We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900
Open access books available

185,000
International authors and editors

200M
Downloads

154
Countries delivered to

Our authors are among the

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

CLARIVATE ANALYTICS

BOOK CITATION INDEX

INDEXED

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

JSEG Algorithm and Statistical ANN Image Segmentation Techniques for Natural Scenes

Luciano Cássio Lulio, Mário Luiz Tronco and Arthur José Vieira Porto
Engineering School of Sao Carlos, University of Sao Paulo (EESC/USP)
Sao Carlos, Sao Paulo
Brazil

1. Introduction

Computer vision, when used in open and unstructured environments as in the inspection of crops for natural scenes, demands and requires complex analysis of image processing and segmentation algorithms, since these computational methods evaluate and predict environment physical characteristics, such as color elements, complex objects composition, shadows, brightness and inhomogeneous region colors for texture.

Several segmentation algorithms proposed in literature were designed to process images originally characterized by the above-mentioned items. Additionally, agricultural automation may take advantage of computer vision resources, which can be applied to a number of different tasks, such as crops inspection, classification of fruits and plants, estimated production, automated collection and guidance of autonomous machines.

Bearing the afore-named in mind, the present chapter aims the use of JSEG unsupervised segmentation algorithm (Deng et al., 1999a), Statistical Pattern Recognition and Artificial Neural Networks (ANN) Multilayer Perceptron (MLP) topology (Haykin, 2008) as merging processing techniques in order to segment and therefore classify images into predetermined classes (e.g. navigable area, planting area, fruits, plants and general crops). The intended approach to segment classification deploys a customized MLP topology to classify and characterize the segments, which deals with a supervised learning by error correction – propagation of pattern inputs with changes in synaptic weights in a cyclic processing, with accurate recognition as well as easy parameter adjustment, as an enhancement of iRPROP algorithm (*improved resilient back-propagation*) (Igel and Hüsken, 2003) derived from *Back-propagation* algorithm, which has a faster identification mapping process, that verifies what region maps have similar matches through the explored environment.

To carry through this task, a feature vector is necessary for color channels histograms (layers of primary color in a digital image with a counting graph that measures how many pixels are at each level between black and white). After training process, the mean squared error (MSE), denotes the best results achieved by segment classification to create the image-class map, which represents the segments into distinct feature vectors. Several metrics (vector bundle) can be part of a feature vector, however, a subset of those which describes and evaluates appropriate classes of segments should be chosen.

2. JSEG image segmentation

Color images with homogeneous regions are segmented with an algorithm to generate clusters in the color space/ class (different measures classes in spectral distribution, with distinct intensity of visible electro-magnetic radiation at many discrete wavelengths) (Cavani, 2007). One way to segment images with textures is to consider the spatial arrangement of pixels using a region-growing technique whereby a homogeneity mode is defined with pixels grouped in the segmented region. Furthermore, in order to segment texture images one must consider different scales of images.

An unsupervised color-texture regions segmentation algorithm is ideal for this purpose, since it tests the homogeneity of a given color-texture pattern, which is computationally more feasible than model parameter estimation. It deals with the following assumptions for the acquired image:

- Image containing homogeneous color-texture regions.
- Color information is represented by quantized colors.
- Colors between two neighboring regions are distinguishable.

The JSEG algorithm segments images of natural scenes properly, without manual parameter adjustment for each image and simplifies texture and color. Segmentation with this algorithm passes through two major stages, namely color space quantization (number reduction process of distinct colors in a given image), and hit rate regions with similar color regions merging, as secondary stage.

In the first stage, the color space is quantized with little perceptual degradation by using the quantization algorithm (Deng *et* al, 1999b; Deng and Manjunath, 2001) with minimum coloring. Each color is associated with a class. The original image pixels are replaced by classes to form the class maps (texture composition) for the next stage.

Before performing the hit rate regions, the J-image - a class map for each windowed color region, whose positive and negative values represent the edges and textures of the processing image - must be created with pixel values used as a similarity algorithm for the hit rate region. These values are called „J-values" and are calculated from a window placed on the quantized image, where the J-value belongs. Therefore, the two-stage division is justified through the difficult analysis of the colors similarity whital their distributions.

The decoupling of these features (color similarity and spatial distribution) allows tractable algorithms development for each of the two processing stages.
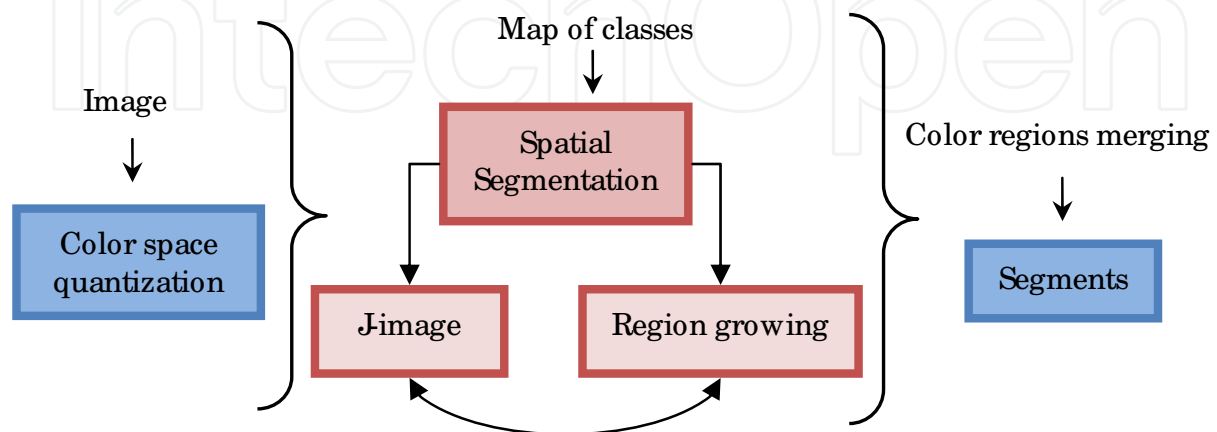
Fig. 1. JSEG image segmentation steps.

2.1 Segmentation algorithm evaluation

Natural scenes present a 24-bit chromatic resolution color image, which is coarsely quantized preserving its major quality. The main idea for a good segmentation criterion is to extract representative colors differentiating neighboring regions in the acquired image, as an unsupervised method.

Therewith, the color quantization using peer group filtering (Deng *et al.*, 199a) is applied through perceptual weighting on individual pixels, to smooth the image and remove the existing noise. Then, new values indicating the smoothness of the local areas are obtained, and a weight is assigned to each pixel, prioritizing textured areas to smooth areas. These areas are identified with a quantization vector to the pixel colors, based on General Lloyd Algorithm (GLA) (Gersho and Gray, 1999), which the perceptually uniform L*u*v color space is adopted, presenting the overall distortion D:

$$D = \sum_i D_i = \sum_i \sum_n v(n)\|x(n) - c_i\|^2 \rightarrow x(n) \in C_i \tag{1}$$

And it is derived for:

$$c_i = \frac{\sum v(n)x(n)}{\sum v(n)} \rightarrow x(n) \in C_i \tag{2}$$

The parameters: c_i is the centroid of cluster C_i, $x(n)$ and $v(n)$ are the color vector and the perceptual weight for pixel n. D_i is the total distortion for C_i.

With the centroid value, as denoted by Equation (2) - after the vector quantization and merged clusters, pixels with the same color have two or more clusters, affected by GLA global distortion. For merging close clusters with minimum distance between preset thresholds for two centroids, an agglomerative clustering algorithm is performed on c_i (Duda and Hart, 1970), as the quantization parameter needed for spatial distribution.

After clustering merging for color quantization, a label is assigned for each quantized color, representing a color class for image pixels quantized to the same color. The image pixel colors are replaced by their corresponding color class labels, creating a class-map.

```
    segmented class-map 1          not segmented class-map 2

    + + + + + + + +                 + # + # + # + # +
    + + + + + + + +                 - + - + - + - + -
    + + + + + + + +                 + # + # + # + # +
    - - - - - - - -                 - + - + - + - + -
    - - - - - - - -                 + # + # + # + # +
    - - - - - - - -                 - + - + - + - + -
    # # # # # # # #                 + # + # + # + # +
    # # # # # # # #                 - + - + - + - + -
    # # # # # # # #                 + # + # + # + # +
```
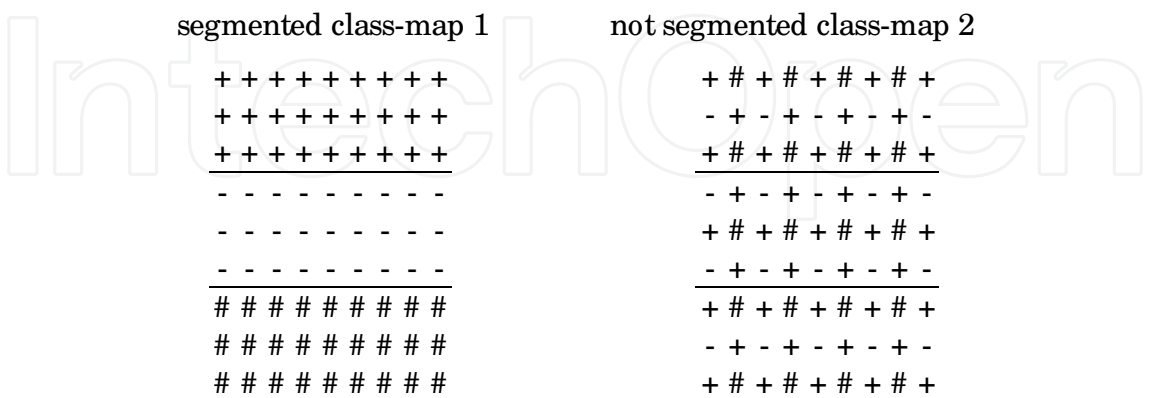
Fig. 2. Two different class-map representing three distinct classes of data points.

In Figure 2, class-map 1 indicates three regions containing a single class of data points for segmentation process, and class-map 2 is not segmented indicating a color uniformity.

