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Curvature-based pattern recognition for cultivar classification of Anthurium flowers

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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

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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

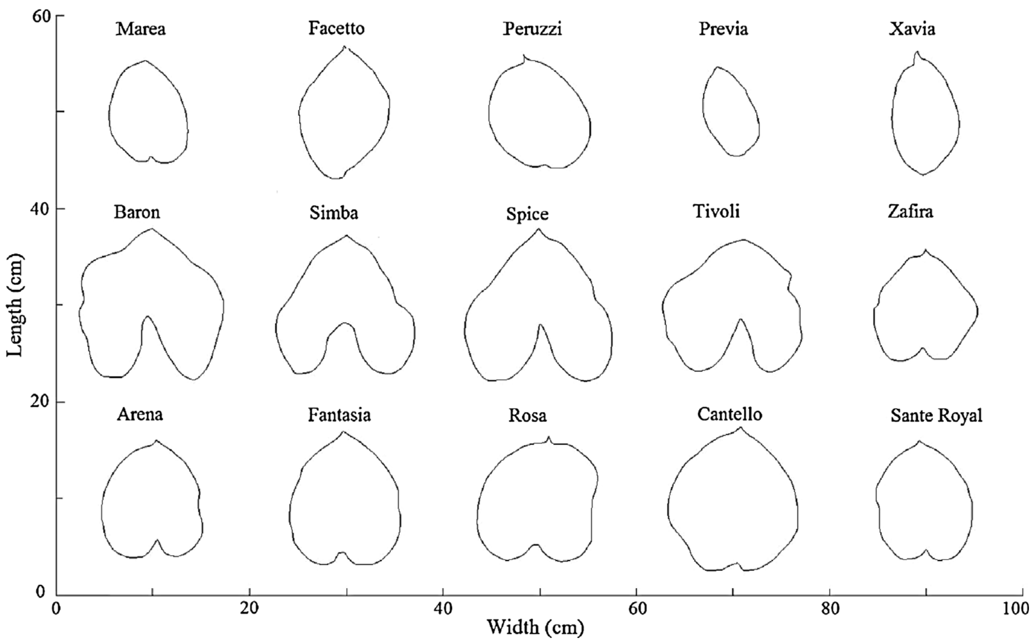

Fig 1. Cultivars of Anthurium flower used in this study.

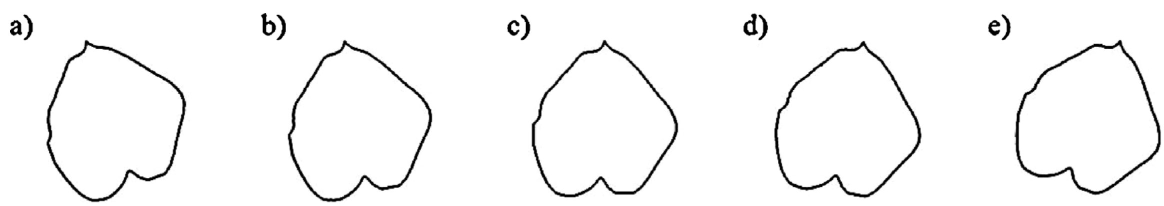

Fig. 2. '*Zafira*' Anthurium flowers with different angles of rotation; a) $-\pi/9$, b) $-\pi/18$, c) 0, d) $\pi/18$, e) $\pi/9$ radians.

