OVERVIEW PAPER

Hyperspectral Imaging for Food Quality and Safety Control

L. Liu and M. O. Ngadi*

Department of Bioresource Engineering, McGill University, Macdonald Campus. 21,111 Lakeshore Road, Ste-Anne-de-Bellevue, Quebec, Canada. H9X 3V9.

***Corresponding author:** E-mail: michael.ngadi@mcgill.ca

ABSTRACT

Hyperspectral imaging (HSI) is an emerging advanced technology in food engineering, especially in food quality and safety analysis and control. The ability of Hyperspectral imaging to obtain both spectral and spatial information of the object of interest makes it a non-destructive, objective, and real-time method for food quality and safety assessment. The present review highlights the fundamentals of HSI; recent advances in the HSI configuration and application of HSI in the food industry; description of image acquisition and processing; and potential for food safety and quality control.

Keywords: Hyperspectral imaging; Food quality and safety; Inspection

INTRODUCTION

With the current need for reduced cost of production, the food industry is facing to a number of challenges including maintenance of high-quality standards and assurance of food safety while avoiding liability issues. Meeting these challenges has become crucial in regards to grading food products for different markets. Food companies and suppliers need efficient, low-cost, quality and safety inspection technologies to enable them satisfy different markets' needs, thereby raising their competitiveness and expanding their market share.

Quality and safety are usually defined by physical attributes (e.g., texture, color, marbling), chemical attributes (e.g., fat, moisture, protein contents, pH, drip loss), and biological attributes (e.g., total bacterial count). Traditionally, assessment of quality and safety involves human visual inspection and/or chemical and biological determination experiments. Visual inspection is subjective measurement which can be difficult and unreliable and has poor repeatability of results. Chemical and biological determination experiments are tedious, time-consuming, destructive, and sometimes harmful to the environment. Therefore, it is desirable to develop an accurate, non-destructive, and real-time technique for food quality and safety assessment.

Recently, hyperspectral imaging has been used to evaluate food quality and safety. This technique was originally developed for remote sensing applications as a mean of overcoming the limitations of spectroscopic and machine vision techniques (Goetz *et al.*, 1985). According to Gowen *et al.* (2007), HSI has several merits over RGB, NIR and multispectral imaging. Applications for food quality and safety control include detection of contaminations (Kim *et al.*, 2002, 2004), identification of defects (Xing *et al.*, 2005; Nagata, Tallada & Kobayashi, 2006), analysis of constituents (Qiao *et al.*, 2005), and meat quality evaluation (Qiao *et al.*, 2007). Recently, the technique has become more and more popular due to the consumer demands as well as the challenge of market segmentation and legal restriction. Thus, HSI has shown a strong potential as a powerful detection technique.

Hyperspectral imaging

Hyperspectral imaging (HSI) combines traditional imaging and spectroscopy technology and can be used to obtain spectral and spatial information of an object of interest over the ultraviolet, visible, and near-infrared spectral regions (200 nm-12 μm) (Bannon, 2009). Hyperspectral imaging systems provide hyperspectral images consisting of numerous spatial images of the same object at different wavelengths. The hyperspectral image, also called *hypercube*, is a three-dimensional data cube which is achieved through the superimposition of the spatial images collected by the hyperspectral sensors. These images are composed of vector pixels, and represent the composition and appearance of that particular food sample. Spectra from the data cube of different samples can be compared. Similarity between the image spectra of two samples indicates similarity of chemical composition and physical features. The *hypercube* usually can be constructed in three ways: *area scanning*, *point scanning*, and *line scanning* (Gowen *et al.*, 2007). Due to the presence of conveyor belts (for in-line inspection) in most food processing plants, *line scanning* is the preferred method of image acquisition.

