

RHEA-2014

Second International Conference on Robotics and associated High-technologies and Equipment for Agriculture and forestry New trends in mobile robotics, perception and actuation

> May 21-23, 2014 Madrid, Spain.

for agriculture and forestry

Edited by Pablo Gonzalez-de-Santos and Angela Ribeiro

ISBN 978-84-697-0248-2 Printed by PGM, Rafael Alberti 14, 28400 Madrid, Spain

Sponsored by the consortium of the RHEA project (FP7 245986)



This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no 245986



APPLICATION OF THE DEMPSTER-SHAFER THEORY TO CLASSIFY MONOCOT AND DICOT WEEDS BASED ON GEOMETRIC SHAPE DESCRIPTORS

P. Javier HERRERA¹, José DORADO², and Ángela RIBEIRO¹

¹Centre for Automation and Robotics, CSIC-UPM, 28500 Madrid, Spain ²Institute of Agricultural Sciences, CSIC, 28006 Madrid, Spain

Abstract. An important objective in weed management is the discrimination between monocots and dicots, because these two types of weeds can be controlled more appropriately by specific herbicides. Monocot and dicot weeds differ in morphological characteristics such as the shape of leaves and stems. For this reason, the regions' structure belonging to weed classes plays a key role in the proposed discrimination process. Thus six geometric shaped descriptors were used as attributes to describe each isolated region in an image. Based on these attributes, this work established a strategy where the decision was taken by a classifier adapted from the Dempster-Shafer theory. Outdoor field images, taken under varying conditions of lighting, were used to test the proposal performance. This methodology based on distinguishing two types of weeds can be extrapolated to any situation where monocots and dicots are present, e.g. to discriminate between maize, a monocot crop, and dicot weeds.

Keywords: Precision Agriculture, weed types discrimination, monocots/dicots discrimination, geometric shape descriptors, DES theory.

1 Introduction

Among the practices associated with the Precision Agriculture, site-specific weed management is effective in decreasing herbicide costs, optimising weed control and preventing unnecessary environmental contamination (Tian et al. 1999, Timmermann et al. 2003, Gerhards and Oebel 2006, Nordmeyer 2006). To carry out suitable site-specific weed management, it is essential to have accurate information on within-field weed distribution.

Weeds often occur in aggregated patches of varying size or as individuals growing among crop plants, yet they are managed uniformly across the whole field. However, the distribution of the most harmful weeds for a particular crop is not uniform and presents an aggregated pattern. Moreover it generally affects less than 40% of the crop (Marshall 1988, Johnson et al. 1995). The variable spatial distribution of weeds must be considered in weed-management strategies. This information can be obtained by different methods, including cameras located on aerial platforms or ground platforms.

RHEA-2014 149

A very important open field for Precision Agriculture is the development of methods for weed detection from images (Onyango and Marchant 2003, Ribeiro et al. 2005, Tellaeche et al. 2008a,b, Burgos-Artizzu et al. 2009). Nevertheless, the discrimination between the crop, weed and soil is a complex task, and the difficulty increases when the objective is to discriminate between types of weeds or to apply herbicide in real time as the position of the infestation is detected (Tian et al. 1999, Lee et al. 1999, Meyer et al. 1998, Ishak et al. 2009, Hemming and Rath 2001, Burgos-Artizzu et al. 2011).

Most studies during the last twenty years have addressed the classification of only two classes, either crop or weed, or distinguished between two types of weeds, broadleaf (dicots) and grasses (monocots) (Tang et al. 2003, Andújar et al. 2011, 2013). Monocotyledonous and dicotyledonous weeds are distinguished because they are used selective herbicides for each of these types of weeds. Therefore, herbicide application efficiency would be increased if specific treatments for each type of weed are performed instead of using a single broadcast herbicide (Tang et al. 2003, Wiles 2009). Besides, the effectiveness in controlling weeds, and hence the improvement of crop yield are achieved when the herbicides are applied early in the cycle of weeds (i.e., the seedling stage) (Giles et al. 2004, Sogaard and Lund 2007, Jeon and Tian 2009). However, precisely classifying a plant species that may be imbedded within other different species is challenging from the point of view of image processing.

