Oct 26th, 11:00 AM - 12:30 PM

Hyperspectral imaging logics: efficient strategies for agri-food products quality control

Giuseppe Bonifazi
Sapienza University of Rome, giuseppe.bonifazi@uniromal.it

Riccardo Gasbarrone
Sapienza University of Rome

Silvia Serranti
Sapienza University of Rome

Hyperspectral imaging logics: efficient strategies for agrifood products quality control

Giuseppe Bonifazi[1,2], Riccardo Gasbarrone[1], Silvia Serranti[1,2]
[1] Department of Chemical Engineering Materials Environment, Sapienza University of Rome, Italy
[2] Research Center for Biophotonics, Sapienza University of Rome, Polo Pontino, Italy
{giuseppe.bonifazi, riccardo.gasbarrone silvia.serranti}@uniroma1.it

Abstract. The increasingly normative severity and market competitiveness have led the agriculture sector and the food industry to constantly look for logic improvements that can be applied in processes monitoring systems. In a context where fast, non-destructive and reliable techniques are required, image analysis-based methods have gained interest, thanks to their ability to spatially characterize heterogeneous samples. The utilization of the HSI approach opens new interesting scenario to quality control logics in agricultural and food processing/manufacturing sectors. Two different case studies are presented in this paper. An HSI system, working in SWIR range (1000-2500 nm), was applied to: i) detect contaminants in dried fruits to be packaged and ii) identify olive fruits attacked by olive fruit flies. The proposed case studies demonstrate that this logic can be successfully utilized as a quality control system on agrifood products coming from different manufacturing stages, but it can even be seen as an analytical core for sorting engines.

Keywords: Near Infrared Spectroscopy, agriculture, food, quality control.

1 Introduction

One of the most challenging aspect in agriculture and food manufacturing sectors is rooted to the necessity of solving quality control issues (i.e. particle detection and contaminant recognition). Product quality plays a key role, in a progressively demanding market where quality standards and products certification have an important role for ensuring a quality product to the consumers. In this scenario, the development and deployment of an effective, fast and robust sensing architecture capable to detect, characterize and sort agrifood products is of primary importance. The utilization of HyperSpectral Imaging (HSI) techniques represents an interesting solution to address quality control issues in agrifood industry from on-farm scenarios to manufacturing stages. Near InfraRed (NIR) based Hyperspectral imaging techniques are utilized to perform both qualitative and quantitative analysis for different purposes in agricultural and food industry [1-4]. To give some examples HIS was successfully utilized to perform ripening evaluation of kiwifruits and olive fruits.

In this paper, three case studies of Short-Wave InfraRed (SWIR)-based HSI approach applied to agri-food products are presented. In the proposed approach, aimed to define quality control logics, a Partial Least Squares – Discriminant Analysis (PLS-DA) classifier was adopted to identify products and/or recognize contaminants occurring into the analyzed samples. In particular, the analyzed materials in the three case studies consist of: i) detecting contaminants in dried fruits to be packaged, ii) identifying olive fruits attacked by olive fruit flies and iii) recognizing flour type for combat counterfeiting. To reach these goals, hyperspectral images, in the spectral range spanning from 1000 nm to 2500 nm, were acquired. Background removal was performed for each of the collected hyperspectral images. Spectra pre-processing algorithms were applied to the stored hyperspectral images for removing occurring sources of noise and/or attenuate un-wanted scattering or other physical phenomena. An exploratory analysis was carried out by means of Principal Component Analysis (PCA) in order to clean training dataset from outliers. Finally, classification models were trained and applied to test sets.

2. HyperSpectral Imaging

HyperSpectral Imaging (HSI), known also as chemical imaging, is an emerging technique combining digital imaging with conventional spectroscopy, enabling the simultaneous collections of spatial and spectral information of the sample [5, 6]. This information is enclosed in a 3D dataset, the hyperspectral image or the so-called “hypercube”, in which two dimensions (x, y) are spatial and the other one gives spectral information (λ). A hypercube not only contains morphological attributes of the investigated sample, but also its physical and chemical characteristics. A reflectance spectrum can be obtained for each pixel. Thus, according to the different investigated wavelengths, each pixel gives information about sample physical-chemical attributes.

