Industrial Defects Discrimination Applying Imaging Spectroscopy and Neural Networks

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Abstract. A non-destructive technique for the detection of non desirable material, or defects, in an industrial raw material chain has been developed. The system incorporates a hyperspectral imaging spectrograph able to register simultaneously the Vis-NIR reflected spectrum of the material under study along all the points of an image line. This system can be fast transferred to field conditions as the image line can cover the whole dimension of the typical conveyor belts employed in the industry. The working material have been different kinds of tobacco leaves mixed with typical defects of this field such as plastics, cords, cardboards, papers, textile threads, etc. The raw material is selected or rejected automatically by a neural network able to perform the classification with a high degree of accuracy. Due to the wide spectral information involved in the process, the developed system is also able to discriminate tobacco leaves from other matured and dried vegetable material. As the data amount generated by the hyperspectral system is huge, algorithms such as Principal Components Analysis (PCA) have been adopted in order to compress the information, to extract the main features of the spectrum and to focus the system into real-time conditions of operation. Obviously, the developed technique could be applied to the classification and discrimination of other materials once their identification spectra will be characterized.

1. Introduction

Raw material discrimination and classification at the input chains of industrial manufacturing processes is one of the key quality control stages in sectors such us food and beverage, tobacco, agricultural, etc. In tobacco industry, for example, a great variety of materials such as plastics, cords, cardboards, papers, etc. can be found mixed with the tobacco leaves due to the manual harvest procedure. These “defects” or not desired materials should be rejected before starting the process of making cigars. In traditional mechanical classification systems only rejection due material differences of weight, size, density, etc is performed. But results have revealed that some undesired material goes through these coarse classification and additional discrimination systems are needed. Optical technologies can be satisfactory applied to develop this fine classification, as figure 1 shows, as they are inherently non-contact and non intrusive techniques. They can be easily installed over the input conveyor belt without minimum modifications of the industrial set-up.

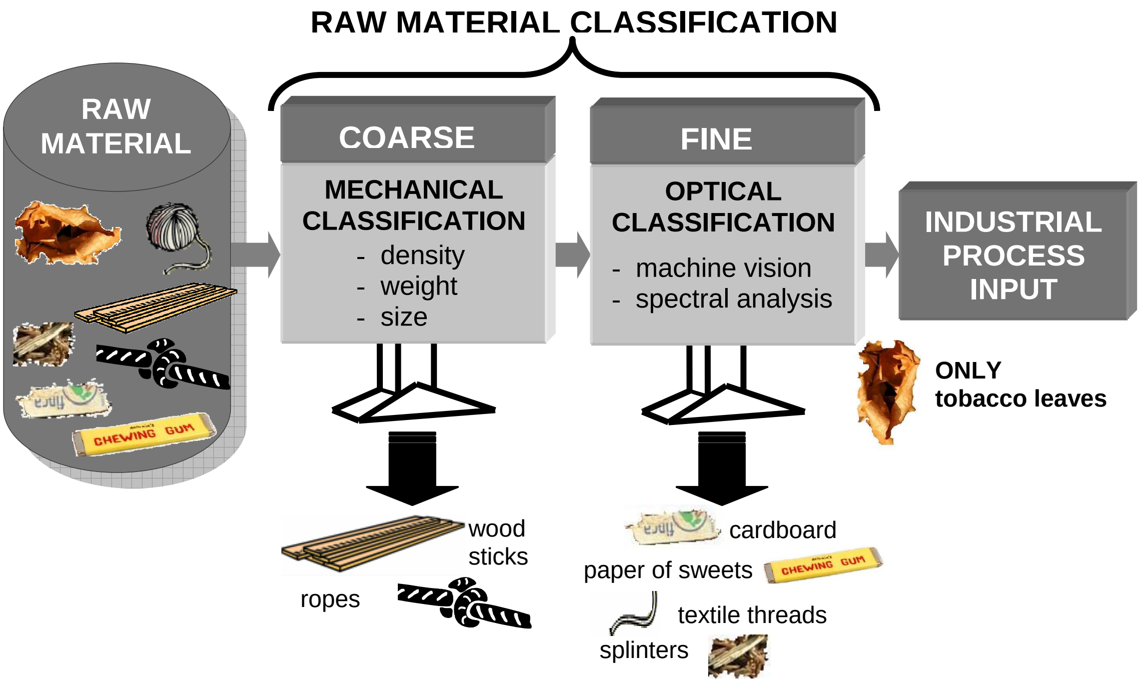

Figure 1. Industrial problem description.

