Spectral-Spatial Classification of Spectral Images with Super Pixel-Based Discriminative Spares Model

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Abstract

Hyper spectral imaging has been widely used in the remote sensing which can acquire images from hundreds of narrow contiguous bands, spanning the visible-to-infrared spectrum. In the hyper spectral image (HSI), each pixel is a high-dimensional vector and its entries represent the spectral responses of different spectral bands. In the existing system, sparse representation has been also applied in HSI classification, using the observation that hyper spectral pixels approximately lie in a low-dimensional subspace spanned by dictionary atoms from the same class. In this paper the system proposed a super pixel-based discriminative sparse model (SBDSM) to effectively exploit the spatial information of the HSI.
Keywords: SBDSM, SVM, MLR

I. Introduction

Hyper spectral imaging has been widely used in the remote sensing which can acquire images from hundreds of narrow contiguous bands, spanning the visible-to-infrared spectrum. In the hyper spectral image (HSI), each pixel is a high-dimensional vector and its entries represent the spectral responses of different spectral bands. The highly informative spectral information of the HSI pixels has many applications, such as classification, target detection, anomaly detection, spectral UN mixing, and others. In the last decades, HSI classification has been a very active research topic in the remote sensing. Given a representative training set for each class, the objective of the classification is to assign each pixel to one of the classes based on its spectral characteristics. To achieve this, many discriminative approaches have been developed. Among these, the support vector machine (SVM) and multinomial logistic regression (MLR) have demonstrated to be very powerful. Dynamic or randomsubspace, which are new version of random forest and exploit the inherent subspace structure of hyper spectral, have proved to be an effective way for analyzing and classifying HSIs. The sparse representation, which can sparsely decompose the input pixel on an over-complete dictionary, is another widely used classifier. Recently, metric learning has also been successfully explored in hyper spectral image processing, which has formulated a novel and adaptive metric learning method for classification and object recognition.

In addition, some other classification approaches have focused on the design of effective feature extraction or reduction techniques, such as the principle component analysis, clonal selection feature-selection, kernel discriminative analysis, and semi supervised discriminative locally enhanced alignment. Note that, kernel has been widely used in the aforementioned approaches, since it can improve the class separability Hyper spectral Imagery (HSI) captures detailed terrestrial information with high resolution in both the spatial and spectral dimensions [1]. While this level of detail is important in many remote sensing tasks such as object detection and material discrimination, acquiring HSI can be more prohibitive than acquiring multispectral imagery (MSI). For example, sensor fabrication cost and image acquisition time (for comparable SNR per spectral bin) increases as the sensor's bandwidth narrows. The financial cost differential leads to MSI being more accessible than HSI, both in terms of currently flown instruments and archived data. In applications where high temporal resolution is required (e.g., due to high velocity of the imaging platform), the decreasing SNR per bin due to shorter acquisition times might make it more desirable to combine HSI bins to collect imagery with MSI-level spectral resolution.1Recent results have shown the potential to use MSI to obtain HSI-level resolution images by performing spectral super-resolution.

The task of super-resolution is to use prior knowledge of the signal statistics in post-processing to infer the content of the signal at a finer resolution than the original observations. In photographic images, signal models based on the notion of sparsity (i.e. images can be described by a small number of atoms in a potentially large dictionary) have been very successful in spatial super-resolution applications. An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. In a (8-bit) greyscale image each picture element has an assigned intensity that ranges from 0 to 255. A grey scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey. A normal grayscale image has 8 bit colour depth = 256 grayscales. A "true colour" image has 24 bit colour depth = 8 x 8

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x 8 bits = 256 x 256 x 256 colours = ~16 million colours.Some grayscale images have more grayscales, for instance 16 bit = 65536 grayscales. In principle three grayscale images can be combined to form an image with 281,474,976,710,656 grayscales. There are two general groups of 'images': vector graphics (or line art) and bitmaps (pixel-based or 'images'). Some of the most common file formats are: GIF — an 8-bit (256 colour), non-destructively compressed bitmap format. Mostly used for web. Has several sub-standards one of which is the animated GIF. JPEG — a very efficient (i.e. much information per byte) destructively compressed 24 bit (16 million colours) bitmap format. Widely used, especially for web and Internet (bandwidth-limited). TIFF — the standard 24 bit publication bitmap format. Compresses non-destructively with, for instance, Lempel-Ziv-Welch (LZW) compression. PS — Postscript, a standard vector format. Has numerous sub-standards and can be difficult to transport across platforms and operating systems. PSD – a dedicated Photoshop format that keeps all the information in an image including all the layers. Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter relationships between objects. They portray spatial information that we can recognize as objects.

Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form. An image is digitized to convert it to a form which can be stored in a computer's memory or on some form of storage media such as a hard disk or CD-ROM. This digitization procedure can be done by a scanner, or by a video camera connected to a frame grabber board in a computer. Once the image has been digitized, it can be operated upon by various image processing operations. Image processing operations can be roughly divided into three major categories, Image Compression, Image Enhancement and Restoration, and Measurement Extraction. It involves reducing the amount of memory needed to store a digital image. Image defects which could be caused by the digitization process or by faults in the imaging set-up (for example, bad lighting) can be corrected using Image Enhancement techniques. Once the image is in good condition, the Measurement Extraction operations can be used to obtain useful information from the image. Some examples of Image Enhancement and Measurement Extraction are given below. The examples shown all operate on 256 grey-scale images. This means that each pixel in the image is stored as a number between 0 to 255, where 0 represents a black pixel, 255 represents a white pixel and values in-between represent shades of grey. These operations can be extended to operate on colour images. The examples below represent only a few of the many techniques available for operating on images. Details about the inner workings of the operations have not been given, but some references to books containing this information are given at the end for the interested reader As we mentioned in the preface, human beings are predominantly visual creatures: we rely heavily on our vision to make sense of the world around us. We not only look at things to identify and classify them, but we can scan for differences, and obtain an overall rough feeling for a scene with a quick glance. Humans have evolved very precise visual skills: we can identify a face in an instant; we can differentiate colors; we can process a large amount of visual information very quickly.

However, the world is in constant motion: stare at something for long enough and it will change in some way. Even a large solid structure, like a building or a mountain, will change its appearance depending on the time of day (day or night); amount of sunlight (clear or cloudy), or various shadows falling upon it. We are concerned with single images: snapshots, if you like, of a visual scene. Although image processing can deal with changing scenes, we shall not discuss it in any detail in this text. For our purposes, an image is a single picture which represents something. It may be a picture of a person, of people or animals, or of an outdoor scene, or a microphotograph of an electronic component, or the result of medical imaging. Even if the picture is not immediately recognizable, it will not be just a random blur.Image processing involves changing the nature of an image in order to either1. Improve its pictorial information for human interpretation,2. Render it more suitable for autonomous machine perception.

We shall be concerned with digital image processing, which involves using a computer to change the nature of a digital image. It is necessary to realize that these two aspects represent two separate but equally important aspects of image processing. A procedure which satisfies condition, a procedure which makes an image look better may be the very worst procedure for satisfying condition. Humans like their images to be sharp, clear and detailed; machines prefer their images to be simple and uncluttered. Suppose we take an image, a photo, say. For the moment, lets make things easy and suppose the photo is black and white (that is, lots of shades of grey), so no colour. We may consider this image as being a two dimensional function, where the function values give the brightness of the image at any given point. We may assume that in such an image brightness values can be any real numbers in the range (black) (white).

A digital image from a photo in that the values are all discrete. Usually they take on only integer values. The brightness values also ranging from 0 (black) to 255 (white). A digital image can be considered as a large array of discrete dots, each of which has a brightness associated with it. These dots are called picture elements, or more simply pixels. The pixels surrounding a given pixel constitute its neighborhood. A neighborhood can be characterized by its shape in the same way as a matrix: we can speak of a neighborhood,. Except in very special circumstances, neighborhoods have odd numbers of rows and columns; this ensures that the current pixel is in the centre of the neighborhood.

II. PREVIOUS WORKS

In the existing system, the algorithm implements the following two main steps: 1) learning, where the posterior probability distributions are modeled by an MLR combined with a subspace projection method, and 2) segmentation, which infers an image of class labels from a posterior distribution built on the learned subspace classifier and on a multilevel logistic (MLL) prior on

