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Review

A Short Update on the Advantages, Applications and Limitations of Hyperspectral and Chemical Imaging in Food Authentication

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Abstract: Around the world, the food industry needs to maintain high quality and safety standards in order to satisfy consumers demand for healthy foods and to trace the origin of raw materials and products that are used during food manufacture. These objectives can be achieved by applying analytical methods and techniques that are able to provide information about composition, structure, physicochemical properties, and sensory characteristics of foods. Modern techniques and methods based on spectroscopy (near infrared (NIR), mid infrared (MIR), Raman) are highly desirable due to their low cost and easy to implement, and often requiring minimal sample preparation. This paper reviews some of the advantages and recent applications of hyperspectral and chemical imaging to discriminate and authenticate foods.

Keywords: food; hyperspectral; infrared; authentication; origin

1. Introduction

Worldwide, increasingly significant public concerns about sub-quality foods being linked to increased morbidity, mortality, human suffering, and economic burden have been the drivers towards industry compliance for ensuring both high food quality and requisite safety standards [1]. Through the use of analytical procedures and the analysis of the resulting data, relevant information about food composition [2], its chemical composition and structure [3], physicochemical properties [4], and sensory characteristics [5] can be obtained. Due to the dynamism of a modern food industry and increasing consumer self-awareness, even established analytical techniques are constantly challenged. These are often aligned to expectations of low-cost analysis requiring low to nil sample preparation and environmentally-sustainable methods for assessment and quality monitoring. These attributes critically important and form essential attributes of modern production facilities [6] and an evolving and modern food industry also requires efficient and non-invasive technologies that are able to provide information about food quality [7,8]. Different technologies can offer the food industry with these advantages, where molecular spectroscopy, for example near and mid infrared (NIR and MIR) are the most attractive due to their inherent characteristics (e.g., speed, low cost) [9–11]. Spectroscopy applications that are detailed in the literature by researchers in the field have been primarily rely on spot measurements using either the NIR or visible (Vis) regions of the electromagnetic spectrum. More recently, a diverse range of hyperspectral devices, including cameras and spectral imaging devices, are now readily available providing exciting new possibilities in food analysis and processing. This technology can acquire either single or multiple images at discrete wavelengths, presenting the potential for the detection of specific attributes relating to quality in an extensive range of raw materials and products using in the manufacture of foods [1–8]. Overall, the availability of hyperspectral (HSI) and multispectral imaging (MSI) systems allowed for obtaining spatial, spectral, and multi-constituent information about the sample being analysed [1–8].

For example, for decades, fruit assessment without off-line interruption and sample destruction was a challenge for producers, researchers and food safety agencies [1–8]. Efforts have therefore been exerted towards the introduction and advancements of innovative imaging technologies for fast, non-invasive, and non-destructive monitoring of ripening and maturity stages of fresh produce in the farm and packing shed [1–8]. In the last decade, vibrational spectroscopy, hyperspectral/multispectral imaging, and biomimetic sensors have started to feature with increasing prominence as rapid and efficient methods for the assessment of food quality, safety, and authentication [1–8]. Moreover, these methods present useful alternatives to traditional expensive and time-consuming techniques, such as those on a microbiological platform.

Spectral imaging can be classified as either hyperspectral (HSI) or multispectral imaging (MSI) [1–8]. Multispectral imaging involves the acquisition of spectral images at few discrete and narrow wavebands (bandwidths of between 5 and 50 nm) and it is considered to be an improvement of hyperspectral imaging as this technology is cost effective [1–8]. The result is the ability of MSI to simultaneously predict multiple components, providing a key advantage and rendering a promising future outlook with a single, automated image acquisition [1–8]. Hyperspectral imaging relies on one of two sensing modes as in-line scanning (push broom) mode or as filter-based imaging mode [1–8]. In-line scanning mode involves the imaging system scanning moving product items. This results in three-dimensional (3D) hyperspectral images, also called hypercubes [1–8]. In filter-based imaging mode, spectral images are obtained from stationary targets for a waveband sequence using either a liquid crystal tuneable filter (LCTF) or an acousto-optical tunable filter (AOTF) [1–8]. In-line scanning is the most common as it is relatively easy to implement, particularly for real-time and online applications. In comparison, filter-based HSI systems are not suitable for online applications and they require more complicated calibrations [1–8].

