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Classification of plant species from images of overlapping leaves

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ABSTRACT

Automatic identification of plant species is needed in precision agriculture in order to collect species information and guide sprayers of agrochemicals. Identification methods based on spectroscopic properties, leaf forms and chlorophyll fluorescence have been developed. Leaf overlap is a major difficulty and most of the proposed methods only operate on isolated leaves. The present study focused on the leaf overlap problem by analysing colour photographs of a mixed cultivation of oat (*Avena sativa*) and a dicot weed (dandelion, *Taraxacum officinale*, TAROF). Leaves of the two species appeared to have very similar colours and therefore species identification was based on the different textures of monocot and dicot leaves. An automatic classifier, based on the RankRLS learning algorithm, was developed in the study and trained with manually labelled parts of the photographs. We adopted a strategy in which the misclassification of oat pixels to TAROF was avoided at the expense of classifying most TAROF pixels as oat. This strategy is appropriate when the aim of the automatic identification is to guide a herbicide sprayer. In photograph-wise cross-validation, the misclassification of oat as TAROF was negligible and considerably smaller than the expected amount of misclassifications, indicating that leaf texture is useful for identification of plant species in this very demanding case.

1. Introduction

Precision agriculture applying automatic plant identification has the potential to lead to more environmentally friendly, cost-effective and productive agriculture, as herbicides can be sprayed on weeds only. For example, Zhang et al. (2012) sprayed high-temperature, food-grade oil on the top of intra-row weeds and achieved a weed reduction over 90%. Automatic identification of weeds has been reported to lead to herbicide savings of 4–94% in field experiments (de Castro et al., 2012, 2013). Only a few studies describe an actual device constructed for weed detection and herbicide spraying (Lamm et al., 2003; Zhang et al., 2012). However, distinguishing plants from soil, identification of different species and development of highly accurate and economically sustainable vehicles is a difficult task (for a review, see Slaughter et al., 2008).

Any automatic plant identification machine must be able to distinguish plants from background, usually from soil. For this, the excess green colour index has long been used (Woebbecke et al., 1995). Gerhards and Christensen (2003) distinguished plants from soil by combining visible and near-infrared imaging. The task becomes more challenging when the contrast is weak due to technical imaging limitations or, for example, when plants are smeared with soil after heavy rainfall, but solutions have been developed (Montalvo et al., 2013; Romeo et al., 2013). Chlorophyll *a* fluorescence offers an excellent alternative for distinguishing plants from soil, as the fluorescence signal is specific for plants (Maxwell and Johnson, 2000; Mattila et al., 2013).

Detection and identification of weeds can be done by remote sensing or by vehicles moving on the ground. In the latter case, identification of the plants and subsequent treatment can be done simultaneously. In remote sensing the resolution ranges from several metres down to about 0.1 m and therefore remote sensing is usable mainly in large scale farming for large weed patches (for a review, see López-Granados, 2011). Recently, a weed infestation map of a maize field with 2-cm resolution was obtained using an unmanned aerial vehicle (Peña-Barragán et al., 2013).

Crop rows have also been used to detect weeds growing between rows (for example, see Montalvo et al., 2012). Sainz-Costa et al. (2011) obtained promising results utilising a camera secured to the top of a tractor moving at 6 km/h. Andújar et al. (2011) used the height of plants to identify weeds on a maize field.

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In reflectance imaging, the plant species can be identified by species-specific features of shape, size, colour or leaf texture (for example, see Persson and Åstrand (2008) and Lin et al. (2008)). Spectroscopic methods extract features from reflectance in visible, infrared or multispectral bands (for example, see Wang et al., 2007; Zhang et al., 2012), from chlorophyll fluorescence (Mattila et al., 2013; Tyystjärvi et al., 1999; Keränen et al., 2003, 2009; Tyystjärvi et al., 2011) or from UV-induced bluegreen fluorescence (Panneton et al., 2011).

