DECISION FUSION BASED ON EXTENDED MULTI-ATTRIBUTE PROFILES FOR HYPERSPECTRAL IMAGE CLASSIFICATION

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ABSTRACT

In this paper, a new classification strategy for remotely sensed hyperspectral image data is presented and discussed. The proposed approach adopts a decision fusion strategy which combines a well-established classifier, such as the support vector machine (SVM), with the information provided by extended multi-attribute morphological profiles (EMAPs). EMAPs provide a multilevel characterization of an image created by using a sequence of morphological attribute filters to model different kinds of the structural information contained in such image. In our proposed decision fusion strategy, the SVM classifier is first applied to each of the components (which are associated to different attributes) provided by the EMAP. Then, we apply a decision fusion rule to obtain the final classification result. In our experimental results, conducted with a reference urban hyperspectral data sets widely used in the literature, we show that the proposed strategy provides state of the art results (especially when limited training sets are used.)

Index Terms— Extended multiattribute profiles (EMAPs), decision fusion, mathematical morphology (MM), hyperspectral imaging.

1. INTRODUCTION

During the last two decades, the availability and constantly increasing coverage of the Earth using multi/hyperspectral remote sensing instruments has provided enhanced capabilities for Earth observation applications [1]. Hyperspectral data often provide both detailed structural and spectral information and thus the data can be used to significantly improve the performance of classification techniques.

In recent years, mathematical morphology (MM) has been widely used to extract spatial-contextual information from remotely sensed images in general [2] and hyperspectral images in particular [3]. Morphological gray scale operations such as opening and closing by reconstruction can filter brighter and darker regions which are smaller than the size of structuring element (SE), respectively. In [2], the application of these operators to remotely sensed images was introduced. Differential morphological profiles (DMP) were built by calculating the difference in the values of morphological profiles at different scales. Such profiles were exploited to define a new segmentation method and used for classification by neural networks. This method has been extended to hyperspectral image classification by extracting the first few principal components using principal component analysis (PCA) to build so-called extended morphological profiles (EMPs) [4]. Recently, morphological attribute profiles (APs) [5] were formally defined as an advanced mechanism to obtain a detailed multilevel characterization of a remotely sensed image created by the sequential application of morphological attribute filters that can be used to model different kinds of the structural information. Different parametric features can be modeled according to different attributes considered in the morphological attribute transformation. In, the concept of APs was successfully extended to the processing of hyperspectral data by constructing APs to the first few components using PCA, generating extended morphological attribute profiles (EAP) and extended multi-attribute profiles (EMAPs) when different attributes are considered.

The complementary nature of EAPs (for example, using different attributes) provides different descriptions of the same data set that can be jointly exploited in order to improve the interpretation. In this context, decision fusion approaches become highly relevant in order to take advantage of the complementary nature of different data sources such as those provided by different morphological operations [6–8]. Decision fusion can be defined as the process of fusing information from several data sets after each individual data set has undergone an certain analysis (e.g. classification)

process using a variety of different algorithms. Recently, a decision fusion strategy based on the well-known support vector machine (SVM) classifier [9] has been proposed and applied to multiple sensor data in [10, 11]. Specifically, in [10] multitemporal data were classified separately by an SVM classifier and then three different fusion strategies were employed to fuse the resulting classification results. In [11], an SVM-based decision fusion strategy was extended to a multilevel component. Two original images and their corresponding segmented images were pre-classified by the SVM and the resulting outputs were combined together for further processing using SVM and a random forest classifier.

In this paper, we develop a novel SVM-based decision fusion strategy which integrates different EAPs obtained using a variety of attributes. The proposed approach combines the advantages of SVM-based fusion and extended multi-attribute profiles (EMAPs). Specifically, the proposed strategy will be shown to be particularly effective in urban analysis scenarios, in which spectrally similar classes may exhibit different sensitivity to a specific attributes in the process of classification. This fact allows for the discrimination of spectrally very similar features using multiple spatial attributes.

