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MULTITEMPORAL SEGMENTATION BY MEANS OF FUZZY SETS

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ABSTRACT

A remote sensing user does not photointerprete image pixels, but entities. Therefore, there is a segmentation processing, previous to the recognition itself. What we propose in this paper, is to automate the segmentation by using of monospectral, multispectral and multitemporal properties, measured by several criteria. The combination of these criteria is performed by means of tools of the fuzzy sets theory. A designated entity is automatically segmented by combining a sequence of criteria in order to converge towards the final decision without any thresholding, weighing, ...

The ready access to the multitemporal data belonging to a same designated entity, is obtained by comparing the segmentation results at different dates, through geometric deformation models.

Finally the radiometries, extracted entity/entity, by using this segmentation method, feed the diachronic analysis in the context of the Lauragais experiment.

O. INTRODUCTION

Diachronic ("Through the time") analysis of remotely sensed data augments the more classical multi-spectral analysis, by adding the time dimension in the form of multiple, sequential views of a scene. Specifically : suppose that a remote sensing user wants to analyse the seasonal or even the yearly evolution of cultivated fields, with the goal for example, of predicting crop yields or assessing damages. Since the phenomena at hand evolve in time, it is natural to consider multitemporal measurements, thus adding the time dimension to the more conventional multispectral analysis.

The reduction of multispectral and multitemporal data, which we call diachronic analysis, requires ready access to the measurements (pixels) that pertain to each entity of interest (cultivated fields), which we call segmentation.

The segmentation of data within an image, as performed by a photo-interpreter, to merge pixels into different entities, is the result of combining several visual and qualitative criteria.

We will attempt to automate the segmentation by modelizing both the concept "qualitative criterion" and the operations of combination. The fuzzy sets theory appeared as a good approach for this problem and some basic concepts of this theory, used for our application, are developped in the first chapter.

The chapter 2 details some algorithms used to perform the segmentation of an entity designated by only one inner point : this region growing is based on edge detection and connectivity evaluation.

The chapter 3 describes how to combine the segmented resuls from date to date, by using the geometric corrections, with the goal of minimizing the mislocation errors.

The different results are pooled in the last chapter.

I. MEMBERSHIP FUNCTIONS AND COMBINATION OF CRITERIA

A. Basis in fuzzy sets theory

To define a subset, in the classical theory, is equivalent to give a characteristic function :

$$x \in X \rightarrow f_A(x) = 1 \quad \text{iff} \quad x \in A \subset X$$
$$= 0 \quad \text{else}$$

In a similar way a "fuzzy subset" $\underset{\sim}{A}$ is defined by its "membership function", which is an extension of the concept of characteristic function over the real domain [0,1] :

$$x \in X \rightarrow \mu_A(x) \in [0,1]$$

$\mu_A(x)$ measures the degree of membership of x to $\underset{\sim}{A}$.

To define a fuzzy subset is equivalent to give a membership function, and reciprocally to give a function defined on X, with values in [0,1], allows to build up a fuzzy subset.

A coherent theory of fuzzy subsets grew up, as a very helpful means of handling qualitative criteria [1], from this basic definition.

A photo-interpreter knows how to describe a designated entity in a remotely sensed image, by some qualitative criteria. Then we will define several simple tools of the fuzzy set thory, useful to combine these criteria in order to define the designated entity as a result of intersection or union of the fuzzy sets associated to each criterion.

- intersection of fuzzy sets :

The conjunction of two criteria related to the fuzzy sets $\underset{\sim}{A}$ and $\underset{\sim}{B}$ is related to the intersection $\underset{\sim}{A} \cap \underset{\sim}{B}$ and may be defined by :

$$\mu_{A \cap B}(x) = \text{Min } (\mu_A(x), \mu_B(x)) \quad \forall x \in X$$

- union of fuzzy sets :

The disjunction is related to the union $\underset{\sim}{A} \cup \underset{\sim}{B}$ and may be defined by

$$\mu_{A \cup B}(x) = \text{Max } (\mu_A(x), \mu_B(x)) \quad \forall x \in X$$

- complementation

The negation of a criterion defined by μ_A is given by :

$$\mu_{\bar{A}}(x) = 1 - \mu_A(x)$$

Several other definitions of the intersection or union of fuzzy sets given and compared in [2] and [3], are more or less restrictive on the combination of criteria. A means of weighing the different results is to compute the index of fuzzyness of the combinated set. If the combination yields a binary response, the index of fuzzyness will equal zero, if the incertainty is total, the index will equal 1. This concept is very close to the entropy, as a scale of the information of a signal. Different indexes of fuzzyness may be found in [1].

