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Curvature-based pattern recognition for cultivar classification of Anthurium flowers

Alireza Soleimani Pour, Gholamreza Chegini*, Payam Zarafshan, Jafar Massah

Department of Agrotechnology, College of Aburaihan, University of Tehran, Tehran, Iran

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ABSTRACT

Real-time classification of agricultural products with various cultivars is an important issue in postharvest processing, which speeds up the processing and consumer delivery time. An innovative approach was developed for cultivar classification of Anthurium flowers based on image processing, B-spline curves, mathematical operations and machine learning classifiers. The algorithm was implemented and tested on a database of Anthurium flower images, which included the images of 15 cultivars of the flower with various sizes and shape categories. The boundary of the flowers was detected and reconstructed using a suitable B-spline curve. The signed curvature of the curve was calculated via mathematical operations. Then, several classifiers were implemented using the machine learning methods, Support Vector Machines (SVM), K-Nearest Neighbors, Discriminant Analysis, Decision Trees, and Naive Bayes, to detect and classify the cultivars of the flower. The experiments were carried out using a different number of training samples of the database images. The effect of various classification methods and variations in the angle of rotation of placing the flowers under the camera on classification accuracy were evaluated and the computation time of the classification process was measured. The results showed that in the unrotated sample with 1.5 pixels/mm density, the classification accuracy of the Naive Bayes and SVM algorithms had the highest classification accuracies, more than 98%. Also, the Decision Trees classifier had the lowest computation time, less than 2.5 ms. The proposed approach had proper classification accuracy and low computational load, which could be used in the real-time classification systems for Anthurium flowers.

1. Introduction

Anthurium is popular as a cut flower and pot plant ornamental due to its attractive long-lasting inflorescences, colorful, cylindrical spadix subtended with large heart-shaped spathe and unusually attractive foliage (Higaki et al., 1994). This flower is widely appreciated around the world, primarily for its showy and colorful spadix (Teixeira da Silva et al., 2015). In the global market, the Anthurium sales are second in the world among tropical cut flowers (Galinsky and Laws, 1996; Rikken, 2010). Cultivars of Anthurium flower are different in color, size, and shape. The color of this flower is very diverse and varies from pastel pink and greens to vibrant red and green combinations. The size of different cultivars of the flower varies from less than an inch to almost one foot in length. The flower has been categorized into three main shapes, Cupped, Obake and Standard.

Machine learning and pattern recognition along with image processing techniques have recently become the most popular areas of research in artificial vision. These techniques have been used in the variety of applications such as computer vision-based systems deals with the recognition of objects as well as the identification and localization of their three-dimensional environments. The other applications of the artificial vision include optical character recognition, objects recognition on earth from the sky (by satellites) or from the air (by aeroplanes and cruise missiles), personal identification systems, face recognition, fingerprints identification, visual data mining, bioinformatics and archaeology (Barajas-García et al., 2015; Dutt et al., 2012; Roberts, 1965; Sharafi et al., 2016; Zhao et al., 2003). Agricultural applications of these techniques are included artificial vision systems for classification and grading (Blasco et al., 2003; Clement et al., 2013; Sunoj et al., 2018; Zhang and Wu, 2012), plants species recognition (Neto et al., 2006), flowers cultivar recognition (Zhenjiang et al., 2006), 3D reconstruction of irregular products (Goñi et al., 2007), crop yield estimation (Payne et al., 2013), external and internal quality assessment of fruit (Fernandes et al., 2005; Saad et al., 2016; Throop et al., 2005; Zhang et al., 2014) disease detection in plants (Pujari et al., 2015), bruise detection in fruit (Zhang et al., 2017), crop recognition in natural environment (Bao et al., 2016), size and shape features determination of horticultural crops (Ercisli et al., 2012), as well as food

* Corresponding author.
E-mail addresses: asoleimani@ut.ac.ir (A. Soleimani Pour), chegini@ut.ac.ir (G. Chegini), p.zarafshan@ut.ac.ir (P. Zarafshan), jmassah@ut.ac.ir (J. Massah).

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processing applications (Jackman and Sun, 2013; Soleimani Pour-Damanab et al., 2011; Vithu and Moses, 2016).

Flower life after harvest is generally short and prone to postharvest losses. Research on postharvest issues of flowers, especially, the processes which could be mechanized is valuable and important. Mechanizing the processes like classification, grading and packing will improve the product quality and shorten the delivery time from field or greenhouse to the consumer. The time between picking to the consumer should be as short as possible. On the other hand, the postharvest operations in fields, such as bunching, packing, and grading, are an important determinant of quality and life of cut flowers and foliage (Celikel and Karaaly, 1995). Therefore, developing automatic systems to implement the postharvest operations is a need for all ornamental cultivars, as well as Anthurium, to speed up the processing operations. Among instrumental-oriented inspection approaches, computer vision is one of the methods in which there is no contact between the instrument and object. Also, a lot of data is obtained via only one scanning procedure. Performance and efficiency of these systems are extremely depended on the robustness of applied image processing algorithms and machine learning techniques.