Early weed detection in row crops is an objective that can be planned according to criteria oriented to two different levels with an increasing requirement: 1) estimation of the presence or absence of weeds according to its location in the bare soil or in the crop rows and 2) differentiation between groups of weeds (i.e., monocots vs. dicots) according to discriminant parameters (e.g., spectral characteristics, size and shape). Therefore, the characterisation of the spatial distribution of both groups is essential to the development of an autonomous system for treatments that can adjust the type and dose of herbicide to the dominant infestation.

Shape descriptors are used in many computer vision tasks (Gonzalez and Woods 2002). In general, descriptors describe a given shape so that descriptors for different shapes should be different enough that the shapes can be discriminated. Regions can be either described by contour-based properties or by region-based properties (Zhang and Lu 2004). Geometric shape descriptors assess the geometric shape of the contours of the regions, e.g. the perimeter, the diameter, the eccentricity, etc. (Gonzalez and Woods 2002, Zhang and Lu 2004). Since monocots differ structurally from dicots (as can be seen in Figure 1a and Figure 1b), a strategy based on the use of geometric shape descriptors may be suitable for the recognition of plant shape.

This work proposes a method where six geometric shape descriptors (perimeter, diameter, minor axis length, major axis length, eccentricity and area) are used as attributes for characterising the isolated regions in an image. Then a classifier based on the Dempster-Shafer theory (DES theory) is used to determine if regions belong to monocots or dicots. The DES theory (Dempster 1968, Shafer 1976) has been selected based on positive results obtained in previous works (Kuncheva 2004, Herrera et al. 2009).

This work is organised as follows: Section 2 describes the proposed approach, including a brief overview of the classifier used and how it is adjusted to be applied to

150 RHEA-2014

combining attributes. Section 3 analyses the performance of the method proposed. Finally, Section 4 presents the conclusions and future work.

2 Proposed Approach

The recognition of objects and characteristics of these objects is an essential issue in the field of pattern analysis. Descriptors are numerical assessment that allows to identify and recognize objects in the image. Six geometric descriptors are used in this work:

- 1. *Perimeter*: the distance around the boundary of the region (the pixels on the inside of the object's boundary).
- 2. Diameter: specifies the diameter of a circle that circumscribes the region.
- 3. *Minor axis length*: is the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region.
- 4. Major axis length: is the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region.
- 5. *Eccentricity*: specifies the eccentricity of the ellipse, i.e. the ratio between the minor axis of the ellipse and its major axis.
- 6. Area: is the actual number of pixels in the region.

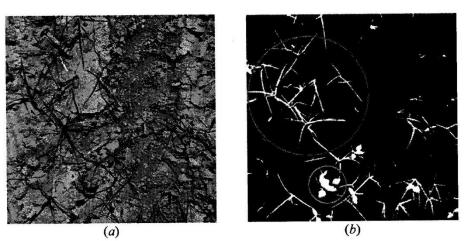


Fig. 1. (a) Image displays a mixture of both types of weeds, monocots (long and slender leaf) and dicots (broadleaf and short). (b) Vegetation cover of image (a). Circles are drawn for visualisation purposes: the big and green circle shows an area where monocots dominate, the small and yellow circle shows an area where dicots prevail.

The proposed approach consists of the following four stages: 1) segmentation of vegetation cover and detection of the isolated regions, 2) labelling of disconnected regions, 3) extraction of the six geometric shape descriptors for each region, and 4) classification of both monocot and dicot regions by means of the classifier based on the DES theory.

The segmentation of the vegetation cover is a two-steps process. First, a linear combination to each pixel of the original image is applied, as in Eq. (1):

$$IS = r \cdot I(R) + g \cdot I(G) + b \cdot I(B)$$
(1)

where r = -0.884, g = 1.262, b = -0.311 (Burgos-Artizzu et al. 2010). Then, the resulting grayscale image is binarised using a threshold, which is set to 10 in this case. Figure 1b shows the binarised image from Figure 1a.

An opening morphologic operation is conducted to enhance the regions and to avoid overlap among regions belonging to different plants. To obtain the isolated regions, the opening operation is accomplished with a structural element that symmetrically operates in all spatial directions, i.e. a 5×5 matrix known as *diamond*.

In the second stage, the regions are labelled following the procedure described in (Haralick and Shapiro 1992), which finds the regions in a binary image. In this method, all pixels in the same region are assigned to the same level. The regions are searched in top-to-bottom scan order, i.e., all pixels in the first region are labelled as 1, those in the second as 2 and so on.