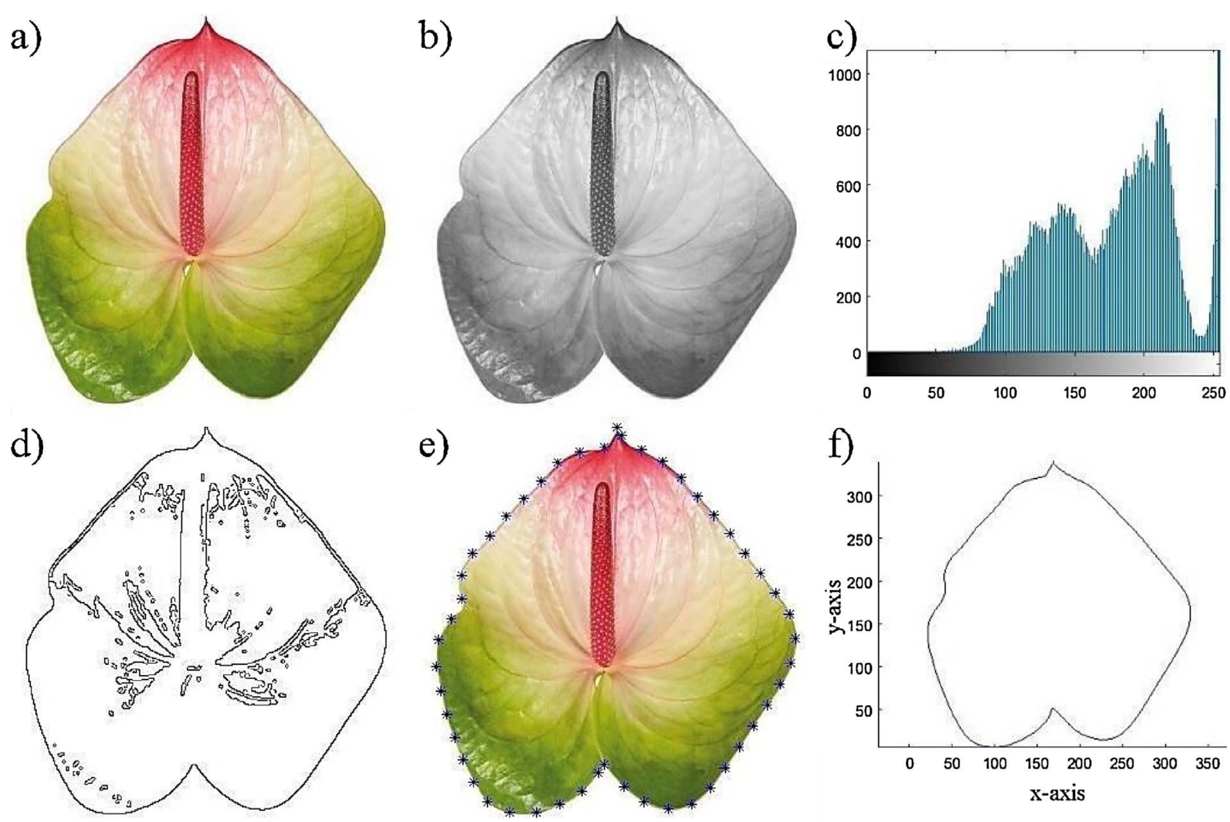

Fig. 3. Image preprocessing and processing steps; a) original image, b) gray-scale image, c) gray-scale histogram, d) edge detection by Canny edge detector, e) original image with some selected points (as knots for the B-spline curve) on its boundary, f) boundary curve in a Cartesian coordinate system.

signed curvature of a curve is the rate of direction change of its tangent vector. A Curve has a positive curvature at the points that the curve swing to the inside and a negative curvature at the points that the curve swing to the outside (Miller, 2007).

Suppose a curve in the plane given by the vector equation:

$$r(t) = x(t)i + y(t)j \qquad a \le t \le b \tag{1}$$

Where $x(t)$, $y(t)$ are defined and continuously differentiable between $t = a$ and $t = b$. In order to get a measure of how fast the curve is turning, the curvature k at a point (x, y) on the curve is defined as:

$$k = \frac{y''x' - y'x''}{(x'^2 + y'^2)^{3/2}} \tag{2}$$

Regardless of any specific parameterization, the curvature k depends on the curve alone. For a plane curve given explicitly as $y = f(x)$, and using primes for derivatives $\frac{d}{dx}$ with respect to coordinate x, the curvature is:

$$k = \frac{\frac{d^2y}{dx^2}}{\left(1 + (\frac{dy}{dx})^2\right)^{3/2}} \tag{3}$$

We used from Eq. (3) to calculate the signed curvature at different points on the boundary of the database images and query images. As the B-spline curve results in a set of (x, y) points on the boundary of the flower image, we used Eqs. (4) and (5) to calculate the first and second derivatives at different points of the boundary curve.

$$\frac{dy}{dx}(n) = \frac{y(n+1) - y(n)}{x(n+1) - x(n)} \tag{4}$$

$$\frac{d^2y}{dx^2}(n) = \frac{\frac{dy}{dx}(n+1) - \frac{dy}{dx}(n)}{x(n+1) - x(n)} \tag{5}$$

where $\frac{dy}{dx}(n)$ and $\frac{d^2y}{dx^2}(n)$ are the first and second derivatives at the n-th point of the boundary curve, respectively.

