Automatic Identification of Relevant Colors in Non-Destructive Quality Evaluation of Fresh Salad Vegetables

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Abstract: Quality loss during storage is often associated to changes in relevant product colors and/or to the appearance of new pigments. Computer Vision System (CVS) for non-destructive quality evaluation often relies on human knowledge provided by operators to identify these relevant colors and their features. The approach described in this paper automatically identifies the most significant colors in unevenly colored products to evaluate their quality level. Its performance was compared with results obtained by exploiting human training. The new method improved quality evaluation and reduced the subjectivity and the inconsistency potentially induced by operators.

Keywords: Non-destructive quality evaluation, Relevant colors, Automatic identification, Iceberg head lettuce.

INTRODUCTION

Assessing the overall quality of fruit and vegetables is an important requirement of food industry [1, 2]. Since chromatic properties of food are strongly related with their overall quality, computer vision systems (CVSs) represent valid tools to satisfy this need. CVSs analyze the complete visible surface of products, avoiding the arbitrary and subjective choice of sampling points that is typical of colorimeters [1-4].

Identifying the most relevant colors for judging the quality of products is a critical task, especially on unevenly colored surfaces [5]. Whenever a CVS uses significant colors selected by operators the resulting performance can be affected by this choice. Pace *et al*. (2014) [6] used green and white patches manually extracted from images of iceberg lettuces at different quality levels (QLs) to train a CVS which achieved a non-destructive evaluation of quality. The same authors [7] developed an automatic identification of relevant colors while studying the fresh-cut radicchio whose unevenly colored surface mix white and red. In this paper, this automatic technique was applied to images of iceberg head lettuce and the results were compared with the manual selection made by operators. The two color selection approaches were compared in terms of their capacity of achieving the QLs separation performed by the ammonium content, an objective chemical parameter.

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MATERIALS AND METHODS

Image Analysis by Computer Vision System

The 45 digital images of the iceberg head lettuce (*Lactuca sativa* L.) were acquired during the experiment reported in Pace *et al*. (2014) [6]: 9 replicates x 5 sensory assessed quality levels (QLs) varying from 5 (very good) to 1 (very poor). QL 3 is the minimum acceptable for sale or consumption while values below 3 indicated wastes. The QL were also evaluated through a chemical method aimed to analyze the ammonium content of lettuce samples belonging to each quality level. In detail the method reported by Cefola and Pace (2015) [8] was used. Five g of chopped iceberg leaves sample was extracted in distilled water, and after the reaction with nitroprusside reagent and alkaline hypochlorite solution, color development was determined after incubation at 37C for 20 min, reading the absorbance at 635 nm using a spectrophotometer (UV-1800, Shimadzu, Kyoto, Japan).

Computer Vision System Description and Setup

Images were acquired using a 3CCD (Charged Coupled Device) digital camera (JAI CV-M9GE) with a dedicated CCD for each color channel and saved using the uncompressed TIFF format. The optical axis of the Linos MeVis 12 mm lens system was perpendicular to the black background. Eight halogen lamps (divided along two rows placed at the two sides of the imaged area) were oriented at a 45° angle with respect to the optical axis.

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Color-Chart Detection and Foreground Extraction

A small X-Rite color-chart with 24 patches was placed into the scene to estimate color variations due to environmental conditions and sensor characteristics by comparing the expected numerical values released by X-Rite with the measured ones. The color-chart was automatically detected regardless its position and orientation. Its white patch was used to white-balance the image.

The CVS automatically separated the product at hand (foreground) from the background using two thresholds automatically derived from the analysis of the whole image in the HSV (Hue Saturation Value) color space, without any human intervention.

Color Segmentation

Segmenting images of unevenly colored products into homogeneous areas increases the effectiveness of a CVS. A hierarchical clustering technique was used to separate the three relevant colors (white, brown and green) of iceberg lettuce without human intervention.

The *a** and *b** channels of the images expressed in the CIE *L*a*b** space were discretized (mathematically rounded) and used to generate a two dimensional histograms. The variance of each (*a**, *b**) pair through the whole dataset of histograms was computed. The pairs with larger variance were selected to decrease the complexity of the resulting image and to remove potential outliers (less relevant colors). These pairs were used to evaluate a dendrogram (based on the Euclidean distance): a hierarchical subdivision of colors that can be stopped at different levels to provide different color quantizations. The segmentation into three colors G (green), W1 (brown) and W2 (white) provided the best features for quality evaluation of lettuce iceberg. Figure **1** shows the produced segmentations on a very good (A) and a very poor (B) iceberg lettuces (QL = 5 and QL = 1 respectively). In detail, the Figure **1** show the green, white and brown segmented parts of the very good and the very poor iceberg heads.

