# Detection of perennial weed patches in ripening cereals with an image analysis approach

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On agricultural fields weeds are not homogeneously distributed but show patchy patterns. Particularly perennial weeds occur in patches that are stable over several years. Due to this characteristic perennial weeds can be controlled site-specifically. Site-specific chemical weed control offers substantial herbicide savings. Furthermore, mechanical control measures can be conducted to weed patches, saving time and money. However, site-specific weed control requires reliable automated recognition and mapping of weed patches. Little research has been done on the recognition of weeds at lactitc ripeness, therefore images were taken during the harvest period. An approach is presented to recognize and classify the perennial weeds *Rumex obtusifolius*, *Cirsium arvense* and *Convolvulus arvensis* based on color and shape features of the weeds flower.

It can be concluded, that these weed species can be recognised within a cereal field at lactic ripeness and distinguished from each other with image processing and the developed automated recognition algorithms. The approach can be used to map perennial weed patches within cereal fields, providing information for site-specific weed control.

**Keywords:** perennial weeds, weed patch detection, image processing, harvest time, site-specific weed control

## 1 Introduction

Due to the development of herbicides, mechanical weed control was mostly replaced by chemical control measures, lowering production costs due to increased performance per time unit and reduced yield losses. Today, in conventional farming, 44% of used agrochemicals are herbicides (Zwerger and Ammon, 2002, p. 12). The Pesticide Authorisation Directive (PAD) 91/414/EEC, which became active in 1993 led to the removal of more than 50% of almost 1000 active ingredients from the market in the EU (Hillocks, 2012). The small number of available pesticides and the expectingly small number of new active substance are predicted to cause serious problems in insect, weed and disease control (Hillocks, 2012; Karabelas et al., 2009). Hillocks (2012) estimates future yield losses caused by the lack of active substances to 25-53%.

In order to comply with new regulations and security issues, the usage of agrochemicals has to be reduced, but the high yield levels should be maintained.

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Site-specific application technologies are a way to reduce the amounts herbicides applied. Several systems for site-specific weed control in field and vegetable crops are under development and testing (Lee et al., 1999; Tian et al., 2000; Gerhards and Christensen, 2003; Goudy et al., 2001). Different approaches from modified boom sprayer to autonomous robotic systems were proposed. Besides precise application techniques, all systems require the reliable recognition of weeds and the knowledge of its exact position in the field (Christensen et al., 2009). The combination of GPS and camera systems provide a possible solution for this task.

Most approaches focus on weed control in pre- and post emergence stages, and the approaches for the latter are based on weed recognition in early growth stages. However, perennial weeds have the capability to emerge later in the season or regrow after herbicide control due to energy reserves in the roots (Jacobs et al., 2006). These weeds establish patches with high infestation levels during the vegetation period and can effectively be controlled between the vegetation periods, either mechanically, chemically or with a combination of both. To reduce labour and chemical inputs for perennial weed control, weed patches could be controlled selectively, if the location of patches is known (Gutjahr et al., 2009). In the following an approach is presented for the image based recognition of perennial weeds in ripening cereals.

## 2 Material and methods

Images of cereal fields (*Triticum aestivum*, *Horedum vulgare*) infested with *Rumex obtusifolius*, *Cirsium arvense* and *Convolvulus arvensis*, were taken during the year 2011, using six different CCD cameras: Canon EOS 5D, Conon PowerShot SX130IS, Nikon COOLPIX P7000, Nikon D300, Panasonic DMC LZ1, Pentax Optio 555.

Images were taken by hand and in different angles on fields near Stuttgart, Germany and Ås, Norway in cereals at lactitc ripeness. Images were grouped according to the three weed species *Cirsium arvense*, *Convolvulus arvensis* and *Rumex obtusifolius*.

An algorithm for image segmentation was developed based on colour thresholding for each series. The colour space of images was transformed from RGB (red, green, blue) to HSB (hue, saturation, brightness), using the image processing software ImageMagick (v.6.7.5). After colour space transformations, images were manually segmented into classes, using the image processing software GNU Image Manipulation Program (GIMP, v.2.7.3) and a rectangular region selecting tool.

