Targeting Input Data for Change Detection Studies by Suppression of Undesired Spectra

Klaus Baggesen Hilger and Allan Aasbjerg Nielsen
IMM, Department of Mathematical Modelling
Technical University of Denmark, 2800 Lyngby, Denmark
e-mail: kbh@imm.dtu.dk, aa@imm.dtu.dk

Abstract

This paper describes fuzzy spectral-spatial clustering of multivariate image data to perform a segmentation into a desired number of clusters and orthogonal subspace projection (OSP) to reduce the influence of undesired spectra. The clustering is used to identify clouds in SeaWiFS data. The influence of the clouds is successfully reduced by means of OSP causing the ocean signal to become much more conspicuous.

1. Introduction

Input data meant for change detection is often corrupted by undesired spectra such as clouds. Here, we suggest a method for reducing the influence of undesired spectra in multispectral images. This is done by first applying a classification algorithm in order to obtain spectral means of which the image is composed. From these the undesired means are empirically selected, and finally the input data are projected onto a subspace orthogonal to the undesired spectra. Some of the work presented here can also be found in [4].

An often occurring task in image analysis is the segmentation of multispectral (or multi-temporal) image data into a number of clusters/classes. Given an image with p spectral bands, the job is to assign to each observation or pixel a degree of membership. This can be done based on spectral characteristics alone, on spatial characteristics alone, or on combined spectral-spatial characteristics.

By applying the fuzzy c-means (FCM) algorithm, [1], we are able to segment an image into meaningful regions. For a given number of classes, the algorithm estimates the cluster centres in the p-dimensional feature space, including the degree of membership of each pixel. By assigning each pixel to the class with the maximum membership (CMM), we are able to segment the image. Optionally, a threshold can be introduced whereby pixels that do not have their memberships dominated by a single class are assigned to a reject (unknown) class.

The resulting cluster centres can be empirically classified according to the most significant related sources. This allows for an unmixing of signals related to different sources. Here the influence of cloud signals, represented by the corresponding cluster centres, is reduced by means of orthogonal subspace projection (OSP), [5].

In this contribution, Section 2 briefly describes a fuzzy spectral-spatial c-means clustering algorithm. Section 3 briefly describes orthogonal subspace projection. In Section 4 cloud signal in SeaWiFS data as identified by the above fuzzy algorithm is removed by means of OSP. Section 5 compares the resulting images with the original data.

2. The FCM algorithm

The spectral fuzzy c-means algorithm

1. assigns values to p-dimensional feature vectors for C cluster centres,

   $\boldsymbol{r}_c,\ c = 1, \ldots, C;$

2. calculates membership weight for cluster $c = 1, \ldots, C;$

$$u_c = \frac{1/d_c^{2/(m-1)}}{\sum_{i=1}^{C} 1/d_i^{2/(m-1)}}$$

   where d_c is the (Euclidean) spectral distance from the running observation $\boldsymbol{r}$ to each cluster centre $d_c^2 = (\boldsymbol{r} - \boldsymbol{r}_c)^T(\boldsymbol{r} - \boldsymbol{r}_c)$, and $m > 1$ is a user defined weight to control the degree of fuzziness which increases with m (default value $m = 2$);

3. calculates new cluster centres from

$$\boldsymbol{r}_c = \frac{\sum_{i=1}^{N} u_c^m \cdot \boldsymbol{r}}{\sum_{i=1}^{N} u_c^m}$$

where N is the number of observations (both u_c and $\boldsymbol{r}$ depend on i). Steps 2 and 3 are iterated until the largest change in cluster membership becomes small or zero.

To boost performance, the FCM algorithm can be embedded into a multi-resolution inheriting hierarchy. In [8] a spatial element is added. [2] adds a multi-resolution aspect.

2.1. Spatial membership

The spatial membership is defined as

$$u_{spat,c} = \frac{1}{Z}\text{exp}(-\beta E_{\mathcal{N}})$$

where $E_{\mathcal{N}} = 1/|\mathcal{N}| \sum_{\mathcal{N}}(1 - u_c)$ is a Markov random field energy function, $\beta \geq 0$ is a weighting parameter, and Z is a normalising constant. The sum over $\mathcal{N}$ indicates a sum over the neighbourhood of an observation and $|\mathcal{N}|$ is the number of neighbours in $\mathcal{N}$. With $\beta = 0$ no spatial context information is included. The spatial membership to a class is large if the observations in the neighbourhood have large memberships to the same class and small if the neighbours tend to belong to other classes.

