



Rapid and non-destructive identification of water-injected beef samples using multispectral imaging analysis



Jinxia Liu^a, Yue Cao^b, Qiu Wang^c, Wenjuan Pan^a, Fei Ma^a, Changhong Liu^a, Wei Chen^a, Jianbo Yang^c, Lei Zheng^{a,b,*}

^aSchool of Biotechnology and Food Engineering, Hefei University of Technology, Hefei 230009, China

^bSchool of Medical Engineering, Hefei University of Technology, Hefei 230009, China

^cRice Research Institute, Anhui Academy of Agricultural Sciences, Hefei 230031, China

ARTICLE INFO

Article history:

Received 18 December 2014

Received in revised form 12 June 2015

Accepted 19 June 2015

Available online 19 June 2015

Keywords:

Multispectral imaging

Water-injected beef

Partial least squares regression

Feature information

Non-destructive analysis

ABSTRACT

Water-injected beef has aroused public concern as a major food-safety issue in meat products. In the study, the potential of multispectral imaging analysis in the visible and near-infrared (405–970 nm) regions was evaluated for identifying water-injected beef. A multispectral vision system was used to acquire images of beef injected with up to 21% content of water, and partial least squares regression (PLSR) algorithm was employed to establish prediction model, leading to quantitative estimations of actual water increase with a correlation coefficient (r) of 0.923. Subsequently, an optimized model was achieved by integrating spectral data with feature information extracted from ordinary RGB data, yielding better predictions ($r = 0.946$). Moreover, the prediction equation was transferred to each pixel within the images for visualizing the distribution of actual water increase. These results demonstrate the capability of multispectral imaging technology as a rapid and non-destructive tool for the identification of water-injected beef.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Beef is one of the most consumed meats in the world, with over sixty percent being consumed by only a handful of developed countries (Li, Shan, Peng, & Gao, 2011). Good-quality beef is an excellent source of protein and minerals, and therefore is highly desired. Recently, there has been a growing public awareness of food safety issues related to meat products, such as the illegal production of water-injected meat, fake beef and lamb, rotten meat, and toxic meat products. Due to the temptation of easy profits as well as technical difficulties in nondestructively identifying water-injected meat, the challenges of these scandals remain serious. In order to ensure the quality and safety of meat products, it is necessary to develop a rapid and effective quality evaluation method for identifying tainted meat.

In recent years, scientists have developed many techniques for nondestructive evaluation of meat quality, based on computer vision, infrared spectroscopy, hyperspectral imaging, magnetic resonance imaging etc. By combining nondestructive techniques with

chemometrics analysis, several calibration models have been established and applied to various analytical determinations, including the evaluation of meat quality (Shiranita, Miyajima, & Takiyama, 1998), classification of bovine muscles (Basset, Dupont, Hernandez, Odet, & Culicoli, 1999), prediction of moisture, protein, fat and caloric content of raw pork and beef (Lanza, 1983), classification of beef tenderness (Cluff et al., 2008; Naganathan et al., 2008), classification of frozen-thawed meats (Lagerstedt, Enfält, Johansson, & Lundström, 2008; Song & Liu, 2014), prediction of heme and non-heme iron contents in pork sausages (Ma et al., 2016), and detection of microbial spoilage of beef (Ma et al., 2014; Peng et al., 2011). However, there is no report to date regarding the application of non-destructive methods for identifying water-injected beef.

As is well known, water is the main component of meat and water content is the key index of meat quality in the meat processing industry (Mathlouthi, 2001). Nowadays, illegally water-injected meat has become one of the major issues regarding the quality controlling and biosafety of fresh meat (Yang et al., 2013). Injection of water into meat samples is an illegal process as it involves violation of the relevant food sanitation and slaughter laws, and the use of artificial tools, such as injectors, and pressure pumps, to inject an amount of water, before or after the livestock

* Corresponding author at: School of Medical Engineering, Hefei University of Technology, Hefei 230009, China.

