Improving weed pressure assessment using digital images from an experience-based reasoning approach

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One of the main goals of Precision Agriculture is site-specific crop management to reduce the production of herbicide residues. This paper presents a computer-based image analysis system allowing users to input digital images of a crop field, and to process these by a series of methods to enable the percentages of weeds, crop and soil present in the image to be estimated. The system includes a Case-Based Reasoning (CBR) system that, automatically and in real time, determines which processing method is the best for each image. The main challenge in terms of image analysis is achieving appropriate discrimination between weeds, crop and soil in outdoor field images under varying light, soil background texture and crop damage conditions. The performance of the developed system is shown for a set of images acquired from different fields and under different, uncontrolled conditions, such as different light, crop growth stage and size of weeds, reaching correlation coefficients with real data of almost 80%.

1. Introduction

Traditionally, management of agricultural fields has not taken into account existing spatial variability, and herbicides have been sprayed over entire fields in a uniform manner. This has two main drawbacks: (a) contamination of soil, with the consequent contamination of subterranean waters, and (b) a considerable increase in the economic costs of agricultural production (Earl et al., 1996).

Moreover, each crop field presents enormous differences both in the nature of the weeds, and in their abundance and distribution. The concept of Precision Agriculture, in contrast to the traditional agricultural methods, proposes the adjustment of the herbicide dosage to each field unit, i.e., applying herbicide only in the zones where the amount of weed requires this.

In order to assess weed infestation level and its potential risks for crop yield, various estimators can be used. The most common method to predict the outcome of weed competition is by comparing crop yield losses with weed density (Cousens, 1985).

Unfortunately, the results of these types of model are often variable between sites and years (Bauer et al., 1991). In addition, this approach requires counting the number of weeds,
which is too time consuming for it to be a realistic option. Using weed biomass instead of weed density usually reduces the variability of the results, probably due to the fact that it takes into account the variation in size of individual plants (Wilson and Peters, 1982). However, this parameter is not appropriate for use in commercial fields. In order to overcome this problem (Harvey and Wagner, 1994) developed the concept of weed pressure. Weed pressure is defined as the visual estimate of the percentage with which weeds contribute to the total volume of both crops and weeds in a given area. Volume estimates are made by simultaneously considering both height and surface area covered by crop and weed species. By using this simple technique, individual farmers were able to rank the severity of weed infestation in their fields. Another possible estimator is the relative leaf area of weeds. This criterion, initially proposed by Kropff and Spitters (1991), has been widely tested and has resulted in reliable results when observations are made at an early stage of development of both crops and weeds (Lotz et al., 1996; Vitta and Fernandez-Quintanilla, 1996). Visual estimation in the field is a tedious task that can benefit from the development of machine-vision-based systems capable of estimating weed coverage using the input of natural images (Stafford, 2000). In fact, the estimation of relative leaf area of weeds (‘weed cover’) is much better adapted to image analysis and artificial vision than all other estimation methods. Therefore, a simple approach would be to perform photographic sampling of the crop field to then analyse the images with an image processing system, calculating the weed cover associated with each picture. With the weed cover data and the image location, an infestation map can be created and, with this, a herbicide treatment map can be generated.

This paper describes the image processing system developed for cereal image analysis, which automatically estimates the percentages of soil, crop and weeds present in a photo. The image processing is divided into different steps that require different methods. In turn, each method requires the adjustment of a series of attributes that determine how the method works. The images used are raw natural images taken outdoors from different fields and on different days, thus showing a high variability in characteristics such as different light conditions, crop and weed growth stages, soil texture, etc. For each particular image, the best combination of methods to be used in each step and their parameter values will be different. An experience-based method has been included in the system to indicate the best configuration for each image. Each time an image is satisfactorily processed, the configuration used to process it is stored in a database, and then a Case-Based Reasoning (CBR) approach based on expert knowledge is used to determine, taking into account previous experience, the best way to process new input images. The performance of the system developed has been tested on a large collection of images acquired under a wide set of different outdoor conditions.

This paper is organized as follows: the problem is described in Section 2. The image processing proposed is presented Section 3, explaining each of the methods developed in each step. Section 4 gives an overview of the basic aspects of the Case-Based Reasoning system developed. Relevant results are discussed in Section 5. Finally, Section 6 provides the main conclusions of this work.

