

Multi-modality Imagery Database for Plant Phenotyping

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1 Introduction

With the rapid growth of world population and the loss of arable land, there is an increasing desire to improve the yield and quality of crops, where the understanding of the genetic mechanisms to control plant growth is a key enabler [Döös, 2002]. For this purpose, plant scientists make various genetic mutant strains of plants, grow them either in growth chambers with simulated environmental conditions or directly in the field, visually observe the plants during the growth period, and finally discover plant morphological or physiological patterns that tightly associate with key growth factors [Houle et al., 2010]. While many factors can be assessed quantitatively, which is essential for high-throughput study, one of the bottleneck in this research pipeline is plant visual phenotyping [Walter et al., 2015].

The objective of *plant visual phenotyping* is to analyze and categorize the visual appearance of plants. In old days, plant phenotyping was conducted through manual visual observation [Erblichkeit, 1903]. Today, motivated by the increasing lower cost of imaging sensors and advances of computer vision technologies, image-based automatic plant visual phenotyping is quickly growing into a desirable and viable solution [Cruz et al., 2015]. In this interdisciplinary field, scientists employ various imaging sensors to capture plants and design advanced algorithms to automatically analyze the captured plant imagery, with the purpose of

Table 1 Plant image databases, where the abbreviation in “Applications” column is defined as Leaf Classification (LC), Leaf Segmentation (LS), Leaf Counting (LO), Leaf Alignment (LA), and Leaf Tracking (LT).

Database	Modality	Appli-cations	Plant Type	Subject/Classe #	Total Image #	Labeled Image #
Swedish leaf	Scanned leaf	LC	Swedish trees	15	1,125	1,125
Flavia	RGB	LC	Leaves	32	2,120	2,120
Leafsnap	RGB	LC	USA trees	184	29,107	29,107
Crop/weed	RGB	Weed detection	Crop/weed	2	60	60
LSC	RGB	LS, LO	Arabidopsis	43	6287	201
MSU-PID	Fluorescence, IR, RGB, Depth	LS, LO, LA, LT	Tobacco	80	165,120	83
			Arabidopsis	20	XXX	XXX
			Bean	5	XXX	XXX

raising testable biological hypotheses to solve the aforementioned problems.

Due to diverse variations of leaf shape, appearance, layout, growth and movement, plant image analysis is a non-trivial computer vision task [Minervini et al., 2015]. In order to develop advanced computer vision algorithms, image databases that are well representative of this application domain is highly important. In fact, computer vision research lives on and advances with databases, as evidenced by the successful databases in the field (e.g., FERET [Phillips et al., 2000] and LFW [Huang et al., 2007]). However, the publicly available database for plant phenotyping is still very limited, with the only exception of LSC database [Scharr et al., 2014], which, nevertheless, has its own limitations on the type of images (RGB only) and is only suitable for a small set of plant image analysis applications.

To facilitate future research on plant image analysis, as well as remedy the limitation of existing databases in the field, this paper presents a new multi-modality plant imagery database collected at Michigan State University (MSU), termed “MSU-PID”. The MSU-PID includes the imagery of two types of plants (Arabidopsis and bean), both are widely used in plant research, captured by four types of imaging sensors, i.e., Fluorescence, infrared (IR), RGB color, and depth. All four sensors are synchronized and are programmed to periodically capture imagery data for multiple consecutive days. Checkerboard-based camera calibration is performed between a pair of sensors, which results in the explicit correspondence between the pixels of *any* two modalities. For a subset of the database, we manually label the ground truth regarding the leaf identification number, locations of leaf tips and leaf segments. To provide a performance baseline for future research and comparison, we apply our automatic leaf segmentation framework [Yin et al., 2014a, Yin et al., 2014b] to the Arabidopsis imagery and demonstrate the unique challenge of image analysis on this database.

In summary, this paper and our database have made the following main contributions.

- MSU-PID is the first *multi-modality* plant image database. This allows researchers to study the strength and weakness of individual modality, as well as their various combinations in plant image analysis.
- Our unique imaging setup and the variety of manual labels make MSU-PID an ideal candidate for evaluating a diverse set of plant image analysis applications, including leaf segmentation, leaf counting, leaf alignment, leaf tracking, and potentially leaf growth prediction and 3D leaf reconstruction.

