An Unsupervised Nonparametric and Cooperative Approach for Classification of Multicomponent Image Contents

Akar Taher, Kacem Chehdi and Claude Cariou
University of Rennes 1, TSI2M, IETR/ENSSAT - 6, rue de Kerampont, 22300 Lannion, France

Keywords: Classification, Cooperative, Unsupervised, Nonparametric, Genetic Algorithm, Multicomponent, Image.

Abstract: In this paper an unsupervised nonparametric cooperative and adaptive approach for multicomponent image partitioning is presented. In this approach the images are partitioned component by component and intermediate classification results are evaluated and fused, to get the final partitioning result. Two unsupervised classification methods are used in parallel cooperation to partition each component of the image. The originality of the approach relies *i)* on its local adaptation to the type of regions in an image (textured, non-textured), *ii)* on the automatic estimation of the number of classes and *iii)* on the introduction of several levels of evaluation and validation of intermediate partitioning results before obtaining the final classification result. For the management of similar or conflicting results issued from the two classification methods, we gradually introduced various assessment steps that exploit the information of each component and its adjacent components, and finally the information of all the components. In our approach, the detected region types are treated separately from the feature extraction step, to the final classification results. The efficiency of our approach is shown on two real applications using a hyperspectral image for the identification of invasive and non invasive vegetation and a multispectral image for pine trees detection.

1 INTRODUCTION

The growth and the availability of multicomponent images (e.g. hyperspectral images with hundreds of spectral bands) which contain rich information have opened new possibilities of applications in many domains. In order to interpret the richness of this information, a large diversity of image classification approaches can be found in the literature. In (Kermad and Chehdi, 2002), these approaches are classified into two groups: non-cooperative and cooperative approaches. Non-cooperative approaches use a single classification method. These methods can be supervised or unsupervised, parametric or nonparametric. Supervised parametric methods like Maximum Likelihood (ML) (Cox and Snell, 1968), Support Vector Machines (SVM) (Vapnik, 1998), Expectation Maximization (EM) (Dempster et al., 1977), are the most commonly used. These methods need *a priori* information to accomplish the classification task. However the required information is not available in all application cases. The most frequently used unsupervised nonparametric methods include: K-Means (McQueen, 1967), LBG (Linde et al., 1980), Fuzzy C-means (FCM) (Bezdek, 1981), and the more recent Affinity Propagation (AP) (Frey and Dueck, 2007). These methods do not require or require little information *a priori* to accomplish the classification task.

Another difficulty to the general problem of segmentation or classification of multicomponent images is the fact that applying several methods to a single image never gives identical results. This situation makes the quality assessment for the choice of a particular method very difficult. Therefore, cooperation between methods is highly desirable to reliably partition images. The cooperation can be done using three different schemes (Kermad and Chehdi, 2002): sequential, parallel, or hybrid cooperation. The drawback of the first scheme is the sequential order of the applied methods which can highly affect the results. Parallel cooperation schemes use different classification methods at the same time. A fusion stage introducing a validation criterion is therefore required at the end of the process. The main difficulty of this scheme is the fusion process which requires a robust decision rule to give optimal results. However, the application of different classification methods in a parallel manner

Taher A., Chehdi K. and Cariou C..
An Unsupervised Nonparametric and Cooperative Approach for Classification of Multicomponent Image Contents.
DOI: 10.5220/0004828502630270
In *Proceedings of the 3rd International Conference on Pattern Recognition Applications and Methods* (ICPRAM-2014), pages 263-270
ISBN: 978-989-758-018-5

allows reducing the computing time. The third cooperation scheme is the hybrid cooperation which combines the two previous schemes. This third scheme has essentially the same drawbacks as the first one.

In the literature, many cooperative approaches of multicomponent image partitioning are available. Part of them uses supervised parametric methods (Tarabalka et al., 2009), (Kalluri et al., 2010), (Benediktsson and Kanellopoulos, 1999) but some others use unsupervised methods (Forestier et al, 2010).