Cultivar of each query flower was recognized by comparing its boundary curvature with the curvature dataset for 15 cultivars using a useful and efficient classifier.

2.3. Classification

The most popular machine learning classification techniques are: logic-based techniques (Decision Trees, Learning Set of Rules), perceptron based techniques (Single Layer Perceptron, Multi-Layer Perceptron, RBF Networks), statistical learning techniques (Naive Bayes Classifier, Bayesian Network, Discriminant Analysis), instance-based learning (K-Nearest Neighbors), and Support Vector Machines (Soofi and Awan, 2017). In this research, five supervised classification approaches (Support Vector Machines, K-Nearest Neighbors, Discriminant Analysis, Decision Trees, and Naive Bayes) were used to classify the cultivars. The Support Vector Machines (SVM) classifier was considered as the main classification strategy, and the results of other methods were used to compare and evaluate the SVM results.

The SVM classifier belongs to kernel methods and is the most known member of them. This machine learning strategy is a principled and very powerful method that has outperformed most other systems in a wide variety of applications (Byun and Lee, 2002; Kampouraki et al., 2009; Zhang and Wu, 2012). The SVM classifier should be used with a kernel function. Four common kernels are included Homogeneous Polynomial (HPOL), Inhomogeneous Polynomial, Radial Basis Function (RBF) or Gaussian kernel, and Hyperbolic Tangent. Whereas the SVM with the Gaussian Radial Basis (GRB) kernel function has had better performance and higher classification accuracy in comparison with other kernel functions (Amari and Wu, 1999; Kavzoglu and Colkesen, 2009; Schölkopf et al., 1997; Zhang and Wu, 2012), we used the SVM classifier with the RBF kernel function in our tests.

$$k(x_i, x_j) = \exp(-\gamma \, \|x_i - x_j\|^2) \quad \gamma > 0 \tag{6}$$

where x_i, x_j are data points from the original space. It is important to find optimal parameters γ and C because different parameter setups are suitable for solving different problems. Also, the SVM method was originally developed as a linear classifier. Several methods have been proposed for multiclass SVMs, and the dominant approach is to reduce the single multiclass problem into multiple binary classification problems. Throughout the methods for multiclass problems, we consider Dense Random method based on our pre-tests. In this method, for each binary learner, the software randomly assigns classes into positive or negative classes, with at least one of each type. Approximately, $10 \times \log2 K$ binary learners are created to implement multiclass classification, in which K is the number of distinct classes (MathWorks, 2015).

The algorithm was entirely developed using the Matlab 2015a (The Mathworks©) computer program. To truly evaluated computational times, all other programs were stopped before running the program on the computer. The algorithm can be run or tested on any computer platforms where Matlab is available. Totally, 15 × 20 images from 15 cultivars (20 images for each cultivar) were used to train and test the algorithm (150 images for train and 150 images for test). To evaluate the strength of algorithm for classifying rotated samples, the database images were rotated $-\pi/9$, $-\pi/18$, 0, $\pi/18$ and $\pi/9$ rad.

3. Results and discussions

In general, the boundary of Anthurium flowers was detected via image processing techniques and Canny edge detection algorithm. Some points on the boundary of the flowers, which have equal distances from each other, specified using an algorithm written in MATLAB computer program. A closed B-spline curve was fitted on the boundary of the flowers, somehow the specified points were the knots of the B-spline curve (Fig. 3e). As Eq. (3) indicates, in order to calculate the flower boundary curvature, the first and second derivatives of the curve calculated by mathematical operations (Eqs. (4) and (5)). Fig. 4 demonstrates the signed curvature of the boundary of flower on its different points for a flower of cultivar *'Zafira'*.