Hyperspectral imaging methods require a high performance digital camera that has the ability to cover the spectral region of interest, in a wide dynamic range with high signal-to-noise-ratio, and good quantum efficiency [1–8]. An imaging spectrograph, with the ability to disperse the line images into different wavelengths is essential [1–8]. Optical resolution and spectral response efficiency with minimal aberrations are also key features of a HSI system. Finally, a highly stable, DC-regulated light source with a smooth spectral response is critical [1–8].

Hyperspectral imaging is particularly attractive for food applications because of the integration of imaging ability with spectroscopy, which enables the simultaneous acquisition of both spectral and spatial information from the target. The gains achieved by this amalgamation can allow for the monitoring of highly spatially variable raw and food products [1–8]. However, this technology is not widely used by the food industry, with key considerations to user uptake depending on several reasons that include cost and instrument availability, whether the application is online or in-field and training of staff [1–8]. This paper reviews some of the advantages and the recent applications hyperspectral and chemical imaging to discriminate and authenticate foods.

2. Recent Application of Hyperspectral in Food Authentication

2.1. Animal Proteins (Meat and Meat Products)

In order to gain consumer faith in the food industry, it is essential that the accurate labelling of meat products be consistently ensured [9]. Verification of correct meat labelling is a critical aspect of good industry practice and important to producers, retailers, and consumers [9]. The distinction between fresh, and frozen and thawed, and matured, and matured frozen-thawed beef meat samples using hyperspectral imaging (500–1100 nm) and CIELAB measurements was reported [9]. According to the authors, they were successfully able to distinguish beef into fresh and frozen-thawed and fresh and matured samples based upon CIELAB between beef met samples. However, superior classification rates were reported using HSI [9].

It is well known that the NIR spectra contain abundant data and heterospectral two-dimensional correlation (H2D-CS) analysis can be considered as a new tool to interpret these kinds of data [10]. The use of H2D-CS was reported to correlate the NIR HSI data with MIR spectra in order to select wavebands for developing screening models to monitor the oxidative damage of pork myofibrils during storage by freezing [10]. The HSI images were acquired at frozen state without thawing and the oxidative damage of myofibrils and calibration models that were developed on a partial least squares (PLS) regression platform [10]. The authors indicated that the PLS models based on H2D-CS identified specific wavebands to predict oxidative damage (coefficient of regression (R^2) of 0.896 and root mean square error in prediction (RMSEP) of 0.177 nmol/mg protein) [10]. NIR HSI has also been used to discriminate between pork, poultry, and fish species in processed animal protein meals [11]. The results showed combining spectral and appearance characteristics in a single classification tree presented better classification results for the samples that were used in the study (92% correct classification) than when using the PLS discriminant analysis (DA) spectral model (83% correct) [11].

A challenge with hyperspectral applications can be the voluminous numerical data associated with the approach. This can be overcome by analysing the outputs using new statistical approaches, such as machine-learning algorithms [12]. It is difficult to identify an optimum pattern recognition or suitable machine learning approach for a given analytical platform, as it involves a comparative analysis of various algorithms for the most accurate predictions [12]. Recently, a web-based application to automate the procedure of identifying the best machine learning method for comparing data from several analytical techniques was reported. It was able to predict the counts of microorganisms that were responsible of meat spoilage independently of the packaging [12]. The authors evaluated up to seven regression methods including least squares (LS) regression, stepwise linear regression (STR), PLS regression, principal component regression (PCR), support vector regression, random forest, and K-nearest neighbours [12]. The application is called "*MeatReg*" and tested minced samples of beef that were stored under aerobic and modified atmosphere packaging [12]. The authors put forward recommendations on suitable analytical platforms that were able to predict each type of bacteria and which machine learning methods to use in each case [12].

