A Vision-based Classifier in Precision Agriculture Combining Bayes and Support Vector Machines

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Abstract – One important objective in Precision Agriculture is to minimize the volume of herbicides that are applied to the fields through the use of site-specific weed management systems. In order to reach this goal, two major factors need to be considered: 1) the similar spectral signature, shape and texture between weeds and crops; 2) the irregular distribution of the weeds within the crop’s field. This paper outlines an automatic computer vision system for the detection and differential spraying of Avena sterilis, a noxious weed growing in cereal crops. The proposed system involves two processes: image segmentation and decision making. Image segmentation combines basic suitable image processing techniques in order to extract cells from the image as the low level units. Each cell is described by two area-based attributes measuring the relations among the crops and the weeds. From these attributes, a hybrid decision making approach, under a Bayesian framework determines, if a cell must be or not sprayed. The hybrid approach uses the Support Vector Machines for computing the prior probability in this Bayesian framework. This makes the main finding of this paper. The method performance is compared against other available strategies.

Keywords – Support Vectors Machines, Parzen’s windows, Bayesian classifier, precision agriculture, weed detection.

Introduction

Nowadays, there is a clear tendency of reducing the use of chemicals in agriculture. Numerous technologies have been developed trying to obtain safer agricultural products and lower environmental impacts. The concept of Precision Agriculture provides a valuable framework to achieve this goal [1,2].

Within this general framework, weeds can be managed site-specifically using available geospatial and information technologies [3]. Initial efforts to detect weed seedlings by machine vision were focused on geometrical measurements such as shape factor, aspect ratio, length / area, etc. [4]. Later, color images were successfully used to detect weeds and other types of pests [5]. Weed coverage and weed patchiness, based on digital images, using a fuzzy algorithm for planning site-specific herbicide applications have been also estimated in [6]. Different approaches have used spectral colour indices to distinguish plant material from the background [3,7,8]. 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 [9,10]. The main problem concerning its detection is that, at the time of herbicide treatment, A. sterilis shape, color and texture are undistinguishable from those of the crop (barley or wheat). Due to this similarity, none of the detection methods mentioned previously are applicable to this case.

Although some A. sterilis plants may grow isolated or forming small patches, the majority of them are aggregated in relatively large patches. On the other hand, weed patches present in early spring, after broadleaf weeds have been controlled by early postemergence treatments, are practically pure stands of A. sterilis according to the criterion of technical people. Due to these two features, it is relatively easy for an experienced farmer or technical consultant to detect visually A. sterilis patches in the early stages of crop growth.

Our work was based on the hypothesis that a high density of green color in the inter row areas (where the crop is not present) after postemergence herbicides have been applied for broadleaf weed control, indicates that these zones are infested by high densities of A. sterilis.

Based on this hypothesis, we have tried to design an automatic image vision strategy to identify zones of the field infested
with *A. sterils*. After a decision making process, these zones could be differentially sprayed with selective herbicides in a separate operation.

Although there are several approaches to compute shapes or areas as attributes [11,12,13], the computation of unary attributes describing each isolated patch form is not appropriated in this particular case due to the irregular distribution and shapes of weed patches. Because of this, we decided to define binary relations among the weed patches and the crop rows. In order to decide whether the selected area was to be sprayed or not, the Bayesian and Support Vector Machines frameworks are combined for making the decision. Here is the main finding of this work.

This paper is organized as follows. In section II the image segmentation process is described. In section III the combined decision making strategy is proposed. The performance of this approach is described in section IV. Finally in section V the conclusions are presented.

**Image segmentation process**

The steps involved in the image segmentation process are: image acquisition, binarization, crop lines detection, grid cell partition and attribute extraction.

**A. Acquisition**

The images used for this study were captured in an experimental field of barley on La Poveda Research Station, Arganda del Rey, Madrid. The area of the field was 1.7 ha. The most common weed in the field was *A. sterils*, with densities ranging from 10 to 400 plants m\(^{-2}\). Although other weed species (*Papaver rhoesas, 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 + meccrop. Images were taken on two different dates on April 2003. At this time, the barley plants were at the early tilling stage (three to five 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 will simplify weed detection. Digital images were captured with a Sony DCR PC110E camera. The area covered by the piece of each image which is to be processed was approximately 1.9x1.5 m\(^2\) and the resolution of an image was 1152x864 pixels.

