Rapid hyperspectral image classification to enable autonomous search systems

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Abstract

The emergence of lightweight full-frame hyperspectral cameras is destined to enable autonomous search vehicles in the air, on the ground, and in water. Self-contained and long-endurance systems will yield important new applications, for example, in emergency response and the timely identification of environmental hazards. One missing capability is rapid classification of hyperspectral scenes so that search vehicles can immediately take actions to verify potential targets. Onsite verifications minimize false positives and preclude the expense of repeat missions. Verifications will require enhanced image quality, which is achievable by either moving closer to the potential target or by adjusting the optical system. Such a solution, however, is currently impractical for small mobile platforms with finite energy sources. Rapid classifications with current methods demand large computing capacity that will quickly deplete the on-board battery or fuel. To develop the missing capability, the authors propose a low-complexity hyperspectral image classifier that approaches the performance of prevalent classifiers. This research determines that the new method will require at least 19-fold less computing capacity than the prevalent classifier. To assess relative performances, the authors developed a benchmark that compares a statistic of library endmember separability in their respective feature spaces.

Keywords: acquisition systems, autonomous vehicles, classification accuracy, endmember separability, hazardous material detection, real-time spectrometer, resolution agility, simple spectral classifier, unmanned aircraft systems, video imaging

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1. Introduction

The recent emergence of golf-ball size hyperspectral cameras that weigh less than a tennis ball will create new capabilities that shift the paradigm in remote sensing. These full-frame cameras[1] also have relatively low power consumption. Hence, they are suitable for integration into small mobile platforms that could navigate autonomously on the surface, in the air, or in water.[2] For a given spatial resolution, hyperspectral imaging offers the benefit of high spectral resolution to minimize missed detections and maximize the accuracy of target identifications.[3] The possibility of adjusting spatial resolution to verify target detections while in operation will preclude the expense of repeat missions to recheck potential targets after offline image processing. The ability to achieve resolution agility will also compensate for trading off some theoretical accuracy for lower classification complexity. Organizations can use such autonomous search systems for many new applications. A few of the most notable are emergency response, post-disaster damage assessment, environmental hazard (e.g. oil spill or chemical release) detection, and the performance evaluation of transportation systems.[4]

To conduct verifications in situ, the system must quickly classify large-scale hyperspectral scenes to identify potential targets, and then be capable of enhancing the spatial resolution of selected areas by moving closer or adapting the optical system. The achievable rate of hyperspectral image classification will dictate the maximum search speed and coverage. Adding computing capacity could accelerate the execution of existing classifiers, but doing so would deplete on-board energy supplies more quickly, reducing ground coverage. Hence, the main idea of this paper is to develop a rapid hyperspectral classifier to enable small, agile, and adaptive autonomous search systems. Subsequently, the following are the main objectives of this research:

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1) to develop a simple hyperspectral image classifier that requires substantially less computing capacity than existing high-performance classifiers.

2) to identify a method of benchmarking the theoretical accuracy of the simple classifier relative to the prevalent classifiers that avoids the common and costly approach of immediately conducting expensive ground truth experiments.

3) to identify a method of estimating and comparing the absolute and relative computational complexities of the proposed empirical and the prevalent classifier.

To set the scene for achieving these objectives, the next section will review the scope of existing methods to classify hyperspectral images and to characterize their overall and relative computational complexities. The third section will achieve the first objective by developing the new classifier using an empirical formulation that hinges on the energy of wavelength rate changes across the spectrum. The fourth section will achieve the second objective by utilizing separability analysis. This method uses typical ground samples from existing spectral libraries to compare the theoretical false positive potential of the new classifier with that of the prevailing classifier that has known performance. The fifth section will achieve the third objective listed above by introducing a new method of benchmarking computational complexity that is most appropriate for digital image processing architectures. The sixth section will use the benchmarks to compare the theoretical performance of the proposed and the prevalent classifier, within the context of a case study. The final section will summarize and conclude the research, demonstrating that the theoretical approach has successfully achieved the performance benchmarking objectives with existing endmember libraries as a first vetting step to avoid the common approach of incurring upfront expenses to conduct extensive field data collection to evaluate a new classifier.