The symbols (+, -, #) denotes the label values (*J-value*) for three distinct data points. All necessary segmentation information, after color quantization, is extracted and relocated to a class-map. A specific region contains pixels from a color class set, which is distributed in image regions. These regions, forming each one, a class-map, has distributed points in all spatial data segments, corresponding a two-dimensional plane, and represents the cartesian position vector *(x,y)*.

In order to calculate the J-value, Z is defined as the set of all points of quantized image, then $z = (x, y)$ with $z \in Z$ and being m the average in all Z elements. C is the number of classes obtained in the quantization. Then Z is classified into C classes, Z_i are the elements of Z belonging to class i, where $i=1,...,C$, and m_i are the element averages in Z_i.

$$m = \frac{1}{N}\sum_{z \in Z} z \tag{3}$$

$$m_i = \frac{1}{N_i}\sum_{z \in Z} z \tag{4}$$

The J-value is as follows:

$$J = \frac{S_B}{S_W} = \frac{(S_T - S_W)}{S_W} \tag{5}$$

$$\text{where: } S_T = \sum_{z \in Z}\|z - m\|^2 \tag{6}$$

$$S_W = \sum_{i=1}^{C}\sum_{z \in Z}\|z - m_i\|^2 \tag{7}$$

The parameter S_T represents the sum of quantized image points within the average in all Z elements. Thereby, the relation between S_B and S_W, denotes the measures of distances of this class relation, for arbitrary nonlinear class distributions. J for higher values indicates an increasing distance between the classes and points for each other, considering images with homogeneous color regions. The distance and consequently, the J value, decrease for images with uniformly color classes.

Each segmented region could be recalculated, instead of the entire class-map, with new parameters adjustment for $\bar{J}$ average. J_K represents J calculated over region k, M_k is the number of points in region k, N is the total number of points in the class-map, with all regions in class-map summation.

$$\bar{J} = \frac{1}{N}\sum_{k} M_k J_k \tag{8}$$

For a fixed number of regions, a criterion for $\bar{J}$ is intended for lower values.

2.2 Spatial segmentation technique

The global minimization of $\bar{J}$ is not practical, if not applied to a local area of the class-map. Therefore, the idea of *J-image* is the generation of a gray-scale image whose pixel values are

the *J* values calculated over local windows centered on these pixels. With a higher value for J-image, the pixel should be near region boundaries.

Expected local windows dimensions determines the size of image regions, for intensity and color edges in smaller sizes, and the opposite occurs detecting texture boundaries.
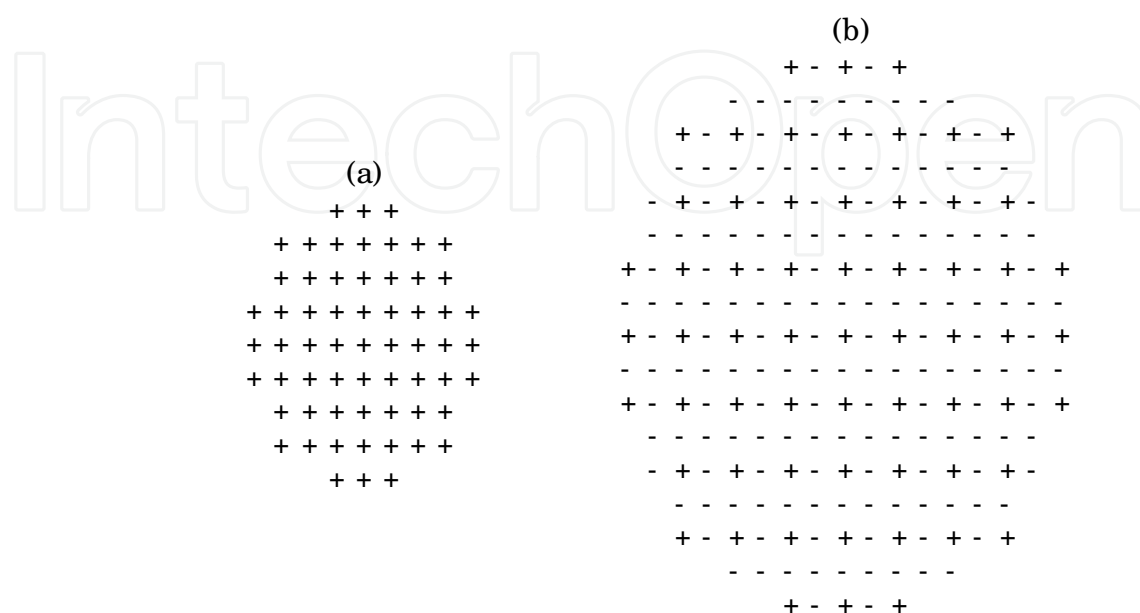
```
                                                    (b)
                                            + - + - +
                                            - - - - - - - - -
                                        + - + - + - + - + - + - +
                                        - - - - - - - - - - - - -
                    (a)               - + - + - + - + - + - + - + -
                  + + +               - - - - - - - - - - - - - - -
              + + + + + +         + - + - + - + - + - + - + - + - +
              + + + + + +         - - - - - - - - - - - - - - - - -
          + + + + + + + +         + - + - + - + - + - + - + - + - +
          + + + + + + + +         - - - - - - - - - - - - - - - - -
          + + + + + + + +         + - + - + - + - + - + - + - + - +
              + + + + + +         - - - - - - - - - - - - - - - - -
              + + + + + +           - + - + - + - + - + - + - + -
                  + + +             - - - - - - - - - - - - -
                                    + - + - + - + - + - + - +
                                        - - - - - - - - -
                                        + - + - +
```

Fig. 3. (a) A 9x9 circular window to avoid rectangular objects bias for local *J* values; (b) A downsampling scale 2, for a 17x17 window.

Using a region-growing method to segment the image, this one is considered initially as one single region. The algorithm for spatial segmentation starts segment all the regions in the image at an initial large scale until the minimum specified scale is reached. This final scale is settled manually for the appropriate image size. The initial scale 1 corresponds to 64x64 image size, scale 2 to 128x128 image size, scale 3 to 256x256 image size, with due proportion for increasing scales and the double image size.

Below, in Figure 4, the spatial segmentation algorithm is structured in flow steps.

2.2.1 Valley determination

A heuristics for the valley determination, presupposes a condition for small initial regions to be determined as the pattern growing. These regions have the lowest *J* values (valleys). As follows:

a. Calculate the standard deviation and the average of the local *J* values in the region, denoted by σ_J and μ_J, respectively.

b. Threshold for parameters above:

$$T_J = \mu_J + a\sigma_J \tag{9}$$

The condition to consider candidate valley points for pixels with local *J* values is determined $T_J > J$. Connect the points based on the 4-connectivity and obtain the valleys.

a. For candidate valleys smaller than the spatial segmentation relation between scale and image size, they are denoted as valleys.

b.   A preset parameter values [-0.6, -0.4, -0.2, 0, 0.2, 0.4] is given for variable *a*, which gives
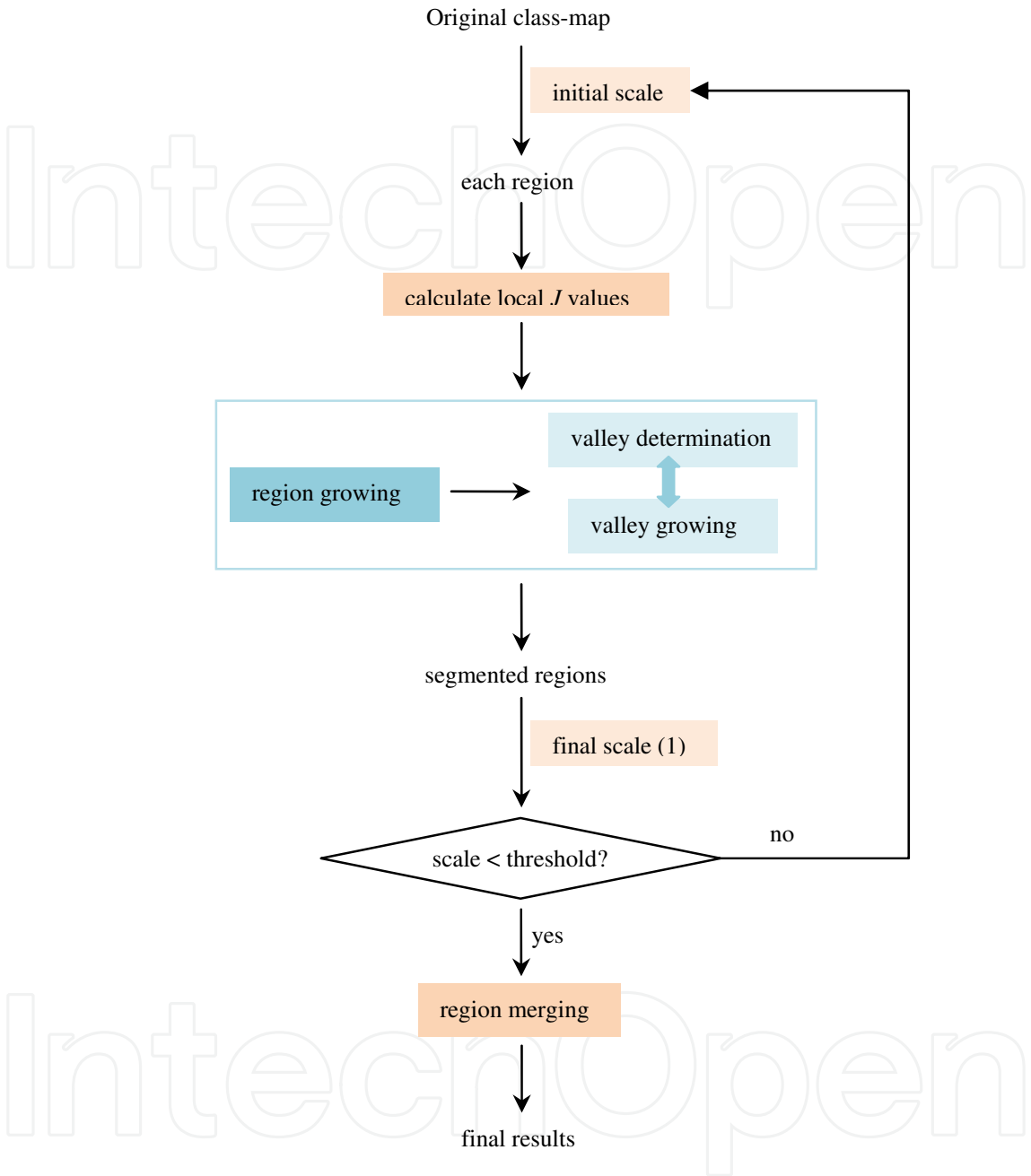   the most number of valleys.

