An easy-to-setup 3D phenotyping platform for KOMATSUNA dataset

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Abstract

We present a 3D phenotyping platform that measures both plant growth and environmental information in small indoor environments for plant image datasets. Our objective is to construct a compact and complete platform by using commercial devices to allow any researcher to begin plant phenotyping in their laboratory. In addition, we introduce our annotation tool to manually but effectively create leaf labels in plant images on a pixel-by-pixel basis. Finally, we show our RGB-D and multiview datasets containing images in the early growth stages of the Komatsuna with leaf annotation.

1. Introduction

Plant growth is affected by various factors such as plant seeds, temperature, CO_2, solar radiation, soil and fertilizers. More precisely, a plant phenotype, which is an appearance characteristic of a plant, is determined by the interaction between its genetic properties and environmental conditions. Since the mechanism of plant growth generally varies depending on plant species and is less clarified, it is important to measure all the factors for each species and analyze the relationship among them to improve the quality and quantity of the plant. Therefore, technologies for sensing plant phenotyping have been a biological research issue for a long time [7, 6].

In computer vision problems in plant phenotyping (CVPPP) workshops, which started in 2014[1], plant images were provided with their leaf annotation for leaf segmentation and counting challenges [15, 23]. From these images, the size and shape change of a leaf in the image can be computed as 2D plant phenotypes [2, 14, 18]. To measure higher dimensional phenotypes, the use of several imaging devices has been investigated [13]. Especially, 3D phenotyping by using 3D imaging devices or laser scanners becomes common because it is not a destructive way to capture phenotypes and measures leaf configurations in 3D space [11, 3, 21, 25, 20, 5]. However, a public dataset for this issue has not been developed in literature and is required for comparing different methods considering the same conditions.

In this paper, we present a platform to create image datasets for 3D plant phenotyping in indoor environments. Our objective is to use commercial devices to measure both plant growth and environmental information so that a complete platform can be easily constructed. Since most of the platforms are designed for use in outdoor environments [1, 8] and there are few discussions about simple phenotyping platforms [16], we propose a compact platform for use in indoor environments and detail selected devices and their installation into the platform. In addition, we introduce our leaf annotation tool, which is used to manually but effectively create leaf labels in plant images on a pixel-by-pixel basis for machine learning tasks. Finally, we show our RGB-D and multiview datasets containing images of a Komatsuna, which is a Japanese leaf vegetable, with leaf annotation for 3D leaf segmentation and counting [15, 23]. The details of our platform will be useful for nonbiological researchers to start the study of plant phenotyping.

2. Platform

As illustrated in Figure 1, we constructed our platform to capture top views of a plant and measure environmental conditions around the plant. This section explains the details of selected devices and their arrangement in the platform.

2.1. Plant and cultivation method

We first selected a plant species and its cultivation method in small indoor environments. Since our primal objective was to construct public image datasets with any type of plants for 3D plant phenotyping, we selected a plant species according to its growth properties. Komatsuna is a Japanese mustard spinach and a leaf vegetable, as illustrated in Figure 2. It can be cultivated in indoor environments un-

[1] https://www.plant-phenotyping.org/CVPPP2014

Figure 1. Platform to create KOMATSUNA datasets in indoor environments. To cultivate plants, a compact and complete platform for 3D plant phenotyping was developed using commercial devices only.

Figure 2. Komatsuna. Komatsuna is a Japanese mustard spinach, and is selected as a plant species for our plant image datasets because it easily grows in indoor environments.

der wide ranges of temperatures. In addition, it is known to be resistant to injurious insects and grows very fast compared with other leaf vegetables. Therefore, we selected Komatsuna to create our plant image datasets.

Soil culture is a standard cultivation method and is normally used in outdoor environments. However, it is not suitable for indoor environments because it pollutes plant surroundings, and soil management and watering are often necessary. Hydroponic culture is an alternative method and has the following advantages: it is clean; watering and fertilization are automated so that the plant growth is accelerated; less agricultural chemicals are necessary compared with soil culture; and replant failures do not normally occur. This implies that plants can constantly be cultivated in a quick cycle without daily upkeeps. Another advantage is that the plant root systems can also be measured because roots that grow in water can be captured through cameras [10, 4]. Since it is difficult to measure the root systems with soil culture, hydroponic culture is sometimes selected in plant phenotyping. Note that hydroponic culture is a standard cultivation

Figure 3. A commercial hydroponic culture toolkit. In the toolkit, a plant grows with the help of water and fertilizer only. Cultivation can be automated because watering and fertilizing are automatically controlled.

method and has practically been installed in indoor plant factories [19].