Typical hyperspectral imaging system comprises of hardware and software. The specific configuration may vary depending on the object to be assessed and the technique of image acquisition. Most hardware platform of HSI systems share common basic components as shown in Figure 1: an illumination to provide light source (usually produced by halogen lamps); light irradiation either directly or delivered by optical fiber; detector (e.g. CCD or CMOS camera, InGaAs based array detector) which obtains both spectral and spatial resolution simultaneously; spectrograph to disperse the wavelengths of the light and deliver signals to the photosensitive surface of the detector; an objective lens to adjust the range of light acquisition; an objective table fixed to a conveyer belt to hold and transport the sample; and a computer to compose and store the three-dimensional hypercube.

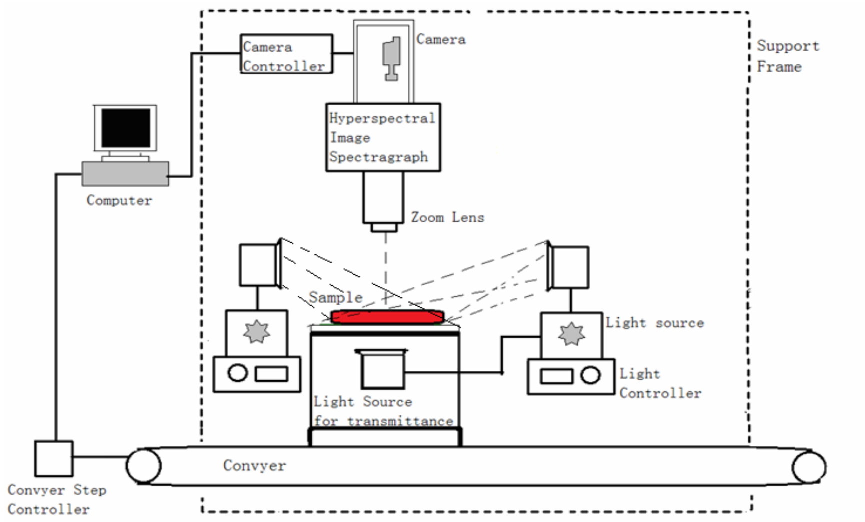

Figure 1. Configuration of a hyperspectral imaging system

Hyperspectral imaging system can be operated either in reflectance or transmittance modes. To acquire images in transmittance mode, thin sample sizes are usually used in order to allow light travelling through the sample. Thick sample can be used in reflectance HSI measurements. Thus, food materials can be inspected as a whole in reflectance mode without the need to make slices. Examples include apples (Peng and Lu, 2008), cucumbers (Ariana and Lu, 2010a), mushrooms (Gowen, Taghizadeh and O'Donnell, 2009), and chickens (Chao *et al.*, 2008).

Hyperspectral imaging system can work in different spectral range such as VIS/NIR range and NIR range. Different detectors are used for different HSI systems due to their sensitivity to the light at different wavelengths. At present, the CCD and CMOS camera (300-1100 nm) are most widely used VIS/NIR detectors in food quality and safety analysis, while the InGaAs array detector (900-1700 nm, 1000-2200 nm, and 1200-2500 nm) is used for NIR hyperspectral imaging that may provide increased accuracy for assessment and analysis of food quality and safety.

Analysis of hyperspectral images

The hypercube contains a mass of information with large dimensionality. The main purpose of hyperspectral data analysis is to reduce the dimensionality and retain the useful data for discrimination or measurement analysis of food quality and safety. Many image processing techniques and chemometric methods can be used to reach the detection goal. Figure 2 illustrates the process of hyperspectral data analysis, including reflectance calibration, segmentation of ROI, image processing and spectral analysis, and classification (qualitative analysis) or prediction (quantitative analysis).

