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Support Vector Machine for Remote Sensing image classification

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***Abstract*— The presented work deals with remote sensing data classification. The major goal is to provide the land characterization for multispectral image observations. Channel images contain data acquired from different wavelength within the frequency spectrum. Due to the multiple radiance reflection, the land characterization in the observation space became complex and inefficient. The goal of this work is to perform a feature space for observations. Then a statically learning classifier using the Support Vector Machine is developed for a reliable land characterization.**

***Keywords*— Fusion, Segmentation, Classification, Support Vector Machine, Feature extraction**

I. Introduction

Remote sensing processing methods have been motivated by the growing number of channels and the spatial resolution enhancement. Various processing schemes and application fields are based on image algorithm and recognition methods. The presented work aims to land segmentation and classification for multispectral image. We aim to develop a fusion data scheme then a classification tool based on learning machines.

First we will deduce a feature space from different region descriptors. This step is based on a fusion scheme from different image channel and from different descriptors. Then regions will be classified into land types. Classification in a feature space gives better accuracy and avoids learning divergence problems.

II. Multispectral Data

Multispectral image are the collected radiance in different channel range from visible to the near infrared in the electromagnetic spectrum. Obtained band images reflect the land cover spectral response in different wavelength. The band number reaches six for some multispectral satellite. A huge number of narrowest bands characterize the hyperspectral satellite.

Collected energy by sensors is in fact the result of many reflections and accurate noises due to the atmosphere and the heterogeneous composition of the land. Many proposed model based on physical assumptions aims to analyse the remote sensing scene. The final goal is improving classification accuracy. Considering the set of instantaneous observations from SPOT4 satellite denoted X.

$$X(t)=[X_1(t),X_2(t),X_3(t),X_4(t)] \quad (1)$$

The band images are correlated as presented in Table 1. Therefore, working in a feature space is most efficient and reliable. In fact, radiance distortion by atmosphere and the pixel heterogeneous composition produce much confusion and affect the classification results.

Considering the presented scene in Fig. 2 located in north Tunisia. The scene size is 3000x3000 and the spatial resolution is 20x20 m. The land cover is heterogeneous. Main classes are urban areas, agricultural parcel, lakes, wetlands and mountains.

Classifying the land cover in a feature space needs to find the suitable descriptors combination that describes the presented classes. Many works uses the wavelet transform and combine two or more types of descriptors. The next part presents the feature space concept and description.

Table 1. Bands Correlation

	Band 1	Band 2	Band 3	Band 4
Band 1	1	0.9496	0.7531	0.6502
Band 2	0.9496	1	0.8275	0.8050
Band 3	0.7531	0.8275	1	0.8685
Band 4	0.6502	0.8050	0.8685	1

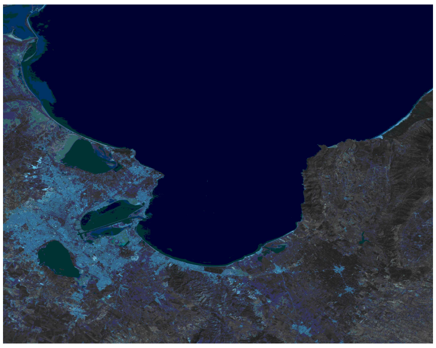


Fig. 1. Composite image.

III. REGION DESCRIPTORS AND DATA FUSION SCHEMES

When the observation data are the result of many distortions and non linear mixture, it is suitable to find another space of presentation. The obtained space is based on a set of feature descriptors and provides better presentation for the land cover. Fusion system is also reliable in case of correlated data and redundancy in the observation space.

Many data descriptors have been developed for data recognition, detection and estimation. To find whether the descriptors are sufficient to describe data stills the main problem. Existent works uses experiments and comparisons. Combining different descriptors gives also a reliable data representation within the feature space. Although the feature space have greater dimension, the classification thematic became more efficient and reliable.