2 Prior Work

Databases drive computer vision research. Hence, it is always important to develop and promote properly captured databases in the vision community. While there is a clear desire to apply computer vision to plant image analysis, the lack of publicly available plant image databases has been an obstacle for the further study and development.

We summarize all existing publicly available databases that are related to plant imagery in Table 1. In terms of potential applications of these databases, they can be categorized into two types. The first type is for the general purpose of recognizing a particular species of tree or plant. The Swedish leaf database [Söderkvist, 2001] is probably the first leaf database even though the images are captured by scanners. The Flavia database [Wu et al., 2007] is considerably larger and a neural network is utilized to train a leaf classifier. The most recent leafsnap project is an impressive effort that includes a very large dataset of leaves for 184 tree types [Kumar et al., 2012]. A mobile phone application is also developed to make the leaf classification system portable. Finally, the crop/weed image database [Haug & Ostermann, 2014] is captured

by a robot in the real field, and used for the classification of crop vs. weed. Note that in this type of databases, normally only a *single* leaf is imaged in a relatively constrained imaging environment and as a result, the challenging problem of leaf segmentation has been bypassed.

The second type of databases is for plant phenotyping, where it is important to capture plant images without interfering the growth of plants. Thus, non-destructive imaging approaches are taken and the entire plant is imaged. The LSC database [Scharr et al., 2014] is the most relevant one to our database. It captures a large set of RGB images for the *Arabidopsis* and *Tobacco* plants. The provided manual labels allow the evaluation of leaf segmentation and leaf counting. In comparison, our MSU-PID database utilizes four sensing modalities in the data capturing, each providing different aspects of plant visual appearance. Our diverse manual labels also enable us to develop algorithms for additional applications such as leaf tracking and leaf alignment.

One of our data modalities is dense depth measurement. This has been a component of a number of recent non-plant RGB-D databases designed for object recognition [Lai et al., 2011], scene segmentation [Silberman & Fergus, 2011], human analysis [Sung et al., 2011, Barbosa et al., 2012], and mapping [Sturm et al., 2012]. By including dense depth for a plant database we anticipate enabling development of new 3D plant shape analysis algorithms.

3 Data Collection

3.1 Plants and Growth Conditions

Arabidopsis thaliana (ecotype Col-0) plants were grown at 20°C, under a 16 hr:8 hr day night cycle with a daylight intensity set at 100 $\mu\text{mol photons m}^{-2}\text{s}^{-1}$. Black bean plants (*Phaseolus vulgaris L.*) of the cultivar Jaguar, were grown under a 14 hr:10 hr day night cycle with night and day temperatures of 18°C and 24°C respectively, and a daylight intensity set at 200 $\mu\text{mol photons m}^{-2}\text{s}^{-1}$. Note that the bean plants were watered with half-strength Hoaglands solution three times per week.

In all cases, seeds were planted in soil covered with a black foam mask in order to minimize the fluorescence background from algal growth. Two-week-old plants (*Arabidopsis* or bean) were transferred to imaging chambers and allowed to acclimate for 24 hours to the LED lighting before the start of the data collection. Growth conditions as described above were maintained

for each set of plants for the duration of image collection.

3.2 Hardware Setup

In this section, we introduce the hardware used for capturing Fluorescence, IR, RGB color, and depth imagery data for both plants.

3.2.1 Fluorescence and IR images

Chlorophyll a fluorescence images were captured once every hour during the daylight period in a growth chamber [Cruz et al., 2015]. A set of 5 images were captured using a Hitachi KP-F145GV CCD camera (Hitachi Kokusai Electric America Inc., Woodbury, NY) outfitted with an infrared long pass filter (Schott Glass RG-9, Thorlabs, Newton, NJ), during a short period (< 400 ms) of intense light saturating to photosynthesis (> 10,000 $\mu\text{mol photons m}^{-2}\text{s}^{-1}$) provided by an array of white Cree LEDs (XMLAWT, 5700K color temperature, Digi-Key, Thief River Falls, MN) collimated using a 20 mm Carclo Lens (10003, LED Supply, Lakewood, CO). Chlorophyll a fluorescence was excited using monochromatic red LEDs (Everlight 625 nm, ELSH-F51R1-OLPNM-AR5R6, Digi-Key), collimated using a Ledil reflector optic (C11347_REGINA, Mouser Electronics, Mansfield, TX) and pulsed for 50 μs during a brief window when the white LEDs were electronically shuttered. In addition, a series of 5 images were also collected in the absence of the excitation light for artifact subtraction.

