Segmentation of Hedges on CASI Hyperspectral Images by Data Fusion from Texture, Spectral and Shape Analysis

M. Lennon[1], M.C. Mouchot[1], G. Mercier[1], L. Hubert-Moy[2]
[1]Ecole Nationale Supérieure des Télécommunications de Bretagne - Département ITI
Technopôle de Brest Iroise - BP 832 - 29285 Brest Cédex - France
[2]Laboratoire Costel - Université de Rennes 2 - 6, avenue Gaston Berger - 35043 Rennes Cédex- France
Tél : (33) (0)298001069 ; Fax : (33) (0)298001098 ; Email : marc.lennon@enst-bretagne.fr

Abstract – The study figures out the potential of CASI airborne hyperspectral imagery for the fine segmentation and characterization of small size landscape units, the hedges, essential for hydrologists and landscape planners. The segmentation strategy consists in computing every hedge discriminating feature : radiometry, texture and linear shape. Original methods taking into consideration the full spectral information are developed for filtering images and computing linear and texture features. Concepts of fuzzy fusion are used to merge these information in order to get the final segmented image. Classification of the segmented region provides the bocage composition map. With the help of a DEM, 8 parameters are computed, providing a fine characterization for each pixel of the bocage.

INTRODUCTION

The characterization of hedges presents a great interest in the study of the diffuse pollution from the agricultural activity because they are able to absorb an important part of the water flux charged with pollution particules (nitrates, salts…) depending on their location, morphology, composition, direction [1]. Conventional techniques of remote sensing are limited for such a study : spatial resolution of satellital sensors is too low and spectral information from aerial photography are too poor for an accurate characterization. We suggest to take advantage of airborne imaging spectrometry allowing to get very fine spatial and spectral features of the hedges. The main drawback is the large amount of information to process to get the interesting thematic features. The paper shows up different levels of information processing and fusion, allowing to extract the hedges from images acquired with the CASI [2]. Images were acquired in july 1998 above Plounérin (France), region of bocage largely diseased by agricultural pollution. The spatial resolution is 2 m at ground with 9 spectral bands ranging from 400 to 900 nm. 5 flight lines were acquired, corrected from the plane attitude and mosaïcked.

SEGMENTATION STRATEGY

A strategy based only on the spectral features of the bocage would meet two main problems : on one hand, spectral features are multiples depending on the composition of the bocage and on the other hand, they can be the same as other landscape elements such as fields for example. Hence, other discriminant features need to be determined. First of them is the texture. If the spectral features of a group of bocage pixels is almost the same as a group of field pixels, their texture enable most often to discriminate them. Eventually, bocage is most often composed of linear structures. A shape attribute needs also to be extracted from the images. Because of the fuzzy nature of the problem and in order to homogenize the three different concepts (radiometry, texture, shape), methods of fuzzy fusion are used. Membership to each one of the three attributes is computed in parallel. Initially, original radiance images should be calibrated to reflectance in order to allow the method to be reproductible. Because of the large variability in the spectral features of original data, a filtering step is operated before the computing of shape features. This step leads to a largely less noisy result. On the other hand, the computing of the texture features must be operated on the original data set to take advantage of this variability. The result of this parallel process is a membership image to each of the 3 attributes. Concepts of fuzzy fusion are used to merge them in a single image. In order to remove the noise from this image and to take a final decision, morphological post-processing using decisions fusion depending on the context is implemented. The complete scheme of segmentation is shown on Fig.1.

