Int J Appl Earth Obs Geoinformation 67 (2018) 43–53

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

Fusion of pixel and object-based features for weed mapping using unmanned aerial vehicle imagery

Junfeng Gao[a], Wenzhi Liao[b], David Nuyttens[c], Peter Lootens[d], Jürgen Vangeyte[c], Aleksandra Pižurica[b], Yong He[e,*], Jan G. Pieters[a]

[a] Department of Biosystems Engineering, Ghent University, Coupure Links 653, 9000 Ghent, Belgium
[b] Department of Telecommunications and Information Processing, IMEC-TELIN-Ghent University, Sint-Pietersnieuwstraat 41, 9000 Gent, Belgium
[c] Technology and Food Science Unit, ILVO, Burg. Van Gansberghelaan 115, 9820 Merelbeke, Belgium
[d] Plant Sciences Unit, ILVO, Caritasstraat 39, 9090 Melle, Belgium
[e] College of Biosystems Engineering and Food Science, Zhejiang University, Yuhangtang Road 866, 310058 Hangzhou, China

A R T I C L E I N F O

Keywords:
UAVs
Inter- and intra-row weed detection
Feature fusion
OBIA
Random forests
Hyperparameter tuning
Feature evaluation

A B S T R A C T

The developments in the use of unmanned aerial vehicles (UAVs) and advanced imaging sensors provide new opportunities for ultra-high resolution (e.g., less than a 10 cm ground sampling distance (GSD)) crop field monitoring and mapping in precision agriculture applications. In this study, we developed a strategy for inter- and intra-row weed detection in early season maize fields from aerial visual imagery. More specifically, the Hough transform algorithm (HT) was applied to the orthomosaicked images for inter-row weed detection. A semi-automatic Object-Based Image Analysis (OBIA) procedure was developed with Random Forests (RF) combined with feature selection techniques to classify soil, weeds and maize. Furthermore, the two binary weed masks generated from HT and OBIA were fused for accurate binary weed image. The developed RF classifier was evaluated by 5-fold cross validation, and it obtained an overall accuracy of 0.945, and Kappa value of 0.912. Finally, the relationship of detected weeds and their ground truth densities was quantified by a fitted linear model with a coefficient of determination of 0.895 and a root mean square error of 0.026. Besides, the importance of input features was evaluated, and it was found that the ratio of vegetation length and width was the most significant feature for the classification model. Overall, our approach can yield a satisfactory weed map, and we expect that the obtained accurate and timely weed map from UAV imagery will be applicable to realize site-specific weed management (SSWM) in early season crop fields for reducing spraying non-selective herbicides and costs.

1. Introduction

Under natural growing conditions, weeds generally emerge in crop fields. On a global scale, they cause the highest production loss (34%) followed by animal pests (18%) and pathogens (16%) (Oerke, 2006). Therefore, weed control is a crucial measure for crop production management. The most common ways for controlling weeds are mechanical and chemical approaches (Christensen et al., 2009). Herbicides are the dominant choice for weed control in modern agriculture (Harker and O'Donovan, 2013). However, the overuse of herbicides results in the evolution of herbicide-resistant weeds and poses a heavy pollution threat to the environment (Shaner and Beckie, 2014). Site specific weed management (SSWM) refers to the spatially variable application of a weed control strategy rather than spraying herbicides in the whole field (Burgos-artizzu et al., 2011) which enables to minimize herbicide usage and thereby potentially reduces the adverse effects on environment and ecosystem. However, one of the important and challenging components of SSWM is weed recognition and field mapping for an appropriate early automatic weed control (Shaner and Beckie, 2014).

In most weed control approaches including SSWM, it is generally accepted to control weeds at the early season of the crop (López-Granados, 2011). However, the reflectance characteristics of crops and weeds are generally similar in their early growth stages, thus imposing additional difficulties to discriminate between them (López-Granados, 2011; Perez-Ortiz et al., 2016). Moreover, weeds can grow in small patches in the early season, which also adds challenges and requires high resolution imagery to detect them. Broadly, there are three conventional platform options for automatic detection of weeds from crops and soil background: aerial, satellite-based, and ground-based

* Corresponding author.
E-mail addresses: yhe@zju.edu.cn, zjuheyong@sina.com (Y. He).

https://doi.org/10.1016/j.jag.2017.12.012
Received 10 October 2017; Received in revised form 24 December 2017; Accepted 24 December 2017

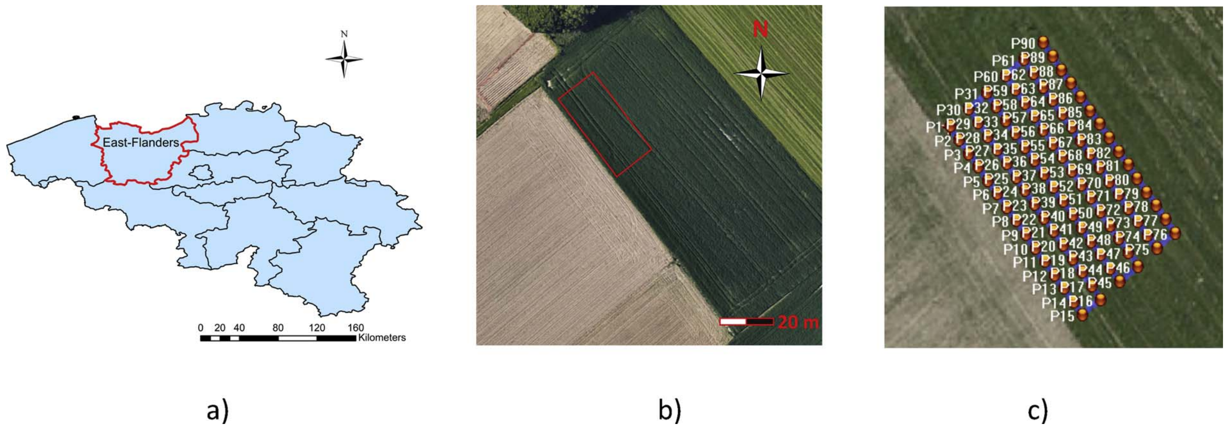

Fig. 1. Study area location. (a) the position of East-Flanders in Belgium, (b) the designed area for study, imagery from 2017 Google Map data, (c) the waypoints of our study area.

