Visible Hyperspectral Imaging for Lamb Quality Prediction

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Abstract Three factors, including tenderness, juiciness and flavour, are found to have an impact on lamb eating quality, which determines the repurchase behaviour of customers. In addition to these factors, the surface colour of lamb can also influence the purchase decision of consumers. From a long time ago, meat industries have been looking for fast and non-invasive objective quality evaluation approaches, where near-infrared spectroscopy (NIRS) and hyperspectral imaging (HSI) have shown great promises in assessing beef quality compared with conventional methods. However, rare research has been conducted for lamb samples. Therefore, in this paper the feasibility of the HSI system for evaluating lamb quality was tested. In total 80 lamb samples were imaged using a visible range HSI system and the spectral profiles were used for predicting lamb quality related traits. For some traits, noise was further removed from HSI spectra by singular spectrum analysis (SSA) for better performance. Considering support vector machine (SVM) is sensitive to high dimensional data, principal component analysis (PCA) was applied to reduce the dimensionality of HSI spectra before feeding into SVM for constructing prediction equations. The prediction results suggest that HSI is promising in predicting some lamb eating quality traits, which could be beneficial for lamb industries.

Keywords: Hyperspectral imaging; lamb quality; singular spectral analysis; principal component analysis; support vector machine.

1 Introduction

Similar to beef production, lamb also plays an important role in UK agriculture, contributing over 10% of total livestock output [1]. To facilitate abattoirs classifying carcasses into different grading levels, lamb quality, especially eating quality, needs to be effectively predicted before entering the market. Eating quality of lamb is related to many chemical and physical properties. It was found that three key factors, which are tenderness, juiciness and flavour, have an influence on the repurchase behaviour of consumers. Among all these factors, tenderness is usually accepted as the most significant quality trait influencing lamb eating quality [2]. In addition to those factors, meat surface colour is considered as the most

significant factor determining retail selection of consumers [3]. However, the evaluation of the above mentioned quality traits is usually achieved by measuring some mechanical properties of the meat sample, which can be costly, destructive and time-consuming. Therefore, meat industries are looking forward to computer based technology for automatic and non-destructive on-line quality assessment [4].

Some objective approaches for predicting meat quality traits have been developed over the past a few decades, including ultrasound [5], near infrared spectroscopy (NIRS) [1, 6], multispectral imaging [7, 8], hyperspectral imaging (HSI) [9] and various computer vision techniques [10]. Among these approaches, NIRS is the most widely used technique for meat quality evaluation due to its simplicity, rapidity and effectiveness, but one major drawback of this technique is its low spatial resolution for analysing non-homogeneous composition of meat samples, resulting in mismatches between predicted and measured traits [6, 11]. To this end, HSI integrating both spatial and spectral information has emerged, which shows great potential in remote sensing applications [12, 13] as well as non-invasive food quality control and analysis [14-16]. In recent years, some researchers have demonstrated that HSI presents great promise for predicting beef quality traits [9]. But to our knowledge, limited research has been conducted using HSI to predict quality traits of lamb samples.

The objective of the paper is to investigate the feasibility of HSI in predicting lamb quality related traits. In this study, ultimate pH was measured as the flavour reference and a tenderness measuring standard defined by Meat Industry Research Institute of New Zealand (MIRINZ) named as MIRINZ shear force (SF) was measured as the tenderness reference. Surface colour was measured in CIE (Commision Internationale de l'Eclairage) colour space as L*, a* and b*, where L* is the lightness, a* is redness and b* is yellowness. The prediction equation was constructed by the support vector machine (SVM) on a calibration dataset and the performance was assessed on the additional validation dataset. Details will be explained in the following sections.

2 Material and Methods

2.1 Lamb Sample Preparation and Image Collection

A total of 80 lamb samples were purchased from a commercial abattoir in Scotland, regardless of sex, age and breed groups. Storing at 3 ± 2 ◦C for 7 days after being slaughtered, left lamb loins were removed from packaging. After blooming for 2 minutes [17], HSI samples were collected using a push-broom HSI system (Gilden photonics) with wavelength ranging from 400 to 862.90 nm at a spectral resolution of about 2.5 nm. Figure 1 shows a schematic diagram of the imaging system.

