification of masked plants, labeled as blue in the image of Fig. 6(*b*). Fig. 6(*c*) displays the labeled pixels obtained by DEM with thresholds *d* (unmasked plants in red) and *b* (masked plants in blue).

Based on the labels displayed in Fig. 6(*b*) and (*c*) we can see that DEM identifies a smaller number of unmasked plants than AES; also AES identifies patches of masked plants that are not identified by DEM. Elliptical and circular lines in Fig. 6(*c*) identify relevant parts and patches verifying the above assertions. The best performance obtained by AES is explained considering the thresholds values from the histogram. Indeed, un-masked plants are extracted with thresholds *c* and *d*, Table 1; because *d* is greater than *c*, DEM identifies less number of unmasked plants, which are posteriorly labeled as masked plants. Also, because *b* is greater than *a* and both thresholds are related to masked plants, some of these last plants are not identified by DEM. From the histogram in Fig. 5(*b*) we

Table 1
Thresholds values obtained by AES and DEM for SET-1 and SET-2.

Thresholds	AES		DEM	
	a	*c*	*b*	*d*
SET-1	83.00	111.99	97.13	139.94
SET-2	87.01	117.98	104.09	146.93



(a) (b) (c)

Fig. 6. (*a*) Binary image obtained with threshold *c* in Table 1 from image in Fig. 1, containing masked and unmasked plants; (*b*) segmented image identifying unmasked (red) and masked (blue) plants obtained by AES; (*c*) segmented image identifying unmasked (red) and masked (blue) plants obtained by DEM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

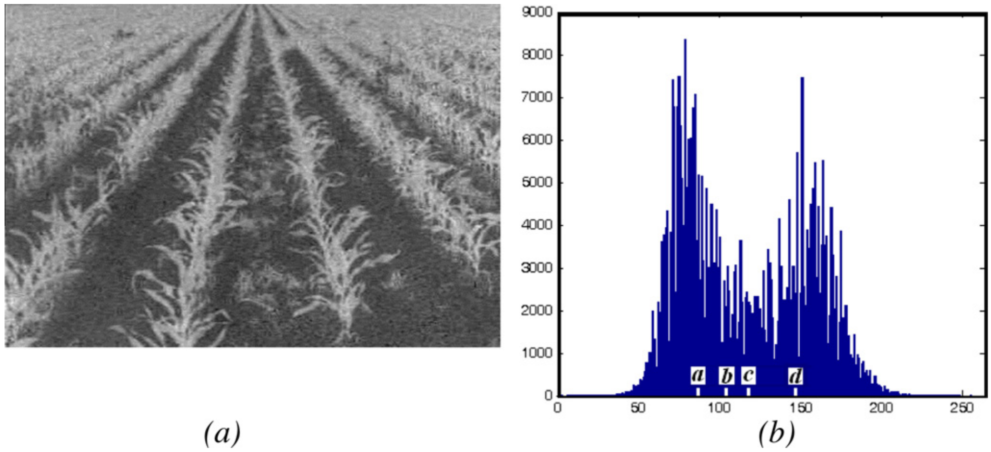


Fig. 7. (*a*) Image obtained from Fig. 3 by applying the COM vegetation index; (*b*) histogram for the image in (*a*) with four thresholds.

can see that there is not clear class separation, this means that clear thresholds cannot be assigned, but AES gets better thresholds than DEM judging by the results. At this point, it is worth mentioning that the use of the statistical mean value as threshold, applied in Guijarro et al. (2011) and Burgos-Artizzu et al. (2011) is not appropriate for our problem because the mean value is always less than the threshold obtained with Otsu and most masked plants and also soil plants are identified as unmasked.

Images in SET-2 contain weeds patches which have started the drying process as a result of a previous treatment. The image displayed in Fig. 3 is a representative element of this set, where we can see important weeds patches in the central inter-row crops, which appear affected by the treatment, but still there are small patches preserving a relative high degree of greenness, i.e. this means that they are unaffected by the treatment. Fig. 7(*a*) displays the resulting image obtained by the application of the COM vegetation index to the image in Fig. 3; Fig. 7(*b*) displays its corresponding histogram ranging in [0,255] with identifiers similar to those above for the thresholds. Table 1 displays the four values for each approach (SET-2).