Existent descriptors are pixel oriented and region oriented. Region descriptors describe the region shape or the region content. Wavelets have been widely used for recognition and detection applications. It consists on transforming original data to many frequencies and scales [1]. Each transform gives a new data presentation and therefore new data characterization. Other descriptors are based on Fourier transform, image moments or gradient orientated histogram. For region content descriptors, texture characterization has proved to be efficient when the image classes have a uniform and repetitive appearance. Wavelet and specially Gabor transform are the principle tools for texture classification. Gabor filtered images give a space-scale analysis for the textured image [2].

For multiband images, the way that we manage the feature extractor process produces different fusion scheme. Whether we extract feature before or after data fusion and whether we take a decision in front-end or in the back-end of data process produces many fusion levels.

Mainly fusion levels are summarized in Fig. 3 [3]. Fusion can concerns only basic data which are observations in our case. Therefore, segmentation and other processing method deal with a combination of data. This method is generally pixel based [4]. For region based algorithm, the segmentation and feature extraction is performed for each data source. Then, fusion will be performed by region. Segmented region will be classified in the upper stage basing on the feature fusion. The last fusion level concerns the decision fusion by a kind of vote or correlated decision function from each elementary decision.

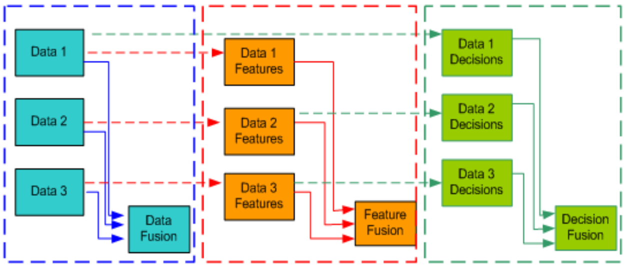


Fig. 2. Fusion Levels.

IV. CLASSIFICATION METHOD BASED ON SUPPORT VECTOR MACHINE

The Support Vector Machine (SVM) classification process is based on finding an optimal separation hyperplan performing the minimum distance. The basic case is a binary classification in class +1 or -1. Let considerate the learning data base containing k coupes {ci, vi} where ci is the class label c_i {-1,+1} and vi the feature vector.

The optimal hyperplan is defined by a subset of feature vectors from the learning database named Support vectors denoted V. The classification problem is equivalent to a quadratic optimization with constraints [5]. Fig. 4 shows the basic linear separability between two classes by hyperplan. The optimization problem is parameterized by a penalty parameter C that describes the separation complexity and the classification error. The optimization problem under constraints is expressed by Eq. 2:

$$\omega(\alpha) = \frac{1}{2}\sum_{i,j=1}^{K} \alpha_i \alpha_j c_i c_j \phi(v_i, v_j) - \sum_{i=1}^{K} \alpha_i$$
$$\text{where} \quad \sum_{i=1}^{K} c_i \alpha_i = 0 \quad \text{and} \quad 0 \le \alpha_i \le C \qquad (2)$$

When the separability is nonlinear as presented in Fig. 5, a nonlinear transform from the feature space to a new space with greater dimension allows a linear separability. There is no need to find the transform function, only a kernel function *K* is needed. The kernel choice is determinative for the separability and depends on the classification application. The optimal solution defines the support vectors *V*. The decision function is the sign of given in Eq. 3.