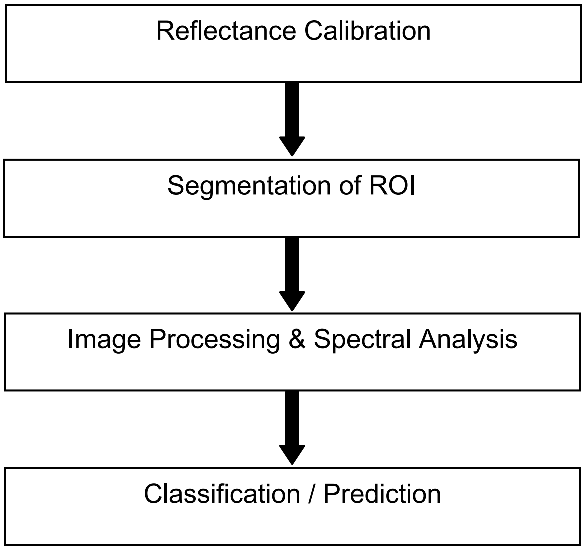

Figure 2. .Flow diagram of hyperspectral data analysis process

All hyperspectral images need to be corrected from the dark current of the camera prior to the following data analysis. At the stage of reflectance calibration, the dark response D and the bright response W are obtained respectively by covering the lens with the cap and by taking an image from a uniform high reflectance standard (a standard white reference). The corrected reflectance value R of the original reflected signal I is calculated on a pixel-by-pixel basis as follows:

$$R = (I - D)/(W - D) .$$

After the reflectance calibration, the region of interest (ROI) will be segmented from the background for the further image processing and spectral analysis. Some image processing algorithms can be used to segment ROI, including thresholding, edge detection, filtering, mathematical morphological algorithm, and so on (Martin and Tosunoglu, 2000).

Image processing and spectral analysis will be applied on segmented ROI to extract useful information for food quality and safety analysis. Image processing algorithms such as GLCM (Qiao *et al.,* 2007), Gabor filters (Liu *et al.,* 2010) and line detection (Liu *et al.,* 2012) can be used to extract image features which can characterize various meat quality attributes at different wavelength bands. Before spectral analysis, the nonchemical biases, i.e. interference signal (baseline drift, particle deviation, surface heterogeneity) should be removed from the spectral information using the spectral processing techniques such as Savitzky-Golay derivative conversion, multiple scattering correction (MSC), and the first or second derivative (Zeaiter, Roger & Bellon-Maurel, 2005). After removing the spectral noise, different statistical procedures such as the analysis of variance (ANOVA), principal component analysis (PCA), linear discriminant analysis (LDA), stepwise regressions, and partial least squares regressions (PLSR) can be used to analyze the spectral data to determine the spectral features which correspond to the various meat quality attributes.

Application of HSI in practice may be limited due to the resulting large and computationally excessive *hypercube.* Thus, it is necessary to extract the characteristic wavelengths by operating qualitative or quantitative analysis for establishment of the relationship between food quality traits and image/spectral characteristics. For qualitative analysis, discriminant analytical tools such as PCA and LDA and machine learning methods such as artificial neural networks (ANNs) and decision trees, are usually employed for classification and evaluation (Camps-Valls & Bruzzone, 2005). Some new methods are also proposed and studied for hyperspectral detection, e.g. the partial least squares discriminant analysis (PLSDA) (Ariana and Lu, 2010a) and spectral information divergence (SID) based classification algorithm (Qin *et al.,* 2009). For quantitative analysis prediction, multivariate analytical tools such as PCA, PLSR, stepwise multi-linear regression (SMLR), are usually employed for chemical content prediction (Cen and He, 2007). PCA and PLSR are the most used and reliable modeling methods. Some advanced techniques such as radial basis function (RBF) (Peng *et al.*, 2008) and PLSDA (Ariana and Lu, 2010a) are also used for prediction and measurement of food quality traits. Table 1 presents a summary of algorithms used for qualitative and quantitative analysis in hyperspectral imaging application for food quality and safety analysis since 2008.

Application of hyperspectral imaging in food analysis

As an emerging process analytical tool, HSI is well suited for food quality and safety control. Recently, intensive research has been carried with regards to the big potential for hyperspectral imaging application in the food industry. Table 1 describes the recent advances in the application of hyperspectral imaging on quality and safety analysis of different food products since 2008. An extensive review about the research work reported before 2008 can be found in Gowen *et al.* (2007).

