



**HAL**  
open science

# Cabbage/Weed Discrimination with a Region/Contour Based Segmentation Approach for Multispectral Images

Nathalie Gorretta, Christophe Fiorio, Gilles Rabatel, John Marchant

► **To cite this version:**

Nathalie Gorretta, Christophe Fiorio, Gilles Rabatel, John Marchant. Cabbage/Weed Discrimination with a Region/Contour Based Segmentation Approach for Multispectral Images. Information and Technology for Sustainable Fruit and Vegetable Production (FRUTIC), Sep 2005, Montpellier, France. pp.371-380. lirmm-00137914

**HAL Id: lirmm-00137914**

**<https://hal-lirmm.ccsd.cnrs.fr/lirmm-00137914>**

Submitted on 22 Mar 2007

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# A region/contour based approach for segmenting complex scenes in multispectral images - application to cabbage/weed discrimination

N.Gorretta(1), C.Fiorio(2), J.Marchant(3)

(1)-*UMR ITAP, Cemagref, 361 rue J-F Breton, Montpellier, FRANCE*

(2)-*Lirmm, Montpellier, FRANCE*

(3)-*SRI, Silsoe, UK*

17 décembre 2004

## 1 Abstract

Image segmentation on outdoor images is a difficult task because it come up against the complexity and the variability of objects to detect and also of natural phenomenums as shadows, highlights, partially overlapping objects. These difficulties conducts us to develop an adapted segmentation tool to this context. Futhermore, accordingly to the development of multispectral sensors, it seems interesting to propose a methodology adapted to multispectral images. Indeed, the segmentation process take advantage of complementary informations. Our approach consists firstly in carrying out an image over-segmentation by use of a region growing algorithm and secondly, in labelling the obtained regions in  $c + 1$  classes with  $c$  equal to the number of class object to detect. The  $c + 1$  label allows us to distinguish regions having ambiguous properties (undetermined regions). To remove this ambiguity, a collaborative contour/region approach is applied on these undetermined regions. This approach has been tested on a set of cabbage images at different growth levels. In each image, all pixels have been labelled by hand for validation process. The results obtained by this method are compared with those obtained by a direct region growing segmentation.

## 2 Introduction

An image is a planar representation of a scene or an object situated in most cases in a tri-dimensional space. Objectives of image analysis are to extract pertinent informations and to treat and interpretate them. To do this, a well-established process is to segment image. A complementary step, allowing to connect these entities to reality, consist in to affect them a label describing their own class (object). Researches about image segmentation, was initially focused on gray levels or monochrome images but by technological progresses turned forward more complex images or more hight dimensions : color or multi-band images, tri-dimensional or volumic images, multi-temporal images ... Selection of adapted segmentation methodology is largely dependant on application. Our work is dediaded to supervised segmentation of outdoor and multiband images with a limited and known number of classes (2 or 3 object classes).

With in the frame work concerning segmentation of natural images, we investigated region growing segmentation methods. Region-based algorithms are able to use several image properties directly and simultaneously and thus are well-adapted to multi-band images.

Futhermore, compared with other segmentation approaches as classification or thresholding based approach they simultaneously take into account both feature space and spatial domain. Thus, in case of supervised segmentation, direct labeling could be obtained by an approach including an oversegmentation using a region growing method followed by a fusion strategy based on a colour criterion to merge region within a same object (region aggregation based on region color similarity). Finally, a labelling process is applied to match each detected region to the best object-model. Nevertheless, in the case of natural and so complex images, we note this methodology generates classification errors particularly in low contrast areas. The proposed approach here aims to reduce these errors by introducing during the labeling step, in addition to object classes a class stated as undetermined. This class gathers the regions for which there are ambiguous affectation to the basic classes. To solve these ambiguities, a more complex segmentation method involving a co-cooperative contours/regions segmentation method, helps when it's possible by contextual informations obtained during the first step, is applied on this undermind areas.

This article is organized as follows. In section one, we were interested in edges-based and regions-based segmentation approaches which could be used in the context of complex and multispectral images. This first study, allowed us to select adapted segmentation tools and to decide about a collaborative contour/region strategy. In the second chapter, we present in details the proposed segmentation process. In a last chapter, we describe results obtained with our approaches on tri-bands (color) outdoor images concerning cauliflower plants at different growth stages. Segmentation objectives in this case is to separate three different objects: plant, weeds and soil. Segmentation results obtained with our approach are compared with thus obtained by region growing segmentation approach.

### 3 Region-based and edge-based segmentation methods adapted to multispectral images

Our aim is to develop a segmentation approach dedied to complex and multi-spectral images and using a collaborative edge-region segmentation strategy. This approach needs to be efficient (low complexity, good segmentation results ...) to use well adapted edges-based and region-based segmentation approach. The objectives of this section is to investigate region-based and edges-based approach which could be satisfied our constraints.