Figure 1: Schematic diagram of the HSI system: components 1-5 refer to the EMCCD camera, spectrograph and lens, halogen lamp, sliding track and scanning tray, respectively.

The HSI system, which consists of an 12-bit Andor Luca electron multiplying charge-coupled device (EMCCD) camera and a Specim V8E spectrograph, could acquire the high spatial and spectral resolution information of the investigated object. Samples were illuminated with an Armley 150 W halogen lamp and the exposure time was set as 6 ms. Since the illuminating

conditions were probably different for several imaging batches, calibration was needed as a pre-processing step and details about calibration are covered in section 2.3. For each pixel, light was reflected from the target sample onto the entrance slit (width of 30 µm and length of 11.84 mm) and dispersed into a spectrum by the grating in the spectrograph. With the help a Zolix KSA 11-200S4N motorised stage set at a scanning speed of 10 deg/s for the screw, the system could achieve the undistorted hyperspectral image in the push-broom way, which only scans a single line of the investigated target at a time. The push-broom technique allows rapid and stable image acquisition, which is ideal for production line measurement in meat industry.

2.2 Measurements of Quality related Traits

Right after imaging, ultimate pH was determined by probing into the lamb sample directly using a calibrated Hanna pH meter with a glass electrode (HI 99613). The surface colour was measured in the L*a*b* scale with a Minolta CR-410 colourimeter, where the machine was set to take 3 scans and then average the results. Then, each lamb sample was labelled, vacuum packaged and frozen at −30 °C to prevent from further ageing. On the night before tenderness measurement, samples were placed in plastic bags and sub-merged in a water bath until reaching an internal temperature of 70 °C and then chilled in the fridge. On the following day, 10 sub-samples with a 10 mm × 10 mm cross section were prepared parallel with the muscle fibre axis. All sub-samples were then sheared orthogonal to the fibre axis with a Tenderscot tenderometer (Pentland Precision Engineering Ltd) according to the MIRINZ protocol [18]. As suggested by the MIRINZ protocol, a wedge shape tooth blade was attached in the tenderometer for imitating the chewing behaviour of human beings. The peak force was extracted during each shear process and the average value of 10 measurements was considered as the MIRINZ SF to avoid error. Therefore, there are 5 lamb quality related traits in total for each sample, which are pH, L*, a*, b* and MIRINZ SF.

2.3 HSI Data Pre-processing

During the imaging process, reflectance of the sample was acquired by the HSI system. But before that, the HSI system has to be calibrated using a white reference image (nearly 100% reflectance) and a dark reference image (0% reflectance), which are 2 extreme illumination conditions. The reason is that the 'dark current' generated from thermal effects of the detectors should be deducted from the produced signal. Thus, the calibration procedures make sure that the sample reflectance is separated from system responses [9]. The following equation shows how the calibrated reflectance is achieved,

$$R = \frac{I - B}{I_0 - B}, \tag{1}$$

where R is the calibrated reflectance image at one spectral band, I is the raw image at that band, B is the dark reference image and I_0 is the white reference image.

There were 250 spectral bands for each acquired hyperspectral image. However, due to the fact that the camera and the spectrograph did not have the same spectral range, not all bands contained useful information. By removing redundant data in the hyperspectral image,

170 spectral bands were left, with working wavelength ranging from 469.47 nm to 862.90 nm.

