World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:1, No:4, 2007

On Combining Support Vector Machines and Fuzzy K-Means in Vision-based Precision Agriculture

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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 determines if a cell must be or not sprayed. The hybrid approach uses the Support Vector Machines and the Fuzzy k-Means methods, combined through the fuzzy aggregation theory. This makes the main finding of this paper. The method performance is compared against other available strategies.

***Keywords*—**Fuzzy k-Means, Precision agriculture, Support Vectors Machines, Weed detection.

I. 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. This work was based on the hypothesis that a high density of green spectral signature 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, it has been designed an automatic image vision strategy to identify zones of the field infested with *A. sterilis.* 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, it has been defined 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 Support Vector Machines (SVM) and the Fuzzy k-Means (FkM) frameworks are combined through the fuzzy aggregation theory. This combined strategy

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makes the main finding of the paper.

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.

II. 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. sterilis, with densities ranging from 10 to 400 plants m-2. Although other weed species (Papaver rhoeas, Veronica hedaerefolia, Lamium amplexicaule) were also present in the field, at the time of image acquisition most of them had been killed by an early treatment with bromoxinil+mecocrop. Images were taken on two different dates on April 2003. At this time, the barley plants were at the early tillering 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 semiarid 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 1.9x15 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 in [8] it has been selected the same approach proposed there for transforming the RGB image into a new gray image as in (1)

$$T(i,j) = rR(i,j) + gG(i,j) + bB(i,j) \tag{1}$$

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 $b = -1$; if $T(i,j) \le 0$ then $T(i,j) = 0$; if $T(i,j) \ge 255$ then $T(i,j) = 255$, 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. It has been 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, Fig. 1(*a*). Each image has been divided in three parts with the same width: left (L), central (C) and (R). 3x3 S_L, S_C and S_R structuring elements have been used 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 plan pixels is plotted in the crop row direction; a maximum value indicates a furrow. After the morphology dilation the weeds appear isolated. In the experiments conducted, this behaviour does not occur. Hence, it is applied 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 ε_1 and ε_2, they are fused in a unique line. These thresholds are set to 5 and 10 respectively in this paper.

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 is 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 the 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 this 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 transformation the cells are different in size and shape. To solve these problems, it is necessary 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 a set of 30 images have been randomly to be segmented from a set of 120 images. From each segmented image 10 cells are selected, i.e. the amount of cells is 300. The number of cells classified as candidate to be sprayed is SY_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. SN_0 = 252 the ratio of the white area in the cell has been computed as follows,

$$r = \frac{1}{SN_0} \sum_{i=1}^{SN_0} W_i / A_i \tag{2}$$

A_i is the full area of a cell i and W_i is 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. It has been found that $r \approx 2/6$ and $r = r_l + r_r$ where r_l and r_r are the corresponding ratios for the L and R crop regions respectively. This means that $r_l = r_r \approx 1/6$, i.e. each crop area is covering $1/6$ of the full cell's area.

For the cell i, two *area-based* attributes are computed and embedded as the components of an area-vector $\boldsymbol{x}_i$, this vector is $\boldsymbol{x}_i = \{x_{i1}, x_{i2}\}$. 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 pixels 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. $\frac{1}{6}$ of A_{ic}). Based on the area measurements the following coverage values have been computed,

$$\text{crop coverage: } C_{ic} = A_{iL} + A_{iR} \tag{3}$$

$$\text{weed coverage: } C_{iw} = \sum_{j=1}^{m} A_{ij} - C_{ic} \tag{4}$$

$$\text{soil coverage: } C_{is} = A_{ic} - (C_{ic} + C_{iw}) \tag{5}$$

From (3) to (5) it is possible to compute the components for the area-vector $\boldsymbol{x}_i$ as follows,

$$x_{i1} = \frac{C_{iw}}{A_{ic}} \quad \text{and} \quad x_{i2} = \frac{C_{iw}}{C_{ic}}\left(1 - \frac{C_{is}}{A_{ic}}\right) \tag{6}$$