Unlike the previous histogram, this is bimodal, where threshold *c* is the one used in AES for obtaining the binary image displayed in Fig. 8(*a*) and also to identify unmasked plants, which are labeled in red, Fig. 8(*b*). Threshold *d* is used in DEM for identifying also unmasked plants, Fig. 8(*c*). Many pixels belonging to unmasked plants are identified by AES but not by DEM, this can be explained because threshold *c* divides the histogram into two parts coinciding better than *d* with the two modal regions. Moreover, all weeds patches identified by DEM are affected by the treatment, elliptical lines in Fig. 8(*c*), when in fact they are not. Discussions above are

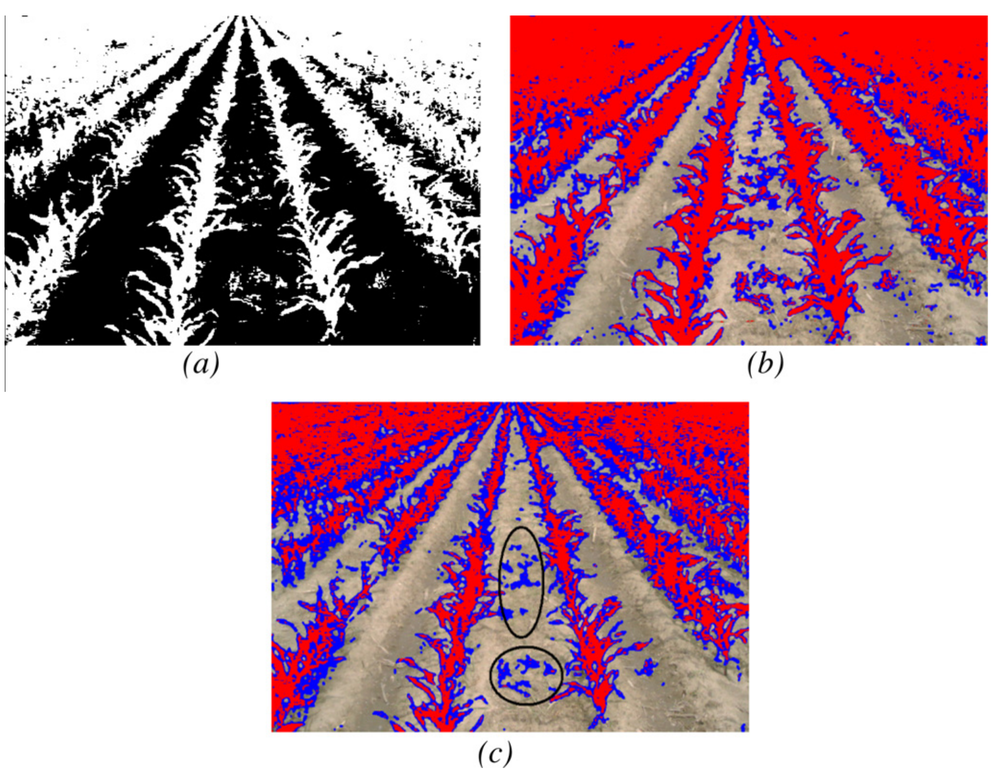


Fig. 8. (*a*) Binary image obtained with threshold *c* in Table 1 from image in Fig. 3, containing masked and unmasked plants; (*b*) segmented image identifying unmasked (red) and masked (blue) plants by AES; (*c*) segmented image identifying unmasked (red) and masked (blue) plants obtained by DEM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Averaged spectral RGB components for unmasked and masked plants obtained by AES, DEM and SVM.

Spectral RGB components	AES			DEM			SVM		
	R	*G*	*B*	*R*	*G*	*B*	*R*	*G*	*B*
Unmasked pixels	129.6	135.5	96.6	131.3	143.5	99.1	130.4	136.1	98.1
Masked pixels	146.1	142.9	111.1	147.8	144.7	109.3	147.0	143.6	112.0

Table 3
Percentage of successes obtained by AES, DEM and SVM for SET-1 and SET-2.

% Successes	AES	DEM	SVM
SET-1	93.4	86.2	93.1
SET-2	91.8	85.3	89.9

applicable to all images in SET-2, i.e. they all display similar behavior with respect to both AES and DEM approaches.

Considering all pixels labeled as unmasked and masked plants for SET-1 and SET-2, we have computed the averaged values for the three RGB spectral components from the original images. These values are obtained for AES and DEM and also for the Support Vector Machines (SVM) approach in Guerrero et al. (2012), obtaining the values displayed in Table 2.

Results in Table 2 display that the green spectral component for unmasked plants is always greater than the red one for the three approaches (AES, DEM and SVM). This means that greenness is clear on these plants, as expected. On the contrary the green spectral component is less than the red one in a small amount for masked plants. This verifies and supports the initial hypothesis.

In order to assess the validity of the proposed AES and to determine its performance as compared to DEM and SVM, we have randomly selected the 20% from each one of the two sets of images analyzed (SET-1 and SET-2). Each image was visually analyzed by an expert to identify weeds and crop plants. The human visual observation is carried out for each image guided by the segmented image through the approach proposed in this paper. The expert concentrates his major effort in identifying the most troubled plants, i.e. those we call masked plants or plants already affected by the treatment. Incorrect assignments are manually marked, corrected or removed, generating new-segmented images, which are considered as ground-truth. Table 3 displays the percentage of successes obtained for the three approaches.