Fig. 4. Sequence for spatial segmentation algorithm.

2.2.2 Valley growing and region merge

After valley determination, the new regions grow from the valleys, which obey the
following rules:

c.   Non-determined pixels must be removed in the valleys, producing the local *J* values
     average in the remaining unsegmented regions. Then, pixels are connected below the
     average to form growing areas, and if these are adjacent to one and only one valley,
     they are assigned to that valley.

d. Calculate local J values for the remaining pixels at the corresponding scale to locate the boundaries regions.

e. Grow the remaining pixels at the final scale. Unclassified pixels at valley boundaries are stored in a buffer. The buffer is updated when all pixels are classified.

An initial segmentation of the image is obtained, after region growing, providing over-segmented regions, merged on their color similarity. The quantized colors represent color histogram bins and their distance features are calculated through the regions extraction. This distance means the Euclidean distance between two neighboring regions. The pair of regions with minimum distance is merged together. All distances are stored in a database and it is updated when an estimate for color feature vector and the corresponding region is calculated. The process continues until a maximum threshold for the distance is reached. After region merging, the final segmentation results are obtained.

3. Programming (Color quantization and spatial distribution)

The sequential images in Figure 5 evince not only the color quantization (spatial distributions forming a map of classes), but also the space segmentation (J-image representing edges and regions of textured side).

Several window sizes are used by J-values: the largest detects the region boundaries by referring to texture parameters; the lowest detects changes in color and/ or intensity of light. Each window size is associated with a scale image analysis. The concept of J-image, together with different scales, allows the segmentation of regions by referring to texture parameters.

Regions with the lowest values of J-image are called valleys. The lowest values are applied with a heuristic algorithm. Thus, it is possible to determine the starting point of efficient growth, which depends on the addition of similar valleys. The algorithm ends when there are spare pixels to be added to those regions.

Figures 6 to 10 illustrate not only color quantization and spatial distributions of J-image in others natural scenes, but the flood fill implemented algorithm, for determining the boundaries edges connected on the region growing areas (using queue data structure provided from region valleys). All scenes were submitted to a gradient magnitude, as segmentation function rating (Sobel masks for higher values at the borders of navigation areas and lower values inside planting areas), then image is segmented with a watershed transform directly on the gradient magnitude. JSEG outperforms the evaluation for all images, with an effective spatial distribution on planting lines.

4. Artificial Neural Networks (ANN) and statistical pattern recognition

Due to the nature of nonlinear vectors, it is fundamental that an ANN-based classification method associated with a statistical pattern recognition be used. *Multi-Layer Perceptron* (MLP) is suitable for default ANN topology to be implemented through a customized *back-propagation* algorithm for complex patterns.

The most appropriate segment and topology classifications are those using vectors extracted from HSV color space (Hue, Saturation, Value), matching RGB color space (Red, Green, Blue) components. Also, the network with less MSE in the neurons to color space proportion is used to classify the entities.

Statistical methods are employed as a combination of results with ANN, showing how accuracy in non-linear features vectors can be best applied in a MLP algorithm with a
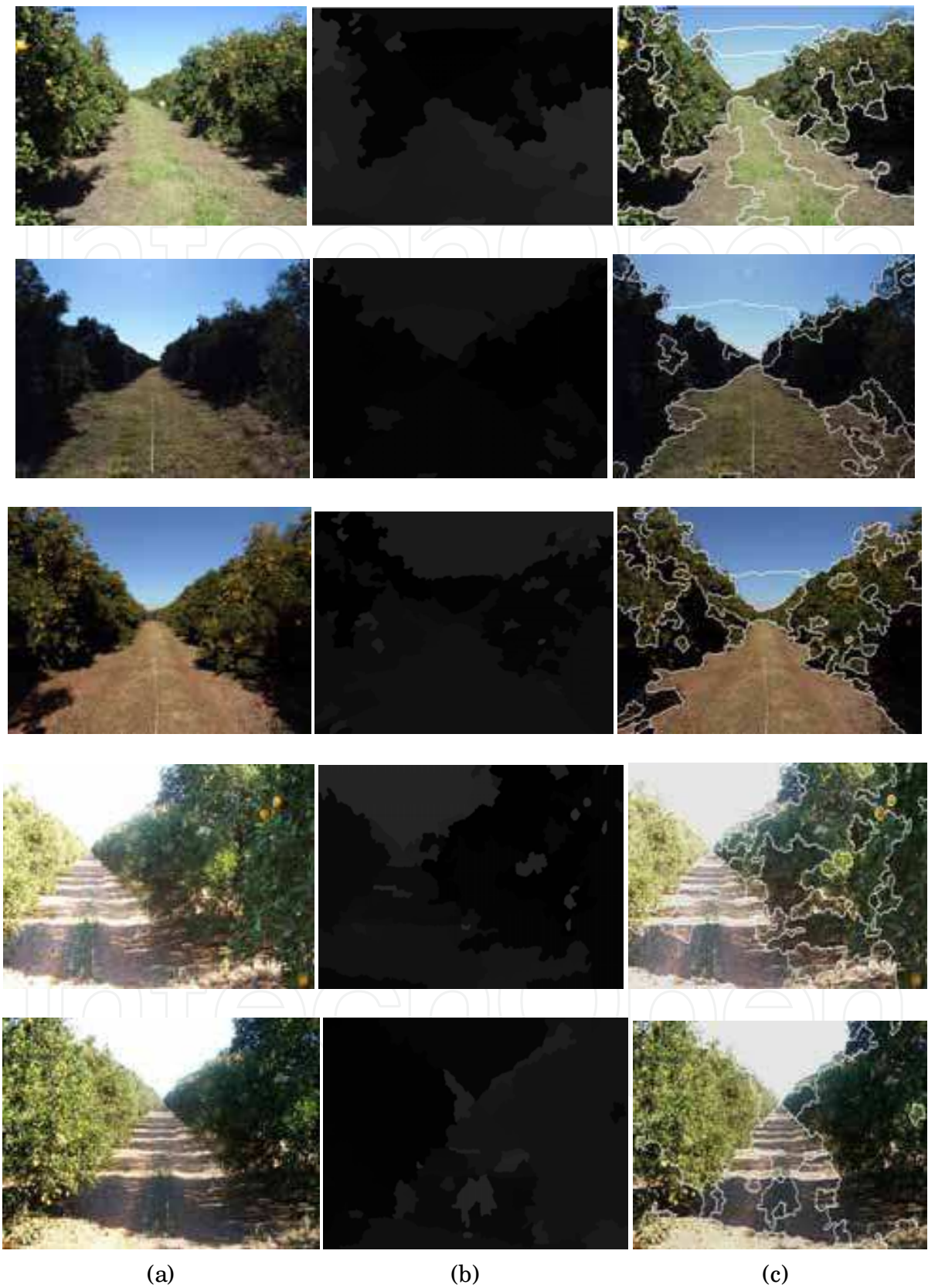
(a)   (b)   (c)