$$\chi = \sum_{i \in V} \alpha_i c_i K(v_i, v) + b \qquad (3)$$

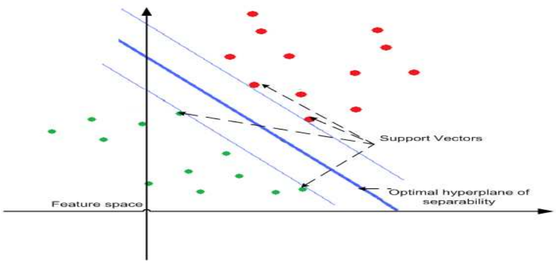


Fig. 3. Linear separability

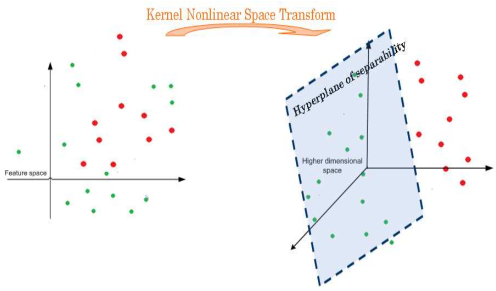


Fig. 4. Non-Linear separability

Commonly used kernels are linear, polynomial and Radial Basis Function (RBF) defined by Eq. 4.

$$K\,(x,\ y)\ =\ \exp^{\gamma * \|x - y\|^2} \tag{4}$$

Another important kernel is the sigmoid function defined by Equation 5.

$$K\,(x,\ y)\ =\ \tanh\left(\gamma x^T y + r\right) \tag{5}$$

The related SVM classification is parameterized by the penalty factor *C* and the kernel parameters.

V. Proposed Classification Method

Multispectral data classification is based on a non-supervised segmentation and then classification by learning method. Fig. 6 details the process algorithm. For the learning data base there are:

- Supervised classification for satellite observations.
- Region Feature extraction for classified image

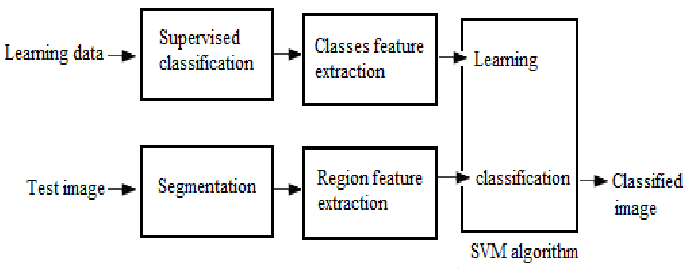


Fig. 5. Feature extraction and classification.

To classify a multispectral image, the test satellite scene will be segmented into homogenous regions. The learning System Vector machine will produce a separation model based on the SVM learning principle [6].

The proposed method is based on the feature fusion level for regions. Spot image are segmented into regions by the watershed algorithm. This algorithm decomposes remote sensing images by three steps:

— Derive variance image from each channel image. Variance within each pixel window is evaluated and assigned to the central pixel. The obtained image is the surface image.

— In the derived surface image, pixels values are treated as elevation. Pixels will be iteratively merged into one watershed if they have closest elevation.

— Merging adjacent watersheds according to spectral similarity.

The Feature extraction will produce a feature vector that will be classified by the SVM. For each region R_i the feature vector is the concatenation of the feature sub-vector from each band image as shown in Eq. 6. For 4 band images and M features we obtain the following feature vector for the region R_i:

$$R_i=[F_{11}, F_{12}, \ldots, F_{1M}, F_{21}, F_{22}, \ldots, F_{2M}, F_{31}, F_{32}, \ldots, F_{3M}, F_{41}, F_{42}, \ldots, F_{4M}] \tag{6}$$

Although the band correlation issue, it was shown that the best segmentation and classification results are given by using all band information's. Within this work, the feature space is deduced from all bands. Feature components are from Haar wavelet transform and Gabor wavelet [7]. Haar descriptors are computed in three directions: horizontal, vertical and oblique [8]. The choice of wavelet type and decomposition level is guided by experiments. Many land covers of the studied zone have textural appearance like parcels, urban areas, bare soil and mountain. Thus using Gabor filters was suitable for the scene classification.

The next step is the region classification based on static learning from a set of recognized regions. Fig. 7 contains some learning database patches for some classes.