2.2. Spectral-Spatial membership

Given the spectral and spatial memberships as defined above, we combine them into a joint membership u_c in this fashion

$$u_c = \frac{u_{spec,c} \cdot u_{spat,c}}{\sum_{i=1}^{C} u_{spec,i} \cdot u_{spat,i}}$$

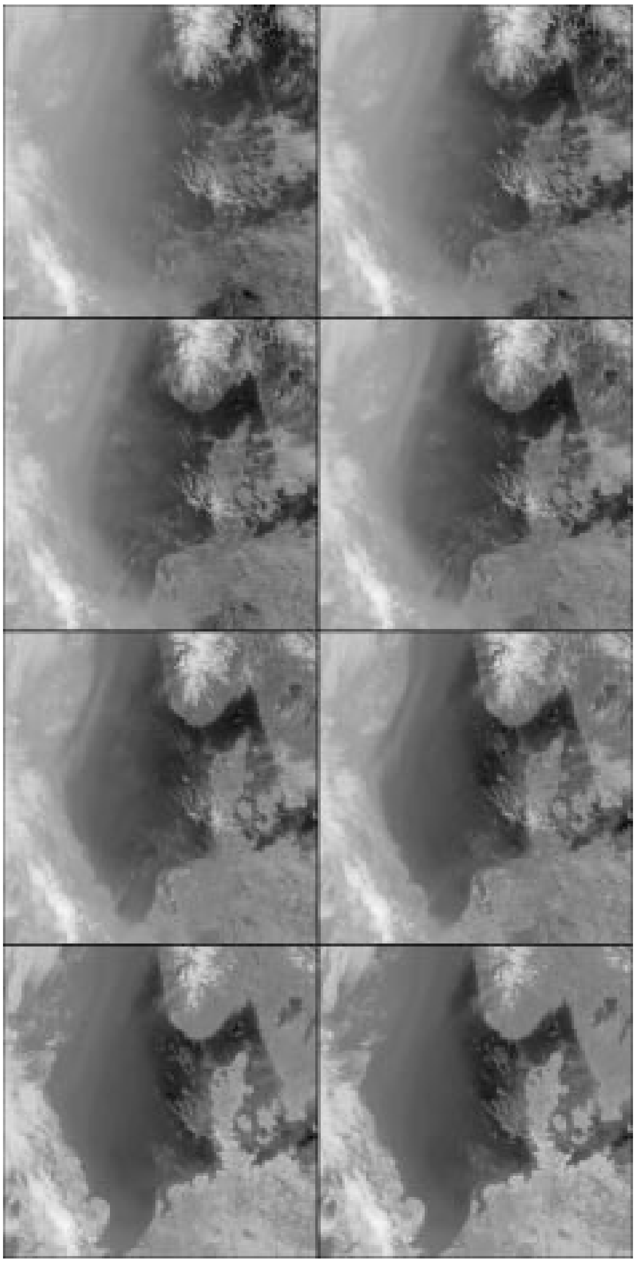

Figure 1. The original SeaWiFS bands 1-8 row-wise. The data is stretched under the whole image.

2.3. Extensions to the fuzzy segmentation

In order to include the spatial context information, additional approaches can be applied. Some of these are briefly described below:

- Add feature bands to the original data set. These feature bands should include textural information. Obvious feature band candidates are e.g. a mean filtered image and an image representing the local variance.
- Apply an external field in the fusion of the spectral and spatial memberships. In this manner a priori knowledge can be included in the analysis.
- Utilise the clustering algorithm in a hierarchical structure such as a scale pyramid. Working top down, the result of segmentation at one level is passed down to the lower levels as e.g. a priori knowledge. By applying the hierarchical framework, fast convergence of the algorithm can be obtained. This is done by passing down the resulting cluster means as initial cluster centres for an analysis at a lower level.

The methods described can be applied both individually and in union. Also, they can be utilised in conjunction with the spatial membership previously introduced in Section 2.1.