In order to save computing time, for each lamb sample, a region of interest (ROI) with size of 200 × 100 pixels (approximately 100 × 50 mm^2) was mainly selected from the lean part and then the median reflectance value at each spectral band was calculated to achieve the median reflectance spectrum. This process is illustrated in Figure 2. As suggested by other researchers, before conducting any data analysis, reflectance spectra (R) should be converted to absorbance (A) by logarithm transformation to linearise the relationship between the concentration of an absorbing compound and the absorption spectrum [19], where the equation is shown below,

$$A = \log_{10}\left(\frac{1}{R}\right). \tag{2}$$

Figure 2: HSI median reflectance spectrum extraction. (a) Pseudo colour image of one lamb sample, with ROI marked by the white frame. (b) The median reflectance spectrum of the same sample.

As a relatively new technique, singular spectrum analysis (SSA), which is commonly used for time series analysis and forecasting, was applied to HSI absorbance spectra for de-noising because of its excellent performance in this area [20-22]. Based on the singular value decomposition (SVD), it is able to decompose the original spectrum into a linear combination of a new orthogonal basis, including eigenvectors generated from the diagonalisation of the data correlation matrix [23]. By decomposing the original series into some interpretable components, such as the trend, oscillations and unstructured noise, SSA could easily separate the noise from the original signal. The algorithm of SSA is introduced as follows.

The first step of SSA is transforming each median reflectance spectrum denoted as $\mathbf{X} = (x_1, x_2 \cdots, x_N)$ into a trajectory matrix. With a window length L $(1 < L < N)$, the original spectrum is mapped into K lagged vectors $\mathbf{X}_i = (x_i, x_{i+1} \cdots, x_{i+L-1})^{\mathrm{T}}$ for $i = 1, 2, \cdots, K$, where $K = N - L + 1$. Then the trajectory matric is formed as follows:

$$\mathbf{T} = (\mathbf{X}_1 \quad \mathbf{X}_2 \quad \cdots \quad \mathbf{X}_K) = \begin{pmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_N \end{pmatrix}. \tag{3}$$

After the trajectory matrix $\mathbf{T}$ is achieved, SVD is performed as the next step. Eigenvalues of $\mathbf{T}\mathbf{T}^{\mathrm{T}}$ are calculated and arranged in the decreasing order as $(\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_L > 0)$, with corresponding eigenvectors denoted as $(U_1, U_2, \cdots, U_L)$. Then the result of SVD is shown in (4),

$$\mathbf{T} = \mathbf{T}_1 + \mathbf{T}_2 + \cdots + \mathbf{T}_d, \tag{4}$$

where d is the rank of $\mathbf{T}$, $\mathbf{T}_i = \sqrt{\lambda_i}\mathbf{U}_i\mathbf{V}_i^{\mathrm{T}}$ $(i = 1,2,\cdots,d)$ are elementary matrices with rank 1, and $\mathbf{V}_i = \mathbf{T}^{\mathrm{T}}\mathbf{U}_i / \sqrt{\lambda_i}$ are principal components of the trajectory matrix $\mathbf{T}$.

The following procedure of SSA is grouping. First, the set of indices $\{1,2,\cdots,d\}$ is divided into m disjointed subsets $I_1, I_2, \cdots, I_m$. Then the resultant trajectory matrix can be calculated for each subset, shown as follows:

$$\mathbf{T} = \mathbf{T}_{I_1} + \mathbf{T}_{I_2} + \cdots \quad \mathbf{T}_{I_m}. \tag{5}$$

The final step is hankelisation of the grouped matrix $\mathbf{T}_{I_p}$ $(p = 1,2,\cdots,m)$ and the denoised spectrum with the same length N could be achieved. Assume $\mathbf{Y}_1 = (y_1, y_2, \cdots, y_N)$ is the hankelised result of $\mathbf{T}_{I_1}$, elements of $\mathbf{Y}_1$ can be represented as (6),

$$y_k = \begin{cases} \dfrac{1}{k}\displaystyle\sum_{j=1}^{k} y^*_{j,k-j+1}, & \text{for} \quad 1 \le k < L^* \\ \dfrac{1}{L^*}\displaystyle\sum_{j=1}^{L^*} y^*_{j,k-j+1}, & \text{for} \quad L^* \le k \le K^* \\ \dfrac{1}{N-k+1}\displaystyle\sum_{j=k-K^*+1}^{N-K^*+1} y^*_{j,k-j+1}, & \text{for} \quad K^* < k \le N, \end{cases} \tag{6}$$

where $L^* = \min(L,K)$, $K^* = \max(L,K)$, $y^*_{j,k-j+1} = y_{j,k-j+1}$ if $L < K$ and $y^*_{j,k-j+1} = y_{k-j+1,j}$ if $L \ge K$.

