

ADVANCES IN HYPERSPECTRAL IMAGING FOR EVALUATION OF QUALITY AND SAFETY IN FOOD PRODUCTS

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Abstract

Hyperspectral imaging that includes imaging and spectroscopic technology is increasing its fame in science as a non-destructive, actual detection tool for quality and safety evaluation of food products. Hyperspectral imaging can be used to instantaneously obtain large numbers of spatial and spectral data on the products that are to be studied. This paper delivers a complete review on the recent advances of hyperspectral imaging uses in food and food products. The probable future work of hyperspectral imaging for food quality and safety control is also discussed.

INTRODUCTION

Due to increasing need for low production costs and high efficacy, the food industry is faced with a lot of challenges, that includes maintenance of high-quality standards and food safety assurance while taking no risk on quality of food. Due these challenges have become very difficult to grade food products for different markets. Food companies and suppliers need well-organized, low-cost, and non-destructive quality and safety inspection methods to satisfy different markets'

thereby they raise their competition against other food companies and increase their market economy. Quality and safety of food are typically clarified by physical characteristics (e.g., texture, color, firmness, tenderness, shape, size of food product), chemical qualities (e.g., fat amount, moisture content, protein amount, pH, drip loss), and biological characteristics (e.g., total bacterial count, total anaerobic count, total plate count and total number of fungal cells). Usually, evaluation of quality and safety includes human

visual inspection, with effect of to chemical or biological determination experiments which are mind-numbing, tiresome, take more time, denature and destroy food product and cause harm to our environment. These require the need for precise, that take less time and non-chemical recognition experiments, in order to enhance quality and assure food safety.

Due to recent progressions in computer and I.T technology and instrumentation, equipment's, methods engineering, there have been noteworthy developments in methods for measurement of food quality and safety. Machine image and NIR spectroscopy are two of the more widely used methods for food quality and safety assessment. Machine vision methods based on red-green-blue (RGB) color vision systems are effectively applied to assess the external physical characteristics of foods [1-6]. Normal machine vision systems cannot capture broad spectral data which is connected to internal features, hence computer vision has very low ability to conduct measurement of chemical parts in food. Spectroscopy is a famous analytical technique for measurement of the chemical components of food. The good relationship between Near Infra-Red spectra and food parts makes Near Infra-Red spectroscopy more prestigious over the other spectroscopic technologies. Moreover, these spectral techniques were known incompetent when applied on heterogeneous materials for example meat, due to the fact that they cannot accomplished of gaining any spatial information about objects [7-10]. To solve this problem, repeated finding or ground of objects were suggested, which would increase the error or make these methods invasive or destructive.

With the limitations of normal machine imaging and spectroscopic methods, hyperspectral

imaging was invented. Hyperspectral imaging was basically invented for remote sensing applications [11].

It can be used to obtain spectral and spatial information of an object over the ultraviolet, visible, and near-infrared spectral regions (300 nm-2,600 nm) [12]. According to Gowen et al. [13], hyperspectral imaging has several merits over RGB imaging, NIR spectroscopy and multispectral imaging, including the ability to collect large and detailed spectral and spatial information. Because of the inherent merits of this technique, it has been put to application in a number of fields including agriculture [14,15], pharmaceutical [16,17], and material science [18]. Applications of hyperspectral imaging in food quality and safety include detection of contaminations [19,20], identification of defects [21,22] and quantification of constituents [23]. Recently, the technique has become more and more popular in food quality control in order to meet consumer demands and the challenge of market segmentation and legal restrictions. Publications in this research area have greatly increased in number since 2008, as shown in Figure 1, which implies the strong potential of hyperspectral imaging as a promising detection technique for food quality and safety control.

In this paper, a complete review of the latest advancements in hyperspectral imaging systems and its uses in food and food products is explained. In comparison to other published review papers or articles [24-27] which only focus on the applications of hyperspectral imaging in food quality examination, this paper highlights the optical basics of hyperspectral imaging and the latest advances in this technique and uses of hyperspectral imaging in food quality and food and food products safety control.

