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Rapid classification of intact chicken breast fillets by predicting principal component score of quality traits with visible/near-Infrared spectroscopy

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ABSTRACT

In this study visible/near-infrared spectroscopy (Vis/NIRS) was evaluated to rapidly classify intact chicken breast fillets. Five principal components (PC) were extracted from reference quality traits (L^*, pH, drip loss, expressible fluid, and salt-induced water gain). A quality grades classification method by PC_1 score was proposed. With this method, 150 chicken fillets were properly classified into three quality grades, i.e., DFD (dark, firm and dry), normal, and PSE (pale, soft and exudative). Furthermore, PC_1 score could be predicted using partial least squares regression (PLSR) model based on Vis/NIRS ($R^2p = 0.78$, RPD = 1.9), without the measurement of any quality traits. Thresholds of PC_1 classification method were applied to classify the predicted PC_1 score values of each fillet into three quality grades. The classification accuracy of calibration and prediction set were 85% and 80%, respectively. Results revealed that PC_1 score classification method is feasible, and with Vis/NIRS, this method could be rapidly implemented.

1. Introduction

Chicken breast meat is considered an important component in healthy diets and its per capita consumption has increased by 10% from 2000 to 2016 in the USA (National Chicken Council. Statistics., 2017). Consequently, the demand for chicken meat rapidly increases and the meat quality assessment and classification become essential for optimizing utilization of raw meat materials for different end-use products (e.g., chilled meat, sausages and ready-to-eat meal). Different quality grades, such as DFD (dark, firm and dry), normal, and PSE (pale, soft and exudative), of raw chicken breast meat have been reported (Barbut, 1997). DFD meat is prone to microbial contamination and PSE meat is regarded as defective because of its pale appearance, and soft texture (Lesiów & Kijowski, 2003). The processing value of PSE meat is limited. It cannot be considered as fully valuable culinary meat, and be sold directly to consumers (Alvarado, 2002).

Currently, there is no reliable method for the classification of PSE and DFD meat in poultry. The most important and intuitive characteristic of PSE and DFD meat is the lightness of meat (Smith & Northcutt, 2009). Some studies classify quality grades of chicken breast meat based on L^* value (Wilkins, Brown, Phillips, & Warriss, 2000; Woelfel, Owens, Hirschler, Martinez-Dawson, & Sams, 2002). Other studies use pH, since changes in meat pH cause corresponding changes in L^* measurements (Kato et al., 2013; Niewiarowicz, 1978). However, Smith and Northcutt (2009) concluded that one single quality trait is not sufficient to classify a true PSE condition in poultry breast meat.

Several studies have combined pH and L^* values to estimate the condition of PSE and DFD (Barbut, Zhang, & Marcone, 2005; Li et al., 2015) but formation of PSE and DFD meat is also involved with other changes in biochemical composition and physical structure in breast meat in addition to pH (Zhang & Barbut, 2005). For example, chicken breast meat that is defined as PSE appears lighter than normal and usually has poor water-holding capacity (WHC) as well as lower pH (Zhuang & Savage, 2010). Therefore, in order to provide better/reliable classification of chicken breast meat into different quality grades, multiple quality traits, such as L^*, pH, and WHC, are always synchronously measured (Barbin et al., 2015; Zhuang & Savage, 2012) and high correlations among those quality traits are reported (Bowker, Hawkins, & Zhuang, 2014).

Multivariate statistical techniques, such as principal components analysis (PCA), can provide more insight into the latent structure of a data set, and highlight the information not available at first glance. (Hotelling, 1933). PCA is a common method to explain the numerous and high correlation variables in terms of few uncorrelated principal components (PCs) without losing useful information (Farnham, Johannesson, Singh, Hodge, & Stetzenbach, 2003). The first PC explains the most variance within the original data set and each subsequent

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component explains progressively less. In recent years, PCA has been widely used in food and water quality assessment (Chen, Jiao, Huang, & Huang, 2007; Ouyang, 2005; Zhang et al., 2014). Use of these PCs in multivariable analysis and modeling has shown high potentials for food quality assessments (Liu, 2015; Xue, 2016).

For meat quality assessment and classification, traditional analytical methods, such as weighing and centrifugation method, are usually destructive, requiring sample preparation, time consuming and consequently unsuitable for on-line application (Liu, Lyon, Windham, Lyon, & Savage, 2004b). The meat processing industry could benefit from an analytical technique that has the ability to detect/predict multiple quality traits simultaneously and non-destructively (Kapper, Klont, Verdonk, Williams, & Urlings, 2012). Visible/near-infrared spectroscopy (Vis/NIRS) has been successfully applied to the quantitative prediction of major constituents (moisture, fat, and protein) in meat and meat products (Prieto, Roeche, Lavin, Batten, & Andres, 2009). It has also been demonstrated to be feasible for predicting meat quality (Barbin et al., 2015; Cozzolino, Barlocco, Vadell, Ballesteros, & Gallieta, 2003; Savenije, Geesink, van der Palen, & Hemke, 2006).

The main objective was to investigate the potential of PC score as new intermediate quality variable to classify intact chicken breast fillets (*pectoralis major*) and its rapid implementation with Vis/NIRS. Specific objectives were to: (1) extract PCs from five reference quality traits (L^*, pH, drip loss, salt-induced water gain, and expressible fluid) of chicken breast fillets; (2) select the optimal PC that is most relevant to quality grades of chicken meat, and propose a quality grade classification method based on the optimal PC score; (3) establish a PLSR model to quantitatively relate spectral information with individual quality traits as well as optimal PC score, acquire the best PLSR model, and then apply the best PLSR model and thresholds of optimal PC score classification method in classification of intact chicken breast fillets.

