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Near InfraRed-based hyperspectral imaging approach for secondary raw materials processing in solid waste sector

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Abstract. In secondary raw materials and industrial recycling sectors there is the need of solving quality control issues. The development and deployment of an effective, fast and robust sensing architecture able to detect, characterize and sort solid waste products is of primary importance. Near InfraRed (NIR) based HyperSpectral Imaging (HSI) techniques to detect materials to recycle and/or solid waste products to process represents an interesting solution to address quality control issues in these sectors. In this paper, are presented two different case studies on the utilization of NIR-HSI to detect contaminants in household plastic packaging waste and recognize materials occurring in processed monitors and flat screen waste. The proposed approach consists of a cascade detection based on Partial Least Squares – Discriminant Analysis (PLS-DA) classifiers applied on hyprspectral images acquired in NIR range (1000-1700 nm).

Keywords: Near Infrared Spectroscopy, raw materials, quality control.

Introduction

One of the most challenging aspect in secondary raw materials and industrial recycling sectors is represented by the need of solving quality control issues (i.e. material and/or 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. The need of achieving high performance in terms of material identification is linked to the necessity of obtaining high-quality secondary materials [1]. Generally, waste chemical composition and physical properties of the materials define the recycling options. Therefore, the importance of characterization is linked to the possibility to design processing actions addressed to perform a secondary raw materials recovery and reuse for various industrial applications. Thus, the implementation of the material valorization chain and the optimization of the material processing phases is so far a technological challenge that starts through an in-depth characterization of the waste stream. In this scenario, the development and deployment of an effective, fast and robust sensing architecture capable to detect, characterize and sort solid waste products is of primary importance [2]. The utilization of HyperSpectral Imaging (HSI) techniques for detecting both materials to recycle and/or products of solid waste processing represents an interesting solution to address quality control issues in solid waste processing and secondary raw materials sector.

In this paper, two case studies of a Near InfraRed (NIR)-based HSI approach applied to solid waste are presented. In the proposed approach, aimed to define quality control/sorting logics in a recycling scenario, a cascade detection logic based on Partial Least Squares – Discriminant Analysis (PLS-DA) classifiers was adopted to identify materials and/or components occurring into the analyzed samples. In particular, the analyzed materials consist of: i) plastic packaging waste from household collection and ii) milled processed products of End-of-Life (EoL) flat monitors coming from a Waste of Electrical and Electronic Equipment (WEEE) stream. Both those two categories of products are very heterogenous. Plastic packaging waste from household collection may contains not only polymer-based fragments, but even contaminants: i.e. cellulose-based fragments and multi-layered laminated materials (cellulose or polymer based). WEEE represents an extremely heterogeneous category of waste, that may contain a significant amount of valuable materials that could be profitably recovered: i.e. metals and/or alloys, precious metals, high-quality plastics and other compounds.

HyperSpectral Imaging

HyperSpectral Imaging (HSI), known also as chemical imaging, is an emerging technique that combines digital imaging with conventional spectroscopy, enabling the simultaneously collections of spatial and spectral information of the sample under study [3, 4]. Those information are 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, that can be analyzed according to the investigated wavelengths of the adopted device. A full spectrum is thus obtained for each pixel and, according to the different investigated wavelengths, each pixel gives information about several sample physical-chemical characteristics. In the last years, HSI has rapidly fast-grown in many sectors, including the solid waste sector. Different HSI-based approaches are proposed for plastic recycling [5, 6], construction and demolition waste recycling [7, 8] and WEEE recycling [9, 10].

Hyperspectral Imaging system and calibration procedure

Hyperspectral data were acquired at the Raw Materials Laboratory (Latina, Italy) of the Department of Chemical Engineering, Materials and Environment (Sapienza - University of Rome, Italy). A Spectral Camera™, equipped with the ImSpectorTM N17E (SPECIM Ltd, Finland) spectrograph, working in the near infrared wavelength range (1000 - 1700 nm), was used to collect hyperspectral images. The detection architecture is based on a pushbroom acquisition platform. Calibration was performed acquiring a dark image (D) and measuring the "white reference image" (W) on a ceramic standard (nominal reflectance at 99%).
The Spectral Scanner (Ver. 1.2) software was used to perform calibration and hyperspectral data acquisition. PLS_Toolbox (Version 8.7, Eigenvector Research, Inc.) and MIA_toolbox running in MATLAB® (Version R2019a, The Mathworks, Inc.) environment were adopted to handle and analyze hypercubes.

