Annotated Image Datasets of Rosette Plants

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Abstract

While image-based approaches to plant phenotyping are gaining momentum, benchmark data focusing on typical imaging situations and tasks in plant phenotyping are still lacking, making it difficult to compare existing methodologies. This report describes a benchmark dataset of raw and annotated images of plants. We describe the plant material, environmental conditions, and imaging setup and procedures, as well as the datasets where this image selection stems from. We also describe the annotation process, since all of these images have been manually segmented by experts, such that each leaf has its own label. Color images in the dataset show top-down views on young rosette plants. Two datasets show different genotypes of Arabidopsis while another dataset shows tobacco (Nicoticana tobacum) under different treatments. A version of the dataset, described also in this report, is in the public domain at `http://www.plant-phenotyping.org/CVPPP2014-dataset` and can be used for the purpose of plant/leaf segmentation from background, with accompanying evaluation scripts. This version was used in the Leaf Segmentation Challenge (LSC) of the Computer Vision Problems in Plant Phenotyping (CVPPP 2014) workshop organized in conjunction with the 13^{th} European Conference on Computer Vision (ECCV), in Zürich, Switzerland. We hope with the release of this, and future, dataset(s) to invigorate the study of computer vision problems and the development of algorithms in the context of plant phenotyping. We also aim to provide to the computer vision community another interesting dataset on which new algorithmic developments can be evaluated.

1 Introduction

A key factor for progress in agriculture and plant research is the study of the phenotype expressed by cultivars (or mutants) of the same plant species under different environmental conditions. Identifying and evaluating a plant's actual properties, i.e., its phenotype, is relevant to, e.g., seed production and plant breeders. Image-based approaches are gaining attention among plant researchers to measure and study visual phenotypes of plants. In the last decades a variety of approaches based on images have been developed to measure visual traits of plants in an automated fashion [1, 2, 3]. Several laboratories developed customized image processing pipelines to analyze the image data acquired during experiments [2, 4, 5, 6].

Nonetheless, benchmark data focusing on typical imaging situations and tasks in plant phenotyping are still lacking, making it difficult to compare existing methodologies. We introduce three image datasets: two datasets showing Arabidopsis plants and one dataset showing Tobacco plants. We describe the details of acquisition setups, plant material, and growing conditions. The images present several challenges from an image analysis and computer vision perspective, which we expand upon on a dedicated section. We also detail the annotation protocol where we describe how ground truth leaf segmentations have been derived.

In a dedicated section, we describe the part of the dataset which has been utilized in the Leaf Segmentation Challenge (LSC) of the Computer Vision Problems in Plant Phenotyping (CVPPP 2014) workshop[1] organized in conjunction with the 13$^{\text{th}}$ European Conference on Computer Vision[2] (ECCV), in Zürich, Switzerland. Images together with the 'ground truth' hand segmentations have been released as training images, while the rest of the images has been released for testing, where we kept the 'ground truth' secret. The LSC focused on multi-label image segmentation of leaves of rosette plants, where only single images are given, as opposed to image sequences. Full rosette foreground/background segmentation (i.e., the delineation of the plant from the surrounding scene) can be regarded as a simpler task but the LSC dataset can be used there. We should note that the same LSC dataset can also be used for detection and counting problems, albeit plant or leaf.

The release of these data in the public domain is done in an effort to motivate development of novel methodologies for the segmentation of plants and leaves in images from phenotyping experiments. We hope that this publicly available data will also stimulate contributions from researchers in computer vision, so far not considering plant phenotyping data in their research or willing to augment the range of data their method has been tested on. We also do intend to use this report as a reference for new annotated datasets (e.g., on leaf tracking) that may arise from the same raw material described herein.

2 Image Data

The three imaging datasets described here were acquired in two different labs with highly different equipment. Arabidosis images have been acquired at the PRIAn research unit of IMT Lucca[3] using a setup for investigating affordable hardware for plant phenotyping. Tobacco images have been acquired at IBG-2, Forschungszentrum Jülich[4] using a robotic setup for the investigation of automated plant treatment optimization by an artificial cognitive system.

In the following we first describe arabidopsis image datasets, including sections on imaging setup and plant material, followed by the description of the tobacco dataset with the same text organization. Finally, in Section 4 we delineate the composition of the datasets, shorthanded as 'A1', 'A2', and 'A3', released for the LSC.

2.1 Arabidopsis Image Datasets

The arabidopsis image datasets were acquired in the context of the European project 'PHIDIAS: Phenotyping with a High-throughput, Intelligent, Distributed, and Interactive Analysis System'[5]. We completed two data collections, the first in June 2012 and the second in September-October 2013, obtaining two image datasets, hereafter named 'Ara2012' and 'Ara2013', respectively, both consisting of top-view time-lapse images of Arabidopsis thaliana rosettes. Parts of the datasets have been manually annotated, to provide a benchmark for analysis methods, such as plant and leaf segmentation approaches (Section 2.1.2). Table 1 summarizes relevant information regarding the datasets, which are discussed in detail in the following paragraphs.