High-fidelity, reliability and real time operation are also required for the classification task. This implies first determining their presence and spatial positions and, afterwards, automatically removing them from the conveyor belt of the production plant. Alternatives among the optical techniques can be those included under the machine vision scope [1] where color, size, shape and surface texture of the material should be analyzed. Another approach is provided by imaging spectroscopy, where simultaneous measurement of the optical spectrum components and the spatial location of the object surface are provided. That is, the spectra of all the points in the line of vision are measured at a time and they can be processed together achieving a considerable reduction in classification time. A passive Prism-Grating-Prism (PGP) device has been used to simultaneously acquire both dimensions, spectral and spatial [2]. Imaging spectroscopy based on this kind of hyperspectral device have been widely used in airborne applications, but few references can be found in other fields: industrial [3], biological [4], food [5], and fruit [6], for instance.

This contribution presents a system based on the above mentioned technique. It is a non destructive, non-contact and real time operating system for quality control industry where an artificial neural network (ANN) [7-8] is employed for the discrimination task. In addition, a pre-processing stage has been added. It consists in applying Principal Component Analysis (PCA) [9] to the data and provides an improvement in the time performance of the neural network. As stated, tobacco has been successfully employed to experimentally demonstrate the proposed technique.

The paper is divided in six sections as follows: Section 2 introduces imaging spectroscopy as the physical phenomenon where is based the classification method. Section 3 surveys the software processing of the spectral images. In Section 4 the optical set-up and its components are thoroughly described. Finally, in Sections 5 and 6, results are presented and some final remarks are outlined.

2. Hyperspectral Images

Spectroscopy measures the radiant intensity and energy of the interaction between light and any material to determine the molecular and dynamic structure of the latter. In the particular case of absorption spectroscopy the compound that interacts with light is a passive element. It absorbs some of the emitted photons depending on their wavelength, known as "*spectral signature*". Light which is not absorbed can be transmitted through the sample of the compound or reflected on it. In this work, the spectrum of this reflected light, also known as diffuse reflectance, is measured.

The developed tobacco classification system works as follows: it obtains the spectrum of the diffuse reflectance of an unknown sample. Afterwards, the measured spectrum is compared with the previously known features of tobacco leaves. This allows concluding if the unknown sample is or is not tobacco. The way in which the comparison of spectra is performed, i.e. the spectral interpretation process, will be the goal of the following section.

In imaging spectroscopy the spectrum of diffuse reflectance is measured, at a time, in all the points across a spatial line. Traditional spectrometers measured the spectrum of the diffuse reflectance as a whole, losing the spatial information of the object. Imaging spectrometers, however, do it individually for every point in one specific vision line. As a result, hyperspectral images as the ones depicted in Figure 2 are generated.

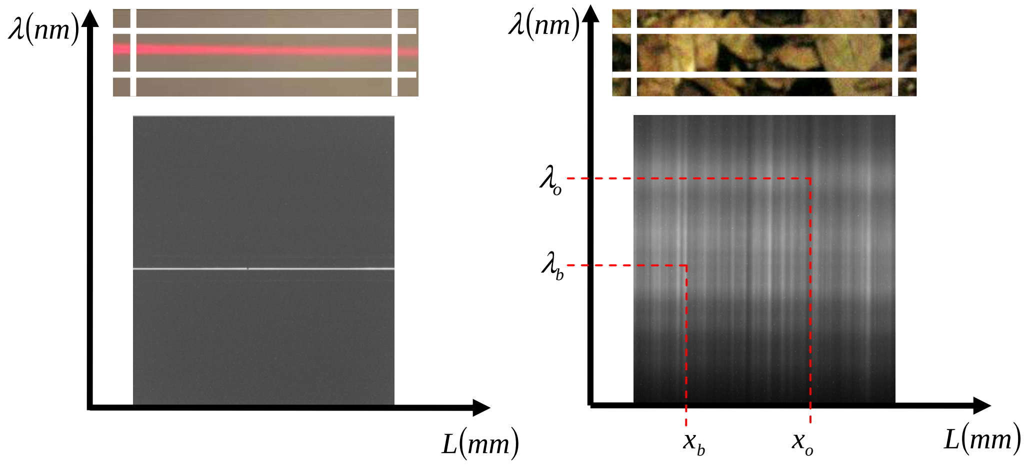

Figure 2. a) Image of a laser of 670 nm peak emission wavelength.

b) Image obtained with tobacco across a line of 2 cm

As shown, the horizontal axis corresponds to the spatial axis while the vertical one is the spectral axis. Therefore, each vertical line is the diffuse reflectance spectrum at that particular spatial position. Let's consider the two pixels of the image (x_b, λ_b) and (x_d, λ_d). The first one is brighter than the second one. It means that the intensity of the diffuse reflectance is greater. With this kind of images, one can realise the great amount of information generated in the process and how the introduction of compression techniques is highly recommended.

