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Sweet pepper maturity evaluation

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This paper focuses on maturity evaluation derived by a color camera for a sweet pepper robotic harvester. Different color and morphological features for sweet pepper maturity were evaluated. Side view and bottom view of sweet paper were analyzed and compared for their ability to classify into 4 maturity classes. The goal of this study was to differentiate between the two center classes which are difficult to separate. Statistical analysis of 13 different features in reliance to the maturity classification and the views indicated the best features for classification. The results show that the features that can be used for classification between the two central classes from both bottom and side views are: Hue range, Equal2Real – the ratio between the equivalent equal sized circle perimeter to the shape perimeter and Area2Peri – the ratio between the area to the perimeter.

Keywords: Computer vision, Fruit maturity, Robotic harvesting, Sweet peppers, Agricultural robots

Introduction

Over the last 30 years robots have been actively developed in order to automate the harvesting process (Bac *et al*., 2014). An agricultural robot must operate in the unstructured and dynamic environment (e.g., changing illumination, clouds), and deal with random and difficult locations of the fruit which are highly variable in size, shape and structure and obstructed by foliage (Edan *et al*., 2000). A crucial task in a robotic selective harvester is maturity detection which is fruit dependent and therefore usually requires targeted research and development (Edan, 1995). Maturity detection can be a big challenge for fruits like sweet pepper where parts of the fruit are not visible (Bac *et al*., 2014) or must be examined from different views (Jachen *et al*., 2014). Research to date in sweet pepper harvesting focused mostly on fruit detection (Bac *et al*., 2014; Kitamura *et al*., 2008; Kitamura and Oka, 2005) with only a few works dealing with maturity evaluation (Jun *et al*., 2012).

Maturity at harvest is the most important factor that determines the fruit quality and storage life (Kader, 1999). In order to determine the quality and the maturity level of a fruit or vegetable there are four categories: visual parameters (e.g. color, shape, size), firmness, soluble solids content and titratable acidity (Lorente *et al*., 2012; Mitcham *et al*., 1996). The visual aspects are commonly used since they can be extracted using machine vision systems by external non-destructive measurements (Brosnan and Sun, 2004). Most of the maturity detection research involve color as part of the detection (Bac *et al*., 2014; Tantrakansakul and Khaorapapong, 2014; Wang *et al*., 2012) since it is an important fruit quality characteristic which represents the degree of maturity, sugar content, acidity and taste (Li *et al*., 2009). It is also a main factor in customer's selection of sweet peppers (Brosnan and Sun, 2004; Frank *et al*., 2001). In other machine vision investigations the morphological features are widely used in addition to the color features or as the main features (Jayas *et al*., 2000). Morphological features such as area, perimeter and circularity can by calculated from a binary image that can be derived from the processing of color image (Gomes and Leta, 2012).

In order to fulfill the development of selective harvester fruit maturity must be detected. The goal of this study was to determine the best features to derive the sweet pepper maturity level using machine vision.

Materials and Methods

Dataset

RGB images of 50 red sweet peppers (Cultivar: Banji Seed company: Efal) were acquired in a special designed illumination cubicle (Figure 1), this allowed to ensure that images were acquired under fixed and consistent illumination. The peppers were harvested from the 12th fruit harvesting cycle from a commercial greenhouse in southwest Israel, Camehin.

Four maturity classes were selected (Figure 2); classes 3 and 4 defined as the "mature" classes were selected from the packing house, based on visual evaluation of professional pickers; the fruit were harvested the same morning. Class 4 included peppers with mostly red color and class 3 included a mixture of green and red colors (with approximately 80% red). The "immature" classes, classes 1 and 2 were manually selected and harvested from the greenhouse after the commercial harvest. Class 1 included peppers with mostly green color and class 2 included a mixture of green