2.1.1 Imaging Setup

Following the setup proposed in [7], we devised a small and affordable laboratory setup (overall, monetary cost of the system was below €300, cf. Figure 1), composed of a growth shelf and an automated low-cost sensing system, able to acquire images of the scene and send them through wireless connection to a receiving computer. Example images captured with this setup are shown in Figure 2, illustrating the arrangement of the plants and the complexity of the scene.

[1] http://www.plant-phenotyping.org/CVPPP2014
[2] http://eccv2014.org/
[3] http://prian.imtlucca.it/
[4] http://www.fz-juelich.de/ibg/ibg-2
[5] http://prian.lab.imtlucca.it/PROJECTS/PHIDIAS/phidias.html

Table 1: Summary of statistics of the arabidopsis datasets where images for 'A1' and 'A2' were taken from.

Dataset	Subjects	Wild-types	Mutants	Period	Total images	Resolution before cropping	Annotated plants as of 7/2014
Ara2012	19	Yes (1)	No	3 weeks	150	7 megapixel	161
Ara2013 (Canon)	24	Yes (1)	Yes (4)	7 weeks	4186	7 megapixel	40
Ara2013 (Rasp. Pi)	24	Yes (1)	Yes (4)	7 weeks	1951	5 megapixel	–

To provide illumination to the plants, we installed two cool-white daylight fluorescent lamps, 80 cm above the pots. The camera was positioned between the lights, at approximately 100 cm distance from the plants. No modifications of the configuration were done after the experiments were started.

The plants were imaged with a 7 megapixel commercial grade camera (Canon PowerShot SD1000), equipped with an Eye-Fi Pro X2 memory card, providing 8 GB SDHC capacity for storage and 802.11n wireless networking capabilities for Wi-Fi communication with a computer. We installed on the camera the open source CHDK (Canon Hack Development Kit) firmware[6], to enable control on a richer set of camera features (e.g., saving raw images) and the ability to run scripts (e.g., software-simulated intervalometer) [8]. Flash was disabled, while other camera settings (e.g., exposure, focus distance) were obtained automatically from the camera before acquiring the first image, and were subsequently kept unchanged throughout the experiment. For the Ara2013 dataset, at each time instant, we acquired two images of the same scene at different focus distances, e.g. to have the possibility to fuse them in a single image that is in focus everywhere [9], or to enable 3D surface estimation using depth-from-defocus techniques [10]. Using the Lua scripting language [11], we programmed the camera to capture time-lapse images of the scene, that were subsequently transmitted to a nearby workstation for storage. All acquired images (width × height: 3108×2324 pixels) were stored in both raw uncompressed (DNG) format, to avoid distortion introduced by compression, and also JPEG format, to save the EXIF (EXchangeable Image File) metadata [12].

For the Ara2013 experiment we also deployed a Raspberry Pi[7] single-board computer, equipped with a 5 megapixel camera module, to capture static images (width × height: 2592×1944 pixels) of the same scene. We adopted the *raspistill* application, using the following command line options: `raspistill -n -e png -awb fluorescent -rot 180 -o filename`. In a distributed sensing and analysis scenario [13], where the acquired data needs to be transmitted via the Internet to centralized locations for processing, it becomes necessary to compress the images effectively. In this context, a single-board computer such as the Raspberry Pi controlling (or attached to) the sensor allows to perform (low-complexity) pre-processing operations and run compression schemes, thus offering the possibility of improving quality of reconstructed images.

Raw image files from the Canon camera were developed using the *dcraw*[8] software tool (version 8.99), to obtain RGB images in TIFF format. We used the following command lines:

- `dcraw -v -w -o 1 -q 3 -T filename` for Ara2012; and
- `dcraw -v -w -k 31 -S 1023 -H 2 -o 1 -q 3 -T filename` for Ara2013.

In order to reduce disk occupancy, TIFF images were subsequently encoded using the lossless compression standard available in the PNG file format [14].

[6]Available at `http://chdk.wikia.com/wiki/CHDK`

[7]`http://www.raspberrypi.org/`

[8]Available at `http://www.cybercom.net/~dcoffin/dcraw/`

Figure 1: Acquisition setup for 'Ara2012' and 'Ara2013' datasets, from which 'A1' and 'A2' datasets were obtained.

