

Hyperspectral Imaging – From Laboratory to In-line Food Sorting

Robin Gruna,¹ Kai-Uwe Vieth,¹ Matthias Michelsburg,² Fernando Puente León²

¹Fraunhofer-Institute of Optronics, System Technologies and Image Exploitation, Germany

²Institute of Industrial Information Technology, Karlsruhe Institute of Technology, Germany

Robin Gruna, Fraunhoferstraße 1, 76131 Karlsruhe, Germany

robin.gruna@iosb.fraunhofer.de

ABSTRACT

Perfect quality control of food becomes more and more a matter of course. Foreign materials like pieces of rocks, insects, plastics, carton etc. have to be identified and sorted out. For many years, near-infrared spectroscopy has been a widely-used analytical offline method for quality inspection for small samples in the food and agriculture industry. Up to now, high-speed automatic sorting machines work usually on the basis of visual inspection, not near-infrared inspection. This article describes how an in-line food sorting system can be developed on the basis of hyperspectral imaging data. We focus on analyzing the vast amount of data to yield minimum band selection with optimal classification results required for an industrial sorter.

Keywords: Near-infrared hyperspectral imaging, food sorting, quality inspection, feature selection, band selection, Germany

1. INTRODUCTION

From the customer's point of view, the perfect quality of food becomes more and more a matter of course. People of many nations increasingly buy semi-finished food. Thus, the food is not washed, sliced, and prepared by the end customer, i.e., quality control is not performed "at home in the kitchen." Therefore, food has to be prepared in advance such that only perfect food is the output without any defect and especially without any foreign objects like pieces of rock, insects, plastics, carton etc. Premium quality food is expected to look appealingly. Thus, besides objects which are obvious foreign bodies even for a layman, also parts of the good product, i.e., the fruit, vegetable, tea, or herb etc. have to be removed from the product stream. Several aspects motivate companies to put in sorting machines: the achievable quality is constant, sorting machines can run 24 hours a day, the sorting result is better than with manual sorting, and the sorting costs are decreased.

1.1 Machine Vision

Machine vision has been refined to a high level of sophistication and has been applied extensively in manufacture engineering. It combines visual, infrared (IR), ultra-violet (UV), or x-ray sensing with digital video technology and image processing. Machine vision has been applied for many years almost exclusively to the inspection of engineering components, manufactured by processes such as casting, stamping, pressing etc., which produce close tolerance arte-

R. Gruna, K.-U. Vieth, M. Michelsburg, F. Puente León. "Hyperspectral Imaging - From Laboratory to In-line Food Sorting". CIGR Workshop on Image Analysis in Agriculture, 26-27. August 2010, Budapest.

facts (Graves and Batchelor, 2003). In contrast, natural products exhibit wide variations in overall size and shape, internal structure, color and surface texture. As a consequence, machine vision has been applied for a much shorter time to the food industry.

The Fraunhofer Institute for Optronics, System Technologies and Image Exploitation (IOSB) has performed research of inspection systems for over 20 years, e.g., inspection of blisters for the pharmaceutical industry, and has developed sorting machines especially for the tobacco and food industry for about 10 years. While in the past the focus was mainly on inspections using the visual wavelength range by means of RGB line cameras, research and development is shifting towards non-visual wavelength ranges.

1.2 Spectroscopy

Visible and near-infrared (Vis/NIR) spectroscopy, which covers the spectral region between 400 nm and 2500 nm, has become an important non-destructive technique for chemical analysis and quality assessment of a large class of agricultural and food products (Williams and Norris, 2001). Conventional Vis/NIR spectroscopy only provides point or area measurements, and therefore cannot quantify the spatial variation or distribution of properties and attributes in the product item. Moreover, the technique is largely empirical, relying on the development of calibration models relating spectral information to reference measurements that are often destructive (Lu, 2007).

1.3 Hyperspectral Imaging

The limitations mentioned above can be overcome with hyperspectral imaging, an extension of spectroscopy from single-point inspection to two-dimensional measurement. Hyperspectral imaging was first developed for remote satellite sensing of the earth and for military reconnaissance over 20 years ago. In the past decade, the technique has received increasing attention for assessment of the quality and safety inspection of food and agricultural products (Lu, 2007; Zude, 2009). With the spatially resolved spectral data at hand, chemometric methods and image processing methods can be combined for the analysis of heterogeneous products, such as agricultural or biological samples in the laboratory or food products during in-line automated visual inspection (Mehl et al., 2004; Gomez et al., 2005; Ariana et al., 2006b).