Fig. 5. (a) Original images; (b) Color quantization (map of classes); (c) J-image representing edges and regions of textured side (Spatial distributions).
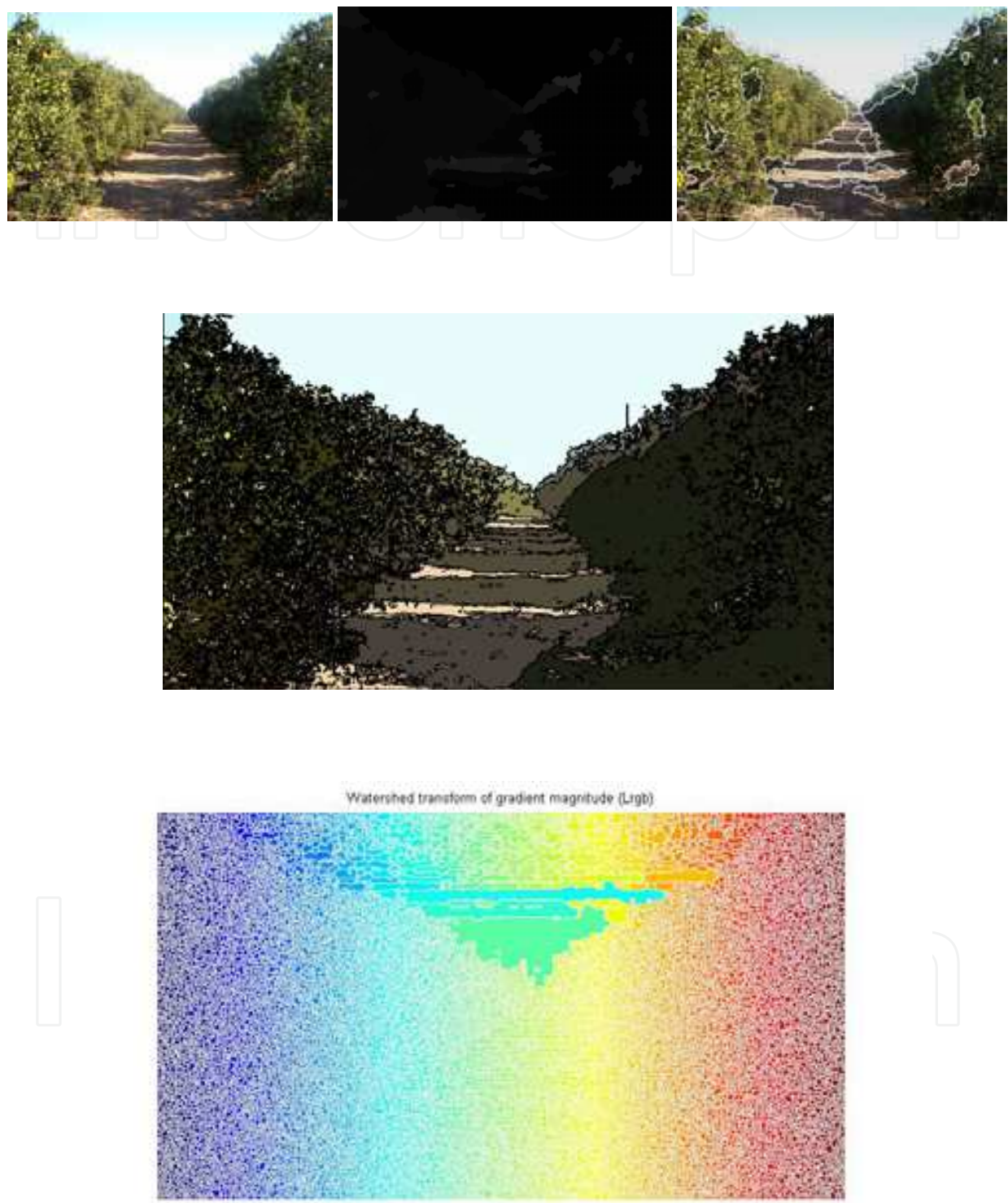
Fig. 6. JSEG segmentation and watershed transform of gradient magnitude in flood fill class-map for scene 1.
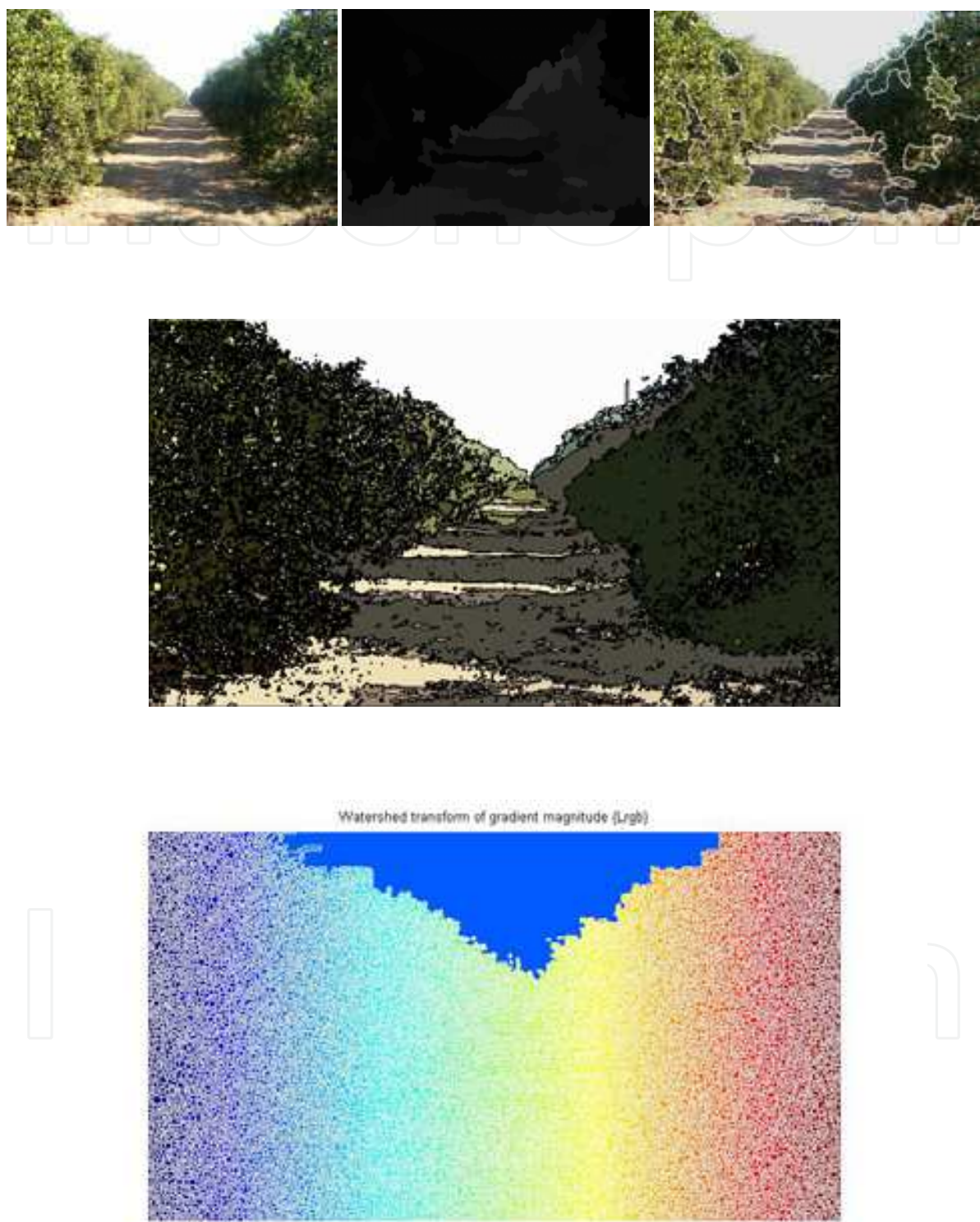
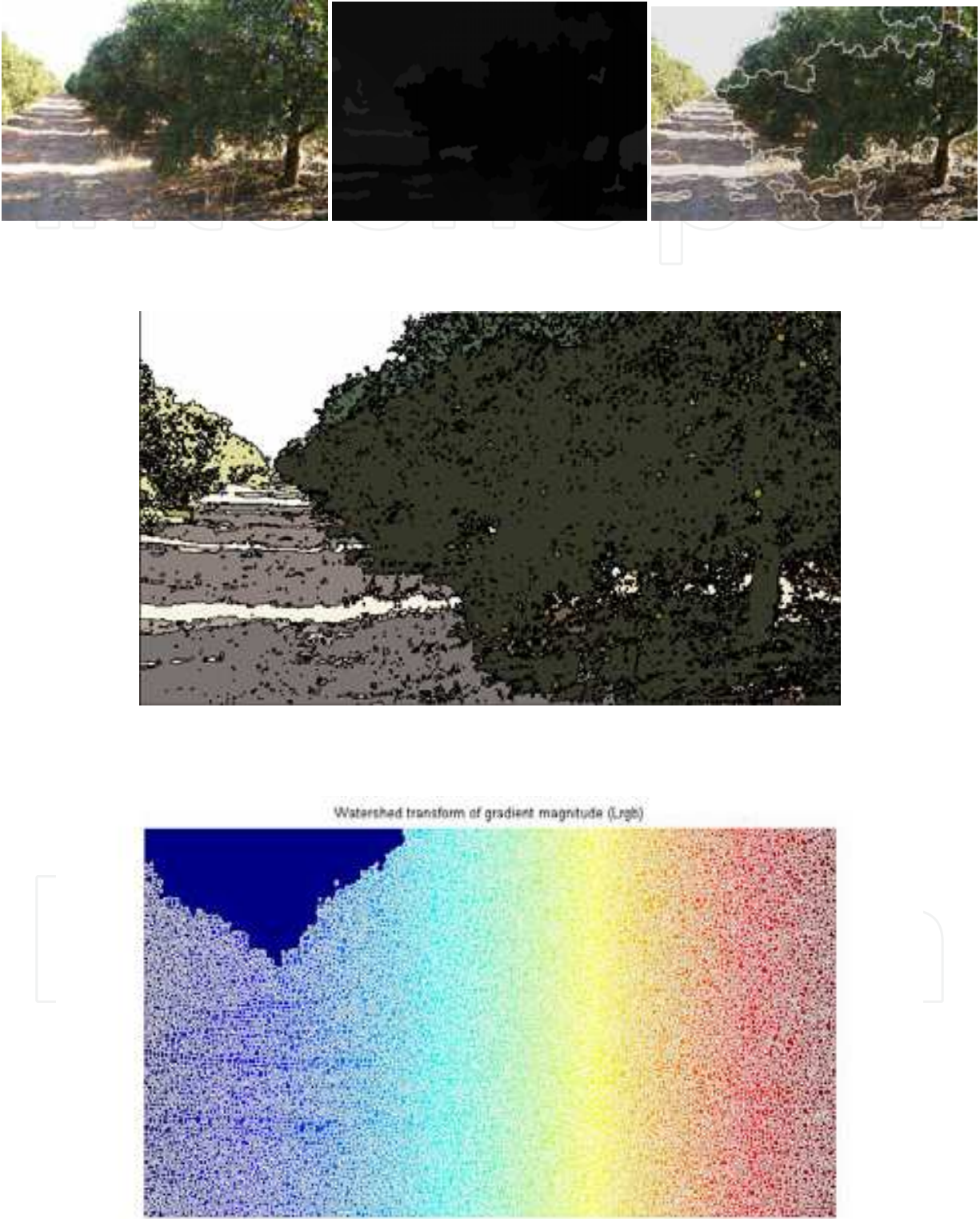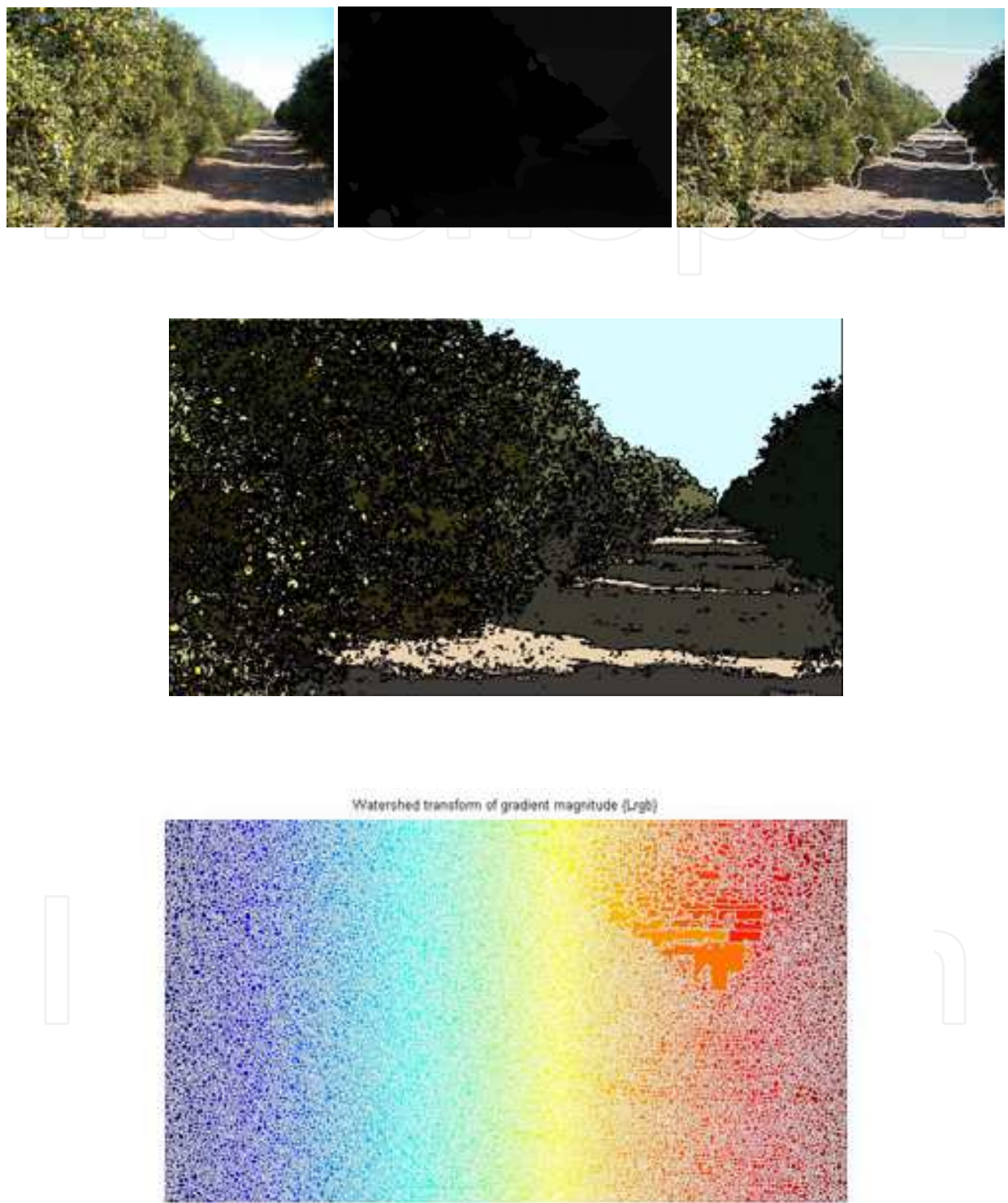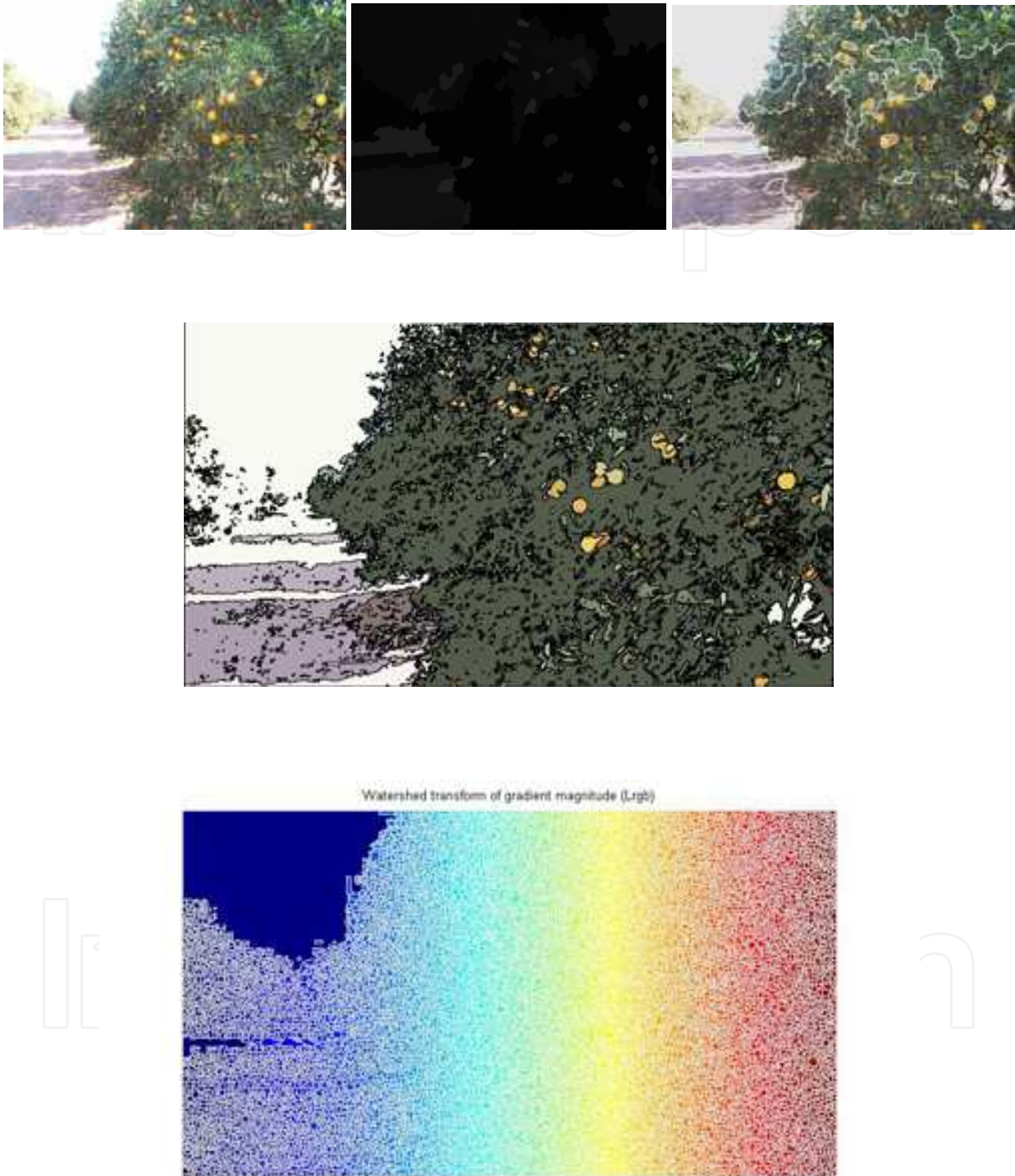Fig. 7. JSEG segmentation and watershed transform of gradient magnitude in flood fill class-map for scene 2.

