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

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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 multiband images, tri-dimensional or volumic images, multi-temporal images ... Selection of adapted segmentation methodology is largely dependant on application. Our work is dediated 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 approachs as classification or thresholding based approach they simultanously take into account both feature space and spatial domain. Thus, in case of supervised segmentation, direct labeling could be obtain by an approach including an oversegmentation using a region growing method followed by a fusion strategie 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 particulary 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 ambigus 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 underminded areas.

This article is organized as follows. In section one, we were interested in edges-based and regions-based segmentation approches 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 stratregy. In the second chapter, we present in details the proposed segmentation process . In a last chapter, we describe results obtained with our approches 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 developp a segmentation approach dedied to complex and multi-spectral images and using a collaborative edge-region segmentation stratregy. 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 caracterised 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 $S = R_1,R_2,\ldots,R_n$ of I such as :

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

Thus, in region approach, we tend to agregate 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 approches, 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 homogenity 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 adjency. 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 adjency [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 develloped 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 [Nevatia, 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 monochromes image. Classicals edge operator (Sobel, Robert ...) are applied on each of the image's spectral plan. Finals edges are obtained by combining the information on each plan using logical operator (OR, AND ...) or by fusing them with more complexes methods *Fan et al* [Fan et al., 2001], *Carron* [Carron, 1994], *Delcroix et Adibi* [Delcroix and Abidi, 1988], *Chu et Arggarwal* [Chu and Aggarwal, 1993]...This kind of approach , meanwhile, is often criticised because it supposes a total independance of the different image plans. This assumption is false in the case of the color space or multiband images. Futher 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 $f : \Re^2 \longmapsto \Re^n$ 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 developped in the most case for color images but could be extended to the multispectral domain. Thus, *Shiozaki* [Shiozaki, 1986] has develloped 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 Venetsanopoulous* [Trahanias and Venetsanopoulos, 1996] have developped 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. Nerveless, these operators are sensitive to noise or have a hight 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. *Dizenzo* [DiZenzo, 1986], *Novak et Shafer* [Novak and Shafer, 1986], *Lee et Cok* [Lie and Cok, 1991], *Cumani* [Cumani, 1989] et *Drewniock* [Drewniok, 1994] are interested in devellopping gradient operator. Novak and shafer [Novak and Shafer, 1986] used matrix jacobian to define a gradient operator but only on three bands. Drewniock [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 segmention 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 $I_L = \{\lambda(pi)\}$, $i = 1 \ldots M$, $\lambda_i \in \Omega$, 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 $\omega = \{\varpi_1 \ldots \varpi_c\}$ with c number of object to classify in the image I_N.

To obtain this labelling image, our multiband image segmentation system is divided is 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