From results in Table 3 we can see AES outperforms DEM and SVM. This behavior is explained on the fact that thresholds obtained by DEM behave as explained before. Moreover, SVM requires training and although in our experiments we obtain similar results than AES, this could vary, getting worse, depending on whether samples used for training becomes insufficient; AES is free of this circumstance, i.e. it is a desirable approach for solving the problem of identifying masked and unmasked plants in outdoor images coming from maize fields.

4. Conclusions

We propose a new automatic expert systems for image segmentation in maize fields. It is based on three consecutive stages where the main underlying idea is the successive application of automatic image processing tasks mapping the expert knowledge.

The expert system is able to identify plants (weeds and crops) when they have been contaminated with materials coming from the soil, due to artificial irrigation or natural rainfall. It is also valid for monitoring post-treatments; this is based on the assumption that weeds, after chemical or mechanical treatments, must initiate a progressive degradation expressed by the loss of the greenness displayed during the pre-treatment stage. The damage in the crop, when it occurs, can also be analyzed based on the same criterion because of loss of greenness.

In addition once green plants are identified, the remainder parts belong to the soil and cover a number of ecologically relevant categories (Luscier, Thompson, Wilson, Gorham, & Dragut, 2006), thus the proposed expert system could be extended to deal with the analysis of soil materials.

The expert system has been designed with an open architecture, so that in the future be possible to replace or add new modules, being of particular interest to study new automatic thresholding methods (Avci & Avci, 2009) or add a knowledge-base for improving image segmentation based on the accumulated knowledge (Gonzalez-Andujar, 2009).

Acknowledgments

The research leading to these results has been funded by the European Union's Seventh Framework Programme [FP7/2007-2013] under Grant Agreement No. 245986 in the Theme NMP-2009-3.4-1 (Automation and robotics for sustainable crop and forestry management). The authors wish also to acknowledge to the project AGL2011-30442-C02-02, supported by the Ministerio de Economía y Competitividad of Spain within the Plan Nacional de I+D+i.

References

Avci, E., & Avci, D. (2009). An expert system based on fuzzy entropy for automatic threshold selection in image process. *Expert Systems with Applications, 36*(2), 3077–3085.

Burgos-Artizzu, X. P., Ribeiro, A., Guijarro, M., & Pajares, G. (2011). Real-time image processing for crop/weed discrimination in maize fields. *Computers and Electronics in Agriculture, 75*, 337–346.

Burgos-Artizzu, X. P., Ribeiro, A., Tellaeche, A., Pajares, G., & Fernández-Quintanilla, C. (2009). Improving weed pressure assessment using digital images from an experience-based reasoning approach. *Computers and Electronics in Agriculture, 65*, 176–185.

Davies, G., Casady, W., & Massey, R. (1998). Precision agriculture: An introduction. Water Quality Focus Guide (WQ450, available on-line http://extension.missouri.edu/explorepdf/envqual/wq0450.pdf).

Demirkaya, O., Asyali, M. H., & Sahoo, P. K. (2008). *Image processing with MATLAB: Applications in medicine and biology*. Boca Raton: CRC Press – Taylor and Francis Group.

Gebhardt, S., & Kaühbauch, W. A. (2007). A new algorithm for automatic *Rumex obtusifolius* detection in digital image using colour and texture features and the influence of image resolution. *Precision Agriculture, 8*(1), 1–13.

Gebhardt, S., Schellberg, J., Lock, R., & Kaühbauch, W. A. (2006). Identification of broad-leaved dock (*Rumex obtusifolius* L.) on grassland by means of digital image processing. *Precision Agriculture, 7*(3), 165–178.

Gée, Ch., Bossu, J., Jones, G., & Truchetet, F. (2008). Crop/weed discrimination in perspective agronomic images. *Computers and Electronics in Agriculture, 60*, 49–59.

Gonzalez-Andujar, J. L. (2009). Expert system for pests, diseases and weeds identification in olive crops. *Expert Systems with Applications, 36*, 3278–3283.

Guerrero, J. M., Pajares, G., Montalvo, M., Romeo, J., & Guijarro, M. (2012). Support vector machines for crop/weeds identification in maize fields. *Expert Systems with Applications*, 39, 11149–11155.

Guijarro, M., Pajares, G., Riomoros, I., Herrera, P. J., Burgos-Artizzu, X. P., & Ribeiro, A. (2011). Automatic segmentation of relevant textures in agricultural images. *Computers and Electronics in Agriculture, 75*, 75–83.