**B. Binarization**

In precision agriculture several techniques have been proposed in order to isolate weeds and crops [8,12,13,14]. A thresholding approach applied to the gray level image coming from the RGB original one is commonly applied. Based on the analysis carried out in [8] we selected the approach proposed in such work for transforming the RGB image into a new gray image as follows,

\[ r g b = \{ r, g, b \} \]

(1)

where \( r, g \) and \( b \) are the set of real coefficients to be selected, and whose possible values are discussed in [13]. The best performance is achieved with: \( r = -1, g = 2 \) and \( b = -1 \); then ; then , i.e. the grey level output values range in \([0,255]\).

The thresholding methods try to set the contrast breakpoint between pixels containing vegetation and pixels containing non-vegetation, including shadows, stones, straw, and other debris, and then to transform the gray level image into a black/white image to obtain the binary image. We have verified that the best thresholding approach is that described in [15] as reported in [16]. The binarized image is morphologically opened as in [13] in order to remove spurious white pixels and to smooth white contours. The opening operation is applied with three different structuring elements. This is because the crop lines have different orientations due to the perspective transformation, figure 1(a). We divide each image in three parts with the same width: left (L), central (C) and (R). We use the 3x3 \( S_L, S_C \) and \( S_R \) structuring elements with three ones in the minor diagonal, second column and main diagonal respectively. The remainder values are set to zero.

**C. Crop lines detection and grid cell partition**

In the resulting binary image, after the opening operation, plant material from both weeds and crops is white and the rest, coming from soil, stones and residual is black. On the basis of the binary image the next step is to detect the crop lines in the image.

In [17], after the binarization, the frequency of the plant pixels is plotted in the crop row direction; a maximum value indicates a furrow. After the morphology dilation the weeds appear isolated. In our experiments this behaviour does not occur. Hence, we apply the Hough transform as a well-known and robust technique in the normal parameter space (polar coordinates) [18,19]. This method accumulates values in a bidimensional array. Values greater than a threshold \( T_h \) are considered as straights lines.
associated to a furrow. \( T_h \) is set to 100 in this paper. Given two lines, if the differences between the polar angles and distances are less than two respective thresholds and, they are fused in a unique line. These thresholds are set to 5 and 10 respectively in this paper after experimentation.

By drawing horizontal lines vertically spaced in steps of 50 pixels and taking the computed crop lines, the image is split in cells. The basic unit to be analyzed becomes now the cell. Due to the perspective transformation the shape and size of the cells differ among them along the image, Fig. 1(b).

### D. Attribute extraction

Different attributes have been used for identifying the weeds in crop fields. In [4, 12] are used topological properties (area, invariant moments, etc.); colour (variance, skewness of the intensity histogram, etc.) or texture. Unfortunately, the weeds which are to be identified in our experiments appear in patches under irregular sizes and shapes. Its spectral signature and texture are also similar to that of the cereal in the field. Hence, the above attributes are not applicable in our work.

Moreover, this kind of weeds grows uncontrolled in the field. This means that white patches in soil areas between crops should be weeds and the surrounding crop areas are probably affected by weed seeds. This represents a serious handicap when a decision must be made about if the cell must be sprayed. Another important problem is the irregular distribution of the cereal in the furrows. This is because there are cereal seeds lost during the birth and growing phases. Additionally, given the perspective projection the cells are different in size and shape. To solve these problems, we need to extract attributes that are independent of the distribution of weeds and crops and also from the size and shape of the cells. With such purpose we have randomly selected a set of 30 images to be segmented from a set of 120 images. From each segmented image we select 10 cells, i.e. the amount of cells is 300. The number of cells classified as candidate to be sprayed is \( S N_0 = 48 \), i.e. this represents the 16% of 300. This relative small percentage reinforces the interest for selective spraying. From the remainder set of cells (i.e. \( S N_0 = 252 \)), we have computed the ratio of the white area in the cell,

\[
A_c = \text{the full area of a cell } c \text{ and } W_c = \text{the white area in the cell. In this kind of cells, free of weeds, the white area represents only crops. Each cell contains left (L) and right (R) patches representing the crop areas. We have found and where } r_l \text{ and } r_r \text{ are the corresponding ratios for the } L \text{ and } R \text{ crop regions respectively. This means that, i.e. each crop area is covering of the full cell's area.}
\]

For each cell \( i \), two area-based attributes are computed and embedded as the components of an area-vector \( x_{ic} \), this vector is.

