Intelligent Techniques for Efficient Generation of Ground Cover Maps

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Abstract - **In this work, a new methodology based on artificial neural networks (ANN) and indexing techniques is used with the aim to improve memory requirements for storing multi-source or multispectral remote sensing (MRS) data and at the same time increase classification speed. This methodology features: a) data quantization using a self-organizing map, b) training set reduction to speed up ANN training, c) fast clustering of prototypes, and d) fast indexed classification. Results obtained for both supervised and unsupervised classification to ground-cover categories using, at no loss of generality, a Landsat TM image, show savings in time and memory without a significant compromise of classification performance.**

I. INTRODUCTION

Several techniques have been recently proposed for multispectral satellite image classification. Such techniques include traditional statistics, neural networks and fuzzy logic and can be distinguished in the following two general categories: a) supervised techniques in which labeled training samples are used for parameter optimization [1,2], and b) unsupervised techniques (automatic classification) using a data clustering algorithm [3,4].

In this work we consider the following supervised classification techniques: a) a single-layer ANN trained with the LVQ algorithm [5], b) a multi-layer ANN trained with a variant of the backpropagation algorithm [6] enhanced with constrained optimization techniques (the ALECO algorithm [7]) and c) the k-nearest neighbors (k-NN) algorithm [8].

Although, supervised techniques perform generally better in the production of thematic maps, the unsupervised techniques are mainly used when no training sets are available and constitute a valuable objective alternative as they do not depend on previous knowledge and photointerpreter's experience. These algorithms, first apply a similarity criterion to cluster the data, then assign a label to each cluster (usually a gray level or color) that corresponds to a (thematic) category and, finally, substitute each pixel of the original image with the cluster label to which it belongs. The unsupervised algorithms considered in this paper are: a) Kohonen's self-organizing maps (SOM) [5] for quantizing the input space followed by a hierarchical min-max clustering algorithm [8], and b) the fuzzy Isodata algorithm [4].

The goal of the present work is a time and memory efficient supervised and/or unsupervised classification of MRS data to ground-cover categories using a general purpose methodology based on self-organizing maps and indexing techniques.

II. PROPOSED METHODOLOGY

In this section, we present an efficient methodology for both supervised and automatic classification of MRS data based on self-organizing maps and indexing techniques. This methodology offers the following advantages: a) memory savings through SOM data quantization, b) neural network training speedup due to training set compression, c) clustering speedup, due to the relatively small number of SOM prototypes, allowing the use of even the most computationally demanding algorithms, and d) supervised as well as unsupervised classification speedup by using fast indexing techniques. For the presentation, we will assume Landsat TM image data of MxN pixels and n bands. The input space $\mathbf{R}^n$ is used to represent the image as a set of MxN points (spectral signatures) whose coordinates are the gray levels of each band.

The first stage of the proposed methodology involves vector quantization of the input space using a 2-D lattice of neurons trained with the SOM algorithm. Following a random presentation of spectral signatures, the result is to obtain a catalogue of prototypes (the asymptotic weights of the neurons) that quantize the satellite image.

Next, we use indexing techniques for mapping the pixels of the original image to their corresponding prototypes. To this end, an MxN *index table* is constructed to store pointers from pixels to their closest prototypes. The replacement of the original image with the SOM prototypes and the index table (Fig. 1) constitutes the indexed representation of the

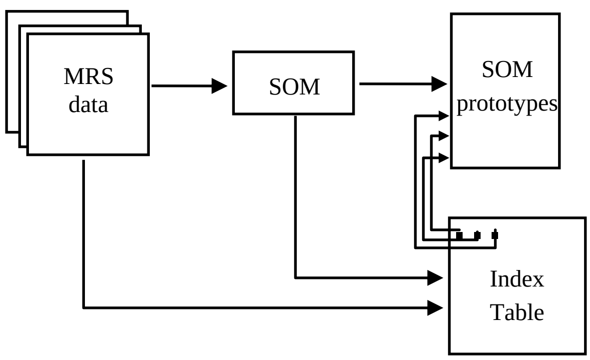

Fig. 1. Indexed representation of MRS data.

multispectral image and results not only in data compression but also in a significant speedup of ANN training, data clustering, and, final classification.