Hence, the original spectrum $\mathbf{X} = (x_1, x_2, \cdots, x_N)$ can be decomposed into m spectra:

$$\mathbf{X} = \mathbf{Y}_1 + \mathbf{Y}_2 + \cdots \quad \mathbf{Y}_m. \tag{7}$$

Usually the first reconstructed vector $\mathbf{Y}_1$ is regarded as the one containing most useful information while the rest are considered as either oscillations or noise. By reconstructing the spectrum with only the first component, subtle noise can be discarded. The comparison of the absorbance spectra without SSA and with SSA applied are plotted for the tenderest sample and the toughest sample in Figure 3. As can be seen, only the trend of the spectrum was kept after the treatment of SSA, with oscillations/noise removed.

Figure 3: HSI absorbance spectra without SSA applied and with SSA applied for the tenderest sample and the toughest sample.

2.4 Regression Analysis

A variety of statistical regression methods could be applied to construct prediction equations, including multiple linear regression, partial least squares regression (PLSR), principal components regression (PCR) and neural networks [6]. For predicting meat related traits, PLSR is the most common regression approach that researchers choose to build prediction models with NIRS [24–28]. However, PLSR is designed based on the linear algorithm so that the best performance might only be achieved when there is a linear

relationship between spectra and quality traits [29], which is not applicable in our study. In [29], PLSR was compared with SVM for constructing beef eating quality prediction models for NIRS spectra. There were also 5 quality traits involved in the study, including L*, a*, b*, pH and slice shear force (SSF). The performance for predicting beef quality traits was evaluated quantitatively by the coefficient of determination (R^2) and the ratio of performance deviation (RPD). Equations for these metrics are given below:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - f_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \tag{8}$$

$$RPD = \frac{SD}{RMSE} = \frac{SD}{\sqrt{\frac{\sum_{i=1}^{n}(y_i - f_i)^2}{n}}}, \tag{9}$$

where y_i is the original quality trait value measured in the lab, f_i is the predicted value either by SVM or PLSR, $\bar{y}$ is the mean of all original trait values, n is the sample number and $RMSE$ is the root-mean-square error in the investigated dataset. The coefficient of determination ranges from 0 to 1, where 0 represents a poor correlation between the predicted trait values and the reference trait values and 1 standards for a high degree of correlation. For RPD, values higher than 2 indicate that the prediction model is suitable to use and values higher than 3 indicate that the model is adequate for analytical purposes. Results of [29] using both SVM and PLSR approaches are given for reference in Table 1 and Table 2, where PC stands for number of principal components and PLSC represents number of partial least squares components. It can be noticed that, for both the calibration dataset and the validation dataset, SVM always gave higher prediction results than PLSR, where R^2_{val} of SSF was even more than double of that predicted by PLSR. Therefore, instead of using PLSR, SVM was employed to build regression models in the present study.

Table 1: Performance of NIRS for predicting instrumental meat quality in beef *M. longissimus thoracis* using SVM and PLSR in the calibration dataset with noise-removed spectra (495 – 1800 nm) [29].