#### 3.1 Multispectral region segmentation methods

Defined by *Zucker* [Zucker, 1976], a region segmentation is an image partition with a topological sense. Each region is thus characterised by homogeneity features. By introducing a mathematical formalism, we obtain the next definition: region-based segmentation of an image  $I$  using a homogeneity criterion  $P$  is defined as a partition  $S = R_1, R_2, \dots, R_n$  of  $I$  such as:

1.  $I = \bigcup R_i, i \in [1 \dots n]$ ;
2.  $R_i \cap R_j = 0$  for all  $i \neq j, i \text{ et } j \in [1 \dots n]$ ;
3.  $P(R_i) = true$  for all  $i \in [1 \dots n]$ ;
4.  $P(R_i \cup R_j) = false$ , for all adjacent pair regions  $R_i, R_j$ ;

Thus, in region approach, we tend to aggregate pixels or areas which are similars. The approaches for region segmentation are numerous but it is possible to distinguish two large families of methodologies: region segmentation by classification and region-based segmentation.

In the first family, the methodologies are most from multidimensional data classification and try to find a space allowing to distinguish pixels classes according with their attributes. Amongst classical approaches, we find clustering based [Vemuri et al., ] and histogram based segmentation [Cheng et al., 2001]. K-clustering methods as ISODATA or Fuzzy c-means are widely used for satellite images because they are computationnaly attractive. K-means clustering divides data into groups based on their features. The aim is to find clustering solution that minimizes the within-cluster sum of distances . However,they often not work well when the clusters are of different size, shape and density [Ertoz et al., 2003]. The histogram-based algorithms perform mode seeking or multi-thresholding operation and relate the modes of a spectral histogram to homogeneous regions in the image [Haralick and Shapiro, 1985]. These methods does not work well for image without any obvious peaks or with broad and flat valleys [Cheng et al., 2001]. **Since these technics neglect all the spatial relationship information of the image** [Cheng et al., 2001], [Wesolkowski, 1999]. Indeed, in complex images as outdoor images, it seem very important to take into account spatial relationship to improve segmentation results.

In the second family, we try to gather iteratively related points or sets of points using homogeneity properties. Thus, we can find segmentation approaches by markov fields [Rouquet et al., ], , by splitting and merging [Strasters and Gerbrands, 1991] and finally by aggregation of pixels (or region growing) [Trémeau, 1998]. Markov random fields approaches (RMF) are based on models building expressing global relationships in terms of local statistics. They help to combine spatial and temporal information by introducing strong generic knowledge about the features to be estimated. This technic is very efficient on textured and noisy images. Splitting and merging methods successively divides an image into smaller and smaller regions until homogeneity criteria are satisfied. These approaches are guided by structures of data such as diagrams of voronoi, quadtree or more by graph adjacency. Lastly, approach by aggregation of pixels is a bottum-up method that gathers pixels or sub-regions into larger regions according to a set of homogeneity criteria and adjacency [Cocquerez and Philipp, 1995]. All fo these last methods uses spatial and multi-band informations in the segmentation process. However, methodology by region growing have data structure helping the design of a region/contour collaboration for the segmentation since we always start from an element (a pixel) in order to find a set (a region). It is thus enough to attach to each pixel the contour information to be able to integrate this new parameter in the merging process. In addition, some authors have developped region growing segmentation algorithm allowing a low complexity.

### 3.2 Multiband edges detector

Concerning gray images, the notion of edge (contour) is associated to a variation of intensity and/or discontinuities in between two connected pixels set. Thus, to be able to detect the visibles edge within an image, many authors have oriented their research towards derivatives methods in order to demonstrate these variations. Operators either exploit image 's maxima of first derivative ( gradient by filter of Robert [Robert, 1965], sobel [Sobel, 1970]...) or zero crossing of second derivative (Laplacian operator , Marr and Hildreth operator [Marr and Hildreth, 1980] ...).

By extended the defintion, given by Cheng [Cheng et al., 2001], of an edge in color image to a multiband image, an edge should be defined by a discontinuity in a m-dimensional space. However, as Navatia emphasized it [Navatia, 1977], "Central to the problem of multi-spectral edge detection is the question of how to integrate the contrast information contained in the various channels into one meaningful result". Two approachs are proposed in literature. The most straightforwards approaches, stated as marginal, consists in

applying a similar method on each of the image's components separately. In this case, methodologies are extensions of methods used in the case of monochrome image. Classical edge operator (Sobel, Robert ...) are applied on each of the image's spectral plan. Final edges are obtained by combining the information on each plan using logical operator (OR, AND ...) or by fusing them with more complex methods *Fan et al* [Fan et al., 2001], *Carron* [Carron, 1994], *Delcroix et Adibi* [Delcroix and Abidi, 1988], *Chu et Aggarwal* [Chu and Aggarwal, 1993]. ... This kind of approach, meanwhile, is often criticised because it supposes a total independence of the different image plans. This assumption is false in the case of the color space or multiband images. Further more, these approaches will tend to forget (overlook?) edges which have the same intensity but in opposed directions within two of the color components [Lambert, 1999].