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2.   Review of Existing Methods

Existing hyperspectral libraries[5] contain the spectral signature of target materials obtained from ground truth data. These signatures are so-called library endmembers because of their careful measurements and spectral purity. Noise and distortions from the data collection equipment and the long path lengths from remote sensing distorts the spectral signature of captured images. Therefore, the main purpose of a hyperspectral image classifier is to associate each noisy hyper-pixel of the image to an endmember (supervised methods) or into clusters (unsupervised methods), based on some measure of similarity.

The Euclidean n-space distance is one of the most popular measures of similarity.[6] Therefore, the average separation distance of endmembers (separability) in a given feature space is a predictor of the potential for a candidate classifier to produce false positives at some level of noise. Hence, comparing the proportional separability of a fixed sample of library endmembers within the feature space of the candidate classifier and the feature space of a classifier with known performance offers a first step in vetting their potential performance with actual field data. The common approach to evaluate a new classifier is to collect field data immediately to assess its accuracy. However, the alternative of benchmarking the theoretical performance of the new classifier against the performance of a prevalent classifier with known field accuracy characteristics will minimize the risks of incurring the high cost of data collection to vet a potentially useless classifier. This approach is analogous to the classic methods of evaluating the theoretical bit-error-rate (BER) performance of information encoding schemes as a function of signal-to-noise ratio (SNR). The separability analysis of this research uses the same finite sample of library endmembers that typifies a scene containing the target material, for example spilled crude oil, and the contaminated materials such as soil, water, snow, and vegetation.

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Methods of image classification vary in performance and computational complexity as a function of both the number of hyper-pixels P and the number of spectral bands N. Methods of supervised classification use statistical and machine learning techniques to establish their measures of similarity. The most popular methods are Spectral Angle Mapper (SAM), Minimum Distance Classifier (MDC), Maximum-Likelihood Classifier (MLC), Spectral Information Divergence (SID), and Spectral Correlation Mapper (SCM). The SAM is the prevalent method. The computationally complexities of present supervised methods range from $O(N^2)$ to $O(N^3)$. Methods of unsupervised classification use techniques such as principle component analysis (PCA), independent component analysis (ICA), and singular value decomposition (SVD); they are at least $O(PN^2+N^3)$ computationally complex.[7] Algorithms such as the Iterative Self-Organizing Data Analysis Technique (ISODATA) assign hyper-pixels with similar characteristics into clusters. Convergence depends on the heuristics of setting a threshold for the number of endmember re-assignments. Such algorithms are $O(PKN^2I)$ complex where K is the number of clusters, and I is the number of iterations.[8] To minimize their computational complexity, analysts typically incorporate methods of feature selection to identify a minimum number of subset bands that would maintain some measure of sufficiency in class separability. However, the feature selection algorithms themselves typically have $O(PN^K)$ complexity.[9]

3.   The Proposed Rapid Classifier

We propose a new method of rapid classification based on empirical influences from both supervised and unsupervised techniques. The unsupervised aspect is a feature extraction that operates once per new hyper-pixel acquired and once per library endmember. The supervised influence is a radial or a rectangular distance threshold comparison in a two-dimensional (2D)

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feature space. The method precomputes the features for each available library endmember for comparison with features of captured hyper-pixels. Hence, the extracted endmember features could occupy a much smaller amount of digital memory than the entire library of endmember signatures. The reduced computational complexities of one-time feature extraction per new hyper-pixel, and the simpler similarity comparisons with endmember features enable the potential for real-time classification.

3.1   Empirical Feature Extraction

The typical spectral library contains a list of endmembers represented as albedo values for each of the available spectral bands. The albedo is a measure of the portion of incident solar energy reflected from a material. This simple statistic is still powerful, relevant, and very important. NASA's earth observation satellites regularly measure and report the average albedo of the earth's surface in the visible wavelength ranges. Figure 1 plots the albedo as a function of the spectral band for typical ground cover materials.[5]

We modify the albedo to improve its effectiveness when using signatures of different signature lengths and spectral resolutions from the same or multiple libraries. We also designed a second feature based on a heuristic that summarizes the waviness of the signature. Together, these two features form a 2D feature space.

