A Fast Hyperspectral Hit-or-Miss Transform With Integrated Projection-Based Dimensionality Reduction

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I. Introduction

The Hit-or-Miss transform (HMT) [1] is a common tool in Mathematical Morphology (MM) used in template matching and object detection and subsequent classification applications [2]. The HMT probes a query image with a pair of structuring elements (SEs) which are designed to detect specific objects of interest. The relative size of hyperpectral image data in particular provides a wealth of information on a scene however, it also makes object detection via a HMT a computationally expensive process. We aim to solve this problem through employing both spatial and spectral dimensionality reduction (DR) techniques to transform a hyperspectral image and its associated SEs designed for the HMT into a reduced space.

II. Multivariate HMT

Historically the HMT was restricted in its use to binary images and was later extended for use in greyscale images [1]. In MM in general, a complete lattice or ordered set is required to define any morphological operators [3]. There is no one, intuitive way to order multivariate data, however, there are multiple ways to circumvent this issue through different multivariate ordering schemes [4]. One technique for multivariate ordering is reduced ordering, or r-ordering, which works by reducing a multivariate observation to a scalar value through some metric, this is commonly a distance. These distance measures can be ordered according to the MM framework and appropriate operators can be defined, including the HMT [5], which this work is based on. The Multivariate Distance Percentage Occupancy HMT (MDPOHMT) of an image, I, can be defined as:

$$\mathrm{MDPOHMT_S}(I)](x) = \begin{cases} 1 & \text{if } [\xi_{S_{FG},k_{100-p}}(D)](x) < [\xi_{S_{BG},k_p}(D)](x) \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Where $\xi_{S_{FG},k_{100-p}}$ and ξ_{S_{BG},k_p} are rank order filter implementations of the distance-based foreground erosion and background dilation respectively on the set of distances, D. The rank order filters allow for some disparity between the image and SEs which would cause a standard HMT to fail. The rank of these rank order filters are set using the notion of Percentage Occupancy (PO) [6] with the PO value, p in this instance, dictating the rank of the two operations.

III. Dimensionality Reduction Techniques

While a multivariate HMT can now be defined using (1), the dimensionality of a hyperspectral image produces a large overhead when calculating pixel-wise distances, especially if analysing large images or if large SEs are used. As a result, employing DR techniques improves the efficiency of object detection. PCA is a commonly used technique for DR which exploits the natural correlation in data and aims to produce a set of orthogonal, uncorrelated observations called Principal Components (PCs) [7]. These PCs are found by projecting an $M \cdot N \times L$ data matrix, X, into the principal component space using a matrix of sorted eigenvectors, Q, to give the projected data, $\hat{X}$, as shown in (2).

$$\hat{X} = X \cdot Q \quad (2)$$

The eigenvectors are sorted by the descending order of their eigenvalues, the value of each eigenvalue represents how well the PC explains the data. As a result, the first $l \ll L$ PCs can be retained producing a reduced dimension, projected representation of X, $\hat{X}^{[l]}$.

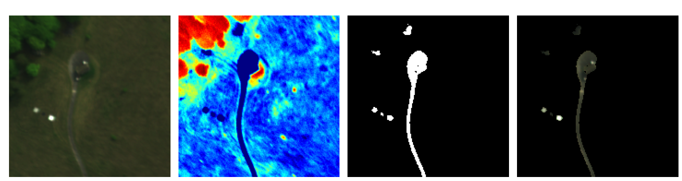
One desirable feature of PCA that makes it useful in our proposed HMT is the ability to project supplementary observations, that were not present while calculating the PCA, into the reduced space. This is analogous to projecting SEs into the same space as an image which can be achieved by using the projection matrix calculated in the image's PCA, Q_{IM}, as shown in 3.

$$\hat{X}_{\mathrm{SE}} = X_{\mathrm{SE}} \cdot Q_{\mathrm{IM}} \quad (3)$$

With the image and SEs in the same reduced space, a HMT can be performed with the advantages of reduced dimensionality. The Normalised Difference Vegetation Index (NDVI) [8] is a simple yet effective technique in determining the amount of vegetation present in a scene. It works by taking frames at two discrete wavelengths, one in the red part of the spectrum, λ_{red}, where vegetation absorbs light and another in the near infra-red (NIR), λ_{NIR}, where it is mostly reflected. The NDVI is calculated as:

$$\mathrm{NDVI} = \frac{\lambda_{\mathrm{NIR}} - \lambda_{\mathrm{red}}}{\lambda_{\mathrm{NIR}} + \lambda_{\mathrm{red}}} \quad (4)$$

In areas of vegetation, the outcome of (4) will be a relatively high value, conversely, in areas of non-vegetation it will produce a low value. In remote sensing applications, where outliers may exist in areas of vegetation, the NDVI offers a rapid identification and segmentation of any non-vegetative material and potential outliers. An example of the NDVI process for image segmentation can be seen in Figure 1 where a binary threshold is applied to create a mask.