Let \( m \) the total number of connected regions in the cell \( i \) (i.e. the number of white pixels in the cell) and \( A_{ij} \) the area of the \( j \)-th region. \( A_{ic} \) is the total area of the cell. \( A_{il} \) and \( A_{ir} \) the areas for the \( L \) and \( R \) crop regions respectively. \( A_{il} \) and \( A_{ir} \) are computed taking into account the amount of pixel inside of the regions bounded by the left and right crop lines respectively and the corresponding limits defined by \( r_l \) and \( r_r \) (i.e. of \( A_{ic} \)). Based on the area measurements we compute the following coverage values,

- crop coverage: \( i_l \) (3)
- weed coverage: \( i_w \) (4)
- soil coverage: \( i_c \) (5)

From equations (3) to (5) we compute the components for the area-vector as follows,

\[
\text{The component } x_{i1} \text{ is defined as the weed coverage rate in [14] and } x_{i2} \text{ is the weed pressure defined in [8].}
\]

The following analysis allows us to determine the range of variability for these two values. Indeed, if the weed coverage is null, there is not weeds in the cell, i.e. \( x_{i1} \) and \( x_{i2} \) are both null; but if the weeds cover the full intermediate region (i.e. ) then, hence, \( x_{i1} \) ranges in. The upper limit of \( x_{i2} \) is achieved when \( C_{iw} \) is maximum (i.e.) and \( C_{ic} \) minimum (i.e.); but if \( C_{ic} \) is null this means that the cell has not crops. We have not found this special case in our experiments. The minimum value obtained for \( C_{ic} \) was. Now, assuming that , then. Finally, the upper limit for \( x_{i2} \) can be computed and fixed from the equation (6) as 4.2. Based on these limits, we map linearly the component values of the area-vector to range both in the interval [0, 1]. This is
intended so that both components contribute equitably during the decision making process.

Bayesian and Support vector Machines combination

Given \( x_j \), representing the attributes of the cell \( i \), the problem is to make a decision about if the cell must be or not sprayed. This is carried out through the Bayesian theory. Indeed, the Bayes rule computes the posterior probability,

\[
\begin{align*}
\text{c} = y, n,
\end{align*}
\]

where \( w_y, w_n \) represent classes of cells to be and not to be sprayed respectively. \( P(w_c) \) is the a priori probability that the cell belongs to the class \( w_c \); \( p(x_j) \) is the twofold mixture density distribution. So, the decision is made as follows,

\[
\begin{align*}
\text{c} = y, n, \text{ otherwise}
\end{align*}
\]

The main problems to be solved are the estimations of both the class-conditional probability density functions, and the a priori probabilities. The first ones are estimated via the non parametric Parzen windows estimator and the second ones are derived from a decision function provided by the Support Vectors Machines (SVM) approach. This combination makes the main finding of this paper.

Let and two subsets of attribute vectors representing the cells to be and not to be sprayed respectively, with; the number of cells belonging to each subset is \( n_y \) and \( n_n \) respectively and . Initially both sets are selected under the supervision of the technical consultants and farmers.

\[A.Parzen’s windows density estimation\]

The Parzen’s windows density estimation is carried out by,

\[
\begin{align*}
\text{c} = y, n, \text{ otherwise}
\end{align*}
\]

where \( d \) is the dimension of the pattern space (which is 2) because \( x_j \) is a 2-dimensional vector; \( t \) denotes transpose. \( C_c \) is the covariance matrix representing the cross-correlation between attributes into the class \( c \). The smoothing parameter \( h_c \) is often expressed as follows,

\[
\begin{align*}
\text{c} = y, n
\end{align*}
\]

The choice of the bandwidth \( h \) is very critical in Parzen density estimation [20]. An overlay small \( h \) gives a spiky or noisy estimate of, with each spike corresponding to the kernel itself at the training patterns. When \( h \) is very large, each training pattern provides essentially the same contribution toward density estimation at every point \( x \) and the result is an over smoothed estimate of. As shown in [20], the window-width parameter appears to be fixed according to the set of data from the images processed. A more in-depth discussion of window width may be found in [21]. Based on the study carried out there we have applied a cross-validation approach [21] for estimating \( k \). In our experiments, the best performance is achieved for \( k = 0.3 \).