From the user's point of view, an imaging spectrometer is a line-scan camera with a few hundred pixels per line. However, in contrast to a grayscale camera, this camera does not just measure one radiance value for each pixel, but hundred and more color values, distributed across the spectrum at which the sensor is sensitive. Each color value represents the energy of the light measured within a portion of a narrowband spectrum of, e.g., 10 nm width. The images are captured line by line synchronized with the motion of a sliding-table which yields a data cube representing spatial information in two directions and spectral information in onedirection (see figure 1).

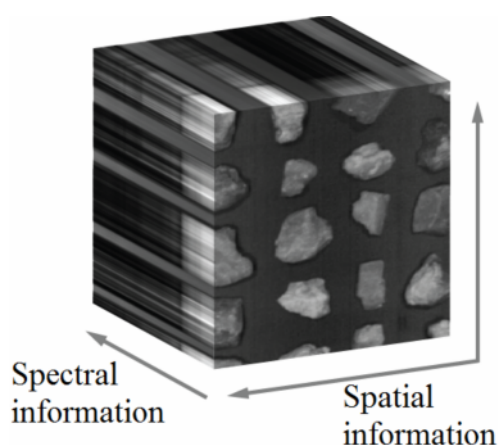


Figure 1. Hyperspectral data cube.

1.4 Band Selection

The first application where the IOSB got in contact with hyperspectral imaging was the development of an in-line color measurement system to determine exactly the color of plastic granules by means of a hyperspectral imaging system in the visual range (Vieth et al. 2009). While it is important to describe the color of plastic granules using the complete visual spectrum – using only RGB would not encompass the whole visual range and could produce ambiguous results due to metamerism effects – we want to focus on using as less wave bands as possible.

Several aspects motivate to use only a minimal number of wave bands. The already good sorting quality of existing and future sorting machines which are based on RGB line cameras should be extended by one or several additional “colors” of the invisible light instead of a complete hyperspectral imaging system. The costs of such a system are much higher than just one or two additional line-scan cameras. Due to the low frame rate of a hyperspectral imaging system, a line camera is to be preferred. This also yields a higher resolution and consequently smaller foreign bodies can be classified and sorted. First experiments support the suggestion that a few bands are adequate for obvious improvement of sorting results compared to sorting based on solely RGB line scan cameras.

The reduction of the number of bands and the consequential reduction of data allow applying more algorithms for image analysis and classification.

The drawback of a reduced number of bands is the specific design for a certain product, i.e., material type.

1.5 From Laboratory to In-line Food Sorting

In order to characterize the product to be inspected, the material is first analyzed by means of hyperspectral imaging systems, e.g., from 1000 – 2500 nm, i.e., up to the shortwave infrared (SWIR) wavelength range. The material is moved with a constant velocity on a sliding table below the hyperspectral imaging system.

R. Gruna, K.-U. Vieth, M. Michelsburg, F. Puente León. “Hyperspectral Imaging - From Laboratory to In-line Food Sorting”. CIGR Workshop on Image Analysis in Agriculture, 26-27. August 2010, Budapest.

Secondly, data analysis is applied to determine characteristic wavelength regions which discriminate between product and foreign bodies.

Thirdly, the output of the analysis describes the required bands which are the basis for the design of a sorting system. With this knowledge, camera sensors, filters, and suitable illumination have to be selected.

Fourthly, the overall sorting system has to be designed and built which has to be set up in the industrial environment and fulfill the requirements of the customer.

A typical sorting system for dried food is composed of a vibration pan, a conveyor belt with a typical velocity of 3 m/s, the camera and lighting components, and the valve block which rejects the foreign bodies with compressed air. The resolution is adapted in order to meet the customer's needs. A typical setup is shown in figure 2.

