RAPID INFRARED MULTI-SPECTRAL SYSTEMS DESIGN USING A HYPERSPECTRAL BENCHMARKING FRAMEWORK

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ABSTRACT

We present a benchmarking framework to design multi-spectral systems working in the NIR range for multiple purposes. This framework is composed of a hyperspectral imaging hardware and an ad-hoc software that performs pattern recognition experiments (image acquisition, segmentation, feature extraction, feature selection, classification and evaluation steps) comparing different algorithms in every step. For each experiment, we obtain a solution using a generic hyperspectral system, but we also obtain enough data to design a specific multi-spectral system in order to decrease the overall execution time. This improvement is based in the feature selection step, that provides the most relevant wavelengths for the problem. The framework has been tested for detecting internal and external features in potatoes, determining the origin of honey, and studying fecundity parameters in hen eggs.

Index Terms— hyperspectral, multi-spectral, computer vision, image processing, infrared

1. INTRODUCTION

Hyperspectral imaging is an emerging technology originally designed for military remote satellite inspection [1], but is also used for remote sensing, astronomy and Earth observation. It is a reliable approach to classical spectroscopy, because despite a little loss of accuracy, an object can be analyzed in significantly less time and in a non-destructive way.

Hyperspectral imaging joins two quite different technologies: spectroscopy, which obtains spectral information from an object, and computer vision, which obtains spatial information from an object. The output of a hyperspectral acquisition system is a set of images within a wavelength range, known as a hyperspectral cube. This means that, for each pixel in the image, we have a set of values indicating how this pixel varies along a certain frequency range.

The scientific community has started in the last years to show interest in hyperspectral imaging possibilities for food quality. Thus, some groups have worked or are working in applications of hyperspectral imaging in food quality assessment. We can find contributions oriented to multiple products like chicken [2], mushrooms [3], cucumbers [4] and mandarins [5], as well as extensive reviews, e.g., [6].

Hyperspectral systems usually take hundreds of images that correspond to consecutive wavelengths in the spectra, but in the practice, each problem of detection or classification uses a limited number of wavelengths, so the problem can be handled as a multi-spectral system.

2. HYPERSPECTRAL FRAMEWORK

2.1. Motivation

Designing specific multi-spectral systems is a tedious and complex task. Using a multiple purpose benchmarking system, we have the chance of testing multiple options in the search of the optimum combination of algorithms to solve the problem. This benchmarking system should be hyperspectral to allow a continuous search within a wavelength range.

A generic hyperspectral system is usually slower than a specific multi-spectral one, because it needs to scan the object in some way to obtain one spectral image for each inspected line building eventually the hyperspectral cube. A multi-spectral approach avoids the scanning of the object and no movement is needed, just acquiring one image for each wavelength of interest, previously selected using some feature selection algorithm. From this point of view, and for each problem, an experimental general-purpose hyperspectral system provides a valid solution possibly in an inadequate time (depending on the user requirements), meanwhile each specific multi-spectral system gives the same solution in less time, but it is oriented to just one problem. Figure 1 presents the system diagram.

This work presents a hyperspectral benchmarking system for multi-spectral systems design in the NIR range. The procedure will be capture the images from the objects using a
general purpose infrared hyperspectral system. Then, hyperspectral cubes will be built from the frequency images. Image processing algorithms are executed both for segmentation and for feature extraction purposes as described in the sequel. Afterwards, feature selection algorithms are executed, obtaining datasets that represent the same data using different combinations of features. These datasets are then tested with some classification algorithms in order to classify the objects into the proposed classes. A result is obtained, as well as enough information to design a specific multi-spectral system.

2.2. Image acquisition

The concept of hyperspectral imaging is to perform a spectroscopic analysis of the light reflected or transmitted by the object of interest. This is accomplished by coupling a spectrograph with a matrix camera, hence, obtaining both spectral and spatial information. Our hyperspectral system has been designed for non-destructive food inspection in the NIR region. We coupled an infrared camera and a swir-nir spectrograph, both sensitive from 900 nm to 1700 nm. The camera is a Xenics Xeva 1.7–320 with an InGaAs 320 × 256 pixel sensor and USB connection. The spectrograph is a Specim Imspector N17E. The system has also three 50 W AC halogen lamps placed in the inspection plate to provide diffuse illumination to the object surface. The diffuse light is obtained by the reflection in a plastic dome over the plate made.