Weeds that grow in close proximity to crop plants cause more yield loss than weeds growing further away (Heisel et al., 2002) which makes the identification of single plants necessary. Therefore, it is essential to develop methods that achieve weed identification even if weed and crop plant leaves overlap. In the present study, weed detection was done in challenging conditions where live plants were deliberately planted so that their leaves strongly overlapped. The leaf surface texture was used as the basis of identification.

Automatic classification of plants into species (or weed/crop) can be done by studying their digital images. The classifier can utilise a large number of features to increase the proportion of correct classifications. Such features include leaf colour, size, overall shape, edge structure, various texture properties (variance, coarseness, directionality) of the leaf surface, vein structure, and spectroscopic features.

In the present work we construct an automatic plant species recognizer that classifies the leaves to either weed or crop. The classifier is based on the supervised learning principle that uses a prelabeled training data for constructing the classifier. The training data was created in two steps. First, plants were distinguished from the background with a colour-based automatic method. Second, the remaining plant regions are segmented to crop and weed areas by a semi-automatic method. Automatic segmentation of the leaves to coherent areas was also tried but a human expert was needed to finalize labelling of pixels belonging to one leaf. This information was used only to generate labelled training data and to test the prediction performance of the automatic classification method.

2. Materials and methods

2.1. Plant material

Wild dandelion (*Taraxacum officinale* Wigg; seeds collected from a local field), hereafter TAROF, and oat (*Avena sativa* L., cv. Aslak) were grown in a research greenhouse at the mean photosynthetic photon flux density (PPFD) of 150 μmol photons m^{-2} s^{-1} in a 16 h light period. The seeds were sown randomly to mimic a natural situation with overlapping leaves (Fig. 1). 2–4 week-old plants were photographed (resolution 5184 × 3456) with a digital colour camera (Canon EOS 60D, objective Sigma 30 mm F1.4 EX DC HSM, Japan).

2.2. Segmentation of plant images

The image pixels were initially classified into plant and background pixels, by applying the *excess green* (Woebbecke et al., 1995) condition to the RGB (Red–Green–Blue) representation of colours. More precisely, pixels satisfying simultaneously the following two conditions were considered as plant pixels:

$$G > \max(R, B, threshold_1), \text{ and } \frac{2G - R - B}{R + G + B} > threshold_2$$

In the experiments $threshold_1$ was set to 15, and $threshold_2$ to 0.2. These values were obtained by manual tests, trying to reach a sufficiently low level of plant pixels misinterpreted as background. The opposite is not so harmful, because the final classification will most often recognize the background correctly. No filtering was applied to the images before the excess green check.

Fig. 1. Results from automatic segmentation of a sample image containing oat and TAROF leaves. Top: Original image. Bottom: Segmented image.

Segmentation for the extraction of leaf forms was also attempted. Several approaches to image segmentation have been suggested in the literature—for reviews, see e.g. Pal and Pal (1993), Russ (2011) and Sonka et al. (2008). The two main alternatives are region-based and edge-based segmentation, of which the former concentrates on local similarity of the pixels, whereas the latter looks for local changes of the image content. Region-based segmentation can proceed top-down (split), bottom-up (merge), or as a combination of these two. The edge approach is based on the gradient magnitudes of luminance or colour values at different points of the image. Edge detection, though straightforward, suffers from the problem of fragmented, non-closed edges, i.e. unconnected gaps usually remain on the borders of the true segments. In this work, the region-based, bottom-up approach to segmentation was applied in order to produce tentative segments that might be usable for classification.

Bottom-up region expansion into segments was performed by starting from a set of selected *seed* points, cf. (Adams and Bischof, 1994), and extending the related regions pixel by pixel, as long as there were neighbours satisfying both the excess green condition and a homogeneity condition. As for the homogeneity of pixel values in the segments, a threshold was set for the allowed maximum of colour channel distances between the compared pixels:

$$\max(|R_o - R_c|, |G_o - G_c|, |B_o - B_c|) < threshold_3$$

Value 11 for $threshold_3$ was experimentally found to work well. Index *o* refers to the seed pixel and index *c* to the new candidate