TOWARDS THE DEFINITION OF A FLEXIBLE HYPERSPECTRAL PROCESSING CHAIN: PRELIMINARY CASE STUDY USING HIGH-RESOLUTION URBAN DATA

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ABSTRACT

In this paper, we describe a first approximation to the relevant issue of defining a part of the hyperspectral processing chain in a flexible manner. An ultimate goal of our study is to objectively quantify the impact of different (standard and new) processing stages on the generation of a realistic, user-oriented product in the context of an urban land cover mapping problem by means of hyperspectral data, selected in this work as an application case study for demonstration purposes. Although the proposed study is linked to a specific application domain, our experimental results reveal interesting considerations that may help image analysts in defining customized processing chains based on parameters which can be identified and objectively evaluated a priori, such as available sensor resolution or ancillary information. In addition, our study also demonstrates the importance of incorporating information related to both the spatial and the spectral domain in the different steps that comprise the hyperspectral processing chain; particularly when such chain can take advantage of the combined use of both sources of information as it is the case in the considered urban characterization application.

Index Terms— Hyperspectral imaging, data processing chain, urban characterization.

1. INTRODUCTION

The Hyperspectral Imaging Network (Hyper-I-Net)[1] is a four-year Marie Curie research training network[2] designed to build an interdisciplinary European research community focused on hyperspectral imaging activities [1]. One of the main activities of Hyper-I-Net is to settle the basis for the definition and testing of a flexible hyperspectral data collection and processing chain, in which individual elements can be integrated in such a way that the resulting chain can be dynamically adapted and reconfigured to satisfy the requirements of different application scenarios with little effort [2]. Since efficient hyperspectral data processing can be a really complex procedure, Hyper-I-Net approaches this problem in the context of a multidisciplinary collaboration so that the proposed activity can benefit from the complementary expertise of partners with focus in heterogeneous disciplines such as sensor design and calibration [3], pattern recognition, signal and image processing [4], and Earth observation related products [5]. The outcome of this joint activity is expected to be a set of hardware/software processing techniques able to deal with the complexity of hyperspectral data in an effective manner.

Generally, a hyperspectral data processing chain may be defined from two perspectives: 1) the provider's viewpoint, and 2) the user's viewpoint, where the first approach generally results in the first part of the chain, and the second approach results in a chain that is placed immediately afterwards. As a result, the first part of the chain comprises data correction activities such as sensor specification, geometric corrections, radiometric calibrations, etc [3]. Once the data has been preprocessed and geo-corrected, an information extraction process from collected data is needed for the second part of the chain. Several processing steps are available in the literature for this purpose [6], including data transformation (e.g., for dimensionality reduction), spectral matching (requiring centralized spectral libraries of multiple materials), feature extraction/selection, and data classification. Another important and essential requirement for the user-oriented part of the processing chain is to define precisely characterized and accurately validated high-level products. It is important to note that the elements in the user-oriented chain should be flexible enough to be accommodated not only to different application scenarios, but also to different hyperspectral imaging instruments with varying spatial and spectral resolutions.

In this work, we adopt a user-oriented perspective and further explore the suitability of defining a flexible hyperspectral processing chain in a specific and challenging application domain, namely, urban environment monitoring. This is a complex problem which may serve as an adequate case study to demonstrate the validity of our approach in a real application context, using a limited number of processing steps for a preliminary assessment focused on dimensionality reduction, feature selection/extraction, and data classification [6].

[1]http://www.hyperinet.eu
[2]http://cordis.europa.eu/mc-opportunities

The remainder of the paper is organized as follows. Section 2 describes the individual modules that will be used to form our proposed hyperspectral data processing chains. Section 3 describes eight different processing chains that will be evaluated as possible solutions for the considered problem. Section 4 validates the previously introduced processing chains using four different data sets, collected at multiple spatial and spectral resolution by the DAIS 7915 and ROSIS imaging spectrometers over the city of Pavia in Italy. Finally, section 5 concludes with some remarks and hints at plausible future research lines.