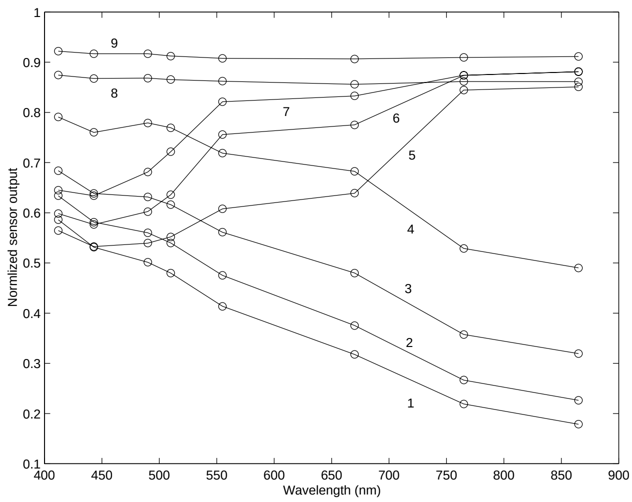

Figure 2. Cluster centres 1 through 9.

3. Orthogonal subspace projection, OSP

Say we want to predict the running $p \times 1$ vector observation $\boldsymbol{r}$ by means of a set of variables written as columns in a matrix $\boldsymbol{U}$,

$$\boldsymbol{r} = \boldsymbol{U}\boldsymbol{\alpha} + \boldsymbol{n}.$$

We want to minimize $n^2 = \boldsymbol{n}^T\boldsymbol{n} = (\boldsymbol{r} - \boldsymbol{U}\boldsymbol{\alpha})^T(\boldsymbol{r} - \boldsymbol{U}\boldsymbol{\alpha})$.

Setting the partial derivative $\partial n^2/\partial\boldsymbol{\alpha} = \boldsymbol{0}$ we get

$$\begin{aligned} \partial n^2/\partial\boldsymbol{\alpha} &= 2(-\boldsymbol{U})^T(\boldsymbol{r} - \boldsymbol{U}\boldsymbol{\alpha}) = \boldsymbol{0} \\ &\Rightarrow \boldsymbol{U}^T\boldsymbol{U}\boldsymbol{\alpha} - \boldsymbol{U}^T\boldsymbol{r} = \boldsymbol{0} \\ &\Leftrightarrow \boldsymbol{\alpha} = (\boldsymbol{U}^T\boldsymbol{U})^{-1}\boldsymbol{U}^T\boldsymbol{r}. \end{aligned}$$

For the residual we now obtain

$$\begin{aligned} \boldsymbol{n} &= \boldsymbol{r} - \boldsymbol{U}\boldsymbol{\alpha} \\ &= (\boldsymbol{I} - \boldsymbol{U}(\boldsymbol{U}^T\boldsymbol{U})^{-1}\boldsymbol{U}^T)\boldsymbol{r}. \end{aligned}$$

An application of OSP, [3, 5, 6], is the projection of $\boldsymbol{r}$ onto a subspace orthogonal to undesired spectra. Now, assume that $\boldsymbol{U}$ contains exactly the undesired spectra in the columns. Applying the $p \times p$ matrix

$$\boldsymbol{P} = \boldsymbol{I} - \boldsymbol{U}(\boldsymbol{U}^T\boldsymbol{U})^{-1}\boldsymbol{U}^T$$

to $\boldsymbol{r}$ we obtain the desired projection.

By its nature OSP is a rank reducing transformation. Performing OSP on k spectra reduces the dimensionality of the data from p to $p - k$.

4 A SeaWiFS case study

SeaWiFS is an 8 channel optical scanner on the SeaStar spacecraft which orbits sun synchronously at a 705 km altitude. On a daily basis, SeaWiFS provides 10 bit data in the 402-422, 433-453, 480-500, 500-520, 545-565, 660-680, 745-785 and 845-885 nm regions. The pixel size is 1.1 km $\times$ 1.1 km. See also [7].