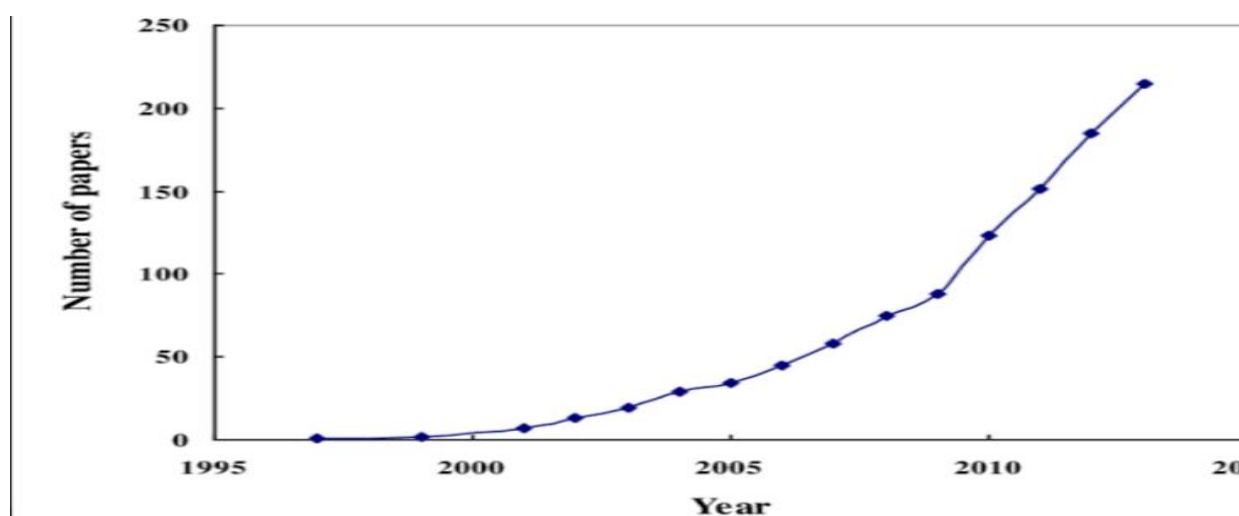


Figure 1. The number of publications about hyperspectral imaging applications in food

2. Hyperspectral Imaging

2.1. Optical Basics of Hyperspectral Imaging

At the level of molecules, all food samples unceasingly emit and absorb energy by dropping or increasing their energy levels. Those wavelengths at which molecules absorb, reflect, and transmit electromagnetic radiation are individualities of their molecular structure [28]. Electromagnetic waves are basically consisting of ultraviolet radiation (UV), visible light (VIS), Near Infra-Red, mid-infrared, and far-infrared (FIR). Every part is associated to a exact kind of atomic or molecular transition matching to different frequencies. So in any biological material, food tissues are bonded together by numerous different molecular bonds and forces. The rich sources of O-H or C-H bonds are Water, Carbohydrates and Fats. Similarly, the rich sources of C-H or N-H bonds are organic compounds and petroleum derivatives. Whenever a food sample is visible to light, there are transmissions of electromagnetic waves through it, the energy of incident electromagnetic wave fluctuates because of the extending and bending vibrations of chemical bonds such as O-H, N-H and C-H.

By applications of these observed fluctuations in energy levels of molecules spectroscopy is able to provide distinguishing and thorough fingerprints of food samples. At the comprehensive level, the electromagnetic wave is known as light, and the transitioning of the incident electromagnetic wave is visible to us as the reflection, scattering, and transmission of

light. The strength and wavelengths of emission and absorption depends on the physical and chemical states of the sample material when absorbed region of light penetrates into the tissues of sample. The light emerging from the sample tissues is obtained and is changed to a spectrum of wavelengths and reshaped to images by hyper spectrometers with high signal-to-noise ratios. These images that are called hyperspectral images, can show the chemical ingredients and physical properties of the food samples.

2.2. Knowledge about Hyperspectral Images

The systems of Hyperspectral imaging provide us with hyperspectral images that consist of abundant spatial image angles of the same object at altered wavelengths. The final hyperspectral image is completed through the superimposition of the spatial images composed by the hyperspectral sensors, eventually forming a three-dimensional information cube that is called hypercube which is more and more times investigated and demonstrated. In order to show the composition and form of that specific food sample the images are made up of vector pixels. Spectra from the different samples of their data cubes can be matched with other. The chemical composition and physical features of same samples is same and they show similarity in their images of spectra too this indicate that the samples are identical.

The hypercube is created in three ways: area scanning, point scanning, and line scanning [13]. The preferred image achievement method

is line scanning or push broom one because most of the food processing industries have conveyor belts for in line inspection for food products. The hypercube of line scanning is developed by constituting numerous whole lines of an image instead of a single pixel at a time, and it is deposited in the form of Band Interleaved by Line (BIL) which is a system for storing the actual pixel values of an image in a file band by band for each line or row of the image. The spatial and spectral information that is deposited in BIL are investigated instantaneously.

Hyperspectral imaging systems are used either in form of reflectance of light or transmittance of light modes. We use thin sample sizes to allow light to travel or pass through the sample in order to gain images in transmittance mode of light. Thicker samples are used in reflectance of light hyperspectral imaging measurements. So it is possible to analyze whole form of food material in reflectance mode without the essential to make slices. Examples that are the most common ones are apples [29], cucumbers [30], mushrooms [31], and chickens [32].