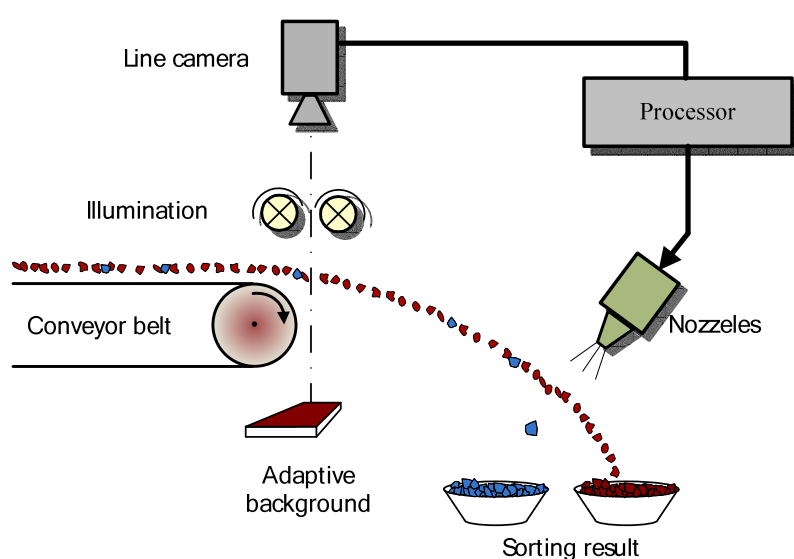


Figure 2. Sorting system.

2. RELATED WORK

2.1 Band/Feature Selection in NIR Data Analysis

In general, there are two different approaches for using hyperspectral images for classification purposes. Firstly, one can use all hyperspectral bands for the classification and determine class-separating features by taking (linear) combinations of all bands. A review and comparison of different feature extraction algorithms is shown in Paclik et al. (2006). A very well-known example for feature extraction is the Karhunen–Loève transform (PCA). It is used in several applications. However, the principal components cannot be interpreted physically in a meaningful way, as they are linear combinations of all measured spectral bands. For the same reason, the PCA cannot be realized in a simple and fast sensor design which is necessary for sorting devices. A

R. Gruna, K.-U. Vieth, M. Michelsburg, F. Puente León. "Hyperspectral Imaging - From Laboratory to In-line Food Sorting". CIGR Workshop on Image Analysis in Agriculture, 26-27. August 2010, Budapest.

very good separation of classes in hyperspectral data can be achieved by usage of support vector machines (Gualtieri and Chettri, 2000).

Secondly, a hyperspectral image can be used to select a number of subbands. This can either be done by picking single bands (feature selection) or by combining adjacent spectral bands. The latter approach is often called band selection and can easily be implemented in hardware, as different bands can be extracted by customized optical filters. Therefore, cheaper and faster camera setups can be used. A collection of different sensor designs is presented in the following section.

There are different strategies for implementing band selection. It can be done by iteratively dividing the spectrum (Serpico and Moser, 2007) or by merging neighboring bands (Withagen et al., 2001). De Backer et al. (2005) uses weight-functions for extracting and combining bands. These weight-functions can be interpreted as the transmittance of optical filters. Hence, this approach is very promising for the presented problem of determining filter characteristics.

For evaluating any band selection and the corresponding separability of classes, different distance measurements are used, e.g., the Bhattacharya distance by De Backer et al. (2005) or the Mahalanobis distance by Withagen et al. (2001). The distance measurements are used to define a criterion function which needs to be optimized. As the number of possible band selections is very large, the global optimum cannot be determined with reasonable effort. Hence, global optimization procedures like genetic algorithms, simulated annealing, sequential forward (floating) selection, or sequential backward (floating) selection are used to find an optimal selection.

2.2 Approches to Sensor Design

There are different ways for making a multispectral image. As the objects move on a conveyor belt, it is possible to install several monochrome cameras with different optical filters attached. In this case, the illumination most likely but not necessarily has to be the same at all camera positions and the objects must not move themselves on the conveyor belt. Otherwise, the cameras observe different scenes which makes data analysis more complex. To avoid these problems, the multispectral image has to be recorded at the same position. Therefore, different detector designs are possible. Firstly, a rotating wheel containing different optical filters can be mounted between the camera and the conveyor belt (Ariana et al. 2006a). As the conveyor belt moves on while one multispectral dataset is being recorded, the use of a filter wheel is only possible for conveyor belts moving at moderate speed. A second possibility is a three-CCD camera, e.g., developed by Duncan et al. (2009) and used by Withagen et al. (2001). Here, three monochrome CCD-cameras and a trichroic prism are used. The prism separates the image in different spectral bands. These bands can be adapted by selecting different coatings at the prism surfaces. By this design, it is possible to record the same scene with three different bands at the same time. Another design allows doing this with only one camera. Therefore, a beam splitting unit divides the light from a single lens into different channels. Each channel is filtered to a specific spectral region and imaged on one single CCD-array. This setup is used by Lu et al. (2007).

