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Predicting the ripening of papaya fruit with digital imaging and random forests

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ABSTRACT

Papaya grading is performed manually which may lead to misclassifications, resulting in fruit boxes with different maturity stages. The objective is to predict the ripening of the papaya fruit using digital imaging and random forests. A series of physical/chemical analyses are carried out and true maturity stage is derived from pulp firmness measurements. Imaging and image analysis provides hand-crafted color features computed from the peel and random decision forests are implemented to predict ripening stage. More specifically, a total of 114 samples from 57 fruits are used for the experiments, and classified into three stages of maturity. After image acquisition and analysis, twenty-one hand-crafted color features (comprising seven groups) that have low computational cost are extracted and evaluated. Random forests with two datasets (cross-validation and prediction set) are employed for the experiments. Concerning all image features, 94.3% classification performance is obtained over the cross-validation set. The prediction set obtained 94.7% misclassifying only a single sample. For the group comparisons, the normalized mean of the RGB (red, green, blue) color space achieved better performance (78.1%). Essentially, the technique can mature into an industrial application with the right integration framework.

1. Introduction

Papaya is a berry fruit with high nutritional and commercial value due to its non-seasonality and reduced time to harvest. In 2013, the world production of papaya reached 1.25×10^7 mt (Faostat, 2016). Papaya grading (as carried out in packing houses) is performed manually by human operators which may lead to misclassifications, resulting in fruit boxes with different maturity stages (Savakar and Anami, 2015). Visual inspection has been serving the fruit industry for many years, but it may lead to inconsistencies and variations despite the professional training of the graders. The variability associated with human assessment pertinent to automated inspection tasks accentuates the need for objective measurement systems providing reliable information throughout production (Damez and Clerjon, 2008). However, this must not sacrifice the essential benefits of human grading, e.g. intuition (Valous et al., 2016).

The identification of ripening stage is important, as it is related to internal properties of the fruit such as sweetness and firmness (Magwaza and Opara, 2015). In addition, it helps to determine storage time prior to consumption. The determination of these properties is carried out by analytical techniques commonly used for agricultural products. These techniques are time-consuming and destructive, plus they usually require chemical reagents and lengthy sample preparation procedures. In addition, they are applied to a limited number of samples which are not representative of the typical physico-chemical variability found in such batches. Thus, rapid, intelligent, and non-destructive techniques are required in this application domain (Wu and Sun, 2013).

Computer vision systems have been used for agri-food quality evaluation and control (Jackman et al., 2012). Quality assessment can be performed by such systems and is based on consumer digital cameras which are widely available. This approach has several advantages: rapid time of analyses, low cost, high accuracy and precision. For example, in a study researchers extracted color features to predict the ripening of stone fruits with low misclassification rates (Eyarkai Nambi et al., 2016). In addition, researchers applied laser-induced fluorescence spectroscopy to classify papaya into four quality grades (Obledo-Vazquez and Cervantes-Martínez, 2017a). It is reported that this technique is able to distinguish between ripe and unripe fruits from fluorescence measured at 690 and 740 nm. However, the study has a small

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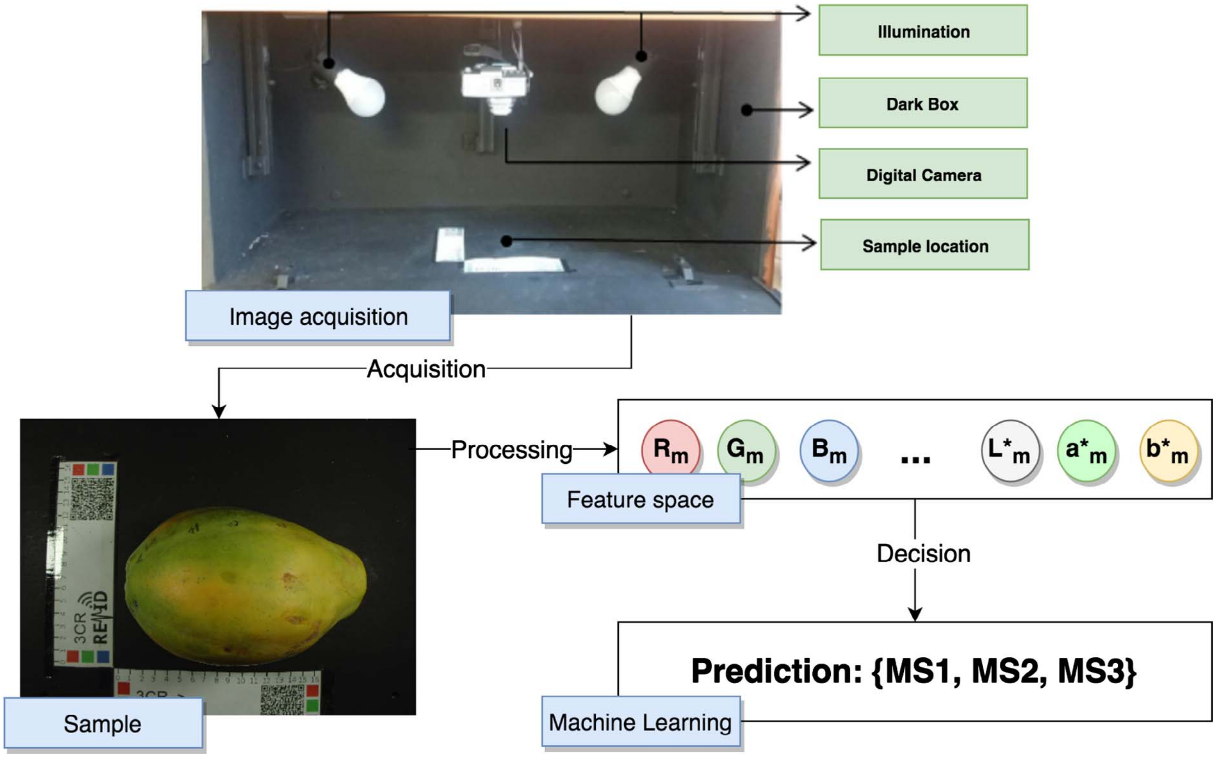

