A Multi-features Fusion of Multi-temporal Hyperspectral Images using a Cooperative GDD/SVM Method

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Abstract: Considering the emergence of hyperspectral sensors, feature fusion has been more and more important for images classification, indexing and retrieval. In this paper, a cooperative fusion method GDD/SVM (Generalized Dirichlet Distribution/Support Vector Machines), which involves heterogeneous features, is proposed for multi-temporal hyperspectral images classification. It differentiates, from most of the previous approaches, by incorporating the potentials of generative models into a discriminative classifier. Therefore, the multi-features, including the 3D spectral features and textural features, can be integrated with an efficient way into a unified robust framework. The experimental results on a series of Hyperion images confirm the improved performance and show that this cooperative fusion approach has consistence over different testing datasets.

1 INTRODUCTION

Presently, the considerable archive produced by satellite remote-sensing sensors is becoming an increasingly valuable source of information. This leads to a better interpretation of land-cover and land-use evolution by analyzing the spectral response of the different earth's surface elements. Hyperspectral signatures afford a compact recording of reflectance values over a large domain of the electromagnetic spectrum. They allow practitioners to map, quantify and qualify effectively the spatio-temporal variations of land surface (Heinz et al., 2010). The goal of fusion techniques is to extract complementary information from different sources to allow for a more informed decision than one could gain from any of the sources alone. In theory, data fusion provides significant advantages over single source of features. In addition to the statistical advantage, the use of multiple kinds of features may increase the possibility of a target of interest being observed and characterized resulting in a reduced error rate. In contrast, fusion may not always result in an improved decision over simply selecting the most appropriate source for the task because accurate data may be fused with very inaccurate data (Nakariyakul and Casasent, 2004).

2 PROBLEM STATEMENT

The semantic categorization of remote-sensing images requires analysis of many features of the images such as texture, spectral profiles, etc. Current feature fusion approaches commonly concatenate different features. It gives, generally good results and several approaches have been proposed using this schema. However, most of them have various conditional constraints, such as noise and imperfection, which might retain the use of such systems under degraded performance. However, how to fuse heterogeneous features in a flexible way is still an open research question.

Similarly, in the area of Supervised Machine Learning (SML), diversity with respect to the errors committed by component classifiers has received much attention (Bishop, 2006). Generative and discriminative approaches are two distinct schools of probabilistic machine learning. It has shown that discriminative approaches such as SVM (Cristianini and Shawe-Taylor, 2000) outperform model based approaches due to their flexibility in decision boundaries estimation. Conversely, since that discriminative methods are concerned with boundaries, all the classes need to be estimated conjointly (Ulusoy and Bishop, 2006). Complementary, one of the interesting characteristics, that generative models have over discriminative ones, is that they are learnt indepen-

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dently for each class. Moreover, following their modeling power, generative models are able to deal with missing data. An ideal fusion method should combine these two approaches in order to improve the classification accuracy (LeBlanc and Saffiotti, 2007).

3 COOPERATIVE SVM/GDD METHOD FOR HYPERSPECTRAL IMAGES CLASSIFICATION

3.1 Overview of the proposed Fusion Schema

In this paper, we propose a new technique in remote-sensing images classification by fusing heterogeneous representations. The proposed approach involve several steps including preprocessing; features extraction; features fusion; matching and classification stages. The block diagram of the proposed technique is shown in Fig. 1. In our previous work (Farah et al., 2010), we proposed a novel 3D model which design the spectral signature as a three dimensional function which are the time, reflectance, and wavelength band (equation 1). For each pixel, we generated a surface (3D Mesh) which generalizes the usual signature by adding a time dimension. We call this new representation the *multi-temporal spectral signature*. Interested readers can refer to (Farah et al., 2010).