Light penetration depth is explained as the depth at which the incident light is reduced by 99%. It depends upon the factors such as the status of sample, type of sample, and the detection waveband. The light penetration depths optical features are mostly determined by strong absorbing ingredients in the sample. Research concerning the penetration depth of light in VIS and Near Infra-Red range is very limited. Lammertyn et al. [33] showed that light penetration depth in apples depend on the detection wavelength by pushing forward a non-linear model unfolding the correlation between the reflectance and thickness of apple slices. The penetration of apple is 4 mm in the 700–900 nm range and between 2 and 3 mm in the 900–1,900 nm range. In the research paper of Qin and Lu [34], the light penetration depth in tissues of apple, peach, pear, kiwifruit, tomatoes, zucchini, cucumber, and plum were considered according to the absorption and condensed

scattering spectra of the test samples at dissimilar wavelengths. The minimum light penetration depths ranged from 7.1 mm at 535 nm for the plum to 13.8 mm at 720 nm for the zucchini. The wavelengths were due to the absorption points of the more amount of pigments in the fruits and vegetables. The maximum penetration depths fluctuated from 18.3 mm for the apple to 65.2 mm for the zucchini. This study showed us that penetration depth differs a great amount depending on the kind of object under study and the applied depth. The penetration depth has impactful effects on the hyperspectral imaging detection. Fruits were being commonly used for the study about penetration depth. Further research in future regarding penetration depth would show helpful by on condition that references for thickness determination are studied and could be appreciated for designing a suitable and precise sensing configuration, particularly in meat and meat products.

2.3. Arrangement of Hyperspectral Imaging System

The most common hyperspectral imaging systems consist of hardware and software. The precise arrangement may differ depending upon the sample to be examined and the image gaining technique used. Mostly hyperspectral imaging systems hardware stands consist of common simple machineries (shown in Figure 2): a light source to deliver illumination, most commonly formed by halogen-tungsten lamps; light irradiation of models either directly or distributed by an optical fiber; a detector that obtains both spectral and spatial information instantaneously; a hyper-spectrograph to scatter the wavelengths of the reflected, transmitted, or scattered light and transport signals to the photosensitive surface of the detector; an objective lens to adjust the choice of light attainment; an objective table which is secure to a conveyer belt to grip and carrying the sample and finally a computer to constitute and store the three-dimensional hypercube.

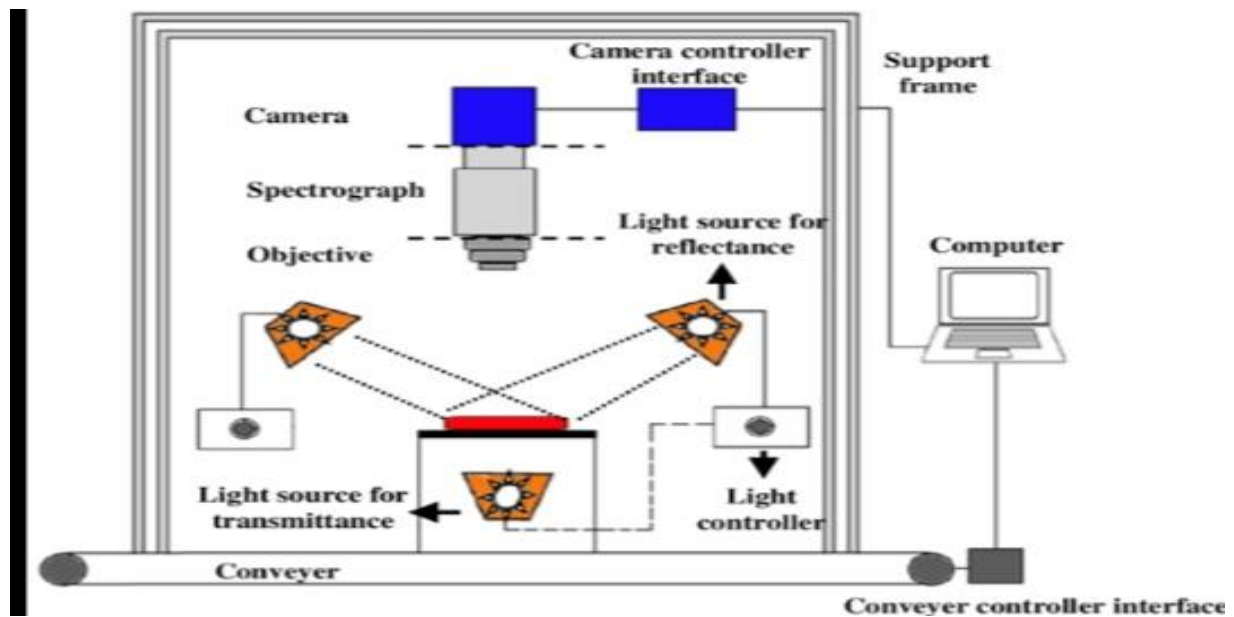


Figure 2. Arrangement of a hyperspectral imaging system.

For the hyperspectral imaging system detector, there are three most common and important choices of cameras for this purpose, including silicon (Si)-based charge-coupled device (CCD) or complementary metal oxide semiconductor (CMOS) cameras, indium gallium arsenide (In GaAs)-based array detectors, and mercury cadmium telluride (HgCdTe)-based array detectors. The choice of the camera in a specific hyperspectral imaging system be determined by the mandatory wavelength, the quantum efficiency (QE) representative of the sensitivity, and the price. Nowadays the most commonly used cameras are CCD camera (300–1,100 nm) with the VIS/NIR detector basically used for food quality and safety examination, lower cost and more availability in the market make it more appealing to scientist (compared to In GaAs and HgCdTe). Due to the advancement in instrumentation allowed the use of near infrared cameras in food processing, that consist of the In GaAs array detector (900–1,700 nm, 1,000–2,200 nm, and 1,200–2,500 nm) and the HgCdTe array detector (1,000–2,600 nm). In the recent times a potable or we can say a hand held hyperspectral imaging system (400–720 nm) was recommended to help in food

processing services [37].