3. Spectral Imaging Processing

Figure 3 depicts the global block diagram of the classification system. The spectrum of the diffuse reflectance of an unknown sample is acquired by a camera through a PGP device in the Spectral Image Adquisition unit. Then, the image is processed in the Data Compression block using PCA analysis. Finally, a specifically trained ANN performs the discrimination of the wanted from the unwanted raw material.

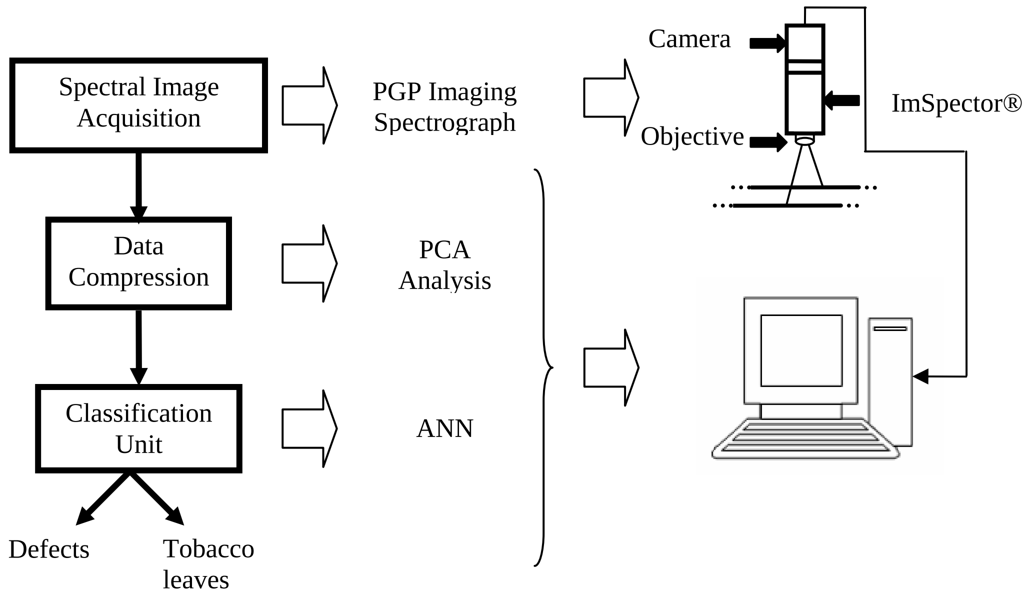

Figure 3. Global block diagram of the proposed system

- The *Spectral Image Acquisition* is based on a new PGP (Prism-Grating-Prism) imaging spectrograph [2]. It consists in a totally passive element connected between an objective lens and a standard monochrome camera 640 x 480, with IEEE1394 interface.
- The compression of both, spatial and spectral, axes is performed in the *Data Compression Block*. In the first case, it only consists in an average where the length of the average stretch is 5 spatial positions going from the initial 480 spatial positions to the final 96. Due to the low spatial resolution of the system of mechanic extraction, this average provides a noise reduction without affecting the classification results. Principal Component Analysis is the compression technique used in the spectral axis. But the way in which PCA is performed is different from its application to computer vision as here the number of total images is kept. In this case, the spectrum of each point in the spatial line is expressed in another basis, maintaining the main features of the spectrum. This means that an elimination of the redundancy in the data, as a consequence of the high spectral resolution of the imaging spectrograph, is performed simultaneously with the spectral axis compression. As a result, 18 wavelengths have been chosen from the 640 original values providing a data compression rate of the 97%. Including both spectral and spatial axis compression, a total reduction of 99.4% is reached for each of the images in the data set, and this reduction is performed without causing an appreciable increase in the misclassification probability.
- On the final *Classification Unit* a non linear classification algorithm as an Artificial Neural Networks [6-7] have been considered for the spectral interpretation and discrimination of the raw material due to their performance once the adequate training and topology have been selected. The topology of the employed network consists in two layers, the input one with 10 neurons and the output one with just only one. The output of the ANN is ‘1’ for tobacco detection and ‘0’ if a defect is found. The designed ANN is a feed-forward network that uses the supervised backpropagation scheme as learning algorithm.