The shape is an important feature of flowers, petals, and leaves. It is much more difficult to describe shape than attributes like color and size. The shape is easily comprehended by humans but very difficult to quantify or define by computer (Alfatni et al., 2011). Various features for shape description and measurement have been studied. Size-dependent features (including compactness, convexity, elongation, roundness, length, width and length/width ratio), boundary encoding,

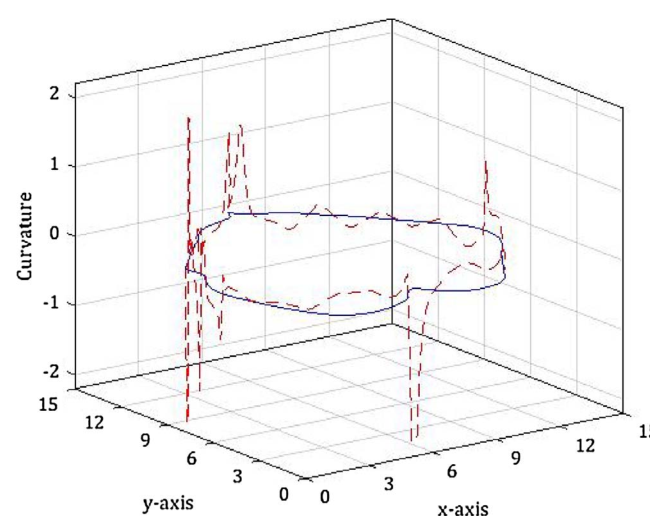

Fig. 4. The curvature of a '*Zafira*' flower at its different boundary points.

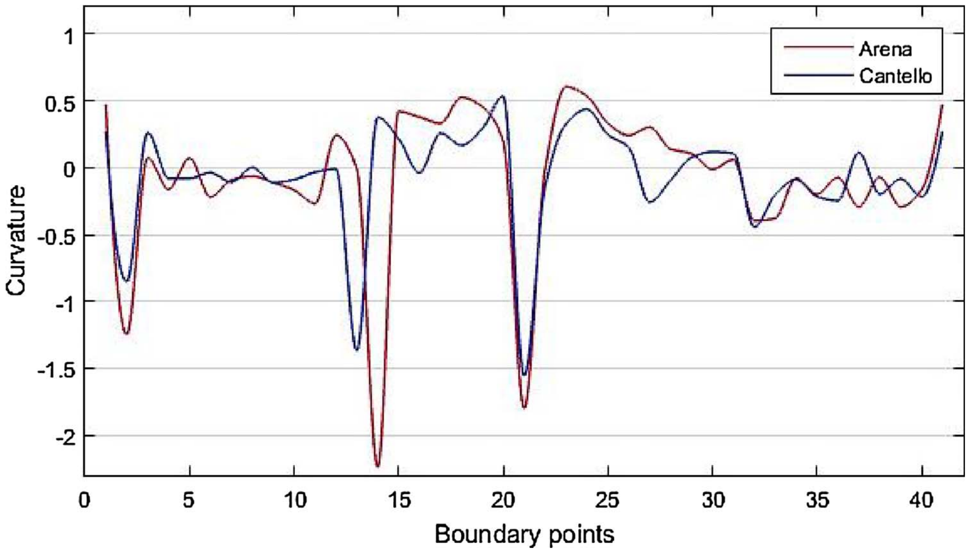

Fig. 5. Boundary curvature of *'Arena' and 'Cantello'* Anthurium flowers at different points of their boundary.

invariant moments, and Fourier descriptors are the most popular shape features applied in the quality inspection of food industry (Zhang et al., 2014). Generally, flower shapes symbolically describe as round, irregularly round and star-shaped. We have used the curvature measurement to mathematically describe shapes of Anthurium flowers. For instance, the curvature at different boundary points for two cultivars is presented in Fig. 5. Each cultivar has a relatively distinct and unique trend of change in its boundary curvature that distinguishes it from others. The trends of change of boundary curvatures were our criterion for classifying different cultivars.

The results of the experimental tests for classification accuracy as well as computation time of the proposed cultivar classification method with different parameters values and different machine learning techniques are presented in Table 1. Fig. 6 shows the results of different machine learning methods included SVM, K-Nearest Neighbors (KNN), Discriminant Analysis, Decision Trees, and Naive Bayes. Among the methods, the SVM and the Naive Bayes were better for most cultivars and number of training samples. The accuracy reached its maximum, averagely, at image pixel density of 1.5 pixels/mm for various cultivars of the flower and the number of training samples of 150. Also, the classification accuracy of cultivars with Obake shape was better than others (Table 1).