3. EXPERIMENTAL RESULTS

As argued in Section 1.4, in many sorting applications where different materials have to be qualitatively identified and detected, the measurement of a complete NIR spectrum with a spectrograph can be avoided. Instead, the measurement can be reduced to selectively measure the spectral reflectance of the product to be inspected at discriminating wavelengths. This spectral selectivity can be achieved by using optical band-pass filters or by using selective spectral illumination techniques. In this section, the proposed approach to develop an in-line sorting system based on NIR sensitive sensors and selective optical filters is illustrated on a realexample from the food inspection domain. In particular, chopped and dried onions should be monitored for foreign materials such as stones or packaging residues like paper scraps (see Figure 3).

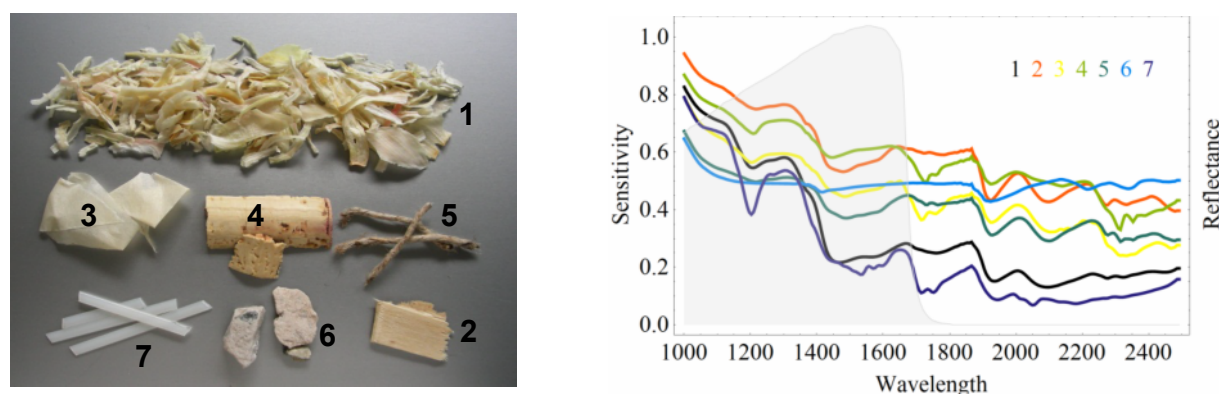


Figure 3. (Left) Dried onions and foreign material which have to be detected by the sorting system: (1) dried onions, (2) wood splitter, (3) paper scraps, (4) cork, (5) cord, (6) stones, (7) plastic. (Right) Mean spectra of the training data set which was acquired from the materials shown left with hyperspectral imaging. The filled gray curve represents the quantum efficiency of the spectral sensor that is deployed in the sorting system.

As outlined in Section 1, in the first step, hyperspectral data of the good product and the foreign materials, which are likely to get into the good product during various processing steps, is performed. Then, a subsequent data analysis of the hyperspectral reflectance data aims to identify spectral regions that capture distinct characteristics of both material types, i.e., good and foreign materials, and therefore permit a good material separation. In view of sensor design, these spectral regions then serve as decision basis for the choice of a set of optical band-pass filters that make a NIR sensor selective for these specific spectral regions. As a result, such a sensor is able to capture single- or multispectral inspection images which allow a material-based segmentation.

In the following, the band selection technique proposed by De Backer et al. (2005) is explained and illustratively applied to the task of in-line inspection of dried onions. Since in this work, band selection is performed by the optimization of a parameterized set of Gaussian optical filters, this method is particularly interesting for the purpose of sensor design.