\[B.Support Vector Machines: prior probability\]

The goal of the SVM approach is to estimate a decision function as follows [22, 23],

\[
\begin{align*}
H \text{ is chosen as the Radial Basis kernel given by: with. We have tested others kernels without apparent improvement.}
\end{align*}
\]

The parameters, in the equation (11) are the solution for the following quadratic optimization problem:

Maximise the functional:

\[
\begin{align*}
\text{subject to:}
\end{align*}
\]

Avoiding the superscripts, for simplicity, in the data points: If then \( y_j = +1 \) otherwise \( y_j = -1 \). This is applicable for each member in \( X \). \( C \) is a regularization parameter set to 2000 as suggested in [22].
The data points \( x_i \) associated with the nonzero \( i \) are called support vectors. Once the support vectors have been determined, the SVM decision function has the form

\[
\text{(13)}
\]

Given, the attribute vector \( x_i \) for the cell \( i \), we can compute \( f(x_i) \) through (13), obtaining a scalar output value ranging in \([-1,+1]\) whose magnitude can be interpreted as a measure of belief or certainty about its membership grade to the classes \( w_y, w_n \). From the definition of \( y_i \), if then \( y_i = +1 \), but if then \( y_i = -1 \). This means that the polarity of \( f(x_i) \) determines this membership degree, i.e. positive/negative values allows us to assign \( x_i \) to \( w_y/w_n \) respectively. Theoretically, \( f(x_i) \) can take positive and negative unlimited values. Hence, we apply the sigmoid function to \( f(x_i) \) obtaining,

\[
\text{(14)}
\]

in order to avoid severe bias the parameter \( a \) is estimated experimentally and set to 0.1 in our experiments; ranges in \([0,+1]\), this means that a value of \(+1\) determines the maximum value indicating that the cell must be sprayed and vice versa for the minimum value. Hence, we identify the \textit{a priori} probabilities as \( P(w_y) = \) and \( P(w_n) = 1– \).

Comparative analysis and performance evaluation

In order to assess the validity of the proposed approach, we have designed a test strategy with the following three goals: 1) to compare the performance of the attributes used
2) to verify the performance of the proposed combined approach against single strategies
3) to compare the performance with respect the number of images processed.

In our approach we use two attributes, \( x_{i1} \) and \( x_{i2} \). As described in the section III-D \( x_{i1} \) and \( x_{i2} \) are two attributes used individually in [8] and [14] respectively. During the tests we identify three tests, i.e. Test 1 (using \( x_{i1} \) and \( x_{i2} \)), Test 2 (using \( x_{i1} \)) and Test 3 (using \( x_{i2} \)). Hence, this allows the testing of our approach against the referenced two methods.

Combination classification strategies are well suited in classification applications. We compare our combined method (Parzen and SVM) under the Bayesian framework against the Parzen approach without prior information and also against the SVM, both individually. When no prior information is known, we apply also a Bayesian framework by setting the \textit{a priori} probability to the fixed value of 0.5 (intermediate value in the range 0 to 1).

The Parzen’s windows estimates a density function according to (9) and the SVM the decision function given in (11). Both use the number of cells (patterns) to do that. Hence, we can verify the behavior of the different strategies against the number of cells used for estimating the density and decision functions. With such purpose the images are processed in four STEP’s from 0 to 3. At each STEP, a new set of 30 images with 10 cells per image, i.e. 300 patterns are added at each STEP. Hence, the total number of cells used for the STEP’s 0 to 3 is 300, 600, 900 and 1200 respectively.

The set of images processed in the STEP 0 (initial STEP) is described in the section II-D when computing \( r \). This set is also used for estimating the parameter \( k \) in the section III-A. Then, for STEP’s 1 to 3 the cells classified as belonging to the class \( w_y/w_n \) are added to the corresponding set / respectively, from which we estimate the new probability density and decision functions.

The results obtained for each strategy are checked by technical experts and farmers, i.e. under an expert human criterion. The different Tests analysed are based on the following values:

\textit{True Spraying (TS)}: i.e. number of cells correctly identified to be sprayed.