The other approach, stated as vectorial, consists to consider each pixel of an image as a  $n$  dimension vector and apply a single treatment on image. Indeed, it can be considered a multispectral images as a fonction  $f : \mathbb{R}^2 \mapsto \mathbb{R}^n$  which corresponds to each image dot (pixel)  $p(x,y)$ , a vector  $\vec{p}$  such as  $\vec{p}=(f_1(x,y),f_2(x,y)...f_m(x,y))$  with  $f_i(x,y)$  value of pixel  $p(x,y)$  on band  $i$  (with  $1 \leq i \leq m$ ). Different approaches use this principle and has been developed in the most case for color images but could be extended to the multispectral domain. Thus, *Shiozaki* [Shiozaki, 1986] has developed an entropy operator. Edges can be extracted by detecting the change of entropy in a window region of image. This operator is very sensitive to noise. *Trahanias et Venetsanopoulos* [Trahanias and Venetsanopoulos, 1996] have developed methodologies based on vector order statistics inspired by the morphological edge operator. These detectors (vector mean or VD, vector median or VM, vector range or VR, minimum vector dispersion or MVD ...) operates by detecting local minima and maxima in the image function and combined them (linear combinations) in a suitable way in order to produce a response on edge. Nevertheless, these operators are sensitive to noise or have a high complexity [Zhu et al., 1999]. *Ruzon et Tomasi* [Ruzon and Tomasi, 1999] defined a vectorial gradient using the knowledge of color signature proposed by *Rubner et Tomasi* [Rubner et al., 1998] and the mover earth distance proposed by *Smith et Brady* [Smith and Brady, 1995]. This approach allows to detect edge in low contrast areas, but is difficult to implement and presents also a high complexity. *Dizzeno* [DiZenko, 1986], *Novak et Shafer* [Novak and Shafer, 1986], *Lee et Cok* [Lie and Cok, 1991], *Cumani* [Cumani, 1989] et *Drewniok* [Drewniok, 1994] are interested in developing gradient operator. Novak and shafer [Novak and Shafer, 1986] used matrix jacobian to define a gradient operator but only on three bands. Drewniok [Drewniok, 1994] extended this last gradient operator in the case of multispectral data. This operator is easy to implement and has also a low complexity. In this sense, it is well-adapted to our segmentation project.

## 4 Proposed approach

The input of the segmentation algorithm is a multispectral image  $I_N$  with  $N$  spectral bands. The algorithm output is the image labelling  $I_L = \{\lambda(pi)\}$ ,  $i = 1 \dots M$ ,  $\lambda_i \in \Omega$ , where  $M$  denotes the number of image pixel and  $\lambda(pi)$  are  $pi$  pixel label. Labels take value from a set of mutually exclusive classes  $\omega = \{\omega_1 \dots \omega_c\}$  with  $c$  number of object to classify in the image  $I_N$ .

To obtain this labelling image, our multiband image segmentation system is divided in two main parts as described in figure 1 :

- In the first part, using a region growing algorithm, we generate  $H$  regions according to a merging criteria. These regions (and then pixels including in these regions) are