2. Description of the problem

As a summary, the goal of the approach proposed is to correctly assess, using a geographically referenced image, the associated weed, crop and soil coverage (expressed as percentages) so that, when these values have been estimated for all the sampling points, an infestation map can be generated using various interpolation techniques such as kriging.1 The digital images used in this study were taken with Nikon Coolpix 5700 and Sony DCR PC110E cameras. All images were taken on different days over the past four years, always in February and March, the dates for post-emergence herbicide application. The most common weeds found were Avena sterilis (wild oat) and Papaver rhoeas. Barley was planted in very wide rows (37 cm) in order to facilitate weed discrimination in the middle of the rows. This practice is commonly used in organically grown fields. Images were taken with the same focal length and as overhead views, covering two crop rows and the space between them. The area covered by each image was of approximately 0.51 m² (0.6 m x 0.85 m).

At the early growth stage, the aforementioned weeds are indistinguishable from cereal in colour, shape and texture, as seen in Figures from 1 A to H. Consequently, it is not feasible to use techniques like pattern recognition (Perner, 1999; Gonzalez and Woods, 2003), feature extraction (Onyango and Marchant, 2003; Blasco et al., 2002; Lee et al., 1999; Granitto et al., 2005) or classification by natural colour/texture (Pajares Martisanz and de la Cruz, 2002; Astrand and Baerveldt, 2002; Pérez et al., 2000; Tian et al., 1999). Therefore, the only possible method for discrimination left is by its position.

Discriminating weeds from crops implies many difficulties. For example, Fig. 1 F shows a case in which weeds are somehow connected to the crops, making it difficult to separate them. Fig. 1 E and H shows crops that are not clearly marked, due to a sowing error. Other difficulties are generally related to the growth stage of the cereal. In fact, there can be enormous differences from one image to another; for example, in Fig. 1 C the crop is practically non-existent while in Fig. 1 B and G, the crops are very well established. Moreover, it is even possible to have one crop row larger than another, as can be seen in Fig. 1 D. Also, the lighting condition were not the same for all images. The images in Fig. 1 show different types of lighting, depending on whether the image was taken on a sunny or a cloudy day. The soil texture could also be different, depending on whether it was raining or not. Needless to say, the system has to be robust and flexible in all these situations if good overall results are to be obtained.

3. Image processing proposed

As a result of the reasons stated above, weed pressure (WP) can be useful to assess the risk weeds represent and, therefore, to decide on the herbicide dosage required. This risk measurement can be expressed in the form of a percentage ratio of

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1 The extrapolation of the unknown values is done so that the value of the nearest points will have more influence on the prediction than the farthest points, (Cressie, 1993).
weed cover, crop cover, and soil, (Ribeiro et al., 2005). Therefore, the main objective of the image processing system is to calculate these three percentages from each image.

Fig. 2 shows the three different steps involved in the image processing proposed. (1) The input image 2 A is segmented, obtaining a image where white pixels represent vegetal cover (crops and weeds), and black ones, soil: (Fig. 2 B). (2) The zones corresponding to crops are identified and eliminated: (Fig. 2C), the percentage of crop cover is calculated in this step. (3) The image is improved filtering noise and errors from previous steps and finally, weed percentage is estimated (shown as red pixels, Fig. 2D).

Different techniques have been developed for each step, resulting in two methods for segmentation (S1 and S2), three for elimination (E1, E2 and E3) and another two for filtering (F1 and F2). Examples of the results of each method, using Fig. 1 A, B and E as the input, can be seen in Fig. 3.

In the segmentation step, the type of light with which the image was taken plays a decisive role. Both segmentation methods, S1 and S2, use colour information to discriminate vegetation from non-vegetation (soil). S1 linearly combines the RGB planes of the image input to obtain a monochrome image where vegetation pixels have a high value, and afterwards sets a contrast breakpoint using a threshold value to obtain the final black&white image. The values of linear combination indices are input parameters in the method and will determine the adequacy of the solution. S2 is more straightforward, and directly selects which pixels belong to vegetation and which not, depending on whether the RGB values are within a specific range or not. Both achieve a good discrimination between vegetation and non-vegetation, as can be seen in rows one and two of Fig. 3. S1 has proved to be more accurate than S2, but the value of its input parameters is difficult to adjust, making S2 more convenient in some cases.