\textit{True No Spraying (TN)}: i.e. number of cells that do not require spraying correctly detected.

\textit{False Spraying (FS)}: i.e. number of cells that do not require spraying but identified as cells to be sprayed.

\textit{False No Spraying (FN)}: i.e. number of cells requiring spraying that they are identified by the method as cells that do not require spraying.

Traditionally, from these four quantities several measures have been used for classification [24]. The best ones are those combining the above four values. We have chosen the correct classification percentage (CCP),

\[
\text{(15)}
\]

Figure 1(a) displays a representative original image of a cereal crop field to be sprayed. In (b) the segmented image with the set of cells labeled as \( F \) identified as to be sprayed.
Table I displays the results in terms of the correct classification for the three STEPs. Test 1 (Parzen + SVM) represents our proposed strategy. For each STEP the CCP values are displayed under the CCP columns. Larger score values indicate better performances in the classification. The percentages of cells classified as cells to be sprayed is also displayed (%). For clarity these results are also drawn in Figure 2, in (a) the CCP scores and in (b) the percentage of cells which have been sprayed after applying the methods through the different steps.

TABLE I.

<table>
<thead>
<tr>
<th></th>
<th>STEP 1</th>
<th></th>
<th>STEP 2</th>
<th></th>
<th>STEP 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CCP %</td>
<td>CCP</td>
<td>CCP</td>
<td>CCP</td>
<td>CCP</td>
<td>CCP</td>
</tr>
<tr>
<td>Test 1 PSV1: Parzen + SVM</td>
<td>79</td>
<td>24</td>
<td>87</td>
<td>21</td>
<td>91</td>
<td>19</td>
</tr>
<tr>
<td>Test 1 PAR1: Parzen</td>
<td>74</td>
<td>26</td>
<td>82</td>
<td>25</td>
<td>86</td>
<td>22</td>
</tr>
<tr>
<td>Test 1 SVM1: SVM</td>
<td>73</td>
<td>28</td>
<td>80</td>
<td>27</td>
<td>85</td>
<td>24</td>
</tr>
<tr>
<td>Test 2 PSV2: Parzen + SVM</td>
<td>65</td>
<td>34</td>
<td>68</td>
<td>33</td>
<td>66</td>
<td>32</td>
</tr>
<tr>
<td>Test 3 PSV3: Parzen + SVM</td>
<td>66</td>
<td>33</td>
<td>71</td>
<td>31</td>
<td>73</td>
<td>30</td>
</tr>
</tbody>
</table>

(a) (b)

Fig. 2. Results against the number of STEPs: (a) CCP score values original image; (b) percentage of cells labeled as to be sprayed

From results in table I and figure 2, one can infer that the best performance is achieved by our proposed approach at each STEP. Hence, the fusion of classifiers becomes a suitable approach, which achieves better results than the single methods. During the Test 3 we obtain better results than those obtained in Test 1 and Test 2, i.e. the use of the two attributes in Test 1 perform better than the single attribute used in Test 2 and 3.

Also, the performance improves as the number of pattern samples increases. This is applicable for all strategies. This means that the number of samples is important.

Additionally, we can see that less percentage of cells classified as units to be sprayed is achieved by our PSV1 approach. This and its best performance imply that the amount of herbicide to be applied is reduced by using the proposed hybrid method achieving an important saving in cost and ground pollution.

Conclusions

A new automatic process for detecting weeds in cereal crops is proposed. The weeds and the crops have similar spectral signatures and textures. This represents an important problem which is addressed under two strategies: segmentation and decision making. We apply a segmentation process which combines different techniques. This implies that the image is ready for making the decision about its spraying.

The decision is based on the fusion of two well-tested single classifiers (Parzen and SVM) under the Bayesian framework making the most important contribution of this paper. Additionally, the strength of the probability allows us to determine the amount of herbicide to be applied, making another important finding against methods where the decision is only discrete (yes or not).

The combination of the weed coverage and weed pressure attributes improves the performance of the approach as compared with the use of these attributes separately. An important issue that is to be analysed in future works is the robustness of the proposed approach against illumination variability. This is because the robot-tractor where the system is installed goes in a direction and its opposite, i.e. the illumination coming from the natural environment varies.

Acknowledgment

Part of the work has been performed under project AGL-2005-06180-C03-03.