Hyperspectral to Multispectral: Video Rate Spectral Imaging Applications

Sam Henry[1], James Jafolla[1]
[1]Surface Optics Corporation, San Diego, CA

I. INTRODUCTION

While hyperspectral imaging (HSI) spectroscopy has proven to be a valuable tool for applications in many fields, there is a fundamental trade-off between spatial, spectral and temporal resolution. Most current HSI systems with hundreds of bands and mega-pixel spatial resolutions have hyperspectral frame times on the order of seconds to minutes. This is generally adequate for doing science and algorithm development, but many applications require much higher temporal resolution. Biological [1], medical [2] and industrial [3] applications often require image acquisition and processing at video rates, 30 hyperspectral frames per second.

Spectral information relative to these fields is often disparate, and selecting a reduced number of bands is essential to achieve video rates. An effective multispectral system can be produced by collecting non video-rate hyperspectral data and applying band selection techniques. This paper demonstrates a technique using genetic algorithms to select 16 bands from 128 band data, which are used to produce a video rate system. Results are shown for vehicle detection in military applications.

II. MOTIVATION

To accommodate the varying needs of industries Surface Optics has created the SOC716. This 16-band video rate hyperspectral imager captures 3-D data at 30 frames per second. Custom band selection is achieved via replacement of the front filter, which leaves the majority of the components standardized. This allows custom video-rate systems tailored to specific applications to be produced without major part changes. Determining the appropriate band locations and band widths is a combinatorial problem that must be addressed.

III. HARDWARE DETAILS

The imagers used for this paper are:

SOC710-VP - hyperspectral imager with a spectral coverage of 400-1000nm and a spectral resolution of 4.6875nm. Resultant data is 128 bands with 696 pixels per line.

SOC716-VNIR – multispectral video rate imager with a spectral coverage of 450-950nm and a minimum spectral resolution of 10nm. 16-band data is captured at 30 frames per second with spatial dimensions of 640x540.

IV. BAND SELECTION

Band selection has been a focus of hyperspectral imaging research however the motivation is often increased processing speeds [4]. As a result many techniques rely on linear combinations of spectral data. Rather than finding optimal band combinations the design of a multispectral system requires that specific band locations and widths be selected. This constrains the band selection process but yields similar benefits in terms of processing speed. When used in conjunction with video-rate imagers systems can capture and process data at video rates.

Determining optimal band locations and widths presents a combinatorial problem in which an exhaustive search exceeds computational limits, and a heuristic search algorithm must be applied. Genetic Algorithms (GAs) have been used extensively for machine learning applications [5] [6], and have been applied for band selection of hyperspectral data [7] [8], but have not been applied to selecting bands for a multispectral system.

GAs simulates natural selection in that an optimal solution is evolved from a population of possible solutions. For this application the population consists of combinations of 16 band locations and widths. The effectiveness of each solution, 'the fitness' is determined by the area under an ROC curve (AROC) [9]. The ROC curve is generated by down-sampling an image according to the parameters defined by the solution and classifying via spectral angle mapper (SAM) at various thresholds.

V. EXPERIMENTAL DETAILS

The technique was tested using a target detection dataset of military vehicles in the field. The genetic algorithm was trained on a single hyperspectral image cube gathered by the SOC710. Training data contained several representative targets at varying distances.

The GA's starting population was created randomly, and it iterated 100 times with a population of 100, and a mutation rate of 1%. Recombination is achieved via roulette selection [6]. ROC curves are created by generating results at 50 evenly spaced threshold values.

Algorithm Overview

1: Determine Endmembers
2: Determine Target Pixels
3. Run GA Band Selection
5. For N times
6. For each solution
7. downsample image
8. downsample endmembers
9 create rule image
10. create ROC curve
11. fitness = AROC
12. Recombination
13. Mutation

VI. RESULTS/ANALYSIS

Results were verified using an independent test set. The data was collected on a different day and contains targets similar to but not present in the training dataset.

Fig 1. Example DataCube with Highlighted Targets

To verify the robustness and generality of the band selection solution several algorithms were used to generate AROC scores. Table 1 shows the AROC scores for multiple algorithms using all 128 bands, 16 evenly spaced bands, and the 16 bands selected by the genetic algorithm. Algorithms are ENVI implementations.

Classification Algorithm	128 Band	16 Band (Even)	16 Band (GA)
SAM[1]	0.53	0.93	0.90
CEM[2]	0.97	0.52	0.65
ACE[3]	0.68	0.85	0.93
OSP[4]	0.90	0.92	0.84
MF[5]	0.63	0.51	0.63
MTMF[6]	0.82	0.70	0.79
TCIMF[7]	0.58	0.94	0.70
MTTCIMF[8]	0.83	0.89	0.88
Average	0.75	0.78	0.79

Table 1. Test Data AROC Scores

1) Spectral Angle Mapper
2) Constrained Energy Minimization
3) Adaptive Coherence Estimator
4) Orthogonal Subspace Projection
5) Matched Filter
6) Mixture Tuned Matched Filter
7) Target-Constrained Interference-Minimized Filter
8) Mixture Tuned Target-Constrained Interference-Minimized Filter

VII. CONCLUSIONS

The band selected data performed on par with the 128-band data. This can be explained by the Hughes Phenomenon [10]. Although the GA selected bands did not outperform the evenly spaced bands, the band locations and widths (shown in Fig. 2) indicate that a 4 band system should be sufficient. This creates an opportunity for increased spatial or temporal resolution on the final system. A 16-band system has been built and performs as expected.

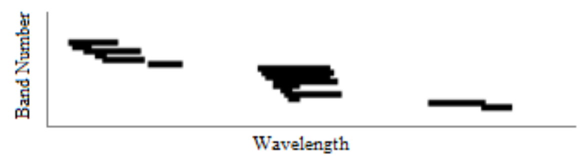

Fig 2. Band Location and Widths Selected by GA

For this application there are a large variety of targets and non-targets and we expected an evenly spaced system to be the best solution. The results of the genetic algorithm indicate that we can achieve improved performance by intelligently choosing bands. For many other applications there are known specific spectral features of interest and genetic algorithms will prove to be a valuable band selection tool.

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