Hyperspectral image was used to discriminate between Chinese sausages from different commercial standards (e.g., top-class, first-class, and second-class) [13]. The NIR hyperspectral band information of sausage applied the successive projection algorithm (SPA) to extract the characteristic bands, and then respectively established grading model of PLS regression and SPA-MLR (characteristic band). The decision coefficient of the SPA-MLR model that is based on NIR was 0.93, and the correct rate of classification was 100% [13]. The results showed that information derived from the NIR HSI system could be used for rapid and non-intrusive analysis of sausage samples from China [13].

2.2. Cereals

When considering food security in the cereal industry, it is necessary to use reliable and efficient methods to ensure the authenticity and the origin of raw materials and foods [14]. Hyperspectral imaging was explored (900–1700 nm) in order to identify and quantify the levels of adulteration in Irish organic wheat flour (OWF) with other commercial flours, such as wheat (WF), cassava, (CaF) and corn (CoF) [14]. Second derivative (2nd Der) and standard normal variate (SNV) were used to pre-process the acquired spectra before modelling, where PLS regression and PCR were used for quantitative analysis of the levels of adulteration or contamination [14]. The authors of this study indicated that the best results were obtained by the use of pre-processing methods, such as first-derivative and mean centering iteration algorithm [14]. The R^2 and RMSEP for the prediction of OWF adulterated with CoF, CaF, and WF were 0.97 (0.03), 0.98 (0.026) and 0.97 (0.038), respectively [14]. These results indicated that HSI integrated with multivariate analysis has the potential to authenticate the admixtures in specific wheat flour in the range of 3–75% (*w*/*w*) [14].

Hyperspectral imaging has also been evaluated for the prediction of the origin of rice [15]. The authors of this study analysed rice samples (n = 240) from four geographic regions in China using a HSI system [15]. The highest accuracy in terms of classification (>91%) was reported using a combination of spectral, morphological, and texture properties that were measured using instrumental methods [15]. The study demonstrated the suitability of HSI as a tool to rapidly identify the origin of rice from four Chinese regions [15].

2.3. Fruits and Vegetables

The use of HSI analysis has been expanded to the analysis of fruits and horticultural products [16–20]. To increase the classification accuracy and the stability of the prediction model, an approach to evaluate the quality of samples' HSI is needed, accordingly to these authors [16–20]. The spectral correlation analysis of each pixel is used to determine the quality of the samples analysed using the hyperspectral image system [16]. For example, apple samples (n = 400) (waxed and non-waxed) were analysed using hyperspectral images where LS—support vector machine (LS-SVM) model was applied to establish the classification model between the hyperspectral image and the fruit treatment (waxed vs non-waxed) [16]. The prediction result showed that the classification accuracy rates were 94% and 86% when the low-quality sample data for training were filtered by spectral correlation analysis [16]. By evaluating the quality of the hyperspectral images measured, more reliable prediction results can be obtained, which can make the non-invasive discrimination of foods according to quality and safety come to the practice application sooner [16].

The texture of the grain/seeds is a major quality parameter for the acceptability of canned whole beans [17]. Prior knowledge of this quality trait before processing would be useful to guide variety development by bean breeders and to optimize handling protocols by processors [17]. The use of HSI was used to predict texture of canned black beans from intact dry seeds [17]. Spectral pre-processing methods (i.e., smoothing, first and second derivatives, continuous wavelet transform, and two-band ratios) were used to optimize the prediction accuracy of the PLS models developed [17]. The authors showed the great potential that hyperspectral imaging has for predicting the texture of canned beans [17]. In addition, the robustness of the models was influenced by variety, planting year, and phenotypic variability [17]. The authors stated that for canned bean texture robust models can be built based on data sets with high phenotypic diversity in textural properties, and periodically maintained and updated with new data [17].