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

The following analysis allows 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. $C_{iw} = \frac{4}{6} A_{ic}$) then $x_{i1} = \frac{4}{6}$, hence, x_{i1} ranges in $\left[0, \frac{4}{6}\right]$. The upper limit of x_{i2} is achieved when C_{iw} is maximum (i.e. $C_{iw} = \frac{4}{6} A_{ic}$) and C_{ic} minimum (i.e. $C_{ic} = 0$); but if C_{ic} is null this means that the cell has not crops. This special case has not been found in the experiments conducted. The minimum value obtained for C_{ic} was $\frac{1}{10} A_{ic}$. Now, assuming that $C_{iw} = \frac{4}{6} A_{ic}$, then $C_{is} = 0.23 A_{ic}$. Finally, the upper limit for x_{i2} can be computed and fixed from the equation (6) as 5.13. Based on these limits, the component values are mapped linearly of the are-vector to range both in the interval [0,1]. This is intended so that both components contribute equitably during the decision making process.

III. Support Vector Machines and Fuzzy K-Means Combination

Given $\boldsymbol{x}_i$, representing the attributes of the cell i, the problem is to make a decision about if the cell must be or not sprayed. This work has combined the decision provided by the SVM and the FcM under the fuzzy set aggregation theory.

Let $X^y = \{\boldsymbol{x}_1^y, \boldsymbol{x}_2^y, ..., \boldsymbol{x}_{n_y}^y\}$ and $X^n = \{\boldsymbol{x}_1^n, \boldsymbol{x}_2^n, ..., \boldsymbol{x}_{n_n}^n\}$ two subsets of attribute vectors representing the cells to be and not to be sprayed respectively, with $X = X^y \cup X^n$; the number of cells belonging to each subset is n_y and n_n respectively, i.e. $N = n_y + n_n$. Initially both sets are selected under the supervision of the technical consultants and farmers.

A. Support Vector Machines

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

$$f(\boldsymbol{x}) = \sum_{j=1}^{N} \alpha_j y_j H(\boldsymbol{x}_j, \boldsymbol{x}) \tag{7}$$

H is chosen as the Radial Basis kernel given by: $H(\boldsymbol{x}, \boldsymbol{y}) = \exp\left\{-\|\boldsymbol{x} - \boldsymbol{y}\|^2 / \sigma^2\right\}$ with $\sigma^2 = 3.0$. Others kernels have been tested without apparent improvement.

The parameters α_j, $j = 1,..., N$, in the equation (11) are the solution for the following quadratic optimization problem:

Maximise the functional

$$Q(\alpha) = \sum_{j=1}^{N} \alpha_j - \frac{1}{2} \sum_{j,k=1}^{N} \alpha_j \alpha_k y_j y_k H(\boldsymbol{x}_j, \boldsymbol{x}_k) \tag{8}$$

$$\text{subject to: } \sum_{j=1}^{N} y_j \alpha_j = 0;\ 0 \le \alpha_j \le C/N,\ j = 1,..., N \tag{9}$$

Avoiding the superscripts, for simplicity, in the data points: $\boldsymbol{x}_j, \boldsymbol{x}_k \in X$. If $\boldsymbol{x}_j \in X^y$ 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 $\boldsymbol{x}_i$ associated with the nonzero α_i are called *support vectors*. Once the support vectors have been determined, the SVM decision function has the form

$$f(\boldsymbol{x}) = \sum_{\text{support vectors}} \alpha_j y_j H(\boldsymbol{x}_j, \boldsymbol{x}) \tag{10}$$

Given, the attribute vector $\boldsymbol{x}_i$ for the cell i, it is possible to compute $f(\boldsymbol{x}_i)$ through (10), obtaining a scalar output value ranging in the interval [–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_j, if $\boldsymbol{x}_i \in X^y$ then $y_i = +1$ but if $\boldsymbol{x}_i \in X^n$ then $y_j = -1$. This means that the polarity of $f(\boldsymbol{x}_i)$ determines this membership degree, i.e. positive/negative values allows to assign $\boldsymbol{x}_i$ to w_y/w_n respectively during the decision phase.