2.4. Spatial Resolution of Hyperspectral Imaging System

The hyperspectral imaging system acquired the information in the form of spatial information as well as spectral information. A proper spatial resolution system should be selected depending upon to the size and shape of the sample to be measured. Spatial resolution is calculated by dividing the scanned spatial distance to the pixel numbers in each image. The spatial resolution is dependent on the pixel resolution of the camera. The spatial resolutions if taken in the two spatial dimensions are basically identical. By the research of Lara et al. [15], spatial resolution of 0.26 mm/pixel was applied to study the shelf-life of spinach using a line scanning system. Similarly, Kamruzzaman et al. [38] applied a spatial resolution of 0.578 mm/pixel for imagining of minced lamb meat. Mendoza et al. [39] used a spatial resolution of 0.20 mm/pixel for image acquirement of apple fruit. Food quality control can be made for effective if the spatial resolution of line scanning hyperspectral imaging condensed to the micron close or near to micron.

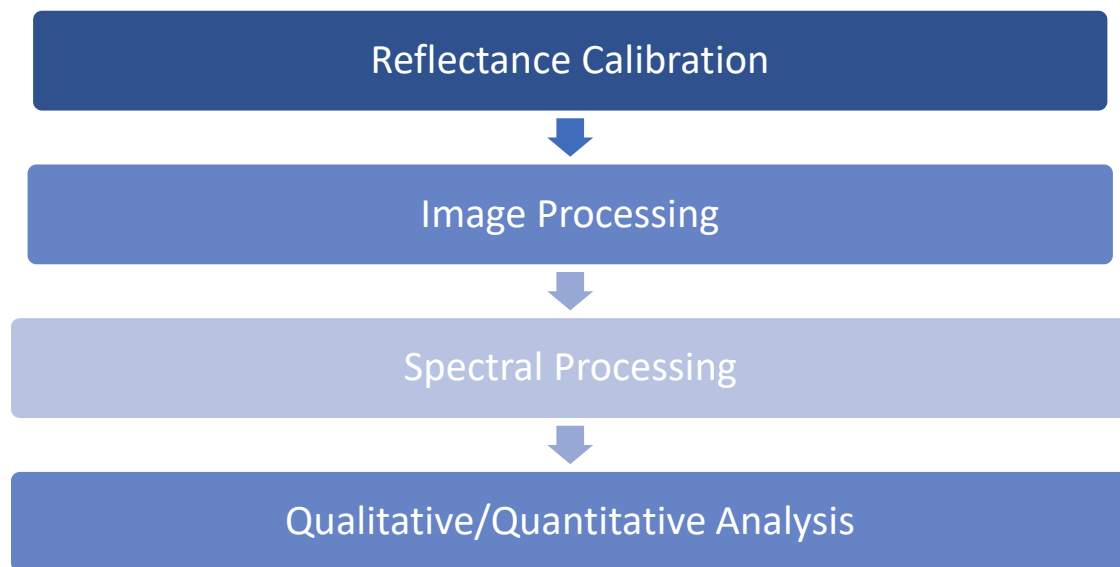


Figure 3. Flow diagram of hyperspectral data analysis process.

3. Study of Hyperspectral Images:

The hyper cube formed by hyperspectral imaging systems comprises of a large amount of information. According to image processing method a large number of methods could be implemented to do finding. The main steps in analysis of hyperspectral imaging follow as Figure 5 describes, including reflectance calibration, image processing, spectral preprocessing, and qualitative analysis or quantitative analysis.

3.1. Reflectance Calibration

Reflectance calibration main purpose is to correct the sample images from the dark background of the camera. The dark reaction D is the background reaction of camera due to the dark current. The dark reaction is acquired by getting off the light, fully covering the lens, and do the recording. The bright reaction W demonstrating the total reflected light strength. The optical reflected sign, I of sample is calculated as:

$$R = I \cdot D \backslash W \cdot D$$

3.2. Image Processing

Hyperspectral cube contains, grayscale images with intensity scaling have dissimilar values in dissimilar pixels. In a hyperspectral cube, the strength of each pixel in the image signifies dissimilar light reflectance or transmission. When the signals are calculated by Equation (1).

The characteristic image preprocessing methods include edge detection techniques, filters, trend removals, band ratio, grey-level segmentation or thresholding techniques, digital morphology, texture, thinning and skeletonization algorithms [40], etc. Region of interest (ROI), is acquired after image preprocessing.

After image preprocessing, a lot of number of image examination methods can be used to abstract image structures for the further examination. These comprise principal component analysis (PCA), minimum noise fraction, Gabor filter, wide line detector, grey level co-occurrence matrix (GLCM), variogram analysis, wavelet transform, etc. [41–43].

