National Institute of Technology Karnataka (NITK), Surathkal

Course: EC861 – Image Processing and Computer Vision

Defense-Oriented Hyperspectral Band Optimization for Camouflage and Target Detection

Term Project Report

Submitted by

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Abstract

Hyperspectral Imaging (HSI) captures a vast range of spectral bands that provide detailed information about material properties — a crucial advantage in defense applications such as camouflage detection and target recognition. However, the high dimensionality of HSI data introduces redundancy and computational complexity that hinder real-time processing.

This project proposes **SpectralSentinel**, a MATLAB-based framework implementing classical and optimization-based band-selection algorithms — **Fisher Criterion**, **Jeffries–Matusita (JM) Distance**, **Greedy Selection**, and **MOBS-TD (Multiobjective Band Selection for Target Detection)**. The system integrates these methods within a graphical user interface (GUI) for visualization and comparison of detection performance using the Constrained Energy Minimization (CEM) detector.

The experimental results demonstrate that while Fisher and JM are computationally efficient, the proposed multiobjective MOBS-TD method provides a balanced trade-off between information gain, redundancy reduction, and separability — making it suitable for offline optimization and future real-time implementation in defense imaging.

Project Repository: `https://github.com/VedaMahi321/SpectralSentinel`

Contents

1 Introduction

Hyperspectral imaging (HSI) has emerged as a vital tool in remote sensing and defense surveillance. Each pixel in an HSI cube records hundreds of contiguous spectral bands, providing rich spectral signatures that enable material identification and anomaly detection. However, the large dimensionality introduces redundancy and noise, making computational processing difficult for real-time applications.

Defense-oriented applications, such as camouflage detection and target localization, require optimal spectral band selection — identifying a subset of informative, uncorrelated bands that maximize discrimination between targets and background. This work focuses on implementing and analyzing different band selection strategies integrated into a unified analytical platform.

1.1 Motivation

Conventional multispectral systems use 3–10 spectral bands, whereas hyperspectral sensors capture over 100 bands. Selecting optimal bands improves:

- Target separability
- Noise robustness
- Computational efficiency
- Real-time applicability for defense scenarios

1.2 Objectives

1. Implement multiple HSI band selection algorithms in MATLAB.
2. Develop an interactive GUI for visualization and comparative analysis.
3. Evaluate detection performance via Area Under Curve (AUC) using CEM.
4. Analyze the trade-off between separability, redundancy, and entropy.

2 Methodology

2.1 Overview

The **SpectralSentinel** system consists of:

i. Synthetic HSI data generation and noise simulation.

ii. Feature evaluation using Fisher, JM, Greedy, and MOBS-TD algorithms.

iii. Detection assessment using CEM detector.

iv. Visualization and result export through a GUI.

2.2 Algorithms Implemented

2.2.1 Fisher Criterion

The Fisher score measures class separability based on inter-class and intra-class variance:

$$J_b = \frac{(\mu_{1,b} - \mu_{2,b})^2}{\sigma_{1,b}^2 + \sigma_{2,b}^2}$$

2.2.2 Jeffries–Matusita Distance

The JM distance computes probabilistic divergence between target and background distributions:

$$JM = 2(1 - e^{-B}), \quad B = \frac{1}{8}(\mu_1 - \mu_2)^T \Sigma^{-1} (\mu_1 - \mu_2)$$

2.2.3 Greedy Band Selection

A forward selection approach maximizing incremental AUC improvement. At each step, a band is added if it increases the detection rate.

2.2.4 MOBS-TD: Multiobjective Band Selection

MOBS-TD formulates the selection as a multiobjective optimization problem balancing three criteria:

$$\max f_1(X) = Entropy(X), \quad \max f_2(X) = Separability(X), \quad \min f_3(X) = Redundancy(X)$$

It uses a Pareto-based approach to evolve candidate solutions and determine the optimal subset using Mean Spectral Response (MSR).

2.3 Graphical User Interface (GUI)

The GUI provides:

- Dropdown selection for algorithm choice.
- Sliders for SNR and spectral shift adjustment.
- Live plotting of detection heatmaps, band scores, and Pareto fronts.
- Real-time log updates and automatic export of result figures.