E-mail addresses: lzheng@hfut.edu.cn, lei.zheng@aliyun.com (L. Zheng).

and poultry is slaughtered, in order to increase the weight of the meat. Water injection can cause a dramatic expansion of cellular volumes, rupture of cells and protein loss, leading to a degradation of meat quality. Moreover, the injected water usually contain microorganisms, pathogens, toxins and other harmful substances, which would accelerate the spoiling of meat and shorten the freshness lifetime (Liu, Ai, Lu, & Liu, 2012). Till now, water-injected contamination has been reported in a wide range of meat, including beef, lamb, pork, poultry meat and other meat products. The permitted level of moisture in meat of livestock and poultry is specified by a couple of international and national standards. For example, Chinese standard GB 18394-2001 stipulates that the moisture content of pork, beef and chicken should not be more than 77%; while the moisture content of lamb is required to be less than 78%. At present, the two most widely used methods for meat moisture measurement are infrared moisture analyzer (Sleagun & Popa, 2009) and classic weight measurement method using oven-drying or microwave drying (Benedito, Carcel, Rossello, & Mulet, 2001). Infrared moisture analyzer can obtain stable recordings on sample with good uniformity, but its ability to cope with raw meat with inhomogenous texture is relatively weak. Classic weight measurement method is quite precise, yet it is time-consuming and invasive. The disadvantages of these two methods make them unsuitable for monitoring the moisture content in meat product continuously and non-destructively. Meanwhile, traditional methods such as touching, smelling, visual inspection etc., cannot accurately identify water-injected meat (Liu et al., 2012). Therefore, it is in urgent need of developing a rapid and effective method for identifying water-injected meat.

Hyperspectral/multispectral imaging is an emerging nondestructive technology that integrates conventional imaging and spectroscopy to attain both spatial and spectral information from an object simultaneously. Previous studies showed that the moisture content of meat during different dehydration stages could be determined by hyperspectral imaging (Wu et al., 2013). Also, visible-near-infrared spectroscopy has been examined as a tool for rapid determination of the water-holding capacity (WHC) of meat (Prevolnik, Čandek-Potokar, & Škorjanc, 2010; Samuel, Park, Sohn, & Wicker, 2011). Chemical-free determination and mapping of the major constituents (water, fat and protein) of meat has been performed using near-infrared spectroscopy (Ripoll, Albertí, Panea, Olleta, & Sañudo, 2008; Tøgersen, Isaksson, Nilsen, Bakker, & Hildrum, 1999). However, the rich information in hyperspectral imaging results in difficulties in data processing, which makes it hard for industrial online applications. Recently, a simplified multispectral imaging (MSI) has been increasingly applied as a powerful analytical tool for nondestructive quality determination for the agri-food (Liu, Liu, Lu, Ma, et al., 2014).

Recent studies showed that multispectral imaging is especially suitable for rapid and non-invasive identification of a range of quality-related components, provided that these components have spatially variable spectral responses (Liu, Liu, Chen, Yang, & Zheng, 2015; Liu, Liu, Lu, Chen, et al., 2014; Ma et al., 2014; Xiong et al., 2015). By combining with chemometrics, multispectral imaging use both spectral and spatial information to establish prediction models, resulting in much more stable prediction performances than NIR spectroscopy. Multispectral imaging technology has also been reported to perform better than colorimeter for the assessment of meat color, as multispectral vision system with diffuse illumination could provide a color-rich assessment of fresh meat samples with a glossier surface (Trinderup, Dahl, Jensen, Carstensen, & Conradsen, 2015). Due to the advantages of the multispectral imaging technology, the objective of this study was to investigate the feasibility of using this technique for the identification of water-injected meat and visualization of the water distribution pattern in meat samples.

2. Materials and methods

2.1. Beef samples

Beef was purchased from Carrefour supermarket, Hefei, China as a single stock sample. The fresh and vacuum-packaged beef was placed into an ice-box and transported to the laboratory. The beef was sectioned into four pieces, and then frozen and stored at -20°C until it was used (within 4 days). Immediately prior to analysis, the frozen beef was removed from the refrigerator and cut into uniformly sized samples (length \times width \times height = 3 cm \times 2 cm \times 1 cm). After the beef samples had been thawed for 12 h in the refrigerator (4°C), water was injected into the exact center of the sample with a syringe (0.5 mL). After the water injection, the unabsorbed water of the beef samples were sucked by filter paper and the samples allowed to stand for 10 min at room temperature prior to performing subsequent analyses.

The beef samples were divided into two sets, calibration and prediction sets. The calibration set had 15 beef samples and the percentage of injected water in each sample was in this order: 0%, 3%, 6%, 9%, 12%, 15%, 18% and 21%. The prediction set had 12 beef samples and the percentage of injected water in each sample was: 4%, 6%, 8%, 10% and 12%.