(Tarabalka et al., 2009) propose a parallel cooperative approach that uses three classification methods: Support Vector Machines (SVM), Maximum Likelihood (ML), and ISODATA. A sequential approach, presented by (Benediktsson and Kanellopoulos, 1999), involves the cooperation of Neural Networks and ML methods. Another recent parallel approach proposed by (Kalluri et al., 2010) uses only ML classification method to partition an image. The partitioning process is repeated several times, changing the features extracted from the image each time, and then the results are fused to get the final result. The drawback of these cooperative approaches resides in the use of supervised and/or parametric methods, which require the availability of some prior information that is not available in all applications cases. The approach proposed by (Forestier et al, 2010) makes cooperation between different unsupervised methods in parallel but requires some background knowledge about the data while fusing the results of the different methods.

The main ideas of the approach presented in this paper are based firstly, on the use of unsupervised nonparametric classification methods and, secondly, on the management of conflicting partitioning results. The developed approach belongs to the family of parallel cooperation scheme.

This paper is organized as follows: the second section describes the proposed approach, the third section presents applicative experiments on different real images and finally, the last section gives the conclusions and provides some perspectives.

2 APPROACH DESCRIPTION

The proposed partitioning approach is composed of four steps (for the first three steps, see Figure 1):

The First Step is the adaptive feature extraction, in which the image is divided into two types of regions, i.e. textured and non-textured. The adaptive characterization of pixels, taking into account the textured or non-textured nature of the region to which they belong, is an essential step before the classification. Indeed, the features dedicated to the description of regions with low variance do not have sufficient discriminating power for textured regions, and vice versa.

The Second Step is the unsupervised parallel classification, in which the image is partitioned using two different unsupervised nonparametric classification methods (FCM and LBG) where the number of classes is estimated automatically. In this step, the pixels belonging to textured or non-textured regions are classified separately and in parallel using appropriate feature sets.

The Third Step includes the results management of the same component (monocomponent image) which is done at two levels, firstly by validating pixels which are coherently classified by the two methods (FCM and LBG), and secondly by processing conflicting classification results using a genetic algorithm (GA). The objective function of the genetic algorithm depends on between-class and within-class disparities to evaluate and manage the conflicting pixels between the partitioning results. The last block of fusion is the union between the results of textured and not textured regions

In the case of multicomponent images the above three steps are applied independently on each component.

The Fourth Step is the identification of similar pixels between the classification results of adjacent components. In this step the results from the different components are grouped into subsets, which are formed depending on the number of pixels that are classified to the same class in different components. Then these subsets are processed independently to get one classification result for each of them. The same process as in the third step is used to get the final result of the multicomponent image.

In the following subsections the approach is described in details.

2.1 Adaptive Feature Extraction

This step is composed of two processes. In the first one, the image is globally analyzed, in order to be divided into two types of regions: textured and non-textured. In the second process, features are extracted taking into account the type of detected regions.

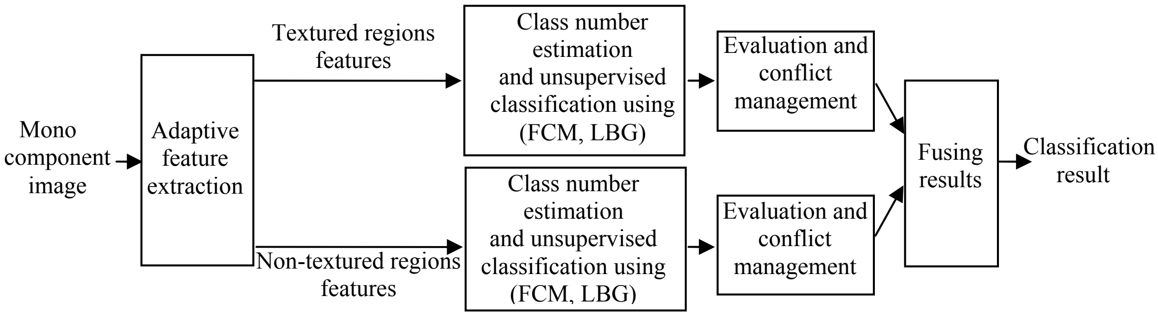

Figure 1: The general layout of the proposed approach (case of monocomponent image).