As illustrated in Figure 3, we selected a commercial hydroponic culture toolkit for a small kitchen garden. To cultivate a plant, a seed is first sowed into a cube urethane foam, and then placed into one of the holes in the toolkit. The plant then naturally grows as it is planted into the soil. Since the toolkit surface is made of styrene foam and its color is white, leaf segmentation would be easier than that when using soil culture. One of the important factors for cultivating plants in indoor environments is to control the lighting condition because plants do not grow in conditions lacking lighting. In the next section, we explain our lighting equipment.

2.2. Lights

To analyze the relationship between plant growth and lighting condition, it is necessary to control lighting durations and intensities while cultivating plants; the easiest way is to use controllable switches, such as Belkin WeMo[2], at power sources for lights. Since the switches are programmable, power supply is automatically turned on or off at predetermined durations, hence allowing the lighting duration to be controlled.

The lights are of three types: incandescent, fluorescent, and LED lights. Normally, incandescent and fluorescent lights are not suitable because they output heat at high light intensities, and their light spectrum is invariable. Compared with these lights, LED lights are more controllable because the composition of their spectrums is possible. In recent years, phenotypes have been investigated with respect to light spectrums owing to the advent of multi-functional LED lights [24]. In our platform, we selected a Philips hue[3],

[2] http://www.wemo.com

[3] http://www2.meethue.com

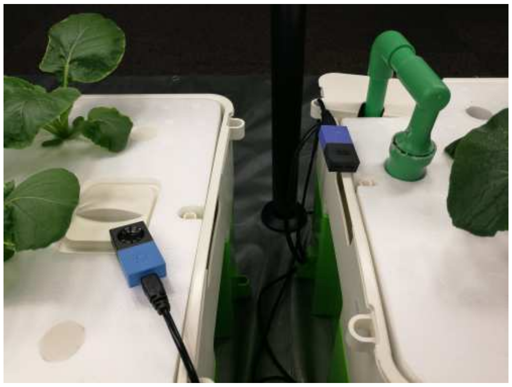

Figure 4. Sony MESH (two color boxes at the center of the image). Ambient temperature, humidity and brightness can be measured. The unit of brightness is in lux. The data is transferred to a smartphone using Bluetooth.

with lighting durations and colors programmable by using the provided software.

As illustrated in Figure 1, we constructed a bony framework and installed duct rails and sockets into the framework for lights and cameras. For one hydroponic culture toolkit, seven lights were installed at both sides with heights of approximately 30 cm from the toolkit. Since the intensities of LED lights may not be enough to cultivate plants even though the lights are extremely bright for human eyes, it is important to determine the height and arrangement of lights. To check the light intensity at many locations on the toolkit, we introduced an Internet of Things(IoT) device, described in the next section.

2.3. Sensors for environmental information

To measure ambient temperature, humidity, and light intensity, we used a Sony MESH[4], as illustrated in Figure 4. The MESH was originally designed for developing personal IoT systems as gadgets. It is also useful for our phenotyping platform because it is compact, easy-to-use, and cheap for measuring the aforementioned data. By using the provided software, the operations are programmable such that the data is constantly measured and transferred to a smartphone through Bluetooth.

By using MESH, the light intensities can be measured in lux. However, lux may not be appropriate in a precise sense because it is based on the property of human eyes. To measure the pure energy of lights, photosynthetic photon flux density (PPFD) is more appropriate in biology. In our platform, lux is used as a simplified index in environmental information.

[4]http://meshprj.com

Figure 5. RGB-D camera. Intel RealSense SR300 is selected because it is optimized for capturing an object at a short distance such as 20-150 cm.

2.4. Cameras

Various sensing technologies are available to acquire 3D object shapes [9]. In our platform, we developed two imaging systems by using an RGB-D camera and multiple RGB cameras.

2.4.1 RGB-D camera

An RGB-D camera is composed of an RGB camera and a structured light or time-of-flight using infrared-lights-based depth camera. With the advent of Microsoft Kinect, various RGB-D cameras have become widespread in many applications and are used in plant phenotyping [3, 20]. The main differences between each of such cameras are the resolutions of the depth image and depth range. Since the size of plant leaves in early growth stages is small, the depth images must usually be captured at a closer distance from the plant to enlarge the size in captured images. However, some RGB-D cameras are not designed for such short depth ranges.

