INDEPENDENT COMPONENT ANALYSIS OF AIRBORNE HYPERSPECTRAL DATA FOR THE STUDY OF WEED AND NITROGEN STRESS IN CORN CROPS

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ABSTRACT

Airborne hyperspectral remote sensing imagery is an efficient way to obtain an accurate spatial information at the scale of the field or group of fields because of its fine spatial resolution and its ability to acquire simultaneously a great number of spectral bands. This paper presents an unsupervised analysis tool enabling us to extract information from this type of data, the Independent Component Analysis. This tool particularly allows the influence of different treatments on a crop to be independently extracted.

1 INTRODUCTION

1.1 Background

This paper is the fruit of an experiment conducted by members of the GEOIDE's research project 54. The main goal of this project is to search for representative indicators of stresses of agricultural plants to be used in remote and/or in-situ validations of satellite observations. An interdisciplinary mini-network of researchers including specialists in geomatics, airborne and satellite remote sensing, optical and fluorescent properties of vegetation, laser spectroscopy of environmental targets, micrometeorology in-situ sensor technologies, and agronomy has been assembled for this purpose. In the present paper the authors concentrate on the unsupervised study of weed and nitrogen stresses in corn crops.

1.2 Study Area and Data Set

The study was conducted using a corn field, located at the Macdonald experimental farm (McGill University, Canada), divided into 48 equal blocks of 20 by 20 meters (*fig.1*). The experimental setting includes a combination of 3 levels of nitrogen (low, medium, high) and 4 levels of weed control (no weed control, narrow leaf, broad leaf, narrow and broad leaf). Each treatment combination was repeated 4 times. For this study it is assumed that the soil characteristics are homogeneous and that no other effect alters the reflectance of the corn. CASI images were recorded at an early stage of growth (late june) for a final 2×2 meters pixel size. Reflectance calibration of data including atmospheric corrections was performed using the flat field calibration method. Furthermore, the images have undergone geometric corrections and geo-referencing, resulting in a RMS error of 0.5 pixel. For the purpose of this paper, 60 spectral bands spanning over the 490.44 - 939.33 nm range were selected and pixels were extracted for one replicate (12 cases) of the combination of treatments (*fig. 2*).

2 INDEPENDENT COMPONENT ANALYSIS

2.1 Objectives and interest of the method

The images from the CASI sensor used in this study include 60 spectral bands and conventional multivariate methods are not robust for such high dimensionnality data. Moreover, the visualisation of such data asks for the creation of new channels allowing the data to be represented the most synthetic way according to a particular criterion. Often, it is necessary to include a dimensionality reduction step in the process of data analysis. Principal Component Analysis (PCA) is one of the techniques commonly used for this purpose. It allows the data to be represented by statistically *uncorrelated* components. The authors propose here to use Independent Component Analysis (ICA) enabling the data to be represented by statistically *independent* components [Jut91]. Statistical independence takes into account higher order moments and is hence a stronger statistical property than correlation, a second order statistic. ICA has been largely studied these last few years by researchers from the signal processing community in the field of blind source separation [Com94]. The technique is based on the optimisation of an independance criterion between the observed signals. ICA leads to a new representation of hyperspectral data which reveals to be very interesting in our study, enabling the effects of weed and nitrogen treatments on corn crops to be independently extracted.

2.2 Model and hypothesis

The model of ICA if given by :

$x = A\,s$	*(1)*	with	x :	Vector of observed images
			A :	Scalar matrix of mixing
			s :	Vector of independent source images

ICA lies on two hypothesis : *(H1)* The components s_i of s are statistically independent and *(H2)* The components s_i of s have non gaussian distributions (it can be shown that no more than one component can be gaussian). The goal of ICA is to find the matrix $W = A^{-1}$ so that one can estimate $s_{est} = W\,x$ from the vector x of the observed images.