To determine a set of optical filters which is adequate for the described inspection task, various spectra of the dried onion samples and the polluting materials were acquired by using a hyperspectral imaging system in the near-infrared wavelength range from 1000 nm to 2500 nm. A halogen lamp was used to illuminate the samples. In order to obtain reflectance spectra of the samples that are independent of the spectrum of the light source as well as independent of the quantum efficiency and the dark current of the hyperspectral imaging sensor, the measured spectral radiances were standardized. For this purpose, the measured radiance of a white reference panel and a dark current image were used for reflectance calibration. Finally, a labeled and equally sized training data set was set up, consisting of one class with spectra obtained from the dried onions and another class composed of equal portions of spectra from the foreign material depicted in Figure 3.

With the labeled training data set at hand, supervised band selection was conducted to select a small number of waveband regions that provide a high discrimination between the dried onions and the foreign material. However, rather than to consider the spectra as feature vectors and to select a subset of spectral variables, the spectra are treated as continuous functions and features are extracted by a set of Gaussian-shaped weight functions as proposed by De Backer et al. (2005). This approach to feature extraction mimics the process of sampling the spectral reflectance with a set of optical filters

$$f(\lambda; c_i, w_i) = \exp\left(-\frac{(c_i - \lambda)^2}{2w_i^2}\right), \quad \text{for } i = 1, \dots, d,$$

where c_i denotes the central wavelength and w_i the width of the optical band-pass filter. Features from a spectrum $s(\lambda)$ are then extracted by the linear transformation

$$m_i = \int s(\lambda) q(\lambda) f(\lambda; c_i, w_i) d\lambda, \quad \text{for } i = 1, \dots, d$$

which simulates the measuring of $s(\lambda)$ with a spectral sensor with quantum efficiency $q(\lambda)$ and an optical filter $f(\lambda; c_i, w_i)$ in front of it. That is, m_i is the intensity (in digital numbers) that would be measured by a spectral sensor. For simplicity, the influence of the illumination is neglected by assuming a constant spectral irradiance with respect to wavelength. Therefore, given a sensor with quantum efficiency $q(\lambda)$ which should be deployed in the sorting system, the problem of selecting an adequate set of d optical band pass filters for the specific sorting application can be addressed by choosing a set of filter parameters c_i and w_i and evaluating the extracted features m_i from the labeled training data. Since in food sorting foreign material detection is the goal, the optical filters $f(\lambda; c_i, w_i)$ have to be selected so that the features m_i exhibit high discrimination potential for material classification. At the same time, the number of extracted features d should be small in order to keep the complexity of the classification problem low and to alleviate the curse of dimensionality when the number of training samples is limited (see Hastie et al. (2003) for an in-depth discussion). Moreover, from a technical point of view, only a small number d of optical filters can be used in sensor design (see Section 2).

In De Backer et al. (2005), the adjustment of the filters $f(\lambda; c_i, w_i)$ is formulated as continuous optimization problem, where the objective is to maximize the Bhattacharya distance between the extracted features from a two-class labeled training data set. From a theoretical point of view, the Bayes error provides the lower bound on the expected classification error and hence would be the best criterion to evaluate the extracted features for their classification potential. However, in general, the Bayes error cannot be computed directly and, therefore, other statistical measures like the Bhattacharya distance are proposed in the literature to estimate the separability of two classes of features (Simin et al., 2009). Another possibility is feeding the extracted features directly to a classifier and evaluate these according to their classification performance, e.g., which could be estimated by using cross-validation within the training data set or by using a separate test data set. These two approaches to feature selection are referred to as *filter* and *wrapper* approaches in literature (Kohavi and John, 1997).

In our experiments, the Bhattacharya distance is used as criterion for selecting a set of filters $f(\lambda; c_i, w_i)$ that produce discriminative features from the training data set. Since this criterion function has many local maxima (De Backer et al., 2005), the differential evolution method (Storn and Proce, 1997) was used as global stochastic optimization procedure to find a set of good filters. Due the restriction that practically only imaging sensors with a small number of selective filters can be built, the optimization problem was restricted to small dimensions with $d = 1, 2, 3$.