The spectrograph has a linear input (one pixel height), where the x-axis represents the same x-axis (spatial) of the object. The y-axis (spectral) is then studied to obtain how every pixel in the row varies along the spectral range. With one spectral image, we are inspecting only one spatial line, so we need to inspect the whole object. This is accomplished joining a rotary Mirror Scanner to the spectrograph. The complete scanning of an object takes approximately 30 seconds. It is based on performing a rotation of the mirror to scan the object, taking care of the synchronization between mirror stepping and image acquisition (Figure 2). Then, these images are transposed to create the hyperspectral cube (Figure 3). Our system obtains 320 spectral images (320 × 240 pixels), that are transposed into hyperspectral cubes formed by 256 images with 320 × 320 pixels, corresponding to 256 consecutive wavelengths from 900 nm to 1700 nm.

2.3. Segmentation

We are going to handle two types of problems depending on the result that the user requires. The first type of problems are those where each hyperspectral cube has only one object, and this object is related with one class (1o1c). The result of analyzing the hyperspectral cubes will be the class the object belongs to. For instance, we have studied the origin of honey samples, where one sample belongs only to one class. The other type of problems are intended to classify each pixel in the hyperspectral cube in order to build a map that indicates which zones in the object belong to a specific class (mapping). For instance, we have studied the detection of common scab (a skin disease) in potato tubers. Thus, some pixels are classified as scab, and others as healthy surface. The user obtains an incidence map and incidence percentages.

Independently of the type of problem, we need to segment the object from the background in every hyperspectral cube for later feature extraction tasks. We segment only one image from the hyperspectral cube so that we obtain a mask that will be applied in the rest of the hyperspectral cube.

Segmentation runs in several steps using the open source library OpenCV [7]. First, we binarize the image with Otsu’s method [8] that calculates the optimum binarization thresh-
old. Then, a Gaussian blurring clusters the noise in the image. A connected-component labelling is performed to remark contiguous areas in the image. At this point, we know that the blob with the largest area (excluding the background) is the object of interest. We select this blob and create the mask to segment all the images in the hyperspectral cube (full). Other segmentation algorithms have been implemented to capture zones where the incidence of light is different, taking into account central (core) and external (border) portions. The Figure 4 visualizes examples of these processes.

![Figure 4](image)

**Fig. 4.** 1: Otsu’s binarization. 2: smooth operation. 3: blob analysis. 4: full mask. 5: core mask. 6: border mask.

### 2.4. Feature extraction

The different types of problems need specific algorithms to extract their features. With mapping problems, the samples are provided by selecting manually regions of interest (ROI). From each hyperspectral cube, we can select many samples, always indicating the class each sample belongs to. In the case of IoIc problems, each hyperspectral cube provides just one sample. We take into account just the zone selected by a segmentation algorithm (full, core or border).

The objective of feature extraction is to represent each sample with one vector of values. Hyperspectral imaging provides spectral information, so we calculate the average luminance value of the pixels in the ROI or in a segmented zone for each image in the hyperspectral cubes (i.e., for each of the 256 wavelengths). In some IoIc problems, we included three morphological features to the feature list, namely the area, the perimeter, and the relation area–perimeter of the object, that could be useful depending on the problem.

### 2.5. Feature Selection

Feature selection is a common task in pattern recognition problems, specially in those cases where the initial number of features is high. In our case feature selection is a fundamental step to decrease the overall execution time, because we use feature selection to identify which wavelengths are sufficient to solve each problem in order to design a specific multi-spectral system with this information.

We have tested some techniques regarding spectral bands selection on hyperspectral imaging systems (implemented on Weka [9]): Genetic Search [10], Scattered Search [11], Greedy Stepwise, Linear Forward Selection (LFS) [12], and Correlation-based Feature Subset Selection (CFS) [13]. Other techniques such as PCA and LDA do not reduce the number of wavelengths needed, as required, rather they generate a linear combination of the 256 features into a new feature space composed of less dimension.