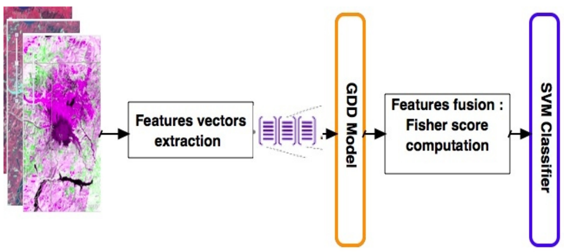


Figure 1: General workflow of the proposed approach.

3.2 Images Pre-processing and Features Extraction

In this study multi-temporal hyperspectral images constitutes the source data. Spectral and textural features are the foundational data for this kind of images. The 3D spectral features are extracted from the relative mesh of a given pixel (multi-temporal spectral signature) while the textural ones are derived directly from images. Mainly, two features vectors are generated for each pixel as follows:

Heat Kernel Signature (HKS). The HKS is a signature computed only from the intrinsic geometry of an object. Suppose (m,g) is a compelte Riemannian manifold, g is the Riemannian metric. δ is the Laplace-Beltrami operator. The eigenvalues $\{\lambda_n\}$ and eigenfunctions $\{\phi_n\}$ of δ are $\delta\phi_n = \lambda_n\phi_n$, where ϕ_n is normalized to be orthonormal in $L^2(M)$. The Laplace spectrum is given by $0 = \lambda_0 < \lambda_1 \leq \lambda_2 \leq \ldots, \lambda_n \rightarrow \infty$. $\triangle$ is the Laplace-Beltrami operator. As a local shape descriptor, Sun et al. (Sun et al., 2009) defined the heat kernel signature (HKS) by :

$$h(x,t) = K_{x,t}(x,x) = \sum_{i=0}^{\infty} e^{-\lambda_t}\phi_i^2(x) \qquad (1)$$

where $\lambda_0, \lambda_1, \cdots \geq 0$ are eigenvalues and $\phi_0, \phi_1, \ldots$ are the corresponding eigenfuctions on the Laplace-Beltrami operator, satisfying $\delta_X\phi_i = \lambda_i\phi_i$. Let's denote this vector by Y.

Spatio-temporal Gabor Filters. Texture is one of the important characteristics used in identifying objects or regions of interest. It contains important information about the structural arrangement of surfaces. Fusing texture with 3D spectral information is conducive to the interpretation of remote seeing image (Wang and Chua, 2005). We use a method for dynamic texture modeling based on spatio-temporal Gabor filters. Briefly, the sequence of images is convolved with a bank of spatiotemporal Gabor filters and a feature vector is constructed with the energy of the responses as components. Let's denote this vector by Y'.

3.2.1 Multi-features Fusion based on a Cooperative GDD/SVM Classifier

In this section, we present an approach that combines an SVM classifier (Burges, 1998) with a generatively trained GDD model and profits, accordingly, from the advantages of both techniques. The key idea here is to concatenate the extracted features into one vector and to project it in a new space. First, a straightforward feature combination approach is used to concatenate feature vectors (Y and Y') to a single feature vector $X = (X_{i1}, \ldots, X_{idim})$. The *dim* size may differ from one pixel to another making the fusion and classification a challenging tasks. To overcome this limit, we use the Generalized Dirichelet Distribution (GDD) model (Bouguila and Ziou, 2010) to map each feature vector into its Fisher score. Therefore, the Fisher kernel function from the GDD is used to replace the Gaussian kernel in the classical SVM.

Let $(X_1, \ldots, X_N)$ denote a collection of N multi-temporal hyperspectral pixels. Each data X_i is assumed to have *dim* size, $X = (X_{i1}, \ldots, X_{idim})$. Each data X_i is assumed to be drawn from the following finite mixture model :

$$p(X_i/\theta) = \sum_{j=1}^{M} p(X_i/j,\theta_j)P(j) \quad (2)$$

where M is the number of components, the $P(j)$, $(0 < P(j) < 1$ and $\sum_{j=1}^{dim} P(j) = 1)$ are the mixing proportions and $p(X/j,\theta_j)$ is the Probability Density Function PDF. θ is the set of parameters to be estimated : $\theta = (\alpha_1,\ldots,\alpha_M,P(1),\ldots,P(M))$.