Fruit

Most of the products studied with hyperspectral imaging are fruits, e.g. apples, citruses, pears, and peaches. The majority of these studies were conducted in reflectance mode and in the VIS-NIR range (400-1100 nm), while some recent research has been carried out in the NIR range (900-1700 nm) (Wang *et al.*, 2009; Sugiyama *et al.*, 2010). For apple, hyperspectral imaging was used to measure quality attributes such as firmness, soluble solids content, and mealiness (Peng and Lu, 2008; Huang and Lu, 2010). These studies demonstrated that hyperspectral scattering technique was potentially useful for nondestructive detection of apple quality attributes. The same spatially resolved diffuse reflectance HSI system was also used to study optical properties of fruits and vegetables including apple, pear, cucumber, tomato (Qin and Lu, 2008). This research reinforced the potential of hyperspectral imaging technique as a convenient attribute classification tools for fruits as well as vegetables.

Qin *et al*. (2009) explored the potential of using hyperspectral imaging to detect citrus canker lesion. The hyperspectral images were processed and classified to differentiate citrus canker lesion from normal and other peel diseased conditions including greasy spot, insect damage, melanose, scab, and wind scar. The analysis method was SID based classification and the overall classification accuracy was 96%. Since this research used full spectral information which was not desirable for online citrus canker detection, more work needs to be done for optimization of waveband selection.

Vegetable

A number of papers about mushroom quality detection using HSI have been published since 2008. Hyperspectral imaging was used to detect the bruise damage on white mushrooms (Gowen *et al*., 2008a) and to identify freeze damage of mushrooms using PCA (Gowen *et al*., 2009). The quality deterioration of sliced mushrooms during storage was also measured using HSI in terms of moisture content, colour and texture (Gowen *et al*., 2008b). These studies showed the potential of HSI for damage detection and quality measurement of mushroom. Taghizadeh *et al.* (2010) investigated the shelf life (using parameters including weight loss, color, maturity index) of mushrooms under different packaging polymer films. This research demonstrated that hyperspectral imaging has potential as an analytical tool for evaluation of shelf-life of fresh mushrooms. It also indicated that HSI can be used to evaluate the effect of different packaging solutions especially packaging materials. Hyperspectral imaging was also applied to predict polyphenol oxidase (PPO) activity on mushrooms in the VIS/NIR range (Gaston *et al*., 2010). The result of this study revealed the possibility of developing a sensor that could rapidly identify mushrooms with a higher likelihood to develop enzymatic browning. This study highlights the utility of HSI in terms of safety and quality management in the food industry.

Ariana and Lu (2010a) developed a VIS-NIR HSI system to classify pickling cucumbers and pickles and detect inner defected pickle pieces. This system combined reflectance mode and transmission mode together and used a moving transport platform. The results showed the capability of hyperspectral imaging to identify inner defects of cucumber and pickles which was invisible to the naked eyes.

Meat

Most meat researches related to hyperspectral imaging were performed on pork and beef. Lamb (Kamruzzaman *et al*., 2010) and ham (ElMasry *et al*., 2011) have also been investigated.

Hyperspectral imaging was used to classify pork quality groups and predict pork quality traits such as marbling scores (Barbin *et al*., 2012; Liu *et al*., 2010, 2012). Barbin *et al.* (2012) studied the grading and classification of three pork quality groups i.e. RFN, PSE, and DFD, using NIR hyperspectral imaging (900-1700 nm). Six wavelengths were selected using the 2nd derivative spectra and PCA was carried out on the selected 6 wavelengths. The high accurate results of this study indicated that pork quality groups could be precisely discriminated using NIR hyperspectral imaging. Instead of three pork quality groups, four pork quality groups (RFN, RSE, PFN, PSE) were classified using VIS/NIR hyperspectral imaging in Liu *et al*. (2010). Automatic and objective measurement methods were established for pork quality classification and quality trait prediction by employing advanced image processing techniques such as Gabor filters and the wide line detector (Liu *et al*., 2010, 2012). The high accuracy of results indicated the big potential of HSI in meat quality analysis especially when combined with advanced image processing techniques.