2.2. Measurement of moisture content of beef samples

The experimental determination of the moisture content of beef samples was performed in two sections. In the first section, the percentage increase of the water content in the beef samples was determined based on the classic weight measurement method. For this method, the beef samples were weighed using an analytical balance (accuracy, 0.0001 g) before and after injection of water to measure the weight changes. In the second section, the drying method was used to measure moisture content of the 27 beef samples (calibration set had 15 samples, prediction set had 12 samples), according to the procedure specified by GB/T 5009.3-2010. All beef samples were weighed (the weight of each sample was between 6–9 g) before performing the injection test. After completing all the experiments, the beef samples were placed into glass weighing bottles, which were then placed in an Electrothermal Constant-temperature Drying Box at 105°C for 4 h. The bottles were then removed and immediately cooled in glass vacuum desiccators (containing allochroic silica gel) for 30 min. The beef samples were then weighed again to get a constant weight.

2.3. Multispectral imaging system

The multispectral images of beef samples (placed in a petri dish of 90 mm diameter and 11 mm depth) were captured using a VideometerLab equipment (Videometer A/S, Hørsholm, Denmark), which acquired multispectral images at 19 different wavelengths ranging from the visible (VIS) region to the NIR region. The actual wavelengths used in the study were 405, 435, 450, 470, 505, 525, 570, 590, 630, 645, 660, 700, 780, 850, 870, 890, 910, 940, 970 nm, and it can be seen that the majority of the wavelengths are in the visible region of the spectrum (400–800 nm). Fig. 1 shows the instrumental setup of the multispectral imaging system. The VideometerLab is a high performance spectral imaging system which has a wide range of applications including imaging of chemical composition, colors or surface structures. The unit is an easy-to-use system which integrates illumination, camera, and computer technology with advanced digital image analysis and statistics. The technology is particularly useful for

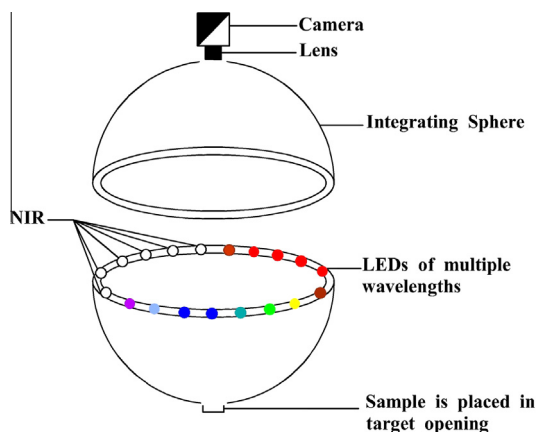


Fig. 1. Principal setup of the multispectral imaging system. An integrating sphere coated with a matte white coating ensures optimal lighting conditions. The light emitting diodes are located at the rim of the sphere. The image acquisition is performed by a CCD camera mounted at the top of the sphere.

quantitative determination of biochemical components and for evaluating quality attributes (Liu et al., 2015). Using strobed LED (Light Emitting Diode) technology, VideometerLab combines measurements at up to 19 different wavelengths into a single high-resolution spectral image. Every pixel in the image is a spectrum and the system includes wavelengths in the range from 405 to 970 nm. The images of beef samples (without the background) can be transformed into spectra based on a mean calculation. Thus, each image contributes a single spectrum for the calibration model.

2.4. Acquisition and processing of RGB images

RGB images of the beef samples were captured by using a Canon EOS 700D (EFS 18–135 mm) camera. The images were then processed and the color components (R, G and B) were extracted using Matlab 2010 software (The Mathworks Inc., Natick, MA, USA). The similar methods of images analysis were used in the studies published previously (Adelkhani, Beheshti, Minaei, Javadikia, & Ghasemi-Varnamkhasti, 2013; Manickavasagan, Al-Mezeini, & Al-Shekaili, 2014; Swain, Thomas, Philip, & Pillai, 2015).

2.5. Data analysis

2.5.1. PLSR

To develop correlations between the extracted data (spectral, RGB) and the increased percentages of water in beef samples, the partial least squares regression (PLSR) method was applied to build the prediction model, which was carried out in Matlab 2010 software. PLSR works by projecting data from high dimensional space to a low-dimensional space in a linear correlation, instead of finding hyperplanes of minimum variance between the response and independent variables. PLSR shows far better performance in process monitoring and prediction applications than the traditional multiple linear regression models (Wold, Sjöström, & Eriksson, 2001). Typically, the data is analyzed with the strongly collinear, noisy and numerous variables in the predictor matrix X (i.e., independent variables) and responses matrix Y (i.e., dependent variables) (Panagou, Mohareb, Argyri, Bessant, & Nychas, 2011). The quality of the calibration model is determined by the correlation coefficient (r) between the predicted and measured, standard error of calibration (SEC) and standard error of prediction (SEP). The correlation coefficient for calibration set is r_c ; the correlation coefficient for prediction set is r_p . These equations are defined as follows:

$$SEC = \sqrt{\frac{1}{I_C - 1} \sum_{i=1}^{I_C} (\hat{y}_i - y_i)^2} \quad (1)$$

$$SEP = \sqrt{\frac{1}{I_P - 1} \sum_{i=1}^{I_P} (\hat{y}_i - y_i - \text{bias})^2} \quad (2)$$

$$\text{Bias} = \frac{1}{I_P} \sum_{i=1}^{I_P} (\hat{y}_i - y_i) \quad (3)$$

where, \hat{y}_i is the predicted value of percentage of increased water in sample number i ; y_i , the measured value of percentage of increased water in sample number i ; I_C , the number of samples (spectral, RGB) in the calibration set; and I_P , the number of samples (spectral, RGB) in the prediction set.

2.6. Statistical analysis

All image analyses and statistical analyses were carried out using Matlab 2010 software (The Mathworks Inc., Natick, MA, USA), Statistical Package for the Social Sciences 19.0 (SPSS Inc., Chicago, IL, USA) and Origin 8.5.

2.7. Visualization of increased water content

Visualizing the moisture distribution in water-injected beef is helpful to understand the location and migration of water after it is injected into the beef. Chemical imaging can be used to visualize this phenomenon. The multispectral image is a three-dimensional (3D) matrix which provides a large amount of spectral and spatial information. Each pixel in a multispectral image has a corresponding spectrum. Thus, the increased water content can be calculated at each pixel (point) in the sample, resulting in the creation of a prediction image, i.e., the distribution image of water content in water-injected beef. However, it is impossible to detect the precise value of increased water content in every pixel within a sample. Therefore, the PLSR model that was previously computed from the average spectra at region of interest (ROI) could be used to interpolate the measured values of increased water in all spots of the sample.

3. Results and discussion

3.1. Weight difference method and moisture content of beef samples

The detailed values of range, mean and standard deviation (SD) for the percentage of increased water in water-injected samples are shown in Table 1. As seen from this table, the largest increased water content in beef samples was 8.077%. When the percentage of increased water was not more than 6%, the percentage of increased water of samples were about half of the injected water. When the percentage of increased water exceeded 6%, the rate of increase of increased water was reduced as the increased content of injected water, and samples eventually reached saturation.

The moisture content of the 27 beef samples was also determined according to GB/T 5009.3-2010. The maximum moisture content was 73.196%, the minimum moisture content was 70.091%, the average moisture content was 72.094% and the standard deviation was calculated to be 0.723%. As all 27 beef samples were from the same piece of beef, they had uniform moisture content and low experimental error.

Table 1

Range, mean and standard deviation (SD) for water-injected samples.

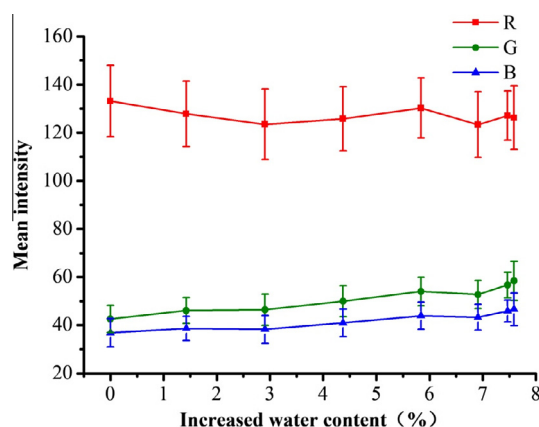
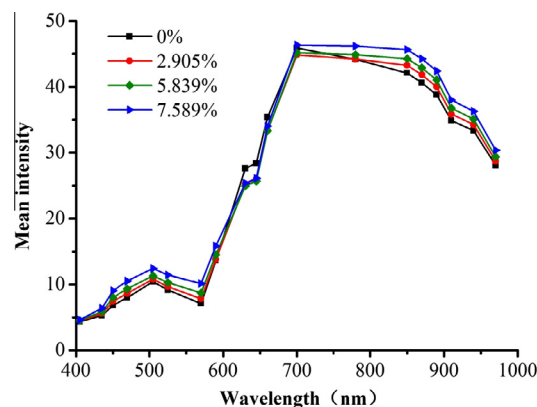
Injected water percentage/%	Increased water percentage/%		
	Range	Mean	SD
<i>Calibration set</i>			
0	0	0	0
3	1.217–1.696	1.425	0.147
6	2.611–3.295	2.905	0.209
9	4.114–4.687	4.374	0.183
12	5.541–6.242	5.839	0.207
15	6.584–7.403	6.911	0.264
18	7.064–7.966	7.468	0.281
21	7.206–8.077	7.589	0.275
<i>Prediction set</i>			
4	1.875–2.049	1.973	0.047
6	2.836–3.070	2.974	0.070
8	3.837–4.091	3.984	0.078
10	4.827–5.112	4.989	0.095
12	5.781–6.131	5.972	0.119