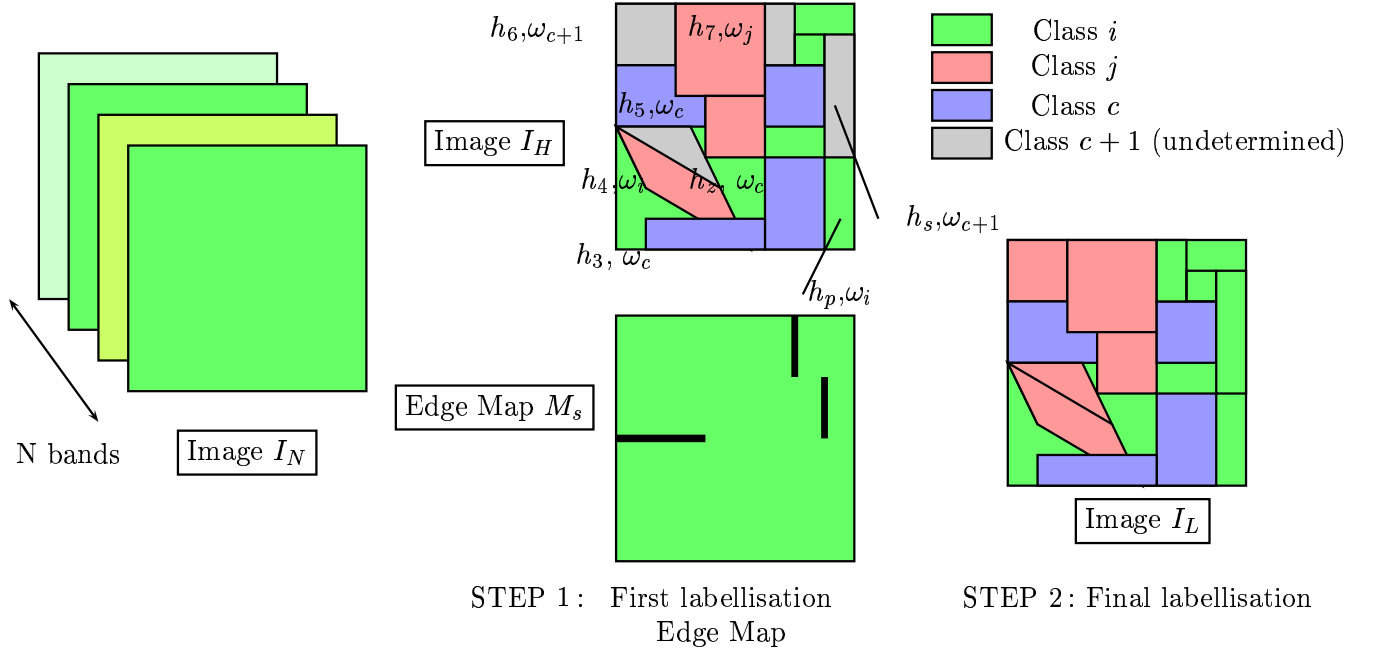


FIG. 1 – Proposed segmentation scheme

then labelled according to a set of criteria  $C$  with a label  $\lambda$ , taking value from a set of mutually exclusive classes  $\Omega = \omega \cup \phi = \{\varpi_1 \dots \varpi_c \varpi_{c+1}\}$  with  $\omega = \{\varpi_1 \dots \varpi_c\}$  and  $\phi = \{\varpi_{c+1}\}$ . The label  $\varpi_{c+1}$  is affected to regions for which there are ambiguous affection to basic classes  $\varpi_1$  to  $\varpi_c$  (undetermined region). In addition, the strong edges in original image  $I_N$  are detected by using an adapted multiband edges operators. Thus, an edge map  $M_s$  is obtained.

- In the second part, to resolve these ambiguities a more complex segmentation process using a collaborative regions/contours approach is applied on the regions labelled  $\varpi_{c+1}$ .

#### 4.0.1 Region growing process and first labellisation

Let  $P(i, j)$  be a pixel located at coordinate image  $(i, j)$  of multiband image  $I_N$ . Each pixel  $P(i, j)$  is described by a vector  $\vec{p}$  such as  $\vec{p}(i, j) = (p_1(i, j), p_2(i, j), \dots, p_m(i, j))$  with  $p_k(i, j)$  value of pixel  $P(i, j)$  on band  $k$ ,  $k = 1 \dots m$ . Then,  $d_E^2 = \sum_{k=1}^m (p_k - p'_k)^2$  denotes the euclidian distance separates the two pixel vector  $P$  and  $P'$ .

In the same way, if  $\vec{R}^p$  and  $\vec{R}^t$  are two regions (set of neighboring pixels),  $d_E^2 = \sum_{k=1}^m (r_k^p - r_k^t)^2$  denotes the euclidian distance separates the two region  $R^p$  and  $R^t$  described by their region vector  $\vec{R}^p$  and  $\vec{R}^t$  such as  $\vec{R}^p = (r_1^p \dots r_m^p)$  and  $\vec{R}^t = (r_1^t \dots r_m^t)$ . Each region vector  $R^i$  is computed as the mean vector of all the pixels contained in the region.

According to our experience and experiments we decided to adopt a region growing process based on the disjoint set union problem or Union find implemented through a scanline algorithm [Muerle and Allen, 1968], ([Fiorio, 1995], [Fiorio and Gustedt, 1996]). The scanline algorithm allow to obtain a quasi-linear complexity.

The algorithm is initialized by identifying each pixel to an elementary region. The merging criteria (*Crit1*) used is the euclidian distance  $d_E^2$  between two regions vectors: two region  $R^k$  and  $R^p$  are merged if their euclidian distance is below a threshold  $S_0$  (Equ: 1).

$$d_E^2(R^k, R^t) \leq S_0 \quad (1)$$

After the previous step, the image is divided in  $H$  homogeneous areas according to the criteria *Crit1*. Each area  $R_k$ ,  $k = 1 \dots H$  is then labelled with a label  $\lambda_z$  take value in the label set  $\Omega$  using the process described below.

Statistical distributions of the  $c$  objets are described by their covariance matrix using a reference image. For each region  $h$ ,  $h = 1 \dots H$ , the mahalanobis distance  $d_M$  to each class object is calculated ([Mahalanobis, 1938]). Thus, according to the different distance measures obtained a label decision is taken. Let  $d_M(R_t, C_q)$  be the Mahalanobis distance calculated between region  $R_t$  and the class object  $C_q$ . The region  $R_t$  will be labeled  $\varpi_{c+1}$  if at least one of the next conditions is verified:

1.  $d_M(R_t, C_q) \geq S_1, \forall q = 1 \dots c$  or
2.  $d_M(R_t, C_q) \leq d_M(R_t, C_p) + \epsilon$  with  $q = 1 \dots c, p = 1 \dots c, p \neq q$  or
3.  $\sum_{z=1}^m r_t^z \leq S_2$

The first condition tends to identify areas for which distance to original class object is too large.

The second one identify regions with ambiguous affectations (Mahalanobis distance between region and two or more class object is identical to epsilon).

The third one identify regions with low intensity (dark regions and so difficult to classify).

If neither one of these condition is verified, the region  $R^k$  will take the label  $\varpi_i$  corresponding to the nearest class object  $C_i$ ,  $i = 1 \dots c$  regarding to the Mahalanobis distance:  $\lambda(R^k) = \lambda(C_i) = \varpi_i$  with  $\varpi_i \in \omega$  and  $i \in [1 \dots c]$  if  $d_M^2(R^k, C_i) = \min(d_M^2(R^k, C^p))$ , with  $p = 1 \dots c$ .