Histograms for each class were calculated for the colour channels with ImageMagick. The histograms were then plotted and analysed using the statistics software R (V. 2.12) as shown in figure 1. Thresholds for the colour channels were identified and set according to the histogram analysis. For the example in figure 1 (*Cirsium arvense*) intervals can be selected on a range of [0;255] (8 bit channels). The derived thresholds were [5;25] for hue and [105;160] for saturation (table 1). In figure 2 they were applied and visualised.

These thresholds were then used to automate image segmentation. The resulting binary images of each channel were combined by addition and subtraction operations, resulting in multi-level grey images (figure 2, centre). A further thresholding of these grey-level images led to binary images in which the objects of interest are represented in black (foreground) against a white background (black pixels in figure 2, centre). However, the presence of noise objects made further post-processing steps necessary. The post-processing had to be adapted to different image series.

Morphological operators were applied to the binary images: a dilation step combined

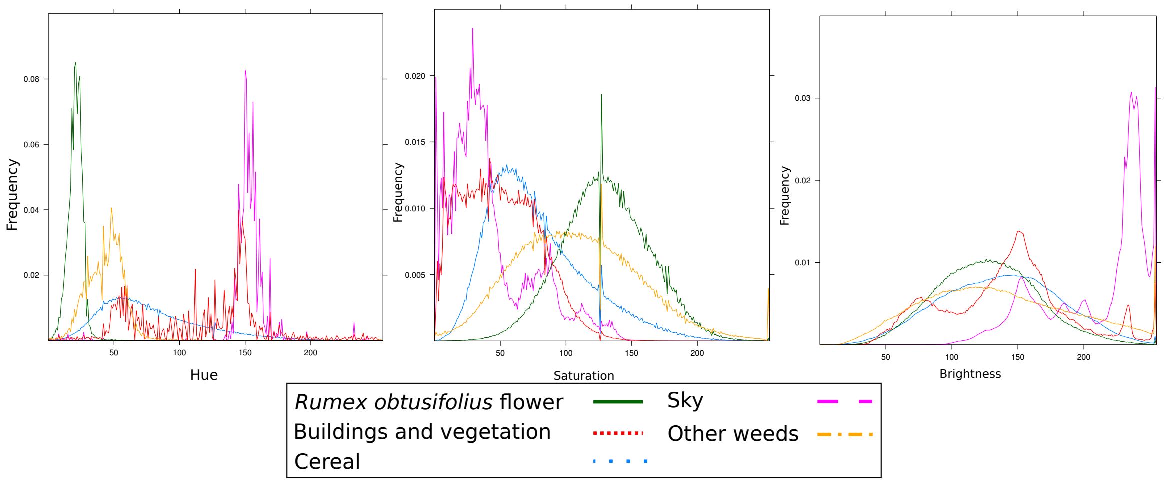


FIGURE 1: Colour channel histograms (left to right: hue, saturation, brightness) of *Rumex obtusifolius* leaves and background classes.

TABLE 1: Colour channel thresholds overview for the three weed species.

| | *Rumex obtusifolius* | *Convolvulus arvensis* | *Cirsium arvense* |
|---|---|---|---|
| Hue | [5;25] | [2;127] | [0;117] |
| Saturation | [105;160] | [50;] | [30;] |

with a following erosion operation (closing). For *Rumex obtusifolius* and *Convolvulus arvensis* flowers, a closing operator (five iterations) was applied, connecting foreground regions with small gaps in between. After this operation segments with a size of more than 50 pixels were selected and smaller objects discarded as noise. Both operations are visualised in figure 2 (right). For *Cirsium arvense* flowers the segment selection size was set to 10.