2.1.1 Region Nature Detection

The detection of regions' types is done by local extraction of the uniformity feature issued from the co-occurrence matrix (Haralick, 1979). The uniformity features are calculated using the following equation (Rosenberger and Chehdi, 2003):

$$Unif = \frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{L} P_{d,\theta_j}(g_i, g_i) \tag{1}$$

Where L is the number of gray levels in the monocomponent image, g_i is an gray level, M is the number of orientations θ_j used to compute the co-occurrence matrices, and $P_{d,\theta}$ (.,.) are the entries of the co-occurrence matrix obtained with inter-pixel distance d.

The co-occurrence matrix is very time consuming for an image in its original gray levels. In order to reduce the gray levels number of an image and while preserving the significant information at the same time, we have used the multi-thresholding method described in (Kermad et al., 1995).

In order to consider different texture scales, this feature (uniformity) is extracted for each pixel using five different sizes of an analysis window. These extracted features are injected into an FCM classifier and pixels are partitioned into two classes; by this procedure, the textured and non-textured regions are identified. This process enables the adaptativity of feature extraction in the further processing steps.

To validate this procedure of region nature detection we have applied it on a set of 30 images. The database of images used includes images which are composed of two types of regions: two textured regions (textures are taken from the Brodatz album) (Brodatz, 1966) and three non-textured regions. Figure 2 shows a sample image and the corresponding region nature detection map. The Average Correct Detection Rate (ACDR) for all the tested images is 98.60%.

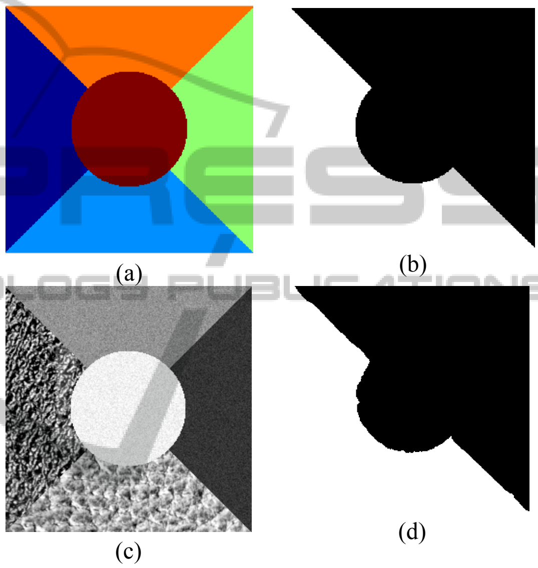

Figure 2: Region nature detection results. (a) Image ground truth mask (b) region type mask: white is textured, black is non-textured, (c) Original sample image, (d) Detected region types.

2.1.2 Feature Extraction

Two types of features are extracted to characterize pixels in an image: the local average of pixel values is a sufficient feature in the case where pixels belong to a non-textured region; however in the case of a textured region, several texture descriptive features are needed. In (Rosenberger and Chehdi, 2003), 23 features are analyzed and 15 of them are selected after removing the most redundant ones. These features are:

- Mean, variance, skewness, and kurtosis.
- 9 features issued from the co-occurrence matrix (Haralick, 1979): contrast, correlation, inverse difference moment, sum average, sum entropy, entropy, first and second information measure of correlation, contour information.

- 2 features from the curvilinear integral.

All the features are calculated locally by sliding an analysis window with maximum overlapping of size *WxW* pixels (*W* odd). We have chosen a window size of 3x3 pixels to compute the local average for the non-textured regions, and extended it to 9x9 pixels for features of the textured regions.

Identifying pixels belonging to one among two types of regions brings two advantages, i.e. a natural adaptation of feature extraction, and a computation time gain in feature calculation.