In our platform, we selected the Intel RealSense SR300 because its depth range is approximately 20-150 cm. Compared with other RGB-D cameras, SR300 is specifically optimized for the short range capture because it is originally used for face modeling on laptops. As illustrated in Figure 5, SR300 was attached at the framework to capture top views of a plant. Note that some plant species cannot be captured using infrared lights because of their surface reflectance properties.

2.4.2 Multiple RGB cameras

The drawback of existing RGB-D cameras is the low resolution of depth images, for example, 640×480 pixels, at most. Since the size of plant leaves in early growth stages is small, the shape may not clearly be captured. Therefore,

Figure 6. Multiple RGB cameras. Three high-resolution cameras are installed to acquire the dense 3D structure of leaves from the top.

we also installed three high-resolution RGB cameras in our platform as illustrated in Figure 6.

We installed FLIR cameras[5] with resolutions of 2048×1536 pixels and Kowa lenses[6] with a view angle of 89×74 degrees for the cameras. The wide angle lens was selected to capture multiple plants at a close distance. Since leaves do not normally move in a second, we set up a slow shutter speed without using gain to adjust the intensities of pixels with less noise.

3. Annotation tool

The annotation of ground-truth regions of leaves in plant images on a pixel-by-pixel basis is usually a time-consuming task, and the development of annotation tools is an important research issue for machine learning tasks [17]. As illustrated in Figure 7, we developed our manual annotation tool on Python by using the following functions to manually but efficiently create ground truth labels for leaves in plant images.

Color segmentation An initial mask for leaves was created from an input image by using both thresholding-based binarization for each channel and the AND operation for all the binarization results. A track-bar was set to control the threshold value for each color channel. Since a generated mask is always superimposed onto an input image with alpha blending, it is easy to adjust the value by checking the generated mask.

Manual segmentation Since the initial mask is simply based on color segmentation, several leaves are generally extracted as one region in the mask because they are physically connected or overlapped. To separate them into individual leaves, we implemented a manual segmentation tool such that users can simply write a splitting curved line by freehand and divide one region into two with new leaf labels.

Erasing The initial mask may include false positive regions, which do not emanate from leaves, and it is necessary to prepare a function to erase them. We implemented an eraser tool with an adjustable size option as a brush size to allow the easy and quick removal of any size of false positive region. By using this function, the boundaries of leaves can be refined.

Label assignment One leaf label of a unique color must be assigned to one of the closed regions in the mask. The label color must be defined beforehand, and is loaded into the tool. By selecting a label and clicking a pixel in a region, the region is filled with a colored label. In addition, a region label can be modified by clicking a pixel in the region with another label. Note that one label can be assigned to multiple regions in the image because one leaf can be divided by another leaf.

In our annotation work, the combination of color and manual segmentations was useful enough to correctly separate large regions into each leaf region and decreased the processing time. In addition to the above-mentioned functions, we implemented functions of image pan and zoom and undoing and redoing of operations; these were obviously useful. Since our datasets include both spatial and temporal plant images in multiview datasets, it is necessary to assign the same label to the same leaf in different images. Therefore, the label image of a previous image can also be superimposed onto the image to easily check it.

4. Dataset

We created two types of datasets using an RGB-D camera and multiple RGB cameras publicly available on the web[7]. The environmental conditions for both datasets are common and constant for all days such that the lighting, temperature, and humidity were approximately 2400 lux, 28 °C and 30%, respectively. To accelerate the growth of Komatsuna, the lighting was continued for 24 h. Under these conditions, images of five plants were captured every 4 h for 10 days in each dataset so that the shape and size changes of leaves could be measured in 3D space for both short and long terms.