Cascade detection logic

A cascade detection approach can be adopted to simulate a sorting processing core, in order to identify materials occurring in samples under study. In each step, of the cascade detection procedure, one or more classifier can be utilized. When the classifier identifies a material or an object, the material can be excluded or classified in a subclass by another classification model. The adopted logic is based on Partial Least Squares-Discriminant Analysis (PLS-DA) classification models. PLS-DA is a supervised pattern recognition technique [11, 12]. PLS-DA model are calibrated with pre-processed spectra extracted from Region of Interests (ROIs) depicting known samples, cross-validated and validated on a test set.

Case studies

Material cascade identification applied on plastic packaging for contaminant detection

Issues and state of the art. Post-consumer plastic packaging waste is one of the primary sources to recover polymers [6]. Thier recycling involves different activities [13]. The complexity of the processing is linked to the heterogeneity of this waste stream from separate collection. Heterogeneity is due to the presence of contaminants and cellulose fragments, and secondary to the presence of multi-layer materials. Those materials are difficult to separate using classical methods (i.e. gravimetric separation), due to similar physical characteristics, and sometimes end up in the plastic outlet of the sorting line. Waste materials recognition can be obtained through their surface spectral response. The response, in terms of reflectance spectra of the investigated material surface properties, provides useful information about the physico-chemical state of the analyzed sample.

Fig. 1. Digital image of post-consumer household plastic packaging fragments.

Those physical-chemical features can be used to set-up and develop on-line procedures aimed to recognize different materials occurring in a waste stream as they result after specific processing/selection actions [14].

Analyzed materials and procedure set-up. The material (Figure 1), comes from a sorted waste stream of post-consumer household plastic packaging. Sampling was performed on a waste bale composed of post-consumer packaging fragments. Two steps cascade model, PLS-DA based, was built to recognize polymeric fragments from cellulosic ones and to identify multi-layer laminated materials (i.e. laminated plastic and cardboard). The 1st model was calibrated using hyperspectral images depicting know samples of: cellulose-based fragments (“Paper & Cardboard”) and polymer-based materials (“Polymer”). In the 2nd step a classifier was calibrated to discriminate laminated card from other paper-based particles. The other classification model was developed to discriminate laminated plastic and polymer-based particles. As training set were used 40 fragments. The decision tree is shown in Figure 2. The spectra used to build the classification models were extracted from Region of Interests (ROIs) and pre-processed for scattering attenuation and spectra enhancement with the algorithm combination [15]: Standard Normal Variate (SNV) + Smoothing + Mean Center (MC).