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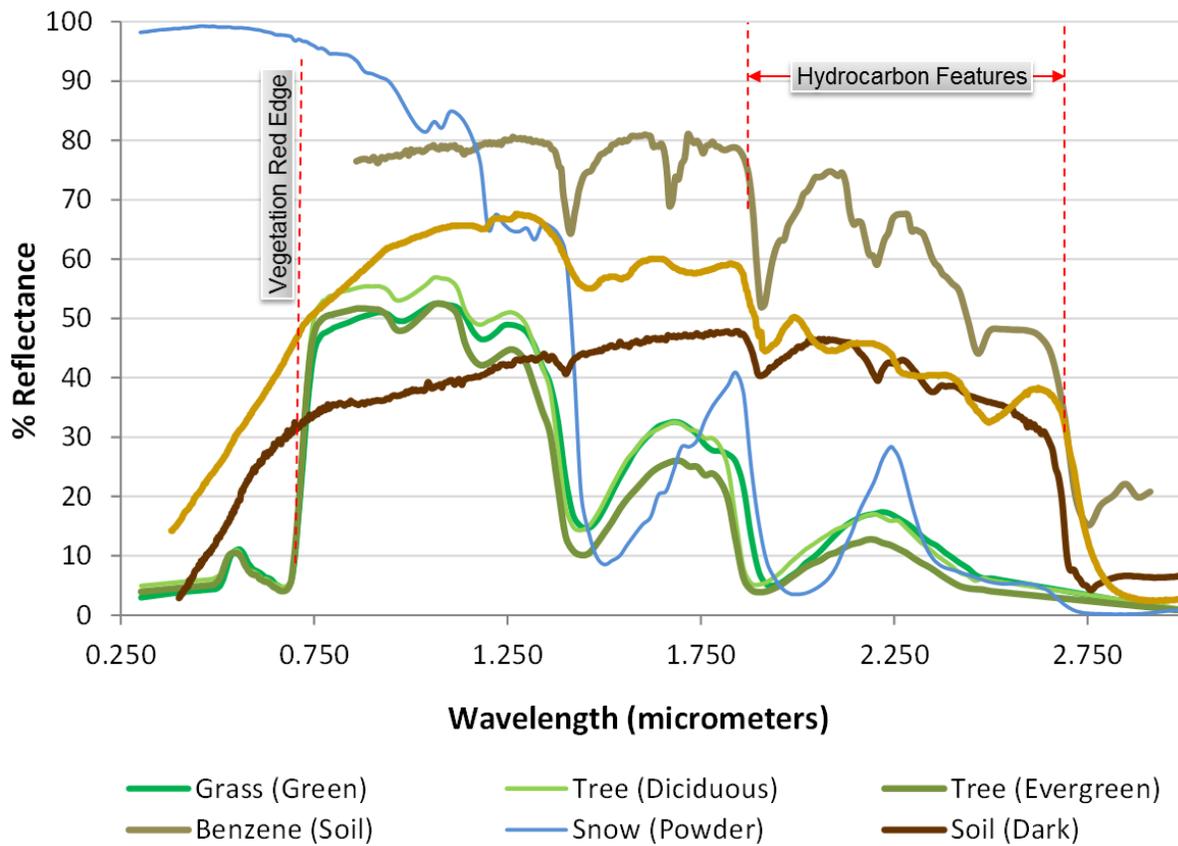
Figure 1. Spectral signatures for typical ground cover.

3.1.1   The wavelength normalized average albedo

The average albedo μ_g of a spectral signature $\boldsymbol{g}$ is

$$\mu_g = \frac{1}{N} \sum_{n=1}^{N} g_n \tag{1}$$

where the albedo in spectral band n is g_n. The wavelength normalized average albedo (AVN) is

$$AVN = \frac{\mu_g}{\lambda_H - \lambda_L} \tag{2}$$

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where λ_H and λ_L are the highest and lowest wavelength bands, respectively. The normalization

per wavelength band facilitates comparisons between endmembers with different spectral

resolutions and bandwidths, potentially from combining different libraries. Hence, normalization

accommodates band selection methods that attempt to eliminate wavelength channels that do not

appreciably decrease the separability between selected endmembers.

3.1.2   The wavelength sensitivity index

We call the new feature the wavelength sensitivity index (WSI) because it characterizes the

shape or waviness of a spectral signature. We define the corresponding wavelength sensitivity

transform as

$$W_S = \sqrt{\frac{1}{\lambda_H - \lambda_L} \sum_{n=1}^{N} \left(\frac{g_n - g_{n-1}}{\lambda_n - \lambda_{n-1}} \lambda_n \right)^2} \tag{3}$$

where W_s is the WSI, and λ_n is the centre of each available wavelength band in units of

micrometres. The origin of the WSI is purely empirical. Its formulation is fundamentally a

measure of the band-normalized energy of the wavelength slope signature. Conceivably, this

definition could include higher order derivatives instead of or in addition to the wavelength

slope, but at the expense of increasing computational complexity. The weight λ_n of the

wavelength slope maximizes the separability of materials that might have similar wavelength

slope energies in different portions of the spectrum. The fact that the weight tends to emphasize

the wavelength slopes at the higher end of the spectrum is inconsequential because of the feature

space normalization. The authors have previously reported[4] on other measures of waviness such

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as the normalized standard deviation, which is less effective and entropy, which is substantially

more computationally complex.