4.1. RGB-D dataset

Since an RGB-D camera was attached to capture the whole part of the toolkit, each plant region was manually segmented as a plant image and labeled as a label image, as illustrated in Figure 8. To use the dataset for temporal leaf

[5] BFS-U3-32S4C-C

[6] LM5JC1M

[7] http://limu.ait.kyushu-u.ac.jp/~agri/komatsuna/

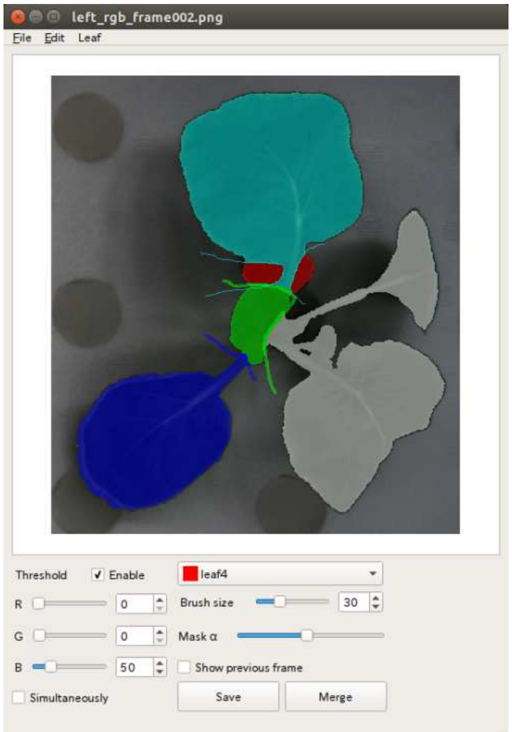

Figure 7. Leaf annotation tool. An initial mask for leaves is created using thresholds for RGB channels. Then, the mask is divided into individual leaves by using manual segmentation and refined by using eraser tools. The label is finally assigned by selecting a color and clicking a pixel at a region.

tracking, the same leaf label was assigned to the same leaf in images captured at different times. The original resolution of the camera was 640×480 and the resolution of the plant images was, for example, 166×190 pixels. Since the viewpoints for RGB and depth images were aligned by the library of the camera, the labels were valid for both images.

The alignment between the RGB and depth images is an issue when an RGB-D camera is used because these viewpoints are physically different. If the viewpoint of an RGB image is aligned into that of a depth image, the aligned RGB image may contain missing parts where depth values are not measured in the depth image. These types of RGB images with holes may not be suitable for segmentation tasks. Therefore, a depth image was aligned into an RGB image in our platform. Note that the accuracy of a depth value in the aligned depth image may be degraded because the alignment needs some interpolations. For this reason, we provided the original depth image and a transformation matrix from the viewpoint of depth images to that of RGB images so that the point cloud can also be transformed as necessary without any interpolations.

One advantage of using the RGB-D camera is that the object shape can be measured even when the lights are turned off because of the emitting of infrared lights. This implies that the movement of a leaf for 24 h can be measured so that the relationship between leaf shape and light source positions can be clarified. Note that each of the cameras and distance between the cameras can be calibrated using a standard calibration technique for 3D reconstruction with images for calibration.

4.2. Multiview dataset

As illustrated in Figure 9, we captured five plants from three viewpoints and manually segmented into individual plants as plant images. To use the dataset for spatial-temporal leaf tracking, the same leaf label was assigned to the same leaf in images captured with different cameras at different times. The ground truth of 3D shape was not measured because it was not easy to capture more accurate 3D shapes than when using high-resolution multiple-view images. One solution may be to use a RGB-D sensor; however its resolution is small, as discussed earlier. Therefore, the preparation of the ground truth for 3D shapes is a future research issue.

This dataset will be useful to evaluate spatial-temporal instance segmentation for multiple views. In relevant literature, instance segmentation was normally performed using a single view image [12, 22]. From the technical point of view, instance segmentation using a single view may be more difficult than that that using multiple views. However, from the application point of view, the use of multiple-view images is reasonable and leads to the acquisition of higher dimensional phenotypes. Therefore, instance segmentation using multiple views should be investigated as a next research issue. It may be solved by combining instance segmentation and stereo matching.

5. Conclusion

We proposed our platform to measure both plant growth and environmental conditions in small laboratory environments for 3D plant phenotyping. We selected Komatsuna as the target plant species because of its easy-to-grow properties. In addition, we constructed a platform by using hydroponic culture, Philips hue for lights, Sony MESH for sensing temperature, humidity and lighting intensities, and 3D imaging by using an RGB-D camera or multiple cameras. This platform is easy to setup and can be constructed by nonbiological researchers. Furthermore, we introduced our annotation tool with which users can quickly create labeled images for plant images manually. Since phenotypes differ according to plants, it is necessary to prepare this type of dataset for each plant. The relationship between plants can then be further analyzed in phenotyping.