A. *Fast Neural Network Training*

In satellite image classification applications, the training sets are usually composed of several thousands of pixels and, along with the complexity of the classification task (i.e., the number of categories as well as the optimal shapes of class boundaries), are responsible for the long training times observed. On the other hand, using the SOM prototypes, we can quantize the training set and reduce its size by deleting duplicate (prototype) samples. In doing so, and in order to preserve the between-- and within--class relative frequencies needed to specify optimal boundary placement in overlapping regions, the new (compressed) training set as well as the supervised training algorithms are modified to include the multiplicities of the deleted samples. The result is to reduce redundancy from the training data and, thus, achieve a significant training speedup, approximately proportional to the ratio between the original training set size and the number of prototypes (provided that most of the prototypes exist in the compressed training set).

B. *Fast Clustering*

Typically, automatic land-cover classification involves clustering of the data space followed by label assignment. However, due to the large number of data points (spectral signatures), clustering performed on the original image data is inefficient. On the other hand, in the proposed methodology clustering is performed on the SOM prototypes, thus, achieving orders of magnitude a speedup, allowing us to use even the computationally complex hierarchical algorithms [8].

C. *Efficient Indexed Classification*

At the final stage of the proposed methodology, instead of the traditional pixel by pixel classification that requires a computational time proportional to the original image dimensions, only the SOM prototypes need to be classified. The result is to obtain a catalogue of labels (e.g., gray levels or colors) in complete correspondence with the SOM prototypes (Fig.2). For the supervised techniques it is the ANN

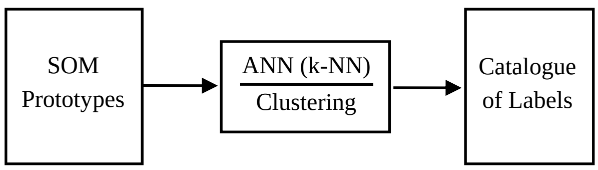

Fig. 2. Creation of the catalogue of labels.

(or k-NN) that is used to label the SOM prototypes whereas for the unsupervised techniques, labels are given directly following the clustering procedure. This, in turn, allows for fast indexed classification (thus avoiding expensive computations) since the result is now obtained by following the pointers of the index table and accessing the corresponding labels as shown in Fig. 3.

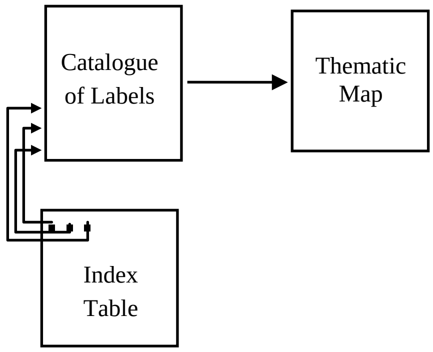

Fig. 3. Fast indexed classification.

III. SUPERVISED/AUTOMATIC LAND-COVER CLASSIFICATION

The multispectral data used in this work consisted of the three bands TM3, TM2 and TM1 (256 gray levels each) of a Landsat TM 512x512 image over the Lesvos island in Greece (the original RGB image is shown in Fig. 4). The goal is to classify the original image to the following 4 land-cover categories: *a) forest, b) sea, c) agricultural* and *d) inhabited areas-bare rock-quarries-land with less than 10% vegetation*. Two labeled sets of 6011 and 3324 samples from the above four categories, were selected by the expert for ANN training and testing their classification performance respectively. Thus, in addition to a qualitative evaluation of the results, quantitative results are also possible.

All programs have been run on a SUN ULTRA II Enterprise workstation. A 16x16 map has been used for quantization of Fig. 4a. SOM training (100000 iterations) and index table construction required 23.12 sec and 54.30 sec respectively leading to a compression ratio of 2.96. The resulting quantized image is shown in Fig. 4b. At this point, it should be noted that both SOM training and index table construction usually involve off-line computations with larger compression ratios being possible for more spectral bands or smaller maps. However, reduction of map sizes should be applied with caution in order not to avoid a significant increase of quantization distortion.