Figure 1 shows the eight channels of a SeaWiFS scene acquired on 14 May 1998. The image is segmented into 9 classes using the FCM algorithm. In Figure 2 the estimated cluster centres are presented. The memberships of each pixel to the clusters, along with the CMM estimated classes, are illustrated in Figure 3. Empirically, cluster 1 is recognised as a water class, 2-4 cloud classes, 5-7 vegetated land classes, and 8-9 cloud/ice classes. In Figure 4 the eight channels of SeaWiFS data are stretched under the CMM obtained water mask. The OSP is performed on the cluster centres 2-4 and the result is presented in Figure 5. The Figure shows the enhanced ocean related signal after OSP cloud signal reduction. The stretch is under the water mask and the Figure is to be compared with Figure 4. All SeaWiFS images are stretched using histogram matching to an approximated Gaussian distribution.

5. Discussion and conclusions

Looking at Figure 3 we see that the applied unsupervised fuzzy clustering produces meaningful classes. In an attempt to enhance the ocean related signal, the undesired cloud cluster means are extracted from the FCM results and OSP is performed. Figures 4 and 5 clearly show the ability of OSP to allow us to “see through” some of the clouds. Thus, OSP successfully reduces the influence of the undesired spectra.

Acknowledgements

The work reported here is carried out under the GEOSONAR (http://manicoral.kms.min.dk/PK/ geosonar.-html) project funded by the Danish National Research Councils (http://www.forskraad.dk) under the Earth Observation Programme. Use of the SeaWiFS data is in accord with the SeaWiFS Research Data Use Terms and Conditions Agreement.