Infrared images were collected once every hour with the same camera and filter used for chlorophyll a fluorescence. Pulses of 940 nm light were provided by an array of OSRAM LEDs (SFH 4239, Digi-Key), collimated using a Polymer Optics lens (Part no. 170, Polymer Optics Ltd., Berkshire, England). Since 940 nm light does not influence plant development or drive photosynthesis, images were also collected during the night period. Sets of 15 images were collected for averaging, in the absence of saturating illumination. As with chlorophyll a fluorescence, images were captured in the absence of 940 nm light for artifact subtraction.

3.2.2 RGB color and depth images

The RGB color and depth images were collected using a Creative Senz3D sensor [Nguyen et al., 2015]. The sensor contains both a 1280 × 720 color camera directed parallel to, and separated by roughly 25 mm from, a depth camera which has a resolution of 320 × 240 pixels. The depth sensor uses a flash near IR illuminator

and measures the time-of-flight of the beam at each pixel to obtain dense depth estimates along with an IR reflectance at each pixel.

There are a number of limitations to the depth sensor that become the sources of depth errors. The primary measurement limitation on the range-to-target is the strength of the reflected beam. As a result, dark, matt surfaces are measured reliably only at a close range on the order of 20 or 30 cm. Highly reflective surfaces also pose problems with direct reflections leading to saturation and highly unreliable depths. In addition reflective surfaces at grazing angles are less reliably measured since little signal is reflected. Hence in our data portions of the chamber floor visible in Figure 1 are highly reflective and have incorrect depths. Fortunately the primary goal of the depth measurements are to obtain leaf depths, and plants provide good, roughly Lambertian reflections of IR [Chelle, 2006]. Therefore for these reasons the non-leaf depth pixels in the 3D depth data are unreliable and should be ignored in data analysis. Another limitation is that the IR illuminator has a slight offset to the left of the sensor, which results in shadows to the right of some objects, as well as mixed pixels on depth discontinuities. Both of these can be readily detected as large standard deviations in the depth image.

The imagery data were collected once every hour. These include the fluorescent image, the IR reflectance image with the same camera, the color image, the 3D depth and a confidence image. The 3D depth image is built from the depth sensor by transforming the points into the world coordinates and is expressed in the unit of mm. The confidence image is the standard deviation of the depth pixels. This is useful for identifying pixels at depth discontinuities that are unreliably detected and result in large standard deviations. In addition pixels with no response or saturated pixels are assigned with the maximum standard deviation, and should be filtered out.

3.3 Sensor Calibration

A checkerboard pattern was used to calibrate all three cameras to obtain both intrinsic and extrinsic parameters. While the checkerboard pattern is not visible as variations in depth, it is nevertheless observed as variations in the reflected IR image whose pixels correspond to the depth pixels. This enables the use of Zhang's method [Zhang, 2000] to calculate the intrinsic parameters including a 2-parameter radial distortion of each camera, as well as a calculation of their relative poses. The optical center of the color camera is used to define the world coordinates of our data. The depth val-

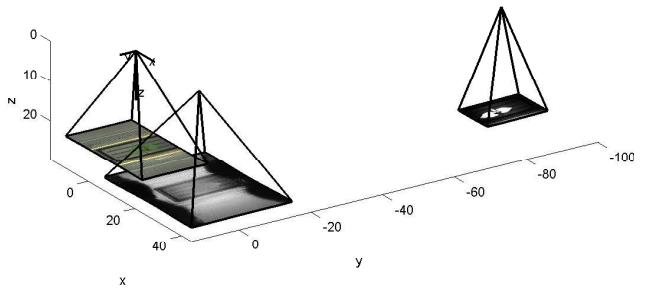


Fig. 1 A plot of the three cameras showing their relative configuration and fields of view as obtained through calibration. Units are in mm. The optical center of the color camera (on the left) defines the world coordinate system. Close to it is the depth camera. Its points are projected into the world coordinate system. On the right is the combined fluorescent and IR camera.

ues of the depth camera are projected along their pixel rays and then rotated and translated by the pose of the depth camera, and thus recorded as 3D points in the world coordinate system. Therefore it is straight forward to project these points onto any of the three camera images.