Watershed transform of gradient magnitude (Lrgb)

Fig. 8. JSEG segmentation and watershed transform of gradient magnitude in flood fill class-map for scene 3.

Fig. 9. JSEG segmentation and watershed transform of gradient magnitude in flood fill class-map for scene 4.

Fig. 10. JSEG segmentation and watershed transform of gradient magnitude in flood fill class-map for scene 5.

statistical improvement, which processing speed is essentially important, for pattern classification. *Bayes Theorem* and *Naive Bayes* both use a technique for iterations inspection, namely MCA (*Main Component Analysis*), which uses a linear transformation that minimizes co-variance while it maximizes variance. Features found through this transformation are totally uncorrelated, so the redundancy between them is avoided. Thus, the components (features) represent the key information contained in data, reducing the number of dimensions. Therefore, RGB space color is used to compare the total number of dimensions in feature vectors with HSV. With a smaller dimension of iterations, HSV is chosen as the default space color in most applications.

Bayes Theorem introduces a modified mathematical equation for the Probability Density Function (PDF), which estimates the training set in a conditional statistics. Equation (4) denotes the solution for $p(C_i|y)$ relating the PDF to conditional class i (classes in natural scene), and y is a n-dimensional feature vector. *Naive Bayes* implies independence for vector features, what means that each class assumes the conditional parameter for the PDF, following Equation (5).

$$P(C_i \mid y) = \frac{p(y \mid C_i)P(C_i)}{\sum_{j=1}^{K} p(y \mid C_j)P(C_j)} \tag{10}$$

$$P(y \mid C_i) = \prod_{j=1}^{n} p(y_j \mid C_i) \tag{11}$$

Thus, the following items detail these merging techniques for image processing and pattern recognition as far as generated and customized segmenting algorithms are concerned withal. As a result, a modular strategy with JSEG algorithm, ANN and Bayes statistical theorem approach is essential for based applications on agricultural scenes.

4.1 Multilayer perceptron customized algorithm

Derived from back-propagation, the iRPROP algorithm (improved resilient back-propagation) (Cavani, 2007) is both fast and accurate, with easy parameter adjustment. It features an Octave (Eaton, 2006) module which was adopted for the purposes of this work
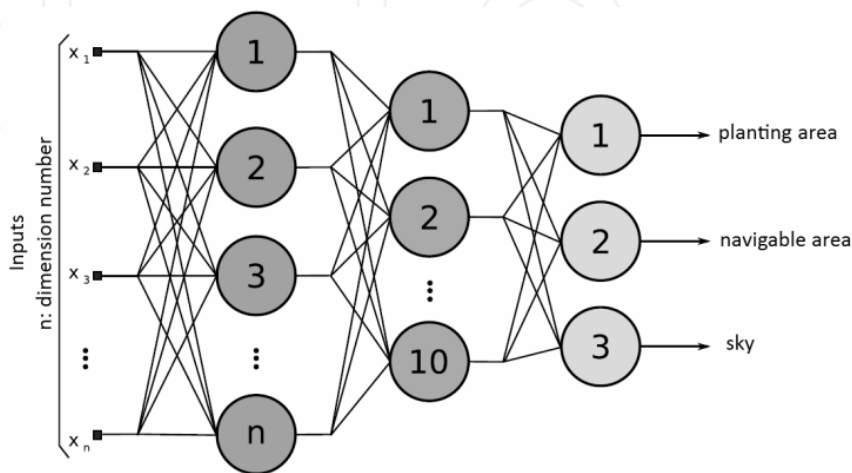

Fig. 11. ANN schematic topology for planting lines with three classes.

and it is classified with HSV (H – hue, S – saturation, V – value) color space channels histograms of 256 categories (32, 64,128 and 256 neurons in a hidden layer training for each color space channel: H, HS, and HSV). The output layer has three neurons, each of them having a predetermined class.