(a) **(b)** **(c)** **(d)**

Fig. 1: Stages of NDVI segmentation: a) Pseudo-colour image of the OP7 Site b) NDVI measurement of the scene c) Thresholded image specifying synthetic ROI d) Masked pseudo-colour image

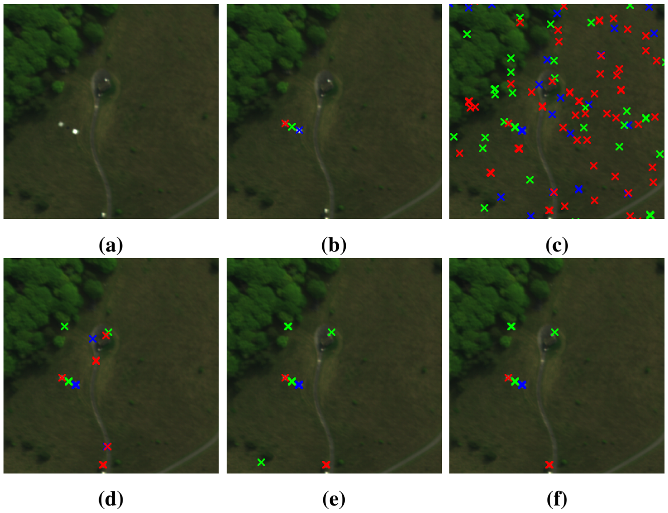


Fig. 2: Results of the HMT after dimensionality reduction:
a) Pseudo-coloured hyperspectral image b) Ground truth highlighting target locations c) HMT of the raw image d) HMT after NDVI e) HMT after PCA f) HMT after NDVI + PCA

IV. Results and Analysis

The HMT and DR methods were tested on multiple images of the same scene from multiple flight-paths containing three target objects amongst grass and trees. An example of the scene and various results from it are shown in Figure 2. Each of the images were captured from an aerial platform at roughly 0.7km altitude on the 18th May 2014.

Figure 2a shows the three spectrally different targets (marked with red, green and blue crosses respectively in Figure 2b) where each had an individual SE designed for it which could be used over each of the multiple images. Figures 2c - 2f display the results of each HMT after each DR technique.

Figure 2c displays the result of the HMT on the raw image, which produces a large number of false positive results, most of which occur in areas of vegetation. Such false positives are caused by areas of the image being a closer match to the foreground SE than the background SE. The false positives can be filtered out by applying a variable distance threshold or performing matched filtering or similar methods. Using the NDVI as a preprocessing step removes the majority of false positives, as they occur in areas of vegetation which are removed in the NDVI-based segmentation of the image, as shown in Figure 2d.

The number of false positives can be further reduced by projecting the image and its SEs into the reduced PC space as seen in Figure 2e. As this projection is based on variance the targets are generally pronounced in this space, resulting in more robust detection. Typically, between 3 and 5 PCs are enough to retain $\geq 99\%$ of the variance in the dataset, greatly reducing the dimensionality of the data.

Applying the mask produced by the NDVI-based segmentation further reduces the execution time as only definite non-vegetative pixels are analysed. The results of combining the PCA and NDVI techniques are shown in Figure 2f.

In order to reduce the computation time of a hyperspectral HMT, both spatial and spectral DR techniques were applied to the data. The resulting decrease in processing time as well as the percentage of pixels, in this case the number of spatial and spectral elements, retained after dimensionality reduction is shown in Table I. Both PCA and NDVI reduce the processing time required to perform the HMT. Combining both methods provides the fastest time without compromising results as highlighted in Figure 3.

TABLE I: Comparison of execution time and effects of each DR method

Timings for each of the HMTs				
Pre-processing	Raw	PCA	NDVI	PCA + NDVI
Average Time (s)	124.1903	7.6360	2.2747	0.1383
No. Pixels retained	16800000	480000	319410	12168
% of Total Pixels	100%	2.8571%	1.9013%	0.0730%

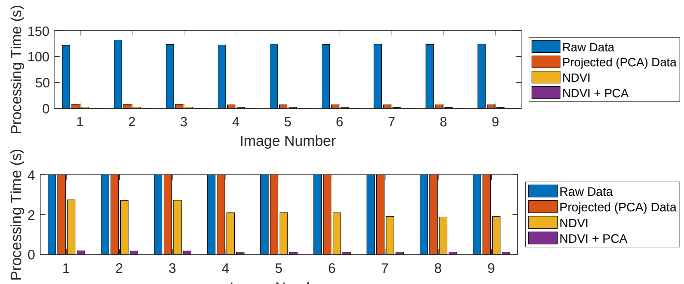


Fig. 3: Execution time of each dimensionality reduction method over a set of nine images - where the lower image is a magnified version of the top

V. Conclusion and Future Work

We have presented an efficient implementation of the Hit-or-Miss Transform for hyperspectral images which utilises projection based dimensionality reduction to tackle the high dimensionality problem in hyperspectral data by performing the transform in a reduced space. While PCA has been used here, other DR and band selection schemes can be used. Spatial dimensionality reduction techniques allow for the definition of a region of interest based on the spectral information present in the scene and assist to decrease computation time further.

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