B. *Fuzzy k-Means*

Given the number of clusters c and following [21,24,12] the FkM algorithm is based on the minimization of the objective function J,

$$J(U;\boldsymbol{v}) = \sum_{i=1}^{N} \sum_{j=1}^{c} \mu_{ij}^m d_{ij}^2 \tag{11}$$

subject to

$$\mu_{ij} \in [0,1]\,;\ \sum_{j=1}^{c} \mu_{ij} = 1\,;\ \sum_{i=1}^{N} \mu_{ij} < N\,;\ 1 \le j \le c\,,\quad 1 \le i \le n \tag{12}$$

In this approach the clusters are w_y and w_n (i.e. $c = 2$) and $\boldsymbol{v} = \{\boldsymbol{v}_1, \boldsymbol{v}_2\}$. These cluster centers are to be updated. The Nxc matrix $U = [\mu_{ij}]$ contains the membership grade of pattern i with cluster j; $d_{ij}^2 \equiv d^2(\boldsymbol{x}_i, \boldsymbol{v}_j)$ is also the squared Euclidean distance. The number m is called the exponent weight [24]. In order to minimize the objective function (1), the cluster centers and membership grades are chosen so that high memberships occur for samples close to the corresponding cluster center. The higher the value of m, the less those samples whose memberships are low contribute to the objective function. Consequently, such samples tend to be ignored in determining the cluster centers and membership degrees [24].

The FkM computes for each $\boldsymbol{x}_i$ at the iteration k its membership grade and updates the cluster centers according to (13) and (14),

$$\mu_{ij}(k) = \left(\sum_{r=1}^{c} \left(d_{ij}(k) / d_{ir}(k) \right)^{2/(m-1)} \right)^{-1} \tag{13}$$

$$\boldsymbol{v}_j(k+1) = \frac{\sum_{i=1}^{N} \mu_{ij}^m(k) \boldsymbol{x}_i}{\sum_{i=1}^{N} \mu_{ij}^m(k)} \tag{14}$$

The stopping criterion of the iteration process is achieved when $\left\| \mu_{ij}(k+1) - \mu_{ij}(k) \right\| < \varepsilon \ \forall ij$ or a maximum number of iterations is reached.

During the decision phase, given a sample $\boldsymbol{x}_i$, it is classified as belonging to the cluster $j \equiv w_y$ if $\mu_{ij} > \mu_{ik}$, $k \equiv w_y$, where the membership grades are computed according to (13) and (14).

C. *Combined Decision: Fuzzy Aggregation Operators*

Given a cell pattern represented by its attribute vector $\boldsymbol{x}_i$ the problem is to make a decision about if it must be sprayed. This is carried out through the fusion of the information supplied by the SVM and FkM approaches.

Theoretically, the decision function $f(\boldsymbol{x}_i)$ provided by the SVM can take positive and negative unlimited values. The sigmoid function has been applied to $f(\boldsymbol{x}_i)$ as follows,

$$g_{iy} = \left(1 + \exp\left(-af(\boldsymbol{x}_i)\right)\right)^{-1} \tag{15}$$

In order to avoid severe bias the parameter a is estimated experimentally and set to 0.1 in the experiments carried out; g_{iy} ranges in [0,+1], this means that a value of +1 determines that the cell must be strongly sprayed and vice versa.

Through (13) and (14) it can be determined the membership degree of $\boldsymbol{x}_i$ to the class w_y, expressed as μ_{iy}.