3.2. Analysis of RGB images

Fig. 2 shows the mean intensity of the R, G and B components of beef samples at different increased percentages of water (calibration set). The intensity of R decreased with the increase of water percentage, while G and B showed the opposite trend. The reason for the difference in trends among R, G and B components of water-injected beef is apparent. Water-injected beef is less bright red in color with increase in water content, thus the intensity of G and B are increased, while intensity of R is decreased.

3.3. Reflectance spectral analysis

Spectral analysis across the visible (VIS) region to the near infra-red (NIR) region is a widely used optical technique for evaluating the moisture content of food (Wu et al., 2012). The main absorption band in the spectrum observed between 940 and 1000 nm is due to O–H third stretching overtone and is assigned to water in the sample (Wu, He, & Feng, 2008). Fig. 3 shows the relative reflectance spectra, in the range of 405–970 nm, of water-injected beef samples in the calibration set at different increased percentages of water. The prediction set also had a similar trend of reflectance spectra (data not shown). Water-injected samples at different percentages of increased water have been clearly identified by multispectral imaging. It was noticed from Fig. 3 that beef with higher moisture content had higher reflectance spectra in the regions of 405–600 nm and 700–970 nm (absorbance decreased), which had a similar result with previous

**Fig. 2.** Mean intensity of R, G and B of water-injected samples (calibration set).**Fig. 3.** Average reflectance from the multispectral images of water-injected samples at different increased percentages of water (calibration set).

study (Wu et al., 2012). The above phenomenon was also likely due to the appearance of water-injected beef as being more green and blue in color (Dissing et al., 2013). However, the result was contrary in the region of 600–700 nm. The samples showed lower spectral reflection intensity with increase in injected water. The reason for this behavior is that the visible wavelength region between 600 and 700 nm corresponds to the reddish color of meat samples (Panagou, Papadopoulou, Carstensen, & Nychas, 2014). Water-injected samples were less bright red in color with increase in injected water. These spectral differences can be utilized for the qualitative and quantitative identification of water-injected beef.

3.4. PLSR analysis

A calibration model was developed using PLSR analysis to predict increased percentage of water in the samples. PLSR has the desirable property that the precision of the model parameters improves with the increasing number of relevant variables and observations. To date, quite a few studies have reported satisfactory applications of PLSR in various disciplines (e.g., Lindberg, Persson, & Wold, 1983; Wold et al., 2001). Meanwhile, PLSR modeling is believed to be an effective method for predicting water content in meat (ElMasry, Sun, & Allen, 2013; Kamruzzaman, ElMasry, Sun, & Allen, 2012). Fig. 4 shows the measured and predicted percentages of increased water based on spectral data and spectral data combined with RGB data. The correlation coefficient r_p for predicting increased water in samples based on spectral data (a) was 0.923. However, the correlation coefficient r_p was 0.946 based on spectral data combined with RGB data (b), and the value of SEP was lower. These results indicate that spectral information combined with RGB data could obtain satisfactory prediction. The possible reasons for this phenomenon were as below: (a) Applying the PLSR is a transformation of the original spectral data and the transformation can give an indication of the importance of each of the variables considered. Then, the top five important spectral bands for the regression were 450, 470, 435, 570 and 780 nm, and these bands were closely related to RGB; (b) Multispectral bands are discontinuous, while R, G and B have the corresponding continuous bands. Then, RGB could add more information regarding the samples. Thus, spectral information combined with RGB data can give a trend for improving the model accuracy. Moreover, when PLSR was used for predicting the increased water in beef samples, we observed that the prediction set gave similar results as the calibration set. This indicates good performance of the model for predicting the increased percentage of water in a non-destructive manner.