B. How to combine criteria

We distinguish three different classes of criteria :

- monospectral criteria

These criteria are computed from the same set of radiometries, using different functions defined over local neigh borhoods of the pixel. Their definitions are weakly independant but it looks useful to examine their conjunction. For example the field we attempt to segment, encompasses inner points (complement of edge points) and homogeneous points. Therefore we will consider the intersection of the two fuzzy sets : $(\overline{\text{edge}}) \cap (\text{homogeneous})$.

- multispectral criteria

The same criteria are computed over different spectral bands. The less the spectral bands are correlated, the greater is the disjunction of the criteria. Therefore we will consider the union of the fuzzy sets : (criterion/band i) ∪ (criterion/band j)

- multitemporal criteria

Some kinds of events are highly correlated between different dates, but the geometric errors (through the deformation models) bring differences in their location. In this case, as it occurs with the edges for example, we will use "compromise operators", such as the mean [2]. If the events look uncorrelated, we will use the disjunction.

II. FROM IMAGE PIXELS TO FUZZY SETS

A. Fuzzy Edge Detection

We didn't introduce a new edge detection algorithm in this paper, but we checked, besides the classical derivative operator, the FOSD fictitious over-sampled derivator [4] and the complex gradient operator [5]. The first one gives good results on images where the pixel size and the elementary objects size are similar in a ratio 1, up to 10 (with Landsat : 5000 to 50 000 square meters). The second gives both an amplitude and a direction information.

The membership function of the fuzzy set of "edges", is computed by the following way :

- plot the histogram of the values given by the operator (ed(i,j)),

- select two thresholds ($t1 < t2$) so as to split the histogram in three zones :

1- from 0 to threshold t1 = fe(i,j)=0	70 % of pixels where the membership function equals 0 (= trusty no-edge)
2- between t1 and t2 : $fe(i,j)=\frac{ed(i,j)-t1}{t2-t1}$	linear function which gives a membership value in the range [0,1] (=fuzzy edge)
3- from t2 to 255 : fe(i,j)=1	10 % of pixels with a value 1 (= trusty edge).

B. Fuzzy Region Growing

The set of inner points, related to a same entity, is included in the complement of the set of edge points, must encompass the designated point (designated by the user or by automatic locating) and must be "connex" (one-piece entity).

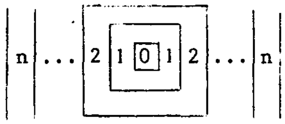
Then, given the designated point (x,y) in the entity of interest, any point (i,j) will belong to the same entity if and only if:

- it is a no-edge point: fe(i,j) is small,
- there is a "path" between (i,j) and (x,y), which never run through any edge point.

This second condition is not related to the edge values themselves (what wouldn't bring more information) but to their local relations.

The "shortest path algorithm" :

- let the "crowns" be defined by



- let the "flat distance" between (i,j) and (k,l) be df=max(|i-k|,|j-l|), what is coherent with the definition of the crowns, instead of the euclidian distance;

- let the "additional distance" be proportional, by a factor a (=10 for example), to the difference of heigth between the edge values fe(i,j) and fe(k,l).

- start by setting each pixel at the value
  fc(i,j)=-1-a.fe(i,j) if $(i,j)\neq(x,y)$
  fc(x,y)=0

- search, for every pixel in the crown n, among its 8 neighbors, if there exists a value i (i=0 at the first step),
if yes, then fc(i,j)=i+a.fe(i,j)
if no, go to next point in the same crown;

- then go to next crown n=n+1, up to n=N;

- then go back to crown 1 with the level i=i+1, up to i=I.