Many SVM implementations exist. LIBSVM [9] gives an easy and reliable tool for SVM application. Learning database is a part of the studied zone and contains many class patches. Scaling feature vectors to [0 1] is a determinative step to optimize computational time. Both learning and test feature vectors are scaled with the same factor.

Fig. 8 is the test image for the proposed classification method. The image is first segmented by watershed algorithm (Fig. 9 a) and then classified by the SVM method (Fig. 9 b) basing on feature vectors extracted from each region.

Table 1 gives the classification accuracy for different kernels and parameters. The best accuracy is 88.35% and is reached by sigmoid kernel. SVM parameters including penalty classification parameter C and sigmoid parameter γ are determined by cross validation tests.

Confusion matrix is detailed in Table 2. Lake, parcels and urban areas are well recognized due to their particular textural appearance. For heterogeneous regions such as scattered vegetation, dense vegetation, wetland and Bare soil the well classified rate is more than 83%. Bare soil is confused with vegetation classes due to the various elements for theses classes including soil.

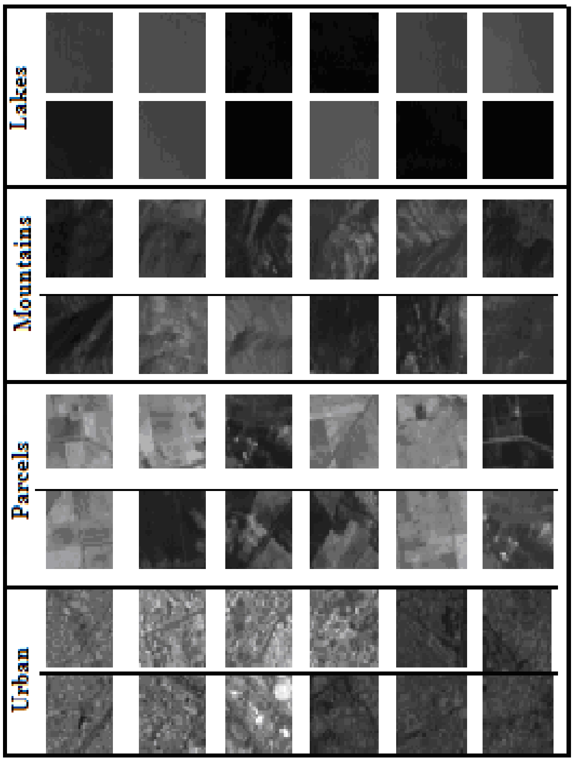
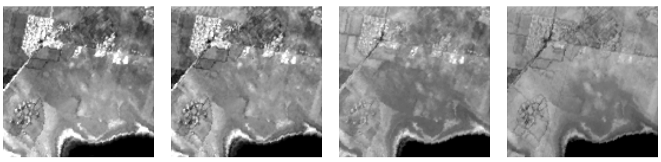
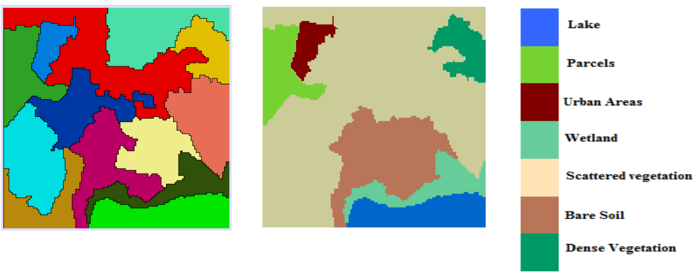


Fig. 6. Learning data base patches.



(a) (b) (c) (d)

Fig. 7. Test mage of SPOT-4, May 31, 1998. (a) Band 1 . (b) Band 2 . (c) Band 3. (d) Band 4.