Since the segmentation step removes any colour component from the image (converting it to a binary black&white image), lighting is no longer a decisive variable during the elimination step. Instead, the elimination methods will have to face different shapes, sizes and distribution of crop and weeds, mainly due to sowing errors and different vegetation conditions.
Fig. 3 – Example of the application of different methods on images in Fig. 1 A, B and E. All elimination methods use result S1 as the input, while all filtration methods use the result of E3 as the input.
growth stages. To overcome all these different situations possible, three different methods have been developed (E1, E2 and E3).

The first and simplest elimination method, E1, makes use of the fact that crop rows have the shape of vertical columns in the sample images: all columns in the binary image whose number of vegetation pixels is greater than or equal to \( \text{image height} \times p_{\text{elimination}}\) are eliminated (set to black). E2 and E3 perform a more thorough analysis of the image, inspecting each image row separately via a horizontal left to right exploration. E2 recognizes crop row pixels as those grouped consecutively, while E3 uses border data, which is useful to point out where there are big transitions of white to black pixels (crop limits).

The results of all three elimination methods, E1, E2 and E3, using the result of S1 as the input, can be seen in rows 3, 4 and 5 of Fig. 3 (eliminated pixels shown in yellow). In standard images (image A), E2 and E3 are more accurate than E1, with E3 being slightly more accurate than E2. In non-homogeneous images (image B), the simplicity of E1 makes it unable to adapt, incorrectly eliminating all pixels, while E2 and E3 still perform reasonably well, again with E3 being more accurate than E2. In images presenting sowing errors, E1 shows better results than E2 and E3, which fail to eliminate faulty crop rows. Another issue to be taken into account is the time required for each method to process an image. Overall, it can be said that each method is more accurate than the previous one, achieving better overall results but, nevertheless, implying a higher computational complexity, which is the reason why sometimes it is preferable to use E2 rather than E3, for example.

After the crop rows have been eliminated, a filtration step is carried out, where weeds are separated from noise resulting from the prior steps. Most of the weed species, wild-oat in particular, grow in small associations called patches, where weeds usually grow around other weeds. This association is the fundamental characteristic taken into account to determine which remaining white pixels belong to weed and which are just noise. The simplest way to discriminate between them is to group each pixel with its neighbours (region extraction) and to eliminate all regions whose size in number of pixels is too small to be considered weed. This is precisely what F1 does. F2 is a further improvement of F1 in that the end enhances the remaining white regions by morphological dilation, in order to get more accurate results. Since the main difference between noise and weeds is the size of the region of white interconnected pixels, the decisive variable will be how large the weeds are. The results of both filtration methods, using the image resulting from the application of method E3 as the input, can be seen in the last two rows of Fig. 3. Again, F2 is slightly more accurate than F1 but also considerably slower. Table 1 specifies the main advantages and drawbacks of each method.

To sum up, the difference in the quality of results is easily assessed since, according to the image type, some methods are more appropriate than others, this being decisive in the same way as the input parameter values chosen for those methods.

4. The Case-Based Reasoning system

Case-Based Reasoning is a problem solving paradigm that uses specific knowledge on previously experienced problems to solve new ones, in contrast with the majority of other Artificial Intelligence approaches, which usually use a general knowledge base of the problem domain. Mainly, there are two different case types: (1) previously experienced problem situations and how they were solved (past cases), and (2) the new unsolved problem situations (new cases). Past cases are
stored in a case-base, constituting the knowledge base of the system. Each time a new case is entered into the system, the typical CBR accomplishes the following 4-step cycle: (1) retrieval of the most similar past case from the case-base, (2) reuse of the solution in the retrieved case for the new case, (3) revision/repair the adequacy of the solution achieved and (4) saving the solved case storing it in the case-base (Aamodt and Plaza, 1994; Leake, 1996). When processing images, it is reasonable to think that the same method of processing used to achieve optimum results on an image will also work for an image presenting similar characteristics. This conception is reinforced when the images present high variability between them, hindering the use of global knowledge methods (Perner, 2001). There are many examples in publications in which CBR is successfully used for processing complex images. This is the case of Grimnes and Aamodt (1996) where a generic architecture for medical images is proposed, combining low and high level processing, dividing each step into knowledge engineering tasks. In Perner (1999), the authors employ an interesting CBR approach to learn how to choose the best threshold value for a correct segmentation in medical images of the brain. However, no publications have been reported on the application of CBR in the processing of agricultural images.