2.1 Hyperspectral Imaging system and data collection

Hyperspectral data have been acquired at the Raw Materials Laboratory (Rome, Italy) of the Department of Chemical Engineering, Materials and Environment (Sapienza - University of Rome, Italy). Samples were scanned using the SisuCHEMA XL™ Chemical Imaging workstation, consisting of a hyperspectral camera working in NIR region (1000 - 2500 nm) with a spectral resolution of 10 nm, and a computer-controlled hyperspectral scanner stage with sample and camera heights adjustment. Calibration was performed by firstly acquiring a dark image (D) and measuring the "white reference image" (W) on a ceramic standard (with nominal reflectance at 99%). Acquisitions were performed setting a frame rate equal to 100 fps. The field of view used is 100 mm - 31 mm lens. The scanning speed of the stage was set equal to 31 mm/s. ChemaDAQ™ data collection software was used to perform the calibration procedure and data collection. PLS_Toolbox (Version 8.7, Eigenvector Research, Inc.) and MIA_toolbox running in MATLAB® (Version R2019a, The Mathworks, Inc.) environment have been adopted to handle and analyze hypercubes.

2.2 Chemometric analysis and Partial Least Squares – Discriminant Analysis set-up

Prior of classification set-up, hyperspectral images were firstly pre-processed by background removal. Depending on the case, a combination of pre-processing algorithms was chosen to attenuate un-wanted occurring sources of noise, enhancing spectral differences among samples [7, 8]. The Principal Component Analysis (PCA) method was used as an exploratory analysis tool [9]. Occurring outlier were thus successfully identified and removed from training sets used to calibrate classification models. In each case study, the adopted classification model is the Partial Least Squares-Discriminant Analysis (PLS-DA). PLS-DA is a supervised technique for pattern recognition, that can predict the class of each sample under study [10, 11]. PLS-DA model were calibrated with pre-processed spectra extracted from Region of Interests (ROIs) depicting known samples, cross-validated and validated on a test set. The procedure followed for each case study is schematically depicted in Figure 1.

The performance metrics used to evaluate the efficiency of the classifiers in prediction are the parameters commonly calculated from the confusion matrix [12]: sensitivity, specificity, precision and accuracy.

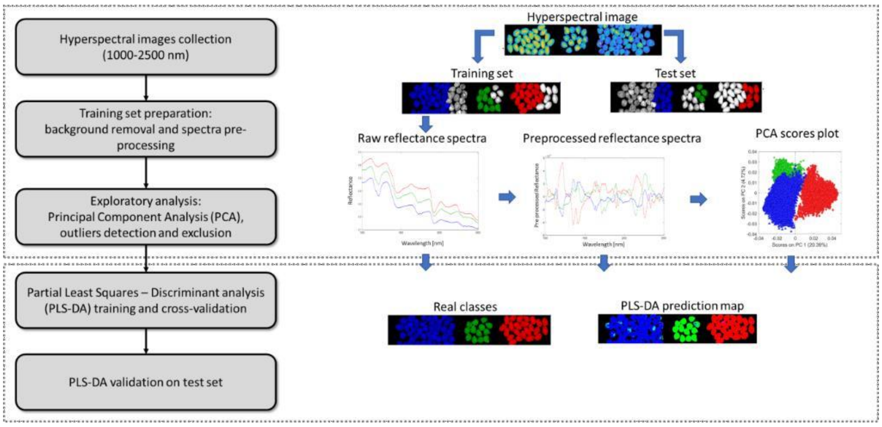
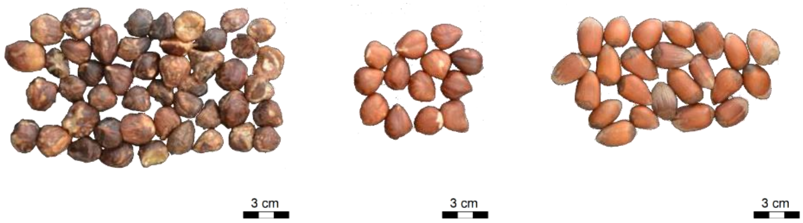


Fig. 1. Schematic drawing of the set-up procedure applied for each case study.