Due to the large quantity of information provided by three dimensional hyperspectral data, it is essential to remove the important structures on the sample images and to compare those features. The 2D Gabor filter. This technique includes a Gaussian function controlled by a symmetric sinusoidal function or oriented harmonic function. The Gabor filter method was effectively practical to remove quality features from pork [41] and egg images [43]. ROI of pork was introductory selected and applied to eliminate the impractical information. Gabor filters were accomplished on the hyperspectral images of the pork to remove the feature and attain the clarified image. Gabor filters can found useful information, which does not eliminate out of

work information. PCA, which is a method that decreases the out of work structures, was useful in the study of Liu et al. [41]. The value of PCA was enlightened by Qin et al. [27]. PCA has been extensively used to decrease dimension, compress data in the use of hyperspectral imaging for food superiority [38,42,44-52].

Additional method that is wide line detector was useful to remove the line structure from red-green-blue images of pork. The red, green, and blue images were developed using a hyperspectral imaging system. Figure 4 shows examples of marbling removal outcomes, where lines with dissimilar width were professionally removed by wide line indicator.

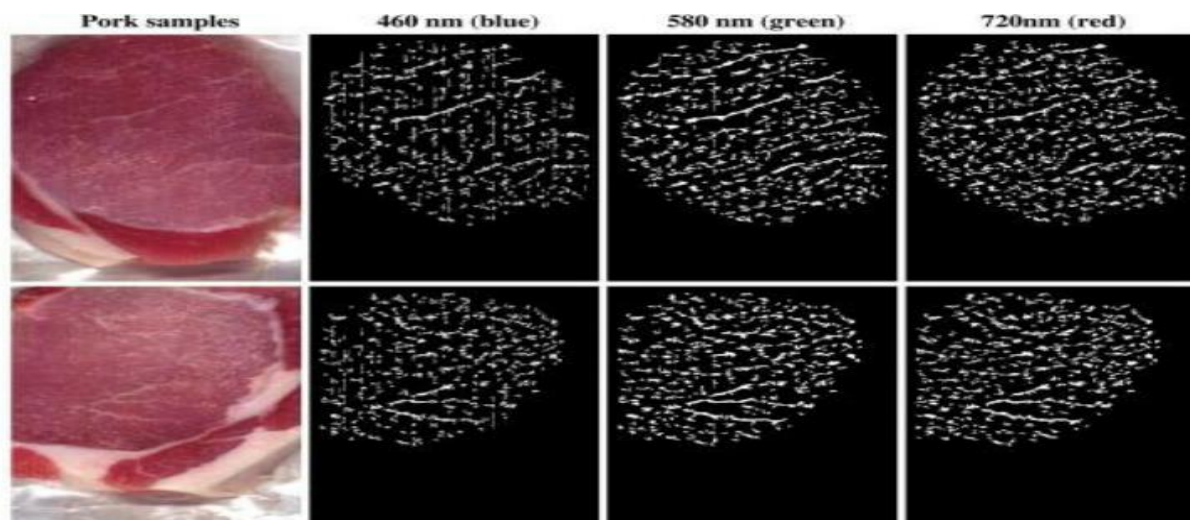


Figure 4. Wide line detector for extracting line feature from red, green, and blue image of pork

3.3. Spectral Processing

The simple spectral processing is spectral averaging. A mean value of spectrum is designed by averaging the rate of pixels comprised in the ROI. Interference indicator (baseline drift, particle unconventionality, surface heterogeneity) these all are included in spectrum. A large numbers of preprocessing methods counting Savitzky-Golay filter, multiple scattering correction (MSC) for particle scattering effect elimination, first or second derivative, smoothing, and standard normal variate (SNV) [54]. Nowadays the latest preprocessing technique named Modified Lorentzian Distribution (MLD) function, that was introduced by Peng and Lu [55], used in forming hyperspectral imaging data cube of beef [29].

3.4. Qualitative Analysis and Quantitative Examination

The most important is to extract the representative wavelength by functioning of qualitative or quantitative examination. These main purpose of these analysis are to recognize the affiliation between food structures and

spectral physical appearance. Separate investigative apparatuses are being used for qualitative analysis such as manual observation, principle component analysis (PCA), linear discriminant analysis (LDA), and k-means clustering [26,56]. Ariana and Lu [30] used partial least squares discriminant analysis (PLSDA), that uses partial least squares regression (PLSR) and LDA, applied on investigation of physical features of cucumber and pickles ($R > 0.80$). K-nearest neighbor (KNN) was used to associate with PLSDA. PLSDA was effectively proficient in researches. The constancy of PLSDA is taken under consideration [14]. Other bunch of scientists [61] established a spectral information divergence (SID)-based cataloguing system. SID is measured from X and Y

$$SID(X, Y) = D(X, Y) + D(Y, X)$$

where X is hyperspectral pixel which is acquired by hyperspectral image; Y is another pixel with possibility value [62]. Multivariate investigative methods are used for quantitative analysis of images such as PCA, PLSR, stepwise multi-linear regression (SMLR) basically used for chemical

amount measurement [27,63]. PCA and PLSR are displaying technique. Support vector machines (SVM) were used for not destroying food superiority and safety of food product [14,40,64]. A group of scientists experienced radial basis function (RBF) built on least square support vector machines (LS-SVM) [65].