The remainder of the paper is structured as follows. Section II presents the proposed methodology. Section III describes the data sets used for evaluation purposes. Section IV performs an evaluation and comparison of the proposed approach with regards to state-of-the-art methods. Finally, section V concludes with some remarks.

2. METHODOLOGY

2.1. Extend multi-attribute profiles

Morphological attribute openings and attribute thinnings were firstly introduced in [12]. In [5], this method was extended to its dual transformation, attribute closings and thickenings, which are used together with attribute openings and attribute thinnings to build morphological attribute profiles (AP). APs are in fact acquired by using attribute thinning and thickening with a set of increasing values of a reference value λ. In general, an attribute A computed for every connected component against the given reference value λ. For a connected component of the image, C_i, if $A(C_i) > \lambda$ then the region is kept unaltered, otherwise it is set to the grayscale value of a darker or brighter surrounding region dependent on whether the operation is thinning or thickening, merging the connected components. Given a sequence of thresholds $\lambda_1, \lambda_2, \ldots, \lambda_n$, the AP of a grayscale image f is obtained by using a sequence of attribute thinning and attribute thickening operations as follows:

$$\text{AP}(f_j(\mathbf{x}_i)) := \{\phi_n(f_j(\mathbf{x}_i)), \ldots, \phi_1(f_j(\mathbf{x}_i)), \\ f_j(\mathbf{x}_i), \gamma_1(f_j(\mathbf{x}_i)), \ldots, \gamma_n(f_j(\mathbf{x}_i))\}, \quad (1)$$

where ϕ and γ denote the thickening and thinning transformations, respectively, and $f_j(\mathbf{x}_i)$ denotes a feature extracted

from the original pixel information $\mathbf{x}_i$ in a multi/hyperspectral image $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_m] \in \mathbb{R}^{m \times l}$ with m samples and l dimensions. Then, the EAP of a hyperspectral image can be obtained by creating the AP on each of the n components which extracted by PCA (or any other feature reduction transformation) and thus building a stacked vector for all the resulting n APs:

$$\text{EAP}(\mathbf{x}_i) := \{\text{AP}(f_1(\mathbf{x}_i)), \text{AP}(f_2(\mathbf{x}_i)), \cdots, \text{AP}(f_q(\mathbf{x}_i))\}, \quad (2)$$

where q is the number of retained features. Attribute filters can be built by taking advantage of the representation of the input image as a rooted hierarchical tree of the connected components, where the tree is obtained by the Max-tree algorithm which is an efficient image representation that associates all the regions in the image to nodes of a tree [13]. Finally, the use of different attributes leads to the concept of EMAP that we will exploit in the following subsection to provide a decision fusion-based classification strategy.

2.2. Decision fusion-based classification

The proposed SVM-based decision fusion strategy is graphically illustrated in Fig. 1. As shown by Fig. 1, the first step in the proposed approach is to build different EAPs from the original hyperspectral image. In this work, we use four attributes: area (EAP_a), moment of inertia (EAP_i), length of the diagonal (EAP_d), and standard deviation (EAP_s) [14]. A full EMAP is also obtained by combining the same four attributes. Afterwards, different rule images were obtained after preclassification of the individual EAPs and the full EMAP using the SVM, where each rule image provides n bands given n land cover classes. These five rule images are simply combined together into one stack of data which are used for a final SVM classification. As a result, the stacked feature vectors (which consist of a preliminary output from the EAPs and an additional output from the EMAP) are to decide the final class membership.
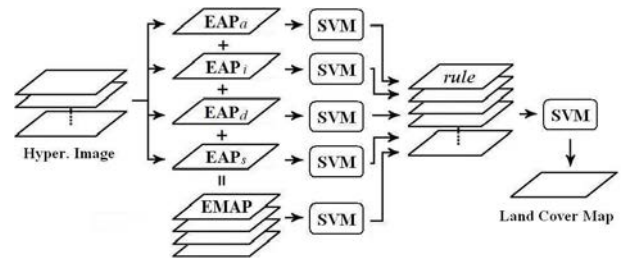

Fig. 1. Schematic diagram of the decision fusion strategy.