2.2 Unsupervised Parallel Classification

In this step the pixels in the textured and non-textured regions are processed independently and in parallel. The features extracted are injected into two classification methods (FCM and LBG) chosen to cooperate with each other due to their respective fuzzy and hard decisions rules. These two methods are used in many applicative domains, and have shown their efficiency (Havens et al., 2012), (Huang and Xie, 2010). Their common advantage is that they are both nonparametric, but both of them require the prior knowledge of the number of classes which is not known in most practical cases.

As our approach is considered to be completely unsupervised, a step of class number estimation is introduced. The pixels are classified in an iterative manner using FCM. More precisely, the pixels are classified using FCM several times by increasing the number of class *k*, starting from *k*=2. The result obtained at the end of each iteration is evaluated using combined within-class and between-class disparities as follows:

$$F(\underline{D}(I),\overline{D}(I)) = \frac{1+\overline{D}(I)-\underline{D}(I)}{2} \qquad (2)$$

The within-class disparity $\underline{D}(I)$ quantifies the homogeneity of each class obtained in the partitioning result. Similarly, the global between-class disparity $\overline{D}(I)$ measures the disparity between the classes (Rosenberger and Chehdi, 2003). This criterion provides some advantages: firstly it is unsupervised; and secondly it adapts itself automatically to the nature of the regions (textured, non-textured). Finally it is composed of a combination of two measures that both control efficiently the issue of under and over classification.

The optimum value of the number of classes is the one which maximizes criterion (2). Then the estimated class number by FCM classifier is directly used in the LBG method.

The motivation for applying FCM before LBG is that, it is more robust in the estimation of the number of classes. Actually, the LBG method gives under-partitioning as shown in Figure 4.

This process is tested on the set of images described previously in section 2.1.1. The average correct class number estimation over the tested image set is 90%. This rate is coherent because in some cases there are high fluctuations within a class so that it is detected as more than one class. For example, the class labelled as “1” in the image in Figure 3-(a) is composed of wood, where a part of this class is defected; it is clear from visual inspection that the area inside the highlighting red oval (wood defect) is not the same as the rest of the class. This class is detected as two classes by our method, which is actually true.

We can point out that if this kind of information were accounted for in the ground truth of the image set, the correct class estimation rate would be greater than 90%.

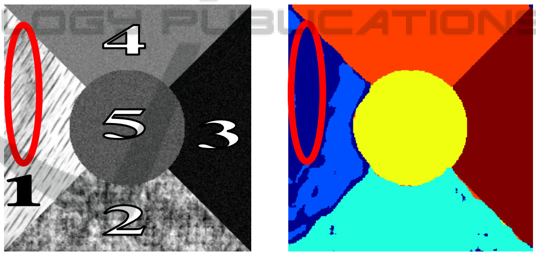

Figure 3: Example of estimation the number of classes. (a) Original image, (b) Classification result (6 classes).

2.3 Evaluation and Management of Conflicts

In the partitioning process each classification method generates a different partition from the same data. Therefore, effective evaluation criteria are important to provide the end users a degree of confidence in clustering results. These assessments should be objective and have no preference to any algorithm (Xu and Wunsch, 2005).

2.3.1 Monocomponent Image Case

To validate the classification results obtained from FCM and LBG, a two-level evaluation process is applied. First, the pixels that are classified to the same classes by both methods are considered directly as valid pixels, and reported to the final partitioning result. These pixels do not enter the second level of evaluation, which dramatically considerably reduces the complexity of processing.

The pixels that are classified to different classes by the two methods are considered as invalidated, and are subject to a second evaluation process using an objective function optimized by a GA. The objective function used is based on within-class and between-class disparities (see Equation (2)).