As a future direction for the platform, we plan to control the environmental conditions by creating an enclosed space. Especially, the relationship between plant growth and temperature/humidity should be analyzed. Therefore, air-conditioning equipment will be installed in our platform. In addition, it is necessary to discuss the format of the dataset including images and environmental data for plant phenotyping. Since there is a standardized protocol[8] to control agricultural systems, it is important to discuss such protocols for the datasets.

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References

[1] P. Andrade-Sanchez, M. A. Gore, J. T. Heun, K. R. Thorp, A. E. Carmo-Silva, A. N. French, M. E. Salvucci, and J. W. White. Development and evaluation of a field-based high-throughput phenotyping platform. *Functional Plant Biology*, 41(1):68–79, 2014. 1

[2] M. Augustin, Y. Haxhimusa, W. Busch, and W. G. Kropatsch. Image-based phenotyping of the mature arabidopsis shoot system. In *European Conference on Computer Vision*, pages 231–246. Springer, 2014. 1

[3] Y. Chéné, D. Rousseau, P. Lucidarme, J. Bertheloot, V. Caffier, P. Morel, É. Belin, and F. Chapeau-Blondeau. On the use of depth camera for 3D phenotyping of entire plants. *Computers and Electronics in Agriculture*, 82:122–127, 2012. 1, 3

[4] R. T. Clark, R. B. MacCurdy, J. K. Jung, J. E. Shaff, S. R. McCouch, D. J. Aneshansley, and L. V. Kochian. Three-dimensional root phenotyping with a novel imaging and software platform. *Plant physiology*, 156(2):455–465, 2011. 2

[5] N. Fahlgren, M. A. Gehan, and I. Baxter. Lights, camera, action: high-throughput plant phenotyping is ready for a close-up. *Current opinion in plant biology*, 24:93–99, 2015. 1

[6] F. Fiorani and U. Schurr. Future scenarios for plant phenotyping. *Annual review of plant biology*, 64:267–291, 2013. 1

[7] C. Granier, L. Aguirrezabal, K. Chenu, S. J. Cookson, M. Dauzat, P. Hamard, J.-J. Thioux, G. Rolland, S. Bouchier-Combaud, A. Lebaudy, et al. PHENOPSIS, an automated platform for reproducible phenotyping of plant responses to soil water deficit in arabidopsis thaliana permitted the identification of an accession with low sensitivity to soil water deficit. *New Phytologist*, 169(3):623–635, 2006. 1

[8] K. Herzog et al. Initial steps for high-throughput phenotyping in vineyards. *Australian and New Zealand Grapegrower and Winemaker*, (603):54, 2014. 1

[9] R. Horaud, M. Hansard, G. Evangelidis, and C. Ménier. An overview of depth cameras and range scanners based on time-of-flight technologies. *Mach. Vision Appl.*, 27(7):1005–1020, Oct. 2016. 3

[10] A. S. Iyer-Pascuzzi, O. Symonova, Y. Mileyko, Y. Hao, H. Belcher, J. Harer, J. S. Weitz, and P. N. Benfey. Imaging and analysis platform for automatic phenotyping and trait ranking of plant root systems. *Plant physiology*, 152(3):1148–1157, 2010. 2

[11] R. Klose, J. Penlington, and A. Ruckelshausen. Usability study of 3D time-of-flight cameras for automatic plant phenotyping. *Bornimer Agrartechnische Berichte*, 69(93-105):12, 2009. 1

[12] K. Li, B. Hariharan, and J. Malik. Iterative instance segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3659–3667, 2016. 5

[13] L. Li, Q. Zhang, and D. Huang. A review of imaging techniques for plant phenotyping. *Sensors*, 14(11):20078–20111, 2014. 1

[14] M. Minervini, M. M. Abdelsamea, and S. A. Tsaftaris. Image-based plant phenotyping with incremental learning and active contours. *Ecological Informatics*, 23:35–48, 2014. 1

[15] M. Minervini, A. Fischbach, H. Scharr, and S. A. Tsaftaris. Finely-grained annotated datasets for image-based plant phenotyping. *Pattern recognition letters*, 81:80–89, 2016. 1

[16] M. Minervini, M. V. Giuffrida, P. Perata, and S. A. Tsaftaris. Phenotiki: an open software and hardware platform for affordable and easy image-based phenotyping of rosette-shaped plants. *The Plant Journal*, 90(1):204–216, 2017. 1

[17] M. Minervini, M. V. Giuffrida, and S. A. Tsaftaris. An interactive tool for semi-automated leaf annotation. 2016. 4