**Thus, In this process, to improve the complexity, we try first to detect the undetermined regions.**

#### 4.0.2 Multiband edges detector

The collaborative regions/contours approach needs a map contour. To obtain this map, we decided to use the Drewniok multiband operators [Drewniok, 1994] (3.2). This operator allow us to obtain a map contours  $M_c$ . Applying a threshold  $S_c$  on this map, we only considers the strong edges in original Image  $I_N$ . The final map contours is noted  $M_s$ .

#### 4.0.3 Collaborative region/contours approach and final labelling

At the beginning of this step, we have some informations:

- An image  $I_H$  segmented into  $H$  regions. Each one is affected with a label  $\lambda$  belonging the set of label  $\Omega$ .
- A map of strong edges  $M_s$

The aim is to affect a new label  $\varpi_p$  including in  $\omega$  to the regions labeled  $\varpi_{c+1}$ .

Let us to consider a set  $\phi$  of the regions in  $I_H$  with  $\varpi_{c+1}$  label. By traversing image line by line, we take into account each regions  $R^p$  including in  $\phi$ , with  $p = 1 \dots q, q \leq H$ . Let  $R^j$  be one of these regions. It is surrounded by  $j$  regions with label including in  $\Omega$ . Using contextual informations (surrounded and labeled region, boundaries between

treated regions), we are able to take a decision to affect a new label to  $R^i$ . Indeed, three configurations can be distinguished :

1. All the neighboring regions to  $R^i$  have a label  $\varpi_{c+1}$  : the decision is then left for later (next scan image).
2. All the neighboring regions to  $R^i$  have an identical label  $\varpi_c$  include in  $\omega$  :  $R^i$  take the label  $\varpi_c$
3. At least two neighboring regions have a different label including in  $\omega$ .

Let  $\Theta$  be the set of these regions : the label affected to region  $R^i$  is the label to the nearest region including in  $\Theta$  according to a distance measure ( $d_{EE}$ ) taking into account euclidian distance and existing contours (map contours  $M_s$ ) between region  $R^i$  and the regions including in  $\Theta$  :  $\lambda(R^i) = \lambda(R^k)$ ,  $R^k \subset \Theta$  such as  $d_{EE}(R^i, R^k) = \min(d_{EE}(R^i, R^p))$  for each  $R^p \subset \Theta$ .

The distance measure  $d_{EE}$  between region  $R^i$  and  $R^k$  is given by :  $d_{EE}(R^i, R^p) = d_M(R^j, R^p) + \eta_o \times \alpha$  with  $\eta_o$  : number of edge point between regions  $R^i$  and  $R^k$  and  $\alpha$  : weigh given to a edge point (dependant on the application).

## 5 Experimentals results

### 5.1 Materials

The implementation of the whole of the software was carried out in 'C'programming on a windows NT workstation. We worked with visual C++ 6.0 software using an open source images analysis library ( CV open Intel)to implement basic images analysis fonctions (gaussian filtering ...) . Several tri-bands (color) outdoor images concerning cauliflower plants at different growth stages were used to test the algorithm. Colour was represented in the conventional manner as a triplet of intensity value, R, G and B, equal to the amount of light reflected from a surface in three bands in the visible electromagnetic spectrum. Segmentation objective in this case is to separate three different objects : plant, weeds and soil. Independant image ground truth was obtained by human operator using a combination of automatic and manual image manipulation techniques. One of these image is used to build the covariance matrix of each population or object (plant, weed, soil) according to the corresponding original image.

### 5.2 Results and discussion

Segmentation results obtained with our approach are compared with those obtained by a direct labelling on a segmented image (regions growing segmentation process) using Mahlanobis distance. The segmentation results are illustred on three exemples in Fig.2 to Fig.4. On each figure, sub-figure A represents the original image, sub-figures B to D, middle and final results obtained with a region growing segmentation approach and sub-figures E to G, middle and final results obtained with the proposed segmentation approach.

In 80% of the cases , the proposed approach improves the results of the segmentation by 2 to 10 % depending the class object. The lower results are obtained for the class weed : objects includes in this class presents hight variability, difficult and small shape and no sharp edges. Futhermore, if our approach gets corrects segmentation results for objects with shadows, partially overlapping objects in image are not well labellised. This weakness is due to color proximity of objects to detect and so the lack of sharp edges in these areas. The principal difficulty of our approach is to well determined the different thresholds to obtain undetermined regions in the first step labellisation. These threshold need to



be enough strict as the regions affected to a class objet are estimated confident regions. Indeed, our algorithm use, amongst other things, these confident regions to determine other label regions. However, the algorithm computation complexity is widely dependent on the number of undetermined regions.

