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Measuring colour of vine tomatoes using hyperspectral imaging

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ABSTRACT

As consumers buy with their eyes, colour is considered one of the most important quality parameters of food products. Traditionally, this is defined by human inspection, or measured using a colorimeter or a spectrophotometer. As the first is subjective and prone to factors like fatigue, this is not ideal for industrial use. The second only measures a small area of the food product, making it difficult to get a clear overview of the colour of the whole sample. To overcome these limitations, hyperspectral imaging has been used in this research to measure the postharvest colour of vine tomatoes. Two methods to calculate the colour based on hyperspectral images are compared. The first is the use of a direct method to calculate the colour from the spectra in terms of CIELab-values, while the second method is a soft modelling approach involving multivariate statistics. The soft modelling method was found to achieve the best results ($R^2_{L*} = 0.86$; $R^2_{a*} = 0.93$; $R^2_{b*} = 0.42$, $R^2_{Hue} = 0.95$, $R^2_{Chroma} = 0.51$), but its applicability is limited to the range of products on which the models have been trained. The direct method is more generally applicable, but was found to lack robustness against intensity variations due to the curvature and glossiness of the tomatoes.

1. Introduction

Tomato colour is determined by the concentration of chlorophyll and carotenoids in the tomato tissue. In the earliest stages of the development of the tomato, chlorophyll is the dominant pigment, resulting in a green colour. During ripening of tomatoes, the chlorophyll degrades, while carotenoids are synthesized (Arias et al., 2000). The two main carotenoids in tomatoes are β-carotene and lycopene (ψ,ψ-carotene), which have both been associated with several health benefits (Arias et al., 2000). β-carotene gives an orange colour, while lycopene gives a red colour. As the concentration of lycopene in ripe tomatoes is much higher than the concentration of β-carotene, this results in a red colour (Saltveit, 2005). As a consequence of this evolution in the pigments during ripening, the colour of tomatoes is considered the most important external factor to describe ripeness and postharvest life (López Camelo and Gómez, 2004). Therefore, it is used for marketing purposes and as a quality parameter for the industry (Arias et al., 2000).

Traditionally, the colour of tomatoes is determined through human inspection. In this case, tomatoes are divided in several different colour classes, based on predefined colour charts. The USDA standard classifies the maturity of tomatoes into six stages based on the colour that is the most dominant (Green, Breakers, Turning, Pink, Light Red and Red) (USDA, 1991). In Europe, a different colour chart is used, which defines 12 ripeness stages (OECD, 2002). The advantage is that human inspection is relatively robust against changes in illumination, but the perception of colour is subjective, tedious and prone to human error (Wu and Sun, 2013).

To describe colour in a deterministic way, many different colour spaces have been proposed. The goal of a colour space is to describe the observed colour numerically in an unambiguous way. The most well-known colour space is the RGB-space, which defines the colours based on their coordinates in a three-dimensional space spanned by the red, green and blue axes. As these axes correspond to the stimuli centres in the human eye, this colour space is commonly used in digital imaging. However, this space is device-dependent, such that different devices measure different values for the same instance. Therefore, the sRGB space has been proposed to standardize these values (Cubero et al., 2011). However, this colour space is not perceptual uniform, meaning that the Euclidean distance between two colours is not the same as the colour difference perceived by the human eye (Cubero et al., 2011; Wu and Sun, 2013). In 1931, the Commission Internationale de l'Eclairage (CIE, International Illumination Commission) developed a colour

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space that is closer related to the way the human eye detects colour, namely Yxy. Using standard observer colour matching filters, the tristimulus values X (red), Y (green) and Z (blue) and their normalized values in x, y and z could be calculated. As the sum of the latter three values is one, 2 of these values are sufficient to represent the Chromaticity. Y is then used as a measure of the brightness, as the green sensitivity of the eye corresponds best with the sensitivity to lightness (Schanda, 2007). As the relation between this colour space and human colour perception was still not linear, a non-linear transformation of this colour space known as CIE 1976 (L*a*b*) has been proposed. This colour space consists of 3 axes, L*, a* and b*. L* describes the luminance of the measured surface (between 0 and +100), while a* goes from −128 (green) to +127 (red) and b* goes from −128 (blue) to +127 (yellow) (Schanda, 2007). As many fruits evolve from green to red during ripening the a* parameter can be very interesting as an indicator for the ripeness stage. However, when the evolution from green to red goes through yellow, the evolution of the b* parameter should also be monitored. In this case, the Hue angle can be more informative. The Hue angle, together with Chroma and L* is a representation of the L*a*b* colour space in polar coordinates instead of Cartesian coordinates (Schanda, 2007).