The resulting foreground objects were then additionally analysed with a shape based approach using the software developed in Weis (2010). For each series, objects in a subset of images were trained as weed species (*Rumex obtusifolius*, *Convolvulus arvensis*, *Cirsium arvense*, depending on the image series) or noise. Shape features were calculated and all objects in the images were classified with a kNN classifier. After classification, images were manually compared with the original RGB images to estimate the classification success. Positive and negative predictive values were calculated.

## 3 Results

By colour based image segmentation, the majority of the objects within the images were correctly classified. The identified thresholds for the weed species are summarised in table 1. Major parts of *Rumex obtusifolius* flower, *Cirsium arvense* flower and *Convolvulus arvensis* flower are classified as foreground, whereas other objects are assigned to background. Segmentation based on shape feature analysis results in high classification accuracy with variations between species.

The best results were achieved for the detection of *Rumex obtusifolius*. 90% of images are correctly classified (94 out of 105). Classification success of the image series '*Convolvulus arvensis*' and '*Cirsium arvense*' are lower: 75% and 69%, respectively. The

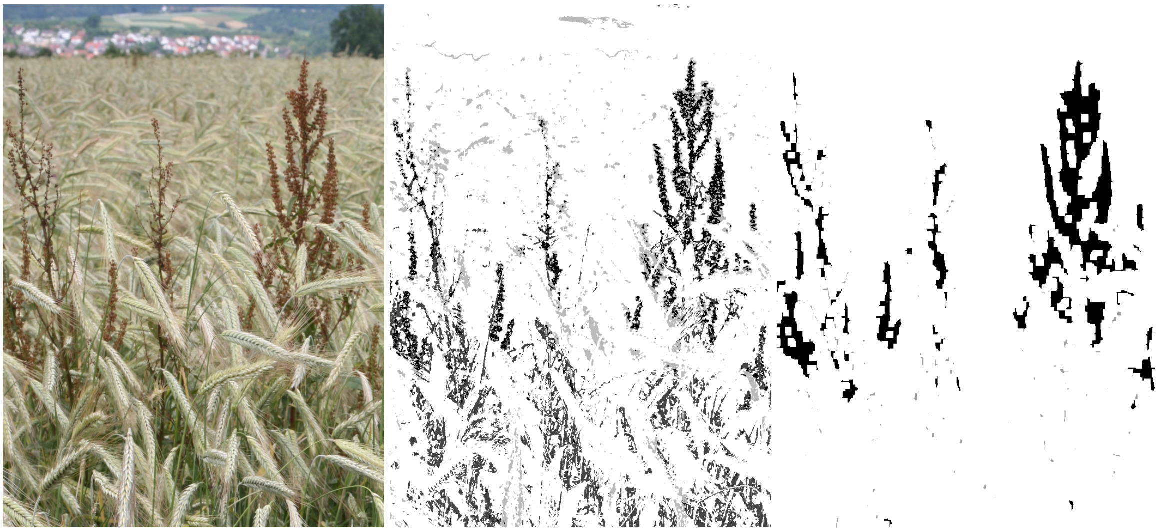

FIGURE 2: Processing of an RGB image (left) to a binary image. Centre: Colour threshold combination of hue (light gray) and saturation (dark gray) to foreground pixels (black). Right: post-processing with morphological opening and a size criterion (gray: discarded small regions). Black pixels denote the identified *Rumex obtusifolius* flowers.

TABLE 2: Recognition rates of the three weed species in this study: confusion tables of image processing results with visual analysis. The presence of weeds within each image is compared, correct classifications are bold.

| Weed species: | Rumex obtusifolius | | Convolvulus arvensis | | Cirsium arvense | |
|---|---|---|---|---|---|---|
| classification: | present | absent | present | absent | present | absent |
| present in image | **65** | 1 | **30** | 0 | **45** | 3 |
| absent in image | 10 | **29** | 32 | **65** | 29 | **26** |

detection results for the three weed species are summarised in table 2.