The bacterial spoilage process in meat was also studied using a VIS/NIR reflectance HSI system (Peng *et al*., 2008, 2011). The best prediction result (correlation coefficient=0.95, standard error of prediction (SEP) = 0.30) was obtained using combination of scattering parameters. These studies demonstrated the great potential of hyperspectral imaging in bacterial activity analysis which is related to food quality change.

Seafood

The shelf life of salmon was studied by VIS/NIR spectral analysis. Huang *et al*. (2011) applied hyperspectral imaging to predict salmon's storage time. PCA based K-means clustering and MLR were developed to relate hyperspectral data to the storage time and texture change of salmon, respectively. The results indicated that it is possible to predict the texture and storage time using HSI. Barely any research on seafood has been reported in last 2 years. Seafood holds promise as an attractive area for HSI research.

Biofilm detection

Recently, Jun *et al*. (2010) reported the utilization of macro-scale fluorescence hyperspectral imaging to evaluate the potential detection of pathogenic bacterial biofilm formations on five types of food-contact surface materials: stainless steel, high density polyethylene (HDPE), plastic laminate (Formica), and two variations of polished granite. These materials are commonly used to process and handle food, and sometimes cause biofilm pollution (such as E. coli O157:H7 and Salmonella biofilm) on food surface. This study showed that the hyperspectral imaging could also be used to develop portable hand-held devices for sanitation inspection of food packaging which has become a big issue for food processing. It was also noted that low cell population density may influence the accuracy of biofilm inspection of food processing surfaces. More studies should be conducted on the HSI biofilm detection in low cell population density.

CONCLUSION

Hyperspectral imaging (HSI) is developing as a platform technology for food quality and safety analysis in food processing and packaging. Since the information are stored in large data cube i.e. hypercube which may slow down the data processing speed, increasing the efficiency of data analysis methods and identifying the key wavelengths should be the center focus of upcoming studies in order to make HSI more suitable for in plant application.

REFERENCES

Ariana, D.P., and Lu, R.F. 2010. Evaluation of internal defect and surface color of whole pickles using hyperspectral imaging. *Journal of Food Engineering*, 96(4): 583-590.

Bannon, D. (2009). Hyperspectral imaging-cubes and slices. Industry perspective technology focus. *Nature photonics*, 3: 627-629.

Barbin, D., Elmasry, G., Sun, D.W., and Allen, P. 2012. Near-infrared hyperspectral imaging for grading and classification of pork. *Meat Science*, 90(1): 259-268.

Camps-Valls, G., and Bruzzone, L. 2005. Kernel-based methods for hyperspectral image classification. *IEEE Transactions on Geoscience and Remote Sensing.* 43: 1351-1362.

Cen, H., and He, Y. 2007. Theory and application of near infrared reflectance spectroscopy in determination of food quality. *Trends Food Sci. Technol.,* 18: 72-83.

Chao, K., Yang, C.C., Kim, M. S., and Chan, D.E. 2008. High throughput spectral imaging system for wholesomeness inspection of chicken. *Applied Engineering in Agriculture*, 24(4): 475-485.

Cluff, K., Naganathan G.K., Subbiah J., Lu R., Calkins C.R., and Samal A. 2008. Optical scattering in beef steak to predict tenderness using hyperspectral imaging in the VIS-NIR region. *Sensing and Instrumentation for Food Quliaty and Safety*, 2: 189-196.

ElMasry, G., Iqbal A., Sun D.W., Allen P., and Ward P. 2011. Quality classification of cooked, sliced turkey hams using NIR hyperspectral imaging system. *Journal of Food Engineering*, 103: 333-344.

ElMasry, G., Wang, N., and Vigneault, C. 2009. Detecting chilling injury in Red Delicious apple using hyperspectral imaging and neural networks. *Postharvest Biology and Technology*, 52(1): 1-8.