platforms. A ground-based vehicle is a common platform to perform field study in agriculture and both imaging and non-imaging sensors could be developed and applied using this platform (Kazmi et al., 2015a; Shapira et al., 2013; Wang et al., 2000). Furthermore, a series of unmanned ground vehicles (UGVs) have been developed and have been tested for online weed detection and control (Bak and Jakobsen, 2004; Bakker et al., 2010; Slaughter et al., 2008). However, with this kind of platform, it is difficult to provide a global view of fields and it requires a robust weed and crop discrimination model as well as powerful hardware assistance. In terms of satellite platforms, previous works (Castillejo-González et al., 2014; De Castro et al., 2013) have studied the use of multi-spectral QuickBird satellite imagery with a spatial resolution of 2.4 m for broad- and field-level weed mapping in winter wheat fields, but the spatial resolution from this platform was insufficient to detect small weed patches in early season (Perez-Ortiz et al., 2016). concern all above factors, a high resolution imagery from an unmanned airborne platform is highly demanded for seedling detection.

Recently, applications of remote sensing using UAVs have shown great promise in precision agriculture as they can be equipped with various imaging sensors to collect high spatial, spectral, and temporal resolution imagery (Du and Noguchi, 2017; Rasmussen et al., 2013). The advantages of their low cost and high flexibility in flight scheduling make them popular for field studies. Concerning UAV-based remote sensing, Object-based Image Analysis (OBIA) is a common methodology in classifying objects. The OBIA first identifies spectrally and spatially homogenous objects according to its segmentation results and then it combines spectral, textural and geometry information from objects to boost classification results (Blaschke, 2010). Previous studies (Borra-Serrano et al., 2015; Peña et al., 2015, 2014, 2013; Peña-Barragán et al., 2010; Perez-Ortiz et al., 2016) about OBIA in precision agriculture investigated for instance crop classification and weed detection by using UAV imagery. Despite recent efforts and progress made, additional work is still required in improving weed map accuracy and robustness to overcome complex agricultural conditions. When considering a real situation of weed detection in row crop fields, crop rows are particularly useful for assisting inter-row weed detection by image analysis (Jones et al., 2009). One of the main advantages of this detection strategy is its relative robustness but it fails to detect intra-row weeds. Comparatively, OBIA has potential to detect weeds regardless of their distribution, while it heavily relies on effective extracted features and has the chance to classify inter-row weeds incorrectly. To the best of our knowledge, no studies have attempted to combine crop row detection based on pixel features and OBIA for weed mapping in UAV imagery.

In our study, an early season maize field with multiple economically important weed species was surveyed by the UAV equipped with a visual camera. We propose an approach to combine conventional crop-row detection algorithms and OBIA for accurate and robust weed mapping by fusing pixel and object-based features. The specific objectives of this research are (1) to develop a pipeline for processing low-altitude, high-resolution aerial UAV imagery; (2) to explore and determine the important features for discrimination of weed and maize plants; (3) to demonstrate the feasibility of fusion pixel and object-based features for accurate weed mapping in the early growth stage of maize. The proposed approach aims at weed detection in the early maize growth stage, specifically, from Zadoks scale 12–14 (Zadoks et al., 1974).

2. Materials and methods

2.1. Site and field measurements

The study was conducted at the experimental fields of the Institute for Agricultural and Fisheries Research (ILVO) in the agricultural region of Merelbeke, which is located in East-Flanders Province, Belgium. The area of the maize plot was about 150 m^2. The naturally infested weed species in the maize plot included bindweeds (*Convolvulus*), lamb's quarters (*Chenopodium album*) and crabgrass (*Digitaria sanguinalis*) species. The seeds of maize (MESSAGO) were automatically sowed on July 7th, 2016. After two weeks on July 18th, the maize emerged and most of them had 2 unfolded leaves (Zadoks scale 12). On that day which was cloudy with 14.8 km/h wind speed, a 12 coaxial rotors UAV (Hydra-12 Onyxstar, Mikrokopter, Germany) shown in Fig. 2, which was equipped with a lightweight visual camera (Sony Alpha 6000, Sony, Japan), was used to collect aerial imagery with 2.5 m/s flight speed at an altitude of 20 m above ground. The overlapping rates of imagery in side and forward direction were both 80%. The flight pattern (Fig. 1c) used 2 m distance of two points in length (15 points) direction and 3 m distance for width direction (6 points). The specific parameters of the camera setting are listed in Table 1.

2.2. Pixel-based crop row detection

The main two processes in our study are pixel-based row detection and OBIA. Each module follows a series of different processing techniques. The flowchart of our methodology is depicted in Fig. 3.

2.2.1. Segmentation of vegetation and soil background

First, aerial images were imported to the Agisoft PhotoScan v1.2.3 (Agisoft LLC, St. Peterburg, Russia) for mosaicking and orthorectifying. General steps for processing aerial images in PhotoScan include photo alignment, dense cloud building, 3D mesh building, texture building, digital elevation model building and orthomosaic photo generation. In our case, we set high accuracy and 4000 key points limited for photo alignment. The blending mode was set as mosaic for generating