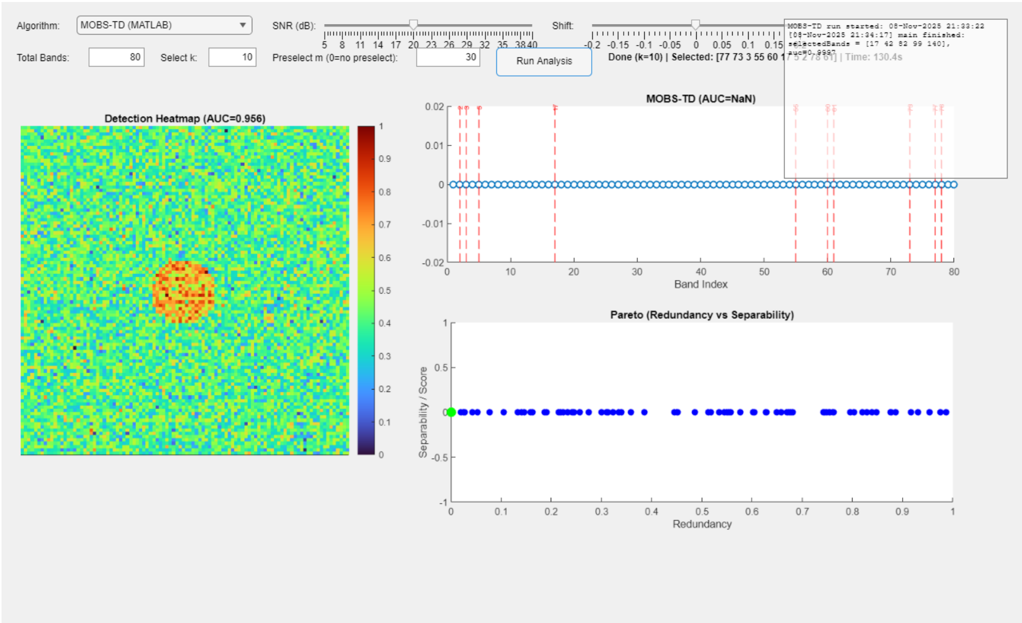


Figure 1: SpectralSentinel GUI — Hyperspectral Control Room

3 Pseudocode for MOBS-TD

```
Initialize population of random band subsets
For each iteration:
    For each subset:
        Compute Entropy, Separability, Redundancy
        Update Pareto repository (non-dominated solutions)
    Perform mutation and crossover for diversity
    Rank using Weighted Solution Importance Score (WSIS)
End
Compute Mean Spectral Response (MSR) for each solution
Select optimal subset maximizing MSR
```