Fig. 7 shows the classification accuracy for various machine learning techniques at different angles of rotations. It is clear that the best classification was done at the position that the flower placed completely vertical. Rotating the flower image had an undesirable effect on the classification accuracy, as by increasing the angle of rotation amount (positively or negatively) the classification accuracy decreased for all cultivar shapes. Therefore, it is recommended that the proposed algorithm is used for the samples at the completely vertical position, or the cultivar database images improved by adding images of cultivars at different positioning angles and using more images to train the classifiers, which may increase the computational load and decrease the recognition speed.

The computation time required for cultivar classification using various machine learning classification methods is different (Table 1). The curvature approximation time is nearly 62 ms, which belong to total preprocessing and processing operations required for detecting boundary curve, fitting a proper B-spline curve, and calculating its curvature at different points. The computation time required for cultivar classification was not affected by the number of training samples (Table 1). The images used for training and test were in 1.5 pixels/mm

Table 1
Classification accuracy and computation time of the proposed cultivar classification method with different machine learning classifiers. The classification accuracy is presented in percentage of correctly recognized query images and is related to the query images at the completely vertical position. The total number of query images was 50 (10 × 5) for each flower shape, so one image corresponds to 2% of the population.

Classifier	Flower shape	Number of training samples							
		105		120		135		150	
		Time (ms)	Accuracy (%)	Time (ms)	Accuracy (%)	Time (ms)	Accuracy (%)	Time (ms)	Accuracy (%)
Discriminant Analysis	Cupped	7.4	90	6.8	92	8.6	92	8.9	92
Decision Trees	Cupped	2.4	84	2	84	2.1	84	2.2	90
Naive Bayes	Cupped	102.9	96	99.2	98	107.8	98	102.4	100
KNN	Cupped	6.8	82	7.2	82	7	86	6.4	84
SVM	Cupped	76.4	98	76.7	98	82.8	98	76.6	96
Discriminant Analysis	Obake	6.9	100	6.3	100	9.3	100	6.5	100
Decision Trees	Obake	2.5	98	2.3	94	2.1	100	2.5	100
Naive Bayes	Obake	98.5	100	103.6	100	99.9	100	101.7	100
KNN	Obake	5.9	96	6.6	96	7.5	98	6.2	98
SVM	Obake	82.9	98	76.4	100	77.1	100	75.8	100
Discriminant Analysis	Standard	6.6	78	7.2	78	6.8	78	8.1	78
Decision Trees	Standard	2.3	56	2.4	98	2.5	96	2.1	96
Naive Bayes	Standard	94.9	100	94.2	100	99.5	100	101.8	100
KNN	Standard	8.8	76	7.5	76	6.7	76	7.6	74
SVM	Standard	80.2	100	73.8	98	78.9	98	85.8	96

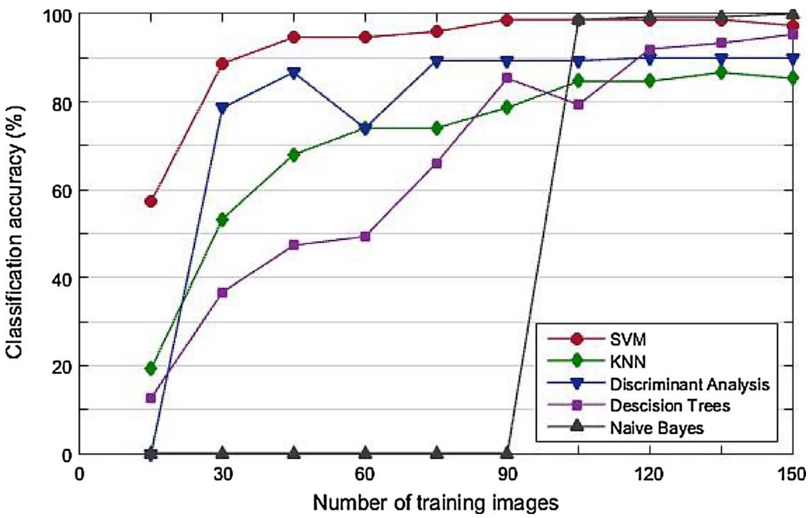

Fig. 6. Classification accuracy for the different machine learning classifiers against the number of training images with the pixel density of 1.5 pixels/mm.