4. Experimental Set-up

As depicted in figure 3 the developed measurement set-up includes a front objective lens, a

PGP imaging spectrograph, a monochrome camera, a computer equipped with IEEE1394 interface for image data capture, processing and illumination system. Figure 4 shows a photograph of the measurement set-up employed in the laboratory and a schematic of its implementation in the production plant.

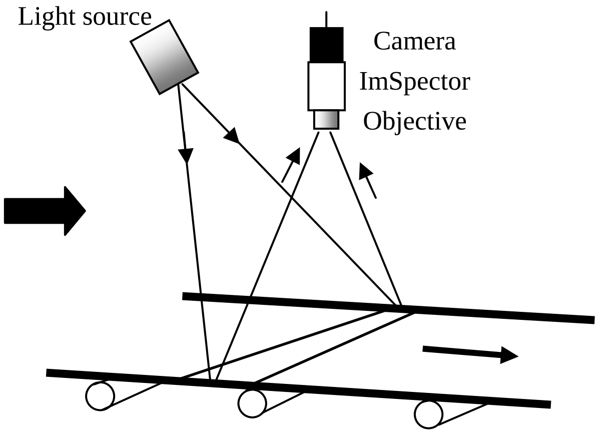

Figure 4. Photograph of the measurement set-up employed in the laboratory and schematic of the set-up in the production plant.

The commercial equipment known as ImSpector has been used as imaging spectrograph. As the classification analysis has been performed in the Vis-NIR range, the V10E version, whose spectral range goes from 400 up to 1000 nm, has been chosen. Usually, the shorter axis is the spectral one. However, the spectrograph has been here turned 90º to get a broader spectral range. ImSpector is designed for the standard 2/3" (6.6 x 8.8 mm) detectors. This is the size of the detector of the monochrome digital camera Pixelink PL-A741 employed. The objective lens Zoom 7000 by Navitar has been used. Finally, the illumination system consists in two halogen floodlights, with a power rating of 500W.

Once the system set-up has been mounted, and before starting to capture the spectral images of the samples, spatial and wavelength calibration processes should be performed. The first one consists in determining the dimensions, length and width, of the vision line. Wavelength calibration is the definition of the spectral axis and it is done using two different light sources whose emission wavelengths are previously known: a laser of 670 nm and an Hg-Ar lamp with multiple emission lines.

The main specifications of the classification system are:

- Spectral range: 400-1000 nm.
- Spectral resolution: 2.8 nm.
- Spatial resolution: 41.667 µm.
- Spatial resolution after averaging: 208.33 µm.

5. Results

As aforementioned, the proposed technique has been successfully checked in the tobacco industry. Tobacco leaves have been provided by Altadis company and the following defects have been considered to be discriminated from them: different coloured cellophanes, brown and green leaves of other vegetable material different from tobacco, cardboard, leather, wood, paper of sweets, foil and textile threads. The conveyor belt has been considered as tobacco, in order to not generate “false defects” in the application due to the absence of material.

Figure 5 illustrates a subset of the analyzed samples and their corresponding results.