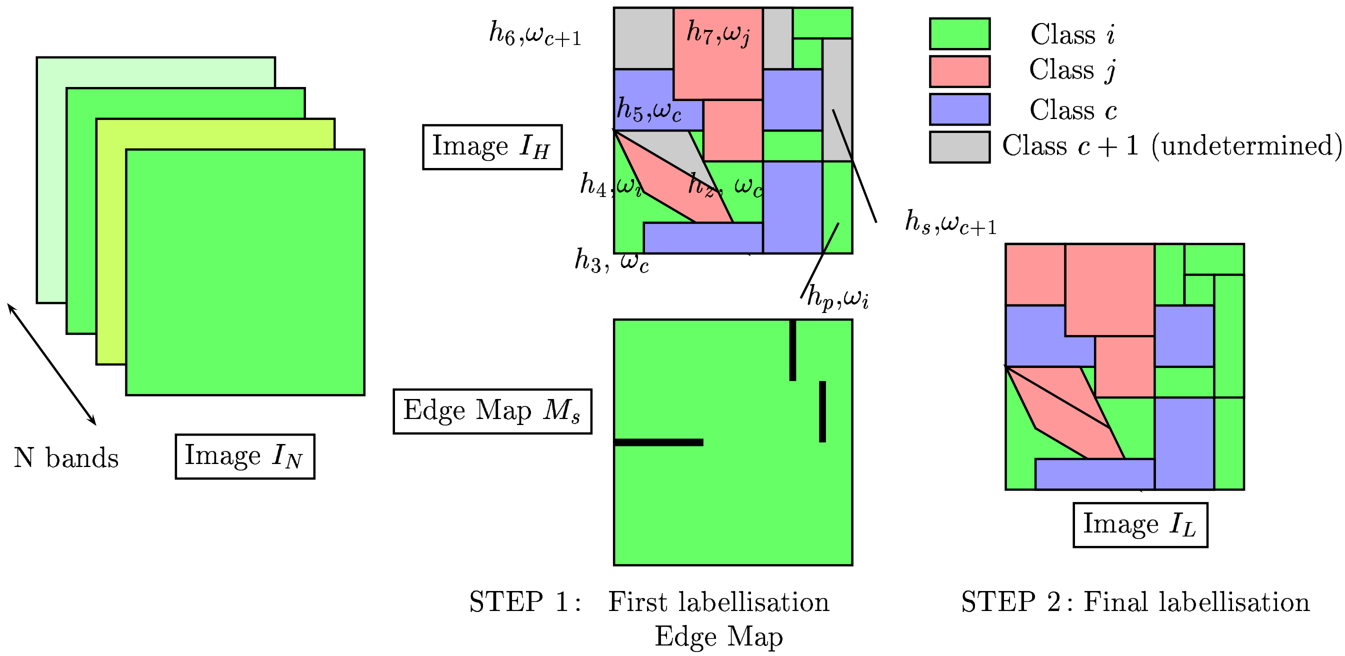


Fig. 1 – *Proposed segmentation scheme*

then labelled according to a set of criteria C with a label λ, taking value from a set of mutually exlusive 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 ϖ_{c+1} is affected to regions for which there are ambigus affection to basic classes ϖ_1 to ϖ_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 ϖ_{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 neighbooring 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 $\vec{R}^t = (r_1^t \dots r_1^t)$. 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 identifiying 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).

$$d_E^2(R^k,R^t) \leq S_0 \tag{1}$$

After the previous step, the image is divided in H homogeneous areas according to the criteria $Crit_1$. Each area R_k, $k = 1 \dots H$ is then labelled with a label λ_z take value in the label set Ω 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 mahananobis 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 Mahananobis distance calculated between region R_t and the class object C_q. The region R_t will be labeled ϖ_{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 ambigous affectations (Mahananobis 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 ϖ_i corresponding to the nearest class object C_i, $i = 1 \dots c$ regarding to the Mahananobis 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 colloaborative regions/contours approach needs a map contour. To obtain this map, we decided to use the Drewniock 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 λ belonging the set of label Ω.
- A map of strong edges M_s

The aim is to affect a new label ϖ_p including in ω to the regions labeled ϖ_{c+1}.

Let us to consider a set ϕ of the regions in I_H with ϖ_{c+1} label. By traversing image line by line, we take into account each regions R^p including in ϕ, 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 Ω. 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 ϖ_{c+1} : the decision is then left for later (next scan image).
2. All the neighboring regions to R^i have an identical label ϖ_c include in ω : R^i take the label ϖ_c
3. At least two neighboring regions have a different label including in ω.

Let Θ be the set of these regions : the label affected to region R^i is the label to the nearest region including in Θ 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 Θ : $\lambda(R^i) = \lambda(R^k)$, $R^k \subset \Theta$ 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 : $d_{EE}(R^j,R^p) = d_M(R^j,R^p) + \eta_o \times \alpha$ with η_o : number of edge point between regions R^i and R^k and α : weigth given to a edge point (dependant on the application).