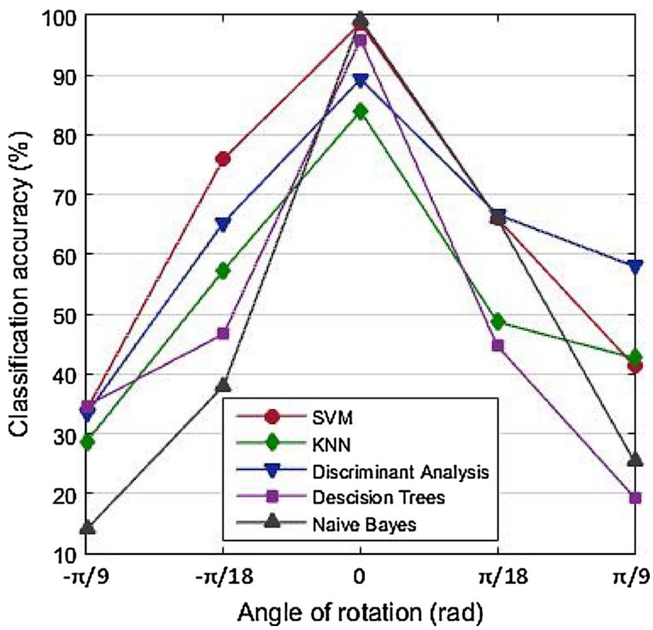

Fig. 7. Classification accuracy for different classifiers at five angles of rotation of $-\pi/9$, $-\pi/18$, 0, $\pi/18$, and $\pi/9$.

Table 2
Classification accuracy (%) for different cultivars of Anthurium flower using the proposed cultivar classification method with the SVM approach. The query images were at the completely vertical position and the total number of query images was 150 (10 images from each cultivar).

Cultivar	Number of training samples									
	15	30	45	60	75	90	105	120	135	150
Marea	30	80	90	90	90	100	100	100	100	100
Facetto	60	100	90	90	90	90	100	100	100	100
Peruzzi	50	100	100	100	100	100	100	100	100	100
Previa	50	60	100	100	90	100	100	100	100	100
Xavia	50	90	70	70	90	90	90	90	90	80
Baron	100	100	100	100	100	100	100	100	100	100
Simba	10	80	100	100	100	100	100	100	100	100
Spice	100	100	100	100	100	100	100	100	100	100
Tivoli	100	100	100	100	100	100	100	100	100	100
Zafira	70	80	80	80	100	100	90	100	100	100
Arena	50	90	100	100	100	100	100	100	100	100
Fantasia	50	90	100	100	100	100	100	100	100	100
Rosa	40	100	100	100	100	100	100	100	100	100
Cantello	90	70	100	100	100	100	100	100	100	100
Sante Royal	10	90	90	90	80	100	100	90	90	80

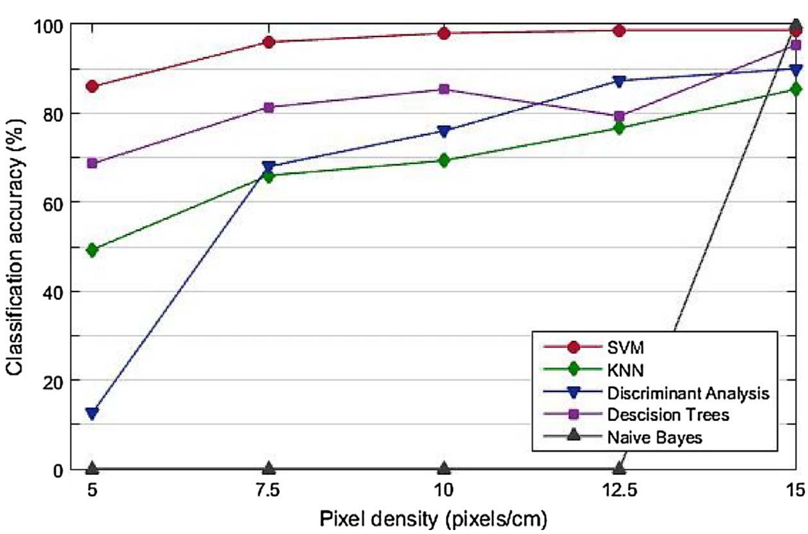

Fig. 8. Classification accuracy for the different machine learning classifiers trained using 150 images against the pixel density of images.

