Weed Detection Dataset with RGB Images Taken Under Variable Light Conditions

Conference Paper · September 2017

DOI: 10.1007/978-3-319-67597-8_11

4 authors:

Petre Lameski
Ss. Cyril and Methodius University in Skopje
102 PUBLICATIONS **926** CITATIONS

Eftim Zdravevski
Ss. Cyril and Methodius University in Skopje
157 PUBLICATIONS **1,426** CITATIONS

Vladimir Trajkovik
Ss. Cyril and Methodius University in Skopje
275 PUBLICATIONS **1,420** CITATIONS

Andrea Kulakov
Ss. Cyril and Methodius University in Skopje Macedonia
85 PUBLICATIONS **762** CITATIONS

Weed detection dataset with RGB images taken under variable light conditions

Petre Lameski, Eftim Zdravevski, Vladimir Trajkovik, and Andrea Kulakov

Faculty of Computer Science and Engineering,
University of Sts. Cyril and Methodius in Skopje, Macedonia,
Ruger Boskovik 16, 1000 Skopje, Macedonia

Abstract. Weed detection from images has received a great interest from scientific communities in recent years. However, there are only a few available datasets that can be used for weed detection from unmanned and other ground vehicles and systems. In this paper we present a new dataset (i.e. Carrot-Weed) for weed detection taken under variable light conditions. The dataset contains RGB images from young carrot seedlings taken during the period of February in the area around Negotino, Republic of Macedonia. We performed initial analysis of the dataset and report the initial results, obtained using convolutional neural network architectures.

Key words: dataset, weed detection, machine learning, signal processing, precision agriculture

1 Introduction

The automation of the agricultural food production is gaining in popularity in the scientific communities and in the industry. The main goal of the automation is to reach the agricultural food demand growth, which currently is lower than the growth of the agricultural food production [1]. The automation in agriculture could be increased by introduction of unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) that can monitor the growth of the crops and automatically react if some factors, such as water shortage, weed or insect infestation or plant illness, is detected. The introduction of robotic systems in the agricultural food or resource production is proven to increase the crops yield per land-unit [2]. There are quite a few challenges that need to be overcome to have a fully automated solution that can be used in the industry. One of the challenges is the sensing of weeds in the fields under variable light conditions from simple RGB images. While multi-spectral solutions have been applied for plant-weed segmentation and other agricultural tasks [3, 4, 5], multi-spectral cameras are still too expensive for small farmers. This introduces the need for an efficient and robust system for weed and other anomaly detection based on RGB cameras that would be more affordable for small farmers.

In this paper we present the Carrot-Weed dataset, containing RGB images of young carrot seedlings taken during the period of February in the area around

Negotino, Republic of Macedonia. It can be used for evaluating and benchmarking algorithms for crop-weed segmentation and weed detection by building machine learning and deep-learning models. The Carrot-Weed dataset is publicly available on `https://github.com/lameski/rgbweeddetection`, and the results of our initial analysis of the dataset are presented in this paper.

In Section 2 we overview some of the existing datasets for weed detection in the literature. Then, in Section 3 we describe the process of generating the dataset, the the characteristics of the dataset. After that, in Section 4, we provide some initial results obtained by using segmentation with convolutional neural networks, and finally in Section 5, we conclude the paper and discuss some ideas for future work.

2 Related work

There are several available datasets for weed detection. The dataset presented in [6] is a crop-weed segmentation dataset with images taken under constant light conditions with Near Infrared (NIR) and Red (R) channels. Authors in [7] describe a dataset that is also taken with constant light conditions and with RGB+NIR images. In [8] authors automatically generate the weed detection dataset based on 3D models of the plants and use them to train weed detection algorithms. Although there are only a few publicly available datasets for weed detection, there more datasets for plant detection and recognition. For example, in [9] a dataset obtained from Pl@ntNet [10] is used for plant identification task in the LifeClef competition. Other datasets exist for plant identification, such as the leaf shape dataset presented in [11], where the images of the segmented leaf contours of 100 different plants are provided for the task of plant classification based on the contours and a set of previously calculated descriptors for each image.

