Detection and Classification of Vegetation and Other Low-Contrast Targets

Final Project

Machine Learning for Remote Sensing

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Abstract

Target detection in hyperspectral imagery generally involves targets that occupy only a few pixels and have a high contrast to the background. For example, likelihood-ratio-based methods such as ACE and MF assume target spectra with a low likelihood of being in a background class measured from the image. However, situations such as detecting specific vegetation species within a vegetation background do not follow the few-pixel or high-contrast assumptions. In this paper we present new data and results on the low-contrast target problem, focusing on carefully ground-truthed imagery.

Background

This experiment aims to investigate the use of gaussian mixture modeling to improve the ability to detect targets within hyper-spectral images by allowing for multiple background models. GMMs allow multiple background models to be used compared to a single gaussian distribution to model the entire heterogeneous background of an image. Compared to k-means which forces rigid spherical boundaries, GMM captures distributions with different shapes/ sizes with degrees of uncertainty, allowing for clusters to be modeled as ellipses with arbitrary orientation (as hyperspectral clusters tend to be).

Current State-of-the-Art

Previous work on clustering-based target detection has shown promising results on k-means paired with MF [1] as well as GMM and Laplacian-Regulatized GMM (LapGMM) paired with MF [2]. I hypothesize that given ACE detection's improvements over MF, as well as Whitening over standard PCA, that GMM paired with ACE after whitening will prove better results. To the best of my knowledge these two papers are the most similar to my proposed research and GMM with ACE for target detection has not been tested yet (although I have only researched this for about a week so "the best of my knowledge" is pretty limited).

- [1] https://www.researchgate.net/publication/3202649_Clustering_to_Improve_Matched_Filter_Detection_of_Weak_Gas_Plumes_in_Hyperspectral_Thermal_Imagery
- [2] https://pdxscholar.library.pdx.edu/cgi/viewcontent.cgi?article=6715&context=open_access_etds

Methods

I tested and analyzed the performance of gaussian mixture modeling paired with MF and ACE target detection algorithms. This method was tested on the Cook City hyperspectral image with associated library spectra of the targets and ground-truth labels. The background spectra was modeled with Gaussian Mixture Models with randomized centroid initialization and full covariance (best model parameters (# of clusters) chosen using BIC). Each cluster has its own mean and covariance. The MF and ACE algorithms were applied to each individual class after Whitening, then combined to create the final image/results. False positive and true positive rates were compared to MF and ACE algorithms with single-gaussian background models.

Results

- Initial results on the Cooke City image do not show GMM to perform better at detecting low-contrast targets than single-gaussian methods when paired with either MF or ACE

GMM

- Best Model Parameters: 4 components, full covariance, random from data initialization

- False Positive Rates

	F1_Cloth_Red	F2_Nylon_Yellow	F3a_Cloth_Blue	F3b_Cloth_Blue	F4a_Nylon_Maroon	F4b_Nylon_Maroon	V1_field_spectrum	V2a_field_spectrum	V3_field_spectrum
MF_GMM	0.001524	0.002598	0.001212	0.001217	0.001929	0.001932	0.002251	0.002400	0.002783
ACE_GMM	0.000450	0.000013	0.000006	0.000016	0.000204	0.000204	0.000137	0.000000	0.000076
MF_Single	0.000795	0.001335	0.000241	0.000254	0.001009	0.001022	0.000763	0.000804	0.000607
ACE_single	0.000393	0.000027	0.000000	0.000000	0.000027	0.000027	0.000000	0.000000	0.000000

- True Positive Rates

	F1_Cloth_Red	F2_Nylon_Yellow	F3a_Cloth_Blue	F3b_Cloth_Blue	F4a_Nylon_Maroon	F4b_Nylon_Maroon	V1_field_spectrum	V2a_field_spectrum	V3_field_spectrum
MF_GMM	0.40625	0.37500	0.09375	0.0	0.09375	0.0	0.0	0.0	0.0
ACE_GMM	0.46875	0.40625	0.15625	0.0	0.00000	0.0	0.0	0.0	0.0
MF_Single	0.62500	0.62500	0.37500	0.0	0.37500	0.0	0.0	0.0	0.0
ACE_single	0.50000	0.50000	0.00000	0.0	0.00000	0.0	0.0	0.0	0.0

Bayesian GMM

- Best Model Parameters: 8 components, full covariance, random from data initialization

- False Positive Rates

	F1_Cloth_Red	F2_Nylon_Yellow	F3a_Cloth_Blue	F3b_Cloth_Blue	F4a_Nylon_Maroon	F4b_Nylon_Maroon	V1_field_spectrum	V2a_field_spectrum	V3_field_spectrum
MF_GMM	0.001680	0.002680	0.001598	0.001603	0.002229	0.002232	0.002608	0.002612	0.002972
ACE_GMM	0.000383	0.000017	0.000003	0.000012	0.000180	0.000181	0.000123	0.000002	0.000093
MF_Single	0.000795	0.001335	0.000241	0.000254	0.001009	0.001022	0.000763	0.000804	0.000607
ACE_single	0.000393	0.000027	0.000000	0.000000	0.000027	0.000027	0.000000	0.000000	0.000000

- True Positive Rates

	F1_Cloth_Red	F2_Nylon_Yellow	F3a_Cloth_Blue	F3b_Cloth_Blue	F4a_Nylon_Maroon	F4b_Nylon_Maroon	V1_field_spectrum	V2a_field_spectrum	V3_field_spectrum
MF_GMM	0.390625	0.312500	0.140625	0.0	0.06250	0.0	0.0	0.0	0.0
ACE_GMM	0.500000	0.359375	0.187500	0.0	0.03125	0.0	0.0	0.0	0.0
MF_Single	0.625000	0.625000	0.375000	0.0	0.37500	0.0	0.0	0.0	0.0
ACE_single	0.500000	0.500000	0.000000	0.0	0.00000	0.0	0.0	0.0	0.0

Limitations

- Compared to assuming a single gaussian distribution for the background, modeling the background with GMM would require re-training on each new image - limiting generalization abilities.
- If the number of clusters is not correctly chosen, varying results on different images could occur.
- The initialization of centroids greatly impacts the final results.
- I did not perform any kind of dimensionality reduction before GMM which was very computationally costly given the high number of bands in each image. The Bayesian GMM method took longer to converge (if ever) - running with larger max iterations helped this but was too time consuming for models with more components.
- I did not remove the target pixels from the spectral image which may have led to incorrect clustering.
- I did not have time to test on the Baccharis image but given the more homogenous background, GMM may perform better on that image

Conclusions

- While initial results on the Cooke City image did not show GMM to perform better at detecting low-contrast targets than single-gaussian methods when paired with either MF or ACE, further tests on additional images with additional time parameter tuning may produce better results as other research has suggested/shown