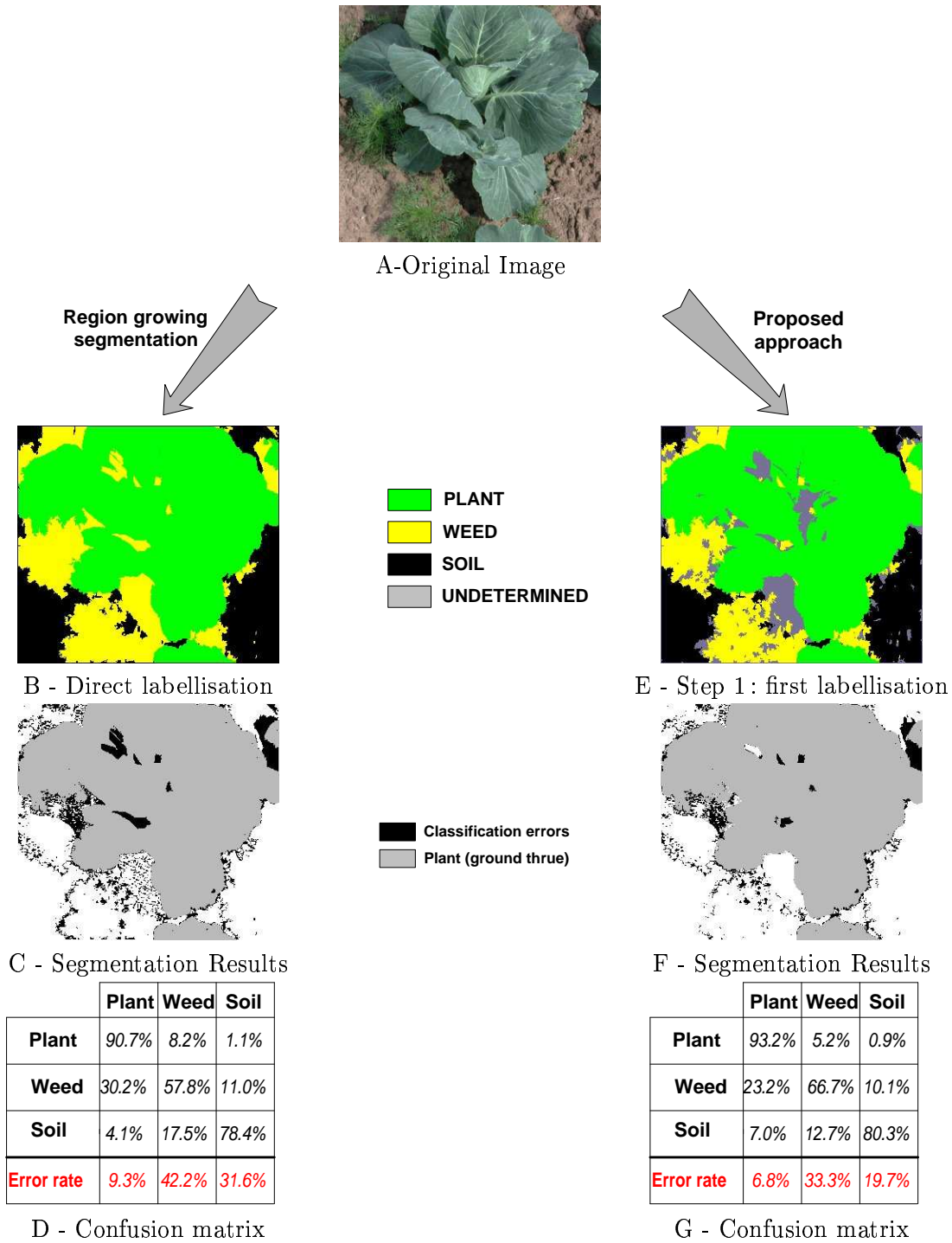


FIG. 2 – Segmentation results: region growing segmentation (left), proposed approach - collaboration region/contour segmentation (right)- first exemple