2.3 Definitions of independence

A set of signals s is said to be independent if a signal s_i gives no information on the other signals of the set. The joint probability density function is then equal to the product of marginal probability density functions. Independence implies uncorrelated signals but the inverse is not true. This observation enables to restrict the estimation procedure of the independent signals to the space of uncorrelated signals. The first step in computing the ICA is then a decorrelation of the observed signals, which can be achieved with a conventional PCA. There is a strong relation between independence and non gaussianity. The Central Limit Theorem tells that the sum of N independent random variables tends in law toward a gaussian distribution when N tends to the infinity. A corollary of this theorem tells that the sum of two independent random variables has a more gaussian distribution than any of the initial random variables. Thus, the estimation of the independent components consists in finding the weights of the matrix W in order that the vector $s_{est} = W\,x$ has the less gaussian components possible. A standard measure of gaussianity is kurtosis but the latter is unfortunately very sensitive to outliers. A more robust measure of gaussianity is given by negentropy $J(x)$ mesured by the deficit of entropy $H(p)$ between x and a gaussian random vector x_g of equal covariance matrix, knowing that the entropy is maximal for this gaussian random vector x :

$$J(x) = H(p_{xg}) - H(p_x) \qquad \text{with } H(p_x) = - \int p_x(u) \log p_x(u)\, du \qquad (2)$$

It can be shown that negentropy $J(x)$ is equal to the Kullback-Leibler divergence $k(p_x, p_{xg})$ between the vector x and the gaussian vector x_g :

$$J(x) = k(p_x, p_{xg}) \qquad \text{with } k(p_v, p_w) = - \int p_v(u) \log[\, p_v(u) / p_w(u)]\, du \qquad (3)$$

Hyvärinen has introduced the following approximation of negentropy [Hyv99] :

$$J(x) = \{ E[G(x)] - E[G(x_g)] \}^2 \qquad \text{with } G \text{ a non quadratic function} \qquad (4)$$

More details on demonstrations of the preceding equations can be found in [Hyv00].

2.4 Optimisation algorithm

The maximisation of the measure of non gaussianity *(4)* calls for an optimisation algorithm. Fast-ICA algorithm [Hyv99] has been used. It is based on a fixed-point iteration scheme and is given by *(5)* for one component. After each iteration, the vectors *wx* are decorrelated using a symmetric decorrelation of the matrix W of vectors w_i. See [Hyv99] for details.

1. choose an initial (e.g random) weight vector w.
2. Let $w^+ = E\{x\, g(w^T x)\} - E\{g'(w^T x)\}\, w$ with $g(u) = \tanh(u)$ *(5)*
3. Let $w = w^+ / \| w^+ \|$

2.5 Preprocessing

Original data include many outliers mainly because of pixels located along the borders of the fields but also because of apparent soil between corn rows. Moreover, increasing the clustering enables the accuracy of ICA to be improved. Original data have hence been filtered on every field with a median filter. It has been shown in *paragraph 2.3* that a necessary preprocessing of ICA involves whitening the data. This is achieved by a conventional non standard PCA which allows us in addition to reduce the dimensionnality of the data before computing the ICA. After the study of eigenvalues and given that the goal of this study is mainly to extract the effects of weed and nitrogen treatments, it was decided to keep only the first two components accounting for 99.73 % of the total variance of the information.

3 APPLICATION OF ICA WITH SIMULATED DATA

In order to show the potential of ICA, three different images have been mixed with a random mixing matrix A. PCA and ICA *(5)* have been performed on these mixed images. Results are shown on *fig. 3*. It can be noticed that the decorrelation produced by the PCA does not imply the separation of original images, which is achieved by the ICA. This exemplifies the notion of independence of phenomena, that in this case produced the original images.

4 APPLICATION OF ICA WITH EXPERIMENTAL DATA

4.1 Principal Component Analysis

The results of a PCA on the filtered data are shown on the *fig. 4*. Only the first two components and the joint distribution of these two components are shown. It can be noticed that the effects of weed and nitrogen treatments are not separated.

4.2 Independent Component Analysis and interpretation of results

ICA *(5)* has been performed after filtering and whitening the data. The results are shown on the *fig. 5*. Only the first two components and the joint distribution of these two components are shown. We can do the following remarks: **(1)** the first component extracts the effect of the weed treatment independently from the effect of the nitrogen treatment. It can be particularly noticed on the joint distribution where the four levels of weed treatments are perfectly linearly separable independently from the three levels of nitrogen treatment, **(2)** the second component tends to extract the effect of the nitrogen treatment but the three levels of treatments are not perfectly linearly separable. The contribution of each spectral band to each of the two first principal and independent components has been evaluated by computing the correlations and angles between bands and components. These statistics are shown on *fig. 6*. PCA shows the spectral bands giving the most of information in the sense of the total variance of original data. ICA enables us to extract the most important bands for the discrimination of weed and nitrogen treatments. It can be particularly noticed that the effect of the weed treatment appears at best on band 60, in the near infrared part of the electromagnetic spectrum (939.33 nm).