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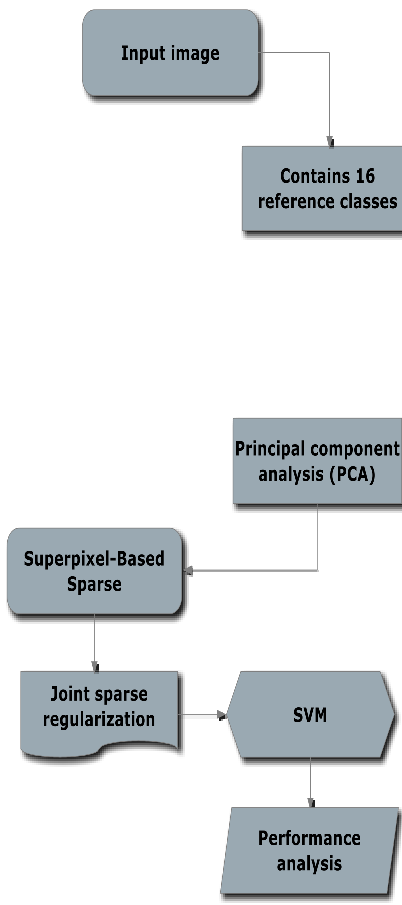
the image of labels. If a subspace projection method with the MLR which is further combined with spatial–contextual information, which will be shown to provide a good characterization of content of hyperspectral imagery in both the spectral and the spatial domain. The proposed Bayesian method exhibits good discriminatory capability when dealing with ill-posed problems, i.e., limited training samples versus high dimensionality of the input data. In addition to this, we emphasize that the proposed approach provides class posterior probabilities which are crucial to the complete posterior probabilities, such that the final MAP segmentation can benefit from the inclusion of both the spectral and the spatial information available in the original hyperspectral data.It do not consider the spatial context. It may not be sufficiently utilized. It may not be robust enough to represent each test pixel. The fixed-size region may not effectively exploit the spatial information of the HSI. It still not possibly being robust to represent each pixel to be classified.

III. PROPOSED SYSTEM

A super pixel-based discriminative sparse model (SBDSM) is proposed to effectively exploit the spatial information of the HSI. The proposed SBDSM can effectively capture the correlations of pixels in each super pixel by utilizing the joint sparse model. Generally, the proposed SBDSM is composed of the following four parts, which are further described in the following sections: 1) super pixel map creation; 2) super pixel-based sparse representation; c) discriminative dictionary learning; and d) super pixel classification. The class-labeled OMP is based on the assumption that each training sample should be ideally represented by dictionary atoms from the same class. Therefore, to make the dictionary compact, representative and discriminative, the SBDSM can apply the discriminative K-SVD algorithm to simultaneously learn one dictionary and one classifier. K-SVD is also known to be a very computationally intensive algorithm. A super pixel-based sparse model that can adaptively exploit the spatial contexts of a HSI is proposed. A reduction in computational cost is obtained with a super pixel-based classification strategy. A class-labeled OMP algorithm is proposed for accelerating the dictionary learning process while enforcing high discriminability on sparse coefficients for training a classifier. The proposed SBDSM algorithm over several well-known classification approaches in terms of both classification accuracies and computational speed.

A. *Architechture diagram of proposed system*



Testing of Product-System testing is the stage of
implementation,which aimed at ensuring that system works accurately and efficiently before the live operation commence. Testing is the process of executing a program with the intent of finding an error. A good test case is one that has a high

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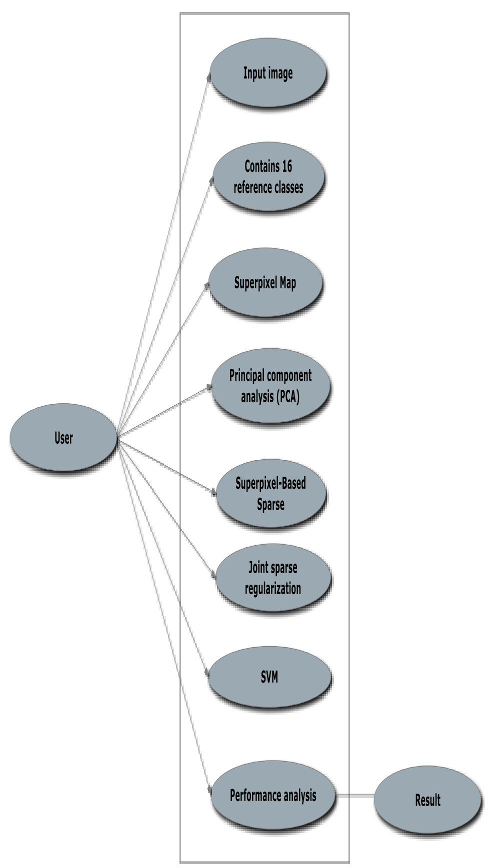
probability of finding an error. A successful test is one that answers a yet undiscovered error. Testing is vital to the success of the system. System testing makes a logical assumption that if all parts of the system are correct, the goal will be successfully achieved. The candidate system is subject to variety of tests-on-line response, Volume Street, recovery and security and usability test. A series of tests are performed before the system is ready for the user acceptance testing. Any engineered product can be tested in one of the following ways. Knowing the specified function that a product has been designed to from, test can be conducted to demonstrate each function is fully operational. Knowing the internal working of a product, tests can be conducted to ensure that “al gears mesh”, that is the internal operation of the product performs according to the specification and all internal components have been adequately exercised.Unit testing is the testing of each module and the integration of the overall system is done. Unit testing becomes verification efforts on the smallest unit of software design in the module. This is also known as ‘module testing’. The modules of the system are tested separately. This testing is carried out during the programming itself. In this testing step, each model is found to be working satisfactorily as regard to the expected output from the module. There are some validation checks for the fields. For example, the validation check is done for verifying the data given by the user where both format and validity of the data entered is included. It is very easy to find error and debug the system. Integration testing:Data can be lost across an interface, one module can have an adverse effect on the other sub function, when combined, may not produce the desired major function. Integrated testing is systematic testing that can be done with sample data. The need for the integrated test is to find the overall system performance. There are two types of integration testing. They are: Top-down integration testing. Bottom-up integration testing .White box testing White Box testing is a te st case design method that uses the control structure of the procedural design to drive cases. Using the white box testing methods, we derived test cases that guarantee that all independent paths within a module have been exercised at least once. Black box testing is done to find incorrect or missing function ,1.Interface error 2.Errors in external database access 3.Performance errors 4.Initialization and termination errors.In ‘functional testing’, is performed to validate an application conforms to its specifications of correctly performs all its required functions. So this testing is also calld ‘black box testing’. It tests the external behavior of the system. Here the engineered product can be tested knowing the specified function that a product has been designed to perform, tests can be conducted to demonstrate that each function is fully operational. Validation testing- After the culmination of black box testing, software is completed assembly as a package, interfacing errors have been uncovered and corrected and final series of software validation tests begin validation testing can be defined as many, but a single definition is that validation succeeds when the software functions in a manner that can be reasonably expected by the customer. User acceptance of the system is the key factor for the success of the system. The system under consideration is tested for user acceptance by constantly keeping in touch with prospective system at the time of developing changes whenever required.