2.1.2 Plant and Leaf Annotations

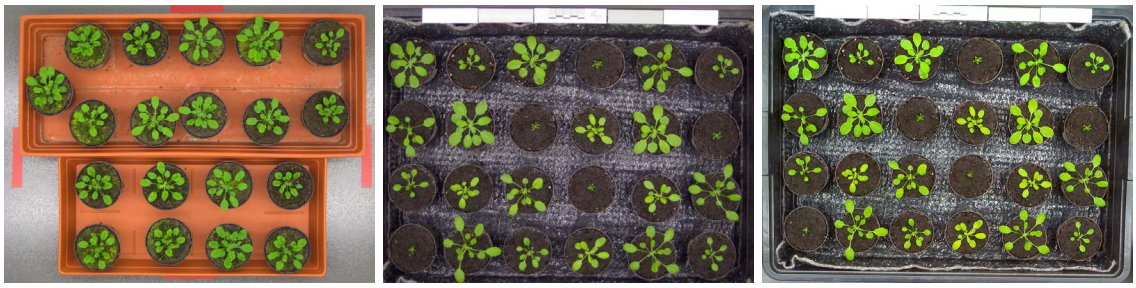
Portions of both Ara2012 and Ara2013 datasets have been used in experiments or released to third parties or in the public domain. Therefore, such data has been manually annotated, to obtain ground truth information of plant pixel locations and individual leaves.

Annotations are provided in the form of images the same size of the originals, stored in PNG format [14]. A pixel with black color denotes background, while all other colors are used to uniquely identify the leaves of the plants in the scene. Across the frames of the time-lapse sequence, we consistently used the same color code to label the occurrences of the same leaf.

Figure 3 depicts the procedure that was followed to annotate the image data. In the first place, we obtained a binary segmentation of the plant objects in the scene in a computer-aided fashion. We used the approach based on active contours described in [15], the result of which was manually refined using a raster graphics editing software (the GIMP[9]). Next, within the binary mask of each plant, we delineated the individual leaves, following an approach based solely on manual labeling. To reduce observer variability, the labeling procedure involved two users, each annotating part of the dataset and inspecting the other. Figure 4 shows example plant images from the dataset, with corresponding annotations.

The type of annotations released together with the images reflect the intended use of the datasets. The first level of information regards what pixels in an image belong, respectively, to a plant object or background. This serves as a ground truth to evaluate plant segmentation approaches. Furthermore, the leaf labeling allows to use the datasets to test leaf segmentation or counting approaches. Finally, consistency of labels in time, allows to validate methods of plant and leaf tracking across the frames of a time-lapse sequence.

[9] `http://www.gimp.org/`



(a) Ara2012 (b) Ara2013 (Canon) (c) Ara2013 (Raspberry Pi)

Figure 2: Example images acquired with the setup shown in Figure 1.

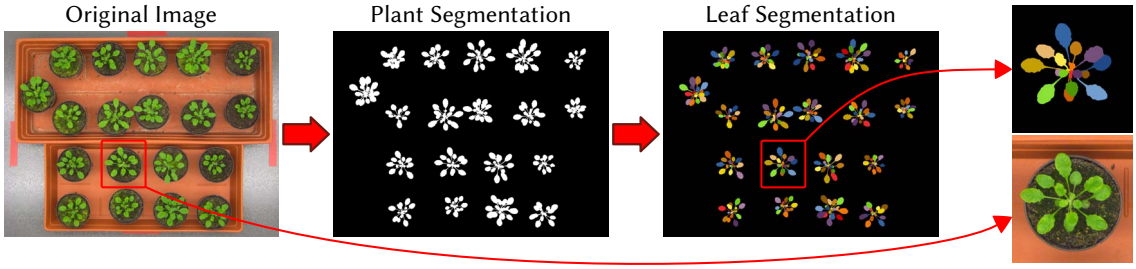


Figure 3: Schematic of the workflow to annotate the images. Plants were first delineated in the original image, then individual leaves were labeled.

2.1.3 Plant Material and Growing Conditions

The Ara2012 experiment involved 19 subjects, all Columbia (Col-0) wild types. On the other hand, the Ara2013 experiment involved 24 subjects, including Col-0 wild types and four different lines of mutants, all with Col-0 background. Specifically, the Ara2013 experimental setup was composed of the following genotypes:

- Col-0, 5 subjects;
- *pgm* (plastidial phosphoglucomutase), 5 subjects – impaired in starch degradation, exhibits reduction in growth and a delay in flowering time;
- *ctr* (constitutive triple response), 5 subjects – exhibits dwarfism and very small rosette leaves;
- *ein2* (ethylene insensitive 2), 5 subjects – exhibits large rosettes, delayed in bolting;
- *adh1* (alcohol dehydrogenase 1), 4 subjects.

Plants were grown in individual pots with 16/8 hour light/dark cycle for Ara2012, and 12 hour light/dark cycle for Ara2013. Watering was provided two or three times per week by sub-irrigation. Images were captured during day time only, every 6 hours over a period of 3 weeks for Ara2012, and every 20 minutes over a period of 7 weeks for Ara2013. For the Ara2013 dataset, the diameter of each plant was also manually measured with a caliper and recorded on a daily basis for reference. Number of subjects was selected according to coverage area of the camera, to obtain satisfactory imaging resolution (we measured pixel size to be $\sim$0.167 mm). Pots were spaced out in the tray, to prevent adult plants from touching (from an image processing standpoint, handling this circumstance in an automated fashion is difficult, and most solutions assume that distinct subjects never touch). Arrangement of genotypes in the tray was randomized for the Ara2013 experiment, to eliminate possible bias in the results due to variations in watering or lighting conditions.

