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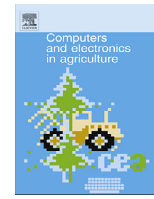

Singular spectrum analysis for improving hyperspectral imaging based beef eating quality evaluation

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ABSTRACT

Detecting beef eating quality in a non-destructive way has been popular in recent years. Among various non-destructive assessing methods, the feasibility of hyperspectral imaging (HSI) system was investigated in this paper. Hyperspectral images of beef samples were collected in an abattoir production line and used for predicting the beef tenderness and pH value. Support vector machine (SVM) was applied to construct the prediction equation. Before utilizing the original HSI spectral profiles directly, we propose to use singular spectrum analysis (SSA) as a pre-processing approach, where SSA has been proven to be an effective technique for time-series analysis in diverse applications. The results indicate that SSA can remove the instrumental noise of HSI system effectively and therefore improve the prediction performance.

1. Introduction

As time goes, food quality control has become a significant issue to human beings. Serving as a very important source of nutrition, the quality of muscle foods including meat and fish, influences the re-purchase behavior of consumers (Weeranantanaphan et al., 2011). Considering food quality control requires non-destructive real-time monitoring on the production line, near-infrared spectroscopy (NIRS) was first established as a fast and promising tool for multi-constituent quality analysis of food materials, which has proved its feasibility especially in meat industry (Gowen et al., 2007; Weeranantanaphan et al., 2011). However, with limited spatial information, internal constituent gradients within food products could not be captured by NIRS, leading to discrepancies between predicted and measured composition (Gowen et al., 2007). Therefore, multispectral imaging (MSI) system, combining images at a small number of narrow wavebands, was developed afterwards to overcome the above mentioned drawbacks and has demonstrated its success for detection of meat quality (Dissing et al., 2013; Panagou et al., 2014). Through capturing hundreds of continuous bands at different wavelengths, hyperspectral imaging (HSI), as an updated version of MSI, has received considerable attention in recent years since it can acquire the spatial and spectral information simultaneously. The information contained in the HSI cube can be utilized in many areas, going from traditional applications in agricultural land use analysis with remote sensing (Lee et al., 2010; Prabhakar et al., 2011; Qiao et al., 2014) and military surveillance (Gill et al., 2011; Zhao et al., 2013) to newly emerging platforms for biomedical imaging (Wang et al., 2013) and non-invasive food quality control and analysis (Baiano et al., 2012; Gowen et al., 2009; Kelman et al., 2013; Naganathan et al., 2008; Sun, 2010). Due to the fact that HSI could collect more information than NIRS and MSI during the same time, there is a growing trend to investigate its ability to predict meat quality in a way that is fast, non-destructive and requires no reagent. In this paper, beef was chosen as a representative of muscle foods since it contributes most to the meat market in EU with 8,000,000 tonnes annual consumption and similar levels of production (Panagou et al., 2014).

Usually, for both NIRS and HSI, pre-processing of the spectral profile is needed, to eliminate undesired effects and noise produced during the data collection process. Common pre-processing techniques, especially for NIRS, include calculating derivatives, standard normal variate (SNV) and multiplicative scatter correction (MSC) (Rinnan et al., 2009). However, using derivatives of spectra may even enhance the noise and lead to more difficult spectral interpretation. For SNV and MSC, it is

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required to apply these transformations to all spectra as the corrected spectra would be more accurate if more spectra were involved, which is infeasible in the abattoir. In practice, ideally a prediction model based on HSI will be installed in the abattoir production line, and for every single piece of beef steak, the model should predict the quality assessment result in a real-time manner. Therefore, it is necessary to use a pre-processing technique that can be applied to every single spectrum itself, without considering other spectra. In this paper, we mainly demonstrate that singular spectrum analysis (SSA) can be regarded as an optimal pre-processing step in de-noising HSI beef spectra, where it will not be restricted by the number of HSI samples. With the beef eating quality references available as ground truth, the support vector machine (SVM), which is a state-of-the-art non-linear regression technique, was employed for data regression. Compared to other regression methods, SVM does not ask for a large amount of training samples to construct the calibration equation. Additionally, it is not affected by sample outliers either (Burges, 1999).

The remaining sections of this paper are organized as follows. In Section 2, sample preparation and collection are presented. Besides, algorithms employed in the experiments will be explained as well. Experimental results and conclusion are given in Sections 3 and 4 respectively.