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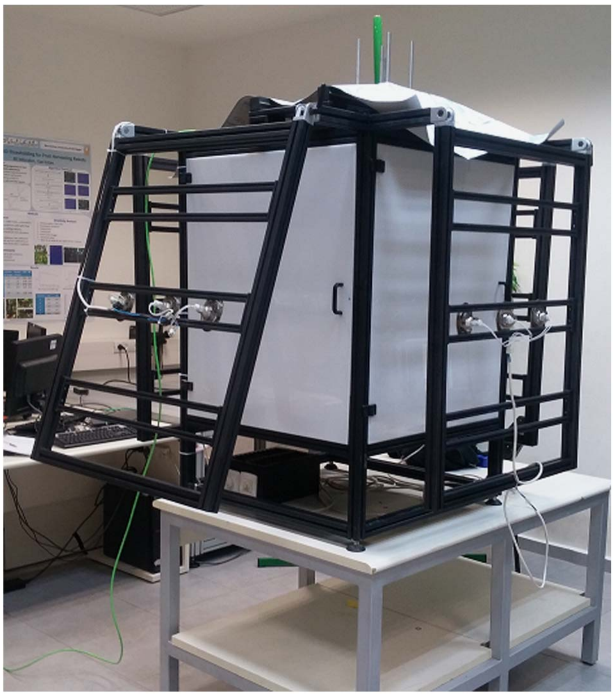

Figure 1 The illumination cubicle.

Figure 2 The four maturity classes left (class 1) to right (class 4).

and red colors (with approximately 30% red color, Table 1). Since it is more difficult to differentiate between classes 2 and 3 more peppers were selected from these classes (15 peppers as compared to 10 peppers from each of classes 1 and 4) as show table 1.

The sides of the special designed illumination cubicle were covered with acrylic glass and the top was covered with a grey non-reflective canvas to create diffused conditions and avoid reflections which caused glare on the fruit (example in Figure 3). Three led spots of 35 watts each were placed outside each of the four sides of the cubicle (Ram *et al.*, 2010). The total illumination inside the photocell was 49 lux. Images were acquired using an IDS MOS, 35.6 fps, 1600×1200 resolution RGB camera placed 38 cm above the cell floor which was colored black. Each pepper was photographed from the bottom and side views.

Table 1 *Sweet pepper classes*

Class	Classification	Pepper color	Number of peppers
1	Immature	Green	10
2	Immature	Majority Green + Some Red	15
3	Mature	Majority Red + Some Green	15
4	Mature	Red	10

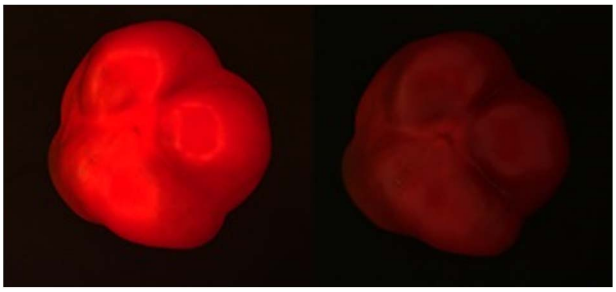

Figure 3 Example of images (a) with glare (b) without glare.

Algorithms

The image processing algorithms were developed in MatLab 2014b using the image processing library. The image processing routines developed included transformation to the HSV color space, segmentation using blob detection algorithm, and features extraction procedures. The segmentation was conducted on the HSV color space using the hue values of 0–35 and 345–360 degrees and saturation values of 240–255. These values were empirically selected. The extracted features are detailed below and included seven color and six morphological features, which were extracted using the binary mask, created by the segmentation algorithm. The bottom view and a random side view were selected for analysis of each pepper.

Color features

Mean – Pepper hue angle average.
Std – Standard deviation of the hue angle of the pepper.
Max value – The maximum hue angle in the pepper.
Min value – The minimum hue angle in the pepper.
Range – The difference between the Max value to the Min value.
Median – The hue values median.
Trimmed mean - Pepper hue angle average after removing the 5% smallest and largest values.

Morphological features

Number of pixels – The number of pixels identified as pepper.
Eccentricity – A scalar that specifies the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. (Eccentricity is 0 is actually a circle, while 1 is a line segment).

Extent – A scalar that specifies the ratio of pixels in the region to pixels in the total bounding box. Computed as the Area divided by the area of the bounding box.
Solidity – A scalar specifying the proportion of the pixels in the convex hull that are also in the region. Computed as Area/ConvexArea.
Equ2real – A scalar specifying the proportion of the perimeter of a circle with the same area as the region to the perimeter of the region. Computed as (π*EquivDiameter)/Perimeter
Peri2Area – A scalar specifying the proportion of the perimeter to the area of the region. Computed as Area\Perimeter

Statistical analysis

The extracted data features of the bottom and the side view were recorded, analyzed and compared in Microsoft office Excel. In order to test which features can be used to classify the maturity status of the pepper a non-paired two independent samples t-test was created using R studio 3.2.3.