A potential limitation of the WSI method could be the reduced separability of materials

that have slope signatures in different portions of the spectrum and with just the right magnitudes

to equalize their single-dimensional WSI feature. However, for such a hypothetical case, it is

also possible that the {AVN, WSI} feature pair will compensate to increase the two-dimensional

separability. Therefore, without an exhaustive separability analysis that involves all materials

known to man, the authors recommend using this method to test application specific targets, for

example spilled crude oil among common contaminated materials such as soil, snow, water, and

vegetation.

3.2   Distance Measure

The wavelength sensitivity classifier (WSC) computes {AVN, WSI} pairs for each hyper-pixel

of the acquired image frame and compares their proximity to target endmembers. Although other

distance measures are possible, we elected to use the Euclidian distance because of its simplicity.

The Euclidian or radial distance D_E is

$$D_E = \sqrt{(g_x - h_x)^2 + (g_y - h_y)^2}$$ (4)

where g and h are the extracted feature sets; the x and y components are the {AVN, WSI}

features for any two materials.

The endmember samples for separability analysis are 15 typical ground cover materials

from the ASTER Spectral Library.[5] Figure 2 shows the result of applying the WSC to the

endmember sample set. The WSC feature space assigns the normalized AVN and WSI to the

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horizontal and vertical axis, respectively. At small zenith angles, materials of the aquatic class

are highly absorptive throughout the spectral region. This characteristic places water and ice at

an extreme lower corner of the feature space. Conversely, snow of different consistency is

typically highly reflective in the visible region and varies in albedo at longer wavelengths. Those

feature combinations place it near the centre of the feature space. Materials of the hydrocarbon

class exhibit a combination of high average reflectivity and high wavelength sensitivity that

places it at the extreme upper right corner of the feature space.
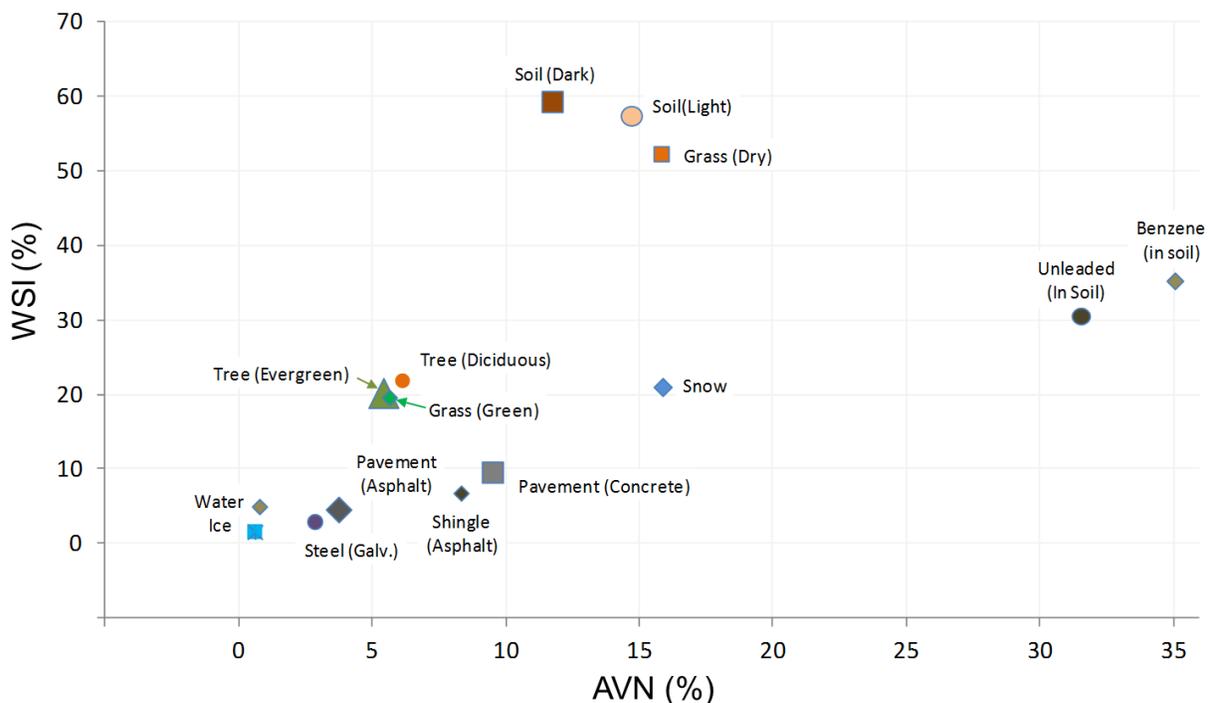
Figure 2. WSC feature space for typical ground cover materials.