After all regions have been labelled, the six geometric descriptors are computed for each region following Eq. (2) where y_i represents one of the six geometric descriptors previously defined. Therefore, each region is characterised with six attributes, i.e., $\Omega = \{d_1, d_2, d_3, d_4, d_5, d_6\}$, where d_1 : perimeter, d_2 : diameter, d_3 : eccentricity, d_4 : minor axis length, d_5 : major axis length, d_6 : area, and $d_i \in [0,1]$.

$$d_i = \frac{y_i - \min(y)}{\max(y) - \min(y)} \tag{2}$$

Once each region is characterised by the six descriptors used in this work, the classification stage must decide the class to which each region belongs. Previously to the classification a training step is needed. The aim of this step is to set the method to the classification problem between monocots and dicots using a set of positive and negative training examples.

The DES method is applied in this approach as follows (Kuncheva, 2004). A region l is matched correctly or incorrectly with its class of weed. Hence, two classes are identified, which are the class of true matches and the class of false matches, c_1 and c_2 , respectively. Given a set of samples from both classes, a 6-dimensional mean vector is built, where its components are the mean values of their descriptors, i.e., $\overline{m}_j = [\overline{d}_{j1}, \overline{d}_{j2}, \overline{d}_{j3}, \overline{d}_{j4}, \overline{d}_{j5}, \overline{d}_{j6}]^T$; \overline{m}_1 and \overline{m}_2 are the mean for c_1 and c_2 , respectively. This process is carried out during the training phase.

Given a region i and Ω_i , the 6-dimensional vector \mathbf{x}_i is computed, where its components are the six descriptors, i.e., $\mathbf{x}_i = [d_{i1}, d_{i2}, d_{i3}, d_{i4}, d_{i5}, d_{i6}]^T$. Then, the proximity Φ between each component in \mathbf{x}_i and each component in $\overline{\mathbf{m}_j}$ is calculated based on the Euclidean norm $\|\cdot\|$ using Eq. (3):

$$\Phi_{jA}(x_i) = \frac{\left(1 + \left\| d_{iA} - \overline{d}_{jA} \right\|^2 \right)^{-1}}{\sum_{k=1}^{2} \left(1 + \left\| d_{iA} - \overline{d}_{kA} \right\|^2 \right)^{-1}} \quad \text{where} \quad A \in \Omega$$
(3)

For every class w_j and every region i, the membership degrees are calculated according to Eq. (4):

$$b_{j}^{i}(A) = \frac{\Phi_{jA}(\mathbf{x}_{i}) \prod_{k \neq j} (1 - \Phi_{kA}(\mathbf{x}_{i}))}{1 - \Phi_{iA}(\mathbf{x}_{i})[1 - \prod_{k \neq j} (1 - \Phi_{kA}(\mathbf{x}_{i}))]}; \quad j = 1,2$$

$$(4)$$

The final degree of support that each region i, represented by x_i , receives for each class w_i is given by Eq. (5):

$$\mu_j(\mathbf{x}_i) = \prod_{A \in \mathcal{O}} b_j^i(A) \tag{5}$$

The class to which a region belongs is chosen based on the maximum support received for the class of true matches (w_1) , i.e., $max_i\{\mu_1(x_i)\}$.

3 Results

The sixty-six images used in this work were taken in maize crops sited in Madrid (Spain) on different days and therefore under varying natural lighting conditions. A Nikon D70 camera equipped with a 18–70 mm AF-S DX Nikon lens was used to capture images. Image collection was performed by placing the camera on a tripod at approximately 1.5 m height pointing vertically downward as illustrated in Figure 2. Each image with a dimension of $1,700\times1,696$ pixels was acquired covering 0.25 m^2 (0.5 m \times 0.5 m), with a resolution of 72×72 dpi.

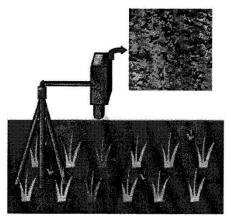


Fig. 2. Acquisition process: camera on a tripod at approximately 1.5 m height pointing vertically downward.

RHEA-2014 153

The vegetation always coincided with weeds (i.e., monocots, dicots or a mixture of both) because the images were taken in the inter-row area. From the sixty-six images available, twenty-eight presented a mixture of weeds, nineteen presented only monocots and nineteen only dicots. A high level of infestation was observed in 14% of the images.