Trait	SVM for data modelling				PLSR for data modelling			
	n	PC	R^2_{cal} (%)	$RMSE_{cal}$	n	PLSC	R^2_{cal} (%)	$RMSE_{cal}$
L*	175	10	83.4	1.05	175	11	83.2	1.04
a*	175	45	69.6	1.34	175	10	55.3	1.60
b*	175	25	66.7	1.13	175	10	64.3	1.17
pH	175	50	90.0	0.07	175	13	76.9	0.11
SSF	175	10	88.7	14.66	175	5	16.1	38.79

Table 2: Performance of NIRS for predicting instrumental meat quality in beef *M. longissimus thoracis* using SVM and PLR in the validation dataset with noise-removed spectra (495 – 1800 nm) [29].

Trait	SVM for data prediction					PLSR for data prediction				
	n	PC	R^2_{val} (%)	$RMSE_{val}$	RPD_{val}	n	PLSC	R^2_{val} (%)	$RMSE_{val}$	RPD_{val}
L*	59	10	80.3	1.27	2.19	59	11	76.2	1.37	2.03
a*	59	45	63.7	1.71	1.56	59	10	59.7	1.71	1.56
b*	59	25	53.6	1.42	1.45	59	10	52.8	1.43	1.44
pH	59	50	73.6	0.12	1.92	59	13	67.1	0.13	1.77
SSF	59	10	19.8	42.40	1.06	59	5	7.6	43.39	1.03

The outstanding performance of SVM has been verified in many applications associated with HSI. However, a problem of SVM is that it is sensitive to the curse of dimensionality [30]. As a result, a commonly adopted feature extraction technique, principal component analysis (PCA) [31, 32], is used to reduce the dimensionality of HSI cubes. In this way, only a small amount of features could explain the whole dataset and the rest can be discarded.

With lower dimensional data, SVM could be applied to construct prediction models. For both classification and regression problems, SVM maps the data to a high dimensional feature space using kernel function. Then it is easy to separate the data by a maximal margin hyperplane. As a popular kernel function, the radial basis function (RBF) kernel was chosen here. Optimal parameters were tuned using the grid search with four-fold cross-validation to avoid model over-fitting.

3 Results and Discussion

Eighty lamb samples were split into the calibration dataset and the validation dataset, where prediction models were learnt from the calibration dataset and verified on the validation dataset. In this way, the ability of HSI for predicting quality of unknown lamb samples could be tested. In order to split the dataset, each quality trait was sorted in the ascending order of its values. By selecting every 4th sample into the validation dataset, the rest of data which contain the interleaving 3 samples were allocated to the calibration dataset [33]. This process makes sure that the validation dataset is a representative of the calibration dataset, with similar mean, standard deviation (SD) and range. Statistics of each quality trait are shown in Table 3, where the unit for MIRINZ SF is Newton (N). The HSI performance for predicting lamb quality was also evaluated quantitatively by the coefficient of determination (R^2) and the ratio of performance deviation (*RPD*).

Table 3: Summary statistics of all quality traits, including mean, standard deviation (SD) and range, where subscripts cal and val represent the calibration dataset and the validation dataset respectively.

Trait	n_{cal}	$Mean_{cal}$	SD_{cal}	$Range_{cal}$	n_{val}	$Mean_{val}$	SD_{val}	$Range_{val}$
pH	60	5.59	0.07	5.46 - 5.90	20	5.61	0.12	5.48 - 6.08
L*	60	41.47	1.83	36.69 - 46.64	20	41.83	2.31	38.74 - 49.63
a*	60	23.28	0.91	20.44 - 25.37	20	23.77	0.83	22.28 - 25.71
b*	60	7.77	0.58	5.89 - 9.15	20	7.85	0.57	7.02 - 9.17
SF	60	51.05	13.32	28.17 - 92.03	20	53.89	18.80	33.69 - 117.65

The number of principal components was tried from 5 to 50 in a step of 5, and both raw HSI absorbance spectra and SSA-treated absorbance spectra were tested. Combinations of best prediction results are shown in Table 4, where 'A' stands for raw absorbance spectra and 'A + SSA' means SSA-treated absorbance spectra.

Table 4: Performance for predicting quality traits in lamb using the visible range HSI system.