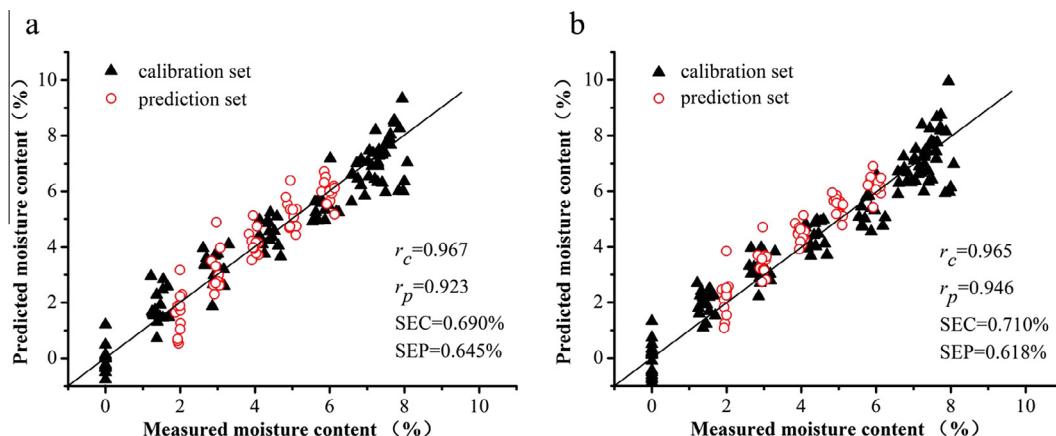


Fig. 4. Measured and predicted increased content of water in water-injected samples for calibration and prediction set by using: spectral data (a) and spectral data combined with RGB data (b).

3.5. Visualization of distribution of increased water

Fig. 5 shows the RGB images and distribution maps of increased water in water-injected samples. The maps were produced by applying PLSR model to the multispectral images at 19 wavelengths (ranging from 405 nm to 970 nm). The fresh beef and water-injected beef could not be distinguished with the naked eye from RGB images. However, the spatial distribution and magnitude of injected water in these samples could be visualized via pixel analysis of multispectral images and inserting processing. The distribution maps show different levels of moisture content will be helpful to understand the locations and movement of water through the samples during different processes (Liu, Sun, et al., 2014; Wu et al., 2012).

In this study, the distribution images were created by mapping the increased water content values with a linear color scale, where the different degrees of increased percentage of water from high to low were shown in different colors from red to blue (color bar at the bottom of the Fig. 5). Similar pixel colors in maps represent same degree of increased water in the sample in proportion to spectral consistency of pixels. As seen from Fig. 5, the fresh beef (0%) contains a small amount of increased water, and the biggest percentage increase of water (7.588%) in beef contains a large amount of increased water as predicted by our model. It must be noted that the water content at the edge of the sample was higher than that inside the sample. This is likely due to the fact that injected water was not completely absorbed within the sample and leaked from the center through the sample towards the edges.

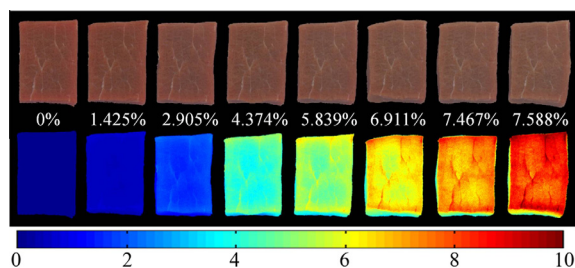


Fig. 5. Ordinary RGB images and maps for the increased water content of a single sample at different percentage increases. The parallel color bar represents the intensity values of the images.

4. Conclusions

The results demonstrate that multispectral imaging technology can be effectively used to identify water-injected beef and measure increased water content in beef samples. The PLSR model developed for predicting increased water percentage in water-injected beef samples shows good performance based on spectral data ($r_p=0.923$). The changes in R, G and B components of water-injected beefs were also analyzed, and we found that the intensity of R decreased with increase in percentage of water, while the trends for intensities of G and B were just the opposite. This work also established the connection between ordinary RGB images and multispectral images. The result shows that water-injected beef can be identified by spectral data combined with RGB data, with an improved prediction accuracy of water-injected beef samples ($r_p=0.946$). Moreover, the constructed prediction map indicates the distribution of increased water content of samples, which could not be achieved by spectroscopy or other conventional methods. In conclusion, our results demonstrate that multispectral imaging is a simple, non-destructive, and real-time monitoring tool for examining the properties of water-injected meat and meat products. This rapid analysis method can facilitate market testing and improve the quality of meat.

Acknowledgements

This study is supported by the Specialized Research Fund for the Anhui Province Key Technologies Research & Development Program (1301031033), the National Key Technologies R&D Programme (2012BAD07B01), the Key Project of Anhui Provincial Educational Department (KJ2014ZD26), the Doctoral Program of Higher Education (20120111110024), the National Natural Science Foundation of China (31401544), the China Postdoctoral Science Foundation (2014M561822), and the Funds for Huangshan Professorship of Hefei University of Technology (407-037019).

