TARGET DISCRIMINATION VIA OPTIMAL WAVELENGTH BAND SELECTION WITH SYNTHETIC HYPERSPECTRAL IMAGERY

Zhong Lu, Andrew Rice, Juan Vasquez

Numerica Corporation
2661 Commons Blvd.
Beavercreek, Ohio 45431

John Kerekes

Rochester Institute of Technology
54 Lomb Memorial Drive
Rochester, New York 14623

ABSTRACT

Hyperspectral imaging (HSI) tracking is an emerging area of research, employing HSI instruments and exploitation techniques with the goal to track moving objects within challenging environments and across frequent ambiguities. Dimensionality reduction through wavelength band selection can help resolve such ambiguities quickly and thereby improving the feature-aided tracking performance in real-time platforms. A novel band selection algorithm is proposed to determine the optimal subset of bands that contain important information for classification. A series of studies have been conducted to evaluate the band selection algorithm and to demonstrate the benefits of optimal wavelength band selection. Synthetic HSI data using the image simulation code DIRSIG has been a key enabler to this effort. A suite of end-to-end synthetic experiments have been conducted, which include high-fidelity moving-target urban vignettes, synthetic hyperspectral rendering, and full image-chain treatment of the various sensor models.

Index Terms— hyperspectral imaging, band selection

1. INTRODUCTION

Hyperspectral data can provide abundant information across the spectrum from visible bands through infrared bands by sampling in a high spectral resolution. This high spectral resolution, however, also introduces a high dimensionality to the data, making the classification difficult for classification algorithms due to the "curse of dimensionality" [1]. As a result, numerous techniques have been proposed for the dimensionality reduction. First, principal component analysis (PCA) and wavelet based techniques achieve impressive dimensionality reduction while preserving most of the image energy [2, 3], but they are not necessarily optimized to discriminate arbitrary materials. Second, the orthogonal space projection based technique combines orthogonal bands that best discriminate pairs of classes to achieve the overall discrimination [4]. The performance of this approach degrades when the intersection of the "orthogonal bands" is empty. The band selection approaches have additional benefits over other dimensionality reduction techniques since it happens closer to the detector reducing computational bandwidth through the entire processing chain. Last, other band selection techniques, such as the spectral angle mapper (SAM) based technique [5], have also been proposed to optimize the discrimination of different classes. Many of these techniques require the number of selected bands as *a priori* information.

Presented in this paper is a novel optimal band selection (OBS) algorithm that addresses the optimal separation of classes as well as the number of bands to be selected. The performance of the selected bands and the full spectrum are compared in terms of classification accuracy. Also, this OBS algorithm is compared to the relevance based band selection algorithm for the same number of selected bands. The goal is to select an optimal subset of bands from the full spectrum while maintaining comparable classification accuracy. The benefits of band selection are to avoid the "curse of dimensionality" and to speed up the classification process in real-time platforms.

2. DATA DESCRIPTION

Synthetic data generated from the Digital Imaging Remote Sensing Image Generation (DIRSIG) tool [7] has been a key enabler to this project. Using the DIRSIG tool, data is simulated for pixels from painted surfaces of four different vehicles (shown in Table 1) in terms of remotely measured sensor-reaching radiance. This radiance is measured in 211 contiguous bands in 10 nm intervals from 0.4 μm to 2.5 μm. This represents the spectrum that contains reflective properties of materials.

The synthetic data accounts for possible dirt and rust on the surface of vehicles, atmospheric attenuation, solar angles etc. As a result, the signatures of materials vary pixel by pixel. A representative set of signatures is generated by taking the average of pixels from each vehicle class. (Fig. 1)

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TABLE 1: List of vehicles and the number of pixels

Vehicles / Classes	# All Pixels	# Training Pixels	# Tested Pixels
White Coupe	450	300	150
Maroon Coupe	436	300	136
Blue Truck	404	300	104
Brown Truck	419	300	119

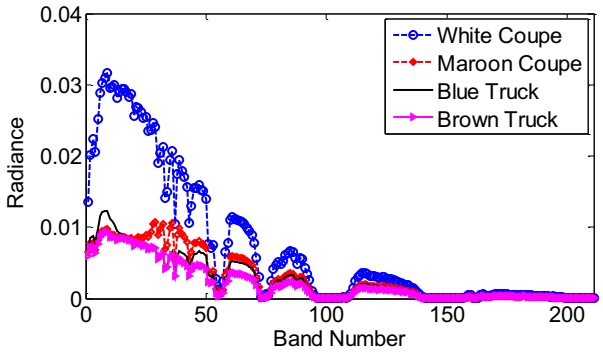

Figure 1: Signatures from four different vehicles.