2. PROCESSING MODULES

This section is intended to provide a general overview of the processing modules that will be used for the second part (i.e., user-oriented) of the hyperspectral processing chain. Usually, these techniques are subdivided into different groups [6], such as spectral analyses, spatial analyses, and spatial/spectral analyses [6]. In our preliminary approach towards the development of a flexible hyperspectral processing chain, the following techniques have been considered:

- *Dimensionality reduction*. In hyperspectral imaging, there is clear need for methods that can reduce the dimensionality of the data to the right subspace without losing the original information that allows for the separation of classes. Standard spectral-based transformations such as the principal component analysis (PCA) and minimum noise fraction (MNF) will be used to transform input data to a dataset in a new uncorrelated coordinate system.

- *Feature selection*. Another interesting approach to reduce input data dimensionality has been the selection of the most highly relevant spectral bands for data exploitation. Along with traditional approaches, a new criterion based on maximum band separation index in terms of entropy is considered to select the most relevant input bands prior to the analysis.

- *Feature extraction*. One of the distinguishing properties of hyperspectral data, as collected by available imaging spectrometers, is the multivariate information coupled with a two dimensional pictorial representation amenable to image interpretation. However, feature extraction from hyperspectral data has been traditionally carried out without incorporating information on the spatially adjacent data. In this work, a multiscale texture features are tested to accurately characterize spatial information jointly with spectral information.

- *Classification*. Often, standard supervised classifiers, for high dimensional data like hyperspectral images, require large volumes of training data, which have to be obtained by costly ground truth measurements. In this work, advanced neural network classifier as Fuzzy Artmap is tested using limited training samples.

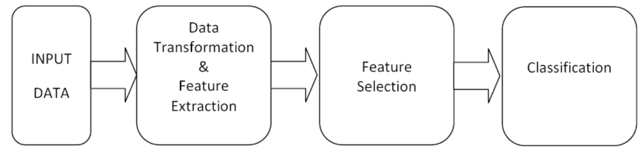

Fig. 1. Generic processing chain.

The impact of the processing modules above is objectively quantified in this work by implementing different chains made up of different combinations of such modules. In the following section, we propose eight different chains that will be substantiated by experiments using DAIS 7915 and ROSIS hyperspectral data collected over urban areas.

3. HYPERSPECTRAL PROCESSING CHAINS

A general, user-oriented hyperspectral processing chain can be described by a small group of interconnected processing modules or blocks. In fact, after pre-processing the input data set (e.g., via radiometric calibrations, geometric or atmospheric corrections, etc.) relevant information can be extracted from the scene. Assuming that we start from a corrected data set, three principal steps can be used to define a simple, user-oriented processing chain: data transformation and feature extraction, feature selection, and classification (see Fig. 1). It should be noted that the representation given in Fig. 1 is a very general one, in which each module can be implemented in very different ways [6]. For instance, feature extraction may be constituted by a spectral analysis procedure (e.g., PCA or MNF) or by a spatial-oriented processing (such as textures, semivariograms), or even by multiscale analysis (differential morphological profiles). On the other hand, feature selection provides best combinations of bands and/or features for a given problem, but the combination of these features is complex and thus, fast and efficient algorithms are necessary. Finally, classification may also be accomplished by different techniques, including approaches in the spectral domain (e.g., spectral angle-based classification), in the spatial domain (context-aware classifiers), or even in both domains (object-oriented classification, morphology-based classifiers).

In this work, we have selected representative techniques to generally describe each processing module. Specifically, feature extraction is described by PCA and MNF. Moreover, texture analysis is included in some chains to obtain best results from a spatial analysis perspective. On the other hand, the feature selection step is supplied by separation index analysis, which permits an efficient selective procedure to choose best

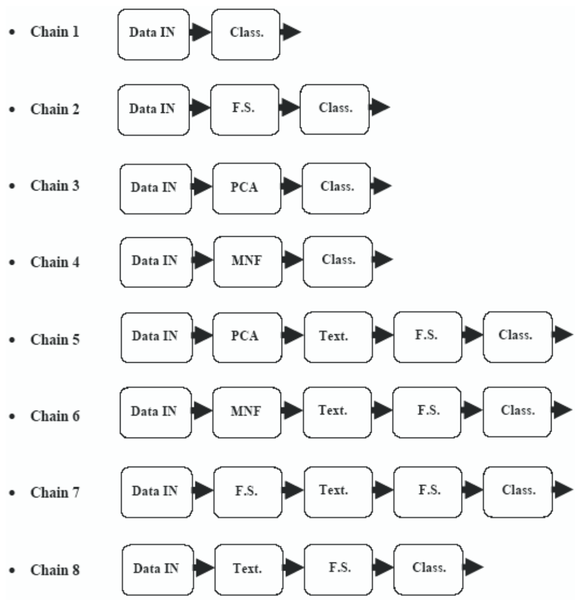

Fig. 2. Processing chains analyzed.