In the system developed, the CBR has been implemented following a classical CBR cycle (Aamodt and Plaza, 1994) including case indexation at the beginning. Each different stage of the CBR proposed is discussed separately in the following sections.

4.1. Case indexation

As the case-base grows bigger, it will be increasingly time consuming to compare each new case with all the previous ones, in particular when considering each image has 1024 × 768 pixels, with 32 bits per pixel, and that the calculation time for image similarity algorithms has a computational complexity of at least O(height × width). Therefore, it would be advisable to separate the cases into different and smaller classes, comparing each case only with those in its same class. The indexation divides the cases into separated classes according to certain image characteristics to reduce the number of images with which each new case has to be compared in the retrieval stage, and therefore speeding up the entire process.

Images are separated in different classes according to four characteristics: (a) light (sunny or cloudy), (b) presence of sowing errors (true or false), (c) crop growth stage (low, medium, high), and (d) infested field (true or false). Taking into account the possible values for this attribute set, there are 2 × 2 × 2 × 2 = 24 classes possible. However, only 14 will be used from all 24, since the classes that represent inconsistent situations are eliminated, as for example those having both infested field and sowing error, or those with infected field and growth stage not ‘high’.

In each case, the system calculates the value for each characteristic attribute of its associated image without any intervention from the user, and saves their values inside the case structure, as follows:

- **Light**: The RGB (Red, Green, and Blue) image is transformed into a HIS (Hue, Saturation, and Intensity) image, and then the histogram maximum for component I (intensity) is computed. A high maximum value indicates that pixels have high intensity values (sunny), while a low value indicates the exact opposite (cloudy). This is shown in Fig. 4, using Fig. 1 E (sunny) and C (cloudy) as the inputs.

- **Crop growth stage**: The crop growth stage can be determined measuring the size of the crop rows. For this, the crop rows are identified using method E2 and then computing the total ratio of pixels eliminated. Depending on this ratio different crop growth stages are identified: (1) low if ratio < 30%, (1) medium if 30% ≤ ratio < 75% and (1) high if ratio > 75%. Fig. 5 shows an example taking Fig. 1 D, A and B as the input, method E2 has eliminated respectively 29% (low), 48% (medium) and 84% (high) of the pixels from each image.

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**Table 1 – Advantages and drawbacks of each processing method.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Decisive variables</th>
<th>Advantages</th>
<th>Drawbacks</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Light</td>
<td>Robustness</td>
<td>Parameters difficult to adjust</td>
</tr>
<tr>
<td>S2</td>
<td>Light</td>
<td>Parameters easy to adjust</td>
<td>Dependent on image nature</td>
</tr>
<tr>
<td>E1</td>
<td>Sowing errors</td>
<td>Robust to sowing errors</td>
<td>Not robust with regard to non-homogeneous images</td>
</tr>
<tr>
<td>E2</td>
<td>Homogeneity and differences in crop and weed growth</td>
<td>Very fast</td>
<td>Poor overall results</td>
</tr>
<tr>
<td>E3</td>
<td>Homogeneity and differences in crop and weed growth</td>
<td>Very robust to all kind of images</td>
<td>Parameters difficult to adjust</td>
</tr>
<tr>
<td>F1</td>
<td>Homogeneity and differences in crop and weed growth</td>
<td>Very fast</td>
<td>Time consuming</td>
</tr>
<tr>
<td>F2</td>
<td>Homogeneity and differences in crop and weed growth</td>
<td>Robust to noise</td>
<td>Parameters difficult to adjust</td>
</tr>
</tbody>
</table>

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Table 1 – Advantages and drawbacks of each processing method.
Fig. 4 – Results from computing the maximum value in histograms from images 1 E and C to determine whether the image was taken on a sunny or a cloudy day: (a) sunny (maximum = 18000); (b) cloudy (maximum = 6000).

Fig. 5 – Result of using E2 to determine the crop growth stages, using images 1 D, 1 A and B as the input: (a) low (ratio = 29%); (b) medium (ratio = 48%); (c) high (ratio = 84%).

Sowing errors: When a sowing error occurs, one or both crop rows present in the image will be incomplete. Therefore, the ratio of image columns with number of vegetation pixels equal to the height of the image will be reduced significantly. This ratio can be easily computed after segmentation, and a threshold is applied afterwards depending on the previously computed crop growth stages, as the ratio will be higher for a crop at a higher stage of growth and vice versa. Fig. 6 shows an example, taking Fig. 1 E and D as the input (both at medium growth stage). While the first one shows only 14% of columns with the number of vegetation pixels similar to the height (presence of sowing error), the second example shows 31% (normal image).