Figs. 5a, 5b and 5c show the classification results obtained with the original methodology for the LVQ, ALECO and k-NN (k=5) algorithms respectively, while Figs. 5d, 5e and 5f show the corresponding results for the proposed methodology. Training and test set performances as well as the training and classification times for the original and the proposed methodologies are shown in Table I. From this table, we can see that the ANN training speedup is about 10 while the classification speedup is about 23, 66 and more than 5000 for the LVQ, ALECO and k-NN algorithms. Moreover, no significant deterioration of the classification results is observed when using the proposed methodology.

The classification result to 8 categories (or clusters) using the fuzzy Isodata algorithm is shown in Fig. 6a, whereby, a

Table I
SUPERVISED PERFORMANCES AND TIMES

Method	Algorithm	Training perform.	Test perform.	Training time(sec)	Classif. time(sec)
Original	LVQ	97.32%	95.73%	2.88	3.45
	ALECO	97.02%	95.61%	62.95	9.92
	k-NN	97.22%	94.61%	-	819.38
Proposed	LVQ	97.14%	95.13%	0.29	0.15
	ALECO	96.99%	95.55%	6.27	0.15
	k-NN	96.95%	94.10%	-	0.15

larger than the desired number of clusters (i.e., 4) is chosen in order to avoid problems due to similarities of the spectral signatures (e.g., shallow sea water looks quite green and is often put in the "forest" cluster). To obtain a thematic map with 4 categories, clusters are merged either by the user or by means of minimum distance in the test set confusion matrix. Fig. 6b shows the result of merging the 8 clusters to 4. Figs. 6c and 6d show the corresponding 8- and 4-cluster thematic maps obtained using the proposed methodology. The fuzzy Isodata clustering speedup induced by the proposed methodology is of the order of $512^2/256 = 1024$ (i.e., size of original image/number of SOM prototypes). Finally, in Figs. 6e and 6f show the clustering result using the computationally intensive hierarchical min-max algorithm. It is worth noting that such an algorithm can not be used directly on the original data (512^2 data samples) due to its high computational complexity (hierarchical data merging) while it took only 11.90sec with the proposed methodology.

IV. CONCLUSIONS

The methodology described in this work offers time and memory savings for supervised and unsupervised classification of MRS data using self-organizing maps and indexing techniques. As multiple training and classification trials with various models, architectures and parameters, are likely to be performed by the user before final acceptance of the classification result, the need for such a fast and memory efficient methodology is justified.

Results on land-cover classification of multispectral satellite data show significant training and classification speedups for both supervised and unsupervised algorithms with no significant compromise of final performance.

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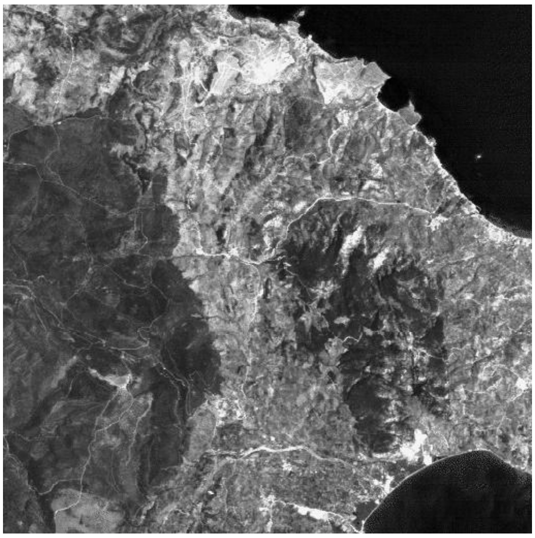
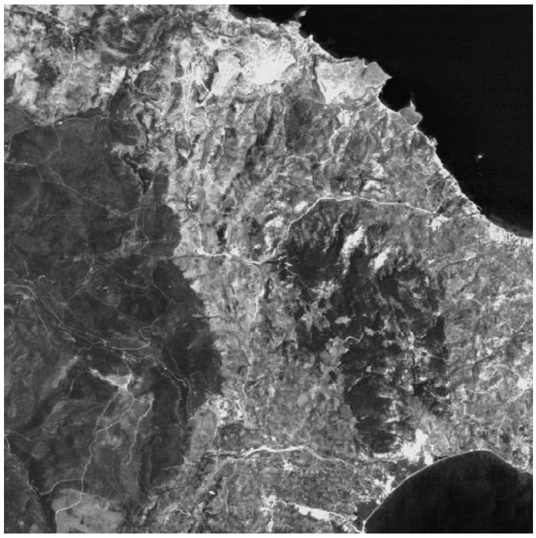