Traditionally, colorimeters or spectrophotometers are used to measure the colour of food in a laboratory environment. Colorimeters obtain the tristimulus values (X, Y and Z) optically, by combining different optical filters. Spectrophotometers measure the reflectance spectra of the sample. The colour is then calculated based on the obtained spectra, taking into account the illumination, the measurement geometry and the observer angle (Pathare et al., 2013).

Clément et al. (2008) achieved very accurate colour predictions using Vis/NIR Spectroscopy in combination with Partial Least Squares Regression (PLS-R) (Hunter a: $R^2 = 0.98$, Hunter L and Hunter b: $R^2 = 0.92$). These methods are fast and simple, but have two important drawbacks. First, these instruments can only measure a small and relatively uniform surface of a sample, which can be problematic for inhomogeneous products such as fruit and vegetables. Secondly, the size and geometry of the sample are of uttermost importance. If the sample window is not completely covered by the product, the colour measurement could become inaccurate. Due to these drawbacks, these point measurement techniques are not suitable for accurate characterization of the colour distribution on a complete fruit or vegetable (Wu and Sun, 2013).

To overcome these drawbacks and to be able to automate colour measurements of food products, many researchers have investigated the potential of machine vision techniques to measure the colour for every pixel of the food product in the image (Wu and Sun, 2013). To classify tomatoes in the 6 different ripeness classes defined by the USDA, Choi et al. (1995) used image analysis. They converted RGB values into HIS (Hue, saturation, intensity) values and were able to classify 77% of the tomatoes in the correct ripeness-class based on the Hue distribution over the complete fruit. León et al. (2006) investigated different regression methods to obtain accurate L*, a* and b* predictions from RGB images. On standards, they achieved an average normalized error ($\bar{e}$) (Eq. (43)) of 0.93%, while for chips, they obtained an $\bar{e}$ of 1.8%. Sharifzadeh et al. (2014) reported that a colour difference (ΔE) (Eq. (37)) smaller than 1 unit distance in the CIELab colour space is not detectable for the human eye, while a ΔE between 3 and 6 units distance is still acceptable for industrial use. Larraín et al. (2008) used digital images to measure the colour of beef meat. By applying linear or quadratic regression to the digital images, a good R^2 could be achieved for a*, Chroma and Hue (≥0.93), but for b* and L* these results were less accurate ($R^2 < 0.6$). Mendoza and Aguilera (2004) achieved good results for the measurement of the colour of bananas with an R^2 of 0.804 for the prediction of L*, 0.972 for the prediction of a* and 0.609 for the prediction of b*. The colour of Atlantic salmon measured with a Minolta colorimeter and a colour vision system was compared by Yagiz et al. (2009). They remarked that the colour readings by the computer vision system were significantly higher than the colour readings by the colorimeter, pointing out that the results of colorimeter and computer vision measurements should be compared with care.

Next to the use of RGB vision systems, also multi- and hyperspectral images have been evaluated to calculate the colour of food products. Hyperspectral imaging can be seen as a combination of digital imaging with spectroscopy, which provides a reflection spectrum for each pixel in the image. As these systems acquire more detailed spectral information than RGB cameras, it is expected that more accurate colour measurements could be made with these. This was confirmed by Polder et al. (2002), who classified tomatoes according to 5 ripeness stages using RGB imaging as well as a combination of hyperspectral imaging with Linear Discriminant Analysis (LDA). Based on RGB imaging, 51% of the pixels were misclassified, while the use of the hyperspectral imaging system reduced the misclassification rate to 19% at pixel level. On object level, all 25 tomatoes were accurately classified using hyperspectral imaging compared to 24 correctly classified tomatoes based on RGB-imaging. Hahn (2002) developed a multispectral imaging system to detect tomatoes that will never ripen during storage with an accuracy over 85%.

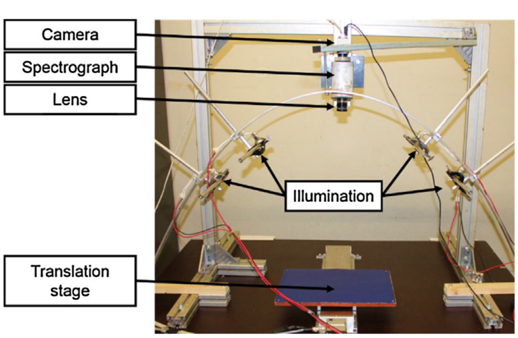

Fig. 1. Hyperspectral setup with indication of the main components.

Fig. 2. Tomato vine of the cultivar Merlice with the marked circles at the bottom of the tomatoes where the calibrated spectrophotometer measurements were performed.