To date, considerable studies concerning flower classification according to visual features and imperfections have been carried out. Examples of applications using artificial vision systems for classification and recognition of flowers have been published (Aquino et al., 2015; Belhumeur et al., 2008; Garbez et al., 2016; Kohsel, 2001; Kumar et al., 2012; Morel et al., 2009; Nilsback and Zisserman, 2006; Timmermans, 1998; Timmermans and Hulzebosch, 1996; Yang et al., 2000; Zhenjiang et al., 2006). Many of these publications discuss on differences among various flower species and were not concerned about cultivars of a single flower type. As different flowers may have a large number of commercial species with clear differences even for an expert person.

Machine learning techniques are mainly classified into two board categories of unsupervised and supervised methods. The supervised techniques attempt to find out the relationship between input attributes (independent variables) and a target attribute (dependent variable) as a class label in classification, or as a continuous variable in the regression. Classification is the problem of identifying which of a set of class a new observation belongs, on the basis of a training set of data containing observations (or instances) whose class is known (Tang et al., 2014). So far many methods are presented to classify objects based on visual data, such as Support Vector Machines, K-Nearest Neighbors, Decision Tree, Discriminant Analysis, Naive Bayes and Artificial Neural Networks.

The overall objective of our research is to design automated flower grading machine equipped with cultivar classification and geometrical features detection algorithms. Both algorithms implemented on a computer vision system, which is mainly based on image processing and machine learning techniques, respectively. It is worth noting that to utilize the machine for various flowers and cultivars, it should be able to recognize the cultivars, before sorting or grading them. In this study, an algorithm was developed to identify cultivars of Anthurium flowers using image processing and machine learning techniques.

2. Materials and methods

Images of 15 commercial cultivars of Anthurium flower from all the three various shape categories were acquired to train and test the algorithm (Fig. 1). The selected cultivars which were classified in three categories include; Cupped shape: '*Marea*', '*Facetto*', '*Peruzzi*', '*Previa*' and '*Xavia*'; Obake shape: '*Baron*', '*Simba*', '*Spice*', '*Tivoli*' and '*Zafira*'; and Standard shape: '*Arena*', '*Fantasia*', '*Rosa*', '*Cantello*', and '*Sante Royal*'. The flowers were obtained from the Pars Flor company (Kebria Flowers and Plant Village, Varamin, Iran).

An innovative algorithm was developed to classify the cultivars. The algorithm firstly detects the boundary of the flower as a set of points in the Cartesian coordinate system, via image processing and B-spline curves. By applying mathematical operations, the curvature of the flower boundary is calculated. Then, to recognize the cultivar of each query image, its curvature data were compared with the curvature database for the different cultivars using machine learning classifiers. The algorithm was developed as a computer program on a computer vision system for image capturing, image processing as well as cultivar classification.

The computer vision system was included a high-resolution IP camera (Grandstream GXV 3601 HD-IP Camera), a proper lighting room and a laptop (Intel B960 2.20 GHz processor and 4.00 GB of RAM running under the Microsoft Windows 7 operating system). The images acquired with a white background plate; this color was selected considering multiple colors of cultivars which used for tests. Images background color is important to perform efficient boundary detection (Goñi et al., 2007). The camera lens was set perpendicularly to background plate and with a distance of 60 cm. Lighting of imaging room was done using 12VDC white LED lamps which installed symmetrically in the room for uniform light distribution on the sample. Images were rotated to 5 angles of rotation of 0 (completely vertical), $-\pi/9$, $-\pi/18$, $\pi/9$, $\pi/18$ rads (Fig. 2).

2.1. Image processing and boundary detection

The captured images preprocessed to enhance boundary detection process using an algorithm developed in MATLAB R2015a computer program. The B-spline curve fitting technique was used to introduce the flower boundary as a curve in a Cartesian coordinate system. The B-spline curve fitting technique has methodological and computational advantages, including flexibility for modeling of complex contours, because of their ability to express as piecewise polynomial. The recursive definition also ensures efficient algorithms for computing basis functions and their derivatives. More importantly, control vertices in a B-spline curve are adaptable in manipulating and controlling the curve (Stanberry and Besag, 2014).

The image preprocessing and processing steps were as follows:

1. Color filter applied to the original image to reduce the lighting undesirable effects and contrast improvement.
2. The original RGB image were converted to gray-scale format.
3. Noise was reduced through a 3×3 median filter to enhance images quality that facilitates the boundary detection.
4. Boundary of the flower images was detected by Canny edge detection algorithm. The interior points were removed by applying "imfill" function on the resulted image in MATLAB computer program.
5. Some points on the boundary of the flowers were specified as B-spline knots. It is worthwhile to mention that the algorithm marked the upper-left point of the flower edge as first boundary point and then rotated clockwise on the periphery to find next boundary points until they returned to the first point. The points had equal distances from each other, and their optimum number determined through evaluating the degree of shape similarity using the Jaccard index (Jaccard, 1912) between the shape of flower in the original image and the shape that reconstructed by the B-spline curve.
6. A subset of the flower boundary pixels interpolated using a closed B-spline curve. The result would be a continuous approximation of the flower boundary instead of the discrete edge of the binary image (Fig. 3).

2.2. Boundary curvature

The curvature of a curve is the rate of change in the direction of the tangent line at that point with respect to arc length (Jia, 2017). According to this measure, large circles have smaller curvature than small circles, which bend more sharply. The absolute value of the curvature is a measure of how sharply the curve bends. The curves that bend slowly and are almost straight lines will have small absolute curvature. The