3.3.1 Depth Bias and Noise Characterization

We characterized both the bias and the variance of the depth cameras as follows. A flat printed checkerboard with a surrounding white board was positioned at a large number of poses in front of the sensor. The pose of the checkerboard is calculated in each case using the color and IR reflectance images. This defines a plane relative to the depth camera, which we use to calculate the ground truth depths for each pixel in the depth camera. At each pose, we collect multiple depth images; this provides both a bias and variance measurement for each pixel at multiple depths.

Next we sought to model the depth bias as a linear function of depth. Two parameters were fit for each pixel (a linear coefficient and an offset). We found that the bias was close to a constant as a function of depth, although it varied across the depth image as shown in Figure 2. The standard deviation of the pixel depth varied as a function of depth and roughly with the distance of the pixel from the optical center. Estimates of the noise are shown in Figure 2.

In the recorded 3D data we subtracted our estimated bias, and averaged five depth images for each record. Hence the actual depth standard deviations for our data are $1/\sqrt{5}$ of the standard deviations shown in Figure 2 (b) and the bias is zero.

Now we noticed that the chamber light shades blocked some of the depth camera field of view, and

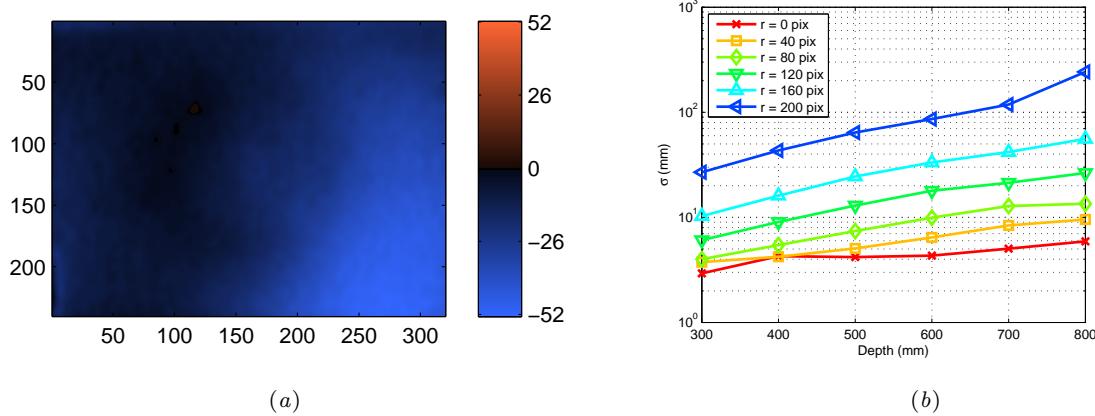


Fig. 2 Noise analysis for a depth camera. (a) Bias was fit and we found it to be roughly constant as a function of depth. This constant offset is shown for the camera pixels with red positive and blue negative offset in mm. Inside the chamber, the obstructions around the depth camera altered the bias somewhat and we re-calibrated the bias there. In all cases we subtracted the modeled constant bias from the depth images. (b) The standard deviation of the depth camera depends on depth as well as roughly on radius from the image optical center. A radius of 200 pixels corresponds to the corners of the depth camera, which can be seen to have large noise.

in doing so reflected some of the IR illumination. This resulted in an additional bias shift which we measured and removed from the depth data.

4 Database and Annotation

4.1 Statistics and protocols

MSU-PID includes two plant databases: Arabidopsis and Bean. The statistic information of these two databases are summarised in Tab. 2. The images were acquired every hour. As there is no light at night, plants can not be captured in fluorescence and RGB color images while IR and depth cameras can still capture plants. Therefore, in order to make it consistent, we release images captured only in day time, which are 16 images per day for Arabidopsis and 14 for bean for all four sensors.