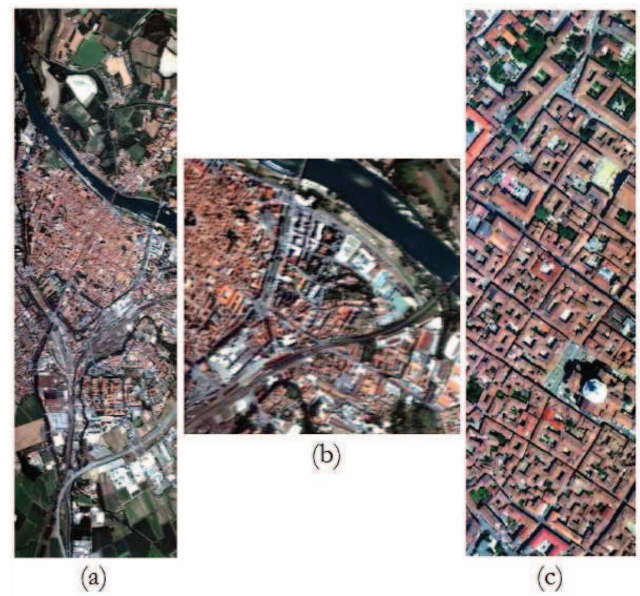

Fig. 3. DAIS 7915 (a-b) and ROSIS (c) hyperspectral scenes.

subsets, starting from high-dimensional data. Finally, each proposed chain contains a classification block performed by a Fuzzy Artmap Neural Network. Using the modules above, eight different processing chains were tested in this work as shown in Fig. 2, where the term "Data IN" denotes the input data set, "F.S." stands for *feature selection*, "Text." stands for *texture analysis*, and "Class" stands for *classification*.

4. EXPERIMENTAL RESULTS

4.1. Hyperspectral data sets

The data sets used in this work have been collected in the framework of the DLR HysenS 2002 flight campaign [3] over the town of Pavia, in northern Italy. The data sets were collected around noon local time on July 8th, 2002, by the DAIS 7915 and ROSIS sensors aboard a Dornier 228 aircraft operated by DLR. Each data set is atmospherically corrected thanks to additional atmospheric and radiation data collected at the same time on the ground. The four flight lines resulted in four data stripes from each of the two sensors. The height of about 1890 meters resulted in a ground spatial resolution of 2.5 m for the DAIS 7915 data, and 1 m for the ROSIS data. The stripes produced by DAIS 7915 were partially overlapped, while the narrower field of view of ROSIS resulted in significant gaps between adjacent stripes. Our experiments are focused on the analysis of urban regions, so only the second obtaned flight line was used as a representative of a high-density urban environment. Specifically, the following data sets have been selected and will be used in our experiments in this work:

- *Data set 1*. The first DAIS 7915 data set considered in this work, with size of 512×1729 pixels and 80 spectral bands (in the spectral range from 496 nm to 12 μm), is displayed in Fig. 3(a). This scene has four ground-truth classes available: urban, water, streets, and shadow.

- *Data set 2*. The second DAIS 7915 data set corresponds to a spatial and spectral subset of the first data set. Its size is 400×400 pixels and comprises 40 spectral bands in the spectral range from 496 nm to 1.756 μm [see Fig. 3(b)]. The ground-truth for this scene is more detailed, with nine ground-truth classes available including three urban-type classes, three vegetation-type classes, water, streets and shadow.

- *Data set 3*. A ROSIS hyperspectral data set [see Fig. 3(c)] was also selected for experiments. It covers the historic center of Pavia, and comprises 223×712 pixels with 102 spectral bands in the spectral range from 430 nm to 770 nm. This scene has four ground-truth classes available: urban, streets, shadow and water.

- *Data set 4*. Finally, another DAIS 7915 data set (not displayed) was used in experiments. The data comprises the same zone in the ROSIS data set [displayed in Fig. 3(c)] for which ground-truth information is available. It was obtained to allow comparisons of processing outcomes on the same spatial area but imaged using two different sensors. The size in pixels of the data set is 76×257, and it comprises 80 spectral bands like the first data set. This scene also has four ground-truth classes: urban, streets, shadow and water.

