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SPATIAL ENTROPY BASED MUTUAL INFORMATION IN HYPERSPECTRAL BAND SELECTION FOR SUPERVISED CLASSIFICATION

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Abstract. Hyperspectral band image selection is a fundamental problem for hyperspectral remote sensing data processing. Accepting its importance, several information-based band selection methods have been proposed, which apply Shannon entropy to measure image information. However, the Shannon entropy is not accurate in measuring image information since it neglects the spatial distribution of pixels and is computed only from a histogram. This paper investigates the potential of spatial entropy in measuring image information and proposes a new mutual information (MI) band selection method based on the spatial entropy. Then selected band images are validated for supervised classification via Support Vector Machine (SVM). Using a hyperspectral AVIRIS 92AV3C dataset, experiment results show that with 20 images selection from 220 bands, the supervised classification accuracy can reach 90.6%. Comparison with a previous Shannon entropy-based band selection method shows that the proposed method selects band images which can achieve more accurate classification results.

Key words. Spatial entropy, mutual information, band selection, support vector machine, classification, hyperspectral remote sensing data

1. Introduction

Hyperspectral sensors measure hundreds of contiguous spectral bands with narrow spectral intervals simultaneously, which can provide fine, detailed and large volume spectral information. For example, an Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) is a premier instrument in the realm of Earth Remote Sensing [9]. It is a unique optical sensor that delivers calibrated images in 224 contiguous spectral bands with wavelengths from 0.4 μm to 2.5 μm. Hyperspectral sensors benefit the potential to detect targets and classify materials with high accuracy.

High dimensionality of the hyperspectral remote sensing images also calls for effective and efficient feature selection methods. For example, for a land use classification task, it is unnecessary to process all spectral bands from the hyperspectral images since some bands may contain less discriminatory information than the others. Besides, the computational cost for hyperspectral image processing with all bands is high; e.g., as the dimension increases, say 224, the computational cost for classification will be unendurable. Therefore, it is an advantage to identify bands that conveys more information.

Band selection refers to the selection of band images with relevant information or with weak correlation [6]. Information-based band selection is an active research topic recently [3, 5, 7, 10], which generally applies Shannon entropy or its variations, e.g., mutual information (MI), as the measurement evaluating the image information. In [10], the Shannon entropy was directly applied to band selection. Band images are ranked in terms of entropy values and ones with higher entropy

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values are selected. Since the Shannon entropy is computed based on a single image, without reference to any ground truth or benchmark, its variation, mutual information (MI), is introduced. MI measures the information shared between each band image and a reference, i.e., the ground truth, and images with higher MI values are selected. In [3], the authors introduced a method using MI based clustering to deal with multispectral images selection. In [7], a MI estimation method was introduced and the band selection method was developed with the objective to choose band images which maximizes the joint MI value.

Each pixel in remote sensing images has spatial attributes, such as row and column, and non-spatial attributes, such as intensity. Even though the existing information-based band selection methods based on Shannon entropy can give good results in many cases, the Shannon entropy is calculated only based on the statistics of the non-spatial attributes. Therefore, it leads to an incomplete evaluation of image information by ignoring spatial distribution of pixels. We will illustrate the consequent problem by the following example.

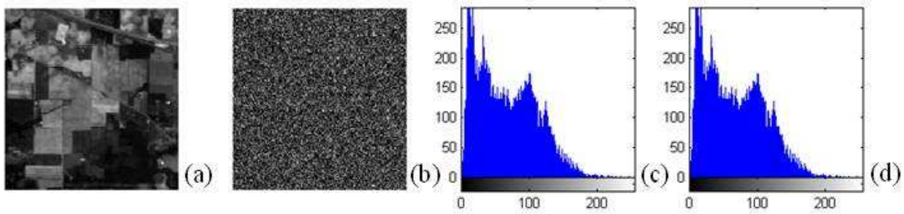

FIGURE 1. Comparison between a qualified remote sensing image and a noise image with the same histogram: (a) Qualified image, (b) Noise image, (c) Histogram of (a), (d) Histogram of (b).

Fig.1 (a) shows a remote sensing image of an area and Fig.1 (b) is a noise image of the same area. Given an image classification task, Fig.1 (b) gives no valuable information since all pixels are noise contaminated while Fig.1 (a) may give relevant information since distinct patterns can be visually observed. Figs.1 (c) and (d) are the image histograms of Figs.1 (a) and (b), respectively. The two histograms indicate that two images have the identical intensity distribution.

In this example, the two images have the identical histograms; if we use the Shannon entropy to measure the image information in Figs.1 (a) and (b), their entropy would be the same value of 0.4481. In this case, the Shannon entropy fails in discriminating the information difference between Figs.1 (a) and (b).

Spatial entropy is the extension of the Shannon entropy with the spatial configuration, which measures the distribution of a non-spatial attribute in the spatial domain [4, 14]. In this paper, we propose to use spatial entropy measuring band image information and develop a new information-based band selection method considering both the pixels' intensity and the spatial location in an image. The main contributions are summarized below:

First, this paper introduces a new spatial entropy-based mutual information (SEMI) function as the image information measurement. The SEMI function is derived from the spatial entropy model in [4, 14] and the classic mutual information definition [11]. SEMI quantifies the shared information between the band image and the reference image with the images' spatial and non-spatial attributes, i.e., the pixels' intensity and location.