Trait	Pre-treatment	No. of principal components	R^2_{cal}	$RMSE_{cal}$	R^2_{val}	$RMSE_{val}$	RPD_{val}
pH	A	45	0.54	0.06	0.38	0.11	1.07
L*	A	15	0.83	0.67	0.77	1.34	1.72
a*	A + SSA	40	0.95	0.22	0.48	0.76	1.09
b*	A + SSA	15	0.83	0.34	0.26	0.50	1.13
SF	A + SSA	40	0.82	6.76	0.41	14.90	1.26

As the study is to test the ability of HSI in predicting unknown lamb quality for on-line use, the results of the extra validation dataset are particularly important. For the prediction of ultimate pH, R^2_{val} is higher than those reported in [1] (R^2_{cv} = 0.03 – 0.19). For colour parameters and MIRINZ SF prediction, limited research has been found on lamb. Nevertheless, our results agree with those predicted with beef sample using NIRS [24–28], whose average R^2 values are 0.76 and 0.44 for L* and a*. However, our result of b* is poorer than that of others (R^2 = 0.57), which may be due to variation between different samples. Similarly, we compare the MIRINZ SF with Warner-Bratzler SF predicted by others on beef sample. It is found that the average R^2 of their research is 0.30, which is lower than ours (R^2_{val} = 0.41). The *RPD* values of the resulting models did not give as much information as R^2. A possible reason is that all lamb samples were purchased from the abattoir fulfilling market standards. Therefore, the standard deviation of those quality traits is low and the range of values are also limited.

In the present study some colour parameters were found to be more correlated with the hyperspectral data, while pH and MIRINZ SF were less predictable. As mentioned previously, pH and SF contribute to tenderness, juiciness and flavour of lamb. However, as admitted by authors in [1], these complex quality parameters could be affected by many factors during production process, and their variation has multiple biological causes, which also lowers the prediction performance with HSI.

4 Conclusion

In this paper, a visible (400-863 nm) HSI system was employed for acquiring hyperspectral images of 80 lamb loins purchased from a commercial abattoir, where these images were used for predicting lamb quality parameters, including ultimate pH, MIRINZ SF and related colour parameters in L*a*b* scale. Before applying machine learning techniques on lamb spectra achieved from calibrated hyperspectral images, SSA was introduced for removing subtle noise from the spectra for some quality traits. Due to the fact that the performance of SVM will be impeded by data with high dimensionality, PCA was applied for feature

extraction and data reduction. After applying models constructed by SVM to external validation datasets, we obtained predictions of pH, L*, a*, b* and MIRINZ SF in terms of R^2 as 0.38, 0.77, 0.48, 0.26 and 0.41, respectively.

The study has shown that HSI system offers an alternative choice for non-destructive measurement of lamb quality traits. Even though prediction performance for some complex quality traits was low and requires further improvement, HSI was still proved to be superior to conventional NIRS by comparing with others. Most importantly, this research has provided a reference for other researchers, since limited research has been conducted in the area of HSI based lamb quality prediction. In conclusion, this paper has demonstrated that HSI could be promising in offering additional information for predicting lamb quality, which might bring beneficial to lamb industries in the future. Further research is needed to investigate more samples with a wider quality range to improve the robustness of the regression models.

5 Acknowledgement

This project is funded by Quality Meat Scotland (QMS) and University of Strathclyde. Authors would like to thank Dr. Cameron Craigie and Scotland's Rural College (SRUC) for helping preparing the data. Also special thanks to the associate editor and the anonymous reviewers for their careful reading and helpful remarks to improve the paper quality. An earlier version of this paper was presented at the 2nd conference on Optical Characterization of Materials (OCM) in 2015.