(a) (b)

Fig. 8. Test mage segmentation by Watershed algorithm (figure a) and SVM classification (figure b)

TABLE 2. CLASSIFICATION ACCURACY FOR DIFFERENT SVM KERNELS

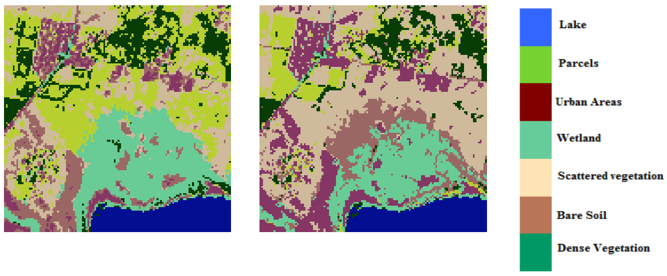
Kernel	***C***	***γ***	**Accuracy**
linear	8	0.0078125	67.70%
Polynomial	0.5	0.5	67.73%
RBF	8	0.5	67.93%
Sigmoid	32768	0.0001220703125	88.35%

TABLE 3. CONFUSION MATRIX FOR SIGMOID KERNEL

	Lake	Scattered Vegetation	Parcels	Dense Vegetation	Wetland	Bare Soil	Urban areas
Lake	100%	0%	0%	0%	0%	0%	0%
Scattered Vegetation	0%	87.43%	0%	2.14%	0%	8.03%	2.40%
Parcels	0%	0%	97.50%	2%	0.5%	0%	0%
Dense Vegetation	0%	10%	3%	87%	0%	0%	0%
Wetland	8.7%	0%	0.7%	2%	88.6%	0%	0%
Bare Soil	0%	13.07%	0%	3.1%	0%	83.33%	0.50%
Urban areas	0%	0%	2.33%	0%	1.5%	0%	96.17%

Classification wit non-supervised classifier like k-means algorithm gives an accuracy of 51,27% . The classified image is presented in Fig. 10 (a).

The supervised classification by Minimum-Distance algorithm gives 85,01% for the accuracy. Moreover the classified image shown in Fig. 10 (b) has many miss-classified classes and heterogeneous zones.



(a) (b)

Fig. 10. Test mage classified by k-means algortihm (figure a) and by Minimum Distance algorihtm (figure b)

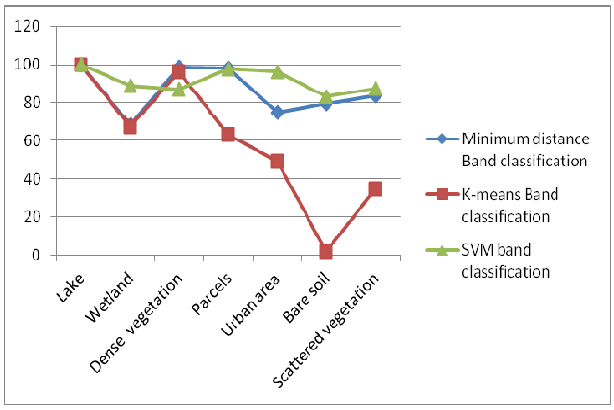


Fig. 11. Classification method comparison by class

To compare in depth the classification accuracy by class, Fig. 11 provides the good classification rat by class for the proposed approach based on SVM and K-means and Minimum-distance algorithms. Lake is well classified in the three cases. Dense vegetation class is better recognised by Minimum Distance and K-means method.. Remain classes are better recognised by the proposed method

Therefore, compared to classical classification method that deals with pixel radiances, the proposed approach provides better accuracy and avoid isolated pixels.

VI. Conclusion

Within this paper we have established a new classification method for multispectral data. The proposed method is based on supervised classification and feature extraction for learning data. Test satellite image will go throw the segmentation process, feature extraction and then SVM classification..

This work aims to find a reliable classification method for remote sensing data. Feature descriptors and learning classification constitute a suitable solution for correlated data and for nonlinear classification problem. The proposed approach could be applied to hyperspectral data and could be ameliorated with other segmentation, classification and feature extraction algorithms

Acknowledgment

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