Infested: An image will be considered to be infested if more than 90% of the pixels are white after the segmentation process (90% of vegetation cover).

4.2. Case representation and case-base structure

Apart from the image, each case contains the index information (indicating the Class it belongs to), the methods to use in each image processing step, and the value of each parameter used for those methods. To increase efficiency, the case-base has been broken down into two separate tables: Indices and Cases. The first table stores the indexation data of each image, so that indexation is only performed once on each image, even

Fig. 6 – Results from computing the ratio of image columns with high quantity of vegetation pixels to determine the presence of sowing errors in images 1 E and D; (a) true (ratio = 14%); (b) false (ratio = 31%).
if the same image is processed several times. The second table stores the methods and parameters used for image processing:

Indices(ImageID, Light, SowError, CropGrowth, Infested)
Case(ImageID, SMethod, EMethod, FMethod, SPar, EPar, FPar)

The initial cases (4 for each indexation class) are labelled via the manual adjustment option in the developed image processing platform (in which the CBR is included). Method combination and the values of their input parameters were always set in such a way that the weed cover values obtained for the input image were as similar as possible to its associated biomass value. An initial analysis conducted on 666 sampling points in two winter barley fields showed there was a good relationship between visual assessments of weed cover and actual weed biomass harvested in those points (Fernandez-Quintanilla et al., 2005). In consequence, the ratio of weeds present in the image can be compared with the biomass value associated to the image in order to evaluate the adequacy of the processing performed.

4.3. Case retrieval

After the new case has been indexed, the system has to decide which case to retrieve, from among the cases solved previously belonging to the same indexation class. This decision will only be based on image similarity: retrieving the case solved with the image that is most similar to the current image.

Therefore, the main issue in this step is how image similarity is computed. The design of image similarity measurement methods is a highly active area of investigation. The number and type of features that can be compared between two images is overwhelming (space distance, neighbourhood, intensity, etc.). The selected features should be dependent on the type of input image and on the final purpose of the similarity measurement. The majority of existing methods are aimed at monochrome images, as the ones used in Perner (1999) and Wang (2003). Exhaustive gathering of simple image similarity measurement methods can be found in Di Gesù and Starovoitov (1999) and Van der Weken et al. (2004). According to the type of images used in this research, and after a careful evaluation, the root-mean-squared error S.E. method from Di Gesù and Starovoitov (1999) was chosen. The equation of this similarity method for two images A and B with sizes M × N is outlined in Eq. (1).

\[
S.E.(A, B) = \frac{1}{MN} \sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} |A_{ij} - B_{ij}|^2}
\]  

4.4. Case reuse

The reuse of the retrieved case solution is performed without any adaptation: the exact same methods and values of parameters are used for the new case without any adjustment. In order to be able to adapt the solution, the system would need to have at its disposal some knowledge on the domain, such as, for example, the effect of increasing or decreasing the value of a parameter in certain circumstances, or to know when it would be better to change one of the methods, and so on.

Unfortunately, this knowledge relies highly on intuition and common sense, making it very difficult to be encoded.

4.5. Case retention—learning

In the learning phase, the system decides if the newly solved case should be included in the case-base or not. At present, the system stores the solved case only if the solution achieves a correlation with biomass higher than 90%.

5. Results

Each different part of the system has been evaluated separately, to help in understanding better the contribution of CBR to the image processing system. Table 2 describes the 4 different system configurations that have been tested. First, two different configurations of the image processing system without CBR were tested (fixed method combinations and value of their parameters): (1) combination S1-E2-F2 (Non-CBR1) and (2) combination S1-E3-F3 (Non-CBR2). Then, a CBR with the indexation step and fixed guidelines on how to process the images depending on their belonging class was introduced: Pseudo-CBR. The guidelines can be seen in Table 3. The Light attribute will fully determine which segmentation method is used, while both elimination and filtration step methods will be determined by the crop growth stage, unless there is either a sowing error or an infestation, in which case the methods to use are set separately. Finally, the complete CBR system was tested (CBR).

