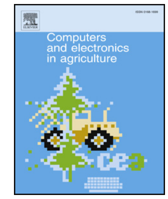
Computers and Electronics in Agriculture 153 (2018) 347–356

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag



Original papers

Improving efficiency of organic farming by using a deep learning classification approach

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A R T I C L E I N F O

Keywords:
Vision based measurement (VBM)
Convolution Neural Network (CNN)
Deep learning
Visual sensors
Colour room processing
Random forest classifier

A B S T R A C T

In this paper, an environmentally friendly non-chemical variant of weed control in organic farming is shown. The main topic is placed on the image processing steps. Therefore, the segmentation and the classification of the individual plants are described in detail. The first step in the vision-based measurement applications after capturing the image is to separate the wanted objects from their surroundings. The presented segmentation algorithm uses pure RGB images to separate the background. A dice score of more than 96% is calculated. However, the biggest problem with this project is to distinguish the individual classes of plants in real-time using the visual sensor data, as they are very similar in the early stages of growth. This project derives its data and measured variables from real data from the field and not from laboratory conditions. Therefore, disturbances such as the influences of, for example, weather, the various stages of growth, the large number of different weeds, the different soil conditions, etc. are also used here. In order to compensate for these disturbances, a self-learning convolutional neural network was used for the classification. This deep-learning approach achieves accuracies of over 98%.

1. Introduction

The increasing computing power in recent years allows more complex algorithms for the implementation of adaptive artificial intelligence. Deep Learning is one approach for adaptive intelligence. For the task of pattern recognition the family of Convolution Neural Networks (CNNs) are applied. The best example is the image classification. Here CNNs are used for classifying 1000 different objects in one picture (Krizhevsky et al., 2012). In addition these networks are used for example for autonomous driving. These networks learn how to behave on the street and also the recognition of the road signs (Jung et al., 2016; Li et al., 2017). Another application is the detection of human faces (Chen et al., 2016) and their emotions. The CNNs are also used as an interface between humans and robots (Liu et al., 2016). CNNs can even be trained to calculate the calories in a meal. The user only has to make an image of his meal with a smartphone (Pouladzadeh et al., 2016). Another use of the CNNs are to recognize emotions in audio data or images (Zhang et al., 2016), to predict the generation of electricity by wind power plants (Ak et al., 2016) or for the profiling of passenger data (Zheng et al., 2017). The first CNN worked for optical character recognition (OCR). Chen has developed networks with an accuracy of about 98% (Chen et al., 2015). In this paper a CNN is used for detecting carrots and weeds in organic farming.

The increase of plant earnings (food or energy plants) with simultaneous consideration of the protection of the environment will be a global task in the future. The manual weed control, used in organic farming, without chemical or synthetical agricultural pesticides is one way to protect our environment. Manual weed elimination is very expensive. Our cooperation partner *Westhof Bio* in Germany for example, spends over 170,000 EUR per year for the manual weed elimination by human worker. Furthermore it becomes more difficult to find human workers for this task. Hence the need for research for automated non-chemical weed control systems is very large. But up to now no commercial system is available.

There are non-chemical physical weed control systems (Gobor and Schulze Lammers, 2006; Melander, 2006; Rueda-Ayala et al., 2010; van der Weide et al., 2008), which can successfully remove weed between plant rows like the Multiplatform-Robot (BoniRob) shown in Fig. 1 However they cannot remove the weed close to the plants (see Fig. 2), which is a very challenging task (Nørremark and Griepentrog, 2004). This project has the task of detecting the weeds within the rows of crops and possibly removing them. There are some companies offering products for the destruction of the bees between the cultivars. Also, there are first machines that are only suitable for crops that are seeded with a well-defined distance, or have a coarse easy-to-classify structure such as cabbage or corn. However, the project presented here aims to classify

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https://doi.org/10.1016/j.compag.2018.08.032
Received 3 April 2018; Received in revised form 29 July 2018; Accepted 26 August 2018
0168-1699/

Fig. 1. Bonirob on the field of the Westhof Bio in Germany.

Fig. 2. Weed and carrot plants on a field of the Westhof Bio in Germany.

crops that are applied randomly and, moreover, also have a weed-like structure. This means that they can hardly distinguish the crop from the weed. Neither through the place nor through the structure. There has been no solution to this problem so far.