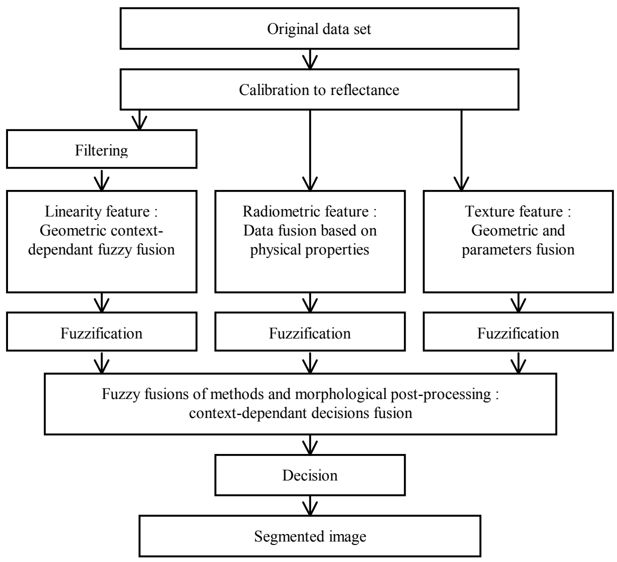

Fig. 1 – Global scheme of segmentation strategy

SEGMENTATION PROCESSING

Preprocessing : Calibration to reflectance and non linear filtering by hyperspectral anisotropic diffusion

A flat field calibration [3] based on the information contained in the image is first performed. Next, the anisotropic diffusion consists in performing a multiscale filtering with the partial derivative equation (1). The function *c(.)* proposed in [4] is computed (2) due to its convergence speed. Doing so, the image will be largely smoothed in relatively homogeneous regions ($|\nabla u|$ low) while filtering will be stopped near the edges ($|\nabla u|$ high) [4]. The process is shown to be equivalent to a heat diffusion process which strength depends on the module of the local gradient [4].

$$\frac{\partial u}{\partial t}(x,y,t) = div\left(c\left(\left|\nabla u(x,y,t)\right|\right)\nabla u(x,y,t)\right) \qquad (1)$$

$$c\left(\left|\nabla u\right|\right) = 1 - \exp\left(-\frac{c_m}{\left(\left|\nabla u(x,y)\right|/k\right)^m}\right) \qquad (2)$$

$m = 4$, $c_4 = 3.31$ and k is the threshold parameter and must be empirically fixed up. Each image corresponding to each wavelength will be separately smoothed but we propose to take advantage of the multispectral information by computing the vectorial gradient (3) :

$$\left|\nabla u(x,y)\right| = \left\|\nabla_{u_x}(x,y), \nabla_{u_y}(x,y)\right\|_2 \qquad (3)$$

With $\nabla_{u_x}(x,y) = \left\|\vec{u}(x,y), \vec{u}(x+1,y)\right\|_2$

and $\nabla_{u_y}(x,y) = \left\|\vec{u}(x,y), \vec{u}(x,y+1)\right\|_2$

Radiometric feature : fusion based on physical properties

The simple Transformed Vegetation Index (*TVI*) is computed. *TVI* can be seen as the fusion of spectral bands leading to a simple radiometric feature expressing the quantity of chlorophyll, physical property related to the amount of vegetation. In order to homogenize the three concepts, *TVI* is fuzzified by a S-Shape function to get the Radiometric Feature Membership (*RFM*).

Linearity feature : geometric context-dependant fuzzy fusion

Following hypothesis are stated for a pattern to be a linearity feature : (H1) Linearity feature can only be defined in its local context. This one should neither be too large (preventing pattern to be approximated by a straight line or showing many landscape patterns) nor too small (non sufficient knowledge of landscape configuration). Given the classical width of hedges, the size of analysing window is fixed at 9 pixels (corresponding to 18 m at ground). (H2) Linearity can be defined by one invariable state in one direction and at least three distinct invariable states in the three other directions (present study is limited to four directions θ_i. $i \in$ [N-S, E-W, NE-SW, NW-SE]). Number of states in one direction, $NS(\theta_i)$, will be quantified by the study of the evolution of vectorial gradient of consecutive pixels $|\sigma u(t)|$ in that direction θ_i ($t \in [1,8]$ represents successive pairs of consecutive pixels in direction θ_i). If a pixel has at least one large gradient value in each of the two sides S_1 and S_2 of one direction θ_i, then it will own three states in this direction θ_i. If a pixel has only small gradients in the two sides of one direction θ_i then it will own only one state in this direction θ_i. $NS(\theta)$ is computed with fuzzy conjonctive and disjonctive operators. Membership to three states in direction θ_i, $\mu_3(\theta_i)$, will be computed by a linear membership function bounded by the maximum value of $NS(\theta_i)$ in direction θ_i. Membership to one state $\mu_1(\theta_i)$ is the inverse of membership to three states $\mu_3(\theta_i)$. Given H2, The *min* operator could be used to compute the degree of linearity in each of the four directions *i*. Unfortunately, the *min* operator leads to a too restrictive result whereas the *max* operator is too lenient. We then propose to use a context-dependant operator allowing to vary between *min* and *max* and depending on a consistency measure $\sigma \in [0,1]$. Computation of the degree of linearity is given in (4) with σ defined as in (5) :