The two databases differs in plant resolutions. As shown in Fig 3, we grow a single bean plant while a whole tray of Arabidopsis are grown at the same time. Therefore, the resolution of each Arabidopsis plant is much lower than that of a bean plant. We manually crop 16 Arabidopsis plants, which have been captured by all four sensors. Table 3 summaries the resolution of each plant in all four channels.

As shown in Tab. 1, MSU-PID can be used for leaf segmentation, leaf alignment, leaf tracking, and leaf counting. To facilitate future research, we separate the database into training set and testing set. 40% of the data is used for training and 60% for testing. Specifically, 6 plants of Arabidopsis and 2 plants of bean are selected for training. We will provide training and test-

ing data in different folders. For fair comparison, both supervised learning and unsupervised learning methods should evaluate the performance on the training and testing sets separately. The evaluation metrics will be discussed in Sec. 5.

4.2 Manual annotations

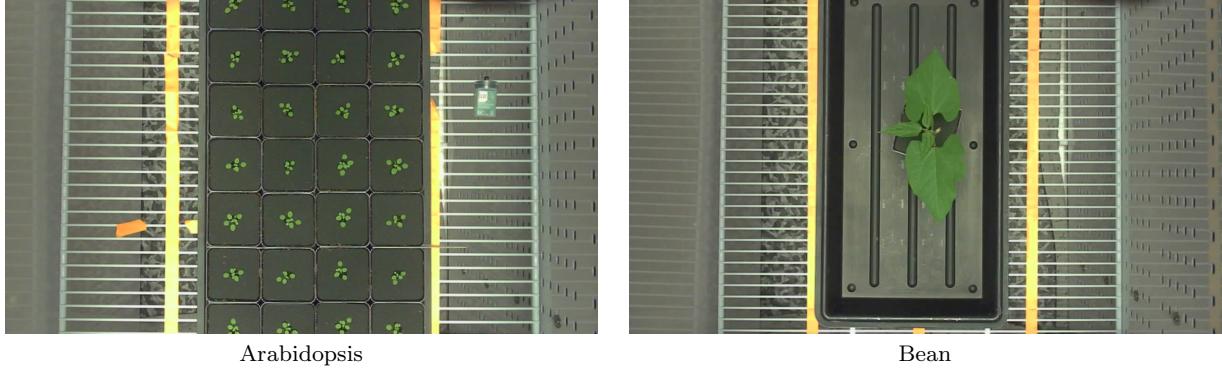
Part of the database is manually annotated to provide ground truth tip locations, leaf segmentation results and leaf consistency overtime. Tip locations are saved in a TXT file for each frame. Leaf segmentation results are stored in a PNG image for each frame with one color for each leaf. The same color is used to represent the same leaf over a sequence of frames.

We use Fluorescence images for labeling because of clear background. For Arabidopsis images, we label 4 frames each day. While for bean images, we label 7 frames each day because of faster leaf movement. A Matlab GUI interface is developed for leaf labeling, as shown in Fig 4. A user can open an image to label the two tips and annotate each leaf. The results will be automatically saved once a user goes to label the next image. For consistent annotation of the same leaf over time, we show a number on the center of each leaf indicating the order of labeling from the previous frame.

Tip label is implemented by clicking pairs of points on the image. The outer tip is always clicked before the inner tip. A line connecting each pair of tips will be shown immediately for visualization. Inaccurate labels can be deleted by clicking the right button of the mouse near the labeled point and relabeled by clicking the left button again.

Table 2 Summary of Arabidopsis and Bean databases.

Database	Subjects	Days	Images/Day	Total Images	Annotated Images
Arabidopsis	16	9	16	2304	576
Bean	5	5	14	350	175

**Fig. 3** Color images of Arabidopsis and bean plants.**Table 3** Plant resolution of Arabidopsis and Bean databases.

Database	Fluorescence	IR	RGB	Depth
Arabidopsis	240×240	240×240	120×120	NA
Bean	1360×1024	1360×1024	1280×720	320×240

Leaf label is implemented by clicking the boundary of one leaf at each time. The labeled leaf boundary is overlaid on the image for better visualization to guide the next action. Incorrect label can be deleted right after the labeling. This process continues until all leaves have been annotated. After the labeling of one plant, we visually go through the results and correct inaccurate labels. One example of leaf label result for one plant is shown in Fig. 5, where one color is used to represent one leaf. As we can see, there is leaf showing up and cover up the leaf underneath, which will not be annotated later (transition between day 4 and day 5).