Statistical Analysis

The performance of the features in evaluating the QL was verified using a one-way ANOVA with the dataset arranged in a completely randomized design [9]. The mean values for QL were separated using the Student-Newman-Keuls (SNK) test.

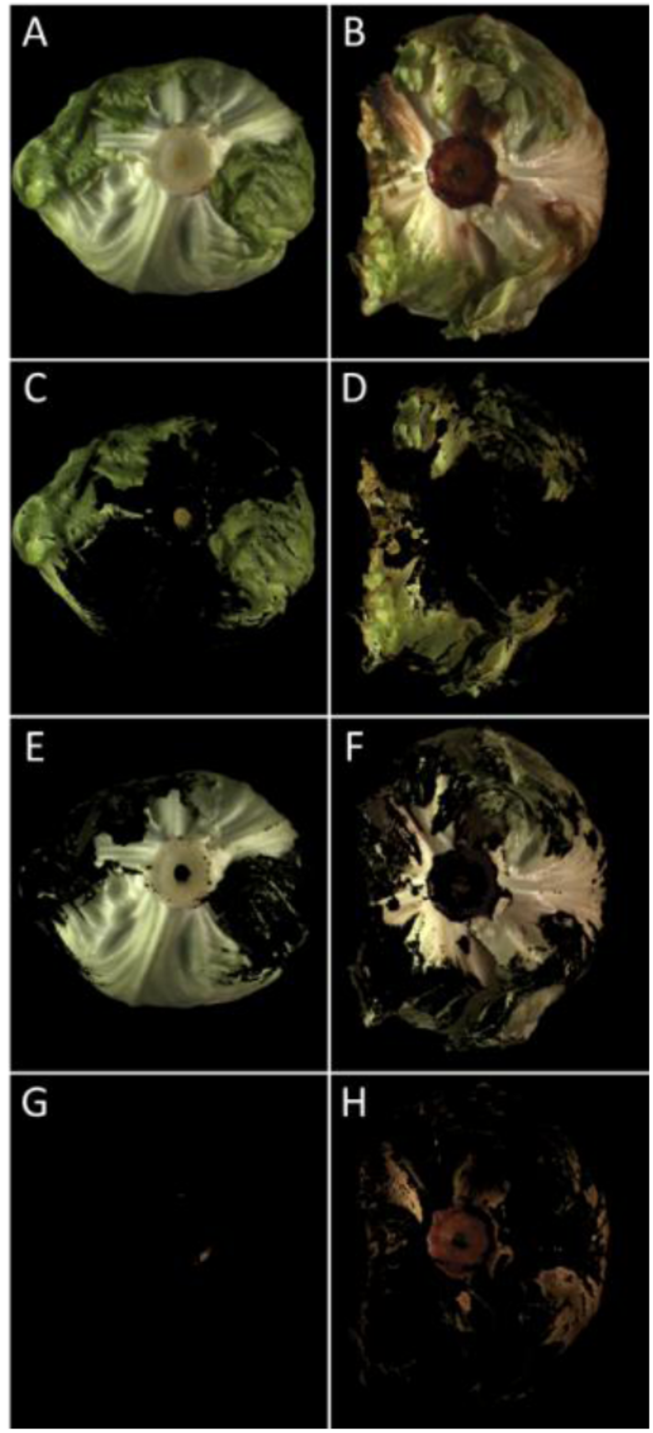

Figure 1: Segmentations automatically obtained by the proposed approach (without any human intervention) on a very good (**A**) and a very poor (**B**) iceberg lettuces. (**C**), (**E**) and (**G**) show the green, white and brown parts of (**A**) while (**D**), (**F**) and **(H)** present green, white and brown regions of (**B**).

RESULTS AND DISCUSSION

The acquired iceberg images belonged to three QL classes (the acceptable product ranging from QL 5 to

QL 3 and the two waste classes QL = 2 and QL = 1) as reported earlier [6] on the basis of the objective measurement of ammonium content, considered a reliable indicator of product freshness and widely accepted as indicator of product freshness [10, 11]. Commonly, low levels of ammonium, are associated to a good product quality while an increase is related to senescence and protein catabolism, as already detected by Chandra *et al*. 2006 [10] on lettuce and reported on head or fresh-cut Iceberg lettuce by Pace *et al*. 2014 [12] highlighting as ammonium represents a real indicator of product quality as for the head, as the for fresh-cut lettuce.