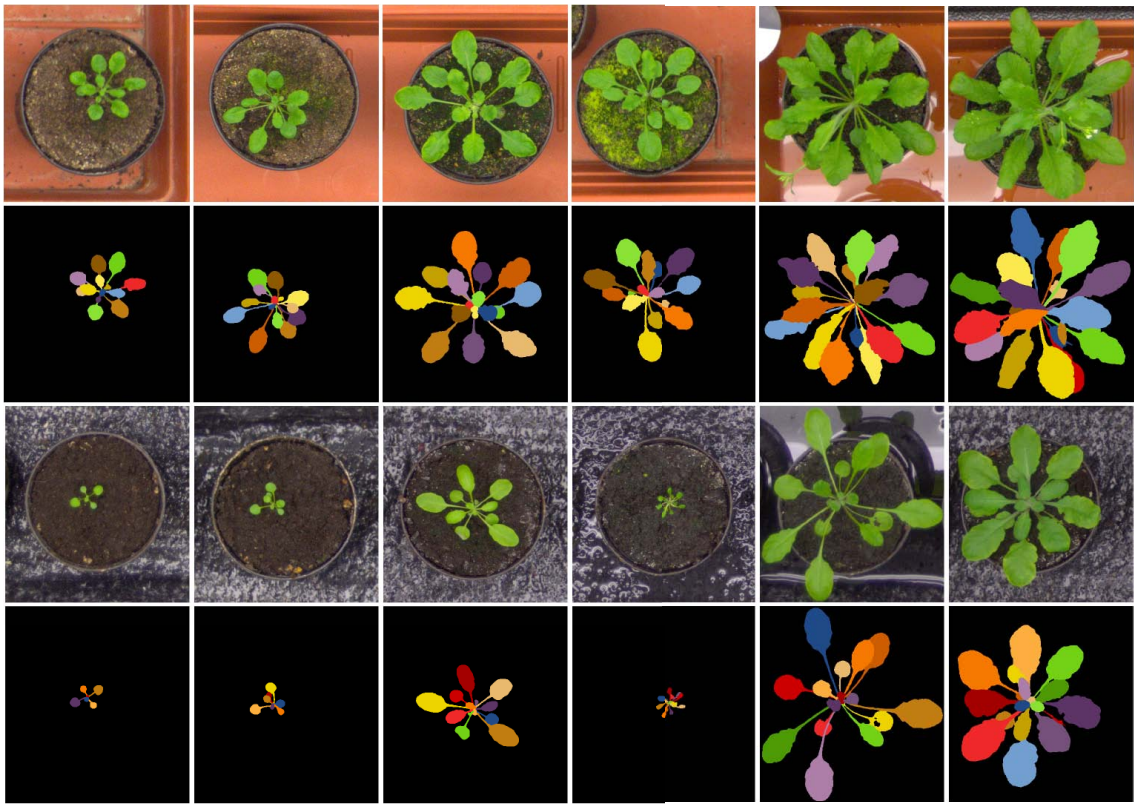


Figure 4: Examples of single plant images released for the LSC, with the corresponding ground truth leaf labeling denoted by color. Top two rows refer to the Ara2012 dataset ('A1'), while bottom two rows refer to the Ara2013 (Canon) dataset ('A2').

2.2 Tobacco Image Dataset

The tobacco image dataset was acquired in the context of the European project 'Gardening with a cognitive system' (GARNICS). The GARNICS project aimed at 3D sensing of plant growth and building perceptual representations for learning the links to actions of a robot gardener. In this context plants are complex, self-changing systems with increasing complexity over time. Actions performed at plants (like watering), will have strongly delayed effects. Thus, monitoring and controlling plants is a difficult perception-action problem requiring advanced predictive cognitive properties. The project thus addressed plant sensing and control by combining active vision with appropriate perceptual representations, which are essential for cognitive interactions. More information about the project can be found in the project's webpage[10].

2.2.1 Imaging Setup

The imaging setup in the project allowed for looking at plants from different poses. We released top views of the plants, only, as top view images are used in many plant screening applications. A setup doing this can then be considerably simpler and more affordable than the setup used here. The implemented system consists of:

- a lightweight 7-dof robot arm (Kuka LBR4) with force-feedback (see Figure 5A);
- mounted on a rollable, heavy table;
- a set of control computers;