(a)



(b)

Fig. 4. (a) Original 512x512 RGB Landsat TM multispectral image (spectral bands used: TM3, TM2, TM1), (b) SOM quantized image using a 16x16 map.

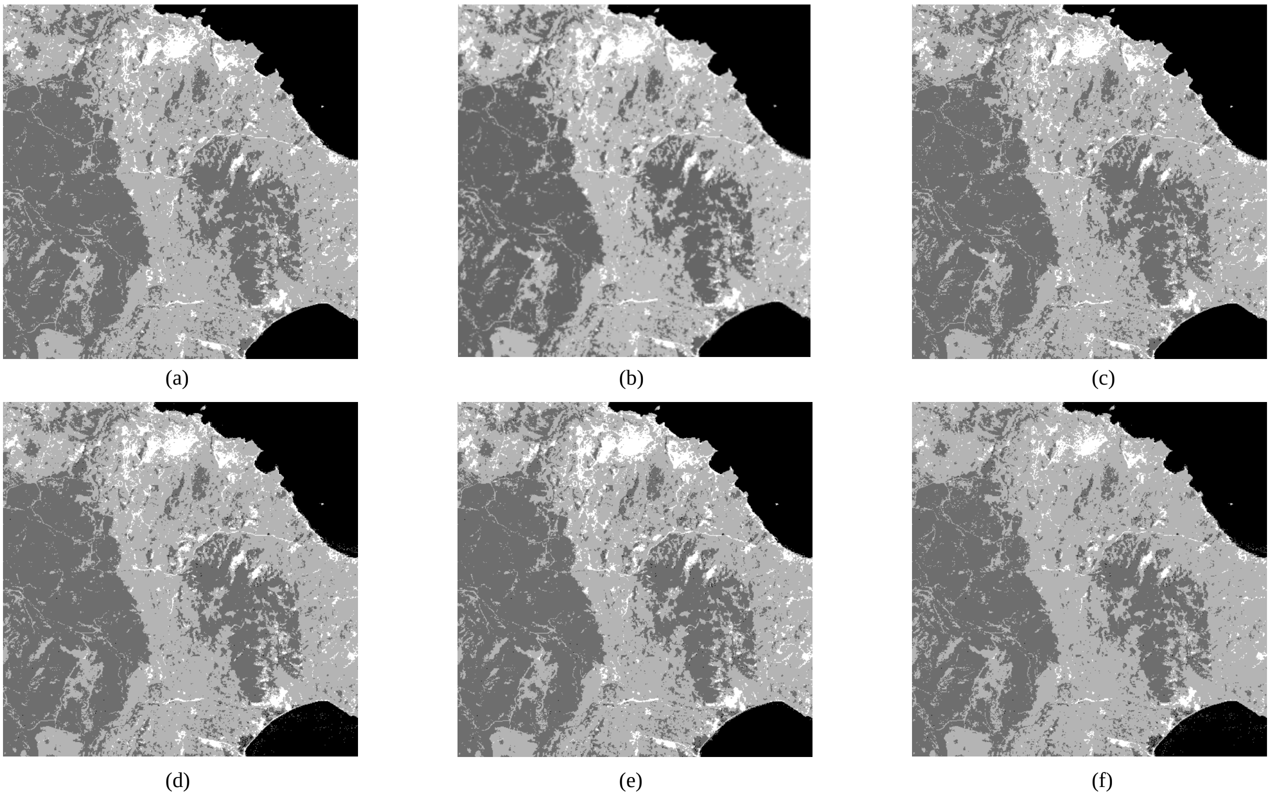


Fig. 5. (a) - (c) LVQ, ALECO and k-NN results for traditional supervised methodology, (d) - (f) LVQ, ALECO and k-NN results for proposed methodology.