[18] A. M. Mutka and R. S. Bart. Image-based phenotyping of plant disease symptoms. *Frontiers in plant science*, 5, 2014. 1

[19] C. Olympios. Overview of soilless culture: advantages, constraints and perspectives for its use in mediterranean countries. *Cahiers Options Méditerranéennes*, 31:307–324, 1999. 2

[20] S. Paulus, J. Behmann, A.-K. Mahlein, L. Plümer, and H. Kuhlmann. Low-cost 3D systems: suitable tools for plant phenotyping. *Sensors*, 14(2):3001–3018, 2014. 1, 3

[21] S. Paulus, J. Dupuis, A.-K. Mahlein, and H. Kuhlmann. Surface feature based classification of plant organs from 3D laserscanned point clouds for plant phenotyping. *BMC bioinformatics*, 14(1):238, 2013. 1

[22] B. Romera-Paredes and P. H. S. Torr. Recurrent instance segmentation. In *14th European Conference on Computer Vision*, pages 312–329, 2016. 5

[23] H. Scharr, M. Minervini, A. P. French, C. Klukas, D. M. Kramer, X. Liu, I. Luengo, J.-M. Pape, G. Polder, D. Vukadinovic, et al. Leaf segmentation in plant phenotyping: a collation study. *Machine vision and applications*, 27(4):585–606, 2016. 1

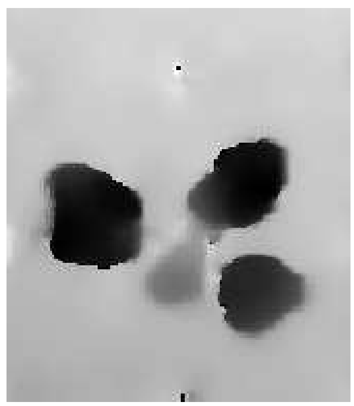
[24] F. Seiler, J. Soll, and B. Bölter. Comparative phenotypical and molecular analyses of arabidopsis grown under fluorescent and led light. *Plants*, 6(2):24, 2017. 2

[25] C. N. Topp, A. S. Iyer-Pascuzzi, J. T. Anderson, C.-R. Lee, P. R. Zurek, O. Symonova, Y. Zheng, A. Bucksch, Y. Mileyko, T. Galkovskyi, et al. 3D phenotyping and quantitative trait locus mapping identify core regions of the rice genome controlling root architecture. *Proceedings of the National Academy of Sciences*, 110(18):E1695–E1704, 2013. 1