4. Application of Hyperspectral Imaging in Food Analysis

Hyperspectral imaging is mostly suitable for food quality and safety control. Fast and good recognition and observing of food quality and

safety are required for online checking in food industries. Hyperspectral imaging is used as influential instrument for the food safety and controlling of food quality.

Table 1 shows us a summary of research papers printed in hyperspectral recognition of food quality and safety since 2008. In Table 1, reflectance mode and VIS/NIR (400–1,000 nm) region and transmittance mode and NIR (900–1,700 nm) region is used to observe external or internal structures of dissimilar kinds of raw and handled food.

Table 1. Summary of camera type used, product type, analysis type, wavelength region, and modeling algorithm in characteristic papers printed on hyperspectral imaging of food since 2008

Camera	Product	Spectral Coverage (nm)	Analysis Type	Image Processing	Modeling	References
Not-mentioned	Mushroom	450–850	Quantitative	Not-mentioned	MLR, Principal components regression (PCR)	[84]
Not-mentioned	Mushroom	450–950	Qualitative	Interactive selection	PCA	[31]
CCD	Oranges	400–1,100	Qualitative	PCA	PCA, BR, TH	[48]
CCD	Pork	400–1,000	Quantitative	Gabor-filter, TH	PCA, K-means clustering, LDA	[41]
CCD	Pork	400–1,100	Quantitative	Not-mentioned	Least square support vector machines (LS-SVM)	[65]
CCD	Pork	460, 580, 720	Quantitative	Wide line detector	MLR	[53]
CCD	Pork	900–1,700	Qualitative	PCA	PLS	[50]
CCD	Pork	900–1,700	Qualitative	TH	PLSDA	[57]
Not-mentioned	Pork	900–1,700	Qualitative	TH	PCA	[85]

CCD	Pork	900–1,700	Quantitative	TH	PLSR	[86]
CCD	Pickling cucumbers	400–740	Qualitative	TH	PLSDA	[30]
CCD	Pickling cucumbers	450–740	Qualitative	TH	PLSDA	[58]
CCD	Prawn	897–1,753	Quantitative	TH	Information variable elimination	[87]
Not-mentioned	Rice seed cultivar	874–1,734	Qualitative	Not-mentioned	PLSDA, SIMCA	[88]
CCD	Salmon	400–1,100	Qualitative & Quantitative	TH	PCA, K-means clustering, MLR	[89]
CCD	Salmon	964–1,631	Quantitative	Predictive effective wavelengths (PEW)	Multiple linear regression (MLR)	[90]
CCD	Smoked salmon	400–1,000	Qualitative	Quartiles segmentation, TH	PLSDA	[59]

Table 1. Cont.

Camera	Product	Spectral Coverage (nm)	Analysis Type	Image Processing	Modeling	References
CCD	Beef	400–1,000	Quantitative	Co-occurrence matrix analysis, PCA	Canonical discriminant	[44]
CCD	Beef	400–1,100	Quantitative	MLD	Multi-linear regression (MLR)	[70]
CCD	Beef	496–1,036	Quantitative	MLD	SMLR	[71]
CCD	Beef	910–1,700	Quantitative	PCA	PLSR	[72]
CCD	Beef	897–1,752	Quantitative	TH	PLSR	[73]
EMCCD	Blueberry	500–1,000	Quantitative	TH	PLSR	[74]
CCD	Chicken	389–744	Qualitative	TH	BR	[32]
CCD	Chicken breast fillets	910–1,700	Quantitative	TH	PLSR	[75]

CCD	Chicken fillets	930–1,450	Quantitative	TH	PLSR	[76]
CCD	Citrus	400–1,100	Qualitative	Geometric factor correction(GFC)	Digital elevation model (DEM)	[77]
EMCCD	Citrus	450–930	Qualitative	TH	Spectral information divergence (SID) mapping	[61]
CCD	Grape seed	914–1,715	Quantitative	PCA	PLSR	[49]
CCD	Lamb	910–1,700	Qualitative	PCA	PCA	[46]
CCD	Lamb	900–1,700	Quantitative	TH	PLSR	[78]
CCD	Minced lamb	890–1,750	Quantitative	PCA	PLSR, MLR	[38]
CCD	Ham	910–1,710	Qualitative	PCA	PCA	[47]
CCD	Dry-cured ham	760–1,040	Quantitative	Not-mentioned	PLSR	[79]
CCD	Mandarin	320–1,100	Qualitative	GFC	LDA, Classification and regression trees (CART)	[80]
CCD	Mushroom	400–1,000	Quantitative	Not-mentioned	PLSR	[81]
CCD	Mushroom	400–1,000	Quantitative	TH	PCA	[82]
Not-mentioned	Mushroom	400–1,000	Qualitative	TH	PCA	[83]