3. Case studies

3.1 Detecting contaminants in dried fruits

Issues and state of the art. Hazelnut dried fruits due to their organoleptic characteristics, constitute one of the most important raw materials for the pastry and chocolate industry. One of the main problems in this sector is the sorting of the hazelnuts according to its characteristics and the detection of possible contaminants (i.e. presence of unwanted foreign matter and/or rotten/rancid hazelnut). The utilization of HSI represent a novelty in quality control application for dried fruits. Since HSI is a technique that enable material surfaces investigation according to its chemical and physical attributes, in the last years it has been successfully applied to dried fruits quality control and sorting [13, 14].



a b c

Fig. 2. Rotten unshelled hazelnuts (a), good unshelled hazelnuts (b) and shelled hazelnuts.

Analyzed materials and procedure set-up. Rotten and good unshelled hazelnuts and shelled hazelnuts, as shown in Figure 2 have been analysed. Classification model was trained by using ROIs (about 70% of the particles) on collected hyperspectral image (Figure 3a) to define the classes (Figure 3b): i) rotten unshelled, ii) good unshelled and iii) shelled hazelnuts. PLS-DA was validated on test set (about 30 % of the particles). The followed procedure is depicted in Figure 1. A multivariate preprocessing was applied: Generalize Least Squares - Weighting (GLSW) followed by Mean Centering (MC) [7, 8].

Results. It can be seen from the prediction map (Figure 3c) and the classification performance metrics in prediction for three classes of hazelnuts, reported in Table 1, as the validated classification model is able to correctly assign each class.

3.2 Detecting olive fruits attacked by olive fruit flies

Issues and state of the art. The evaluation of the presence or absence of olive fruit fly (Bactrocera oleae) in olive fruits can be considered one of the crucial aspects in olive quality control and production.