4.3 File types and name conventions

We release training and testing sets in two separate folders. In each folder, there are two subfolders named Arabidopsis and Bean. The files in each subfolder have the following form:

- plant_XX.day_X.num_XX.rgb.png: the original RGB color images;
- plant_XX.day_X.num_XX.fmp.png: the original fluorescence images;
- plant_XX.day_X.num_XX.ir.png: the original IR images;
- plant_XX.day_X.num_XX.depth.png: the original depth images;

- plant_XX.day_X.num_XX.label.png: the labeled images;
- plant_XX.day_X.num_XX.tips.txt: the labeled tip locations;

where XX is an integer number indicating the specific plant information. For each image in the database, we provide four channels images in PNG files (_rgb, _fmp, _ir, _depth). For annotated images, we have two additional files (_label, _tips) saving the annotation results. Leaf segmentation results are encoded as indexed PNG files, where each leaf is assigned a unique and consistent ID over time. Leaf ID starts from 1 and continuously increase. And the background is encoded as 0. Tips locations are saved in TXT files where each line has the following format:

- leaf ID tip1_x tip1_y tip2_x tip2_y

where leaf ID is an integer number that is consistent with the segmentation label in the PNG file. tip1_x and tip1_y are floating numbers represent the coordinates of the outer tip point. tip2_x and tip2_y are floating numbers represent the coordinates of the inner tip point.

In addition to the original images and annotation results, we provide another folder named Matlab with all Matlab functions that will be used for mapping between different image channels and for performance evaluation purpose. Note that the annotation is provided based on Fluorescence images. In order to evaluate methods de-

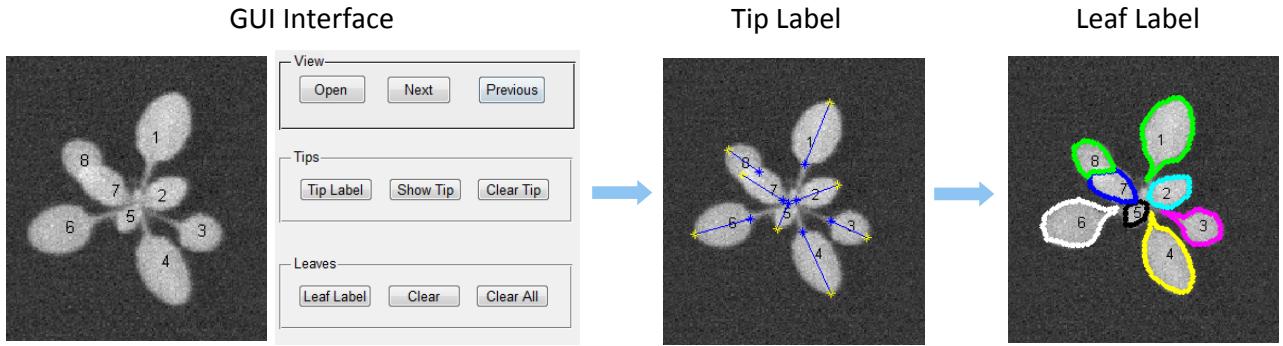


Fig. 4 Leaf labeling process, including tip labels and leaf annotation.