5 Experimentals results

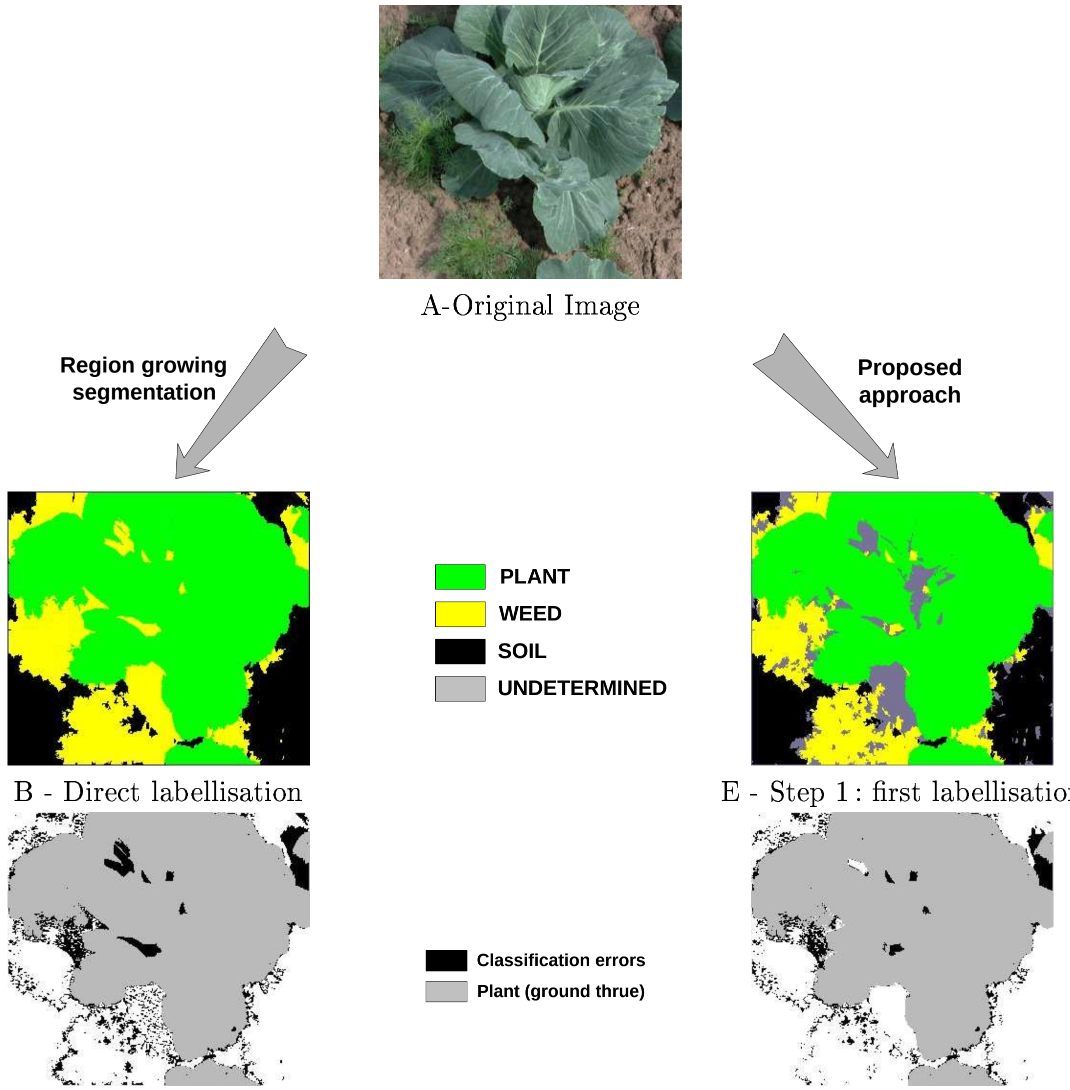
5.1 Materials

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 electromagentic 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.