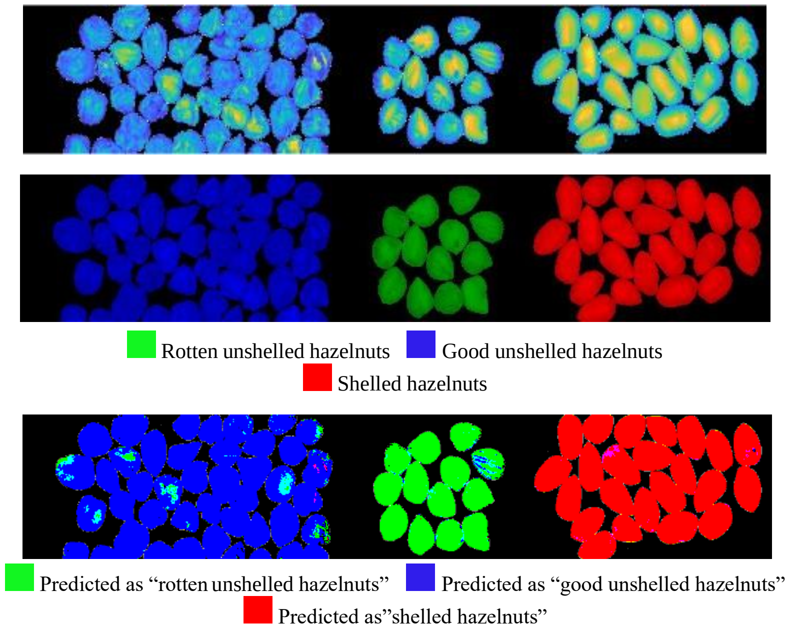


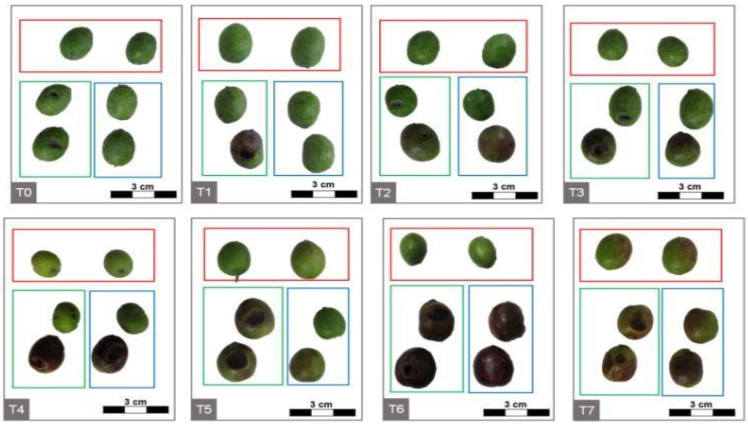
Fig. 3. Hyperspectral image of the hazelnuts samples with removed background (a), real classes (b) and prediction map resulting from PLS-DA classification (c).

Table 1. Classification performance metrics in prediction for three classes of hazelnuts.

Classes	Sensitivity	Specificity	Precision	Accuracy
Shelled hazelnuts	0.999	0.998	0.998	0.999
Rotten unshelled hazelnuts	0.930	0.975	0.968	0.987
Good unshelled hazelnuts	0.956	0.977	0.967	0.986

Aim of this study was to analyze the olive fruit fly maggot presence in the olive fruit both at the early and during the ripening stages. When an olive fruit is attacked by the olive fruit fly, larvae tends to proliferate inside olive fruit and then affecting the taste and pictorial attributes. The final product has to be a quality product, that would go on consumer table. To set up and utilize more and more reliable method to recognize olive fruit fly maggot, at its early stage of incubation in olive fruits, is thus one of the most important goal in this sector.

Analyzed materials and procedure set-up. Analyzed olive fruits (Figure 4) provenience is Sermoneta, a town located in Lazio, an Italian region. The harvesting process for collecting samples were regularly repeated once a week (from T0-first week to T7-eighth week). Each time, olive fruits attacked by olive fruits fly maggots or bruised olive fruits were selected and analyzed. In this case,



____Un-attacked olive fruits (side A and side B) ____Attacked olive fruits (side A)
____Attacked olive fruits (side B)

Fig. 4. Analyzed olive fruits attacked and un-attacked by olive fruit flies, for different times of harvesting. Side A is the side of the olive characterized by the presence of bruise or clearly showing deterioration signs. Side B is the opposite side, not showing evidence of the "fly attack". The first olive reported in the upper part of each olive data set was assumed as reference for the same set not being characterized by any sign of deterioration or larvae presence.

the classification model was trained by using ROIs on collected hyperspectral image (Figure 5a) in order to recognize olive fruits attacked and un-attacked by olive fruit flies.

The model was calibrated by using hyperspectral images acquired on two side of each olive fruit: side A and side B (as shown in Figure 5b). Side A is the side of the olive characterized by the presence of bruise or clearly showing deterioration signs. Side B is the opposite side, not showing evidence of the "fly attack". In this case, the preprocessing used is the multivariate filter GLSW [7, 8]. The followed procedure is based on the steps depicted in Figure 1.

Results. The prediction map resulting from the PLS-DA is shown In Figure 5c. As can be seen from the prediction map and the classification performance metrics in prediction for two classes of olive fruits, reported in Table 2, while validating the classification model some pixels misclassifications occur. Misclassification located mainly on particles boundaries is probably due to curved particle surface.