The two independent samples t-test was created for each of the features for both the bottom and side views in order to check if there is a difference in the feature average between the second and the third classes which are the most difficult to differentiate between; the test hypotheses for each feature were:

$$H_0: \mu_{2ed\text{-}class} = \mu_{3ed\text{-}class} H_1: \mu_{2ed\text{-}class} \neq \mu_{3ed\text{-}class}.$$

Results and discussion

The results of the side view average and standard deviation of each feature within the class and bottom view are detailed in Tables 2 and 3 respectively.

Results analyses indicates that as expected there is a significant difference in most of the features between the first (immature) and the forth (mature) classes and almost every feature can differentiate between them. The challenge is to find the features that will differentiate between the second (not to be harvested) and third (to be harvested) classes. The results of the hypothesis test for the similarity of the averages are detailed in Table 4. For example, the hue mean feature has significant difference in the bottom view (H_1) but does not have significant difference in the side view (H_0), which corresponds to the results in Tables 2 and 3.

The results (Table 4) reveal that there are several features with significant difference in the average between the second and the third classes. Considering both bottom and side views 'Max value', 'Range', 'Extent', 'Solidity', 'Equ2real' and 'Area2Peri ' features can be used for classification between the second and third classes, while all the other features can be used only in the bottom view. From the bottom view all features can be used for differentiation between classes 2 and 3. This corresponds to previous results which indicated that the bottom view was the best viewpoint (Harel *et al.*, 2016). The morphological features are obtained in both views and the color features are obtained mostly from the bottom view.

Table 2 *Side view features average and standard deviation per class*

Values	Feature	1	2	3	4	Grand Total
Average	Hue Mean	23.48	10.81	10.75	3.40	11.61
Standard deviation		(±5.60)	(±5.04)	(±5.47)	(±1.38)	(±7.91)
Average	Hue Standard deviation	7.95	8.46	8.72	3.80	7.49
Standard deviation		(±1.85)	(±1.50)	(±3.27)	(±3.44)	(±3.20)
Average	Max value	62.05	69.76	79.90	69.17	71.33
Standard deviation		(±7.60)	(±8.48)	(±12.33)	(±18.73)	(±13.48)
Average	Min value	3.65	0.51	0.45	0.56	1.08
Standard deviation		(±4.27)	(±0.08)	(±0.06)	(±0.08)	(±2.14)
Average	Range	58.40	69.25	79.45	68.62	70.25
Standard deviation		(±10.98)	(±8.46)	(±12.31)	(±18.69)	(±14.29)
Average	Median	22.40	8.23	8.63	2.49	9.78
Standard deviation		(±6.82)	(±5.35)	(±5.26)	(±0.55)	(±8.14)
Average	Trimmed Mean	23.31	10.36	10.23	3.07	11.21
Standard deviation		(±5.73)	(±5.18)	(±5.52)	(±1.07)	(±8.01)
Average	Pixel size	$13.4*10^4$	$23.4*10^4$	$30.4*10^4$	$18.9*10^4$	$22.8*10^4$
Standard deviation		$(\pm 8.8*10^4)$	$(\pm 10.6*10^4)$	$(\pm 7.8*10^4)$	$(\pm 7.2*10^4)$	$(\pm 10.5*10^4)$
Average	Eccentricity	0.83	0.64	0.56	0.47	0.62
Standard deviation		(±0.16)	(±0.16)	(±0.18)	(±0.08)	(±0.19)
Average	Extent	0.50	0.53	0.73	0.79	0.64
Standard deviation		(±0.14)	(±0.18)	(±0.06)	(±0.04)	(±0.17)
Average	Solidity	0.75	0.71	0.93	0.97	0.83
Standard deviation		(±0.14)	(±0.21)	(±0.06)	(±0.01)	(±0.18)
Average	Equ2real	0.46	0.43	0.72	0.83	0.60
Standard deviation		(±0.11)	(±0.18)	(±0.13)	(±0.04)	(±0.21)
Average	Area2Peri	45.84	62.19	118.04	138.55	91.87
Standard deviation		(±22.22)	(±35.66)	(±25.98)	(±14.27)	(±45.04)

