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Integration of spectral and textural data for enhancing hyperspectral prediction of K value in pork meat

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A B S T R A C T

K value is an important freshness indicator of meat. This study investigated the integration of spectral and textural data for enhancing the hyperspectral prediction ability of K value in pork meat. In this study, six feature wavebands (407, 481, 555, 578, 633, and 973 nm) were identified by successive projections algorithm (SPA). Meanwhile, the texture data of the grayscale images at the feature wavebands were extracted by gray level co-occurrence matrix (GLCM). The spectral and textural data were integrated by feature level fusion and the partial least square regression (PLSR) model built based on data fusion yielded excellent results, an improvement of at least 17.5% was obtained in model performance compared to those when either spectral data or textural data were used alone, indicating that data fusion is an effective way to enhance hyperspectral imaging ability for the determination of K values for freshness evaluation in pork meat.

1. Introduction

Pork is one of the most consumed meats worldwide due to its delicious taste and abundant nutrients, accounting for over 36% of the world meat intake (FAO, 2012; Scheier, Bauer, & Schmidt, 2014). However, pork is highly perishable, therefore techniques such as cooling (Desmond, Kenny, Ward, & Sun, 2000; Sun & Wang, 2000; Wang & Sun, 2004; Zheng & Sun, 2004), freezing (Kiani, Zhang, Delgado, & Sun, 2011) and drying (Cui, Sun, Chen, & Sun, 2008; Delgado & Sun, 2002), are regularly used to extend its shelf life and enhance its quality. The quality of pork is affected by many attributes such as nutrient content, flavor, tenderness, water holding capacity, and freshness, etc (Barbin, ElMasry, Sun, & Allen, 2012; Kazemi, Ngadi, & Gariépy, 2009; Neyrinck, De Smet, Vermeulen, Telleir, Lescouhier, Paelinck, et al., 2015). Among these attributes, freshness is one of the most important for the meat industry. Conventionally, there are mainly two methods to assess meat freshness: sensory evaluation conducted by professional inspectors and chemical or biochemical determination of target bio-indicators (Gil, Barat, Baigts, Martínez-Máñez, Soto, Garcia-Breijo et al., 2011). The former is subjective and tedious, while for the latter, a large number of studies have been conducted to relate freshness to certain physical characteristic or the concentration of certain compounds, such as color, pH, K value, biogenic amine content, and total volatile basic nitrogen content, etc (Chun, Min, & Hong, 2013; Hernandez-Jover, Izquierdo-Pulido, Veciana-Nogues, & Vidal-Carou, 1996; Huang, Zhao, Chen, & Zhang, 2014; Vasconcelos, Saraiva, & de Almeida, 2014). Among them, K value developed based on adenosine triphosphate (ATP) degradation has attracted much attention as an indicator of meat freshness and proved to be very successful (Gil et al., 2011; Mora, Hernández-Cázares, Aristoy, & Toldrá, 2010; Seewald, Iaizzo, Heisswolf, & Eichinger, 1993).

For the use of K value to evaluate meat freshness, most studies focus on the development of different techniques to separate, characterize, and quantify ATP and its related compounds. Among the methods developed are capillary electrophoresis (CE), layer chromatography (TLC), nuclear magnetic resonance spectroscopy (NMR), and the most widely used high performance liquid chromatography (HPLC) (Mora et al., 2010). Although these methods are powerful, they often encounter problems in real-time inspection

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since they are time-consuming, destructive, and require the use of large amounts of chemical reagents, which are not suitable for on-line monitoring. Therefore, rapid and non-destructive detection techniques are needed by the meat industry.

In recent years, hyperspectral imaging (HSI) as a rapid and non-destructive analytical technique has gained importance in the evaluation of food quality (Rady, Guyer, & Lu, 2015; Zhu, Zhang, Shao, He, & Ngadi, 2014; Kamruzzaman, Makino, Oshita, & Liu, 2015; Liu & Ngadi, 2012; Pu, Sun, Ma, Liu, & Cheng, 2014; Yu, Zhao, Liu, Li, Liu, & He, 2014). The fact that HSI integrates conventional imaging or computer vision (Jackman, Sun, & Allen, 2009; Jackman, Sun, Du, & Allen, 2009; Wang, & Sun, 2002; Wu & Sun, 2013) and spectroscopic techniques into one system enables this technique to provide the spatial and spectral information of the sample simultaneously, which is powerful for food quality discrimination (Barbin, ElMasry, Sun, & Allen, 2013; ElMasry, Barbin, Sun, & Sun, 2012; ElMasry, Kamruzzaman, Sun, Allen, & 2012; ElMasry, Sun, & Allen, 2012; Feng & Sun, 2012, 2013; Feng et al., 2013; Kamruzzaman, ElMasry, Kamruzzaman, Sun, & Allen, 2012; Liu, Sun, & Zeng, 2014; Wu & Sun, 2013; Wu, Sun, & He, 2012). In previous literature, HSI has been successfully applied for predicting sensory attributes (ElMasry, Barbin, Sun, & Allen, 2012), chemical compositions (Barbin, ElMasry, Sun, & Allen, 2013; Li, Chen, Zhao, & Wu, 2015), and microbial contamination (Barbin, ElMasry, Sun, Allen, & Morsy, 2013) in meats, and for K value prediction, the only publication is found in fish (Cheng, Sun, Pu, & Zhu, 2015). However, most of these models were established based on spectral data without incorporating spatial information, which is also important for predicting the quality characteristics of meat. Recently, the importance of analyzing the spectral and spatial information of HSI simultaneously has been emphasized by several researchers (Cheng & Sun, 2015a; Liu, Pu, Sun, Wang, & Zeng, 2014; Xiong, Sun, Pu, Zhu, & Luo, 2015), and the results demonstrated that HSI combined with data fusion would be more accurate for non-destructive analysis and predictions.