It should be noted that the SVM classifier used in our experiments adopts a Gaussian Radial Basis Function (RBF) kernel, which has been shown to be able to handle complex nonlinear class distributions. Furthermore, a *one-against-one* (OAO) strategy which trains $n(n - 1)/2$ individual binary

SVMs is used, and the parameters of the SVM are acquired by means of cross-validation. The rule images contain the distance of each sample to the hyperplane in a binary classification problem, and these rule images are used to predict the final class membership of each sample by using classic majority voting.

3. EXPERIMENTAL RESULTS

3.1. Data set used in experiments

In order to evaluate the proposed method, the experimental analysis was carried out using a hyperspectral image was acquired by the Reflective Optics Spectrographic Imaging System (ROSIS) sensor during a flight campaign over the city of Pavia, nothern Italy, in 2001. The number of spectral bands of the considered data set is 103 after 12 bands were removed due to noise and water absorption. The size in pixels of the image is 610×340, and the spatial resolution is 1.3 meters. Nine thematic land-cover classes were identified. For these data, the reference set comprises 42776 labeled samples.

3.2. Experimental assessment

Table 1 shows the classification results obtained for the ROSIS Pavia University data set. As shown by Table 1, the classification accuracies obtained by using EAPs (built on different attributes) and EMAPs were higher than those acquired by only using spectral information or the first three components derived from the PCA transform. EMAPs (which combine all the single EAPs together) generally achieved higher classification accuracies in comparison with single EAPs. The highest classification accuracies were obtained by using the proposed fusion strategy, but with the increase in the number of training samples the gap between the proposed method and other methods decreases. Specifically, the classification accuracies obtained by using the method are slightly higher than those found using EMAPs when 20 labeled samples from each class were used for training purposes. Besides, the classification accuracies achieved by the proposed method are relatively stable compared with other approaches, especially when a very small number of training samples was used. This is due to the incorporation of spatial information in the classification through the use of morphological techniques. The low standard deviations observed for the presented method in this experiment indicated the robustness of the fusion approach is robust, even in the presence of very limited training samples. For illustrative purposes, Fig. 2 shows some of the obtained classification results for the ROSIS Pavia University scene.

4. CONCLUSIONS

In this paper, we have developed a simple SVM-based decision fusion strategy which is based on the use of EMAPs. Our experiments, conducted with one popular hyperspectral scenes, reveal that the incorporation of spatial information through morphological techniques can improve the classification accuracies using limited training samples. Future work will comprise other configurations and use of alternative sources of information for the presented fusion strategy. Additional experiments with other data sets will also be conducted in future studies.

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Table 1. Individual and overall (OA) classification accuracies and kappa statistic (κ) obtained by different methods for the ROSIS Pavia University scene after 10 Monte Carlo runs (standard deviation values are also displayed).