Now both decisions can be fused by applying a fuzzy aggregation operator [24]. Several operators have been tested: *a*) *non parametrized*: bounded difference and sum, Einstein (product and sum), algebraic (product and sum), Hamacher (product and sum), minimum, maximum; *b*) *parametrized*: Hamacher (intersection, union), Yager (intersection, union), Dubois (intersection, union) and "compensatory and". It has been verified that the best performance is achieved with the Einstein sum given in (16). Hence, only the results for this operator are reported because the analysis of the remainder is out of the scope of this paper.

$$h_{iy} = \frac{g_{iy} + \mu_{iy}}{1 + g_{iy}\mu_{iy}} \tag{16}$$

Finally, the decision is made based on h_{iy} which determines the amount of herbicide to be sprayed according to its value, i.e. $h_{iy} = 1$ maximum and $h_{iy} = 0$ minimum.

IV. Comparative Analysis and Performance Evaluation

In order to assess the validity of the proposed approach, a test strategy has been designed 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 the approach used in this work, two attributes have been used, x_{i1} and x_{i2}. As described in the section II-D x_{i1} and x_{i2} are two attributes used individually in [8] and [14] respectively. During the tests three sets have been identified, 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 this approach against the referenced two methods.

Combination classification strategies are well suited in classification applications. The combined method of this paper (FkM and SVM) has been compared against the FkM and SVM used both individually and described in this paper.

Hence, it can be verified the behavior of the different strategies against the number of cells used for estimating the decision function in SVM and the membership degrees in FkM. With such purpose the images are processed in four STEPs 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 STEPS 0 to 3 is 300, 600, 900 and 1200 respectively.

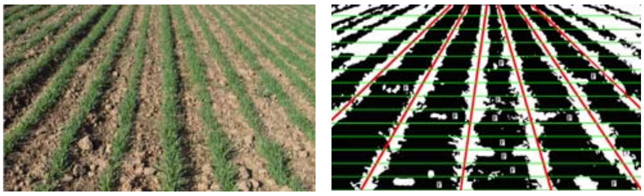
The set of images processed in the STEP 0 (initial STEP) is described in the section III-D. Then, for STEPs 1 to 3 the cells classified as belonging to the class w_y /w_n are added to the corresponding set X^y / X^n respectively, from which new estimations are made.

The results obtained for each strategy are checked by technical consultants and farmers, i.e. under an expert human criterion.

The different *Tests* analysed are based on the following values:

True Spraying (*TS*): i.e. number of cells correctly identified to be sprayed.

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



(*a*) (*b*)

Fig. 1 (*a*) original image; (b) segmented image

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

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 [25]. The best ones are those combining the above four values. Among them, the correct classification percentage (CCP) has been selected,

$$CCP = (TF + TN)/(TF + FF + TN + FN) \tag{17}$$

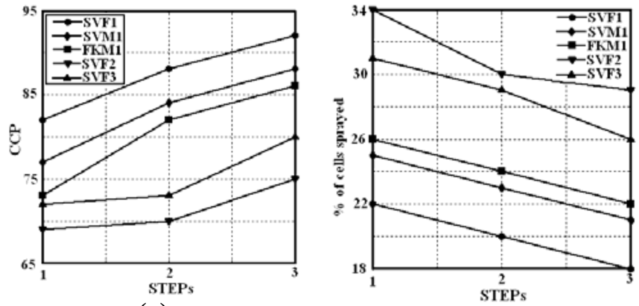
TABLE I
CPP SCORE VALUES FOR THE TESTS DURING THE STEPS

	STEP 1		STEP 2		STEP 3	
	CCP	%	CCP	%	CCP	%
Test 1: SVF1: SVM + FkM	82	22	88	20	92	18
Test 1 SVM1: SVM	77	25	84	23	88	21
Test 1 FKM1: FkM	73	26	82	24	86	22
Test 2 SVF2: SVM + FkM	69	34	70	30	75	29
Test 3 SVF3: SVM + FkM	72	31	73	29	80	27

Fig. 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 (SVM + FkM) represents the 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 Fig. 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.



(*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

V. CONCLUSION

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. A segmentation process which combines different techniques has been used. 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 (SVM and FkM) under the Bayesian framework making the most important contribution of this paper. Additionally, the strength of the probability allows 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 analyzed 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

This work was supported in part by the Spanish CYCIT under project AGL-2005-06180-C03-03.

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