The evaluation has been performed on a set of 182 images from different years and fields chosen randomly. All images were processed to obtain the associated weed coverage values. Afterwards, this weed coverage data was compared with biomass using the Pearson correlation coefficient, in order to evaluate whether the digital image analysis provides a reliable assessment of weed cover. As mentioned above, the base was initially built by 4 cases for each class, that is to say, 4 × 14 = 56 cases, in the case of the CBR systems (Pseudo-CBR and CBR).

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Value</th>
<th>Guidelines</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>Sunny</td>
<td>S1((-1.2, \ldots, 230))</td>
</tr>
<tr>
<td></td>
<td>Cloudy</td>
<td>S1((-0.7, 0.588, 0.136, 245))</td>
</tr>
<tr>
<td>Crop growth stage</td>
<td>Low</td>
<td>E2(35.5); F3(0.10)</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>E3(30.40.7); F2(0.30)</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>E3(10.20.9); F3(0.5)</td>
</tr>
<tr>
<td>Sowing error</td>
<td>True</td>
<td>E1(0.75)</td>
</tr>
<tr>
<td>Infested</td>
<td>True</td>
<td>E3(2.5, 0.999); F3(0.65)</td>
</tr>
</tbody>
</table>

Table 2 – Description of the processing methods tested.

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-CBR1</td>
<td>S1((-1.2, \ldots, 224)); E2(355); F2(0.15)</td>
</tr>
<tr>
<td>Non-CBR2</td>
<td>S1((-0.7, 0.588, 0.136, 247)); E3(30.40.9); F3(0.15)</td>
</tr>
<tr>
<td>Pseudo-CBR</td>
<td>Indexation + guidelines (see Table 3)</td>
</tr>
<tr>
<td>CBR</td>
<td>Complete CBR using S.E. similarity method</td>
</tr>
</tbody>
</table>
Table 4 shows the results of all 4 different system configurations. Both Non-CBR configurations show correlations above 58%, where Non-CBR2 performs slightly better (almost 3%) than Non-CBR1, although it is more time consuming, which is to be expected since the methods used are more sophisticated. Processing each image in a different way according to its class, as in Pseudo-CBR, clearly shows an improvement (68%), only requiring a few tenths of a second more for the processing. Moreover, apart from processing each image in a different manner, doing so according both to their type and characteristics, as CBR does, clearly proves another major improvement, reaching correlations of 79.7%, even though this is more time consuming (almost 0.5 s slower).

Table 4 shows also the overall results for each different type of processing, comparing them also with a visual evaluation of the images performed by experts. Clearly, the proposed image processing proves its adequacy, as it is better than the experts even without CBR. This is mainly due to the fact that the order in which images are presented to the experts has a high influence on their assessment. In other words, the evaluation performed by a human is subjective and thus human perception is in line with the overall situation in the image collection. For example, if the first images presented to an expert show low weed percentages and the last ones are of high percentages, the expert will start with high valuations and finish giving low valuations.

The proposed CBR system clearly contributes to refine image processing, with an improvement of almost 18%, helping image processing to reach correlations of up to 79.7%. These results, considering the high variety of situations presented in the 182 images used as a test, are very satisfactory and above all initial expectations.

6. Conclusions

One of the central concerns of Agriculture is selective treatment of weeds, for which the implementation of methods for automatic detection and location are highly desirable. Discriminating between crops, weeds and the background is a complex task, due to changing conditions regarding light, humidity, vegetation growth stages and the similarities between weeds and crops.

In the approach proposed, the image processing developed discriminating between crops, weeds and soil in cereal images is divided into different steps, for which different interchangeable methods are available. Moreover, due to the high variability presented in natural images taken outdoors, the method combination and the value of its input parameters has to be adjusted in different ways for each image, if robust discrimination that works under all possible situations is to be achieved.

This document proposes a new Case-Based Reasoning system that, given an input image, helps to determine the best way to process this based on expert knowledge stored in the form of cases and solutions. The CBR retrieves from the case-base the previously solved and stored case that is most similar to the new case and processes the image with the same methods and parameter values as the case solved previously. Combining the adaptability and flexibility of the image processing platform, with the ‘knowledge’ and ‘experience’ of the CBR, the system is capable of adapting to each and every image characteristic, adjusting the parameters of the image processing in a different way for each image.

The approach proposed has been evaluated using a large set of natural images from different years and fields, reaching correlation coefficients with biomass of up to 79.7%, clearly showing the contribution of CBR when compared with the results obtained by the same image processing system without CBR (60.1%).

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