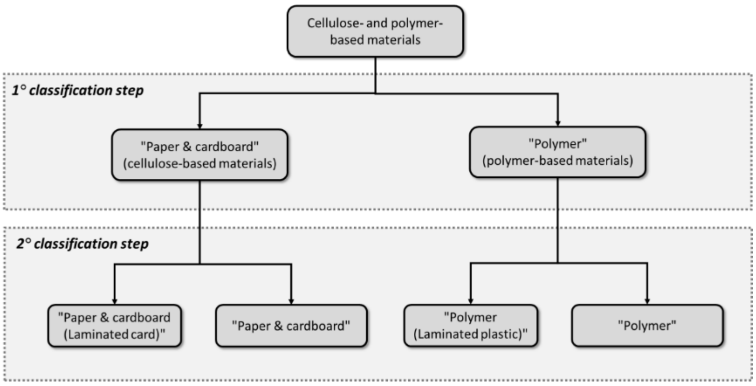
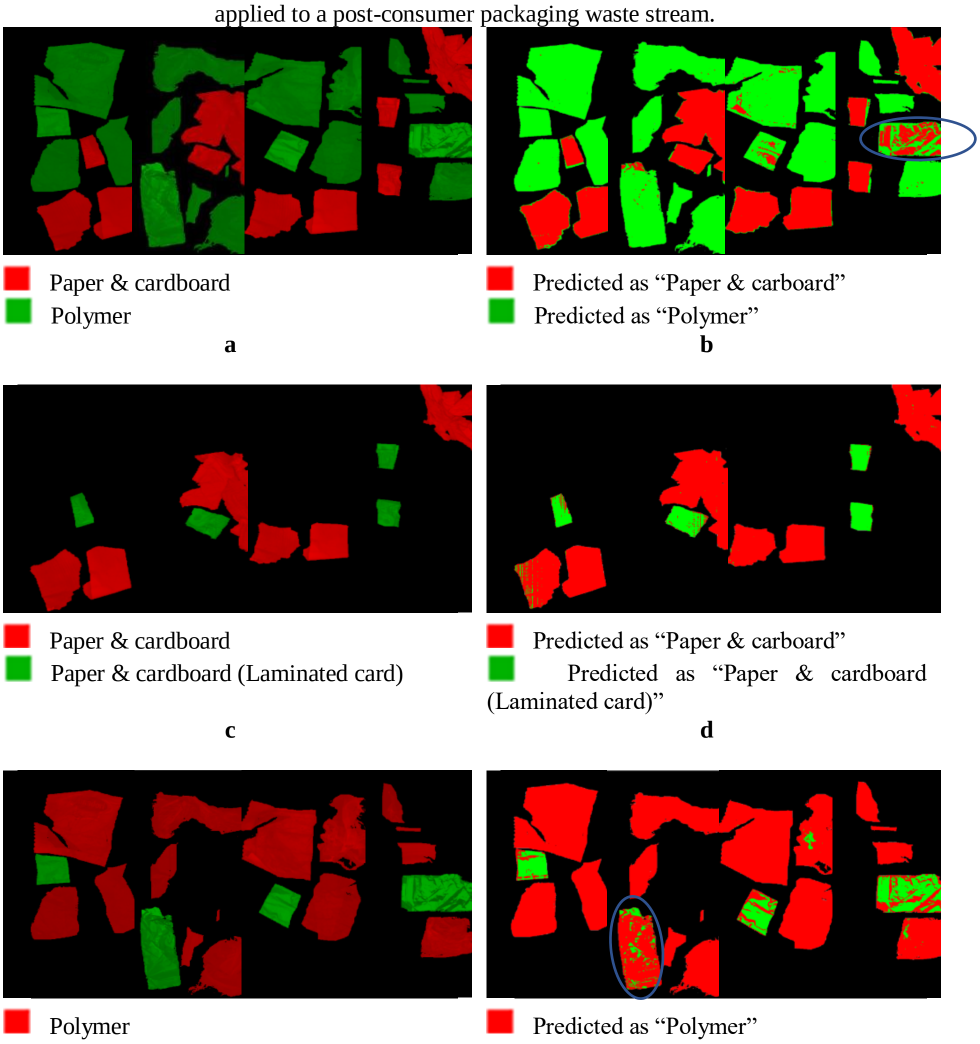


Fig. 2. Decision tree on which is based the two-stage cascaded classifier applied to a post-consumer packaging waste stream.



🟥 Paper & cardboard
🟩 Polymer

🟥 Predicted as “Paper & carboard”
🟩 Predicted as “Polymer”

a b

🟥 Paper & cardboard
🟩 Paper & cardboard (Laminated card)

🟥 Predicted as “Paper & carboard”
🟩 Predicted as “Paper & cardboard (Laminated card)”

c d

🟥 Polymer

🟥 Predicted as “Polymer”

🟩 Polymer (Laminated plastic)	🟩 Predicted as "Polymer (Laminated plastic)"
e	**f**

Figure 3. "Paper & cardboard" and "Polymer" classification: actual (a) and predicted classes (b); Paper & cardboard" - "Paper & cardboard (Laminated card)" classification: actual (c) and predicted classes (d) and "Polymer" - "Polymer (Laminated plastic)" classification: actual (e) and predicted (f).

Results. An overall comparison between the real classes and the predicted classes by the PLS-DA models is shown in Figure 3. The 1st step of the cascade model was able to recognize 27 out of 28 fragments (96 % of the total) a "Polymer" plastic (i.e. a laminated plastic fragment circled in blue, as seen in Figure 3b), was misclassified for over 50 % of pixels as "Paper & cardboard". In the 2nd step of the cascade detection "Paper & cardboard" and "Paper & cardboard (Laminated card)" classes were correctly assigned (Figure 3d), while in "Polymer" - "Polymer (Laminated plastic)" classification 21 out of 22 fragments were correctly assigned to their belonging classes: a "Polymer (Laminated plastic)" fragment (i.e. a laminated plastic fragment circled in blue) (Figure 3f) was misclassified for over 50 % of pixels as "Polymer".