All ANN-based topologies are trained with a threshold lower than 0.0001 mean squared errors (MSE), the synaptic neurons weights are initiated with random values and the other algorithm parameters were set with Fast Artificial Neural Network (FANN) library (Nissen, 2006) for Matlab (Mathworks Inc.) platform, and also its Neural Network toolbox. The most appropriate segment and topology classifications are those using vectors extracted from HSV color space. Also, a network with less MSE in the H-64 was used so as to classify the planting area; for class navigable area (soil), HSV-256 was chosen; as for the class sky, the HS-32.

5. Normalization and feature extraction

This section tackles how statistical methods were employed as a combination of results with ANN, showing how accuracy in non-linear features vectors can be best applied in a MLP algorithm with a statistical improvement, which processing speed is essentially important, for patter classification. The MSE results for each topology, shown in Table 1, were partitioned to eliminate the feature vectors that are distant from the class centroids, so the classifier will deal in less dispersed vectors. Upon observing the following table, which shows the vector distribution in five training sets (20%, 30%, 50%, 70% and 100%), this work approached two probabilistic classification methods in order to match final pattern recognition results with ANN: Bayes theorem and Naive Bayes.

MSE	Neurons	Navigation area	Planting area	Sky
H	32	0,079117	0,098437	0,098574
	64	0,110642	0,098566	0,190555
	128	0,075546	0,079303	0,079874
	256	0,086501	0,023520	0,079111
HS	32	0,089143	0,094905	0,023409
	64	0,099398	0,045956	0,089776
	128	0,049100	0,095064	0,097455
	256	0,057136	0,099843	0,034532
HSV	32	0,089450	0,022453	0,067545
	64	0,059981	0,010384	0,082364
	128	0,049677	0,078453	0,043493
	256	0,038817	0,079856	0,045643

Table 1. MSE results for each topology.

RGB space color is used to compare the total number of dimensions in feature vectors with HSV. With a smaller dimension of iterations, HSV was chosen as the default space color. For such iterations inspection, a technique (main component analysis – MCA) uses a linear transformation that minimizes co-variance while it maximizes variance. Features found through this transformation are totally uncorrelated, so the redundancy between them is avoided. Thus, the components (features) represent the key information contained in data, reducing the number of dimensions (Costa and Cesar Jr, 2001; Haykin, 1999; Comaniciu and Meer, 1999).

In HSV space color, the Bayesian classifiers have produced results which are similar to RGB, where there is a hit rate when the number of dimensions increases in an accuracy average ranging from 20% to 50%. A maximum rate accuracy for HSV is 0.38817, which occurs for 30% and 6777 dimensions. In RGB space color, Bayesian conventional classifiers are identical to Naive results, because as the dispersion of classes increases, there is an average hit rate, which goes up to 50%. The classifiers concerning the number of dimensions are different from the previous ones, which range from 20% and 30%, where hit rates fall as the number of dimensions increases.

	RGB			HSV		
%	NA	PA	Sky	NA	PA	Sky
20	1029	5486	34	1024	5384	26
30	1345	5768	54	1342	5390	45
50	1390	6094	130	1390	6003	103
70	1409	6298	149	1402	6209	140
100	1503	6300	158	1402	6209	145

Table 2. Vector distribution for RGB and HSV space colors. (Navigation area = NA; Planting are = PA)

As a consequence, Bayesian classifiers in HSV space color, outperforms the other classifiers as shown in "Fig. 12". The average rate of achievement value, together with the number of dimensions *draw a linear convergence* for all vector distribution in the five training sets.
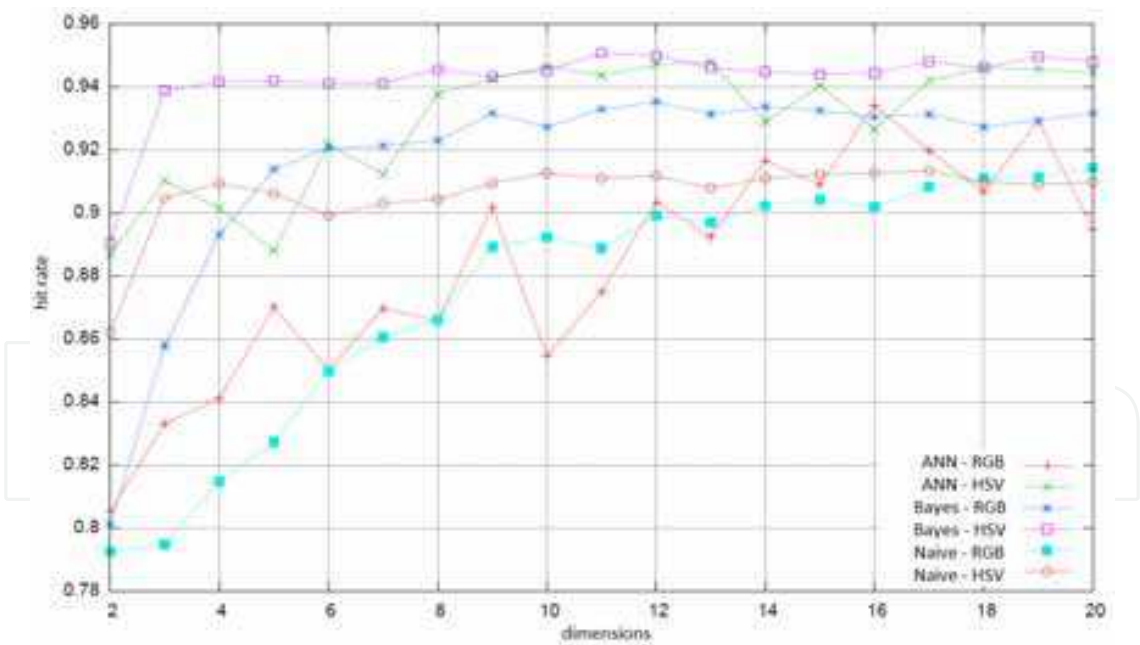
Fig. 12. Average hit rates for the three major training sets.

Although the three methods deliver different performances, yet similar behavior, because the hit rate of the class sky tends to improve owing to the increase in the number of dimensions. Navigation and planting area classes are listed as false feature vectors by the texture similarities in training, which means that ANN and Bayesian must be coupled for improved results.

The following graph about the first components shows that the RGB curves have a higher percentage than most HSV curves. Also, it can be observed that all curves present values lower than 90%.
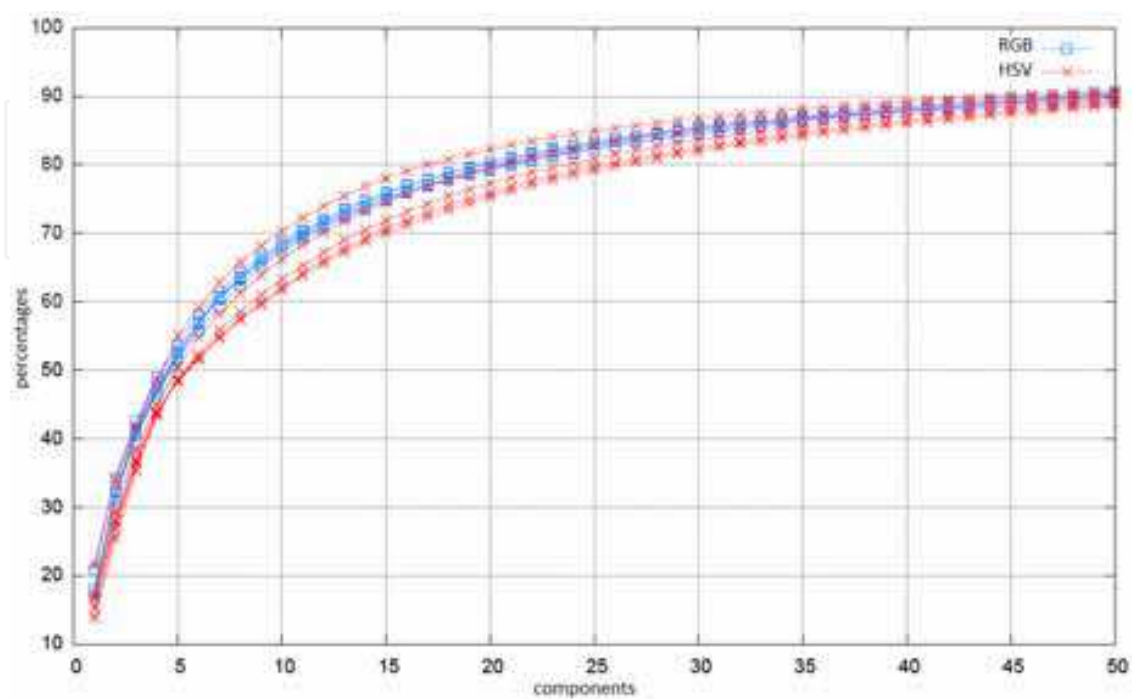
Fig. 13. RGB and HSV relation with amount of dimensions.