$$\mu_L(\theta_i) = \sigma Min\left(\mu_1(\theta_i), \mu_3(\theta_j), \mu_3(\theta_k), \mu_3(\theta_l)\right) + (1-\sigma) Max\left(\mu_1(\theta_i), \mu_3(\theta_j), \mu_3(\theta_k), \mu_3(\theta_l)\right) \qquad (4)$$

$$\sigma = f\left(\alpha\left(\mu_1(\theta_i), \mu_3(\theta_j), \mu_3(\theta_k), \mu_3(\theta_l)\right)\right) \qquad (5)$$

With $\alpha \in [0,45°]$ beeing the spectral angle in the 4-dimensional space between vectors $V_\mu = [\mu_1(\theta_i), \mu_3(\theta_j), \mu_3(\theta_k), \mu_3(\theta_l)]$ and $V_C = [C,C,C,C]$ with $C = cte$. V_C represents the maximal consistency between the four parameters ($\mu_1(\theta_i) = \mu_3(\theta_j) = \mu_3(\theta_k) = \mu_3(\theta_l)$). $\alpha = f(\sigma)$ is defined as a monotone linear decreasing function. From H2, a pixel is linear if it is linear in at least one direction. This leads to the final computation of the Linear Feature Membership (*LFM*) as the fuzzy conjonction of $\mu_L(\theta_i)$.

Texture feature : geometric and parameters fusion

14 parameters have been derived from the coocurences matrices [5] in 2 dimensions. We propose a n-D extension to the two most interesting ones for our study : Correlation (*Cr*) and Local Homogeneity (*Lh*). Analysis window is chosen square of size 3. Module of coocurence vector is 1 pixel and its directions are the same 4 as in the study of linearity. $Lh(\theta_i)$ is computed as in (6) :

$$Lh(\theta_i) = \sum_{\vec{V}_1}\sum_{\vec{V}_2} \frac{1}{1+\alpha^2\left(\vec{V}_1, \vec{V}_2\right)} \cdot CM_t\left(\vec{V}_1, \vec{V}_2\right) \qquad (6)$$

$\vec{V}_1, \vec{V}_2$: 2 vectors separated by coocurence vector $t(\theta_i)$

$\alpha\left(\vec{V}_1, \vec{V}_2\right)$: spectral angle between $\vec{V}_1$ and $\vec{V}_2$

$CM_t\left(\vec{V}_1, \vec{V}_2\right)$: number of coocurences between $\vec{V}_1$ and $\vec{V}_2$

The adopted fusion rule is the following one : a pixel is in a local homogeneous region if local homogeneity is high in every direction. Hence, *Lh* is computed as the fuzzy disjonction of $Lh(\theta_j)$. Weighted means *m* and standard deviations σ of lines *x* and columns *y* of CM_t are needed for computing $Cr(\theta_j)$. With the assumption that CM_t is almost always equal to 1 (given the huge dynamic of hyperspectral images), we make the approximation that $m = m_x = m_y$ and $\sigma = \sigma_x = \sigma_y$. Computing *m* and σ in the local context of size 3×3 does not lead to get discriminant correlation coefficients. Correlation is nor representative of local context if *m* and σ are computed on the entire image. Hence, *m* and σ are computed in a window *W* of intermediate size. A size of 81, empirically chosen is a good compromise. However, to compute statistics in a window of size 81 around every pixel is too expensive in computing time. We then choose to pre-compute statistics in windows W_k with a recover rate of 80%. This leads to an acceptable computing time and error rate. Procedure of computing is eventually the following (7) :