Material cascade identification applied on milled products of EoL flat monitors

Issues and state of the art. WEEE represents a category of waste steam extremely heterogeneous. Materials such as metals and/or alloys, precious metals, high-quality plastics and other compounds could be profitably recovered [16]. Because of the potential risks that could cause the incorrect treatment of WEEE, and the considerable amount of "resources" in them contained, it is essential to improve the WEEE recycling process, both from an economic and an environmental point of view. The importance of characterization is linked to the possibility to design processing actions to perform a secondary raw materials recovery and reuse [14]. An efficient, reliable and low-cost analytical tool is thus needed to perform detection/control actions in order to assess: i) waste composition and ii) physical-chemical attributes of the resulting materials.

Analyzed materials and procedure set-up. Analyzed samples, consisting of EOL milled monitors and flat screens, come from the milling line of a WEEE recycling plant (Figure 4). Sample collection was performed by a coning/quartering procedure, followed by a manual sorting stage. In order to recognize the particles occurring in sample under study, a cascade identification approach, based on NIR - HSI, was carried out. More in detail, a four-steps classification was designed, implemented and set up in order to recognize different materials occurring in a specific WEEE stream (Figure 5): milled EOL monitors and flat screens.

Figure 4. Digital image of the milled EoL monitors and flat screen.

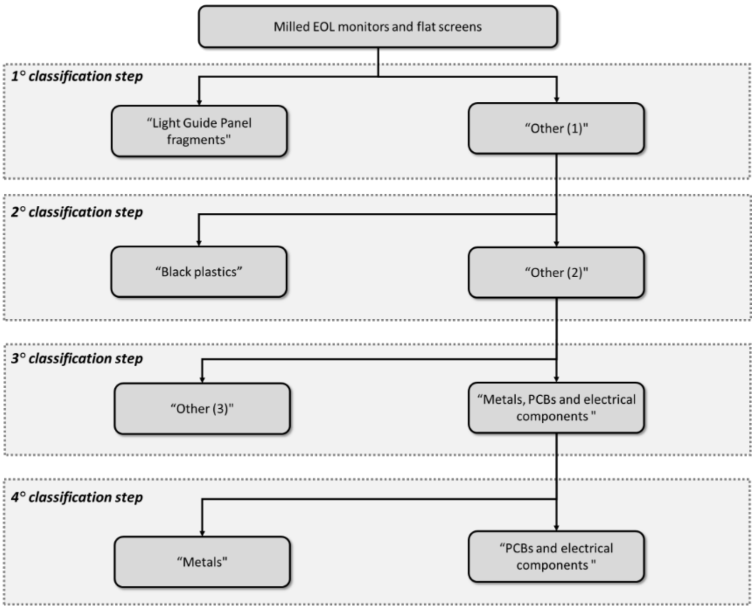
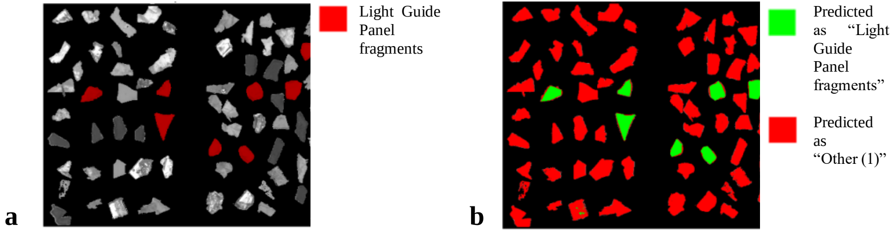


Fig. 5. Decision tree logic of the cascade detection applied to milled EoL flat screen and monitors.

In the 1st classification step, Light Guide Panels (LGP) fragments were recognized from other materials (i.e. "Other (1)"); in the 2nd one, after LGP particles removal from the "Other (1)" class, the "Black Plastic" was recognized from the "Other (2)"; in the 3rd classification step, the particles belonging to the "Other (2)" class were identified or as "Metals, PCBs and electrical components" or as "Other (3)". Finally, in the 4th classification step, the particles belonging to "Metals, PCBs and electrical components" class were recognized as "PCBs and electrical components" or as "Metals". For calibrating the classification models were used about 230 particles. Different pre-processing strategies were adopted for training set in order to attenuate scattering phenomena and enhance spectral information [15]: i.e. Standard Normal Variate (SNV) + Mean Center (MC) for the 1st classification step, MC for the second classification step, SNV + Smoothing + MC for the third classification step and SNV + Smoothing + Detrend + MC for the last classification step.