In this paper we describe the Carrot-Weed dataset that is obtained under natural variable light conditions from RGB camera, which is the main difference from other datasets. In general, the variable light conditions and using a common RGB camera instead of NIR or RGB+NIR cameras should make the segmentation and weed detection tasks more difficult. In the next section, the method that was used to obtain and annotate the dataset is described and some statistics for the dataset are presented.

3 Weed detection dataset

The dataset contains RGB images taken from approximately 1m height. The images are taken using a cell phone camera with 10 mega pixels. After the initial acquisition, the images are processed so that the masks for the weeds, carrot (plant) and ground are generated. Several example images from the dataset are presented in Figure 1. The variable light conditions can be observed from the presented images.

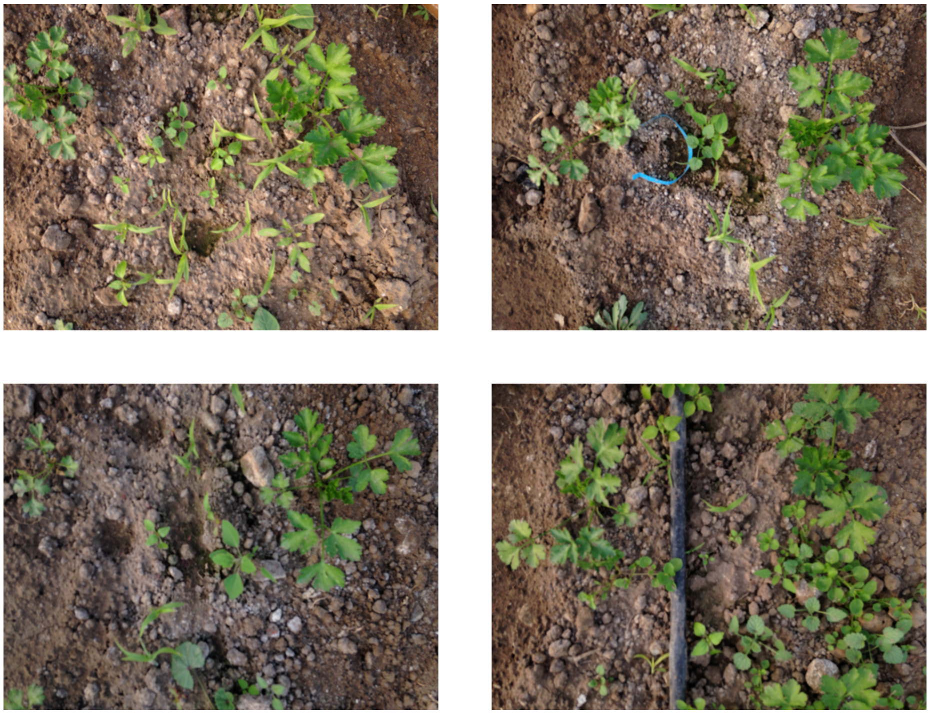

Fig. 1. Example images from the dataset

In the first step, aiming to initially separate the vegetation pixels from the ground pixels, vegetation indices are generated. The ExGExR [12] index was used to perform the initial vegetation segmentation. The ExG (Excess Green) index is calculated using (2). The ExG index, proposed in [13], gives the difference between the detected light values of green channel and the red and blue channels. Prior to calculating the ExG index, the R (Red), G (Green) and B (Blue) channel values in the images are normalized using (1). The normalization is performed to reduce the influence of the different lighting conditions to the color channels. The result of this normalization is shown in Figure 2.

$$r = \frac{R}{255}, g = \frac{G}{255}, b = \frac{B}{255} \tag{1}$$

$$ExG = 2g - r - b \tag{2}$$

$$ExR = 1.4r - b \tag{3}$$

$$ExGExR = ExG - ExR \tag{4}$$

Using the ExG index for segmentation the vegetation pixels from the ground or other object pixels in the images yields good results. The ExGExR index,

