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Fresh meat color evaluation using a structured light imaging system

Camilla H. Trinderup [a], Yuan H. Brad Kim [b,*]

[a] Technical University of Denmark, Richard Petersens Plads, 2800 Kgs. Lyngby, Denmark
[b] Meat Science and Muscle Biology Lab, Department of Animal Sciences, Purdue University, West Lafayette, IN 47906, United States

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ABSTRACT

The objective of this study was to investigate the efficacy of a computer vision system (CVS) with structured light for meat color assessment. Three muscles (*longissimus dorsi* (LD), *semimembranosus* (SM), and *psoas major* (PM)) from eight beef carcasses were obtained at 1 day postmortem, vacuum packaged and assigned to three aging periods (9, 16, and 23 days). After aging, steaks were cut and displayed for 7 days at 3 °C under light. The surface colors were evaluated by using a Minolta, the CVS and trained color panel. In general, the CVS was highly correlated to the sensory scores, and showed an equivalent meat color assessment compared to the colorimeter. The CVS had a significantly higher correlation with the panel scores for the lighter and more color stable samples compared to the colorimeter. These results indicate that the CVS with structured light could be an appropriate alternative to the traditional colorimeter by offering improved precision and accuracy over the colorimeter.

1. Introduction

Fresh meat color is one of the most important meat quality attributes, since consumers rely on the appearance of meat to determine its freshness and wholesomeness (Mancini & Hunt, 2005). In this regard, extensive research and technological advancements have been progressed to develop more precise and consistent methods for meat color evaluation.

In general, colorimeters, such as Minolta Chroma meter and Hunter Lab MiniScan colorimeter are most widely and extensively used for the evaluation of meat color (Tapp, Yancey, & Apple, 2011). The colorimeters measure the L^* (lightness), a^* (redness), and b^* (yellowness) values in CIELAB color space by scanning a number of random spots on the meat surface as representatives of the sample. However, this type of approach also has a limitation in terms of repeatability and accuracy (Larraín, Schaefer, & Reed, 2008; Tapp et al., 2011), since 1) the meat surface is not homogeneous (containing fat and connective tissues), and 2) discoloration occurs on random areas (including the edge of meat, which is very hard to scan with colorimeters). Consequently, this could result in a biased result.

Recently, there has been a growing interest in employing a computer vision system (CVS) for meat color assessment. Several studies have exploited different computer vision systems for color measurement of fresh meat (Gerrard, Gao, & Tan, 1996; Girolami, Napolitano, Faraone, & Braghieri, 2013; Kamruzzaman, Barbin, ElMasry, Sun, & Allen, 2012; Larraín et al., 2008) and processed meat products (Valous, Mendoza, Sun, & Allen, 2009). By using a CVS, it is possible to capture the color variation across a sample, so that the possible bias due to locational variation can be avoided. The digital images captured can also be a basis for other analyses, e.g., marbling structure and fat content estimation (Jackman, Sun, & Allen, 2009; Shiranita, Hayashi, Otsubo, Miyajima, & Takiyama, 2000). Another important advantage of employing a CVS is that images can be stored and thus be evaluated even after the samples are discarded. Yagiz, Balaban, Kristinsson, Welt, and Marshall (2009) and Girolami et al. (2013) have tested the performance of the colorimeter against computer vision systems, and found that the colors returned by the CVS had a higher resemblance with the human perception of meat/food samples compared to the colors assessed by a colorimeter.

While a CVS has a great potential to be used for meat color assessment, it also has some technical limitations to overcome. For example, a CVS often employs an RGB camera for meat color evaluation, which requires consistent calibration of the instrument and illumination (Wu & Sun, 2013). Moreover, the outcome from a CVS with an RGB camera is device dependent and it can therefore be hard to translate the RGB information to other color spaces such as CIEXYZ or CIELAB.

Whenever an RGB camera is a part of a CVS, the above issues are likely present. A multispectral imaging system is one way to overcome the limitations of the RGB systems (Trinderup, Dahl, Jensen, Carstensen, & Conradsen, 2013). However, such a system is complex and the

* Corresponding author. Tel.: +1 765 496 1631.
E-mail address: bradkim@purdue.edu (Y.H.B. Kim).