[10] `http://www.garnics.eu`

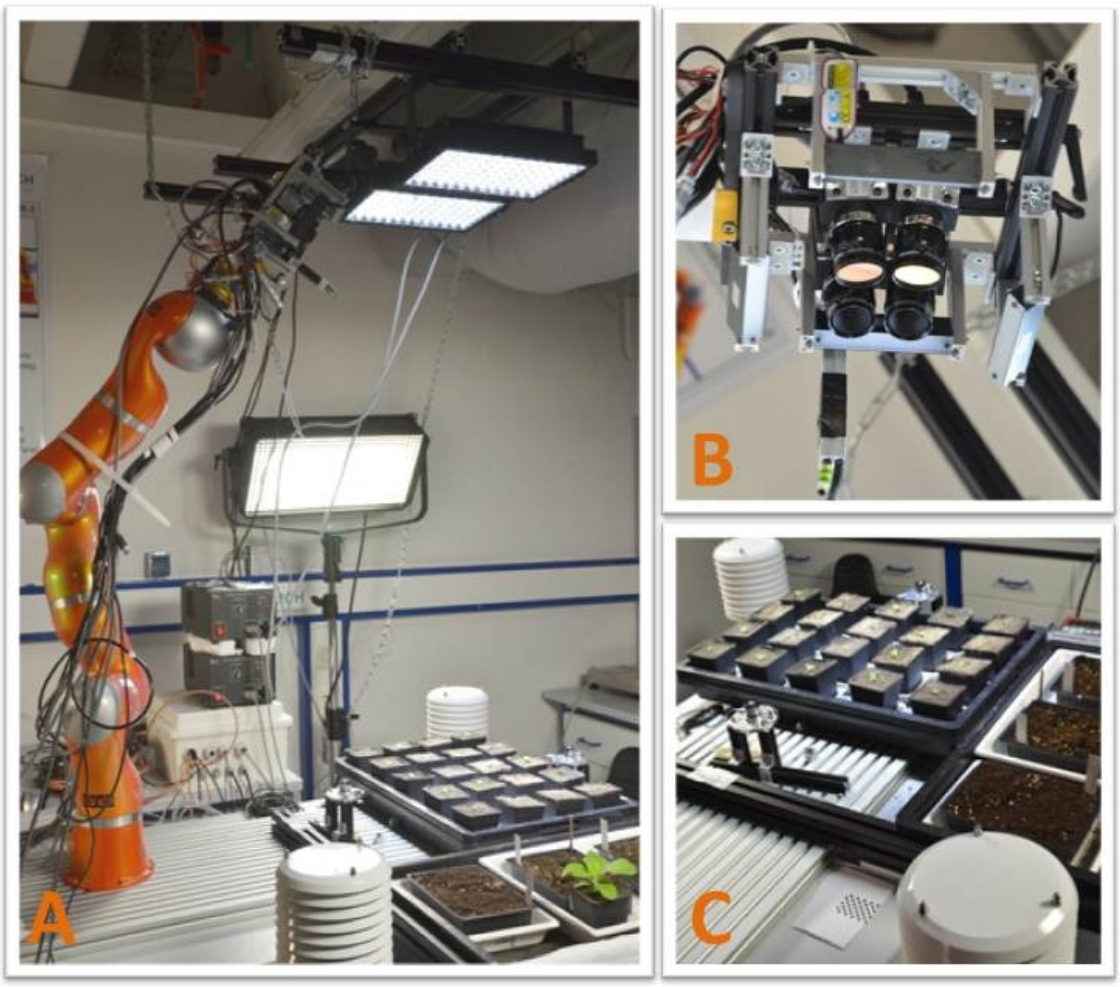


Figure 5: Hardware setup of the robot gardener as used in the GARNICS project. (A) The robot arm, in the lab environment. (B) Camera head with illumination and watering system. (C) Workspace with light, temperature, and humidity sensors.

- teaching buttons at the robots hand and on a switch panel;
- a head with cameras, light sources, and a watering system (see Figure 5B);
- digital and analog IOs for switching lights, pumps, or valves, hardware button presses, etc.;
- sensors for environment monitoring (see Figure 5C);
- a watering and nutrient solution dispensing system;
- high power white LED illumination allowing for photons fluxes of up to $\sim$2000 μmol $s^{-1}m^{-2}$ (see Figure 5A), switched off for imaging in an 'inverse flashing' fashion;
- low power white fluorescence illumination allowing for photons fluxes of up to $\sim$50 μmol $s^{-1}m^{-2}$ (see Figure 5A), used for imaging.

The robot head consists of two stereo camera systems, black-and-white and color, each consisting of 2 Point-Grey Grashopper cameras with 5 megapixel (2448×2048, pixel size 3.45 μm) resolution and high quality lenses (Schneider Kreuznach Xenoplan 1.4/17-0903). We added lightweight white and NIR LED light sources to the camera head.

Table 2: Summary of statistics of the acquired datasets where images for 'A3' were taken from.

Dataset by start date	Subjects	Period	Total images	Resolution per plant	Annotated plants	Annotated images
23.01.2012	20	18 days	34560	5 megapixel	4	26
16.02.2012	20	20 days	38400	5 megapixel	2	13
15.05.2012	20	18 days	34560	5 megapixel	2	8
10.08.2012	20	30 days	57600	5 megapixel	5	36

Figure 6: Overview images of plants in final stages of 4 experiment runs. We refer to the experiments by their start date: A: 23.01.2012, B: 16.02.2012, C: 15.05.2012, D: 10.08.2012. Red squares indicate the plants where images were taken for 'A3'. Red 5 digit numbers are their plant IDs used to identify the plants (see Tables 3 and 4). Generally, plant IDs are increasing from left to right and top to bottom in the trays, respectively. IDs are A: 69665 – 69684, B: 69965 – 69984, C: 75984 – 76003, D: 79329 – 79348.