4.3 Complementary spectral analysis

A simple spectral analysis follows the study of the data with the ICA. *Fig. 7* shows the mean spectra for each field and the mean spectra for all the fields with the same treatments. The dependences between treatments can be noticed and enable the interest of the results from the ICA to be confirmed.

5 CONCLUSIONS

Independent Component Analysis has been used as a tool for unsupervised hyperspectral data analysis with promising results. It particularly enables us to extract independent phenomena present in the scenes. This is very useful in the field of precision agriculture because it allows the effects of different treatments on the crops to be independently extracted, task that was not possible with Principal component Analysis, the standard tool of data analysis.

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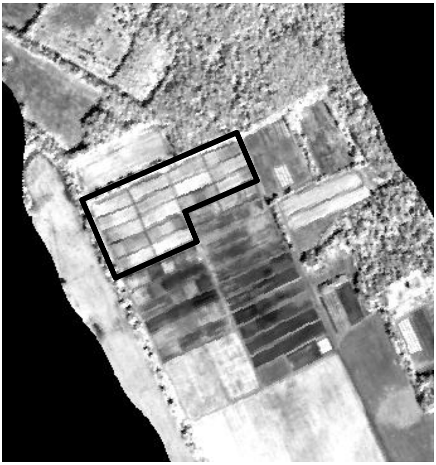


FIGURE 1. The experimental site of McGill

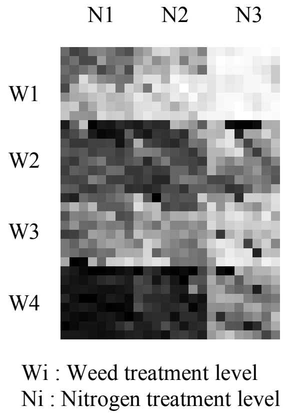
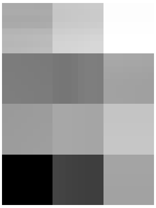


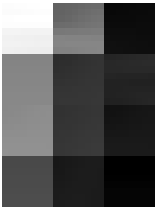
FIGURE 2. Data extraction and treatment combinations

(a) (b) (c)

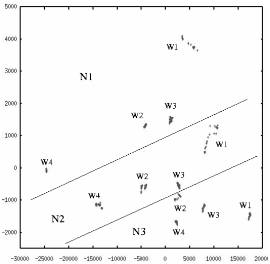
FIGURE 3. ICA on simulated data
(a) mixed observed images, (b) PCA, (c) ICA



(a) PC 1

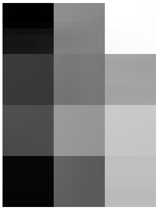


(b) PC 2

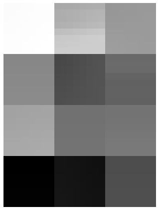


(c) Joint distribution PC1 / PC2

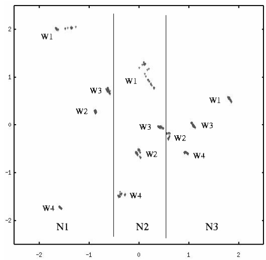
FIGURE 4. Principal Component Analysis



(a) IC 1

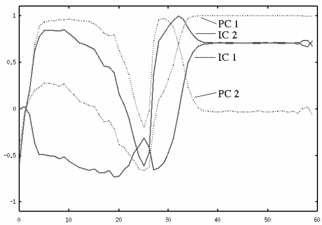


(b) IC 2

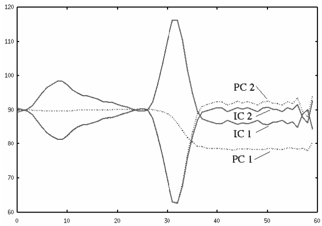


(c) Joint distribution IC1 / IC2

FIGURE 5. Independent Component Analysis

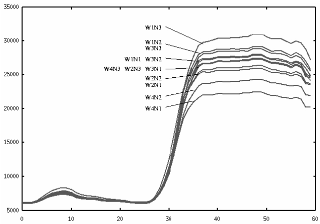


(a) Correlations between bands and components

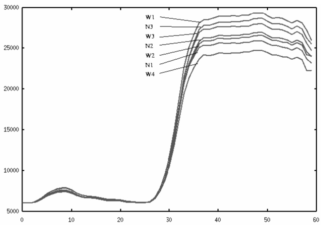


(b) Angles between bands and components

FIGURE 6. Statistics



(a) Mean spectra for each field



(b) Mean spectra for weed and nitrogen treatments

FIGURE 7. Spectral analysis