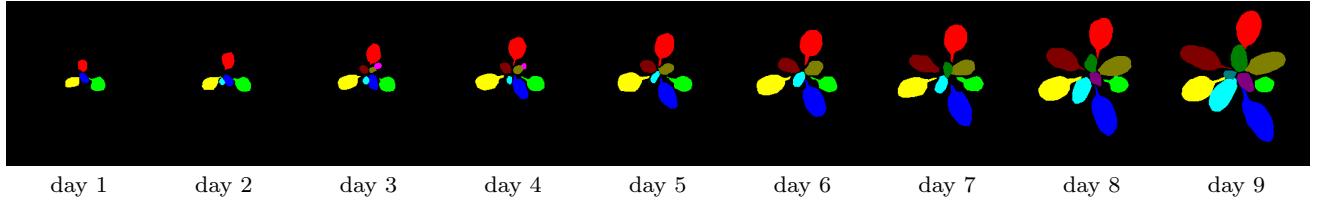


Fig. 5 Leaf label results for one Arabidopsis plant over nine days with one image per day.

veloped on other channels, we provide image mapping functions between every two channels.

5 Baseline Method and Performance Evaluation

5.1 Our framework

We apply our automatic multi-leaf segmentation and tracking framework [Yin et al., 2014a, Yin et al., 2014b] to the testing set of Arabidopsis fluorescence imagery to provide a baseline for future comparison. Leaf segmentation aims at finding the correct number of leaves and the corresponding boundary of each leaf in each image. Leaf alignment is to align the two tips of each leaf. Leaf tracking is designed to track each leaf over time.

As shown in Fig 6, the input of this framework is a plant video and a set of predefined templates with various shapes, scales, and orientations. To generate the template set, we first select 10 templates with different aspect ratios from the labeled images in the training set together with the corresponding tip locations. For each template, we scale it to 12 different sizes in order to cover all size ranges in the database. For each scale template, we rotated every 15° to generate 24 different directions. Tip locations will be scaled and rotated accordingly. Finally, we generate 2,880 leaf templates.

Our work is motivated by Chamfer Matching technique [Barrow et al., 1977], which is used to align two edge maps. We extend it to align multiple objects at

the same time. For each image, we use simple thresholding and edge detection to generate an edge map and mask. First, we find the best location of each template in the edge map that has minimal chamfer matching distance, which will result in an over-complete set of leaf candidates. Second, we apply multi-leaf alignment [Yin et al., 2014a] approach to find an optimal set of leaf candidates on the last frame of the video, which will provide the information of the number of leaves, tip locations and boundaries of each leaf. Third, we apply multi-leaf tracking [Yin et al., 2014b] approach, which is based on leaf template transformation, to track leaves between continuous two frames.

In the tracking process, we develop a procedure to generate new leaves and delete small leaves. For each frame of the video, we can generate a label image with each leaf being labeled with one color and the tip locations for each piece of leaf. The label for each leaf in the video maintain the same during tracking process.

5.2 Evaluation metrics

To evaluate the performance of leaf segmentation, alignment, and tracking, we use four criteria and provide the Matlab implementations. Three of them are based on tip-based error, which is defined as average distance of a pair of estimated leaf tips $\hat{\mathbf{t}}_{1,2}$ with a pair of labeled leaf tips $\mathbf{t}_{1,2}$ normalized by the labeled leaf length:

$$e_{la}(\hat{\mathbf{t}}_{1,2}, \mathbf{t}_{1,2}) = \frac{||\hat{\mathbf{t}}_1 - \mathbf{t}_1||_2 + ||\hat{\mathbf{t}}_2 - \mathbf{t}_2||_2}{2||\mathbf{t}_1 - \mathbf{t}_2||_2}. \quad (1)$$