In this work, fourteen images were selected to represent a wide range of situations. After applying step 1 (vegetation cover segmentation) and step 2 (labelling of disconnected regions) in the selected set of images, one-hundred different regions were extracted and manually analysed. In general, the number of regions extracted per image ranged from five to twenty. In the cases where an important infestation was observed, fewer than five different regions could be extracted.

Four of the images containing twenty-eight regions were used to compute the mean vectors for the DES classifier during the training phase. At this point, the correct class for each region in an image was known according to the expert knowledge, and this information was used to calculate the percentage of hits of the proposed approach. The average percentage of hits was $p_1 = 72.5$ (d_1), $p_2 = 72.5$ (d_2), $p_3 = 72.5$ (d_3), $p_4 = 85$ (d_4), $p_5 = 60$ (d_5) and $p_6 = 60$ (d_6).

At the testing phase, the proposed classifier was applied for each of the seventy-two regions obtained from the remaining ten images, and the success for each region, as well as the average of these hits, were computed. The averaged classification accuracy obtained was 70.5. The results show that the strategy based on combining attributes, worked properly. The best individual results, according to the six attributes, were obtained with the geometric shape descriptor d_4 , i.e. major axis length, confirming that it had proved to be the most relevant attribute. The worst attributes in terms of percentage of hits, were d_5 and d_6 , i.e. eccentricity and area, respectively. These attributes do not contribute in any way (positive or negative) to the final decision.

4 Conclusions

This paper proposes a strategy for discriminating between monocot and dicot weeds. Six geometric shape descriptors (perimeter, diameter, minor axis length, major axis length, eccentricity and area) were obtained to characterise each region in an image. Under the proposed method based on the DES theory, the values of the six attributes were combined and a decision for choosing the unique class (monocots or dicots) for each region was made.

The right timing for herbicide application coincides with the early stage of weed growth. The proposed combined strategy works properly in this stage. Otherwise, the weeds present overlapping and the segmentation process becomes difficult because of occlusions.

Monocots and dicots are the two main types of vegetation. The proposed approach can be applied to weed/crop discrimination, e.g. maize crops (maize belongs to monocot groups). However, additional studies to determine which descriptors primarily affect the final decision are needed. Another way to describe shape uses statistical properties called *moments*. A comparison between geometric shape descriptors and central moments in order to obtain better attributes must be

154 RHEA-2014

accomplished. In this context, site-specific weed management could significantly reduce herbicide use, with undoubted benefits for the environment.

Acknowledgments

This research was partly financed by the Spanish Ministry of Economy and Competition (AGL2011-30442-C02-02 project) and by the 7th Framework Programme of the European Union under the Grand Agreement CP-IP245986-2 (RHEA project). Research of Dr. Herrera was supported by the JAE-Doc Program, financed by the Spanish National Research Council (CSIC) and the European Social Fund (ESF).

References

- Andújar, D., Escolà, A., Dorado, J., Fernández-Quintanilla, C.: Weed discrimination using ultrasonic sensors. Weed Research 51(6), 543-547 (2011)
- Andújar, D., Escolà, A., Rosell-Polo, J.R., Fernández-Quintanilla C., Dorado, J.: Potential of a terrestrial LiDAR-based system to characterise weed vegetation in maize crops. Computers and Electronics in Agriculture 92, 11-15 (2013)
- Burgos-Artizzu, X.P., Ribeiro, A., Guijarro, M., Pajares, G.: Real-time image processing for crop/weed discrimination in maize fields. Computers and Electronics in Agriculture 75, 337-346 (2011)
- Burgos-Artizzu, X.P., Ribeiro, A., Tellaeche, A., Pajares, G., Fernández-Quintanilla, C.: Improving weed pressure assessment using digital images from an experience-based reasoning approach. Computers and Electronics in Agriculture 65, 176-185 (2009)
- Burgos-Artizzu, X.P., Ribeiro, A., Tellaeche, A., Pajares, G., Fernández-Quintanilla, C.: Analysis of natural images processing for the extraction of agricultural elements. Image Vision Computing 28, 138-149 (2010)
- Dempster, A.P.: A generalization of Bayesian inference. Journal of the Royal Statistical Society 30(2), 205-247 (1968)
- Gerhards, R., Oebel, H.: Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Research 46(3), 185-193 (2006)
- Giles, D.K., Downey, D., Slaughter, D.C., Brevis-Acuna, J.C., Lanini, W.T.: Herbicide microdosing for weed control in field grown processing tomatoes. Applied Engineering in Agriculture 20, 735-743 (2004)
- Gonzalez, R.C., Woods, R.E.: Digital Image Processing, 2 ed. Addison Wesley (2002)
- Haralick, R.M., Shapiro, L.G.: Computer and Robot Vision. Addison-Wesley, Reading, MA, USA (1992)
- Hemming, J., Rath, T.: Precision agriculture: computer-vision-based weed identification under field conditions using controlled lighting. Journal of Agricultural Engineering Research 78(3), 233-243 (2001)
- Herrera, P.J., Pajares, G., Guijarro, M., Ruz, J.J., Cruz, J.M.: Combination of attributes in stereovision matching for fish-eye lenses in forest analysis. In: Blanc-Talon, J., Philips, W., Popescu, D., Scheunders, P. (eds.) Advanced Concepts for