### 2.6. Classification

We have tested the problems with four classification algorithms: Random Forest (RF) [14], Support Vector Machines (SVM) [15] with Gaussian kernel (SVM-RBF) and linear kernel (SVM-LIN), and Logistic Regression (LR) [16].

For each dataset, we evaluate the classification algorithms using a method based on randomly generating 10 permutations of the dataset, so that each permutation has the same samples, but differently ordered. Then, each permutation is divided into three parts: training (50% of the samples), validation and parameter tuning (25%), and test (25%). The samples are normalized (zero mean and standard deviation one) to avoid that attributes in greater numeric ranges influence excessively over those with smaller variation.

For each combination of tunable parameters and for each permutation, we train a classifier using the training sets. Then, we test its performance by using the validation sets. We select the parameter values which provide the best average accuracy over the 10 permutations. These parameters are: \( m_{\text{try}} \) (the number of features to be used in random selection) for RF, using \( m_{\text{try}} = p^0, m_{\text{try}} = \sqrt{p}, m_{\text{try}} = p/4 \) and \( m_{\text{try}} = p/2 \), with \( p \) = number of features; the regularization parameter (\( C \)) and kernel spread (\( \gamma \)) for SVM-RBF, using \( C = 2^n, n = -5..14 \) and \( \gamma = 2^n, n = -15..0 \); \( C \) for SVM-LIN, using \( C = 2^n, n = -5..14 \), and LR has the ridge estimator (\( r \)), using \( r = 10^k, k = -9..0 \). Finally, for each permutation, we train the classifier using the training sets tuned with the best parameters found, evaluating its accuracy on the test sets only.

### 3. EXPERIMENTS AND RESULTS

In the Table 1 some results are presented in order to summarize the problems that have been tested. For each problem, different alternatives have been compared, and the best option is chosen as the final solution.

The common scab is a skin disease of the potato tubers that decreases the quality of the product and influences significantly the price. We have used the presented framework to solve the problem, achieving a 97.1% of accuracy using...
Support Vector Machines ($C = 2^{11}, \gamma = 2^{-5}$) and a specific subset of spectral features selected by the CFS algorithm.

The **hollow heart** is an internal disorder of the potato tubers, that causes a star–shaped cavity that grows into the potato. Acoustics and X–Ray examination have tried to detect the hollow heart in the last years, but none of the approaches provide a non–destructive, orientation–independent and size–independent solution. Our system has found that using the *border* segmentation method and the SVM-LIN classification algorithm ($C = 2^{-5}$), we get a 89.1% of accuracy detecting the hollow heart. This option uses a specific subset of spectral features selected by the genetic algorithm feature selection method, as well as three morphological features that represent size and roundness of the samples.

The characterization of different types of honey, on the basis of their botanical origin, is an interesting tool for the food industry. A preliminary stage of the analysis has been performed, getting accuracies next to 99% (SVM-RBF, $C = 2^7, \gamma = 2^{-12}$) that should be confirmed in the future.

Our system was also tested with the aim to classify hen eggs, while they are being incubated, according to their sex. In the past, some methods have been used for this purpose, but none got remarkable non–destructive results. Unfortunately, no more than a 60% of accuracy was achieved.

After the in-ovo sex study, a fecundity determination was tested, getting a 100% of accuracy. Although this problem can be solved using faster and simpler methods, the application of our hyperspectral system shows it is a reliable technology that may be applied to multiple sets of problems.

### 4. CONCLUSIONS

We presented a multiple purpose benchmarking hyperspectral framework for the designing of specific multi-spectral systems, that has been tested in some food quality problems. The specific systems are faster than the equivalent ones in the hyperspectral approach, because less wavelengths are inspected, after using feature selection algorithms. Pattern recognition experiments have been performed for deciding which other algorithms are required to solve the given problem. Moreover, NIR hyperspectral imaging has shown to be an interesting objective non–destructive choice for food quality assessment.

### 5. REFERENCES