References

1. Andrés, S., Murray, I., Navajas, E. A., Fisher, A., Lambe, N., & Bünger, L. (2007). Prediction of sensory characteristics of lamb meat samples by near infrared reflectance spectroscopy. *Meat Science, 76*(3), 509-516.
2. Jeremiah, L., & Phillips, D. (2000). Evaluation of a probe for predicting beef tenderness. *Meat Science, 55*(4), 493-502.
3. Jeremiah, L., Carpenter, Z., & Smith, G. (1972). Beef color as related to consumer acceptance and palatability. *Journal of Food Science, 37*(3), 476-479.
4. Vote, D., Belk, K., Tatum, J., Scanga, J., & Smith, G. (2003). Online prediction of beef tenderness using a computer vision system equipped with a BeefCam module. *Journal of Animal Science, 81*(2), 457-465.
5. Awad, T., Moharram, H., Shaltout, O., Asker, D., & Youssef, M. (2012). Applications of ultrasound in analysis, processing and quality control of food: A review. *Food Research International, 48*(2), 410-427.
6. Prevolnik, M., Candek-Potokar, M., & Skorjanc, D. (2004). Ability of NIR spectroscopy to predict meat chemical composition and quality: a review. *Czech Journal of Animal Science-UZPI (Czech Republic), 49*(11), 500-510.

7. Dissing, B., Papadopoulou, O., Tassou, C., Ersbøll, B., Carstensen, J., Panagou, E., & Nychas, G. (2013). Using multispectral imaging for spoilage detection of pork meat. Food and Bioprocess Technology, 6(9), 2268-2279.
8. Panagou, E., Papadopoulou, O., Carstensen, J., & Nychas, G. (2014). Potential of multispectral imaging technology for rapid and non-destructive determination of the microbiological quality of beef filets during aerobic storage. *International Journal of Food Microbiology, 174*, 1-11.
9. Naganathan, G., Grimes, L., Subbiah, J., Calkins, C., Samal, A., & Meyer, G. (2008). Visible/near-infrared hyperspectral imaging for beef tenderness prediction. *Computers and Electronics in Agriculture, 64*(2), 225-233.
10. Mullen, A., Kerry, J., & Ledward, D. (2002). New techniques for analysing raw meat quality. *Meat processing: improving quality*, 394-416.
11. Gowen, A., O'Donnell, C., Cullen, P., Downey, G., & Frias, J. (2007). Hyperspectral imaging–an emerging process analytical tool for food quality and safety control. *Trends in Food Science & Technology, 18*(12), 590-598.
12. Ren, J., Zabalza, J., Marshall, S., & Zheng, J. (2014). Effective feature extraction and data reduction in remote sensing using hyperspectral imaging. *Signal Processing Magazine, IEEE, 31*(4), 149-154.
13. Qiao, T., Ren, J., Sun, M., Zheng, J., & Marshall, S. (2014). Effective compression of hyperspectral imagery using an improved 3D DCT approach for land-cover analysis in remote-sensing applications. *International Journal of Remote Sensing, 35*(20), 7316-7337.
14. Baiano, A., Terracone, C., Peri, G., & Romaniello, R. (2012). Application of hyperspectral imaging for prediction of physico-chemical and sensory characteristics of table grapes. *Computers and Electronics in Agriculture,87*, 142-151.
15. Sun, D. (2010). *Hyperspectral imaging for food quality analysis and control.* Elsevier.
16. Kelman, T., Ren, J., & Marshall, S. (2013). Effective classification of Chinese tea samples in hyperspectral imaging. *Artificial Intelligence Research, 2*(4), p87.
17. Shackelford, S., Wheeler, T., & Koohmaraie, M. (2005). On-line classification of US Select beef carcasses for longissimus tenderness using visible and near-infrared reflectance spectroscopy. *Meat Science, 69*(3), 409-415.
18. Frazer, A. (1997). New Zealand tenderness and local meat quality mark programmes. In *Proceedings of the Meat Quality and Technology Transfer Workshop, 43rd International Congress of Meat Science and Technology, July–August, Auckland, New Zealand*, 37-51.
19. Rust, S., Price, D., Subbiah, J., Kranzler, G., Hilton, G., Vanoverbeke, D., & Morgan, J. (2008). Predicting beef tenderness using near-infrared spectroscopy. *Journal of Animal Science, 86*(1), 211-219.
20. Zabalza, J., Ren, J., Wang, Z., Marshall, S., & Wang, J. (2014). Singular spectrum analysis for effective feature extraction in hyperspectral imaging. *Geoscience and Remote Sensing Letters, IEEE, 11*(11), 1886-1890.
21. Zabalza, J., Ren, J., Zheng, J., Han, J., Zhao, H., Li, S., & Marshall, S. (2015). Novel Two-Dimensional Singular Spectrum Analysis for Effective Feature Extraction and Data Classification in Hyperspectral Imaging. *Geoscience and Remote Sensing, IEEE Transactions on, 53*(8), 4418-4433.

