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# A new approach for discrimination of objects on hyperspectral images ☆

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ABSTRACT

A new approach for discrimination of objects on hyperspectral images, which combines state-of-art image processing methods and multivariate image analysis, is proposed. The basic idea of the approach is to build a joint principal component space for all objects' pixels, detect patterns, pixels from a particular object shared in this space, and use quantitative evaluation of the patterns as the objects' features. The approach was particularly developed for dealing with challenging cases, when objects from different classes have many similar pixels. It has been tested on several real cases and showed very promising results.

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## 1. Introduction

Classification and discrimination of objects on digital images is one of the most common problems in image analysis. Detection of unripe or spoiled fruits [1,2], counting white and red cells on a microscopic image of a blood smear [3,4], and evaluation of individual components in an untreated waste for further recycling [5,6], — all these and many other similar tasks need the same procedure for solving: take an image, segment objects of interest and classify or discriminate them.

For conventional colour images, a very natural way to do that is to calculate some quantitative features of the objects' pixels and apply well-known classification or discrimination algorithms such as logistic regression, Soft Independent Modelling of Class Analogy (SIMCA) or Partial Least Squares Discriminant Analysis (PLS-DA). Depending on a particular case the features may reflect colour properties (e.g. intensity distribution histograms or their first order statistics) [7,8], shape properties (e.g. area, perimeter, roundness, or more sophisticated shape descriptors) [9], textural properties (e.g. statistics of grey level co-occurrence matrices, wavelet transformations) [10] or their combinations. However in spite of the great diversity of methods for computing features of colour (usually represented by red, green and blue channels, RGB) and grayscale images most of them are not applicable when dealing with hyperspectral data.

Hyperspectral imaging combines benefits of digital imaging and vibrational spectroscopy, allowing to reveal and visualise spatial distribution of various chemical components and, therefore, making many similar looking objects distinguishable [11]. In a hyperspectral image every pixel is a spectrum (usually visible near-infrared, short-wave near-infrared or Raman) of a depicted area. Hyperspectral imaging has many advantages in comparison with traditional colour imaging, however a hyperspectral image consists of hundreds of channels (bands) that make most of the classic methods for image analysis hardly usable.

Multivariate image analysis (MIA) [12] is one of the specific approaches developed for the analysis of multispectral and hyperspectral images, widely spread among chemometricians. In general MIA treats pixels as samples: first an image hypercube has to be unfolded into a matrix, where rows represent pixels and columns — colour channels or spectral bands. So in fact, multivariate image analysis works with an image as with a large set of spectra, without taking into account information about spatial relations of pixels on the image. This works well in general, especially for image regression, exploratory analysis, and multivariate curve resolution [13,14], but for some specific tasks it is not beneficial at all.

One of such tasks is classification or discrimination of objects on images. Thus if objects from opposite classes are not absolutely different (e.g. there are many similar pixels) this can lead to a problem. For example, if two different tablets have the same or chemically similar excipients and different active ingredients, the spectra of most of the pixels will be identical. But these similar pixels will be associated with different classes when a classification or discrimination model is being calibrated. One of the possible solutions of this problem for hyperspectral images is to predict some other properties of every object pixels and deduce appropriate class depending on how many pixels with particular range of properties an object has [15]. However if classification algorithms are applied directly to pixel spectra this can result in the unstable model and poor classification results.

To illustrate this problem and to show later how the approach is going to be proposed in this paper, a simple RGB case will be used for the sake of simplicity. In Fig. 1 colour images of barley grains from two different producers (denoted as A and B) are shown. It can be seen that most of the grains from both images can be barely distinguished by an unarmed eye — most of the pixels are very similar (in this case have similar colour components). However several

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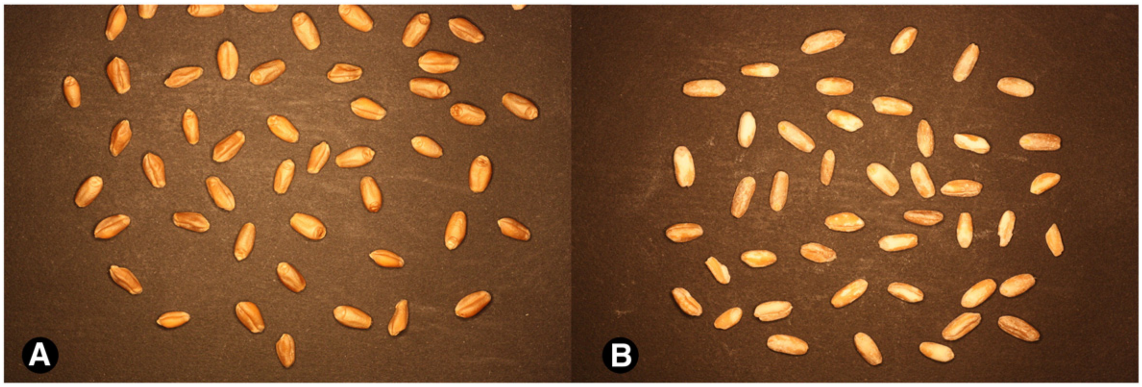


**Fig. 1.** RGB images of barley cereals from two different producers.

objects from the producer B (right picture) are in general lighter than some objects from the producer A (left picture).