Fig. 1. Overview of image acquisition, feature computation, and final prediction workflow for assessing the ripening of the papaya fruit.

amount of samples and a full classification model is not reported. In addition, the region between 690 and 740 nm is in the visible range of the electromagnetic spectrum. Practically, digital imaging systems may be the simpler approach for predicting maturity stages in papaya.

Machine learning techniques are being used in a variety of domains (Ropodi et al., 2016). The application of these techniques in agri-food characterization and evaluation has been also investigated (Wang et al., 2012; Liu et al., 2013; Papadopoulou et al., 2013; Prevolnik et al., 2014). Random decision forests, support vector machines, as well as miscellaneous types of artificial neural networks are implemented in many studies related to agri-food quality evaluation (Granitto et al., 2007; Chen et al., 2010; Valous et al., 2010; Wang et al., 2012; Papadopoulou et al., 2013; Liu et al., 2013; Savakar and Anami, 2015; Muñoz et al., 2015; Rojas-Moraleda et al., 2016; da Costa Barbon et al., 2017). In general, the literature has been reporting comparisons between conventional machine learning methods in various research domains, since there seems to be no clear consensus on absolute winners. On the other hand, an extensive benchmarking report demonstrated that random decision forests (RF) as an ensemble learning method (Breiman, 2001) may provide equal or better performance when compared to other classification algorithms (support vector machines, C4.5, AdaBoost, k-nearest neighbours, logistic regression, stochastic gradient boosting trees, extreme learning machines, sparse representation-based classification, and deep learning) on publicly available datasets (Zhang et al., 2017). For example, researchers compared random forests with neural networks and support vector machines for electronic tongue data classification, with RF achieving 99.07% accuracy (Liu et al., 2013). In another study, RF provided a measure of variable importance in clustering when investigating the similarity of six vegetable oils (Ai et al., 2014). Yet in another example, RF models gave an estimation of the relative importance of each sensory attribute for the discriminant function (Granitto et al., 2007). Finally, in Barbon et al. (2016) RF demonstrated superior prediction results in identifying pork storage time compared to artificial neural networks, fuzzy-based classifiers, support vector machines, *k*-nearest neighbours, and decision trees.

Hence, the aim of this work is to predict the ripening of the papaya fruit using digital imaging and random forests. A series of physical/chemical analyses are carried out and true maturity stage is derived from pulp firmness measurements. Imaging and image analysis provides hand-crafted color features computed from the peel and random decision forests are implemented to predict ripening stage.

2. Material and methods

2.1. Experimental design

Fifty-seven golden papaya fruits were purchased in a retail market in the city of Campinas (Brazil). Two color images per sample were acquired (one from each side) and physical/chemical analyses (pulp firmness, pH, soluble solids, total carotenoids, and ascorbic acid content) were carried out. All samples were classified into three maturity stages: maturity stage 1 (MS1; 58 images), maturity stage 2 (MS2; 30 images), and maturity stage 3 (MS3; 26 images). There were differences in the number of samples from each maturity stage because samples were collected and initially classified visually. Later on, the fruits were classified according to pulp firmness scores. Fruits with pulp firmness > 33 N were classified as MS1. Samples graded as MS2 had pulp firmness < 33 N and > 20 N, and fruits graded as MS3 had pulp firmness < 20 N. Pulp firmness is considered an important trade property since edible fruits should have pulp firmness < 20 N (Blankenship and Unrath, 1988; Kim et al., 1999).

2.2. Image acquisition

Images were acquired by a computer vision system consisting of three main components: an illumination source, a consumer digital camera, and a rectangle box with matte black internal walls to avoid specular reflections (Fig. 1). The lighting system consists of LED lamps (Natural daylight, 100 W). The camera (Sony, Japan) is located vertically over the background at a distance of 17.5 cm from the sample. The camera is mounted on a stand, which allows easy vertical movement and stable support, and connected to the USB port of a workstation to