Using this setup, each plant was imaged separately from different but fixed poses. For each pose in addition small baseline stereo image pairs were captured using each single camera, respectively, by a suitable robot movement, allowing for 3d reconstruction of the plant. For the top view pose, distance between camera center and top edge of pot varies between 15 cm and 20 cm for different plants, but being fixed per plant, resulting in lateral resolutions between 20 and 25 pixel/mm.

Data released here stems from experiments aiming at acquiring training data for the robot gardener of the GARNICS project. Images were acquired every hour in a 24/7 manner for up to 30 days. More details on the four experiments, from which the data is taken, can be found in Table 2. Overview images of the final stage of the plants from these experiments are shown in Figure 6.

Table 3: Time after experiment start per image in 'A3'.

Training				Testing							
Image	Plant ID	Time [h]	Time [d]	Image	Plant ID	Time [h]	Time [d]	Image	Plant ID	Time [h]	Time [d]
1	69665	6	0	28	69678	6	0	56	79329	132	6
2		78	3	29		78	3	57		204	9
3		174	7	30		174	7	58		276	12
4		222	9	31		222	9	59		349	15
5		270	11	32		270	11	60		444	19
6		428	18	33		343	14	61		516	22
7	69676	6	0	34		415	17	62		612	26
8		78	3	35	69684	6	0	63		709	30
9		174	7	36		78	3	64	79332	12	1
10		222	9	37		175	7	65		132	6
11		270	11	38		223	9	66		252	10
12		294	12	39		271	11	67		372	15
13	75984	9	0	40		343	14	68		492	21
14		105	4	41		415	17	69		612	26
15		178	7	42	69966	8	0	70		708	29
16		289	12	43		80	3	71	79339	12	1
17	75985	9	0	44		148	6	72		133	6
18		81	3	45		200	8	73		252	11
19		178	7	46		248	10	74		372	16
20		275	11	47		296	12	75		492	21
21	79348	12	0	48		344	14	76		613	26
22		132	6	49		392	16	77		708	30
23		253	11	50	69973	8	0	78	79347	13	1
24		373	16	51		94	4	79		132	6
25		493	21	52		147	6	80		253	11
26		612	26	53		248	10	81		372	16
27		709	30	54		344	14	82		493	21
				55	79329	12	1	83		612	26

2.2.2 Plant and Leaf Annotations

As for the Arabidopsis datasets, annotations are provided in the form of images the same size of the originals, stored in PNG format [14]. A pixel with label index 0, depicted as black color, denotes background, while all other colors are used to uniquely identify the leaves of the plant in the scene. Across the frames of the time-lapse sequence, label index and color do not depict the same leaf.

For leaf segmentation we followed a similar procedure as described in Section 2.1.2, but using a simple color-based segmentation for foreground background segmentation. The result was manually refined using a raster graphics editing software (Adobe Photoshop[11]). Next, within the binary mask of each plant, we delineated the individual leaves, following an approach completely based on manual labeling. To reduce observer variability, the labeling procedure involved two users, one annotating the dataset and inspecting the other. Figure 7 shows example plant images from the dataset, with corresponding annotations.

The type of annotations released together with the images reflect the intended use of the datasets. The first level of information regards what pixels in an image belong, respectively, to a plant object or background. This serves as a ground truth to evaluate plant segmentation approaches. Furthermore, the leaf labeling allows to use the datasets to test leaf segmentation or counting approaches.

[11] `http://www.photoshop.com/`

Figure 7: Examples of single plant images 'A3' released for the LSC, with the corresponding ground truth leaf labeling denoted by color.

2.2.3 Plant Material and Growing Conditions

Tobacco plants (*Nicotiana tobacum cv. Samsun*) were grown in 7 × 7 cm pots under constant light conditions with a 16h/8h day/night rhythm. Light intensities were measured for each plant individually (cf. Table 4).

Water was always provided by the robot system, where different but constant amounts per plant were given every two hours. Nutrients were either applied manually twice a week (12 ml Hakaphos green 0.3%) or every other hour by the robot system (0.3 ml, 0.45 ml, or 0.9 ml Hakaphos green 1%). Treatments per plant are shown in Table 4. For water and nutrient solution dispensing the GARNICS robot system positions small tubes, one for water and one for nutrient solution, at predefined locations and pumps the liquids using an automated flexible-tube pump.

In the GARNICS project treatments were selected to produce training data for a cognitive system. The actual amounts of water and nutrient solution are therefore well adapted to the soil substrate such that the sets of plants show distinguishable performance of generally well growing plants. Finding an optimal treatment was left for the system. The soil used for the experiment ('Kakteenerde') has low nutrient content and dries relatively fast with an approximately exponential behavior $A = A_0 \exp(-t/\tau)$, where $\tau \approx 7$ days.