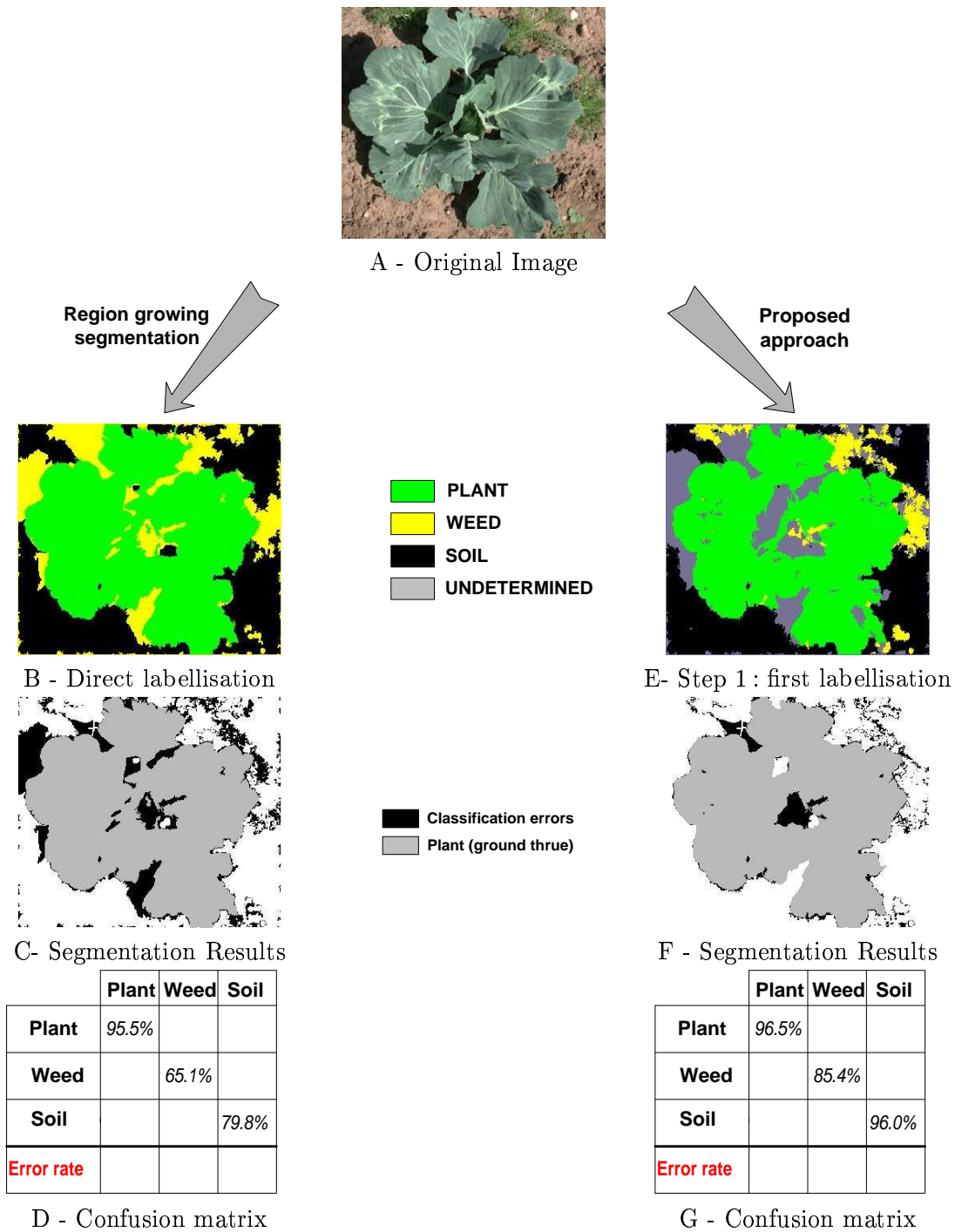
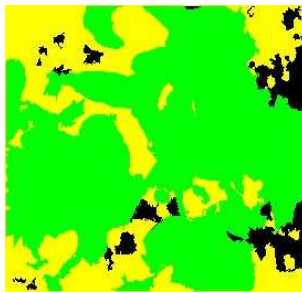


FIG. 3 – Segmentation results: region growing segmentation (left), proposed approach - collaboration region/contour segmentation (right)- second exemple

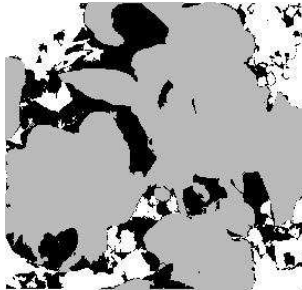


A - Original Image

Region growing segmentation



B - Direct labellisation

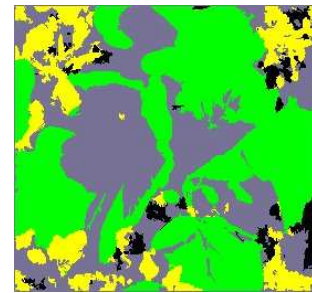


C - Segmentation Results

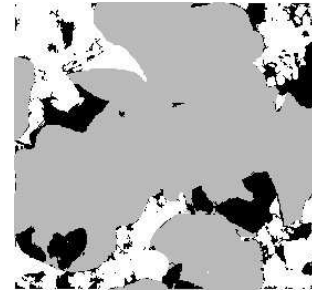
	Plant	Weed	Soil
Plant	86.7		
Weed		57.8%	
Soil			53.6%
Error rate			

D - Confusion matrix

Proposed approach



E - Step 1: first labellisation



F - Segmentation Results

	Plant	Weed	Soil
Plant	86.7		
Weed		57.8%	
Soil			50.6%
Error rate			

G - Confusion matrix

FIG. 4 – Segmentation results: region growing segmentation (left), proposed approach - collaboration region/contour segmentation (right)- third exemple