$$\vec{V}_{moy}(k) = \frac{1}{81^2}\sum_i \sum_j \vec{V}(i,j) \qquad i, j \in W_k$$

$$\vec{V}_{\sigma}(k) = \sqrt{\frac{1}{81^2}\sum_i \sum_j \left(\vec{V}(i,j) - \vec{V}_{moy}\right)^2}$$

$$Cr(\theta_i, W_k) = \frac{1}{\left|\vec{V}_{\sigma}(k)\right|^2}\sum_{\vec{V}_1}\sum_{\vec{V}_2}\left\|\vec{V}_1, \vec{V}_{moy}(k)\right\|_2 \times \left\|\vec{V}_2, \vec{V}_{moy}(k)\right\|_2 \times CM_t\left(\vec{V}_1, \vec{V}_2\right) \qquad (7)$$

Fusion rule : a region is said correlated if the correlation is high in every window W_k and in every direction θ_i. The fusion rule is computed with the fuzzy disjonctive operator. Correlation and local homogeneity are fuzzificated with S-Shape functions. In order to perform the fusion of both parameters, we state the hypothesis that a pixel has a good texture feature if correlation is high and local homogeneity is low. The Texture Feature Membership (*TFM*) is hence assumed to be equal to the disjonction of the two membership images *Cr* and *Lh*. Finally, morphological grey-level closure is performed to smooth noise from *TFM.*

Methods fusion and morphological post-processing with context-dependent decisions fusion

We state the hypothesis that a pixel belongs to the bocage network if it is radiometrically correct and linear (hedges and banks) or if it is radiometrically correct and its texture feature membership is high (groves). Hence, the first step of the fusion method allows to merge results from the three methods (*RFM*, *LFM*, *TFM*) to two new fuzzy variables : *RLFM* (Radiometry-Linearity Feature Membership) and *RTFM* (Radiometry-Texture Feature Membership) with the simple fuzzy disjonctive operator. Different morphological post-processing are performed depending on the context leading to compute the final post-processed *RLFM* (called $RLFM_{pp}$) and *RTFM* (called $RTFM_{pp}$). Simple conjonctive operator allows to merge these fuzzy variables to get the hedges membership image *S*. Final decision is computed thanks to a simple threshold of *S* and a hole filling on the binary image to remove last noisy structures. That leads to the final segmented image (illustrations are available at http://perso-iti.enst-bretagne.fr/~lennon/).

CLASSIFICATION AND QUANTIFICATION

Morphological study of the segmented image enables to compute width and direction of hedges for each pixel of the network. With the help of a digital elevation model of the same region, 5 parameters are computed : module and direction of the slope, distance to the river by the direct and the drainage way, water flux accumulation. A maximum likelihood classification of vegetal species which take place in the bocage network is computed. Training sites are obtained by a field survey. This leads to a set of 8 parameters allowing a very fine characterization of the hedges network.

CONCLUSION

Airborne hyperspectral imagery enables to get a very fine characterization of hedges, essential for environment managers who have to find methods to control the pollution and for landscapes planners. Nevertheless, extraction of relevant infomation from large set of data included in hyperspectral images is not a trivial task. We suggested to take advantage of some concepts of fuzzy data fusion used at different levels (data, parameters, methods, decisions) to segment the specific landscape pattern under consideration.

REFERENCES

[1] L. Hubert-Moy, A. Cotonnec, P. Gouery, *Extraction du réseau bocager à l'aide de données satellitaires Landsat Thematic Mapper. Application à un bassin versant en Bretagne centrale*, Photo-Interprétation, 4,258-263,1995.
[2] *Information on CASI sensor, http://*www.itres.com.
[3] F.H. Goetz, J.W. Boardman, *Atmospheric corrections : on deriving surface reflectance from hyperspectral imagers,* Imaging Spectrometry III, Proceedings of SPIE, 3118, 14-22.
[4] J. Weickert, *Anisotropic diffusion in image processing,* PhD thesis, University of Kaiserslautern, Germany, Laboratory of Technomathematics, January 1996.
[5] R.M. Haralick, *Statistical and structural approaches to texture,* Proceedings of the IEEE, 67(5), 786-804, 1979.