- Intelligent Vision Systems. LNCS, vol. 5807, pp. 277-287. Springer-Verlag, Heidelberg (2009)
- Ishak, A.J., Hussain, A., Mustafa, M.M.: Weed image classification using Gabor wavelet and gradient field distribution. Computers and Electronics in Agriculture 66, 53-61 (2009)
- Jeon, H.Y., Tian, L.F.: Direct application end effector for a precise weed control robot. Biosystems Engineering 104(4), 458-464 (2009)
- Johnson, G.A., Mortensen, D.A., Martin, A.R.: A simulation of herbicide use based on weed spatial distribution. Weed Research 35(3), 197-205 (1995)
- Kuncheva, L.: Combining Pattern Classifiers: Methods and Algorithms. Wiley (2004) Lee, W.S., Slaughter, D.C., Giles, D.K.: Robotic weed control system for tomatoes. Precision Agriculture 1(1), 95-113 (1999).
- Marshall, E.J.P.: Field-scale estimates of grass weed populations in arable land. Weed Research 28(3), 191-198 (1988)
- Meyer, G.E., Mehta, T., Kocher, M.F., Mortensen, D.A., Samal, A.: Textural imaging and discriminant analysis for distinguishing weeds for spot spraying. Transactions of the ASABE 41(4), 1189-1197 (1998)
- Nordmeyer, H.: Patchy weed distribution and site-specific weed control in winter cereals. Precision Agriculture 7, 219-231 (2006)
- Onyango, C.M., Marchant, J.A.: Segmentation of row crop plants from weeds using colour and morphology. Computers and Electronics in Agriculture 39, 141-155 (2003)
- Ribeiro, A., Fernández-Quintanilla, C., Barroso, J., García-Alegre, M.C.: Development of an image analysis system for estimation of weed. In: Stafford, J.V. (ed.) Proceedings 5th European Conf. On Precision Agriculture (5ECPA), pp. 169-174 (2005)
- Shafer, G.: A Mathematical Theory of Evidence. Princeton University Press (1976)
- Sogaard, H.T., Lund, I.: Application accuracy of a machine vision-controlled robotic microdosing system. Biosystems Engineering 96(3), 315-322 (2007)
- Tang, L., Tian, L., Steward, B.L.: Classification of broadleaf and grass weeds using Gabor wavelets and an Artificial Neural Network. Transactions of the ASAE 46(4), 1247-1254 (2003)
- Tellaeche, A., Burgos-Artizzu, X., Pajares, G., Ribeiro, A., Fernández-Quintanilla, C.: A new vision-based approach to differential spraying in precision agriculture. Computers and Electronics in Agriculture 60(2), 144-155 (2008a)
- Tellaeche, A., Burgos-Artizzu, X.P., Pajares, G., Ribeiro, A.: A vision-based method for weeds identification through the Bayesian decision theory. Pattern Recognition 41, 521-530 (2008b)
- Tian, L., Reid, J.F., Hummel, J.W.: Development of a precision sprayer for sitespecific weed management. Transactions of the American Society of Agricultural Engineers 42, 893-900 (1999)
- Timmermann, C., Gerhards, R., Kühbauch, W.: The economic impact of site-specific weed control. Precision Agriculture 4(3), 249-260 (2003)
- Wiles, L.J.: Beyond patch spraying: site-specific weed management with several herbicides. Precision Agriculture 10, 277-290 (2009)
- Zhang, D.S. Lu, G.: Review of shape representation and description techniques. Pattern Recognition 37(1), 1-19 (2004)

ISBN 978-84-697-0248-2



The RHEA project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no 245986





