3. METHOD

This section explains the proposed OBS algorithm in detail. A multi-objective distance is proposed as an overall discrimination measure for multiple vehicle classification. This distance is maximized as a sequential forward floating search (SFFS) method is employed to find the optimal combination of bands [8]. The number of selected bands is determined by comparing performance of optimal band combinations of different dimensions.

3.1. Distance of classes

First, the distance between two signature vectors x and y is defined as a mixed measure of SAM and spectral information divergence (SID) [9] as the following:

$$d(x,y) = \mathrm{SID}(x, y) \times \tan(\mathrm{SAM}(x,y)) \quad (1)$$

$$\mathrm{SAM}(x, y) = \cos^{-1} \frac{\langle x,y \rangle}{\|x\| \cdot \|y\|} \quad (2)$$

$$\mathrm{SID}(x,y) = D(x\|y) + D(y\|x) \quad (3)$$

where $D(x\|y)$ is the cross entropy (also known as Kullback-Leibler divergence) of x with respect to y. This entropy measures the discrepancy of self information distributions of x vs. y across the spectrum. It is defined as the following:

$$D(x\|y) = \sum_j p_j \log(p_j / q_j) \quad (4)$$

$$p_j = \frac{x_j}{\sum_{k=1}^{L} x_k}, \quad q_j = \frac{y_j}{\sum_{k=1}^{L} y_k} \quad (5)$$

where L is the number of bands in the spectrum. Due to the asymmetric property of the cross entropy measure, SID is defined as in Equation (3) to satisfy properties of a distance metric.

The distance defined above can be used as the distance between two classes by assuming the class signature is well represented by the average of training pixels computed at each wavelength. However, this distance is not meaningful when the signature has only one dimension (i.e., a scalar) due to the properties of SID. Consequently, an alternative distance metric, the Fisher discriminant ratio (FDR) [8], is adopted to measure the separation of classes in one dimensional case. FDR is defined as:

$$\mathrm{FDR} = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2} \quad (6)$$

where μ_1, μ_2, σ_1^2 and σ_2^2 are the averages and variances of pixel values from corresponding classes.

Second, the distances of class pairs must be extended to multiple-class scenarios. To integrate these distances, a multi-objective distance average is defined as:

$$d_{avg} = \left(\frac{1}{M} \sum_{j=1}^{M} d_j^{-1}\right)^{-1} \quad (7)$$

where M is the number of class pairs. In general, d_{avg} increases as the sum of individual distances increases. Moreover, d_{avg} defined above penalizes combinations of very large distances and very small distances even if the sum of distances is large.

3.2. Sequential forward floating search

The SFFS algorithm selects the best combination of bands by optimizing the average distance defined in Equation (7). The following steps summarize the algorithm:

Step 1: Find the best band that maximizes the average FDR.

Step 2: Find the best combination of two bands by adding one additional band to the selected band.

Step 3: For k selected bands, add one additional band, and select the best k+1 combination.

Step 4: Replace the least significant selected band by the newly added band if it results in a greater d_{avg}.

Step 5: If replacement of a selected band is executed, initialize the backward search. The backward search drops the least significant band one at a time until the resulted distance shows no improvement over the previous optimal combination.

Step 6: Repeat step 3 to 5 until optimal combinations of all dimensions are generated.

3.3. Selecting optimal bands

The proposed algorithm calculates the distance values for optimal combinations of different dimensions. As an example, the distance vs. dimension curve in Figure 2 indicates that an optimal combination of bands with a dimension between 50 and 100 is sufficient to discriminate the four vehicles. Moreover, the distance increases by a very small margin as the dimension increases from 50 to 100. Therefore, a "smart peak" can be defined as 99.9% of the peak value to further reduce the dimensionality. In this case, 52 bands are selected for classification of the four vehicles. This optimal solution is an approximate solution since the SFFS algorithm is used instead of an exhaustive search due to the computational efficiency.

4. EXPERIMENT

To evaluate the proposed band selection algorithm, the selected bands and the full spectrum are compared in terms of classification performance of two different classifiers, the generalized relevance learning vector quantization improved (GRLVQI) classifier and the SID-SAM classifier. Results are characterized as the probability of correct classification (p_{cc}) defined as the average of classification accuracies of individual classes.

Also, the selected bands are compared to the same number of most relevant bands generated by GRLVQI. Results are compared in terms of classification accuracies and the processing time of these two algorithms.