If the random vector $X = (X_{i1},\ldots,X_{idim})$ follows a Dirichelet distribution, the joint density function is given by :

$$X = (X_{i1},\ldots,X_{idim}) = \frac{\tau(|\alpha|)}{\prod_{i=1}^{dim+1}\tau(\alpha_i)} \prod_{i=1}^{dim+1} X_i^{\alpha_i-1} \quad (3)$$

Since that each feature vector X may has an arbitrary dimension, the proposed method defines the fusion as a projection from one feature vector space (spectral bands) to another with a fixed dimentionnality. Accordingly, the feature-level fusion is done by projecting the vector X combining into one vector in the Fisher space. Thus, the generative model will have its impact on the final classification result through the projection of the extracted features in this new space.

SVM classifier is used to classify the fused features and the multi-temporal dataset of images. Given the generative model obtained by GDD with parameters θ, we compute for each sample X the Fisher score $U_d = \bigtriangledown_\theta log P(x|\theta)$ (the gradient of the log likehood of x for model θ). The Fisher kernel operates in the gradient space of the generative mode and provides a natural similarity measure between data samples. For each sample, this score is a vector of fixed dimentionality. Using this score, the Fisher Information matrix is defined as $\mathbb{I} = E_{X_i}\left\{{U_{X_i}}^T U_{X_i}\right\}$. After Fisher score normalization, we compute the Fisher kernel function on the basis of the Euclidean distance between the scores of the new sample and the training samples :

$$K(X,X^{'}) = U_{X_i}\mathbb{I}^{-1}U_{X_i'^T} \quad (4)$$

In the second stage, suppose our training set S consists of labels input vectors $(X_i,z_j), i = 1,\ldots,m$ where $X_i \in \mathbb{R}^n$ and $z_i \in \{\pm 1\}$. Given a kernel matrix and a set of labels z_i for each sample, the SVM proceeds to learn a classifier of the form,

$$z(x) = sign(\sum_i \alpha_i z_i)K(X_i,X)) \quad (5)$$

where the coefficients α_i are determined by solving a constrained quadratic program which aims to maximize the margin between classes. In our experiments we used the LIBSVM package. Our research deals with multi-class problem. The One-Vs-One approach is adopted to extend the proposed approach to multi-temporal hyperspectral classification.

4 EXPERIMENTAL RESULTS

The images set used in this experiment were jointly collected from the *Tunisian Institute of Remote-Sensing* (CNT) and the USGS library through the *Glovis Viewer* (Clark et al., 2007). Some earlier results and ground truth maps produced by the CNT were also used to perform the analysis of the selected test sites and for validation purposes.

The studied area is being within the line between the northwest tip of Djerba island on the southeast and Ras Yonga on the northwest. The centroid for the study area is at $33°50'16''N$ $10°07'41''E$. It is characterized by typical Mediterranean climate with maximum temperatures reaching, in the period between June and August (48°), whereas the coldest temperatures are measured between December and February. Due to the sea proximity, the climate of the study area slightly differs from the typical arid or semi-arid areas. The rainfall is very irregular and ranges between $150-240mm$ with an average of 30 rainy days per year (September/October). The region has been chosen not only due to the great interest from governmental and non-governmental organizations, but also because of the coexistence of several oasis such as *Mareth* and *Teboulbou* including various types of vegetations that change over time. The vegetation has a cover of 40% to 60%, comprising predominantly annual plants which develop from the autumn rains and persist until the end of the following spring. The vegetation cover is marked by the predominant species, *Palm*, *Lythracea (Henné)* and *Carex*. In this set of experiments, two time series are available, and thus, the season spectral variability can be well mapped through this set of images. An external digital elevation model and a reference land-cover map provided by the Tunisian Institute of Remote-Sensing (CNT) were also available for results assessment. Considering the differences in multi-temporal images acquisition, we first perform a pre-processing step. Images were geometrically corrected and geo-coded to the Universal Transverse Mercator (UTM) coordinate system based on a topographic map of the study area. 45 regularly distributed ground control points (GCPs) were used for this purpose. Then, Hyperion images were converted to reflectance and co-registered and re-sampled to 30×30 m with the nearest neighbor algorithm. The registration was performed at a subpixel level, obtaining a rootmean-squared error of about 0.65 pixels. After co-registration, all images were radiometrically corrected to surface reflectance by Atmosphereic CORrection Now (ACRON) software, which is based on the MODTRAN-4 radiative transfer code. In the following experiments, we se-