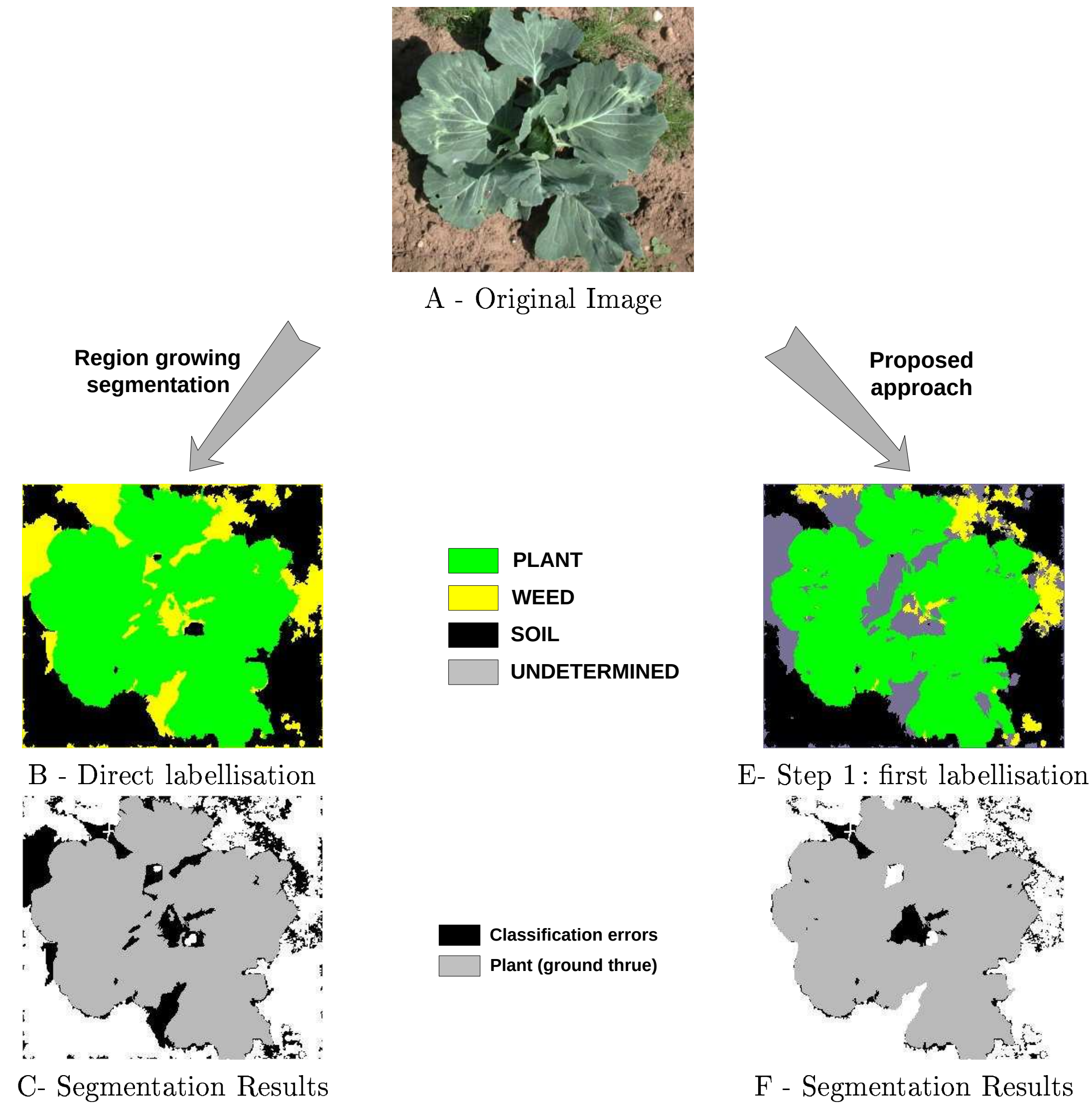
	Plant	Weed	Soil
Plant	*90.7%*	*8.2%*	*1.1%*
Weed	*30.2%*	*57.8%*	*11.0%*
Soil	*4.1%*	*17.5%*	*78.4%*
Error rate	*9.3%*	*42.2%*	*31.6%*

D - Confusion matrix

	Plant	Weed	Soil
Plant	*93.2%*	*5.2%*	*0.9%*
Weed	*23.2%*	*66.7%*	*10.1%*
Soil	*7.0%*	*12.7%*	*80.3%*
Error rate	*6.8%*	*33.3%*	*19.7%*

G - Confusion matrix

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



	Plant	Weed	Soil
Plant	95.5%		
Weed		65.1%	
Soil			79.8%
Error rate			

D - Confusion matrix

	Plant	Weed	Soil
Plant	96.5%		
Weed		85.4%	
Soil			96.0%
Error rate			

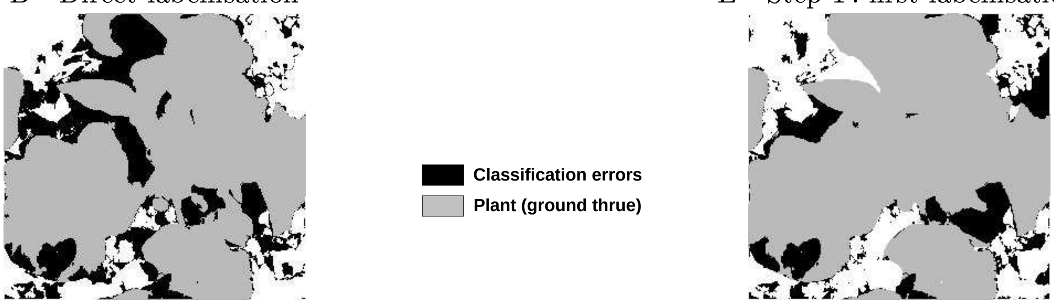
G - Confusion matrix

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

A - Original Image

B - Direct labellisation

E - Step 1 : first labellisation



C - Segmentation Results

F - Segmentation Results

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

D - Confusion matrix

	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*

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