The average values of *L** and *a** evaluated over the whole images of iceberg lettuce significantly affected the QL (Table **1**) but none of these color features was able to perform the QL separation obtained by ammonium analysis. Also in fresh-cut radicchio, features extracted from the complete surface of this unevenly colored product provided an improper QL classification [1, 7].

The average values of *L** and *a** over the white region (W) and of *a** and *b** over the green region (G) significantly affected the QL (Table **1**). *L** of W achieved a inadequate discrimination of QL but *a** of W allowed to differentiate the QL in four quality classes (QL 1, QL2, QL3, and QL4/QL5), matching the ammonium separation of QL (Table **1**). Changes in the G part were not significant for quality evaluation; the same resulted for the red component of fresh-cut radicchio in Pace *et al*. 2015 [7]. Also previous researches [6,13] observed that quality loss of iceberg lettuce mainly generate a browning process of the white regions. Therefore, three colors were generated by separating brown nuances (W1), white ones (W2) and green (G). The extension (percentage) of W1 and W2 colors with respect to indistinct white (W) and to the entire surface (I) were evaluated on the images. Let N^{W1}, N^{W2}, N^{W} and N^{I} denote the number of pixels corresponding to the W1, W2, W and I regions: N^{W1}/N^{W}, N^{W2}/N^{W}, N^{W1}/N^{I} and N^{W2}/N^{I} significantly affected the QL (Table **2**). N^{W1}/N^{W}, N^{W1}/N^{I} and N^{W2}/N^{W} allowed the separation of three QL classes (Table **2**) matching the performance of ammonium as reported before [6]. Thus, iceberg lettuce storage exhibits a reduction of the white component (W2) versus the brown one (W1). In fresh-cut radicchio [7] only the white component (W2) discriminated the QLs. Lettuce contains mainly green and white that, during storage undergo a browning process. Fresh radicchio exhibits red and white which, during storage, transforms in brown hues quite close to red [7].

Table 1: Mean Values of Color Features Automatically Identified. Based on Ammonium QL Classification Three Class are Considered: the Acceptable Product (Ranging from QL 5 to QL 3) and the Two Classes of Waste (QL=2 and QL=1) [6]

		Quality Levels (QLs)					
Iceberg Lettuce Images	**Color Features**	**Very Good 5**	**Good 4**	**Acceptable 3**	**Poor 2**	**Very Poor 1**	**P value**
Entire Image	*L**	69.86 a	70.68 a	69.66 a	66.44 ab	64.21 b	**
	*a**	-8.30 c	-7.37 c	-6.26 bc	-4.58 ab	-2.92 a	***
	*b**	20.70	21.30	21.07	20.36	20.95	ns
Segmentation							
White (W)	*L**	69.05 ab	71.64 a	70.75 ab	67.75 ab	66.17 b	*
	*a**	-9.47 d	-9.14 d	-7.88 c	-6.69 b	-5.05 a	***
	*b**	22.83	23.31	23.20	23.50	23.16	ns
Green (G)	*L**	68.58	66.04	64.79	63.14	60.49	ns
	*a**	-4.52 d	-2.27 c	-1.71 bc	-0.54 ab	0.33 a	***
	*b**	14.22 b	14.74 b	15.29 ab	14.62 b	15.91 a	**

Mean values of 9 replicates. For each parameter the mean values followed by different letters, are significantly different (*P*-value < 0.05) according to Student-Newman-Keuls (SNK) test.
Significance: **and *** = significant at *P*-value ≤ 0.01 and 0.001, respectively.

Table 2: Mean Percentages (%) of the W1 (Brown) and W2 (White) Components over the White Part (W) or Over the Entire Surface (I). The Last Two Rows Report the Results Obtained in Pace *et al*. (2014) [6]. N^B/N^W Represents the Brown Component with Respect to the White Part. N^B/N^T Expresses the Brown Component Over the Whole Surface

		Quality Levels (QLs)					
Method	White Components Percentage	Very Good 5	Good 4	Acceptable 3	Poor 2	Very Poor 1	P value
Adaptive self-configuring CVS	N^{W1}/N^W	4.13 c	5.37 c	7.01 c	14.4 b	26.34 a	***
	N^{W1}/N^I	2.86 c	3.85 c	4.91 c	8.88 b	15.25 a	***
	N^{W2}/N^W	95.9 a	94.6 a	93 a	85.6 b	73.66 c	***
	N^{W2}/N^I	73.6 a	73.5 a	71 a	55.9 ab	45.31 b	***
Manual setting CVS (data from *Pace et al. 2014*)	N^B/N^W	96.00 a	84.00 ab	78.00 bc	65.00 c	34.00 d	****
	N^B/N^W	92.00 a	63.00 b	50.00 bc	37.00 c	6.00 d	****

Mean values of 9 replicates. For each parameter the mean values followed by different letters, are significantly different (P-value < 0.05) according to Student-Newman-Keuls (SNK) test. Significance: *** = significant at P-value ≤ 0.001, **** = significant at P-value ≤ 0.0001.

