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Supervised feature selection for linear and non-linear regression of L*a*b* color from multispectral images of meat

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ABSTRACT

In food quality monitoring, color is an important indicator factor of quality. The CIELab (L*a*b*) color space as a device independent color space is an appropriate means in this case. The commonly used colorimeter instruments can neither measure the L*a*b color in a wide area over the target surface nor in a contact-less mode. However, developing algorithms for conversion of food items images into L*a*b color space can solve both of these issues. This paper addresses the problem of L*a*b color prediction from multispectral images of different types of raw meat. The efficiency of using multispectral images instead of the standard RGB is investigated. In addition, it is demonstrated that due to the fiber structure and transparency of raw meat, the prediction models built on the standard color patches do not work for raw meat test samples. As a result, multispectral images of different types of meat samples (430–970 nm) were used for training and testing of the L*a*b prediction models. Finding a sparse solution or the use of a minimum number of bands is of particular interest to make an industrial vision set-up simpler and cost effective. In this paper, a wide range of linear, non-linear, kernel-based regression and sparse regression methods are compared. In order to improve the prediction results of these models, we propose a supervised feature selection strategy which is compared with the Principal component analysis (PCA) as a pre-processing step. The results showed that the proposed feature selection method outperforms the PCA for both linear and non-linear methods. The highest performance was obtained by linear ridge regression applied on the selected features from the proposed Elastic net (EN) -based feature selection strategy. All the best models use a reduced number of wavelengths for each of the L*a*b components.

1. Introduction

Monitoring the quality of meat products is a significant concern in the food industry. Supplying a consistent high quality product requires a continuous assessment in the meat industry. This requires a development of on-line inspection methods for automation of the inspection process (Sharifzadeh et al., 2012). Conventional assessment methods in this case are based on subjective visual judgment and laboratory tests which are time-consuming, destructive and inconsistent in terms of human accuracy.

The visual appearances such as the texture pattern and the color of the meat are the main criteria for both the manufacturer and customer. These parameters are linked to the chemical properties such as the water-holding capacity, intra-muscular (marbling) and protein content (Sun, 2010). As a result, surface color is an important parameter for quality measurement in the meat industry.

One efficient color space for quantification of food items is the CIELab or L*a*b* color space, due to its precise characteristics (Mendoza et al., 2006; Brewer et al., 2006). It is a device independent color space defined by the International Commission on Illumination – abbreviated as CIE in 1976. L*a*b* has a perceptually equal space. This means that the Euclidean distance between two colors in the CIELab color space is strongly correlated with the human visual perception (Tkalčič and Tasič, 2003). The L* is the luminance component and the a* and b* are chromatic components.

Colorimeters and spectrophotometers are traditional instruments for measurements of colors such as L*a*b* in the food industry. They provide a quantitative measurement in a similar way to the human eye (Wu and Sun, 2013; Balaban and Odabasi, 2006). Colorimeters, such as the Minolta chromameter or the Hunter Lab, are used to measure the color of primary radiation sources that emit light and secondary radiation sources that reflect or transmit external light (León et al., 2006). Therefore, color values are obtained optically but not mathematically. Before doing the measurements, the instrument is usually calibrated.

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Traditional instrumental measurements can only measure the surface of a sample that is uniform and rather small (Balaban and Odabasi, 2006). Hence, they cannot completely represent the surface characteristics especially when it is non-uniform and highly textured as is the case for meat. In order to have a global representation of the target surface, computer vision techniques can be used to quantify the color (Wu and Sun, 2013). This leads to the formation of a 3D map of L*a*b* color values. Such a map represents the spatial characteristics of the whole surface instead of a small area. Color space conversion techniques can be employed to transfer an image into the L*a*b* space with the desired numerical and visual specifications. Thereby, the images of the meat samples from other color spaces such as RGB or CMYK can be transferred into L*a*b* space. In this way, it is possible to convert each image pixel into L*a*b* and therefore, generalize the representation.

Reviewing the literature shows that, conversion to L*a*b* was mainly performed using RGB images. In Larrain et al. (2008) and Mendoza et al. (2006) standard sequential transformation into XYZ color space and then from XYZ to L*a*b* was used for RGB images of beef and vegetables respectively. In Fdhal et al. (2009), conversion for the RGB images of the standard color patches into L*a*b* was performed using BPANN.[1] In Cao and Jun (2011) and Cao and Jun (2008), RBFNN[2] and GRNN[3] were used for conversion from CMYK color space to CIELab respectively.