Finally, the filters obtained by the optimization procedure (see Figure 4) were evaluated on a separate hyperspectral test image. In this test image, samples of dried onions are prepared with various foreign materials from the learning data, so that these could hardly be detected by conventional color imaging (see Figure 5). The obtained filter sets are applied to the acquired test spectra to extract features for classification. By this, a single- ($d = 1$) and two multispectral ($d = 2, 3$) images are obtained by simulating the measuring process of the reflectance by the sensor with the corresponding band pass filters. Afterwards, Linear (LDA) and Quadratic Discriminance Analysis (QDA) (see Hastie et al. (2003) for more details) was used to classify the extracted features, that is, the simulated single-and multispectral images are segmented according to the good product and foreign materials (see Figure 5).

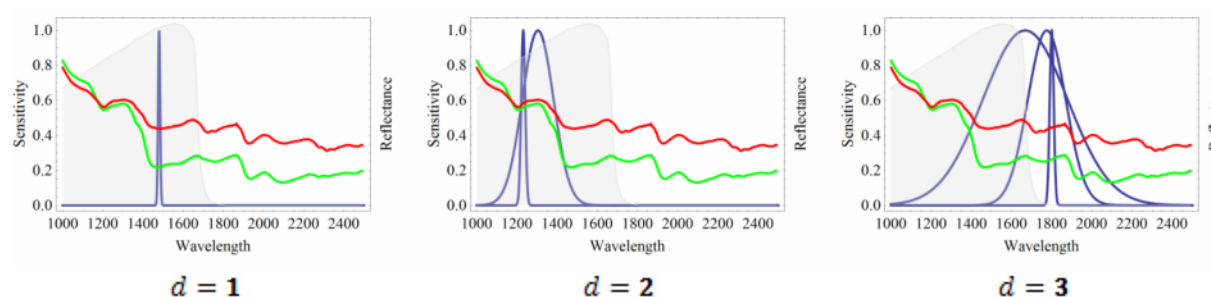


Figure 4. Sets of selective filters obtained by differential evolution. The spectral sensitivities of the filters are indicated as blue Gaussian-shaped curves. The red and green line plots indicate the mean spectra from the training data set (green: dried onions, red: foreign materials). The filled gray curve represents the quantum efficiency of the spectral sensor that is deployed in the sorting system.

Figure 5 shows the simulated sorting results that are expected for the NIR line-scan sensor and the different sets of optical filters obtained by differential evolution. The best result was obtained by a set of $d = 3$ filters and QDA as classification method, where all polluting materials are indicated in the segmented image. By the use of LDA, the wood splitters were not detected, which means, that the extracted features cannot be linearly separated.