2.4. Honey and Honey Products

Recent applications of HSI have focussed on the analysis of honey and honey products in order to trace their origin. A recent paper reported the ability of HSI imaging (NIR and Vis) to detect and trace the origin of honey samples [21]. In this study, the authors analysed several honey samples (n = 52) using a HSI system and the data analysed by applying three different machine learning algorithms [21]. The machine learning algorithms that were tested by the authors were radial basis function (RBF) network, support vector machine (SVM), and random forest (RF) [21]. Before analysis, the dimensionality of the data set was simplified be means of principal component analysis (PCA) [21]. The best results that are reported by these authors were obtained when RBF was used to classify the honey samples (94% correct classification), according to origin [21]. The authors also reported that three types of honey (buckwheat, rapeseed, and heather floral origin) were correctly classified (100% accuracy) [21]. It was concluded that the proposed approach based on HSI has a great potential for the classification of honey samples according to their floral origin [21]. The authors also highlighted that other honey properties aside from its floral origin can be predicted with this method [21].

2.5. Milk and Milk Products

Milk and milk products have been also evaluated and analysed using a combination of HSI and MSI. A recent report on the use of HSI to monitor contamination in cheese is described here. The use of HSI (200–1000 nm) to determine starch content as an adulterant of fresh cheese was reported [22]. The adulterated fresh cheese was prepared using varied concentrations of starch of 0.055–12.705 mg g $^{-1}$ (0.0055–1.2705%) and PLS regression was used to develop the models [22]. A R^2 of 0.9915 and a root mean square error of cross-validation (RMSECV) of 0.3979 was reported by the authors of this study [22].

Although NIR HSI has not been extensively implemented in industry, it shows great potential for the development of an evaluation system to assess cereal grains, especially regarding variety discrimination and grading/classification properties [23–26].

3. Advantages and Limitations

Hyperspectral (HIS) and multispectral imaging (MSI) are becoming more attractive for the analysis of several raw materials and foods. The main advantages of these techniques are related with the possibility of acquiring either single or multiple images as needed, at selected wavelengths in the NIR, MIR, and Vis range, providing with the ability to detect individual traits or properties directly associated with quality, in an extensive range of raw materials and products used in the manufacturing of foods. However, the potential of these techniques to obtain spatial, spectral, and multi-constituent information about the sample being analysed is the most attractive advantages in food analysis. Apart from infrared (IR), other vibrational spectroscopy technologies have been reported as fingerprinting techniques and they have been used to analyse several agricultural products and foods. In recent years, such methods have been prominently re-introduced by several researchers in several applications (feasibility studies) or real world applications. The main advantages that these techniques that are present over the traditional chemical and chromatographic methods are the timeliness and the simplicity of use in routine operations. However, several limitations still exist in the use of these technologies. Issues that are related with the availability of commercial and robust instrumentation, the large amount of data generated during the analysis, the need to complex data analysis and algorithms, the small number of samples in most of the applications reported in the literature are still a drawback on the use of this technology in the food industry. However, the lack of academic training is still a barrier for the worldwide application of these technologies in research and by the industry. Table 1 summarises the advantages and limitation of HSI and MSI.

Table 1. Summary of the advantages and limitations of hyperspectral and multispectral imagine systems for the analysis of foods.

Issue or Topic	Advantages	Limitations
Measurement	Single or multiple images Spatial, spectral, and multi-constituent	-
Hardware	-	Cost of instrument Availability of easy to use instruments/routine
Software	Different algorithms available	Issues related to handling large amounts of data
Data	-	Issues related to handling large amounts of data
Training	-	No generally available for the industry
Application	Traceability, origin, on-line and in-line, chemical and physical properties	-

4. Conclusions

When combined with the multivariate data analysis, the application of NIR and MIR spectroscopy finds extensive use in the food industry to assess chemical composition in many raw materials and foods (e.g., protein, moisture, oil). In recent years, the most important development of these technologies has been as tools or methods for authenticity, discrimination, or traceability of foods.

Integrating these technologies with either hyperspectral or multispectral image analyse shows considerable potential for the efficient and reliable monitoring and control of important steps in the food process. These techniques will add to our set of tools to improve our understanding about the chemistry and biochemical characteristics that are associated with raw material origin, to ensure sustainable food production as well as to assure the consumers of the origin of the food that they consume.

From the literature published in the last 10 years, the strong development of HSI and MSI applications in the food industry steadily emerges with considerably wider applications in the future.

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