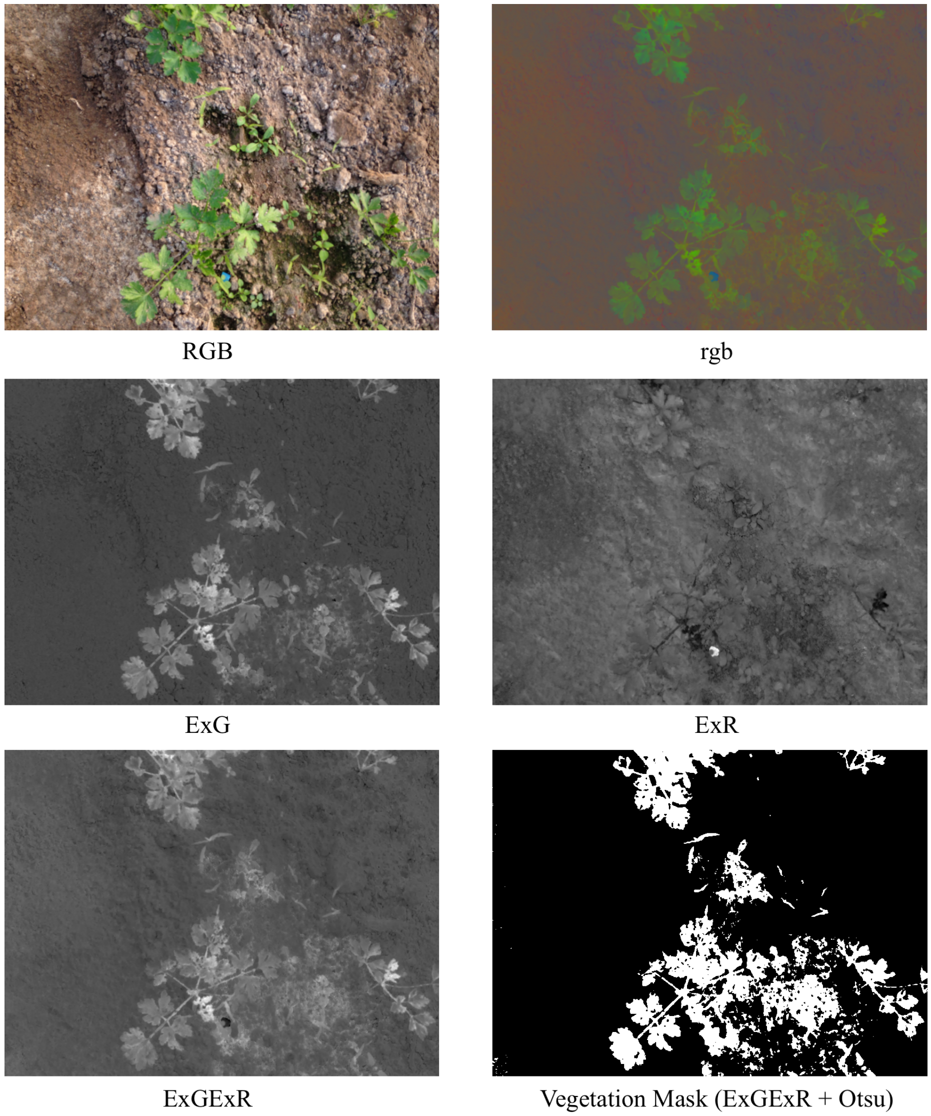

Fig. 2. Example (RGB) image from the dataset, normalized (RGB) image, ExG result image, ExR result image, ExGExR result image and Vegetation Mask obtained using ExGExR + Otsu

calculated with (4), improves the detection. Prior to its calculation, the ExR [12] index is calculated with (3).

A normalized gray-scale representation of the ExG and ExGExR images is presented in Figure 2. One of the best perks of these indices is that after their calculation, the Otsu algorithm for automatic threshold calculation [14], can be applied to segment the vegetation pixels from the other pixels in the image. The combination of the ExGExR index and the Otsu thresholding of the obtained image, yields a good result when used for segmentation of the vegetation pixels. An example of a segmented image using the described approach is presented in Figure 3.

After the initial segmentation, morphological operations are applied on the resulting vegetation mask, such as opening and closure, to reduce the noisy mask pixels and fill in the empty parts of the leaves. Finally, the resulting masks are manually inspected and amended to obtain the final dataset masks.

An exemplary image, along with its mask, is shown in Figure 3. Later, the segmentation of the weed and plant pixels of the images is performed by modifying the mask pixels that belong to the plant. The resulting mask has values 0 for the ground pixels, 1 for the weed pixels and 2 for the carrot plant pixels, which can be used for evaluating segmentation algorithms. In Figure 3, for visualization purposes the pixels are represented with values of 50 and 100 instead of 1 and 2, respectively.