Nevertheless, if we apply Principal Component Analysis (PCA) to the merging of the two images with removed background, only pixels from barley grains are taken into account, the pixels from different classes will be highly overlapped, as it is shown on the score density plots in Fig. 2 (left — PC1 vs. PC2, right — PC1 vs. PC3). Obviously there is no way to distinguish any classes on the score plots at all.

In this paper an approach for discrimination of objects on hyperspectral images that can tackle the described above and similar problems is proposed. The approach combines some traditional image analysis methods and multivariate image analysis. The basic idea is not rather new — to group all pixels from one object and calculate spectral properties of the pixel group to be used further as a vector of predictors for discrimination and classification. It means to use an object as a sample instead of a pixel as most of the MIA methods do. The grouping can be done with image segmentation and mathematical morphology methods, applied, for example, to a score image or to an image from a particular spectral band where objects are well separated spatially.

This paper describes all aspects of the approach and shows some preliminary results of testing it on real colour and hyperspectral images. All calculations have been carried out in MATLAB® 2012a supplemented with Image Processing Toolbox (The MathWorks, Inc., USA) and PLS_Toolbox 6.7 (Eigenvector Research, Inc., Wenatchee, USA).

## 2. The proposed method

As it was already mentioned in the introduction, the basic idea for the approach is to combine classic methods widely used for analysis of colour images and some aspects of MIA, namely grouping pixels from the same objects together and using MIA to calculate spectral features for the pixels from a particular object.

The first step then is to make image segmentation (in most of the cases just to remove background) and to label all objects and their pixels. The methods for both procedures (segmentation and labelling) are very well developed in state-of-art image processing and can be used for hyperspectral images as well. Usually, a score image for first principal component gives a very good separation between objects and background pixels and therefore goes very well for segmentation. Alternatively an image from a selected band where the contrast between objects and background is reasonably high can also be utilized for these purposes.

The result of this step is an image mask — a matrix, with the same number of elements as the number of pixels on the image, and where each element has an index that corresponds to a particular object. Thus all pixels of a first object will have an index = 1, pixels from the second object will have an index = 2 and so on. Index for all background pixels is set to 0. This allows easily grouping pixels either object wise or class wise.

Before describing the next step let us first look at the same score plots as shown in Fig. 2, but instead of colourizing pixels' density we will use colours to see pixels from different classes of grains as it is shown on plots in Fig. 3. Red points on these plots correspond to the pixels from class A objects and blue points — to the pixels from class B. The two sets of plots (bottom and top) are absolutely identical, showing scores for PC1 vs. PC2 and PC1 vs. PC3, but with different order of pixel classes to illustrate how large the overlapping area is.

It seems like it does not show anything new. However, if one looks at the plots carefully, it can be also seen that the orientation and shape of blue and red "clouds" of points are slightly different — the "clouds" are shifted and rotated a bit relating to each other on both plots.

It can be shown even better using score plots with pixels from individual objects as presented in Fig. 4. Plots on the left side show score values of pixels from two randomly chosen individual objects of class A and plots on the right side do the same but for randomly

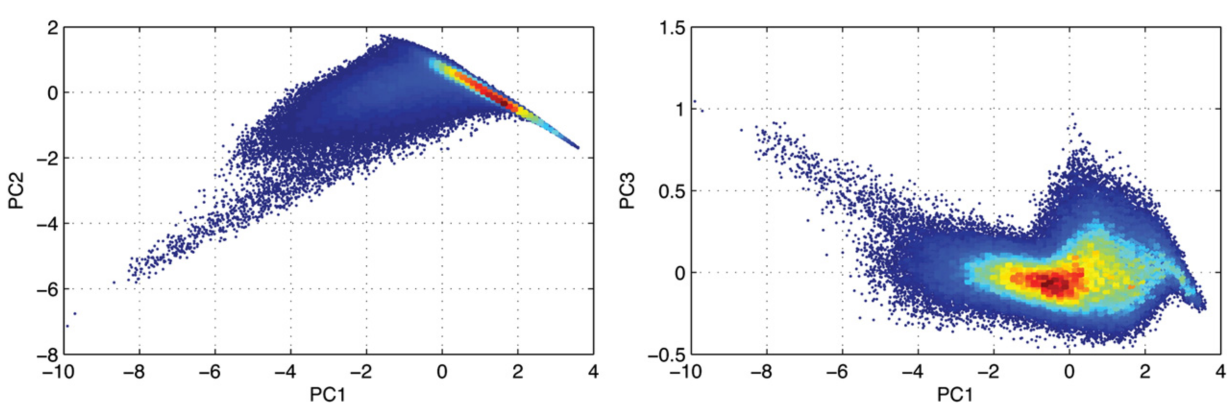


**Fig. 2.** Score density plots for the cereal pixels from both groups.

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