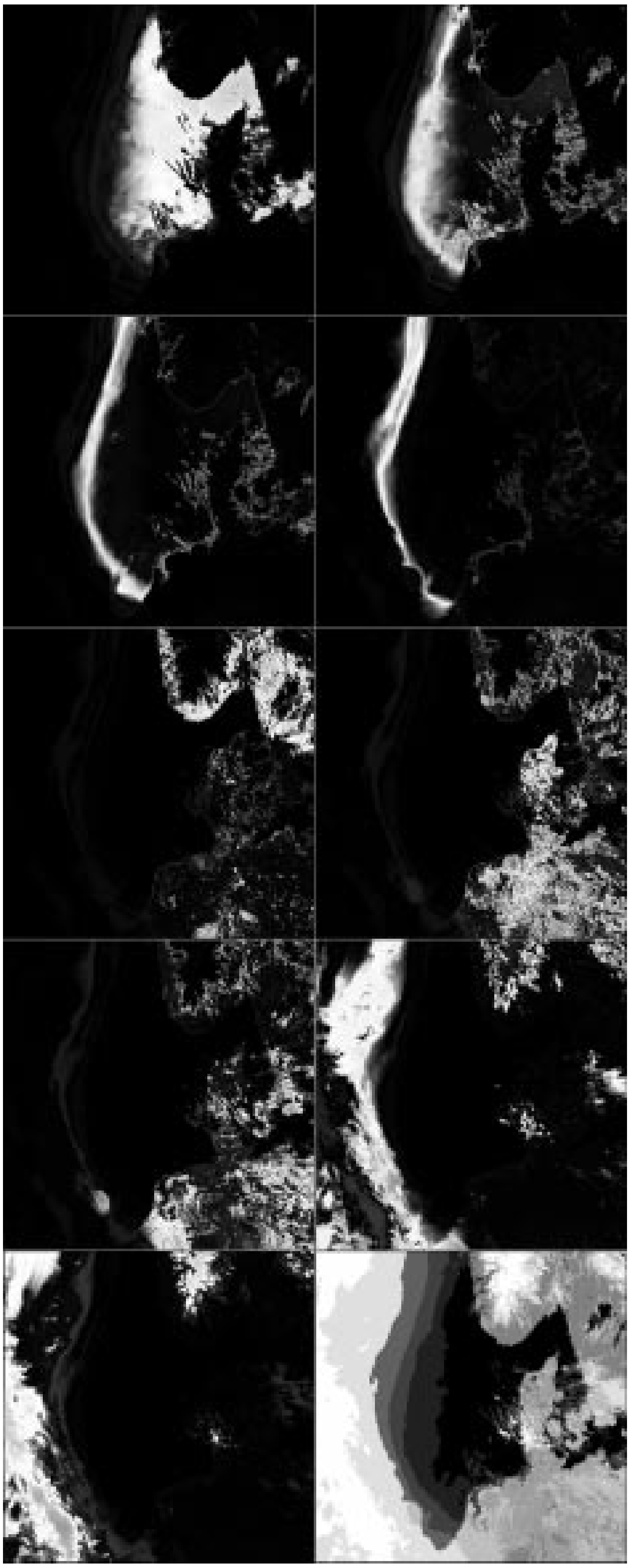

Figure 3. SeaWiFS, fuzzy, spectral segmentation, cluster memberships 1-9 row-wise. Most significant sources empirically related to each cluster: 1 water, 2-4 clouds, 5-7 vegetation, and 8-9 clouds and ice. Bottom right frame is the CMM estimated classes. The black region, corresponding to cluster 1, is the water mask used in Figure 4 and 5 for stretching. The brightest region corresponds to cluster 9.

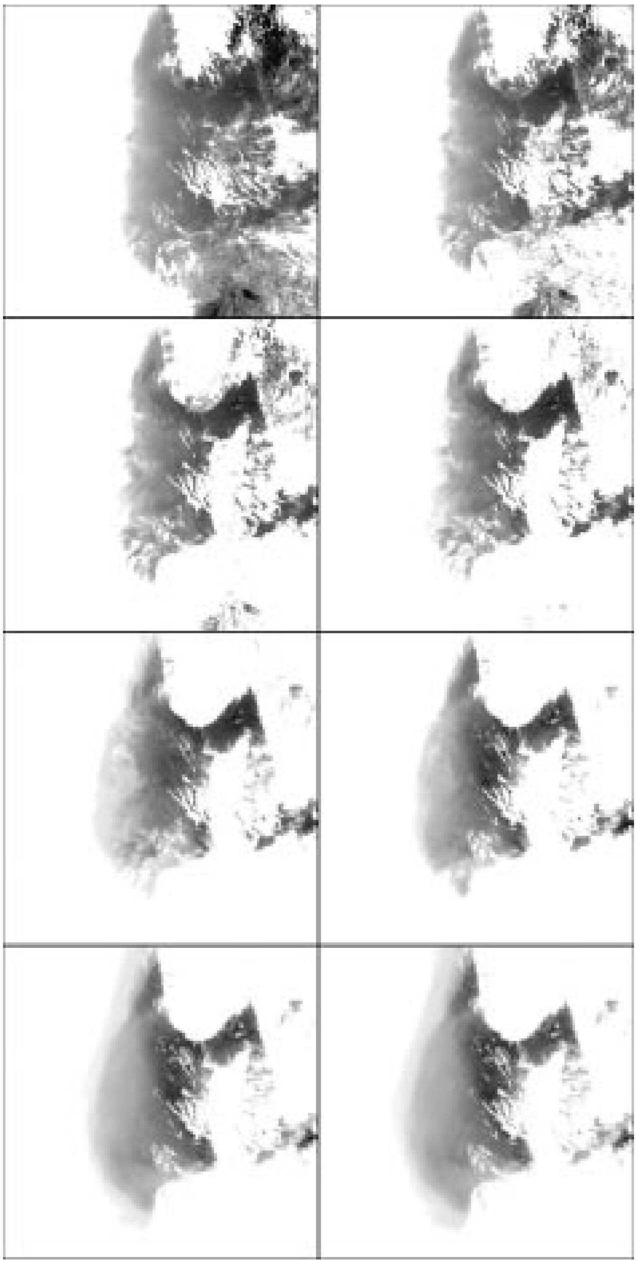

Figure 4. The original SeaWiFS bands 1-8 row-wise. The data is stretched under the CMM obtained water mask.