4.1. Fruit

We have studied Fruits by hyperspectral imaging that include are apple, citrus, pear, peach, oranges, almond nut, blueberry, citrus, grape seed, grape skin, and strawberry. The research is carried in reflectance mode and in the VIS-NIR range (about 400–1,100 nm). Chilling effects, diseases and quality characteristics of fruits comprising of soluble solids amount, mealiness, etc. Also we have research on strawberries and grape seeds in the NIR range (about 900–1,700 nm) [49,100,101]. Soluble solids amount is calculated by hyperspectral imaging of fruits. Mendoza et al. [39] used integrated spectral scattering and image characteristics to gain the knowledge about firmness and soluble solids

content of apples. Leiva-Valenzuela et al. [74] employed VIS/NIR hyperspectral imaging (500–1,000 nm) to acquire the values of soluble solids values in blueberries, gaining accuracy of 0.87 and 0.79.

Huang et al. [68], the mealiness of apple calculated by means of VIS/ NIR hyperspectral imaging. Classification exactness of 82.5% was gained by means of LLE algorithm. Qin et al. [61] measured relation between hyperspectral images and citrus canker, by means of Electron-Multiplying Charge-Coupled-Device (EMCCD). The examination technique was SID constructed grouping. Classification accurateness was 96%. More research should be done at the altering designs of the citrus canker.

Since this research used full spectral information which was not virtuous for online citrus canker recognition. Additional research should think on enlightening the handling speed of the large quantity of hyperspectral information.

4.2. Vegetables

Hyperspectral imaging used on vegetables includes onions, mushrooms, pickling cucumbers and whole pickles, spinach leaves, and tomato. The accepted mode is reflectance mode and some researches are done in transmittance mode and fluorescence modes. Ariana and Lu [93] established a VIS-NIR hyperspectral imaging system. This system used to observe inner deteriorated pickle pieces and categorize pickling cucumbers and pickles by spectral range of 500–1,000 nm. Taghizadeh et al. [81] considered the shelf life (by means of limits comprising weight loss, color, maturity index) of mushrooms in dissimilar packaging polymer films (polyvinyl chloride (PVC), polyethylene terephthalate (PET)). This research established that hyperspectral imaging can calculate shelf life of mushrooms. The PET packaging film punctured with 1mm was a feasible substitute to PVC packaging for getting good quality of mushroom. The PCA technique can be used to acknowledge damages caused by wounds and freezing injury of mushroom. Gaston et al. [82] studied the polyphenol oxidase (PPO) activity on mushroom. PCA method was used for this.

4.3. Meat

The researches of meat and meat products by means of hyperspectral imaging were done on pork, beef, and chicken fillet. Lamb [46] and ham [47,79] were examined too. Liu et al. [41] used Gabor filter for the measurement of patterns by means of hyperspectral images of pork. PCA was applied to compress spectral structures by wavelengths (400–1,000 nm) into principal components (PCs). The statistical cataloguing precision was $84 \pm 1\%$. The research gave us the result that the texture characteristics take out by Gabor filter gave us valuable data. Liu et al. [53] established a wide line detector which is approved in marbling removal. The seven stages of marbling values were categorized with a precision of 99%.

This research acquired the difference between PSE and PFN samples. Huang et al. [99] researched the wide line detector and Gabor filter for NIR spectral image examination of pork marbling. The Gabor filter performed better than the wide line detector for treating of NIR images. Huang et al. [98] used a Gabor filter and GLCM to decide the fat amount in intramuscular in loin cut. The conclusions of correlation coefficients of calculations and cross validation (0.89) were gained for IMF amount of pork applying the Gabor filter. Peng et al. [65,70] calculated the bacterial spoilage in beef and pork by total NIR/VIS reflectance hyperspectral imaging system (400–1,000 nm).

The prediction result (correlation coefficient = 0.95, standard error of prediction (SEP) = 0.30). These two researches established the significance and importance of hyperspectral imaging in activity of microorganisms which are reason of food spoilage. Multi-linear regression (MLR) using SMLR was used to separate fresh beef and unfresh beef and LS-SVM was used to discover pork shelf life in storage. The bacterial amount in beef was 1×10^4 /g. Barbin et al. [85] calculated the classifying of pork by applying near-infrared hyperspectral imaging (900–1,700 nm). Three quality grades (PSE (pale/pinkish-gray, soft and exudative), RFN (reddish-pink, firm and non-exudative) and DFD (dark purplish red, firm and dry)) were calculated as results of pork.

Reflectance differences of 2nd derivative spectra between the pork of three quality grades were observed at wavelengths 960, 1,074, 1,124, 1,147, 1,207 and 1,341 nm. Principal component examination was conducted and the precision was 96%. The outcomes of this research specified that pork classes could be distinguished using NIR hyperspectral imaging. Different types of lamb muscles were imaged and analyzed using PCA in study of Kamruzzaman et al. [46]. The outcomes established the importance of hyperspectral imaging. Successful examples were established for imagining of L^* values (the lightness of the color), pH values, and drip loss in pork, Enterobacteriaceae on chicken fillets, L^* values in lamb, adulteration at different stages in pork. Successful examples were given for picturing of L^* values (the lightness of the color), pH values, and drip loss

in pork, Enterobacteriaceae on chicken fillets, L* values in lamb, adulteration at different levels in pork [38,76,78,86].