In the GA (Holland, 1992), each pixel is considered as a gene and each classification result is considered as a chromosome. In our case, each chromosome is composed of the invalidated pixels only. Since there are two classification methods, the initial population is composed of two chromosomes. This population is evolved using genetic operations, where only selection and cross-over operations are considered. The genetic algorithm stops when no better chromosomes are created, or the quality difference between the best chromosomes of the two last generations is smaller than ε, which guarantees the termination of the GA. In our experiments the value of ε is set to 10^{-10}. The selection operation used in this approach is the fitness proportionate selection (Neumann et al. 2009). With this selection operation type there is a chance for some weaker solutions to survive the selection process; this is an advantage, as though a solution may be weak, it may include some information which could prove useful following the recombination process. The type of cross-over operation used in the approach is the uniform cross-over (Syswerda, 1989), which uses a fixed mixing ratio between two parent chromosomes. The advantage of this cross-over operation type is that it enables the parent chromosomes to exchange at the gene level rather than at the segment level. At termination of the GA, the best evaluated chromosome in the population is considered as the final result for the conflicting pixels. Eventually, these pixels are grouped with the valid pixels from the first level, to get the final partitioning result for a single component).

To have the complete classification result of the monocomponent image, the fusion in the last block of Figure 1, is a union between the partitioning results of textured and no textured regions.

To prove the validity of this process, we have assessed it on the database of images previously described in section 2.1.1. Figure 4 shows a sample image and the obtained results including the detected region natures, the individual results of LBG and FCM, the result of our cooperative approach, and the corresponding average correct classification rates (ACCR). The number of classes in this experiment is correctly estimated to 5 classes. In this example, the result given by the LBG method only mixes up two regions of the image, yielding a low correct classification rate, while the result obtained by FCM is clearly more robust. Another remark is that some pixels from the LBG method result are classified in the correct class, which is not true with the FCM method. The application of the cooperative approach has kept the pixels correctly classified and reassigns those which were not previously correctly classified.

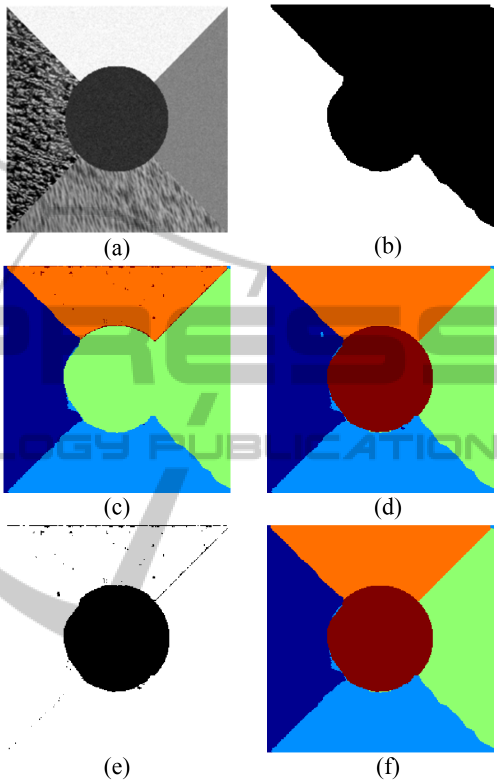

Figure 4: Results of mono-component image. (a) Original image, (b) Region nature detection (white: textured, black: non-textured), (c) LBG result (ACCR: 78.20%), (d) FCM result (ACCR: 98.58%), (e) Validation map (white: valid, black: invalid), (f) Our approach result (ACCR: 98.63%).

The global average correct classification rate, for the set of 30 test images is: 94.71% for FCM method, 88.31% for LBG method and 97.19% for our approach.

2.3.2 Multicomponent Image Case

In this case the results from the different components are fused to get the final classification result.

The steps described in sections (2.1, 2.2 and 2.3.1) are applied to each component in the image independently to obtain N partition results, where N is the number of components of the image. To get the final partition result, the results of different components are compared, and adjacent components with similar classification results are grouped within the same subset. The contents of each subset are fused independently. At the beginning the first component result is taken as reference and compared with the adjacent components result. The reference component is changed if the number of identical pixels decreases. For example, if the first component result is compared with the second component result and some percentage of the pixels where found to be classified identically, then the first component result is compared with the third component result, if the percentage of the identical classified pixels are greater than this percentage, the reference component remains unchanged and compared with a further component result; if not, the first and second component results are considered as one subset and the third component result becomes the reference component, and the same procedure is repeated until the last component is processed.