Images show the growth stages from germination well into the leaf development stage, i.e. we started our observations at growth stage 09 and typically stopped at stage 1009 to 1013 (according to the extended BBCH-scale presented in [16]), due to size restrictions. For each image of 'A3'

Table 4: Plant treatments for tobacco plant experiments. Plants selected for 'A3' are highlighted. Treatments: T1 – T3: 0.6 ml, 1.8 ml, or 3.0 ml water every 2 hours, respectively, T4 – T5: 0.3 ml or 0.9 ml Hakaphos green 1% every 2 hours, T6: 0.9 ml water and 0.45 ml Hakaphos green 1% every 2 hours, T7 – T9: T1 – T3 plus 12 ml Hakaphos green 0.3% 2 times per week, respectively.

23.01.2012			16.02.2012			15.05.2012			10.08.2012		
Plant ID	Treatment	Light $\frac{\mu mol}{m^2 s}$	Plant ID	Treatment	Light $\frac{\mu mol}{m^2 s}$	Plant ID	Treatment	Light $\frac{\mu mol}{m^2 s}$	Plant ID	Treatment	Light $\frac{\mu mol}{m^2 s}$
69665	T7	933	69965	T7	515	**75984**	T1	295	**79329**	T2	295
69666	T8	1505	**69966**	T8	760	**75985**	T2	335	79330	T5	335
69667	T9	1415	69967	T9	655	75986	T4	320	79331	T6	320
69668	T7	1430	69968	T7	745	75987	T5	360	**79332**	T2	360
69669	T8	1095	69969	T8	715	75988	T1	330	79333	T5	330
69670	T9	1310	69970	T9	805	75989	T2	470	79334	T6	470
69671	T7	2055	69971	T7	1200	75990	T4	570	79335	T2	570
69672	T8	1825	69972	T8	1005	75991	T5	530	79336	T5	530
69673	T9	1715	**69973**	T9	1060	75992	T1	600	79337	T6	600
69674	T7	1365	69974	T7	990	75993	T2	545	79338	T2	545
69675	T2	1200	69975	T2	790	75994	T4	545	**79339**	T5	545
69676	T3	1910	69976	T3	1240	75995	T5	670	79340	T6	670
69677	T1	1700	69977	T1	1035	75996	T1	630	79341	T2	630
69678	T2	1455	69978	T2	1010	75997	T2	715	79342	T5	715
69679	T3	1135	69979	T3	945	75998	T4	660	79343	T6	660
69680	T1	705	69980	T1	560	75999	T5	470	79344	T2	470
69681	T2	1110	69981	T2	880	76000	T1	590	79345	T5	590
69682	T3	1030	69982	T3	755	76001	T2	550	79346	T6	550
69683	T1	930	69983	T1	700	76002	T4	610	**79347**	T2	610
69684	T2	700	69984	T2	620	76003	T5	565	**79348**	T5	565

acquisition times and plants shown are given in Table 3. Overview images of the final growth stages are given in Figure 6.

3 Analysis Challenges of the Acquired Image Data

Due to complexity of scene and plant objects, the datasets present a variety of challenges with respect to analysis. Since our goal was to produce a good range of test images, several challenging situations were allowed to occur by design.

For 'A1' and 'A2', occasionally, a layer of water in the tray due to irrigation causes reflections. As the plants grow, leaves tend to overlap, resulting in severe leaf occlusions. Nastic movements make leaves appear of different shape and size from one time instant to another. For 'A3' beneath shape changes due to nastic movements, also different leaf shapes appear due to different treatments. Under high illumination conditions plants stay more compact with partly wrinkled leaves, severely overlapping. Under lower light conditions leaves are more round and larger.

The Ara2012 dataset ('A1') presents a complex and changing background, that renders the plant segmentation task more challenging. A portion of the scene is slightly out of focus and appears blurred, and some images include external objects, such as tape or other fiducial markers. In some images, certain pots have moss on the soil, or have dry soil and appear yellowish (due to increased ambient temperature for a few days). The Ara2013 dataset ('A2') presents a simpler scene (e.g., more uniform background, sharp focus, no moss), however it includes mutants with different phenotypes related to rosette size (some genotypes produce very small seedlings) and leaf appearance, with major differences in both shape and size. The GARNICS dataset ('A3') has much higher image resolution, making computational complexity more relevant.

Also in the tobacco dataset plants undergo a wide range of treatments changing their appear-

ance dramatically, while Arabidopsis is known to have different leaf shape among mutants. Thus, shape-based segmentation is a challenging undertaking. In addition, self-occlusion, shadows, leaf hairs, leaf color variations, and others make the scene even more complex.

4 The Leaf Segmentation Challenge Dataset Version

As we mentioned previously, a specially formatted part of these data was released to support the Leaf Segmentation Challenge component, of the Computer Vision Problems in Plant Phenotyping which was organized in conjunction with the European Conference of Computer Vision (ECCV), that was held in Zürich, Switzerland in September 2014.