4.4. Seafood

The research work on seafood is done in the last years. The samples that includes are fresh and smoked salmon, cod, prawn, and shell-free cooked clams. Seafood is a very impressive region for hyperspectral imaging research. Huang et al. [89] used hyperspectral imaging on salmon's shelf life estimation. PCA based K-means gathering and MLR were used to communicate hyperspectral data to the shelf life and textural differences of salmon. Wu et al. [90] applied hyperspectral imaging to ration the color scattering in salmon gut. Correlation coefficients of 0.876, 0.744, and 0.803 were gotten for L*, a*, and b* (the lightness of the color, the color between red/magenta and green and the color yellow and blue).

Ivorra et al. [59] researched the NIR hyperspectral imaging for finding of expired vacuum-packed smoked salmon. The cataloguing rate of 82.7 was gotten. VIS/NIR hyperspectral images were examined by Wu et al. [87] to notice the gelatin contamination in prawn. A coefficient of determination of 0.965 was gotten and gelatin in prawn was imagined. Coelho et al. [106] applied hyperspectral imaging to notice the parasite in shell-free heated clam *Mulinia edulis*. Transmittance mode was applied. The range of wavelengths was 600–950 nm applied. Decrease in the regularized transmittance of clam's layer designated a parasite. Transmittance modes over 720 nm attained 100% accuracy.

4.5. Grains

Hyperspectral imaging is used for organization of grains that includes maize, wheat, barley, oat and groat, soybean, and rice seed. A Near Infra-Red hyperspectral imaging system (900–1,700 nm) was established to classify pregerminated barley at an initial level to separate the barley seeds into low or high superiority [45]. A little organization mistake of 3% showed feasible for relating the level of pregermination of barley seeds. Williams et al. [36] designated the use of In GaAs and HgCdTe detector-based NIR hyperspectral imaging (960–1662 nm) methods

in separating amongst hard, intermediate and soft maize grains. PCA and multivariate information examination were used to distinguish glassy (hard) and floury (soft) endosperm.

The In GaAs detector-based NIR hyperspectral imaging system gotten coefficient of determination of (84.9%) associating to the HgCdTe detector-based NIR hyperspectral imaging system (76.3%). Serranti et al. established an NIR hyperspectral imaging system (1,006–1,650 nm) organization of oat and groat kernels [51]. The gotten hyperspectral images were examined by applying PCA and PLS-DA. Three basic wavelengths, i.e., 1,132, 1,195 and 1,608 nm, were recognized by applying bootstrap-VI. The good organization outcome (100%) specified importance of hyperspectral imaging on industrial level. NIR hyperspectral image system (960–1,700 nm) was established for difference between wheat groups developed in Canada.

Dissimilar sorting models were applied. Cataloguing precisions of 94%–100%, 86%–100%, and 80%–100% were gotten from LDA, quadratic discriminant analysis (QDA) and ANN prototypes. In the conclusion NIR hyperspectral imaging relating to statistical and ANN models has the possibility to categorize Canadian wheat. Williams et al. [96] established the NIR hyperspectral imaging system (1,000–2,498 nm) to know the fungal adulteration of maize seeds. PLS regression models were recognized. The outcomes showed the likelihood of the initial uncovering of fungal adulteration and action. NIR hyperspectral imaging knowledge is being used to spot spoiled wheat seeds.

A NIR hyperspectral imaging system in wavelengths 1,000–1,600 nm was established for discovery of insect-bitten wheat seeds [103]. LDA and QDA were engaged to categorize fit and insect-bitten wheat seeds. The cataloguing precision was 85%–100%. NIR hyperspectral imaging system (700–1,100 nm) was recognized to distinguish strong and midge-damaged wheat seeds. The cataloguing precision (95.3%–99.3%) designated the possible of NIR hyperspectral imaging for discovery of injured wheat seeds.

5. Discussion and Conclusions

Hyperspectral imaging is emerging as a stage method for food quality and safety examination in food processing and packaging of food. Hyperspectral imaging could get the interior spectral data of samples but also detect three-dimensional signals that tell us about the physical and chemical structures of a huge quantity of food samples and food-contact surface supplies. These signals are deposited in huge data cube. Growing the efficacy of the identification of basic wavelengths should be the important focus of future researches. Developments in the statistics examination would raise the dispensation speed of hyperspectral imaging data that will make hyperspectral imaging appropriate for online uncovering, and providing the base of multiple-spectral system production. The improvement of the sensitivity and pixel determination of camera would increase the calculation precision of hyperspectral imaging. NIR hyperspectral imaging has a huge importance in noticing quality and safety of meat and seafood products. Additional uses of hyperspectral imaging technology in food quality and safety examination during food processing and packaging will be examined. Future research in hyperspectral imaging could focus on problems such as advanced sensitivity cameras, higher determination systems, developments in data processing techniques, growing uncovering precision.

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