Therefore, the objective of this study was thus to investigate the integration of spectral and textural data for enhancing the hyperspectral prediction ability of K value in pork meat. The result of this study is expected to further improve the accuracy of HSI technique in pork meat freshness evaluation, which could also provide a reference for future research on monitoring freshness in other meat products.

2. Materials and methods

The main data-processing procedures for determination of K values in pork meat by HSI are presented in Fig. 1. The K value is calculated from the ATP-related compounds and defined as follows:

$$K = \frac{HxR + Hx}{ATP + ADP + AMP + HxR + Hx} \times 100\% \qquad (1)$$

where ADP is adenosine diphosphate, AMP is adenosine monophosphate, IMP is inosine monophosphate, HxR is inosine, and Hx is hypoxanthine. They are breakdown products of ATP according to the following sequence: ATP→ADP→AMP→IMP→HxR→Hx (Shahidi, Chong, & Dunajski, 1994).

2.1. Pork samples

Fresh pork samples (*longissimus dorsi*) from 12 pigs were

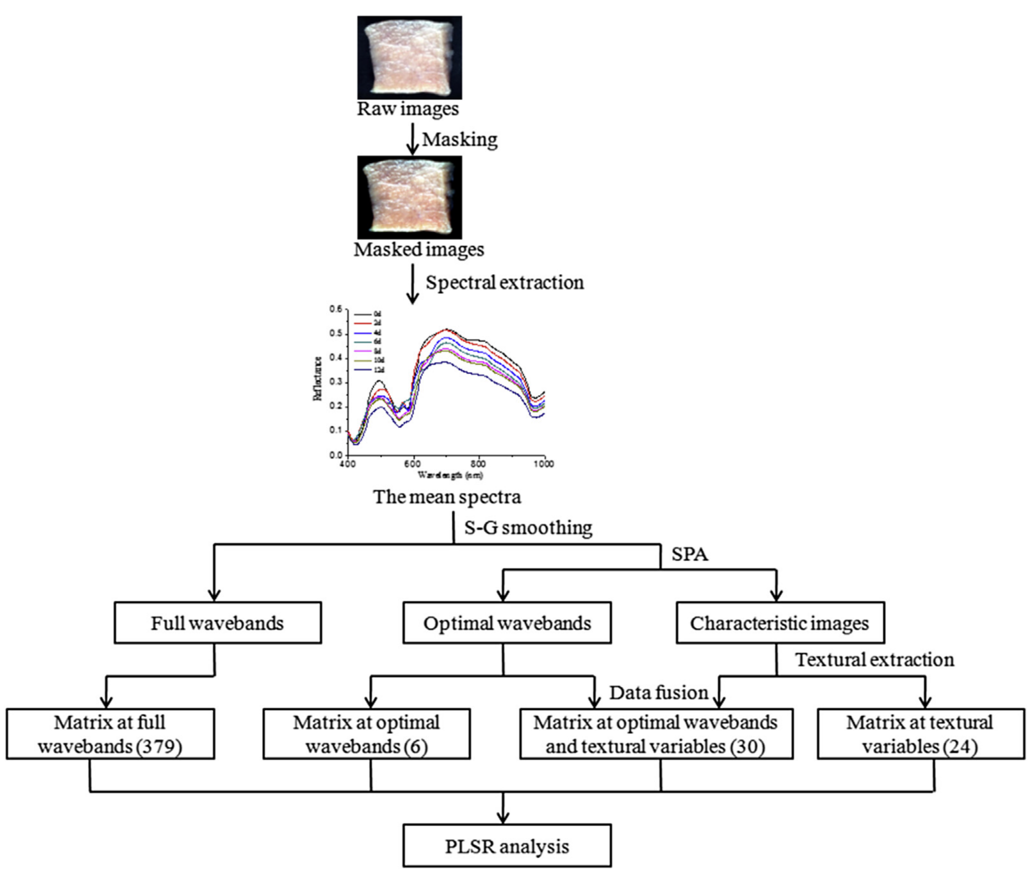

Fig. 1. Flowchart of main data-processing procedures for predicting K values of pork meat cuts by hyperspectral imaging enhanced by data fusion.