The component results in each subset are fused separately, and then the results of the subsets are fused to get the final partitioning result of the multicomponent image. GA is used in the fusion process where the objective function is the same as the one described previously.

To validate this approach of evaluation and fusion, it is applied on a hyperspectral test image which is constructed from regions of interest of a real image. The ground truth of the image is available (used for estimation of the results only). The original hyperspectral image was collected by an AISA Eagle sensor on October 1st 2010 over the region of Cieza in southeastern Spain. It was acquired at 0.5 meter spatial resolution in 62 spectral bands within the range [400, 970] nm. The data used to construct the test image are taken randomly from 5 different regions of the original image. The 5 land covers are: Water, *Pinus halepensis*, Peach trees, *Arundo donax*, and Buildings. The estimated number of class for this test is 5 classes. The result for this test is shown in Figure 5.

3 ASSESSMENT ON REAL APPLICATIONS

Our classification approach was also evaluated on two real applications using respectively a hyperspectral image for identification of invasive and non invasive vegetation in the region of Cieza (Spain) and a multispectral image for pine trees detection in the region of Baabdat (Lebanon). For

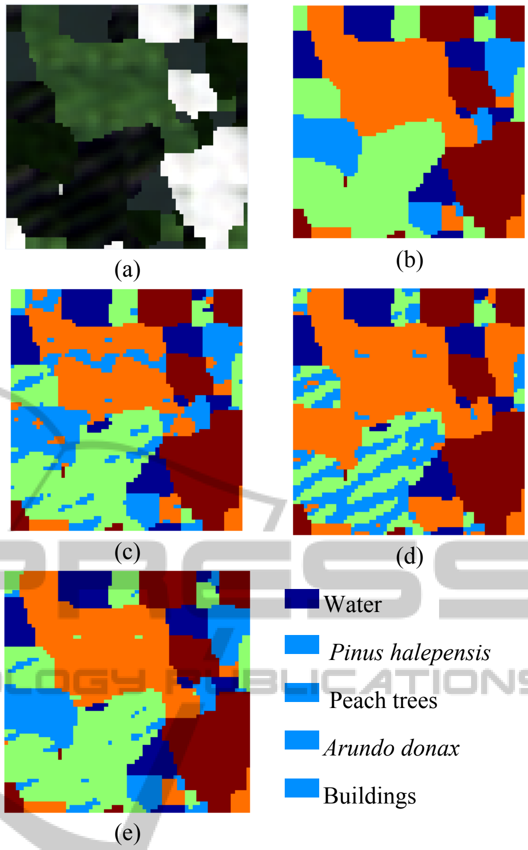

Figure 5: Hyperspectral test image classification results. (a) Original image (RGB components over 62 for visualizing only), (b) ground truth masks, (c) FCM result (ACCR: 91.68%), (d) LBG result (ACCR: 69.59%), (e) Our approach result (ACCR: 97.95%).

these experiments, a ground truth data is available, which allows us to assess the performances of our approach.

The characteristics of the hyperspectral image are described in section 2.3.2. The spatial size of this image is1000 lines by 1000 columns.

The ground truth of the image includes six different classes, namely: *Phragmites australis*, *Arundo donax*, *Tamarix*, *Ulmus minor*, *Pinus halepensis*, and Peach trees.

The multispectral image was acquired by the Earth observation satellite Ikonos on July 11, 2005, in the region of Baabdat (Lebanon) and it is used to detect pine trees. The ground pixel size of this three components (RGB) image is 0.8m.

To assess our unsupervised approach on these two applications, the correct classification rates are calculated using available ground truth areas.

For the detection of invasive and non invasive vegetation, Figure 6 and Table 1 respectively show the result of our classification approach and the corresponding confusion matrix. The estimated number of classes for this experiment is 6 classes. The average correct classification rate for FCM, LBG, and our approach are: 98.70%, 98.55%, and 99.13% respectively.