2. Materials and methods

2.1. Sample preparation

A total of 150 boneless broiler breast fillets (2 h postmortem) were collected after water chill (pre-chill and chill time averaged 60–65 min) from a commercial processing plant on 5 separate trial dates (30 fillets per date). The fillets were placed on ice and transported to the laboratory (Russell Research center, USDA, USA) within 15 min. Each fillet was trimmed to remove skin, fat tissue, and bone before further analysis.

2.2. Quality traits measurements

2.2.1. Color

Lightness values were measured on the bone side of intact fillets with a Minolta spectrophotometer CM-700d (Konica Minolta Inc., Ramsey, NJ). Each measurement was recorded as the average of three different reading positions (cranial, central and caudal side) and expressed in terms of CIE values for lightness (L^*).

2.2.2. pH

The pH of fillets was measured with a Hach H280 GB pH meter and a pH57ss spear-tipped pH probe (Hach Inc., Loveland, CO) inserted into the bone side of intact fillets. Each measurement was recorded as the average of two different reading positions (both at the cranial end). Between measurements, the probe tip was rinsed and cleaned (Zhuang & Savage, 2008).

2.2.3. Water-holding capacity

Water-holding capacity (WHC) is an important parameter for meat quality. In this study, WHC of the fillets was estimated with 3 different methods: drip loss, salt-induced water gain, and expressible fluid. They represent different water characteristics in meat and had different indications for meat functionality.

Drip loss is commonly used to indicate the capability of the muscle to hold water, especially the free water (unbound water) that comes out from meat due to gravity. Drip loss was measured according to a modified procedure (Honikel, 1998). Thirty grams of samples were removed (cored) from the central portion of fillets, weighed, and placed on a mesh screen in a covered plastic container, and stored at 2 °C. The sample were reweighed at 48 h postmortem, and drip loss (%) was calculated as [100 × (weight of drip/initial weight)] (Zhuang & Savage, 2012).

Salt-induced water gain indicates the maximum potential for muscle to gain water in the presence of salt. Salt-induced water gain was measured by a swelling and centrifugation method (Wardlaw, McCaskill, & Acton, 1973). Ten grams of the minced meat sample and 15 mL of 0.6 M NaCl solution were added to a 50-mL centrifuge tube and mixed with a vortex mixer for 1 min. Before being centrifuged (3000*g* for 15 min), the tube was refrigerated at 4 °C for 15 min. After centrifugation, supernatants were decanted, the sample was reweighed, and the salt-induced water gain (%) was calculated as [100 × ((final pallet weight − initial weight)/initial weight)] (Bowker et al., 2014).

Different from the weighing and centrifugation method (drip loss and salt-induced water gain), expressible fluid measures the release of juice from meat after application of external forces and consists of both extracellular and intracellular free and loosely bound water. Expressible fluid was measured by the filter paper press method (Honikel & Hamm, 1994). Meat tissue (300 mg) from the cranial end of fillets was placed on filter paper (11-cm diameter), which had been dried before use, and pressed at 50 kg (a 50-kg load cell) for 5 min by a TA-XTPlus texture analyzer (Stable Micro Systems Inc., Godalming, UK). The filter paper was then scanned into a computer with a scanner. The meat area and the total fluid area were measured using Adobe Photoshop software (CS3 Extended Inc., San Jose, CA). Expressible fluid (%) was calculated as [100 × (fluid area/total wet area)] (Zhuang & Savage, 2012).

2.3. Vis/NIR spectra measurements

Meat samples (intact) were trimmed and contained in a 38-mm diameter sample cup with a quartz window for Vis/NIR spectral collections. The spectra were collected in the diffuse reflection mode and recorded as absorbance (log 1/R) using a Foss XDS spectrometer (Foss Inc., Hillerød, Denmark). Each spectrum was an average of 32 scans with 2 nm intervals over the wavelength range of 400–2500 nm. The container was thoroughly cleaned between samples.

2.4. Data processing and statistical analysis

2.4.1. Principal component analysis

PCA is a common technique for dimension reduction and information extraction in multivariate data analysis (Wu, Sun, & He, 2012). In this study, five quality traits (L^*, pH, drip loss, expressible fluid, and salt-induced water gain) were used to find new intermediate variables by orthogonal transformation of PCA. The application of PCA included follow steps: data standardization, PC extraction, and PC interpretations (Ouyang, 2005; Zarei & Bilondi, 2013). Firstly, data standardization kept the correlation variables and tended to lessen the influence of large magnitude gap, the original data were converted into standardized format by *z*-score method. Secondly, PCs were extracted. Based on eigenanalysis of the correlation or covariance matrix, PCA converted several high correlation quality traits to a few uncorrelated PCs. Thirdly, the loadings of each quality trait were then used to interpret these extracted PCs. Quality traits with the greatest positive and negative loadings make the largest contribution. Finally, the PC scores of each sample were calculated. To examine the suitability of the data for PCA, Kaiser-Meyer-Olkin (KMO) and Bartlett tests were performed. PCA, KMO and Bartlett tests were carried out by using SPSS 17.0