References

- Adelkhani, A., Beheshti, B., Minaei, S., Javadikia, P., & Ghasemi-Varnamkhasti, M. (2013). Taste characterization of orange using image processing combined with ANFIS. *Measurement*, 46(9), 3573–3580.
- Basset, O., Dupont, F., Hernandez, A., Odet, C., & Culioli, J. (1999). Texture image analysis: Application to the classification of bovine muscles from meat slice images. *Optical Engineering*, 38(11), 1950–1959.

- Benedito, J., Carcel, J. A., Rossello, C., & Mulet, A. (2001). Composition assessment of raw meat mixtures using ultrasonics. *Meat Science*, 57(4), 365–370.
- Cluff, K., Naganathan, G. K., Subbiah, J., Lu, R., Calkins, C. R., & Samal, A. (2008). Optical scattering in beef steak to predict tenderness using hyperspectral imaging in the VIS-NIR region. *Sensing and Instrumentation for Food Quality and Safety*, 2(3), 189–196.
- Dissing, B. S., Papadopoulou, O. S., Tassou, C., Ersbøll, B. K., Carstensen, J. M., Panagou, E. Z., et al. (2013). Using multispectral imaging for spoilage detection of pork meat. *Food and Bioprocess Technology*, 6(9), 2268–2279.
- ElMasry, G., Sun, D. W., & Allen, P. (2013). Chemical-free assessment and mapping of major constituents in beef using hyperspectral imaging. *Journal of Food Engineering*, 117(2), 235–246.
- Kamruzzaman, M., ElMasry, G., Sun, D. W., & Allen, P. (2012). Non-destructive prediction and visualization of chemical composition in lamb meat using NIR hyperspectral imaging and multivariate regression. *Innovative Food Science & Emerging Technologies*, 16, 218–226.
- Lagerstedt, Å., Enfält, L., Johansson, L., & Lundström, K. (2008). Effect of freezing on sensory quality, shear force and water loss in beef *M. longissimus dorsi*. *Meat Science*, 80(2), 457–461.
- Lanza, E. (1983). Determination of moisture, protein, fat, and calories in raw pork and beef by near infrared spectroscopy. *Journal of Food Science*, 48(2), 471–474.
- Lindberg, W., Persson, J. A., & Wold, S. (1983). Partial least-squares method for spectrofluorimetric analysis of mixtures of humic acid and lignin sulfonate. *Analytical Chemistry*, 55(4), 643–648.
- Liu, C., Liu, W., Chen, W., Yang, J., & Zheng, L. (2015). Feasibility in multispectral imaging for predicting the content of bioactive compounds in intact tomato fruit. *Food Chemistry*, 173, 482–488.
- Liu, C., Liu, W., Lu, X., Chen, W., Yang, J., & Zheng, L. (2014). Nondestructive determination of transgenic *Bacillus thuringiensis* rice seeds (*Oryza sativa* L.) using multispectral imaging and chemometric methods. *Food Chemistry*, 153, 87–93.
- Liu, C., Liu, W., Lu, X., Ma, F., Chen, W., Yang, J., et al. (2014). Application of multispectral imaging to determine quality attributes and ripeness stage in strawberry fruit. *PLoS One*, 9(2), e87818.
- Liu, D., Sun, D. W., Qu, J., Zeng, X. A., Pu, H., & Ma, J. (2014). Feasibility of using hyperspectral imaging to predict moisture content of porcine meat during salting process. *Food Chemistry*, 152, 197–204.
- Liu, D. Y., Ai, Y. F., Lu, C., & Liu, L. D. (2012). Advancement on detection methods of water-injected meat. *Meat Industry*, 1, 25.
- Li, Y., Shan, J., Peng, Y., & Gao, X. (2011). Nondestructive assessment of beef-marbling grade using hyperspectral imaging technology. In: *New technology of agricultural engineering (ICAE), 2011 international conference on* (pp. 779–783). IEEE.
- Ma, F., Qin, H., Shi, K., Zhou, C., Chen, C., Hu, X., et al. (2016). Feasibility of combining spectra with texture data of multispectral imaging to predict heme and non-heme iron contents in pork sausages. *Food Chemistry*, 190, 142–149.
- Ma, F., Yao, J., Xie, T., Liu, C., Chen, W., Chen, C., et al. (2014). Multispectral imaging for rapid and non-destructive determination of aerobic plate count (APC) in cooked pork sausages. *Food Research International*, 62, 902–908.
- Manickavasagan, A., Al-Mezeini, N. K., & Al-Shekaili, H. N. (2014). RGB color imaging technique for grading of dates. *Scientia Horticulturae*, 175, 87–94.
- Mathlouthi, M. (2001). Water content, water activity, water structure and the stability of foodstuffs. *Food Control*, 12(7), 409–417.