and a constant resolution of 400 × 400 pixels. However, the pixel density had a significant effect on the computation time, but the classification accuracy in lower pixel densities was not so good (Fig. 8). Among various machine learning methods, the Decision Tree classifier had the minimum computation time, less than 2.5 ms, and the Naive Bayes method had the maximum computation time, about 0.1 s. It is concluded that the SVM classifier with Radial Basis Function (RBF) kernel function and Dense Random multiclass coding method was the most optimal classifier, with high classification accuracy and relatively low computation time, which is proper for real-time classification procedures. Table 2 shows the results for classifying various Anthurium cultivars using the proposed cultivar classification method with the SVM classifier. All cultivars were classified perfectly except for *'Xavia' and 'Sante Royal'*. The Boundary shape of flowers is a determinant factor in this cultivar classification approach. Thus the cultivars with more special boundary shapes will be classified more accurately than the cultivars with a typical boundary shape.

The machine learning and pattern recognition techniques have been employed for various agricultural purposes, such as recognition of Scots pine boards (Johansson et al., 2015), cucumber recognition in natural environment (Bao et al., 2016), diseases detection in plants (Pujari et al., 2015; Zhou et al., 2014), field monitoring of Cercospora leaf spot in sugar beet (Zhou et al., 2015), cachaca type recognition (Rodrigues et al., 2016), rose cultivar recognition (Zhenjiang et al., 2006). Although, no similar approach has been developed to determine Anthurium cultivars as a means of the pre-grading process. Also, the proposed algorithm is based on pattern recognition of the flower boundary shape using curvature criteria, which do not depend on various parameterizations. For this reason, the algorithm developed here is especially intriguing.

Based on the results, we conclude that outline shape of flowers will be an important factor to identify species of various flowers as well as cultivars of a specified flower, while described mathematically. Other researchers also used shape descriptors to classify flowers. For example, Zhenjiang et al. (2006) presented a rose analysis and recognition system. They have discussed on mathematical description methods for features such as shape, size, and color of the flower, petal and leaf, and the object-oriented pattern recognition (OOPR) approach which mathematically deals with how to comprehensively use all different rose features rationally in the recognition scheme. Their results demonstrate the efficiency of the mathematical description methods and the OOPR approach in their cultivar recognition system. (Nilsback and Zisserman, 2006) combined a generic shape model of petals and flowers with a color-based segmentation algorithm. Hong et al. (2004) used a color histogram segmentation method and then combined it with the centroid contour distance and angle code histograms to form a classifier. They concluded that outline shape is an important character to consider for flower species identification purposes, especially in combination with other features.

The proposed classification method could be used for identifying the Anthurium cultivars before grading in an automatic grading system. By recognizing cultivar of a flower before the sorting process, grading criteria that are related to the recognized cultivar would selected to properly evaluate the flower quality. Such cultivar classification approaches can be developed to identify various cut flowers from each other. Also, it is possible to develop this method for other flower types. For this aim, it is firstly required to prepare an image database for the given flower. The proposed classification method in this research is based on appearance or shape of the object. Such methods have several advantages in comparison with feature-based methods, as these methods facilitate automatic and real-time classification of the flowers with respect to their shape. In particular, obtaining features in feature-based methods is difficult and perhaps different for various flower species, which would cause the methods to be semi-automatic.

4. Conclusions

Cultivar classification of flowers before grading helps to consider proper grading criteria for each flower. This paper described a cultivar classification algorithm for Anthurium flower based on the flower shape and template matching. A novel approach was presented to mathematically describe the flower shape using the signed curvature of its boundary. Flowers of Anthurium cultivars have been classified using five machine learning classifiers, include SVM, KNN, Discriminant Analysis, Decision Trees, and Naive Bayes. The training database contained 150 images from 15 different cultivars of the flower with three shape categories. The computation time of classifiers trained with a different number of training samples had no significant difference with each other, while the classification accuracy was affected by the number of training samples. The SVM classifier had more advantages than four others, with respect to its high classification accuracy and relatively low computation time, and is recommended for real-time applications. In general, the advantage of such automatic methods for cultivar classification of flowers using artificial vision is that it facilitates the classification of flowers with respect to its visual features.

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