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illumination becomes a great challenge. It would be ideal to have diffuse illumination of a sample when measuring color to limit the specular reflectance, but this could be a difficult task. A way to overcome the illumination issues could be by applying structured light to the image acquisition method. Structured light is often used in stereo optics to obtain a 3D representation of a scene (Valkenburg & McIvor, 1998). However, it can also be of use in separating the diffuse and specular components of a scene as shown by Nayar, Krishnan, Grossberg, and Raskar (2006). For a translucent material like meat, this combined approach could be a viable option, since the diffuse component depicts the true color information, whereas the specular component depicts the direct reflections of the illumination (Martelli, 2010). Therefore, it can be hypothesized that the CVS system coupled with structured light will enable data transformation of RGB to color spaces and thus precisely and accurately assess meat color. The objective of this study was to determine the efficacy of using a structured light CVS system to evaluate fresh meat color changes during retail display. To test our hypothesis, the most appropriate transformation from RGB to CIELAB was evaluated by comparing the transformed data with color data obtained by a trained sensory color panel evaluation and using a traditional colorimeter. Furthermore, three different bovine muscle samples with different aging times (*longissimus dorsi* (LD), *semimembranosus* (SM), and *psoas major* (PM)), which are known to have different color stability (Kim, Keeton, Smith, Berghman, & Savell, 2009), were evaluated to determine the efficacy of the CVS system in meat color evaluation.

2. Materials and methods

2.1. Raw materials and processing

A total of eight beef carcasses (USDA Select; A maturity; average 24 months old) were harvested at the Purdue University Meat Laboratory. Three beef muscles (LD, SM, and PM) were separated from the carcasses at 1 day postmortem, resulting in $n = 8$ replicates for each muscle type. Each muscle from each of the eight carcasses was split in three parts and vacuum packed, and randomly assigned to three different aging times of 9, 16, and 23 days postmortem. After the assigned aging time, a steak was cut from each muscle (≈2 cm), placed on a Styrofoam tray and wrapped with PVC film. The steaks were displayed under continuous fluorescent natural white light (3500 K) for 7 days at 3 °C. At display days 1, 4 and 7, a trained sensory panel ($n_{\text{panel}} = 10$) evaluated the lean meat color and discoloration scores based on the AMSA color guidelines (AMSA, 2012). The sensory color panelists, who all passed the Farnsworth–Munsell 100 Hue Test, were trained twice by exposure to images of meat samples and actual samples. Lean color was assessed using eight scale points (1 — extremely dark/brown; 8 — extremely bright red), and discoloration was evaluated in seven scale points (1 — no discoloration; 7 — total discoloration). On the days of evaluation for the trained panel, the sample colors were assessed with a Minolta CR-400 colorimeter (D65, 1 cm diameter aperture, and 2 standard observer; 3 spot measurements) and a computer vision system (CVS) employing structured light. The colorimeter calibration and measurements were performed through PVC wrap, whereas the imaging was performed without cover of the samples.

2.2. Computer vision system

The CVS consisted of an industrial RGB camera from JAI (8 M pixels) and a TI LightCrafter 3000 pico-projector. These instruments were connected to a computer running the software controlling the projections and camera trigger. The camera and projector set-up is illustrated in Fig. 1. The set-up was enclosed in a black box to keep the lighting conditions similar for all samples.

The projections used in this set-up are checkerboard patterns. For each projection, this checkerboard pattern was shifted at a fixed amount of pixels right or down. This approach results in a sequence of images,

Fig. 1. Illustration of the computer vision system set-up. Camera and projector are placed in the same height. Both instruments are connected to a computer handling projections and camera trigger.

$\boldsymbol{I}_s \in \mathbb{R}^{m \times n \times p}$, where a point in the scene is either fully lit or unlit at least once. In the fully lit points specular reflections arise. The unlit points are not totally black, since they receive light scattered underneath the surface – also denoted subsurface scattering – as illustrated in Fig. 2. This light would hold information about the color of a scene. By making some simple assumptions the diffuse and specular components in a pixel (i, j) can be found as

$$\boldsymbol{I}_{diffuse}(i,j) = \frac{1}{2}\min_n \boldsymbol{I}_s(i,j,n) \tag{1}$$

$$\boldsymbol{I}_{specular}(i,j) = \max_p \boldsymbol{I}_s(i,j,n). \tag{2}$$

This way a diffuse and a specular image of size $m \times n$ was obtained. The method is described in further details in Nayar et al. (2006). In this study checkerboard patterns with checkers of 4×4 projector pixels were applied. Since the projector had a lower resolution (480×640 pixels) than the camera (3926×2472 pixels), 45 projections were needed in order to reach a separation of the two components without artifacts.

2.2.1. Camera characterization

In order to obtain color information in CIELAB coordinates – the common color space within color measurement in foods – the RGB

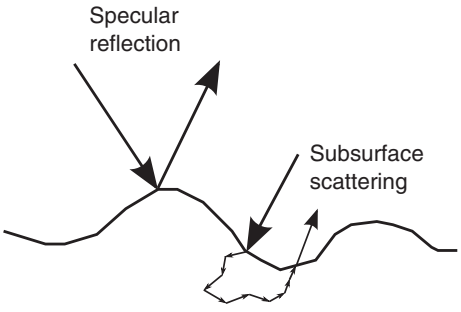

Fig. 2. Specular reflection, where the light is reflected on the sample surface. In subsurface scattering the light rays are scattered multiple times underneath the surface.