22. Qiao, T., Ren, J., Craigie, C., Zabalza, J., Maltin, C., & Marshall, S. (2015). Singular spectrum analysis for improving hyperspectral imaging based beef eating quality evaluation. *Computers and Electronics in Agriculture, 115*, 21-25.
23. Pereira, W., Bridal, S., Coron, A., & Laugier, P. (2004). Singular spectrum analysis applied to backscattered ultrasound signals from in vitro human cancellous bone specimens*. Ultrasonics, Ferroelectrics, and Frequency Control, IEEE Transactions on, 51*(3), 302-312.
24. Andrés, S., Silva, A., Soares-Pereira, A., Martins, C., Bruno-Soares, A., & Murray, I. (2008). The use of visible and near infrared reflectance spectroscopy to predict *beef M. longissimus thoracis et lumborum* quality attributes. *Meat Science, 78*(3), 217-224.
25. Cecchinato, A., De Marchi, M., Penasa, M., Albera, A., & Bittante, G. (2011). Near-infrared reflectance spectroscopy predictions as indicator traits in breeding programs for enhanced beef quality. *Journal of Animal Science,89*(9), 2687-2695.
26. Leroy, B., Lambotte, S., Dotreppe, O., Lecocq, H., Istasse, L., & Clinquart, A. (2004). Prediction of technological and organoleptic properties of beef *Longissimus thoracis* from near-infrared reflectance and transmission spectra. *Meat Science, 66*(1), 45-54.
27. Prieto, N., Andrés, S., Giráldez, F. J., Mantecón, A. R., & Lavín, P. (2008). Ability of near infrared reflectance spectroscopy (NIRS) to estimate physical parameters of adult steers (oxen) and young cattle meat samples. *Meat Science, 79*(4), 692-699.
28. Kamruzzaman, M., ElMasry, G., Sun, D. W., & Allen, P. (2012). Prediction of some quality attributes of lamb meat using near-infrared hyperspectral imaging and multivariate analysis. *Analytica Chimica Acta*, 714, 57-67.
29. Qiao, T., Ren, J., Craigie, C., Zabalza, J., Maltin, C., & Marshall, S. (2015). Quantitative prediction of beef quality using visible and NIR spectroscopy with large data samples under industry conditions. *Journal of Applied Spectroscopy*, *82*(1), 137-144.
30. Melgani, F., & Bruzzone, L. (2004). Classification of hyperspectral remote sensing images with support vector machines. *Geoscience and Remote Sensing, IEEE Transactions on, 42*(8), 1778-1790.
31. Zabalza, J., Ren, J., Ren, J., Liu, Z., & Marshall, S. (2014). Structured covariance principal component analysis for real-time onsite feature extraction and dimensionality reduction in hyperspectral imaging. *Applied Optics, 53*(20), 4440-4449.
32. Zabalza, J., Ren, J., Yang, M., Zhang, Y., Wang, J., Marshall, S., & Han, J. (2014). Novel folded-PCA for improved feature extraction and data reduction with hyperspectral imaging and SAR in remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing, 93*, 112-122.
33. Williams, P., & Norris, K. (1987*). Near-infrared technology in the agricultural and food industries.* American Association of Cereal Chemists, Inc.