The large difference in classification success derives from positive predictive values. These denote the probability that an image contains a weed species, if the image is classified as infested: 87% for *Rumex obtusifolius*. Positive predictive values of other image series are 49% (*Convolvulus arvensis*) and 61% (*Cirsium arvense*). The low positive predictive values are mainly caused by misclassification between the weed species *Convolvulus arvensis* and *Cirsium arvense*. Furthermore, images of series *Rumex obtusifolius* that are falsely classified as infested, show patches of *Cirsium arvense*. Misclassification in those images is caused by stems of *Cirsium arvense*. The shape feature analysis for these two species did not substantially improve the classification success, even though flowers of both species differ in size and shape. It can be assumed that misclassification between the two species results from changing angles and distances during image acquisition. Images that were falsely classified as infested often show only very few objects compared to images that were correctly classified.

Images that contain large areas of soil due to low camera angle were excluded from the segmentation process, since it was not possible to distinguish between brownish soil and the red/brownish flower of *Rumex obtusifolius*.

Negative predictive values of the three classification algorithms are high, 97%, 100% and 90% for *Rumex obtusifolius*, *Convolvulus arvensis* and *Cirsium arvense*, respectively. Reliability of the algorithm, if images are classified as not infested is therefore very high.

## 4 Discussion

Segmentation of flowers of *Cirsium arvense*, *Rumex obtusifolius* and *Convolvulus arvensis* against a cereal background at lactic ripening, based on colour space transformation is possible. Colour of weed flowers vary between weed species, providing important information for species identification.

However, differentiation between *Cirsium arvense* and *Convolvulus arvensis* is difficult, since flowers of both species contain pink and purple pigments. Classification success might be increased, if the number of classified objects and distance between them are considered. The images show large portions of a whole field, and therefore the appearance of the plants in an image changes due to perspective distortion (scale changes). For further developments, images taken with standardised angle and distance to the ground are required to i) define the region of interest within the image (field) and ii) handle the occuring perspective distortions.

The growth habitus of *Rumex obtusifolius* and *Cirsium arvense* enables detection of plants with a camera orientation angle between 0° (nadir) and 90° (horizon). Both species usually grow taller than the surrounding cereals, thus flowers exceed the latter. However, flower of the binding weed *Convolvulus arvensis* does often not exceed the height of cereals, thus a camera angle close to 0° is required. An vertical camera orientation is advantageous to avoid complex background objects such as cars and buildings in the image. The colour of these objects varies largely and is sometimes very similar to the colour properties of weeds flower. However, the high angle, required to detect flower of *Cirsium arvense* especially in dense cereal stands might stand in conflict with the identification of *Rumex obtusifolius* flower, whose colour was found to be similar to soil. Application of colour thresholds to identify *Rumex obtusifolius* might not work in these cases.

For practical applications it is required to mount the camera for image acquisition on a carrier device. One approach are airborne platforms, such as unmanned aerial vehicles (UAVs). These vehicles are able to fly at low speed and low hight, such that images with sufficient resolution can be taken (Grenzdörffer et al., 2008). Besides airborne platforms, images might be taken with a camera mounted on a tractor or, since the detection takes place at harvest time, on a harvester. Moreover, robots are in development that can be equipped with a camera system to map weeds in the field (Slaughter et al., 2008). However, ground bound platforms require low plant heights and thus are limited in their application.

We tried to overcome the problem of sensitivity to illumination by a colour space transformation. In case of *Rumex obtusifolius*, images taken with different cameras under different conditions were available. In all images satisfying results could be achieved, indicating reliability of the presented algorithm even under varying conditions. The creation of perennial weed maps bear the potential to design herbicide applications more efficiently. Weeds that grow in patches, as perennial weeds do, bear a greater potential to save herbicides than weeds that are more homogeneously distributed (Gutjahr et al., 2009). The greatest benefit might be achieved for no-tillage systems, that are characterized by several herbicide application per year.

Tractors equipped with DGPS might use weed maps to mechanically control only patches of perennial weeds. The knowledge about perennial weed patches based on weed maps provides information for these systems, increasing their efficacy. Images with presence of annual weeds flower have to be taken to test the reliability of the developed algorithm in complex situations.

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