After the main component analysis (MCA), the following graph shows the HSV training sets for 100% feature vectors distribution.
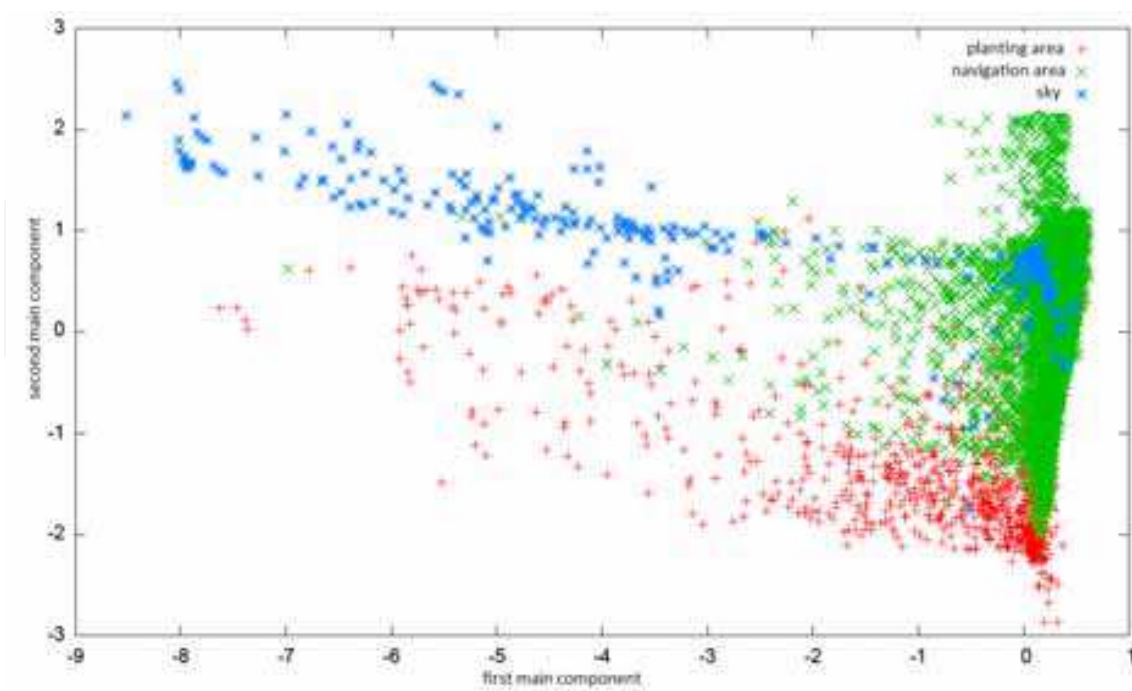
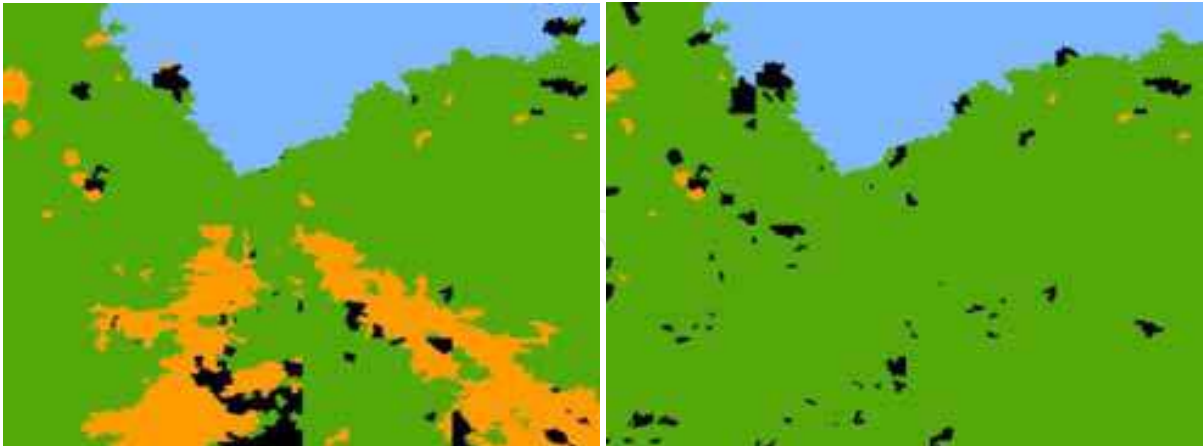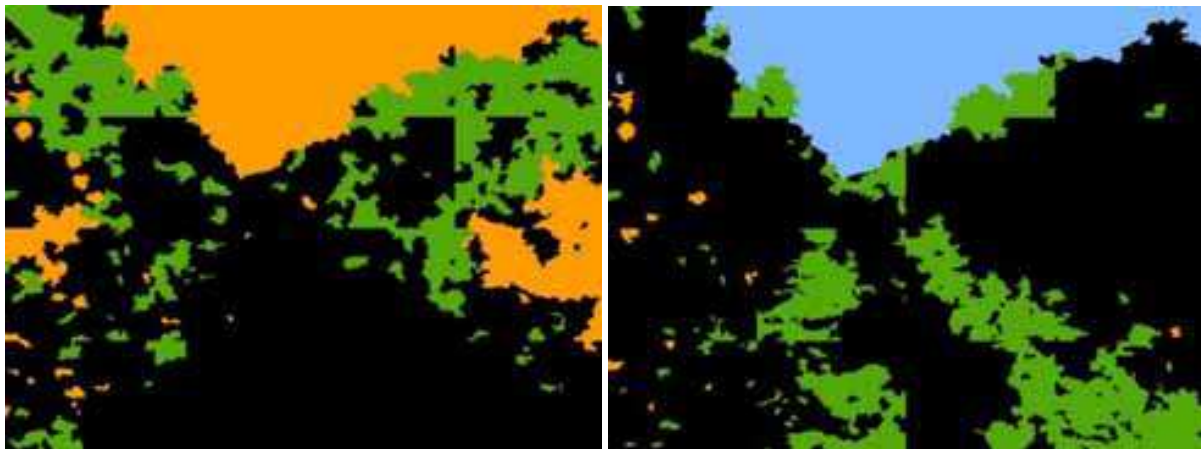Fig. 14. HSV training set for 100% feature vectors distribution.

Fig. 15. Class-map 1 – Bayes/ HSV and Bayes/ RGB.

Fig. 16. Class-map 1 – Naïve Bayes/ HSV and Naïve Bayes/ RGB.
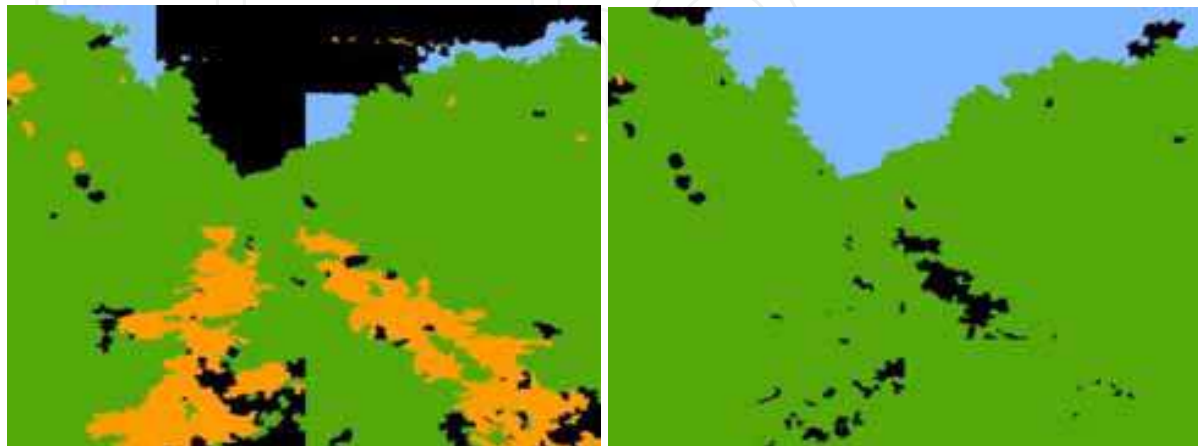
Fig. 17. Class-map 1 – ANN/ HSV and ANN/ RGB.
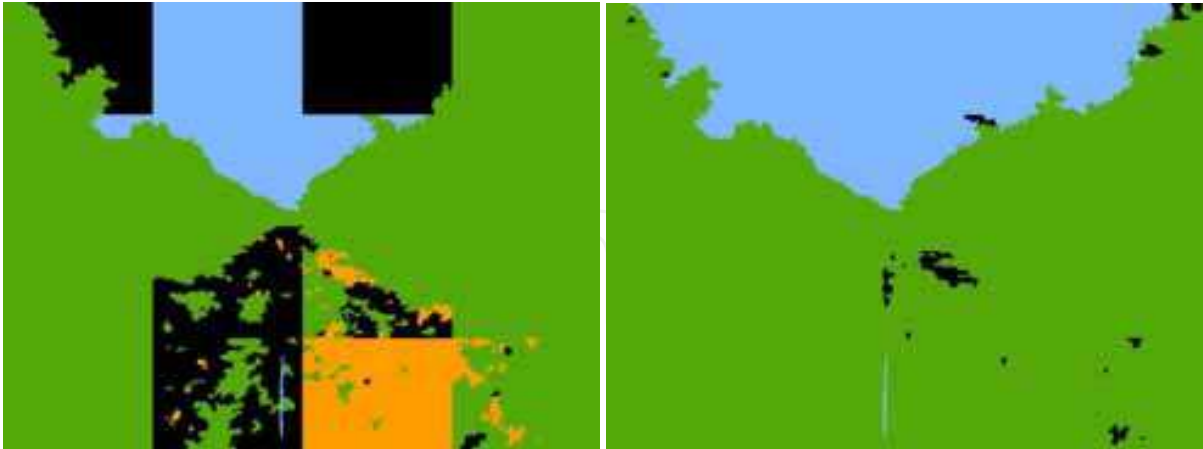
Fig. 18. Class-map 2 – Bayes/ HSV and Bayes/ RGB.
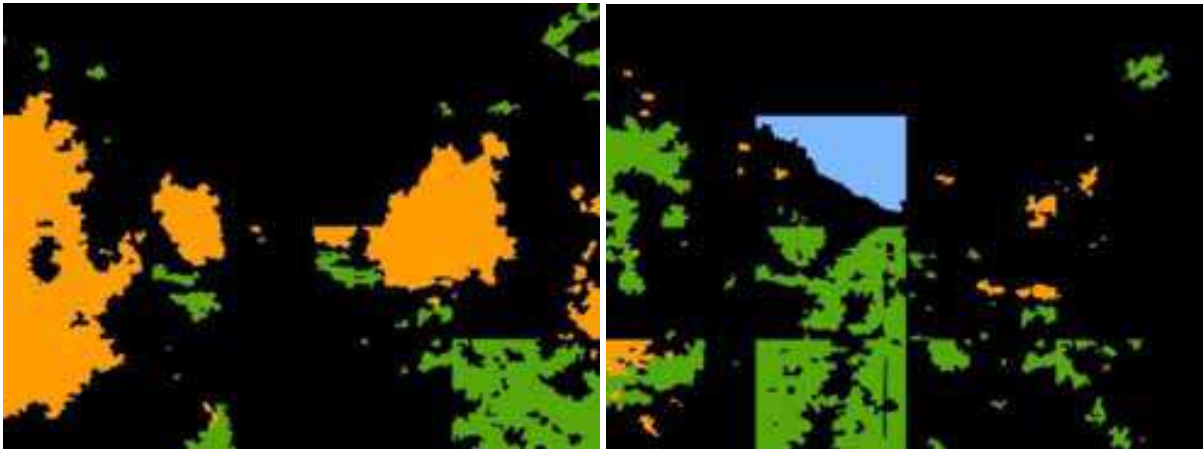
Fig. 19. Class-map 2 – Naïve Bayes/ HSV and Naïve Bayes/ RGB.