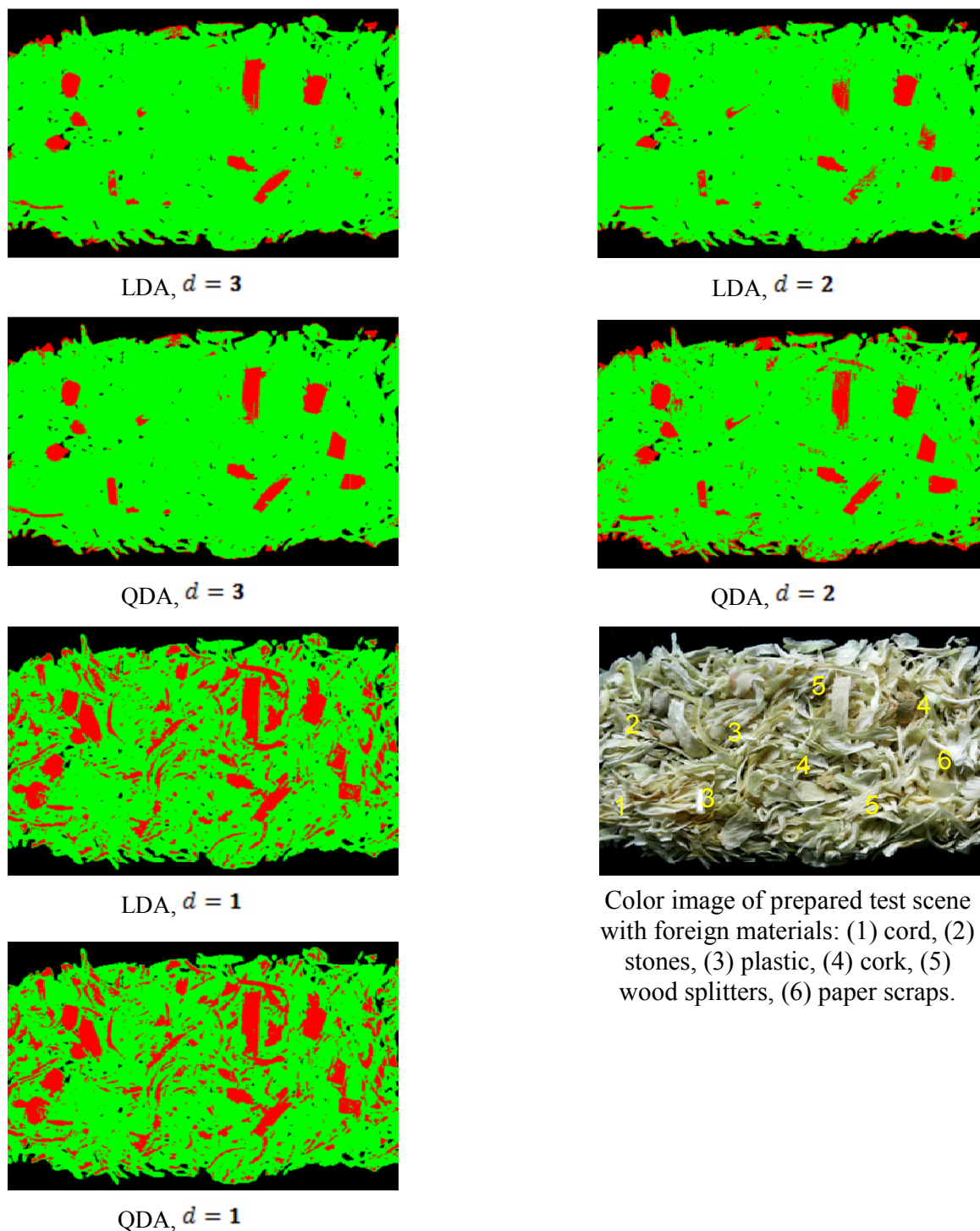


Figure 5. Results obtained by evaluating the optimized filter sets in Figure 4 on a separate hyperspectral test image (lower right). The extracted features are classified using LDA and QDA yielding in a segmentation into good product (green) and foreign materials (red).

However, two of the three mean wavelengths λ_i lay outside the sensitive area of the chosen sensor. It is interesting to see that a comparable result is obtained by using only $d = 2$ features with filters in the sensitive area. However, the QDA segmentation result shows a slightly higher false alarm rate, that is, good product is falsely classified as polluting material. Taking into account the smaller technical effort to develop a sensor with only two selective filters compared to three optical filters, it could be concluded that a sensor with two optical filters is appropriate for this particular food sorting application from a cost-benefit point of view. To reduce the negative effects of falsely classified good product, conventional image processing techniques like morphological filtering can be used to eliminate small falsely classified regions. Finally, the results obtained with a single selective optical filter clearly show that a single feature alone cannot discriminate between the different material types. Although all foreign materials are detected, the false alarm rate is too high to be corrected by subsequent image processing operations.

4. CONCLUSIONS AND OUTLOOK

Hyperspectral imaging allows combining classical laboratory spectroscopy with imaging processing, where the latter is well established in automation processes. By means of band selection methods we showed how to close the gap between the huge amount of laboratory data and the need for speed during food sorting.

We used the Bhattacharya distance as criterion for selecting a set of filters. Then we applied the selected filters to acquired data of dried onions and related foreign materials in order to finally perform LDA and QDA for classification. Firstly, QDA yields better results. Secondly, the classification results with two and three filters are better than those with one filter. Taking, e.g., morphological filters into account, a classification on the basis of two filters would probably yield results which would be sufficient for reaching good product quality.

The presented results can be further evaluated by, e.g., determining the ratio of foreign material detected by the proposed method. In some applications, it could be necessary to distinguish between different kinds of foreign material. In such cases, a more specified classification with several classes of foreign material needs to be developed. The relation between the necessary number of filters and the distinction of classes could be evaluated.