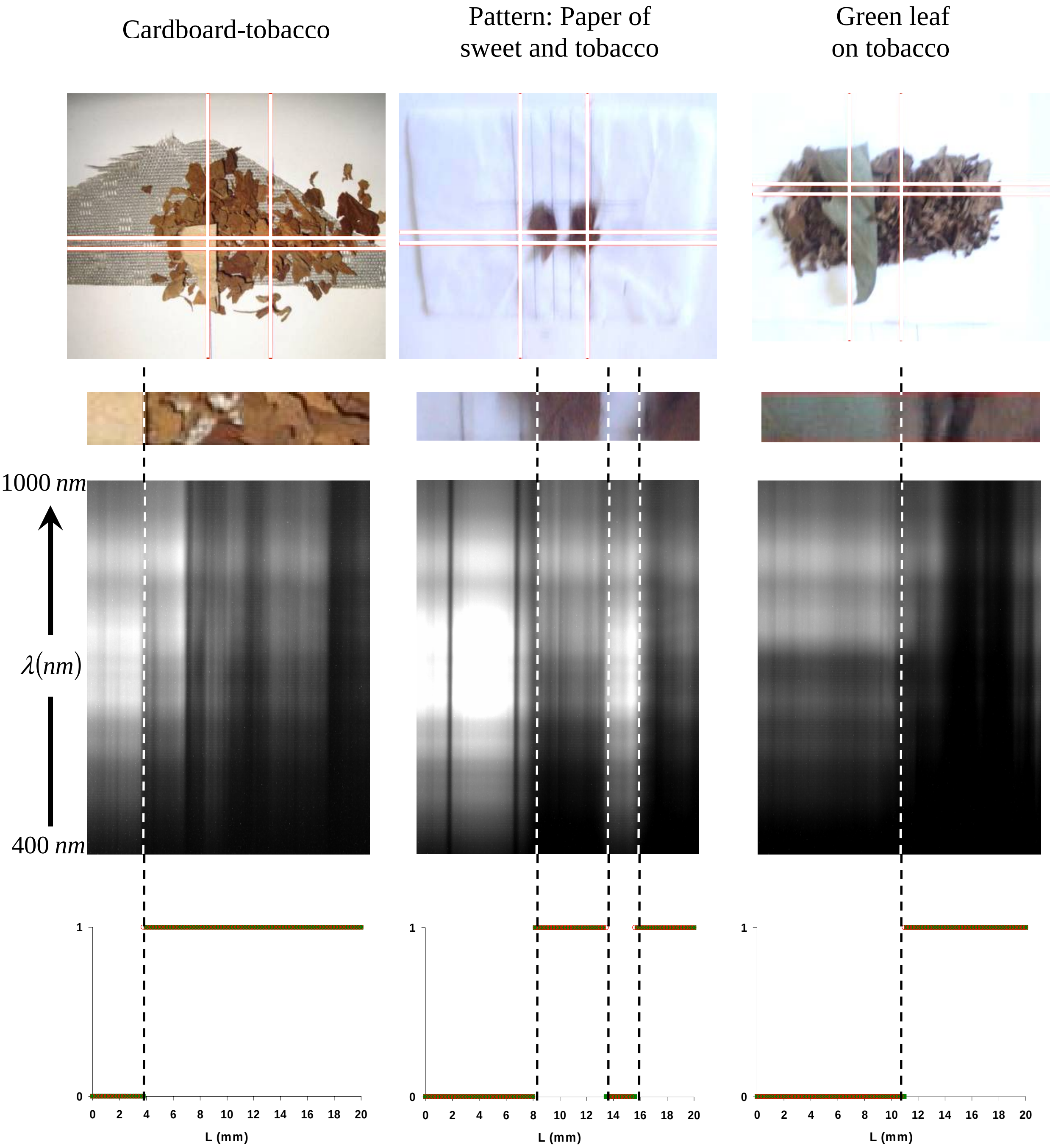

Figure 5. Hyperspectral images and classification results.

In figure 5 it can be found:

- A brief description of the analyzed sample.
- A photograph of the analysis, where the white lines delimitate the scene line. There are, once the averaging process has been performed, 96 spatial positions

to be each classified as tobacco or defect.
- A zoom of the scene line.
- The corresponding hyperspectral image. The spatial axis is the horizontal one with the origin on the left as it appears in the real photograph and in the zoom. The vertical axis is the spectral one and the shortest wavelength is at the bottom of the image.
- The classification result provided by the neural network. If on a spatial position appears a '1' that means that this position corresponds to tobacco and '0' if it does not. If previously to the classification in the neural network, PCA analysis is applied to the spectral axis of the image, the results are printed in green. The results obtained if PCA is not applied are printed in purple. The results are equally valid in both cases. However, the compression provides a reduction of the classification time up to the 44%. This comparison has been carried out in a Pentium® 4 processor of 2GHz with 1.00 GB de DDR-RAM of 2.01 GHz The mean classification time if PCA is not applied to the data is about 410 ms and about 230 ms if it is applied. This figures pointed out the enhancement in the time performance of the system provided by PCA compression.

It should be emphatized that the classification results obtained for all the defects have been successful, validating the proposed optical technique and processing for the objectives of the stated problem.

6. Conclusions

An entirely non-intrusive, non-contacting and real-time operating system able to discriminate wanted raw materials from the un-wanted materials has been fully designed, realized and validated.

By employing the imaging spectroscopy technique, the system simultaneously measures the optical spectrum components of each of the spatial positions along the scene line without the need for any scanning mechanics, providing a strong reduction in measurement and processing times.

A specific designed neural network has been successfully used in this application as the spectral interpretation algorithm due to their advantageous properties, especially its short execution time. Moreover, the time performance of the ANN has been enhanced with the application of the PCA analysis to the images prior to the classification in the net. Figure 5 states that, once the ANN has been properly trained, it has efficiently discriminated different patterns of tobacco and defects.

Finally, pointing out that this strategy of classification of spectral images applying PCA and ANN can be successfully extended to other sorting problems related with different materials. What must be done is to characterize perfectly the spectrum of the material under test and to train conveniently the new neural network.

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