2. Materials and methods

2.1. HSI system

A push-broom HSI system (Gilden photonics) with wavelength ranging from 283 to 863 nm at a spectral resolution of about 2.5 nm was used to collect beef data samples. Fig. 1 shows a schematic diagram of the imaging system, which consists of a charge-coupled device (CCD) camera, a spectrograph with lens that utilizes a wavelength dispersive system to acquire all wavelengths of a single spatial line simultaneously, a tungsten halogen lamp, a sliding track and a black tray for the beef. With the targeted object sliding through the imaging system, a three dimensional HSI cube can be formed. Before the image collection starts, a spectral calibration procedure has to be done at two extreme illuminating conditions, using a white tile that reflects almost 100% of the radiation at all working wavelengths and also the lens cap to get a dark image. These steps make sure that the sample reflectance can be separated from the system response (Naganathan et al., 2008). Eq. (1) shows the calibration calculation,

$$R = \frac{I - B}{I_W - B}, \tag{1}$$

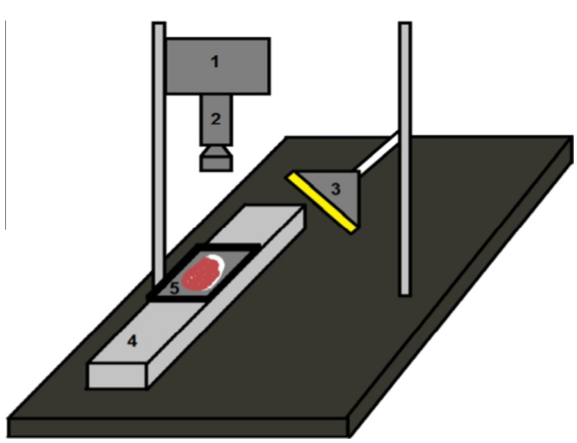

Fig. 1. Schematic diagram of a visible HSI system: components 1–5 refer to the CCD camera, spectrograph and lens, halogen lamp, sliding track and scanning tray, respectively.

where I, I_W and B stand for intensities of the raw image and white/-dark reference images, respectively.

2.2. Sample preparation and HSI data collection

Over 200 carcasses (*M. longissimus* muscle), which are aged for 48 h, were randomly selected in an abattoir production line during two consecutive days, irrespective of gender, conformation, fatness, weight or maturity. For each carcass, a piece of steak with thickness of 25 mm was recovered from the 11th rib position of the strip loin.

Allowing for two minutes of blooming, hyperspectral images were collected. After imaging, each steak was divided into lateral and dorsal halves, labelled and vacuum packaged. The lateral halves were further aged for 5 days and the dorsal halves were aged for 12 days at −1 °C before freezing. A temperature data logger was packed with each batch in order to verify the temperature during the aging process. Thus, these steaks had a total aging time of 7 days and 14 days before quality parameter measurements.

2.3. Sample quality reference measurements

Tenderness, juiciness and flavor of beef are considered as the most important attributes that influence the repurchase behavior of consumers (Shackelford et al., 2001). In our experiments, slice shear force (SSF) was measured as the tenderness reference, while the ultimate pH is found to have a strong relationship with juiciness and flavor of beef steaks. On the day before tenderness and pH tests, steaks were thawed overnight at ambient temperature and ultimate pH values were first measured using a calibrated Hanna meat pH meter (HI 99163) without the knife blade attached. Two measurements were taken at different locations and averaged to give the final result. For offline SSF measurement, steaks were cooked on a clam-shell grill until the center temperature reached 71 °C using a stainless steel temperature probe. Samples were sheared perpendicular to the muscle fiber axis with a Tenderscot tenderometer (Pentland Precision Engineeris, Loanhead, Midlothian), and the highest force during the shear process was picked up as the SSF. In summary, there are four beef quality attributes in total for each steak that need to be predicted, which are SSF7, SSF14, pH7 and pH14.

2.4. Singular spectrum analysis

As a relatively new technique, SSA is commonly used for time series analysis and forecasting. Based on the singular value decomposition (SVD), it is able to decompose the original time series into a few components, including the 'clean' series, oscillations and noise (Zabalza et al., 2014b). The algorithm of SSA is briefly introduced as follows.

The first step in the SSA algorithm is to transform the investigated series into the trajectory matrix. Assume we have a one dimensional series vector with length N as $\mathbf{X} = (x_1, \ldots, x_N)$. Given a window length L ($1 < L < N$), the initial series can be mapped into K lagged vectors, $\mathbf{X}_i = (x_i, \ldots, x_{i+L-1})^T$ for $i = 1, \ldots, K$, where $K = N - L + 1$. Then, the trajectory matrix is formed as Eq. (2). One thing worth of noting is that the matrix $\mathbf{T}$ is a Hankel matrix with size of $L \times K$, where $\mathbf{T}$ has equal elements x_{ij} on the anti-diagonals where $i + j = \text{const}$,

$$\mathbf{T} = (\mathbf{X}_1 \quad \mathbf{X}_2 \quad \cdots \quad \mathbf{X}_K) = \begin{pmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_N \end{pmatrix}. \tag{2}$$