Hague, T., Tillet, N., & Wheeler, H. (2006). Automated crop and weed monitoring in widely spaced cereals. *Precision Agriculture, 1*(1), 95–113.

Kataoka, T., Kaneko, T., Okamoto, H., & Hata, S. (2003). Crop growth estimation system using machine vision. In *The 2003 IEEE/ASME international conference on advanced intelligent mechatronics*.

Kirk, K., Andersen, H. J., Thomsen, A. G., & Jørgensen, J. R. (2009). Estimation of leaf area index in cereal crops using red–green images. *Biosystems Engineering, 104*, 308–317.

Ling, P. P., & Ruzhitsky, V. N. (1996). Machine vision techniques for measuring the canopy of tomato seedling. *Journal Agricultural Engineering Research, 65*(2), 85–95.

López-Granados, F. (2011). Weed detection for site-specific weed management: mapping and real-time approaches. *Weed Research, 51*, 1–11.

Luscier, J. D., Thompson, W. L., Wilson, J. M., Gorham, B. E., & Dragut, L. D. (2006). Using digital photographs and object-based image analysis to estimate percent ground cover in vegetation plots. *Frontiers in Ecology and the Environment, 4*(8), 408–413.

Meyer, G. E., & Camargo-Neto, J. (2008). Verification of color vegetation indices for automated crop imaging applications. *Computers and Electronics in Agriculture, 63*, 282–293.

Meyer, G. E., Camargo-Neto, J., Jones, D. D., & Hindman, T. W. (2004). Intensified fuzzy clusters for classifying plant, soil, and residue regions of interest from color images. *Computers and Electronics in Agriculture, 42*, 161–180.

Meyer, G. E., Hindman, T. W., & Lakshmi, K. (1998). *Machine vision detection parameters for plant species identification*. Bellingham, WA: SPIE.

Montalvo, M., Pajares, G., Guerrero, J. M., Romeo, J., Guijarro, M., Ribeiro, A., et al. (2012). Automatic detection of crop rows in maize fields with high weeds pressure. *Expert Systems with Applications*, 39, 11889–11897.

Neto, J. C. (2004). *A combined statistical-soft computing approach for classification and mapping weed species in minimum tillage systems*. Lincoln, NE: University of Nebraska.

Onyango, C. M., & Marchant, J. A. (2003). Segmentation of row crop plants from weeds using colour and morphology. *Computers and Electronics in Agriculture, 39*, 141–155.

Otsu, N. (1979). A threshold selection method from gray-level histogram. *IEEE Transaction on System Man and Cybernetics, 9*, 62–66.

Reid, J. F., & Searcy, S. W. (1987). Vision-based guidance of an agricultural tractor. *IEEE Control Systems, 7*(12), 39–43.

Ribeiro A., Fernández-Quintanilla C., Barroso J., & García-Alegre, M. C. (2005). Development of an image analysis system for estimation of weed. In *Proceedings of the fifth European conference on precision agriculture (5ECPA)* (pp. 169–174).

Ruiz-Ruiz, G., Gómez-Gil, J., & Navas-Gracia, L. M. (2009). Testing different color spaces based on hue for the environmentally adaptive segmentation algorithm (EASA). *Computers and Electronics in Agriculture, 68*, 88–96.

Shrestha, D. S., Steward, B. L., & Birrell, S. J. (2004). Video processing for early stage maize plant detection. *Biosystems Engineering, 89*(2), 119–129.

Tellaeche, A., Burgos-Artizzu, X., Pajares, G., Ribeiro, A., & Fernández-Quintanilla, C. (2008a). A new vision-based approach to differential spraying in precision agriculture. *Computers and Electronics in Agriculture, 60*(2), 144–155.

Tellaeche, A., Burgos-Artizzu, X. P., Pajares, G., & Ribeiro, A. (2008b). A vision-based method for weeds identification through the Bayesian decision theory. *Pattern Recognition, 41*, 521–530.

The Mathworks. (2012). http://www.mathworks.com/.

Tian, L. F., & Slaughter, D. C. (1998). Environmentally adaptive segmentation algorithm for outdoor image segmentation. *Computers and Electronics in Agriculture, 21*, 153–168.

Woebbecke, D. M., Meyer, G. E., von Bargen, K., & Mortensen, D. A. (1995). Shape features for identifying young weeds using image analysis. *Transactions of the American Society of Agricultural Engineers, 38*(1), 271–281.

Zheng, L., Shi, D., & Zhang, J. (2010). Segmentation of green vegetation of crop canopy images based on mean shift and Fisher linear discriminate. *Pattern Recognition Letters, 31*(9), 920–925.

Zheng, L., Zhang, J., & Wang, Q. (2009). Mean-shift-based color segmentation of images containing green vegetation. *Computers and Electronics in Agriculture, 65*, 93–98.