4.1. GRLVQI classifier

The GRLVQI classifier generates several prototype vectors for each class. The algorithm trains the boundaries of

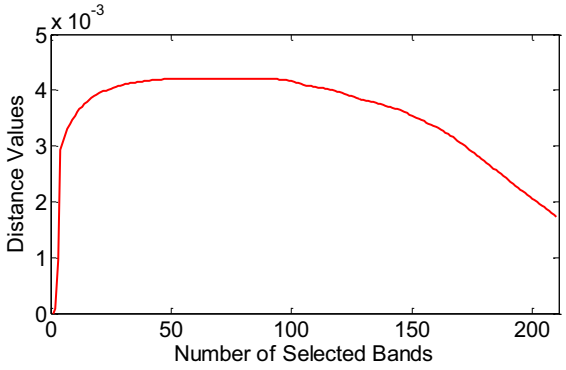

Figure 2: Optimal distance values vs. number of selected bands

classes by iteratively adjusting the prototype vectors closer to correctly classified pixels. Tested pixels are classified to the "nearest" prototype vectors and the corresponding classes based on a relevance weighted distance metric [6].

4.2. SID-SAM classifier

The SID-SAM classifier constructs a spectral signature library by averaging training pixels from individual classes. Tested pixels are classified to the class with the smallest SID-SAM distance metric defined in Equation (1). This classifier combines the strength of SID and SAM, and it discriminates spectral signatures better than using SID or SAM independently [9].

5. RESULTS AND DISCUSSION

5.1. Comparison of selected bands and the full spectrum

The objective of the band selection algorithm is to select the bands that are most useful in discriminating the four vehicles and drop out the redundant bands. This objective is confirmed by the classification results shown in Table 2. For both classifiers, the selected 52 bands have a marginal degradation (about 2% and 3%) in performance compared to the full spectrum of 211 bands. This suggests that most of the 159 bands not selected are redundant.

The proposed OBS algorithm effectively reduces the size of data while retaining important information for classification. This represents a remarkable improvement in processing time of classification algorithms. For instance, the GRLVQI classifier runs 338.63 sec for the full spectrum and 70.45 sec for the selected 52 bands.

5.2. Comparison of OBS and GRLVQI algorithms

There is some overlap in the 52 bands selected by the proposed algorithm and the 52 most relevant bands (Fig. 3). The overlapped bands generally span the wavelengths

TABLE 2: Comparison of classification accuracy in p_{cc}

	GRLVQI Classifier	SID-SAM Classifier
Full Spectrum	72.18%	76.83%
52 Bands (Proposed OBS)	69.23%	74.53%
52 Bands (Most Relevant)	61.27%	63.39%

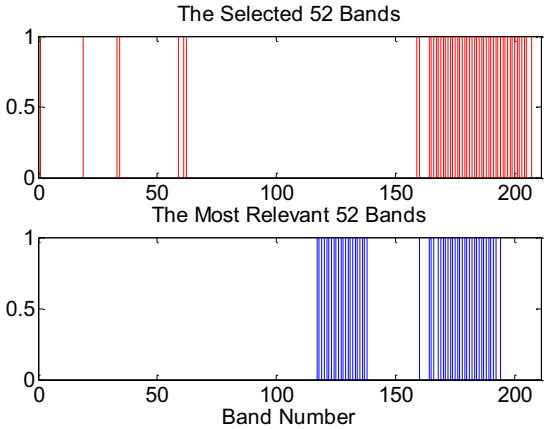

Figure 3: Bands selected by distance metric and by relevance

from 2 μm to 2.34 μm, indicating that these wavelengths are probably the best bands in discriminating the four vehicles.

In terms of classification accuracy, the selected bands perform better than the most relevant bands in both classifiers. This suggests that the proposed OBS algorithm has superior performance in selecting 52 best bands for the classification of the four vehicles.

The significant decrease in classification accuracy from the full spectrum to the 52 most relevant bands (Table 2) indicates that a higher dimension is necessary to maintain the classification performance. The relevance based approach relies on a small subset of bands to contain all significant relevance in order to effectively reduce the dimensionality. The amount of relevance included in selected bands is expected to monotonically increase as more bands are selected. In contrast, the proposed distance in the OBS algorithm increases as salient bands are added and decreases as redundant bands are added. This may be a more reliable method for dimensionality reduction. Also, in terms of processing time, the proposed OBS algorithm runs much faster than the GRLVQI algorithm.

6. CONCLUSIONS

This paper presents a novel band selection algorithm. This algorithm determines the dimension and the best combination of selected bands. Dimensionality reduction is achieved while the classification performance is maintained at a comparable level. Results are justified by the classification performance of two different classifiers. The benefits of optimal band selection are demonstrated by the reduced processing time of classification. For classification algorithms that are prone to the "curse of dimensionality" the band selection alleviates the problem and improves the classification performance. In addition, the comparison of selected bands and the most relevant bands gives some insights on the salient wavelengths for classification. The proposed algorithm may be a more reliable dimensionality reduction method than the relevance based algorithm.

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