Gaston, E., Frias, J.M., Cullen, P.J., O'Donnell, C.P., and Gowen, A.A. 2010. Prediction of Polyphenol Oxidase Activity Using Visible Near-Infrared Hyperspectral Imaging on Mushroom (Agaricus bisporus) Caps. *Agricultural Food Chemistry*, 58(10): 6226-6233.

Goetz, A.F.H., Vane, G., Solomon, T.E., and Rock, B.N. 1985. Imaging spectrometry for earth remote sensing. *Science*, 228: 1147-1153.

Gowen, A.A., Donnell, C.P.O', Cullen, P.J., Downey, G., and Frias, J.M. 2007. Hyperspectral imaging-an emerging process analytical tool for food quality and safety control. *Trends in Food Science & Technology*, 18(12): 590-598.

Gowen, A.A., O'Donnell, C.P., Taghizadeh, M., Cullen, P.J., Frias, J.M., and Downey, G. 2008a. Hyperspectral imaging combined with principal component analysis for bruise damage detection on white mushrooms (Agaricus bisporus). *Journal of Chemometrics*, 22 (3-4): 259-267.

Gowen, A., O'Donnell, C., Taghizadeh, M., Gaston, E., O'Gorman, A., Cullen, P. J., Frias, J. M., Esquerre, C., and Downey, G. 2008b. Hyperspectral imaging for the investigation of quality deterioration in sliced mushrooms (Agaricus bisporus) during storage. Sens. Instrum. Food Q. Eval., 2(3): 133-143.

Gowen, A., Taghizadeh, M., and O'Donnell, C.P. 2009. Identification of mushrooms subjected to freeze damage using hyperspectral imaging. *J. Food Eng.*, 93, 7-12.

Huang, H., Ngadi, M.O., Liu, L., and Benjamin, S. 2011. CIGR Conference.

Huang, M., and Lu, R.F. 2010. Apple mealiness detection using hyperspectral scattering technique. *Postharvest Biology and Technology*, 58(3): 168-175.

Jun, W., Kim, M.S., Cho, B.-K., Millner, P.D., Chao, K.L., and Chan, D.E. 2010. Microbial biofilm detection on food contact surfaces by macro-scale fluorescence imaging. *Journal of Food Engineering*, 99 (3): 314-322.

Kamruzzaman, M., ElMasry G., Sun, D.W., and Allen, P. 2010. Application of NIR hyperspectral imaging for discrimination of lamb muscles. *Journal of Food Engineering*, 104:332-340.

Kim, M.S., Lefcourt, A.M., Chao, K., Chen, Y.R., Kim, I., and Chan, D.E. 2002. Multispectral detection of fecal contamination on apples based on hyperspectral imagery: Part I. Application of visible and near-infrared reflectance imaging. *Transactions of the ASAE*, 45(6): 2027-2037.

Kim, I., Kim, M.S., Chen, Y.R., and Kong, S.G. 2004. Detection of skin tumors on chicken carcasses using hyperspectral fluorescence imaging. *Transactions of the ASAE*, 47(5): 1785-1792.

Liu, L., Ngadi, M.O., Prasher, S.O., and Gariépy, C. 2010. Categorization of pork quality using Gabor filter-based hyperspectral imaging technology. *Journal of Food Engineering*, 99 (3): 284-293.

Liu, L., Ngadi, M.O., Prasher, S.O., and Gariépy, C. 2012. Objective determination of pork marbling scores using the wide line detector. *Journal of Food Engineering*, 110 (3): 497-504.

Martin, A., and Tosunoglu, S. 2000. Image processing techniques for machine vistion. Florida Conference on Recent Advances in Robotics, Florida Atlantic University, Boca Raton, Florida, May 4-5, 2000.

Nakariyakul, S., and Casasent, D.P. 2010. Classification of internally damaged almond nuts using hyperspectral imagery. *Journal of Food Engineering*, 99(3): 314-322.

Naganathan, G.K., Grimes, L.M., Subbiah, J., Calkins, C.R., Samal, A., and Meyer, G.E. 2008. Visible/near-infrared hyperspectral imaging for beef tenderness prediction. Computers and Electronics in Agriculture, 64 (2): 225-233.