Fig. 3. Example image with its annotation. The ground is colored black, the weeds are colored with dark gray and the useful plant (the carrot) is colored in light gray

The dataset contains 39 images with the same size of 3264×2448. Since the image sizes are large, the dataset can be split to smaller images using a sliding window approach.

The dataset consists of $311,620,608$ pixels from which $26,616,081$ carrot plant pixels, $18,503,308$ weed plant pixels and $266,501,219$ ground pixels.

In the dataset there are more pixels of carrot plants than of weed plants. In addition to the imbalanced dataset, the weed infestation in the images is quite large and there is high overlap between the weed plants and the carrot plants, making the weed segmentation task very challenging. Most of the classification algorithms would require a balanced distribution of each classes in order to successfully train the classification model. In this paper, the benchmark results of the pixel classification are obtained by a semantic segmentation approach that uses convolutional neural networks. This approach and its application on the dataset is described in the next section.

4 Initial experiments and results

We performed initial experiments on the dataset using the SegNet [15] convolutional architecture for semantic segmentation. Other classification approaches to classify patches of the image as weed, plant or land, would require to first segment the weed, plant and land patches from the image. Having these segments would have already solved the problem of weed detection in the image, unless we are interested in detecting different types of weeds.

The SegNet architecture uses a combination of convolutional and deconvolutional layers that allow semantic segmentation of the image. We modified the proposed architecture so that it recognizes only three classes: weed, plant and ground, which are presented using the manually performed annotations in the dataset with the pixel labels 1, 2 and 0 respectively.

Since the dataset was obtained under variable light conditions, we built models using the original RGB images and also using the same images converted to the Lab and HSV color-spaces. The Lab color-space transforms the RGB colors in such way that when compared in distance, it gives smaller distances for similar colors and larger distances for different colors, when observed by a human eye. The HSV color space presents the colors as a degree in a circle using the H value. The V value represents the light value of the pixel. These color spaces give good results for object classification and HSV is also used in [16] for plant pixels detection in combination with other parameters. We used these transformations motivated by their successful application in other approaches for both object recognition tasks and segmentation tasks.

Due to the large size of the images, we used a sliding window approach with size of 256×256 to obtain image patches that can be used in the SegNet architecture. For training purposes, we introduced additional limitation that considers patches for the training set only if they contain at least 5% of plant pixels and 5% of weed pixels. This reduced the available patches, but was expected to make the training model to converge faster. This expectation, however was only based on experimental observation and was not measured.

Further, we experimented with two scenarios. In the first scenario, we only used one randomly selected image for the training and the rest of the images for testing. In the second scenario, we used the leave-one-image-out approach for training and testing. The initially obtained results are presented in Table 1.

Similar results were also reported in [8] when using SegNet for plant/weed segmentation from RGB images. It can be observed that SegNet over-fits on the data because the trained model, when tested on the training data, fit the data successfully with over 95% correctly segmented pixels.

As it can be observed from the results, even tough we expected the Lab and HSV color spaces to improve the segmentation accuracy, this was not the case. The usage of the HSV and Lab transformations did not improve the accuracy, but

Table 1. Results obtained with RGB, HSV and Lab conversion of the dataset using 1 image for train and 38 for test and 38 for train and one image for test

(train / test) and Type	Vegetation, Land	Weed, Plant, Land
SegNet (1/38) RGB	0.694	0.590
SegNet (1/38) HSV	0.429	0.481
SegNet (1/38) Lab	0.534	0.521
SegNet (38/1) RGB	0.713	0.641
SegNet (38/1) HSV	0.601	0.609
SegNet (38/1) Lab	0.71	0.630

instead resulted in similar or even worse accuracy compared to using unmodified RGB images.

5 Conclusion and future work

In this paper we presented the Carot-Weed dataset for weed detection and segmentation using RGB images. The dataset contains 39 images taken from approximate height of 1m with 10 MP camera under variable lighting conditions.

The dataset is a good starting point for initial development of machine vision algorithms for weed segmentation or weed detection from RGB images and is one of the rarely available public datasets for weed detection in plant images taken from close proximity. The initial results are promising and give good directions for further development of algorithms for weed detection.