Table 1: Sequence of real images (red/green/blue (rgb) composition, bands [6,19,33]) and their corresponding true classification maps (first time serie: 2009/2010).

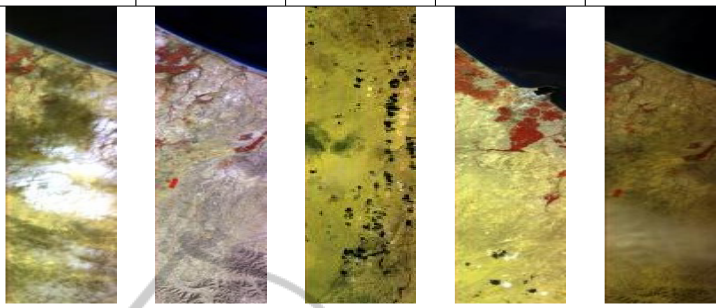
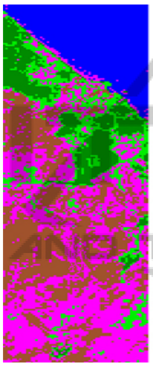
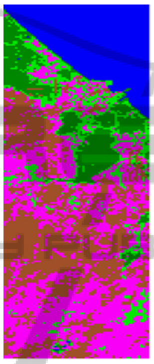
	03/06/2009	23/09/2009	27/12/2009	09/01/2010	30/04/2010
Real Hyperionimages					
Thematic map			True Map		

Table 2: Confusion matrix of the proposed approach for real experience set.

Percentages	Classification Data						
Reference Data	Carex	Lythracea	Bare soil	Palm	Water	Producer's Accuracy	Errors of Omission
Carex	243	17	6	5	0	88.47%	11.52%
Lythracea(henné)	29	514	18	7	11	87.35%	12.64%
Bare Soil	7	33	722	12	25	89.65%	10.66%
Water	2	5	13	279	8	89.96%	10.03%
Palm	0	9	12	19	308	87.01%	12.98%
User's accuracy	84.63%	87.56%	93.65%	84.58%	85.11%	OA=88.48%	
Errors of commission	15.63%	12.45%	06.78%	15.41%	14.28%		

Table 3: Evaluation of the Proposed Approach Aiganest Several Conventionnal Approaches.

Classifier	Overall Accuracy	Kappa
Proposed Approach	88.48	0.73
Maximum-Likelihood Classifier	81.46	0.69
Support Vector Machines (SVMs)	87.84	0.71

lected subset images from the whole temporal data set of images containing 3300 pixels-per-image in areas with substantial changes. Pixels belonging to unknown classes were not considered. Once the features were extracted from the reconstructed images, their potential use for image classification is investigated in the following steps. Tables 2 and 3 the obtained results.

5 CONCLUSIONS AND FUTURE WORKS

We have presented a novel fusion method in the context of multi-temporal hyperspectral images, mixtures of dirichlet and SVM classifiers. Accordingly, the generalization capacity of generative models can considerably be enhanced by training them discriminatively. Our experiments show that the cooperative generative-discriminative model can lead to a thematic maps with superior quality. There are two obvious extensions to the work that has been covered in this project. The first is to improve the estimation accuracy, and the second is to examine the possibility of using other 3D feature vectors.

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