Concerning the detection of pine trees application, the ground truth data contains 11736 pixels, with 11410 of them labeled as pine trees. In this test, the estimated number of classes is 2. The average correct classification rates (ACCR) calculated only on the ground truth zones is: 96.91% for FCM method, 97.09% for LBG method, and lastly 97.22% for our cooperative approach.

A key point to mention is that, in all the experiments, the ground truths provided with the image data is only used for evaluating the results of our approach, since the approach is unsupervised and does not require any training; or any other knowledge about the data.

4 CONCLUSIONS

This paper addresses the design of a cooperative and adaptive classification approach for partitioning mono or multicomponent images. The proposed approach is non parametric and totally unsupervised.

The characterization of pixels according to the nature of the region to which they belong, reduces the computation burden of feature extraction, and makes their processing independent in the classification and result management steps.

The automatic estimation of class numbers allows to better identify or classify the contents of images. Indeed forcing a classifier to a subjective fixed class number generally causes false or less accurate classification results.

The systematic validation of the results from the classification methods used, and the assessment of only conflicting results before their validation leads to consistent and reliable results. Several evaluations on monocomponent and multicomponent (multi and hyperspectral) images show the robustness of the proposed approach results compared to those obtained without cooperation.

The integration of the spectral information in the feature extraction step remains as a perspective for this work.

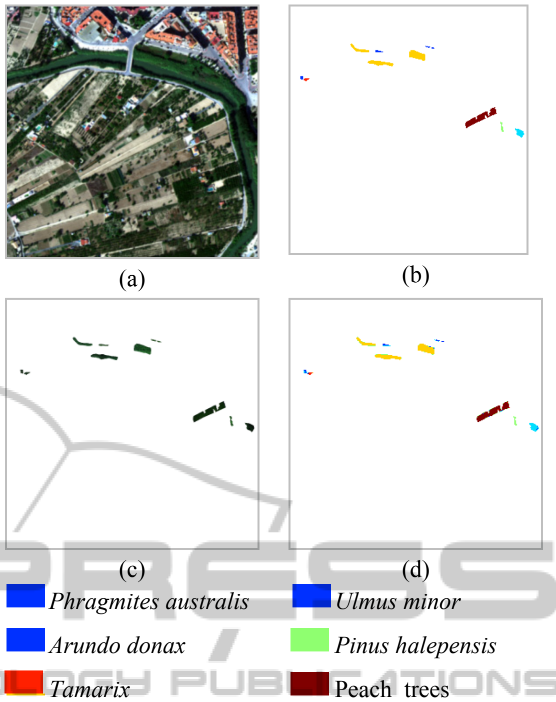

Figure 6: Detection of invasive and non invasive vegetation results from hyperspectral image. (a) Original Image (3 components over 62 for visualizing only), (b) Ground truth masks, (c) Pixels of ground truth to classify, (d) Our approach classification result (ACCR: 99.13%)

ACKNOWLEDGEMENTS

This study was conducted in the framework of the franco-lebanese cedre programme n° 2010/ef/l6. Authors wish to thank the national Council for Scientific Research, Centre for Remote Sensing Lebanon, for providing the dataset on pine trees. They also thank Infraestructura y Ecología S.A.-Aretech Group for providing the dataset on invasive and non invasive vegetation species.

REFERENCES

Benediktsson J. A., Kanellopoulos I., 1999. Classification of multisource and hyperspectral data based on decision fusion. *IEEE Trans. on Geoscience and Remote Sensing*. 37(3), 1367-1377.

Bezdek J. C., 1981. Pattern recognition with fuzzy objective function algorithms. *Kluwer Academic Publishers Norwell, MA, USA*.

Brodatz P., 1966. *Textures: A Photographic Album for Artists and Designers*, Dover Publications, New York.

Table 1: Confusion Matrix of classification result using the proposed approach for detection of invasive and non invasive vegetation: correct classification rate in %, (.): number of pixels. Average correct classification rate: 99.13 %.