The use of RGB images has some drawbacks. An RGB image, captured by a digital camera, is formed by filtering the incoming photons into three broad primary channels representing the color variables; Red, Green and Blue (RGB). These three variables are enough to describe a color sensation. However, the intensity recorded in each channel is an integration over a large range of wavelengths and therefore, two objects with different spectral radiant power distribution may seem to have similar colors in an RGB image. This is called metameric failure, which means matching colorimetrically under one illumination, but differ under another. It occurs when the spectral radiant power distribution of two objects are different, but the rough splitting of photons fails to observe this Dissing et al. (2010). In addition, RGB is a device dependent color space and the color of an object may be slightly different in two different camera records.

Multispectral imaging is an alternative for solving these limitations. In a multispectral imaging system, the sampling frequency of the electromagnetic spectrum is high and images are formed in very narrow bands compared to the three broad intervals used in standard RGB imaging. Therefore, the distribution of incoming photons for each pixel is approximated correctly. Besides the visual bands that characterize the color information, the higher wavelengths such as NIR are related to the chemical characteristics. Therefore, spectral imaging has been widely used for food quality control applications (Gamal et al., 2009; Dissing et al., 2009; Sharifzadeh et al., 2013).

So far, multispectral imaging has never been used in color conversion of food items. Color conversion using the spectral images can be done based on statistical predictive models. The advantage of such methods over the standard matrix transformation was investigated in León et al. (2006). In that work, a sequential transformation was used for conversion of the RGB images of color samples into L*a*b*. In addition, OLS[4] linear regression and ANN[5] with early stopping generalization were employed and their results showed that the ANN model obtained the best performance. In Dissing et al. (2010), the multispectral

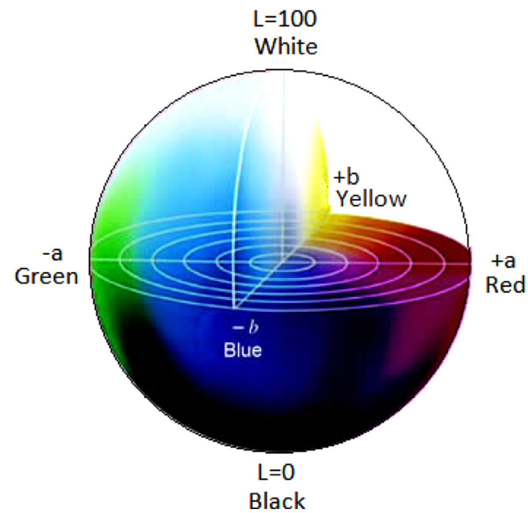

Fig. 1. L*a*b* 3D color space.

images of the standard color patches were transformed into the CIE-XYZ using linear regression models.

This paper focuses on conversion of multispectral images (430–970 nm) of different types of raw meat into L*a*b* units. In the following, we explain the main points investigated in this paper:

Since the food items can have variation, it is important to create and validate the prediction models on food products. Therefore, the use of real meat samples instead of the color patches for building the prediction models was investigated. Uncooked meat is translucent and transparent. Therefore the light reflected from it, not only comes from its surface but part of it comes from below the surface. Meat also has structure due to fibers with orientation. The color patches do not have structure and the light is reflected directly from the surface. Therefore, a model built on color patches do not work well on raw meat samples.

Due to the fact that the vision systems with their spectra are costly and not feasible to implement in the industry for online food productions, the sparsity is important and performing predictions using a minimum number of wavelengths would make the required vision system more cost efficient. Therefore, we propose a new supervised feature selection strategy based on EN and lasso[6] regression as a pre-processing step. The selected features were compared with PCA using three different regression strategies. A complete comparison between linear, non-linear and kernel-based regression methods was performed, which we did not see in the previous works. In order to have a general and fair judgment about the methods, the original data set was divided randomly into 25 training and test sets and the regression methods were tested on all of them and the average results were considered.

Finally, the results of the spectral images were compared with the RGB images.

The rest of the paper is organized as follows; Section 2 is about color description and Section 3 describes the data preparation. In Section 4, we describe linear, non-linear and kernel-based regression methods respectively. Section 5 is about the proposed supervised linear feature selection algorithm. Experimental results are presented in Section 6. Finally, there is a conclusion for this paper in Section 7.

[1] Back Propagation artificial neural network.
[2] Radial basis function neural network.
[3] Generalized regularized neural network.
[4] Ordinary least square.
[5] Artificial neural networks.
[6] Least angle shrinkage and selection operator.