Some researchers are developing laser-based weed control systems for the "close-to-plant" weed control (Gude et al., 2010). But a commercial prototype is still not available. In the majority of cases optical measurement systems (Vrindts and De Baerdemaeker, 1997) (Biller et al., 1997) are used for the close-to-plant detection of weeds. These systems can measure the spectral reflection of plants and soil. As soil and plants have different reflections it is now possible to distinguish both. Furthermore optical measurement systems exits which can also differentiate different plants (Pérez et al., 2000; Yang et al., 2003; Sogaard and Olsen, 2003).

To give an overview of how we designed and build up the proposed optical measurement system for organic farming, the following research steps are listed in chronological order. At the beginning of our research we investigated different plant stem emerging point search algorithms to successful remove the weed (Knoll et al., 2016a). In Knoll et al. (2016b) we investigated the pros and cons of available visual sensors. In Knoll et al. (2016c), we presented the first research results of two RGB vegetation index determination methods, which are used in this manuscript as well. These two methods don't need expensive and sensitive bi-spectral cameras. In this paper we have extended the theoretical and the experimental section of the two RGB vegetation index determination methods, see section II. Furthermore we used the dice score (Dice, 1945) to compare the segmentation results of the proposed methods and the state-of-the-art vegetation index method (Haug et al., 2014) with the ground truth. However the main contribution of this paper as mentioned before is the comparison of three proposed CNNs for classifying plants and weed in organic farming. The presented Convolution Neural Networks achieve a higher degree of accuracy compared to the state of the art random forest classifier (Haug et al., 2014).

2. RGB vegetation index methods

The harsh environment on a field requires robust sensor systems. The mechanical setup of bi-spectral cameras is more sensitive compared to standard RGB-colour cameras. Hence standard RGB-cameras are more suitable for organic farming applications. Furthermore they are cheaper and better available, as a wide range of RGB cameras exist on the market. Hence not only the robustness is better but also the total system costs decrease. This is an important feature as the acceptance of the organic farmer for such systems are only given if the price is much lower than the costs for manual weeding. As already mentioned in Knoll et al. (2016b) there is a list of pros and cons of the different visual sensors used in the field and for the classification.

The next step for the classification is to separate the plants from the background. There are different procedures like the state-of-the-art vegetation index method (Haug et al., 2014) and our developed HSV- and RGB-algorithm (Knoll et al., 2016c). The separation of the plants from the background allows the classifier to examine only the important plant pixels in the image. This approach therefore saves time for the classification of a whole picture. In the following section we only describe the developed HSV-algorithm from Knoll et al. (2016c) as it achieves a better score as the RGB-algorithm. However in this paper we derive Eq. (19) in detail, which can calculate an S-image using only the RGB-colour room. Hence we have developed a new very simple and efficient vegetation index method.

2.1. HSV-colour room vegetation index method

The proposed workflow of the new vegetation index method is shown in Fig. 3. In the first step, the captured RGB image is transformed into the HSV colour room. The HSV room is a colour room which does not represent the colours using the three complementary colours red, green and blue as the RGB colour room. It uses the colours with the three vectors *H* for *Hue*, *S* for *Saturation* and *V* for *Value* which stands for the brightness. Eq. (1) can be derived via a mathematical derivation of the flowchart in Fig. 3.

For the RGB-image $\psi(x, y)$ the following mathematical transformation is applied. The transformation has to be done for every pixel.

$$V(x, y) = MAX(x, y) := \max\left(\frac{\psi_{\text{Red}}(x, y)}{255}, \frac{\psi_{\text{Green}}(x, y)}{255}, \frac{\psi_{\text{Blue}}(x, y)}{255}\right) \tag{1}$$

An auxiliary variable is needed to form an easier equation.

$$MIN(x, y) := \min\left(\frac{\psi_{Red}(x, y)}{255}, \frac{\psi_{Green}(x, y)}{255}, \frac{\psi_{Blue}(x, y)}{255}\right) \tag{2}$$

$$S(x, y)' := \begin{cases} \frac{MAX(x, y) - MIN(x, y)}{MAX(x, y)} & \text{if } MAX(x, y) \neq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

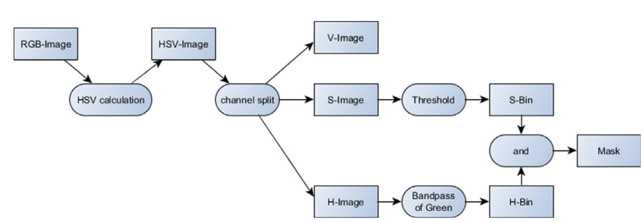

Fig. 3. Workflow of the first alternative vegetation index determination method based on HSV-color room processing.