4. Conclusions

The potentialities offered by HSI system to perform the characterization, the inspection and the quality control of agri-products were investigated. The developed procedure can be seen as an analytical tool to be customized for on-line applications and to develop on-line strategies to perform a continuous monitoring of a particle flow stream, related to food manufacturing of different origin, composition and characteristics. Results (i.e. contaminants detection in dried fruits to be packed and olive fruits attacked by insects/mites) demonstrated as the proposed HSI approach can be successfully utilized. More specifically it can be applied i) to perform a continuous monitor process of the different agri-food products streams before and/or after handling or manufacturing actions, ii) to define innovative logics and procedures for quality certification and iii) specify actions to combat food counterfeiting. This approach opens new scenarios in the field of agrifood manufacturing, such as: i) the possibility of development a system able to recognize particles/products and/or contaminants, in order to be used not only as a sorting engine, but also as an analytical core to perform a quality control at different manufacturing stages and ii) the chance of ensuring a reliable production in both quality and quantity terms.

References

1. Ji Ma, Da-Wen Sun, Jia-Huan Qu, Dan Liu, Hongbin Pu, Wen-Hong Gao and Xin-An Zeng (2016), Applications of Computer Vision for Assessing Quality of Agri-food Products: A Review of Recent Research Advances, Critical Reviews in Food Science and Nutrition, 56:1, 113-127, DOI: 10.1080/10408398.2013.873885.
2. Tsuchikawa, S. and Kobori, H., A review of recent application of near infrared spectroscopy to wood science and technology, J Wood Sci, 61, 213–220 (2015).
3. S. Serranti, G. Bonifazi, R. Gasbarrone (2018), Kiwifruits ripening assessment by portable hyperspectral devices, Proc. SPIE 10665, Sensing for Agriculture and Food Quality and Safety X, 106650S; doi: 10.1117/12.2297353; https://doi.org/10.1117/12.2297353
4. S. Serranti, G. Bonifazi, R. Gasbarrone (2018), "Olive fruit ripening evaluation and quality assessment by hyperspectral sensing devices", Proc. SPIE 10665, Sensing for Agriculture and Food Quality and Safety X, 106650R; doi: 10.1117/12.2297352; https://doi.org/10.1117/12.2297352
5. Hyvarinen, T., Herrala, E. and Dall'Ava A. (1988). Direct sight imaging spectrograph: a unique add-on component brings spectral imaging to industrial applications. Proceedings of SPIE 3302.
6. Geladi, P., Grahn, H. and Burger, J. (2007). Multivariate images, hyperspectral imaging: background and equipment. In: (Grahn, H. and Geladi, P. Eds.) Techniques and Applications of Hyperspectral Image Analysis John Wiley & Sons, West Sussex, England, pp. 1-15.
7. Rinnan, Å., van den Berg, F. and Engelsen, S.B. (2009), Review of the most common pre-processing techniques for near infrared spectra, Trends in Analytical Chemestry, 28, 10.
8. Wise B. M., Gallagher N. B., Bro R., Shaver J. M., Windig W. and Koch R. S. (2006), Chemometrics Tutorial for PLS_Toolbox and Solo. Eigenvector Research, Inc.
9. Wold S., Esbensen K. and Geladi P. (1987). Principal Component Analysis. Chemometrics and Intelligent Laboratory Systems, 2, 37-52.
10. Barker, M., and Rayens, W. (2003). Partial least squares for discrimination. Journal of Chemometrics, 17, 166-173. DOI: 10.1002/cem.785.

11. Ballabio, D. and Consonni V. (2013). Classification tools in chemistry. Part 1: linear models. PLS-DA, Analytical Methods, 5, 3790.
12. Fawcett, T. (2006), An introduction to ROC analysis, Pattern Recognition Letters, 27 (8), 861-874.
13. Serranti, S., Gargiulo, A. and Bonifazi, G. (2012), Dried fruits quality assessment by hyperspectral imaging", Proc. SPIE 8369, Sensing for Agriculture and Food Quality and Safety IV,; https://doi.org/10.1117/12.918561
14. Moscetti, R., Saeys, W., Keresztes, J., Goodarzi, M., Cecchini, M., Monarca, D. and Massantini, R. (2015), Hazelnut Quality Sorting Using High Dynamic Range Short-Wave Infrared Hyperspectral Imaging. Food and Bioprocess Technology. Article in Press. 10.1007/s11947-015-1503-2.