By inspection, the WSC appears to separate hydrocarbon target materials from soil and

snow reasonably well. Conversely, materials within the same macro-class, such as evergreen

trees and green grass, exhibit less separability. Hence, applications that need to distinguish

among similar materials should use a different type of classifier that is likely more

Rapid hyperspectral image classification to enable autonomous search systems computationally or dimensionally complex. This limitation of the WSC points to a trade-off in computational complexity and intra-class separability. This scenario analysis indicates that the rapid classification capability of the WSC will be best suited for custom applications that search for high contrast targets within the scene. Hence, in addition to oil spills (on snow, water, vegetation, or soil), the WSC would be appropriate for tracking vehicles on paved or unpaved roads, and for tracking vessels on water. The primary strength of the WSC is that it allows for immediate repositioning of robotic vehicles to obtain higher spatial or directional resolution for target verification. This resolution agility will likely compensate for any loss of classification accuracy relative to the more computationally complex approaches such as SAM or SVD.

4.   Proposed Performance Benchmark

This research defines the *separability* of a classifier as the average of the normalized separation distance in its feature space, for all target and contaminated material combinations of the selected sample of library endmembers. Normalizing the feature space distance provides a fair means of benchmarking the potential accuracy of classifications relative to the anticipated distance errors in hyper-pixel assignments. Figure 3 graphically illustrates the concept. It shows a hypothetical distribution of the normalized distances between all combination of endmembers in the respective feature spaces of two different classifiers, A and B.

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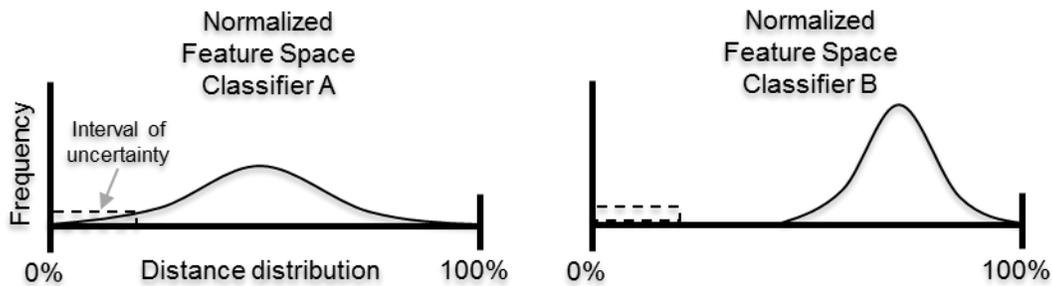
Figure 3. Comparison of the separability of classifiers.

The interval of uncertainty represents the expected normalized distance deviations of candidate hyper-pixel distances from their endmembers, for example with less than 5% significance. This normalized deviation threshold is analogous to an acceptable noise interval for hyper-pixel assignments. For the same set of library endmembers, the mean is closer to the noise interval for Classifier A than for Classifier B. Therefore, the former has a greater potential for misclassifications than the latter. Alternatively, Classifier B could tolerate a higher noise level than Classifier A could. Consequently, Classifier B has the potential to classify more of the hyperspectral scene than Classifier A could. In either case, a larger ratio of average normalized separation distance to an arbitrary interval of uncertainty is desirable.

