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Cloud based Data Acquisition and Annotation Architecture for Weed Control

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Cloud based Data Acquisition and Annotation Architecture for Weed Control

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Abstract—In this paper we present a short evaluation of a cloud based architecture for data acquisition and annotation. We evaluate the implemented system for annotation and give initial results on the ability of the system to produce accurate labels on the data. The used data is consisted of plant field images. The users partially annotate the data and we use segmentation algorithms for enriching the annotation of the images. We compare three different segmentation algorithms used for the annotation. The results show that Grabcut algorithm is better than Watershed and nearest-neighbor approaches, but there is still room for improvement.

Index Terms—weed control, image processing, data acquisition, data annotation, data segmentation

I. INTRODUCTION

The novel algorithms for classification and segmentation in Machine Vision need large amount of data to generate models with substantial classification performance. While deep learning algorithms are very good at extracting information from unannotated data using unsupervised learning methods [1], there is still need for annotated data, especially in niche domains where such data does not exist. The image annotation is a well established research domain and there are quite a few examples in the literature [2].

One of the ways to boost the process of labeling data is to use crowd sourcing [3], however for niche domains, such plant species recognition or weed detection, such approach could not be quite applicable since it is difficult by untrained people to sometimes distinguish different plants. This can also be overcome by using artificial models of the plants which gives good results when building models using deep learning [4]. In agricultural environment there are differences between some types of plants based on their geographic location and the used seeds, resulting in non-standardized types, especially for individual and small scale farmers. For this reason, a platform for image data annotation from plants is needed to resolve the lack of annotated data for different plant phenotypes, especially for resolving the problem of detecting weeds in plantations.

In this paper we present an architecture for data annotation that uses cloud based processing. The expert is able to manually select parts of the plants that need to be annotated and segmentation algorithms are used for inferring the rest of the plants. We present the results of several conventional algorithms for manual or semi-automated segmentation and give conclusion and future directions for the system development.

The paper is organized as follows. In Section II, we describe the used algorithms for segmentation and the used architecture and in Section III, we present the obtained results and give a short conclude the paper.

II. METHODS

The general architecture of a weed control system is presented in [5]. In this paper we describe in more detail the module of the architecture that is used for data annotation. The general flow is already described in the previous work, so the focus of this paper is on the annotation problem, proposing several methods for resolving the data annotation. An example input image and the user selection are depicted in Figure 1. The images are taken from the dataset described in [6].

We use three different segmentation algorithms to enrich the dataset. The first algorithm is one of the most used algorithms for semi-automated segmentation of images, Grabcut [7]. The algorithm uses the user input to initialize the foreground and background regions and can be applied for both plant and weed segmentation. We use foreground-background segmentation of the plant pixels by defining as certain background all markings from the weed and the ground and define as certain foreground only the plant markings. For weed detection we repeat the process, while considering the weed markings as foreground, and plant and ground as background. We use similar approach for the other two segmentation algorithms, Watershed [8] and a nearest-neighbor based segmentation that uses only the users input to generate the pixel distribution for foreground and background segmentation. In this case we use the K-D tree [9] approach to search for the nearest neighbor pixel in each of the classes.

III. RESULTS AND CONCLUSION

Based on the performed experiments using the dataset the best results were obtained with Grabcut. The Watershed algorithm was too restrictive and failed to identify other plant pixels than the ones that were marked by the user, and the K-D tree based search was too inclusive. The plant and weed

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Fig. 1. User selection from plant image, different color lines annotate different parts: weed, useful plant and ground



Fig. 2. Segmentation result using Grabcut

pixels are too similar in color so the K-D tree search included most of the weed pixels when searching for plant pixels and vice versa. The results obtained from the Grabcut algorithm are depicted in Figure 2. As it can be observed, the Grabcut algorithm successfully identifies most of the target pixels. It also includes some of the ground pixels in the vicinity of the plant images, but for some of the classification algorithms this would not be a problem, especially if we are targeting weed patches. However, Grabcut is also not the best choice if there are overlapping leaves of the plants, such as in some of the examples in the analyzed dataset, because it tends to also include pixels from the weed plant which could be a problem for the annotation process. In the future, additional color spaces should be considered for the segmentation task, including vegetation indexes that use RGB images. Unsupervised segmentation algorithms could also be considered prior to including the user input to obtain patches or groups of pixels that belong to a certain class or object.

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