Peng, Y., and Lu, R. 2008. Analysis of spatially resolved hyperspectral scattering images for assessing apple fruit firmness and soluble solids content. *Postharvest Biol. Technol*. 48, 52-62.

Peng, Y. K., and Wang, W. 2008. Prediction of Pork Meat Total Viable Bacteria Count Using Hyperspectral Imaging System and Support Vector Machines. St. Joseph, Michigan: The American Society of Agricultural and Biological Engineers. www.asabe.org. Paper number 7010508, 2008 ASAE Annual Meeting.

Peng, Y.K., Zhang, J., Wang, W., Li, Y.Y., Wu, J.H., Huang, H., Gao, X.D., and Jiang, W.K. 2011. Potential prediction of the microbial spoilage of beef using spatially resolved hyperspectral scattering profiles. *Journal of Food Engineering*, 102(2): 163-169.

Qiao, J., Wang, N., Ngadi, M., and Baljinder, S. 2005. Water content and weight estimation for potatoes using hyperspectral imaging. St. Joseph, Michigan: The American Society of Agricultural and Biological Engineers. www.asabe.org. Paper number 053126, 2005 ASAE Annual Meeting.

Qiao, J., Ngadi, M., Wang, N., Gariépy , C., and Prasher, S. 2007. Pork quality and marbling level assessment using a hyperspectral imaging system. *Journal of Food Engineering*, 83(1): 10-16.

Qin, J.W., and Lu, R.F. 2008. Measurement of the optical properties of fruits and vegetables using spatially resolved hyperspectral diffuse reflectance imaging technique. *Postharvest Biology and Technology*, 49(3): 355-365.

Qin, J.W., Burks, T.F., Ritenour, M.A., and Bonn, W.G. 2009. Detection of citrus canker using hyperspectral reflectance imaging with spectral information divergence. *Journal of Food Engineering*, 93 (2): 183-191.

Sugiyama T., Sugiyama J., Tsuta M., Fujita K., Shibata M., Kokawa M., Araki T., Nabetani H., and Sagara Y. 2010. NIR spectral imaging with discriminant analysis for detecting foreign materials among blueberries. *Journal of Food Engineering*, 101(3): 244-252.

Taghizadeh, M., Gowen, A., Ward, P., and O'Donnell, C.P. 2010. Use of hyperspectral imaging for evaluation of the shelf-life of fresh white button mushrooms (Agaricus bisporus) stored in different packaging films. *Innovative Food Science and Emerging Technologies*, 11 (3): 423-431.

Wang, W.L., Li, C.Y., Gitaitis, R., Tollner, E.W., and Yoon, S.C. 2009. Detection of Sour Skin Diseases in Vidalia Sweet Onions Using Near-infrared Hyperspectral Imaging. Reno, Nevada: The American Society of Agricultural and Biological Engineers. www. asabe. org. Paper number 096364, 2009 ASAE Annual Meeting.

Xing, J., Bravo, C., Jancsók, P., Ramon, H., and De Baerdemaeker, J. 2005. Detecting bruises on 'Golden Delicious' apples using hyperspectral imaging with multiple wavebands. *Biosystems Engineering*, 90(1): 27-36.

Zeaiter, M., Roger, J.M. and Bellon-Maurel, V. 2005. Robustness of models developed by multivariate calibration. Part II: the influence of pre-processing methods. Trends Anal. Chem, 24 (5): 437-445.

Table 1: Summary of measurement mode, product type, analysis type, wavelength region studied and modelling algorithm employed in papers published on hyperspectral imaging of food since 2008.