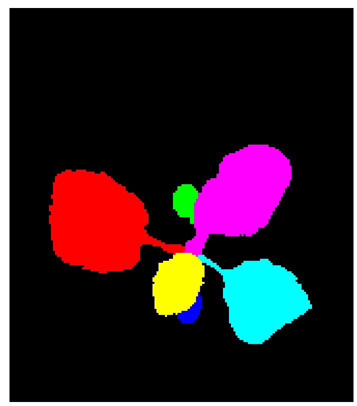
[8] http://www.uecs.jp/index-e.html

(a) Original image

(b) Plant image

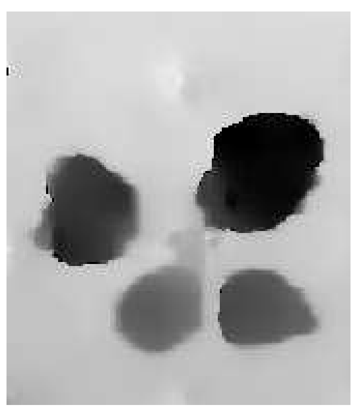


(c) Depth image

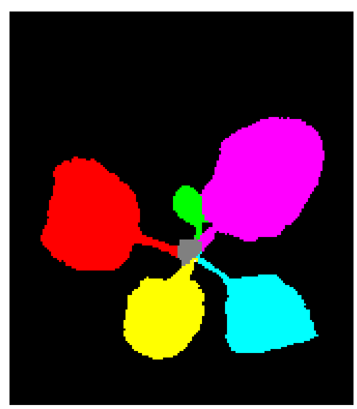


(d) Label image

(e) Plant image

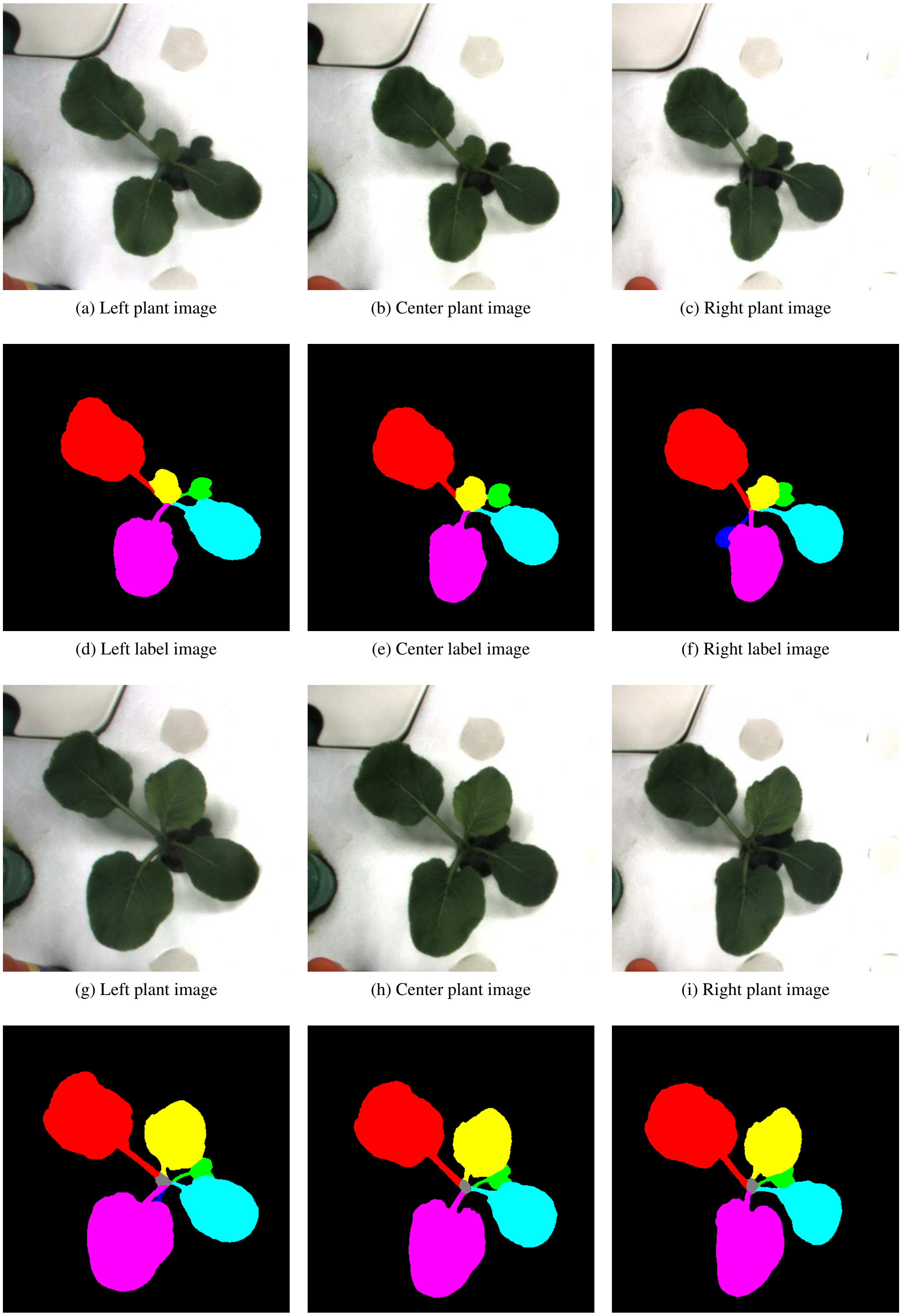


(f) Depth image



(g) Label image

Figure 8. RGB-D dataset. The original image at the first row was acquired from the camera and the plant images were created by manually segmenting the image. The images at the second row were captured one day before the images at the third row were captured. The viewpoint of the depth images is aligned to that of RGB images. From the plant images, the labeled images at the third column were manually created and are valid for depth images at the second column. Note that the intensities of depth images in this figure are modified for improving visualization .



(a) Left plant image (b) Center plant image (c) Right plant image

(d) Left label image (e) Center label image (f) Right label image

(g) Left plant image (h) Center plant image (i) Right plant image

(j) Left label image (k) Center label image (l) Right label image

Figure 9. Multiview dataset. The plant images in the first row were captured one day before the plant images in the third row were captured. The Label images in the second/fourth rows correspond to plant images in the first/third rows.