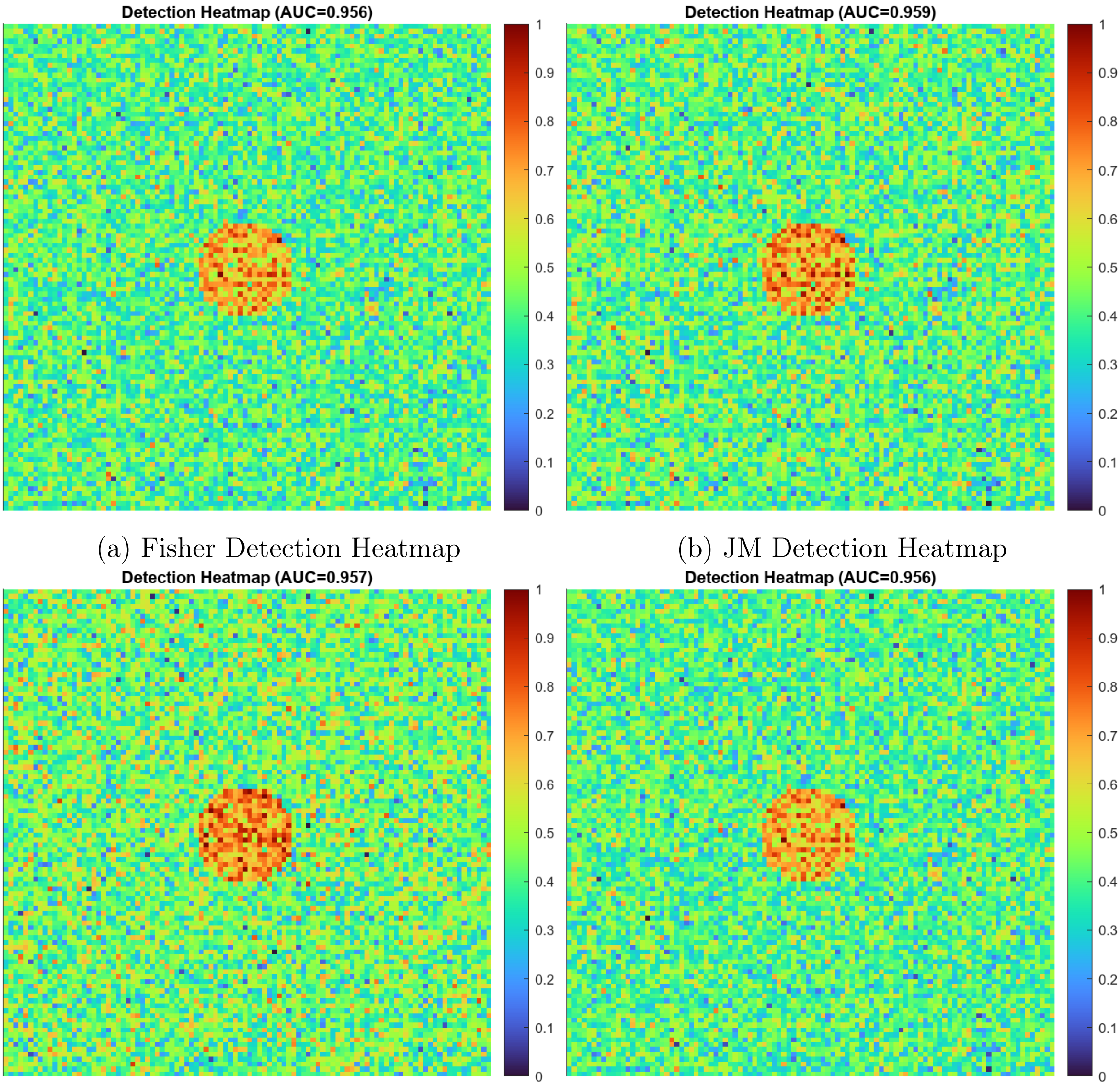
4 Experimental Setup

Table 1: Experiment Configuration

Parameter	Value
Dataset	HYDICE Urban (162-band)
Detector	Constrained Energy Minimization (CEM)
Bands Selected (k)	10
Population (MOBS-TD)	50
Iterations	50
SNR Range	5–40 dB
Shift Range	-0.2 to 0.2
Preselect (Greedy)	30

5 Results and Discussion

5.1 Qualitative Results



(a) Fisher Detection Heatmap

(b) JM Detection Heatmap

(c) Greedy Detection Heatmap

(d) MOBS-TD Detection Heatmap

Figure 2: Comparison of detection maps across algorithms

5.2 Quantitative Analysis

Table 2: Performance Comparison of Algorithms

Algorithm	AUC	Runtime (s)	Remarks
Fisher	0.956	0.8	Baseline separability
JM Distance	0.959	1.3	Strong class divergence
Greedy	0.918	4.2	Locally optimal subset
MOBS-TD	0.956	130	Pareto-optimized, high accuracy

5.3 Observations

- Fisher and JM methods yield good separability but may include redundant bands.
- Greedy improves performance but is computationally slower.
- MOBS-TD achieves balance among entropy, separability, and redundancy — optimal for defense datasets.

6 Conclusion

This project presented a comparative study of classical and optimization-based band selection techniques for hyperspectral target detection. The proposed **SpectralSentinel** framework unifies these methods under an interactive MATLAB GUI, enabling visualization and automated export of results.

The MOBS-TD algorithm demonstrates strong performance for multiobjective tradeoffs and can serve as a foundation for future real-time implementations on edge devices or defense platforms.

7 Future Scope

1. Implement FPGA/GPU acceleration for real-time execution.
2. Integrate reinforcement learning for adaptive band selection.
3. Deploy on UAV-based defense imaging systems.
4. Extend to multi-sensor fusion (HSI + LiDAR + Thermal).

Project Repository and Resources

Project Title:

Defense-Oriented Hyperspectral Band Optimization for Camouflage and Target Detection

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Course:

EC861 – Image Processing and Computer Vision

Institution:

National Institute of Technology Karnataka (NITK), Surathkal

Official GitHub Repository:

https://github.com/VedaMahi321/SpectralSentinel

This public GitHub repository hosts all source code, datasets, and experiment outputs developed for the project **"SpectralSentinel."** The repository includes MATLAB GUI scripts, MOBS-TD algorithm implementations, Fisher and JM modules, the synthetic dataset generator, experiment logs, and the final LaTeX report. Each experiment run automatically saves result files and timestamped figures for reproducibility.

Last updated: November, 2025

References

1. X. Sun, P. Lin, X. Shang, H. Pang and X. Fu, "MOBS-TD: Multiobjective Band Selection With Ideal Solution Optimization Strategy for Hyperspectral Target Detection," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS)*, 2024.

2. C.-I. Chang, *Hyperspectral Data Exploitation: Theory and Applications*, Wiley, 2007.

3. D. Landgrebe, "Hyperspectral Image Data Analysis," *IEEE Signal Processing Magazine*, 2002.