Fig. 20. Class-map 2 – ANN/ HSV and ANN/ RGB.
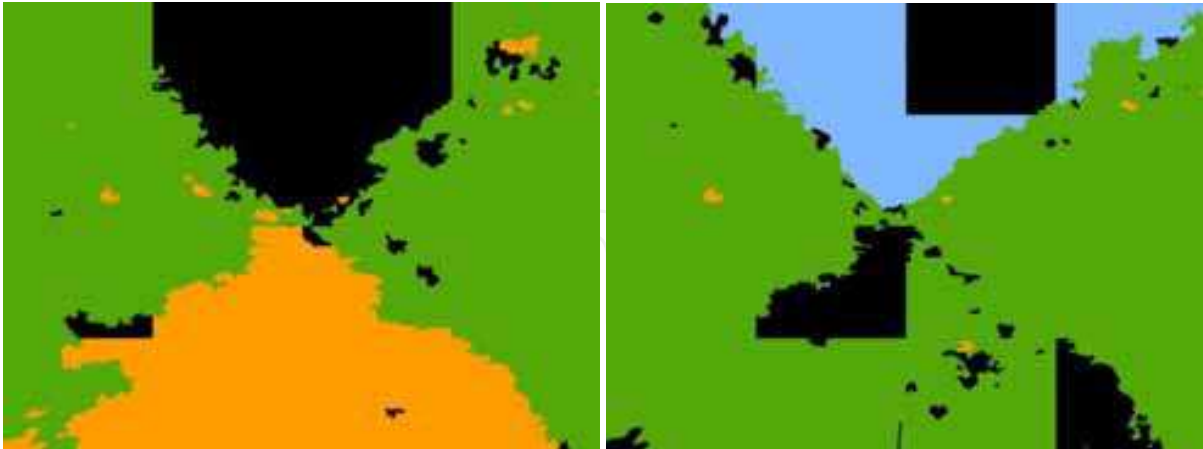
Fig. 21. Class-map 3 – Bayes/ HSV and Bayes/ RGB.
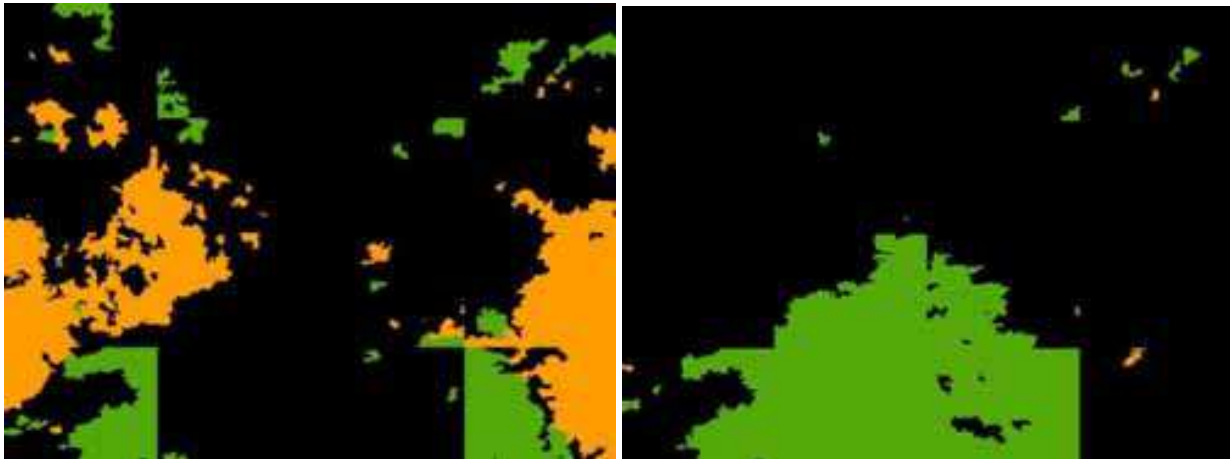
Fig. 22. Class-map 3 – Naïve Bayes/ HSV and Naïve Bayes/ RGB.

Fig. 23. Class-map 3 – ANN/ HSV and ANN/ RGB.

The corresponding class maps, the corresponding class-maps for the three first natural scenes in Figure 4, were shown above, for normalization merging techniques and space colors (Bayes/ HSV), (Bayes/ RGB), (Naive Bayes/ HSV), (Naive Bayes/ RGB), (ANN/ HSV) and (ANN/ RGB).

6. Conclusions

This chapter presented merging techniques for segmentation and ANN-statistical classification of navigation agricultural scenes, running multiple segmentation tests with JSEG algorithm possible. As the data provided evince, this generated algorithms fulfils the expectations as far as segmenting is concerned, so that it sorts the appropriate classes (navigation area, planting area and sky). As a result, a modular strategy with ANN and Bayes statistical theorem can be an option for the classification of segments.

Moreover, the classification using different types of feature vectors caused the classification metric to be more accurate and sophisticated with ANN, as well as the HSV color space to have lower MSE in test values. Both JSEG and MLP proved suitable for the construction of an image recognition system.

7. References

Cavani, F. A. Analysis of natural scenes through image segmentation and pattern recognition, (*Master Thesis*) University of Sao Paulo (EESC/ USP), 2007.

Comaniciu, D. and Meer, P. Robust analysis of feature spaces: color image segmentation. In: *Conference on Computer Vision and Pattern Recognition*, IEEE Computer Society, 1997.

Costa, L. F. and Cesar Junior, R. M. Shape analysis and classification – Theory and Practice. *1. ed. Boca Raton, Florida, EUA: CRC Press LLC*. ISBN 0-8493-3493-4, 2001.

Deng, Y., Kennedy, C., Moore, M.S., Manjunath, B.S. Peer group filtering and perceptual color image quantization. *Proceedings of the 1999 IEEE International Symposium on Circuits and Systems*, 1999a. v. 4, p. 21-25.

Deng, Y., Manjunath, B.S., Shin, H. Color image segmentation. *Conference on Computer Vision and Pattern Recognition*, IEEE Computer Society, 1999b. p. 446-451, v. 2.

Deng, Y. and Manjunath, B.S. Unsupervised segmentation of color-texture regions in images and videos. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (PAMI '01), vol. 23, no. 8, pp. 800-810, Aug. 2001.

Duda, R.O. and Hart, P.E. *Pattern Classification and Scene Analysis*, John Wiley & Sons, New York, 1970.

Eaton, J.W. *et* al. Octave. Avaliable at: http:/ / www.octave.org. (02/ 12/ 2006).

Gersho, A. and Gray, R.M. *Vector quantization and signal compression*, Kluwer Academic, Norwell, MA, 1992.

Haykin, S. Neural networks: a comprehensive foundation. *2. ed. New Jersey, EUA: Prentice-Hall*. ISBN 0-13-273350-1, 1999.

Haykin, S. Neural Networks and Learning Machines. *3.ed. McMaster University, Canada: Prentice-Hall*. ISBN 0131471392, 2008.

Igel, C., Hüsken, M. Empirical evaluation of the improved Rprop learning algorithm.
          Neurocomputing, v. 50, p. 105-123, 2003.
Nissen, S. *et al.* Fann: fast artificial neural network library. Avaliable at:
          http:/ / leenissen.dk/ fann/ (02/ 12/ 2006).
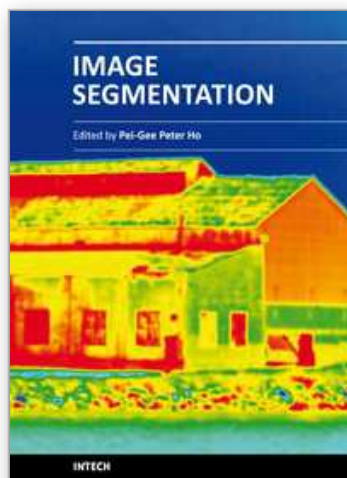
Image Segmentation

Edited by Dr. Pei-Gee Ho

It was estimated that 80% of the information received by human is visual. Image processing is evolving fast and continually. During the past 10 years, there has been a significant research increase in image segmentation. To study a specific object in an image, its boundary can be highlighted by an image segmentation procedure. The objective of the image segmentation is to simplify the representation of pictures into meaningful information by partitioning into image regions. Image segmentation is a technique to locate certain objects or boundaries within an image. There are many algorithms and techniques have been developed to solve image segmentation problems, the research topics in this book such as level set, active contour, AR time series image modeling, Support Vector Machines, Pixon based image segmentations, region similarity metric based technique, statistical ANN and JSEG algorithm were written in details. This book brings together many different aspects of the current research on several fields associated to digital image segmentation. Four parts allowed gathering the 27 chapters around the following topics: Survey of Image Segmentation Algorithms, Image Segmentation methods, Image Segmentation Applications and Hardware Implementation. The readers will find the contents in this book enjoyable and get many helpful ideas and overviews on their own study.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

INTECH
open science | open minds