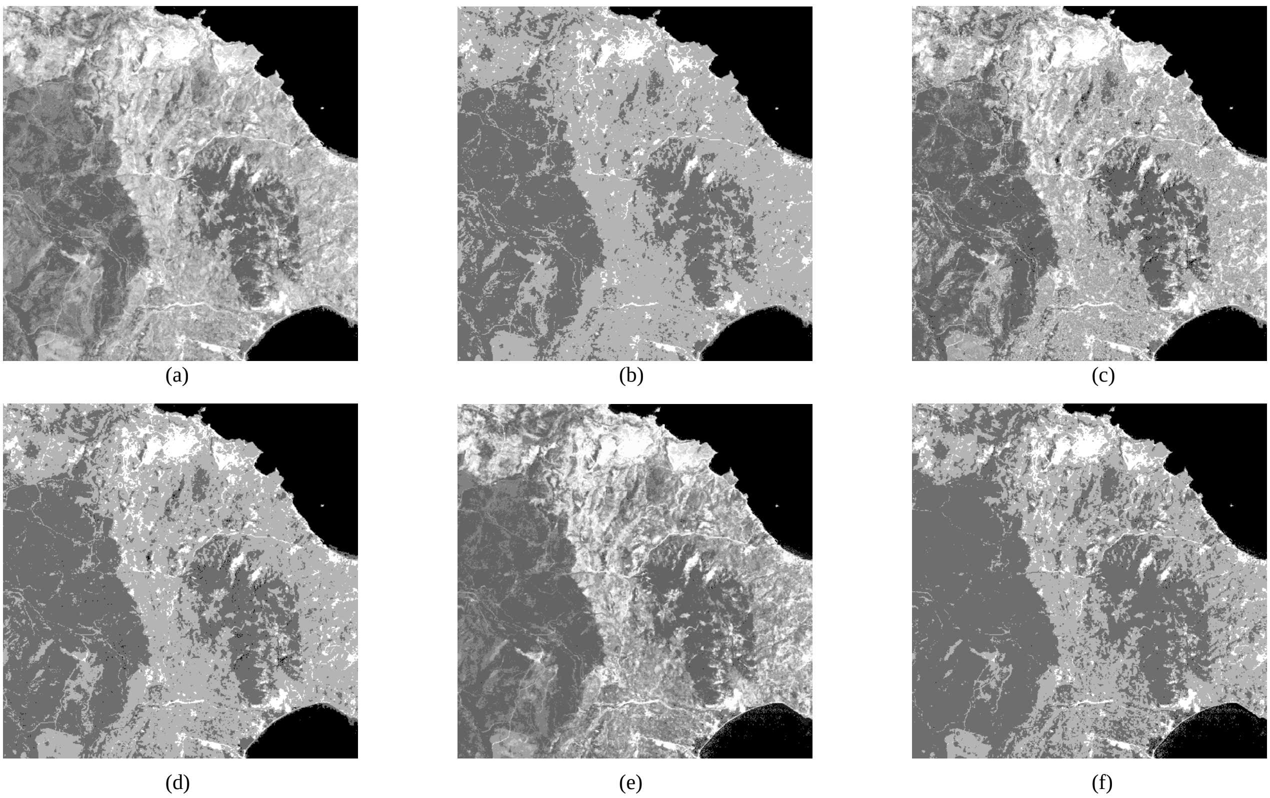


Fig. 6. Fuzzy Isodata results for 8 and 4 clusters on original image (a, b), and on quantized image (c,d); (e, f) Hierarchical clustering using proposed method.