As part of the benchmark data for the LSC we released three datasets, named respectively 'A1', 'A2', and 'A3', consisting of single-subject images of arabidopsis and tobacco plants, each accompanied by manual annotation of plant and leaf pixels, examples of which are shown in Figures 4 and 7.

From the Ara2012 dataset, we extracted 161 images (width × height: 500×530 pixels), i.e. dataset 'A1', spanning a period of 12 days. Additional 40 images (width × height: 530×565 pixels), i.e. 'A2' were extracted from the Ara2013 (Canon) dataset, and span a period of 26 days. From the tobacco dataset, we extracted 83 images (width × height: 2448×2048 pixels), i.e. 'A3'.

The datasets were split into training and testing sets for the challenge. For the training subsets were released in the public domain color images and annotations (i.e., 128, 31, and 27 images for 'A1', 'A2', and 'A3', respectively). For the testing subsets, we released color images only (i.e., 33, 9, and 56 for 'A1', 'A2', and 'A3', respectively) and kept the respective label images secret.

We should note that the LSC did not involve leaf tracking over time, therefore all plant images were considered separately, ignoring any temporal correspondence. Accordingly, the annotations were released as indexed PNG images [14], where index 0 denotes background pixels and subsequent integers denote leaf pixels. The images are mainly intended for plant and leaf segmentation, and range from instances with well separated leaves and simple background, to more difficult examples with many leaf occlusions, complex leaf shapes, varying backgrounds, or plant objects not sharply in focus.

File types and naming conventions. Plant images are encoded as PNG files and their size may vary. Plants appear centered in the (cropped) image. Segmentation masks are image files encoded in PNG where each segmented leaf is identified with a unique (per image) integer value, starting from 1, where 0 is background. A color index palette is included within the file for visualization reasons. The filenames have the form:

- `plantXXX_rgb.png`: the original RGB color image as true-color PNG file;
- `plantXXX_label.png`: the labeled image as indexed PNG file;

where `XXX` is an integer number. Note that plants are not numbered continuously.

To evaluate submissions on the basis of testing data, we utilized several evaluation criteria in a script, some of which are based on the Dice score of binary segmentations, measuring the degree of overlap among binary segmentation masks:

$$\text{Dice } (\%) = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \tag{1}$$

where TP, FP, and FN represent the number of true positive, false positive, and false negative pixels, respectively, calculated by comparing algorithmic result and ground-truth segmentation masks. Overall the criteria used where:

- `SymmetricBestDice`, the symmetric Average Dice among all objects (leaves), where for each input label the ground truth label yielding maximum Dice is used for averaging, to estimate average leaf segmentation accuracy;

- `FGBGDice`, the Dice on the foreground mask (i.e., the whole plant assuming the union of all labels different than background), to estimate how good the algorithm identifies plant from background;
- `AbsDiffFGLabels`, the absolute difference in object count, as number of leaves in ground truth minus the algorithms results, to estimate how good the algorithm is in identifying the correct number of leaves present; and
- `DiffFGLabels`, the difference in object count, as number of leaves in ground truth minus the algorithms results to estimate how good the algorithm is in identifying the correct number of leaves present.

This dataset, and accompanying evaluation scripts, can be downloaded from: `http://www.plant-phenotyping.org/CVPPP2014-dataset`.

5 Discussion and Conclusion

In this report we described design and implementation criteria adopted to collect three image datasets of growing Arabidopsis and Tobacco plants. This effort was intended to promote research and development of computer vision approaches for plant phenotyping applications.

Parts of the datasets Ara2012 and Ara2013 have been already adopted to experimentally validate new approaches that we presented in previous papers. In [13] we propose a distributed sensing and analysis framework for image-based plant phenotyping, and investigate application-aware image compression approaches. In [17] we propose color space transformations to improve compression performance further. In [15] we propose a solution to analyze images from plant phenotyping experiments, with particular focus on plant segmentation. Finally, in [18] we explore efficient approximations of complex image segmentation metrics, that could be adopted at the sensor.

The GARNICS project lead to 74 scientific and 23 non-specialist contributions, as well as 2 patents. For more details we refer to the projects website[12].

As a benefit to the scientific community, we are releasing in the public domain a specially formatted dataset, which contributed to the benchmark data for a leaf segmentation challenge. In the future, we do intend to use this technical report as a reference when releasing augmented datasets or datasets that could address different computer vision problems such as leaf tracking, leaf counting, leaf and plant detection, and others. We also do hope that this dataset and its future versions, would be used from the computer vision community to learn suitable image statistics [19], adapt and test counting algorithms with [20] and without temporal information [21, 22, 23], segmentation algorithms [24, 25, 26, 27, 28], multi-label segmentation [29, 30, 31, 32, 33] or detection [34] approaches, and others. Additional depth information as can be computed from stereo images [35] for the tobacco dataset, to be released in the future, may further facilitate segmentation [36, 37, 38, 39].

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[12] `http://www.garnics.eu`

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