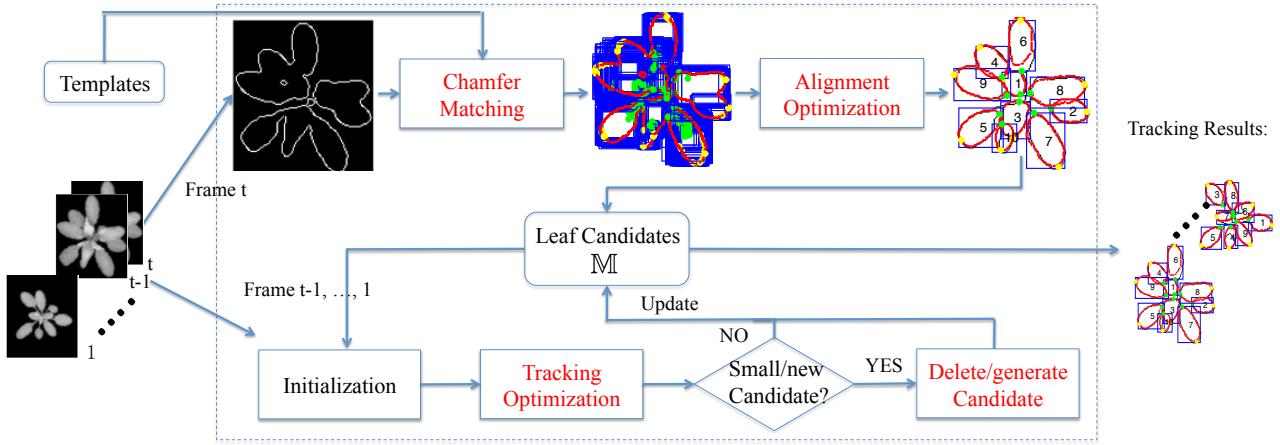


Fig. 6 Overview of the baseline method.

We build the frame-to-frame and video-to-video correspondence respectively and generate two sets of tip-based errors. More details can be find in [1]; We define a threshold τ to operate on the corresponding tip-based errors. By varying τ , we compute the first three criteria as:

- *Unmatched Leaf Rate(ULR)*, the percentage of unmatched leaves w.r.t. the total number of labeled leaves. This can attribute to two sources. First, miss detections and false alarms. Second, matched leaves with tip-based errors larger than τ .
- *Landmark Error(LE)*, the average tip-based errors smaller than τ of all frame-to-frame correspondent leaves.
- *Tracking Consistency(TC)*, the percentage of video-to-video correspondent leaves whos tip-based errors are smaller than τ .

In order to evaluate the leaf segmentation accuracy, we adopt an additional metric [Scharr et al., 2014] based on the Dice score of estimated segmentation result and ground truth label:

- *Symmetric Best Dice(SBD)*, the symmetric best Dice among all labeled leaves.

The Matlab function for computing *SBD* is provided by [Scharr et al., 2014]. The instruction on how to use the evaluation functions are included within the functions.

5.3 Performance and analysis

The results of our algorithm by varying τ from 0 to 1 is shown in Fig. . And the *SBD* score is 0.51 by averaging over all plants.

6 Conclusions

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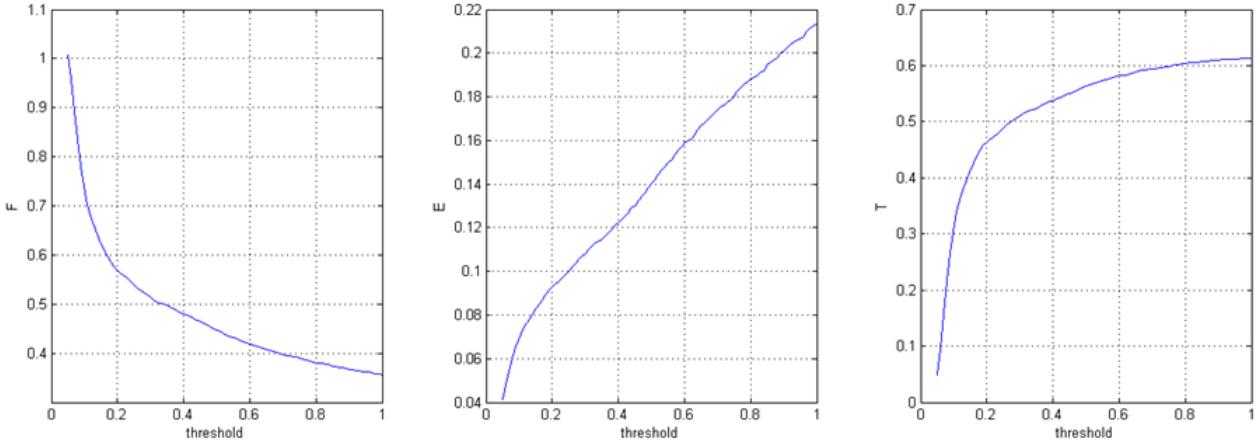


Fig. 7 Performance of the baseline method.

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