At the end of this algorithm, we got, for every (i,j) in the (2N+1).(2N+1) window around (x,y) the additional distance da, cumulated along the shortest path from (x,y), what can be compared with the flat distance df at the same point.

Hence we define the membership function:
  fc(i,j)=1-da/(b.df) ,where b=1/4 for example
  fc(i,j)=0 ,if da>b.df

This function defines the fuzzy set of the points connected to (x,y), and the algorithm is what we call the fuzzy region growing.

III. THE TIME DIMENSION

A. Geometric corrections

Each view of a same scene, among a multitemporal sequence, is geometrically deformed with respect to a cartographical reference. Even in the Lauragais experiment [6], where we chose one image of the sequence as a cartographical reference, instead of a map, the relative deformations between aerial scanner images are very strong.

A large part of the work was devoted to automate the correction of these deformations. From no more than 10 to 20 points, visually located on both images, we automatically locate 100 to 200 points, what is enough to build up a model between two images. Nine images were processed.

In order to fit the deformation as well as possible, the processing approximes it by a sequence of local models, joined to each other by a smoothing function; this is called the Sliding Model [7].

In spite of these corrections, mislocations holds on and residual errors don't move down 2 or 6 pixels RMS, depending on the date, and maximal errors may reach 10 pixels on image ends.

The segmentation is successfully performed date/date, by using only the location of the designated point on the reference, under the assumption that its locations on the different dates, as computed by the models, are still inside the entity.

B. Multitemporal extraction of radiometries

In order to limit the importance of the geometrical errors, we compare the fuzzy sets grown at each date with the fuzzy sets resulting from the deformation, by each model, of the fuzzy set segmented on the reference.

If the fuzzy edges overlay each other within margins less than a chosen threshold, we conclude they are identical. The thresholds are chosen equal to the RMS errors computed with the corresponding models, as illustrated by the following table [7]:

date	#lines	# RCPs auto	post	succ. %	RootMeanSq. Error along	across	global	#local models
may 30 1978	3636	99	-	16.2	3.3	2.9	4.5	15
apr. 12 1979	2060	80	4	15.2	4.4	4.7	6.5	7
june 19	3000	73	-	11.3	3.8	3.5	5.2	8
july 07	2950	93	4	14.2	3.9	5.3	6.5	8
sep. 17	2500	85	-	11.5	4.6	4.6	6.5	10
oct. 30	2070	89	-	15.7	1.8	5.8	6.1	11
may 10 1980	2060	reference	image	reference	image	reference	image	reference ima
june 03	2070	252	-	33.2	1.9	2.5	3.1	19
june 16	2200	301	-	38.6	2.2	1.4	2.6	17

In the opposite case, we conclude the edges are different : that happens several times because of crop changes, harvesting ...
therefore we consider the intersection of the fuzzy sets as the final segmented entity.

Finally the diachronic analysis will use the radiometries extracted from the classical set S associated to the fuzzy segmented entity A by :
  $S=\{x\in X, \mu_A(x)\neq 0\}$

the smaller is the index of fuzzyness of A, the better is the segmentation.

IV. SAMPLED APPLICATION AND RESULT

The extraction of the radiometries of a rectangular field (about 50 by 60 pixels) is illustrated in a two spectral bands example.

Figure (a) shows the original histogram of the 256x256 image in the green band.

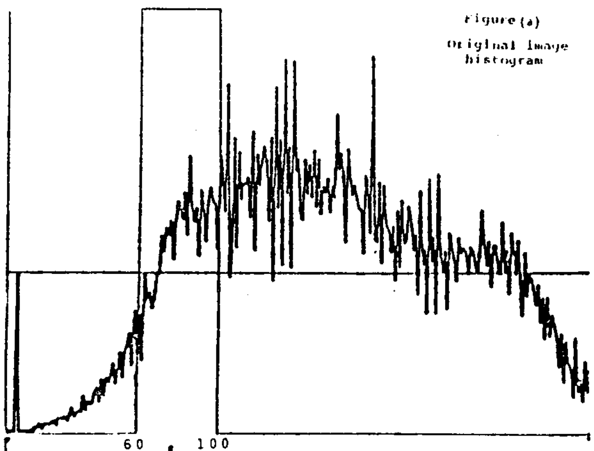
Figure (a)bis shows the histogram computed over a rectangular window superimposed, by the operator, over the designated field. The min and max values were selected from this histogram by the operator : 60 and 100.