## Références

- [Carron, 1994] Carron, T. (1994). *Segmentation d'images couleur dans la base Teinte Luminance Saturation: approche numérique et symbolique*. Thèse de doctorat, Université de Savoie, France.
- [Cheng et al., 2001] Cheng, L., Jiang, X., Sun, Y., and Wang, J. (2001). Color image segmentation: advances and prospects. *PATTERN RECOGNITION*, 34:2259–2281.
- [Chu and Aggarwal, 1993] Chu, C. and Aggarwal, J. (1993). The integration of image segmentation map using region and edge information. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 15(12):1241–1552.
- [Cocquerez and Philipp, 1995] Cocquerez, J. and Philipp, S. (1995). *Analyses d'images: filtrage et segmentation*. MASSON.
- [Cumani, 1989] Cumani, A. (1989). Edge detection in multispectral images. Technical Report R.T. 373, Istituto Elettrotecnico Nazionale "Galileo Ferraris".
- [Delcroix and Abidi, 1988] Delcroix, C. and Abidi, M. (1988). Fusion of edge maps in color images. *SPIE*, 1001:545–554.
- [DiZeno, 1986] DiZeno, L. (1986). A note on the gradient of a multi-image. *Computer vision, graphics, and image processing*, 33:116–125.
- [Drewniok, 1994] Drewniok, C. (1994). Multi-spectral edge detection. some experiments on data from landsat-tm. *Int. J. Remote sensing*, 15(18):3743–3765.
- [Ertoz et al., 2003] Ertoz, L., Steinbach, M., and Kumar, V. (2003). Finding clusters of different sizes, shapes, and densities in noisy, high dimensional data. In *Second SIAM International Conference on Data Mining*.
- [Fan et al., 2001] Fan, J., Aref, W., Hacid, M., and Elmagarmid, A. (2001). An improved automatic isotropic color edge detection technique. *PMR*, 22:1419–1429.
- [Fiorio, 1995] Fiorio, C. (1995). *Approche interpixel en analyses d'images, une topologie et des algorithmes de segmentation*. Thèse de doctorat, Université Montpellier II, Montpellier, France.
- [Fiorio and Gustedt, 1996] Fiorio, C. and Gustedt, J. (1996). Two linear time union-find strategie for image processing. In *Theoretical Computer Sciences*, 54:165–181.
- [Haralick and Shapiro, 1985] Haralick, R. M. and Shapiro, L. G. (1985). Image segmentation techniques, and image processing. *Computer Graphics and Image Processings*, 29(1):100–132.
- [Lambert, 1999] Lambert, P. (1999). Prétraitement des images couleurs. In *Ecole d'été sur la couleur*.
- [Lie and Cok, 1991] Lie, H.-C. and Cok, D. (1991). Detecting boudaries in a vector field. *IEEE Transactions on signal processing*, 39(5):1181–1194.
- [Mahalanobis, 1938] Mahalanobis, P. (1938). On the generalized distance in statistics. *Processings of the National Institute of Sciences of India*, 2:49–55.
- [Marr and Hildreth, 1980] Marr, D. and Hildreth, E. (1980). Theory of edge detection. In *Proc. Roy. Soc.*, volume B-207.
- [Muerle and Allen, 1968] Muerle, J. and Allen, D. (1968). *Experimental evaluation of technics for automatic segmentation of objects in a complex scene*, pages 3–13. G.C. CHENG et OTHERS, Pictorial Pattern Recognition.
- [Nevatia, 1977] Nevatia, K. (1977). A color edge detector and its use in scene segmentation. *IEEE Transactions on systems, mans and cybernetics*, 7:820–826.
- [Novak and Shafer, 1986] Novak, C. and Shafer, S. (1986). Color edge detection. In *DARPA Image Understanding Workshop*, volume I, pages 35–37.

- [Robert, 1965] Robert, L. (1965). *Machine perception of three dimensional solids*, pages 159–197. Opt. Elec.-Optical Inform. Processing (J. T. Tippet et al., Eds.). Cambridge, MA: MIT Press.
- [Rouquet et al., ] Rouquet, C., Bonton, P., and Tomckat, R. Etude comparative de stratégies de segmentation non supervisée en régions par champs de markov. *Traitement du signal*, 15(1).
- [Rubner et al., 1998] Rubner, Y., Tomasi, C., and Guibas, L. (1998). A metric for distributions with applications to images databases. In *IEEE International Conference on Computer vision*, pages 59–66.
- [Ruzon and Tomasi, 1999] Ruzon, M. and Tomasi, C. (1999). Color edge detection with the compass operator. *IEEE Computer Vision and Pattern Recognition*, 2:160–166.
- [Shiozaki, 1986] Shiozaki, J. (1986). Edge extraction using entropy operator. *Comput. Vus. Graph. Image Process*, 33:116–126.
- [Smith and Brady, 1995] Smith, S. and Brady, J. (1995). Susan: A new approach to low level image processing. Technical Report TR95SMS1c, Oxford University, Departement of Engineering Sciences.
- [Sobel, 1970] Sobel, I. (1970). *Camera modelS and perception*. PhD thesis, Standford University, Electrical Engineering Departement.
- [Strasters and Gerbrands, 1991] Strasters, K. and Gerbrands, J. (1991). Three-dimensional image segmentation using split, merge and group approach. *Pattern recognition letters*, 12:307–325.
- [Trahanias and Venetsanopoulos, 1996] Trahanias, P. and Venetsanopoulos, A. (1996). Vector order statistics operators as color edge detector. *IEEE Transactions on system man, and cybernetics*, 26(1):135–143.
- [Trémeau, 1998] Trémeau, A. (1998). *Analyse d'images couleurs : du pixel à la scène*. Habilitation à diriger des recherches, Université Jean Monnet, St Etienne, France.
- [Vemuri et al., ] Vemuri, B., Rahman, S., and Li, J. Multiresolution adptive k-mean algorithms for segmentation of brain mri. In *Conference on Image Analysis adn Computers graphics*.
- [Wesolkowski, 1999] Wesolkowski, S. (1999). *Color Image Edge Detection and Segmentation : A comparaison of the vector angle and euclidian distance color similarity measure*. Master of applied sciences, University of Waterloo, Ontario, Canada.
- [Zhu et al., 1999] Zhu, S.-Y., Plataniotis, K., and Venetsanopoulos, A. (1999). Comprehensive analysis of edge detection in color image processing. *Optical Engineering*, 38(4):612–625.
- [Zucker, 1976] Zucker, S. (1976). Childhood and adolescence. *Computer Graphics qnd Image Processings*, 5:382–399.