B. Flowdiagram of Proposed system



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Modules**:** Input image, Super pixel Map,Super pixel-Based Sparse Representation,SVM, Performance analysis.

Input image The image contains 16 reference classes, most of which are different types of crops (e.g., corns, soybeans, and wheat).The system show the color composite of the Indian Pines image and the corresponding reference data.

The image has a spatial resolution of 3.7 m per pixel and is of size 512 × 217 × 224. As for the Indian Pines image, 20 water absorption spectral bands are discarded and the reference image contains 16 different classes

Super pixel Map-The super pixel map is created by applying an efficient over segmentation approach on the HSI. Then, the HSI can be clustered into L non-overlapping super pixels. To reduce the computational cost, before the segmentation, principal component analysis (PCA) is applied on the original HSI. Since the principal component corresponding to the highest Eigen-value (i.e., the first principal component) should contain the most important information in terms of variation for the whole HSI, it is used as the base image for the over segmentation.

Super pixel-Based Sparse Representation-When the super pixel map has been created, it can be utilized with the original HSI to extract super pixels. Each super pixel is composed of a number of spectral pixels [y i, 1 , y i, 2 ,...] , which can be arranged into a matrix Y Spi.Then, pixels within each super pixel are assumed to have very similar spectral characteristics and their correlations can be exploited by joint sparse regularization.

Specifically, the joint regularization requires that pixels within each super pixel YSPi shall be simultaneously decomposed by linear combinations of a few common atoms from a dictionary.

SVM-The Super pixel-SVM is a combination of the super pixel segmentation and SVM classifier, which first uses the method to create the super pixels and then applies the SVM to determine the class label of each super pixel.Since the original SVM can only classify each spectral pixel, majority voting is used to fuse the SVM's results within each super pixel. The SVM classifier was implemented with the LIBSVM library and the spectral-only Gaussian kernel was adopted without considering spatial information.

C. *Performance analysis*

Therefore, 80% of the number of the training samples is chosen as the dictionary size used in our experiments.

Furthermore, as the dictionary size decreases from 70% to 40% of the number of the training samples, the overall accuracies of the proposed SBDSM method slightly decreases.

It should be also noted that when the dictionary size reaches about 20% of the number of the training samples, the overall accuracies of the proposed SBDSM method for all the test images are higher than 87%.

IV. RESULT ANALYSIS

Fig. 1: Output

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Fig. 2: Output

Fig. 3: Output

V. CONCLUSION AND FUTURE WORK

The proposed SBDSM can classify one super-pixel at a time and, thus, is more efficient than other sparsity-based approaches for HSI classification. In addition, the size and shape of each super pixel can be adaptively changed according to the spatial structures of the HIS, and therefore, the spatial contexts can be effectively exploited. Furthermore, by utilizing the class label information for both training samples and dictionary atoms, a class-labeled OMP algorithm for the dis-criminative K-SVD learning algorithm is proposed, which can efficiently train both a discriminative dictionary and a classi-fier.

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