Mode	Camera	Product	Wavelength region (nm)	Analysis type	Image processing	Modelling	Author, Year
Reflectance	CCD	Almond nut	700-1000, 950-1390	Qualitative	Non	Band ratio(BR), Support vector machines (SVM)	Nakariyakul & Casasent, in press
	CCD	Apple	600-1000	Quantitative	Thresholding(TH)	Partial least squares regression(PLSR), Partial least squares discriminant analysis (PLSDA)	Huang & Lu, 2010
	CCD	Apple	450-1000	Quantitative	Not-mentioned	Stepwise multi-linear regression(SMLR)	Peng & Lu, 2008
	CCD	Apple	400-1000	Qualitative	TH	Artificial neural networks (ANN)	ElMasry, Wang & Vigneault, 2009
	CCD	Apple, Peach	500-1000	Quantitative	TH	Manual analysis	Qin & Lu, 2008
	CCD	Beef	400-1000	Quantitative	Co-occurrence matrix analysis, PCA	Canonical discriminant	Naganathan *et al.*, 2008
	CCD	Beef	400-1100	Quantitative	MLD	Multi-linear regression (MLR)	Peng *et al.*, 2011
	CCD	Beef	496-1036	Quantitative	MLD	SMLR	Cluff *et al.*, 2008
	CCD	Chicken	389-744	Qualitative	TH	BR	Chao *et al.*, 2008
	CCD	Citrus	400-1100	Qualitative	Geometric factor correction(GFC)	Digital elevation model (DEM)	Gómez-Sanchis *et al.*, 2008a
	EMCCD	Citrus	450-930	Qualitative	TH	Spectral information divergence (SID) mapping	Qin *et al.*, 2009
	CCD	Mandarin	320-1100	Qualitative	GFC	Linear discriminant analysis(LDA), Classification and regression trees (CART)	Gómez-Sanchis *et al.*, 2008b
	CCD	Mushroom	400-1000	Quantitative	Not-mentioned	PLSR	Taghizadeh *et al.*, 2010
	CCD	Mushroom	400-1000	Quantitative	TH	PCA	Gaston *et al.*, 2010
		Mushroom	400-1000	Qualitative	TH	PCA	Gowen *et al.*, 2008a
		Mushroom	450-850	Quantitative	Not-mentioned	MLR, Principal components regression (PCR)	Gowen *et al.*, 2008b
		Mushroom	450-950	Qualitative	Interactive Selection	PCA	Gowen *et al.*, 2009
	CCD	Pork	400-1100	Quantitative	Not-mentioned	Least square support vector machines (LS-SVM)	Peng *et al.*, 2008
	CCD	Pork	400-1100	Quantitative	MLD	MLR	Wang *et al.*, 2010
	CCD	Pork	400-1000	Quantitative	Gabor-filter, TH	PCA, K-means clustering, LDA	Liu *et al.*, 2010
		Pork	900-1700	Qualitative	TH	PCA	Barbin *et al.*, In press
	CCD	Pickling cucumbers and whole pickles	400-740	Qualitative	TH	PLSDA, K-nearest neighbor(KNN)	Ariana & Lu, 2010a
	CCD	Salmon	400-1100	Qualitative, Quantitative	TH	PCA, K-means clustering, MLR	Huang *et al.*, 2011
	CCD	Whole pickles	400-675	Qualitative	TH	PCA	Ariana & Lu, 2010b
	InGaAs	Onion	1000-1600	Qualitative	TH	Manual analysis	Wang *et al.*, 2009
	InGaAs, HgCdTe	Maize	960-1662, 1000-2498	Qualitative	TH	PLS-DA	Williams *et al.*, 2009
	InGaAs	Strawberry	1000-1600	Qualitative	TH	LDA	Sugiyama *et al.*, 2010
Transmittance	CCD	Pickling cucumbers and whole pickles	740-1000	Qualitative	TH	PLSDA, KNN	Ariana & Lu, 2010a
	CCD	Whole pickles	675-1000	Qualitative	TH	PCA	Ariana & Lu, 2010b
	CCD	Egg	550-899	Qualitative	Not-mentioned	PCA	Smith, Lawrence & Heitschmidt, 2008
Fluorescence	EMCCD	Microbial biofilm formation	421-700	Qualitative	TH	PCA	Jun *et al.*, 2010