Table 1. Overall classification accuracies (in percentage) for different processing chains and data sets.

		Data set 1			Data set 2			Data set 3			Data set 2		
Processing chain	**Textures**	1%	5%	10 %	1%	5%	10 %	1%	5%	10 %	1%	5%	10 %
1	–	82.26	84.65	88.37	66.28	85.59	88.07	80.31	80.36	87.26	90.09	90.47	88.22
2	–	79.40	88.21	87.35	59.42	77.58	82.33	80.31	80.36	88.16	90.57	91.85	91.42
3	–	88.32	88.38	85.80	70.15	72.92	84.56	82.80	83.23	82.67	89.27	92.90	93.07
4	–	78.66	86.56	89.16	84.55	90.22	90.96	82.80	83.23	82.67	93.56	95.06	94.99
	3×3	87.16	89.60	83.36	62.54	83.59	85.67	80.31	81.71	86.14	91.52	95.64	95.42
5	5×5	89.10	92.08	84.87	71.70	85.98	86.98	80.31	84.48	85.32	90.26	94.50	94.01
	7×7	87.32	88.36	84.74	73.33	85.00	88.14	80.31	82.98	84.24	86.09	92.56	92.46
	3×3	73.01	86.11	90.86	81.06	89.86	90.92	80.31	81.00	84.27	93.92	88.41	90.76
6	5×5	70.52	85.27	78.68	79.77	88.37	88.23	80.31	81.37	84.31	89.10	93.51	93.62
	7×7	68.41	86.00	84.76	80.65	88.01	90.52	80.31	82.46	88.83	84.68	91.03	91.83
	3×3	80.03	80.22	87.15	65.59	69.70	76.73	80.31	80.31	88.83	85.72	84.91	89.50
7	5×5	64.90	76.98	85.66	73.17	69.93	78.37	80.31	83.98	87.52	80.76	88.40	88.92
	7×7	80.90	78.67	84.47	74.11	64.03	81.38	78.44	80.64	71.87	70.27	89.70	88.40
	3×3	65.05	76.31	79.53	52.11	55.00	75.35	80.31	80.21	82.29	61.87	89.28	85.78
8	5×5	60.63	71.91	77.28	59.70	69.57	76.35	80.25	79.86	81.40	69.34	87.54	87.57
	7×7	56.29	59.41	74.95	64.93	66.69	64.12	79.50	83.30	79.72	62.88	87.15	86.20

4.2. Experimental validation of processing chains

For illustrative purposes, Table 1 shows the overall accuracies obtained by the different processing chains on the four data sets tested. In all cases, different percentages of training samples (1%, 5% and 10%) and different sizes for the spatial window used to calculate textures (3×3, 5×5 and 7×7) were used when the processing chain included a "Class" module (always supervised) or a "Text." module.

From Table 1 it is possible to have a general perspective on the obtained results. In general, direct classification of the input data set (chain 1) provides good results. The accuracy increases when the size of the training set is increased. After applying band selection on the original data (chain 2), accuracies are only slightly better. Dimensional reduction (chains 3 and 4) increases accuracies, with the best results obtained when MNF is used except for data sets 1 and 3. Here, good results are also obtained using small training sets. Texture analysis after PCA or MNF (chains 5 and 6) also increased classification accuracies. We experimentally observed that texture analysis reduces classification errors in large objects like the water basins, but in those cases it is more difficult to derive accurate information on object borders. Finally, chains 7 and 8 produce the worst overall results both in terms of accuracy and processing time (resulting from the large number of texture features needed).

5. CONCLUSIONS AND FUTURE WORK

In this paper, we have taken a first step towards the challenging goal of defining a flexible hyperspectral data processing chain by evaluating several custom-designed chains in the context of an urban classification problem. Our experimental results, obtained after combining different basic processing modules, provide interesting findings. Althouth hyperspectral data provides very rich information that can be interpreted in spectral terms to achieve high classification accuracies, our study demonstrates that the joint use of spatial and spectral information can significantly improve classification results, in particular, when spatial information provides an added value to spectral information, as it is the case in the considered application. Given the preliminary nature of our study, further work should comprise testing of additional processing chains and case studies in order to try to derive general observations across different application domains.

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