The convolutional neural network approach used in the experiments reported in this paper could be modified and further simplified in order to avoid the reported over-fitting on the data.

Further research is needed to design an adequate deep learning architecture that could be successfully applied for the purpose of weed detection from RGB images. Some conventional approaches, such as unsupervised segmentation and patch classification should also be investigated.

A model with a good weed detection accuracy from RGB images could pave the way to a cheap and robust weed detection sensor that could be used by both farmers with large plantations and also small farmers that cannot afford the significantly more expensive multi-spectral recording equipment.

Acknowledgments

The work presented in this paper was partially financed by the University of Sts. Cyril and Methodius in Skopje, Macedonia, Faculty of Computer Science and Engineering.

References

1. Ray, D.K., Mueller, N.D., West, P.C., Foley, J.A.: Yield trends are insufficient to double global crop production by 2050. PloS one **8**(6) (2013) e66428
2. Cosmin, P.: Adoption of artificial intelligence in agriculture. Bulletin of University of Agricultural Sciences and Veterinary Medicine Cluj-Napoca. Agriculture **68**(1) (2011)
3. Mulla, D.J.: Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems Engineering **114**(4) (2013) 358 – 371 Special Issue: Sensing Technologies for Sustainable Agriculture.
4. de Castro, A.I., Jurado-Expósito, M., Peña-Barragán, J.M., López-Granados, F.: Airborne multi-spectral imagery for mapping cruciferous weeds in cereal and legume crops. Precision Agriculture **13**(3) (2012) 302–321
5. Torres-Sánchez, J., López-Granados, F., De Castro, A.I., Peña-Barragán, J.M.: Configuration and specifications of an unmanned aerial vehicle (uav) for early site specific weed management. PLOS ONE **8**(3) (03 2013) 1–15
6. Haug, S., Ostermann, J.: A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks. In: Computer Vision - ECCV 2014 Workshops. (2015) 105–116
7. Potena, C., Pretto, A., Nardi, D.: Fast and accurate crop and weed identification with summarized train sets for precision agriculture. In: IAS, IAS (2016)
8. Di Cicco, M., Potena, C., Grisetti, G., Pretto, A.: Automatic model based dataset generation for fast and accurate crop and weeds detection. arXiv preprint arXiv:1612.03019 (2016)
9. Goëau, H., Joly, A., Bonnet, P., Selmi, S., Molino, J.F., Barthélémy, D., Boujemaa, N.: Lifeclef plant identification task 2014. In: CLEF2014 Working Notes. Working Notes for CLEF 2014 Conference, Sheffield, UK, September 15-18, 2014, CEUR-WS (2014) 598–615
10. Barthélémy, D., Boujemaa, N., Mathieu, D., Molino, J., Bonnet, P., Enficiaud, R., Mouysset, E., Couteron, P.: The pl@ ntnet project: A computational plant identification and collaborative information system. In: Technical report, XIII World Forestry Congress. (2009)
11. Mallah, C., Cope, J., Orwell, J.: Plant leaf classification using probabilistic integration of shape, texture and margin features. Signal Processing, Pattern Recognition and Applications **5** (2013) 1
12. Meyer, G.E., Neto, J.C.: Verification of color vegetation indices for automated crop imaging applications. Computers and Electronics in Agriculture **63**(2) (2008) 282–293
13. Woebbecke, D., Meyer, G., Von Bargen, K., Mortensen, D., et al.: Color indices for weed identification under various soil, residue, and lighting conditions. Transactions of the ASAE-American Society of Agricultural Engineers **38**(1) (1995) 259–270
14. Otsu, N.: A threshold selection method from gray-level histograms. IEEE Transactions on systems, man, and cybernetics **9**(1) (1979) 62–66
15. Badrinarayanan, V., Kendall, A., Cipolla, R.: Segnet: A deep convolutional encoder-decoder architecture for image segmentation. arXiv preprint arXiv:1511.00561 (2015)
16. Moorthy, S., Boigelot, B., Mercatoris, B.: Effective segmentation of green vegetation for resource-constrained real-time applications. In: Precision agriculture'15. Wageningen Academic Publishers (2015) 93–98