- Naganathan, G. K., Grimes, L. M., Subbiah, J., Calkins, C. R., Samal, A., & Meyer, G. E. (2008). Visible/near-infrared hyperspectral imaging for beef tenderness prediction. *Computers and Electronics in Agriculture*, 64(2), 225–233.
- Panagou, E. Z., Mohareb, F. R., Argyri, A. A., Bessant, C. M., & Nychas, G. J.-E. (2011). A comparison of artificial neural networks and partial least squares modelling for the rapid detection of the microbial spoilage of beef fillets based on Fourier transform infrared spectral fingerprints. *Food Microbiology*, 28(4), 782–790.
- Panagou, E. Z., Papadopoulou, O., Carstensen, J. M., & Nychas, G. J.-E. (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.
- Peng, Y., Zhang, J., Wang, W., Li, Y., Wu, J., Huang, H., et al. (2011). Potential prediction of the microbial spoilage of beef using spatially resolved hyperspectral scattering profiles. *Journal of Food Engineering*, 102(2), 163–169.
- Prevolnik, M., Candek-Potokar, M., & Škorjanc, D. (2010). Predicting pork water-holding capacity with NIR spectroscopy in relation to different reference methods. *Journal of Food Engineering*, 98(3), 347–352.
- Ripoll, G., Albertí, P., Panea, B., Olleta, J. L., & Sañudo, C. (2008). Near-infrared reflectance spectroscopy for predicting chemical, instrumental and sensory quality of beef. *Meat Science*, 80(3), 697–702.
- Samuel, D., Park, B., Sohn, M., & Wicker, L. (2011). Visible-near-infrared spectroscopy to predict water-holding capacity in normal and pale broiler breast meat. *Poultry Science*, 90(4), 914–921.
- Shiranita, K., Miyajima, T., & Takiyama, R. (1998). Determination of meat quality by texture analysis. *Pattern Recognition Letters*, 19(14), 1319–1324.
- Sleagun, G., & Popa, M. (2009). Determination of the moisture content in infrared dried apples. In: *International symposium euro-aliment. Galati, Romania* (pp. 9–10).
- Song, X. Y., & Liu, B. L. (2014). The optimization of volumetric displacement can uniformize the temperature distribution of heated ham during a vacuum cooling process. *Food Science and Technology Research*, 20(1), 43–49.
- Swain, D., Thomas, B. P., Philip, J., & Pillai, S. A. (2015). Novel calibration and color adaptation schemes in three-fringe RGB photoelasticity. *Optics and Lasers in Engineering*, 66, 320–329.
- Tøgersen, G., Isaksson, T., Nilsen, B. N., Bakker, E. A., & Hildrum, K. I. (1999). On-line NIR analysis of fat, water and protein in industrial scale ground meat batches. *Meat Science*, 51(1), 97–102.
- Trinderup, C. H., Dahl, A., Jensen, K., Carstensen, J. M., & Conradsen, K. (2015). Comparison of a multispectral vision system and a colorimeter for the assessment of meat color. *Meat Science*, 102, 1–7.
- Wold, S., Sjöström, M., & Eriksson, L. (2001). PLS-regression: A basic tool of chemometrics. *Chemometrics and Intelligent Laboratory Systems*, 58(2), 109–130.
- Wu, D., He, Y., & Feng, S. (2008). Short-wave near-infrared spectroscopy analysis of major compounds in milk powder and wavelength assignment. *Analytica Chimica Acta*, 610(2), 232–242.
- Wu, D., Shi, H., Wang, S., He, Y., Bao, Y., & Liu, K. (2012). Rapid prediction of moisture content of dehydrated prawns using online hyperspectral imaging system. *Analytica Chimica Acta*, 726, 57–66.
- Wu, D., Wang, S., Wang, N., Nie, P., He, Y., Sun, D. W., et al. (2013). Application of time series hyperspectral imaging (TS-HSI) for determining water distribution within beef and spectral kinetic analysis during dehydration. *Food and Bioprocess Technology*, 6(11), 2943–2958.
- Xiong, C., Liu, C., Pan, W., Ma, F., Xiong, C., Qi, L., et al. (2015). Non-destructive determination of total polyphenols content and classification of storage periods of Iron Buddha tea using multispectral imaging system. *Food Chemistry*, 176, 130–136.
- Yang, Y., Wang, Z. Y., Ding, Q., Huang, L., Wang, C., & Zhu, D. Z. (2013). Moisture content prediction of porcine meat by bioelectrical impedance spectroscopy. *Mathematical and Computer Modelling*, 58(3), 819–825.