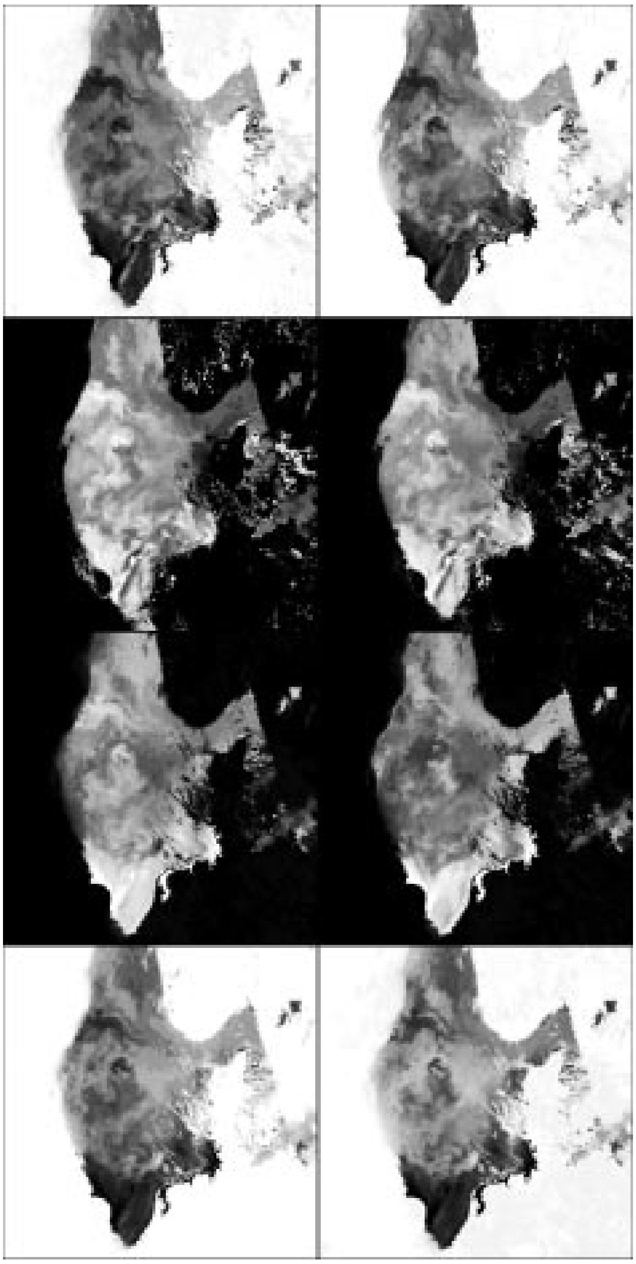

Figure 5. The SeaWiFS bands 1-8 row-wise after OSP cloud signal reduction. The data is stretched under CMM obtained water mask.

References

[1] J. C. Bezdek. *Pattern Recognition with Fuzzy Objective Function Algorithms*. Plenum Press, 1981.

[2] C. A. Bouman and M. Shapiro. A multiscale random field model for Bayesian image segmentation. *IEEE Transactions on Image Processing*, 3(2):162–177, 1994.

[3] J. C. Harsanyi and C.-I. Chang. Hyperspectral image classification and dimensionality reduction: An orthogonal subspace projection approach. *IEEE Transactions on Geoscience and Remote Sensing*, 32(4):779–785, 1994.

[4] K. B. Hilger, A. A. Nielsen, and P. Knudsen. *Fuzzy spectral-spatial segmentation and orthogonal subspace projection for reduction of cloud signal in SeaWiFS image data*. Submitted to the 15th International Conference on Pattern Recognition (ICPR2000), http://www.cvc.uab.es/ICPR2000, Barcelona, Spain, 2000.

[5] A. A. Nielsen. Linear mixture models, full and partial unmixing in multi- and hyperspectral image data. In B. E. Ersbøll and P. Johansen, editors, *Proceedings of the Scandinavian Image Analysis Conference (SCIA'99), vol. 2*, pages 898–902, Kangerlussuaq, Greenland, 7-11 June 1999.

[6] A. A. Nielsen. Partial unmixing in hyperspectral image data. In ERIM, editor, *Proceedings from the Fourth International Airborne Remote Sensing Conference and Exhibition, Vol. II*, pages 535–542, Ottawa, Ontario, Canada, 21-24 June 1999.

[7] SeaWiFS. http://seawifs.gsfc.nasa.gov/SEAWIFS.html. Goddard Space Flight Center, National Aeronautics and Space Administration, Greenbelt, Maryland, USA.

[8] R. Wiemker. Unsupervised fuzzy classification of multispectral imagery using spatial-spectral features. In I. Balderjahn, R. Mathar, and M. Schader, editors, *Data Highways and Information Flooding, A Challenge for Classification and Data Analysis*. Springer, 1997.