Results. In the 1st classification, as shown in prediction map (Figure 6b), all the particles belonging to "Light Guide Panel fragments" category are correctly classified. In the second classification, all the "Black plastics" are well recognized (Figure 6d). While in the third classification set-up for discriminating Metals, PCBs and electrical components identification from other materials, some



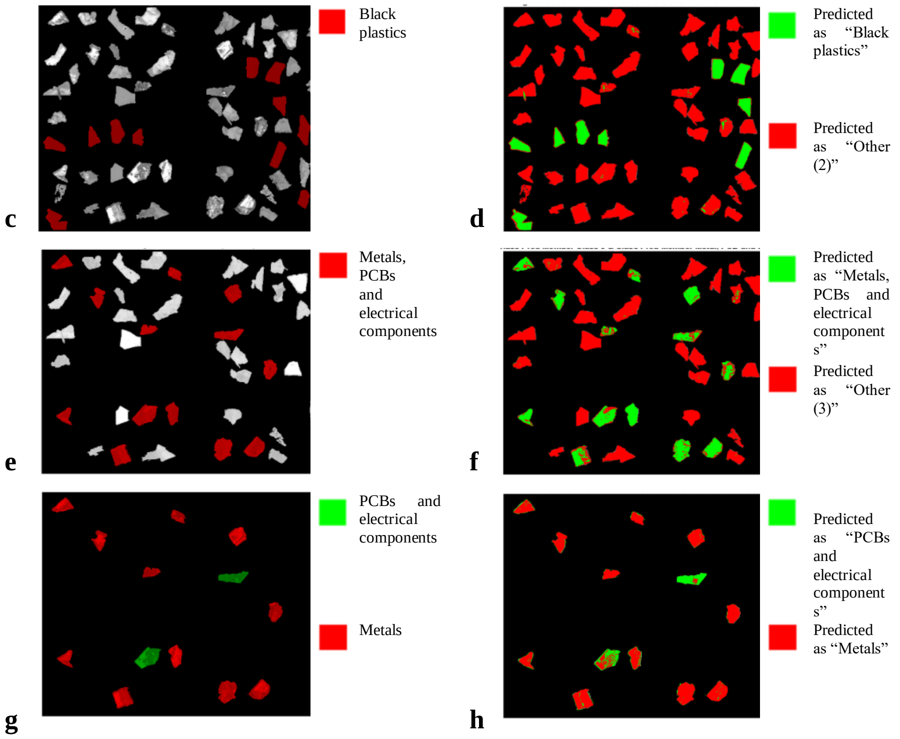


Fig. 6. "Light Guide Panel fragments" and "Other (1)" classification: actual "Light Guide Panel fragments" class (a) and predicted (b); "Black plastics" - "Other (2)" classification: actual "Black plastics" class (c) and predicted (d); "Metals, PCBs and electrical components" - "Other (3)" classification: actual "Metals, PCBs and electrical components" class (e) and predicted (f); "PCBs and electrical components" - "Metals" classification: actual classes (g) and predicted (h).

misclassified pixels occur (Figure 6f). However, with reference to each single object, more than the 50% of the pixels belonging to each particle are recognized as the correct class. In the last classification step, liberated "Metals" and "PCBs and electrical components" were correctly recognized (Figure 6h).

Conclusions and future perspective

The potentialities offered by a cascade detection logic based on a NIR-HIS system to perform the characterization, the inspection and the quality control of waste particulate solids fed and/or resulting from different processing actions finalized to their recovery, have been 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 waste materials coming from end-of-life product of different origin, composition and characteristics. Results of the reported examples (i.e. plastic packaging and WEEE) demonstrated as the proposed NIR-HIS approach can be successfully utilized: i) to perform a continuous monitor process of the different waste particles streams before and/or after handling or processing actions and ii) to define innovative logics and procedures for quality certification of waste-derived products. This approach opens the door to future innovations in the field of resources and recycling, such as: i) the possibility of development a system able to recognize processed materials and / or pollutants, in order to be used not only as a sorting engine, but also as an analytical core to perform a quality control on products and byproducts coming from different manufacturing stages and ii) the chance of ensuring a reliable production of recycled product in both quality and quantity terms. However, in order to improve the classification, a "machine vision" logic able to assign only one of the available classes according to a set threshold has to be implemented.

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