In Table **2** the comparison of the QL classification obtained through the adaptive and self-configuring CVS with the manual CVS setting [6] was reported. The automatic identification of relevant colors provided a more clear and robust separation of QL classes with respect to human setting, a more subjective and less efficient approach (Table **2**).

CONCLUSION

This paper showed that the automatic identification of relevant colors is helpful to reduce the subjectivity in setting CVS's parameters and to provide improved performances. The comparison of the results obtained using this approach, with what achieved using human selected colors, assessed more clear and robust separation of the classes of interest. These results confirm the evidences provided by previous experiments on fresh-cut radicchio. The proposed approach works well on unevenly colored products and makes easier to extend the application of CVS to different vegetables.

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REFERENCES

[1] Wu D, Sun DW. Colour measurements by computer vision for food quality control–A review. Trends Food Sci Tech 2013; 29: 5-20. https://doi.org/10.1016/j.tifs.2012.08.004

[2] Zhang B, Huang W, Li J, Zhao C, Fan S, Wu J *et al*. Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. Food Res Int 2014; 62: 326-343. https://doi.org/10.1016/j.foodres.2014.03.012

[3] Pace B, Cefola M, Renna F, Attolico G. Relationship between visual appearance and browning as evaluated by image analysis and chemical traits in fresh-cut nectarines. Postharvest Biol Technol 2011; 61: 178-183. https://doi.org/10.1016/j.postharvbio.2011.03.005

[4] Manninen H, Paakki M, Hopia A, Franzén R. Measuring the green color of vegetables from digital images using image analysis. LWT-Food Sci Technol 2015; 63: 1184-1190. https://doi.org/10.1016/j.lwt.2015.04.005

[5] Balaban MO. Quantifying nonhomogeneous colors in agricultural materials part I: method development. J Food Sci. 2008; 73: S431-S437. https://doi.org/10.1111/j.1750-3841.2008.00807.x

[6] Pace B, Cefola M, Da Pelo P, Renna F, Attolico G. Non-destructive evaluation of quality and ammonia content in whole and fresh-cut lettuce by computer vision system. Food Res Int 2014; 64: 647-655. https://doi.org/10.1016/j.foodres.2014.07.037

[7] Pace B, Cavallo DP, Cefola M, Colella R, Attolico, G. Adaptive self-configuring computer vision system for quality evaluation of fresh-cut radicchio. Innov Food Sci Emerg 2015; 32: 200-207. https://doi.org/10.1016/j.ifset.2015.10.001

[8] Cefola M, Pace B. Application of oxalic acid to preserve the overall quality of rocket and baby spinach leaves during storage. J Food Process Pres 2015; 39: 2523-2532. https://doi.org/10.1111/jfpp.12502

[9] Stat Soft, INC. STATISTICA (data analysis software system), version 6. 2001; Tulsa, USA, 150.

[10] Chandra D, Matsui T, Suzuki H, Kosugi Y, Postharvest changes in some physiological traits and activities of ammonia-assimilating enzymes in lettuce during storage.

Asian J Plant Sci 2006; 5: 378-384.
https://doi.org/10.3923/ajps.2006.378.384

[11] Cefola M, Amodio ML, Rinaldi R, Vanadia S, Colelli G. Exposure to 1-methylcyclopropene (1-MCP) delays the effects of ethylene on fresh-cut broccoli raab (Brassica rapa L). Postharvest Biol Technol 2010; 58: 29-35.
https://doi.org/10.1016/j.postharvbio.2010.05.001

[12] Pace B, Cardinali A, D'Antuono I, Serio F, Cefola M. Relationship between quality parameters and the overall appearance in lettuce during storage. Int J Food Process Technol 2014; 1: 18-26.
https://doi.org/10.15379/2408-9826.2014.01.01.3

[13] Zhou T, Harrison AD, McKellar R, Young JC, Odumeru J, Piyasena P *et al.* Determination of acceptability and shelf life of ready-to-use lettuce by digital image analysis. Food Res Int 2004; 37: 875-881.
https://doi.org/10.1016/j.foodres.2004.05.005

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