Samples per class (total)		Sources of information for SVM classification							
		Spectral info	PCA (3 components)	EAP_a	EAP_d	EAP_i	EAP_s	EMAP	Fusion strategy
5 (45)	OA	52.49 ±11.01	55.01±6.46	61.74±10.78	63.72±8.85	72.14±6.64	68.83±12.11	72.77±10.11	79.28±4.79
	κ	44.35±9.99	45.50±6.55	54.06±11.66	55.64±9.78	65.59±8.08	61.46±14.52	66.65±10.87	73.84±5.33
10 (90)	OA	61.71±5.81	59.65±3.22	79.89 ± 6.65	73.13±4.21	82.87±4.08	84.43 ± 3.38	86.20± 6.74	89.06±4.12
	κ	53.69±5.77	51.12±3.23	74.91±7.71	66.78±4.61	78.46±4.78	80.21±4.05	82.59±8.08	85.97±5.07
15 (135)	OA	72.19±3.35	59.32±4.15	85.97± 4.44	76.70±5.20	87.15±4.04	87.42±3.91	89.97±5.78	91.78±3.77
	κ	65.42±3.83	51.21±4.29	82.06±5.47	70.93±5.58	83.56±4.85	83.90±4.70	87.18±7.13	89.36±4.71
20 (180)	OA	75.27±4.26	63.34± 5.60	90.18±3.38	78.93±3.68	87.64±4.79	91.54 ±2.43	94.38±3.19	94.45±2.93
	κ	68.78± 4.97	55.03±5.52	87.35±4.16	73.50±4.18	84.26±5.76	88.98±3.06	92.71±4.05	92.78±3.72

Ground-truth   Spectral info (56.54%)   PCA (52.36%) EAP_a (59.51%) EAP_d (61.45%)

EAP_i (70.66%) EAP_s (64.41%)   EMAP (73.45%)   Fusion strategy (75.31%)
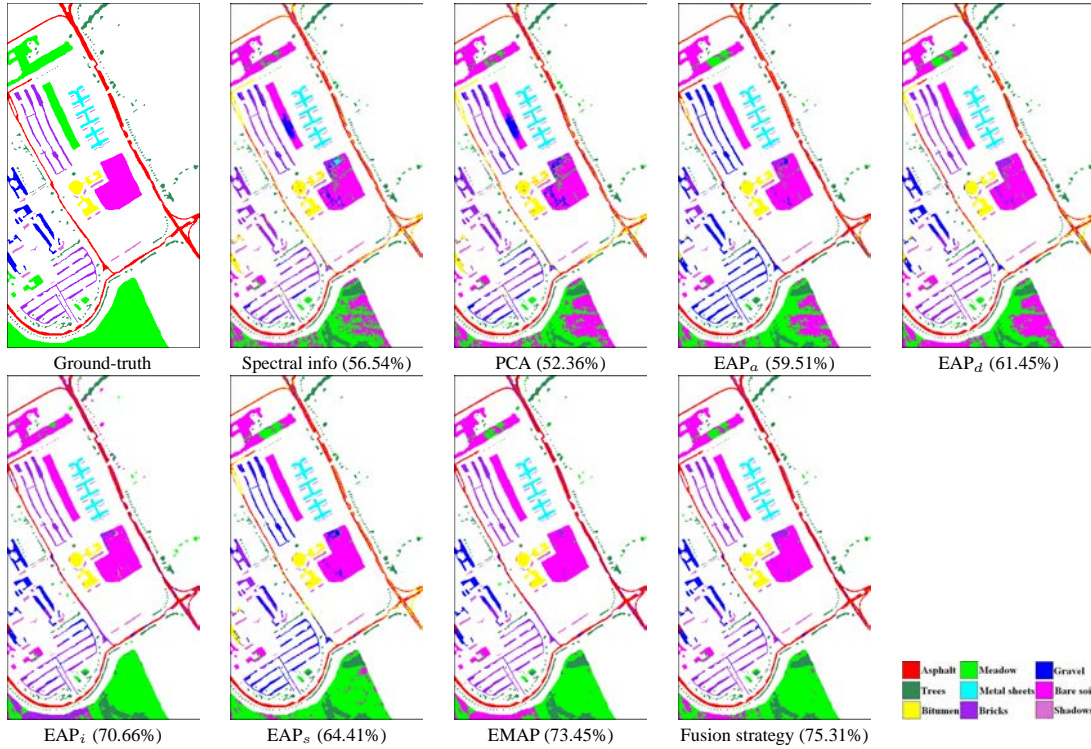
Fig. 2. Classification results for the ROSIS Pavia University scene (using only 5 samples per class for training).