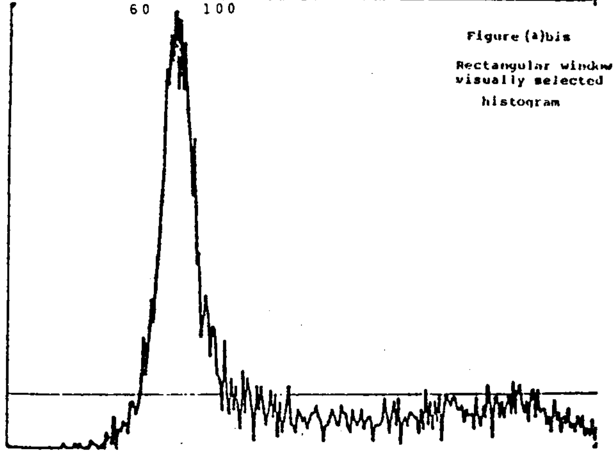
Figure (b) shows the histogram computed from the data extracted by the segmentation in the green band. Note that the histogram is less noisy in the right side. The min and max values are automatically selected as thresholds corresponding to 5% and 95% of the histogram : 58 and 165. This is not satisfying, but let us wait what follows.

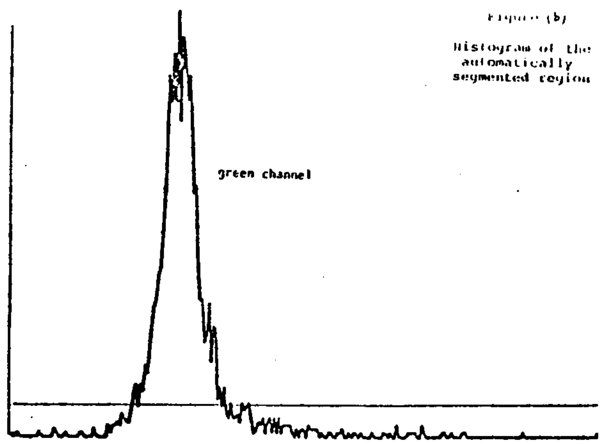
The same segmentation is performed over the red band, then merged in the multispectral combination of fuzzy sets. We can compare the numerical results obtained with mono- and multi-spectral segmentation in the following table :
(note the values 58 and 106 in the green band)

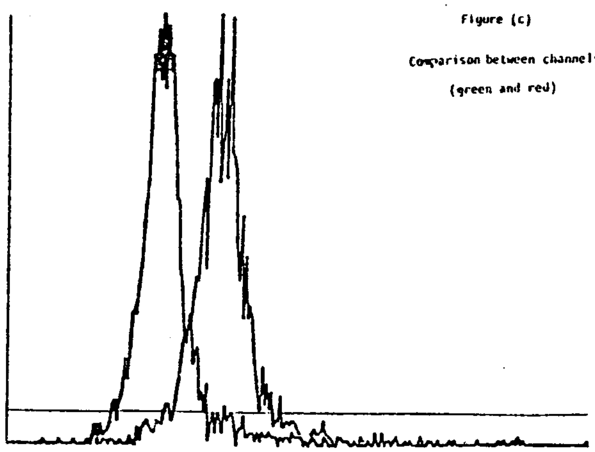
	mono		multi	
green band	mean	83	mean	76
	std.dev.	32	std.dev.	19
	min (5%)	58	min (5%)	58
	max(95%)	165	max(95%)	106
red band	mean	102	mean	99
	std.dev.	23	std.dev.	16
	min (5%)	80	min (5%)	80
	max(95%)	142	max(95%)	124

Figure (c) shows the histograms of green and red band, for comparison and selection of a multispectral signature.









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VI. ACKNOWLEDGEMENTS

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