Finally, the proposed setup could be tested with real optical filters and the sorting results could be compared to the predicted ones.

5. REFERENCES

Ariana, D., D. Guyer and B. Shrestha. 2006. Integrating multispectral reflectance and fluorescence imaging for defect detection on apples. *Computers and Electronics in Agriculture* 50(2): 148-161.

Ariana, D., R. Lu and D. E. Guyer. 2006. Near-infrared hyperspectral reflectance imaging for detection of bruises on pickling cucumbers. *Computers and Electronics in Agriculture* 53: 60-70.

R. Gruna, K.-U. Vieth, M. Michelsburg, F. Puente León. "Hyperspectral Imaging - From Laboratory to In-line Food Sorting". CIGR Workshop on Image Analysis in Agriculture, 26-27. August 2010, Budapest.

- Backer, S. D., P. Kempeneers, W. Debruyn and P. Scheunders. 2005. A band selection technique for spectral classification. *IEEE Geoscience and Remote Sensing Letters* 2(3): 319-323.
- Duncan, D. and G. Leeson. 1999. Cost Effective Real-Time Multi-Spectral Digital Video Imaging. *Proceedings of the SPIE* 3649: 100-108.
- Gómez, A. H., Y. He and A. G. Pereira. 2005. Non-destructive measurement of acidity, soluble-solids and firmness of Satsuma mandarin using Vis/NIR-spectroscopy techniques. *Journal of Food Engineering* 77 (2): 313–319.
- Graves, M. and B. Batchelor. 2003. *Machine Vision for the Inspection of Natural Products*. London: Springer.
- Gualtieri, J. and S. Chettri. 2000. Support vector machines for classification of hyperspectral data. In *Proc. International Geoscience & Remote Sensing Symposium 2000*, 813-815. Honolulu, HI.
- Hastie, T., R. Tibshirani and J. H. Friedman. 2003. *The Elements of Statistical Learning*. New York: Springer.
- Kohavi R. and G. H. John. 1997. Wrappers for feature subset selection. *Artificial Intelligence* 97(2): 273-324.
- Lu, R. 2007. Quality evaluation of Fruit by Hyperspectral Imaging. In *Computer Vision Technology for Food Quality Evaluation* ed. D. Sun, 319-348. New York: Springer.
- Lu, R. and Y. Peng. 2007. Development of a multispectral imaging prototype for real-time detection of apple fruit firmness. *Optical Engineering* 46(12).
- Mehl, P. M., Y. R. Chen, M. S. Kim and D. E. Chan. 2004. Development of hyperspectral imaging-technique for the detection of apple surface defects and contaminations. *Journal of Food Engineering* 61: 67-81.
- Paclik, P., R. Leitner and R. Duin. 2006. A study on design of object sorting algorithms in the industrial application using hyperspectral imaging. *Journal of Real-Time Image Processing* 1(2): 101-108.
- Serpico, S. and G. Moser. 2007. Extraction of spectral channels from hyperspectral images for classification purposes. *IEEE Transactions on Geoscience and Remote Sensing* 45(2): 484-495.
- Storn, R. and K. Price. 1997. Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces. *Journal of Global Optimization* 11(4): 341-359.
- Vieth, K.-U., E. Enderle and M. Burkhard. 2009. Online-Farbmessung mittels bildgebendem Spektrometer. In *Proc. 15. Workshop Farbbildverarbeitung*. Berlin, 8./9. October.
- Williams, P. C. and K. Norris. 2001. *Near-Infrared Technology in the Agricultural and Food Industries*, 2nd edition. St Paul, MN: AACC, Inc.
- Withagen, P., E. d. Breejen, E. Franken, A. d. Jong and H. Winkel. 2001. Band selection from a hyperspectral data-cube for a real-time multispectral 3CCD camera. *Proceedings of the SPIE* 4381(84): 84-93.
- Zude, M. (Ed.). 2008. *Optical Monitoring of Fresh and Processed Agricultural Crops*. Boca Raton, FL: CRC Press.

R. Gruna, K.-U. Vieth, M. Michelsburg, F. Puente León. "Hyperspectral Imaging - From Laboratory to In-line Food Sorting". *CIGR Workshop on Image Analysis in Agriculture*, 26-27. August 2010, Budapest.