	Ground truth classes (number of pixels)					
Classes predicted by our approach	*Phragmites australis* (544)	*Arundo donax* (4200)	*Tamarix* (162)	*Ulmus minor* (764)	*Pinus halepensis* (274)	Peach trees (3040)
Phragmites australis	**99.08%** (539)	0.16% (7)	2.47% (4)	0.52% (4)	0.73% (2)	0.33% (10)
Arundo donax	0	**99.84%** (4193)	0	0	0	0
Tamarix	0	0	**97.53%** (158)	0	0	0
Ulmus minor	0,55% (3)	0	0	**99.48%** (760)	0	0.07% (2)
Pinus halepensis	0.37% (2)	0	0	0	**99.27%** (272)	0
Peach trees	0	0	0	0	0	**99.6%** (3103)

Cox D. R. and Snell E. J., 1968. A general definition of residuals. *Journal of the Royal Statistical Society, Series B*. 30(2), 248-275.

Dempster A. P., N. M. Laird and D. B. Rubin, 1977. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, Series B*. 39(1), 1-38.

Forestier G., Gancarski P., and Wemmert C., 2010. Collaborative clustering with background knowledge. *Data and Knowledge Engineering*. 69(2), 211-228.

Frey B. J. and Dueck D., 2007. *Clustering by passing messages between data points. University of Toronto Science 315*, 972–976.

Haralick R., 1979. Statistical and structural approaches to texture. *Proceedings of the IEEE*. 69, 786-804.

Havens T. C., Bezdek J. C., Leckie Ch., Lawrence O., and Palaniswami M., 2012. Fuzzy C-means algorithms for very large data. *IEEE Trans. on Fuzzy Systems*. 20(6), 1130-1146.

Holland J. H., 1992. *Adaptation in natural and artificial system*. 2nd Edition. Cambridge, MA, USA: MIT press.

Huang B., Xie L., 2010. An improved LBG algorithm for image vector quantization. *3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT)*.

Kalluri H. R., Prasad S., and Bruce L. M., 2010. Decision-level fusion of spectral reflectance and derivative information for robust hyperspectral land cover classification. *IEEE Trans. on Geoscience and Remote Sensing*. 48(11), 4047-4057.

Kermad Ch., Chehdi K., 2002. Research of an automatic and unsupervised system of segmentation. *Image and Vision Computing Edition Elsevier*. 541-555.

Kermad Ch, Chehdi K, Cariou C, 1995. Segmentation d'images par multi-seuillage et fusion des régions labellisée minimisant un critère de similarité. In Quinzième Colloque GRETSI, 2, 641-644. Juan-Les-Pins, France.

Linde, Y., Buzo, A., Gray R. M., 1980. An Algorithm for vector quantizer design. *IEEE Transactions on Communications*. 28, 84–94.

McQueen J., 1967. Some methods for classification and analysis of multivariate observations. *In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*. 1, 281-297.

Neumann F., Oliveto P. S., Witt C., 2009. Heoretical analysis of fitness-proportional selection: landscapes and efficiency. *In Proc. of 11^{th} (GECCO),* 835-842.

Rosenberger Ch., and Chehdi K., 2003. Unsupervised segmentation of multi-spectral images. *In Proc. International Conference on Advanced Concepts for Intelligent Vision Systems, Ghent, Belgium*.

Syswerda G., 1989. Uniform crossover in genetic algorithms. *In Proc. 3rd International Conference on Genetic Algorithms,* 2-9.

Tarabalka Y., Benediktsson J. A., and Chanussot J., 2009. Spectral–spatial classification of hyperspectral imagery based on partitional clustering techniques. *IEEE Trans. on Geoscience and Remote Sensing*. 47(8), 2973-2987.

Vapnik V., 1998. A tutorial on support vector machines for pattern recognition. *Statistical Learning Theory, New York: Wiley, 1998. C. Burges, Data Mining and Knowledge Discovery*. 2, 121-167.

Xu R., Wunsch II D., 2005. Survey of clustering algorithms. *IEEE Trans. on Neural Networks*. 16(3), 645-678.