Table 3 *Bottom view features average and standard deviation per class*

Values	Feature	1	2	3	4	Grand Total
Average	Hue Mean	24.79	15.52	6.08	3.04	12.23
Standard deviation		(±6.24)	(±5.86)	(±3.15)	(±1.06)	(±9.18)
Average	Hue Standard deviation	9.33	10.12	4.98	2.29	6.95
Standard deviation		(±1.92)	(±0.91)	(±2.47)	(±0.51)	(±3.52)
Average	Max value	73.98	70.81	88.64	62.87	75.46
Standard deviation		(±12.66)	(±7.72)	(±17.98)	(±20.73)	(±17.45)
Average	Min value	2.22	0.62	0.42	0.57	0.87
Standard deviation		(±1.92)	(±0.23)	(±0.04)	(±0.17)	(±1.09)
Average	Range	71.76	70.19	88.22	62.30	74.58
Standard deviation		(±14.11)	(±7.82)	(±17.97)	(±20.81)	(±17.77)
Average	Median	23.59	13.37	4.78	2.54	10.84
Standard deviation		(±6.89)	(±7.75)	(±2.62)	(±0.99)	(±9.43)
Average	Trimmed Mean	24.60	15.18	5.75	2.89	11.96
Standard deviation		(±6.36)	(±6.06)	(±3.09)	(±1.06)	(±9.24)
Average	Pixel size	$9.6*10^4$	$16.9*10^4$	$28.7*10^4$	$15.7*10^4$	$18.8*10^4$
Standard deviation		$(\pm 9.8*10^4)$	$(\pm 11.2*10^4)$	$(\pm 7.4*10^4)$	$(\pm 4*10^4)$	$(\pm 11.1*10^4)$
Average	Eccentricity	0.88	0.81	0.37	0.37	0.61
Standard deviation		(±0.10)	(±0.14)	(±0.12)	(±0.12)	(±0.27)
Average	Extent	0.40	0.48	0.75	0.75	0.59
Standard deviation		(±0.10)	(±0.16)	(±0.03)	(±0.03)	(±0.18)
Average	Solidity	0.66	0.66	0.97	0.96	0.81
Standard deviation		(±0.10)	(±0.180	(±0.01)	(±0.01)	(±0.19)
Average	Equ2real	0.41	0.42	0.85	0.80	0.62
Standard deviation		(±0.08)	(±0.16)	(±0.04)	(±0.03)	(±0.23)
Average	Area2Peri	30.45	50.41	142.97	126.70	88.68
Standard deviation		(±15.55)	(±33.55)	(±13.20)	(±10.82)	(±52.92)

Table 4 *Results of non-paired two independent samples t-test for each one of the extracted features between the second and third class. Results for both bottom and side views*

Feature	p-value (bottom)	p-value (side views)
Mean	$1.25*10^{-5}*$	0.9737
Standard deviation	$1.09*10^{-6}*$	0.7895
Max value	0.005751*	0.01463*
Min value	0.002334*	0.0521
Range	0.005271*	0.01395*
Median	0.000637*	0.8366
Trimmed Mean	$1.84*10^{-5}*$	0.9479
Pixel size	0.0004952*	0.05117
Eccentricity	$6.33*10^{-12}*$	0.182
Extent	$2.73*10^{-6}*$	0.0006274*
Solidity	$4.15*10^{-6}*$	0.001269*
Equ2real	$1.79*10^{-9}*$	$2.75*10^{-5}*$
Area2Peri	$3.00*10^{-10}*$	$4.52*10^{-5}*$

*Indicates the null hypothesis was rejected at the 0.95 certainty level

Conclusions

The research results reveals the best features used for classification between four sweet pepper maturity classes focusing on differentiation between classes 2 and 3. These features include both color ('Hue range' as the best feature) and morphological ('Equ2Real' and 'Area2Peri' as the best) features. In the bottom view all of features can be applied. Ongoing research is aimed to use these results to classify the maturity level of the peppers in a robotic harvesting process.

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