As mentioned earlier, it is important to consider this benchmarking approach in analogy to the classic approach of comparing the theoretical SNR requirements of different data encoding methods to achieve some desired level of decoding accuracy. That is, this theoretical performance bound is a first indicator of the potential performance of the candidate classifier, and it does not replace the eventual need to conduct extensive field studies with ground truth data. The primary benefit of this first-step vetting is to benchmark the theoretical performance of new methods relative to those of existing methods of known performance levels to assess the value of later conducting expensive field data collection for final performance characterizations.

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5. Proposed Measure of Computational Complexity

This section details new benchmark for computational complexity that is appropriate for computer architectures that manufacturers optimize to process images at high speed.

5.1 The Multiply-Accumulate Complexity

We define a unit of computational capacity $\Pi[D]$ as the multiply-accumulate complexity (MACC), where D is the number of clock cycles that a model requires when implemented on processors capable of single-cycle multiple-accumulate (MAC) operations. The typical digital signal processor (DSP) and some alternative architectures optimized for mobile devices implement a MAC operation within a single instruction cycle. However, they implement divisions using a series of bit shifting and comparison operations that amount to approximately 42 clock cycles for a 32-bit signed division.[10] The MACC notation is more convenient than the Big-O notation to benchmark the computing time on processors optimized for signal and image processing. As is customary with the Big-O notation, the MACC ignores operations that do not include multiplications, such as additions or comparisons (subtractions). The MACC also excludes divisions and multiplications by integer constants that are powers of two because DSPs can calculate those using single-cycle bit-shifting operations that consume negligible resources. Additionally, the MACC excludes operations that algorithms can pre-compute and store in memory for later use. For instance, algorithms can precompute operations that involve only library endmembers. Furthermore, the MACC excludes computations that operations can store from previous cycles of an iteration, for example, when computing a series expansion.

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5.1.1 The SAM complexity

The SAM is the most popular classifier. It represents spectra as a vector in N-dimensional space and computes the "angle" between vectors as the measure of similarity.[11] The SAM maps the separation of two vectors in multidimensional space to an angle α_s in degrees such that

$$\alpha_s = \arccos\left(\frac{\sum_{n=1}^{N} f_n g_n}{\sqrt{\sum_{n=1}^{N} f_n^2 \sum_{n=1}^{N} g_n^2}}\right) \qquad (5)$$

where f is the spectrum of a hyper-pixel, g is the reference or endmember spectrum, and n is the index of the wavelength band.

The SAM has a MAC complexity of $3\Pi[N]$ operations plus one square root, one division, and one arccosine operation. The Taylor series expansion for a square root operation[12] provides the baseline for estimating the number of MAC operations where:

$$\sqrt{1+z} = 1 + \sum_{k=1}^{C} \frac{(-1)^k (2k)!}{4^k (k!)^2 (1-2k)} z^k \qquad (6)$$

The selection of C provides the desired precision. The exponential and factorial operations of each iteration can use extra memory to pre-compute and store intermediate results for future iterations. For instance, the exponent of the argument z requires $\Pi[C]$ operations. Multiplication with the pre-computed constants of each iteration requires one additional MAC. Therefore, the MACC of the square root operation is $2\Pi[C]$.

The Maclaurin series expansion for the arccosine[12] is

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$$\arccos(z) = \frac{\pi}{2} - \sum_{k=1}^{C} \frac{(2k)!}{4^k (k!)^2 (2k+1)} z^{2k+1} \qquad (7)$$

In a manner that is similar to evaluating the square root operation, pre-computing the constants will reduce the iterative computational requirements. The exponential operation requires $\Pi[2C + 1]$ and multiplication by the constant in each iteration will require one additional MAC. Hence, the MACC of the arccosine operation is $2\Pi[2C + 1]$. Subsequently, the total MAC complexity of the SAM classifier per image frame of P hyper-pixels is

$$\Pi_{\text{SAM}} = P \times K \times \{\Pi[3N] + \Pi[8C] + \Pi[44]\}. \qquad (8)$$

Using the same approach, the complexity of the Bhattacharya Distance (B-Distance) is

$$\Pi_{\text{B-dist}} = P \times K \times \{2\Pi[N + 1] + 2\Pi[C + 1] + \Pi[172]\} \qquad (9)$$

and the complexity of the Maximum Likelihood Classifier (MLC) is:

$$\Pi_{\text{MLC}} = P \times K \times \Pi[2N] + \Pi[P(N + 1)] + 2\Pi[C + 1]. \qquad (10)$$

5.1.2 *Wavelength sensitivity index complexity*

Computing WSI requires $\Pi[2N] + \Pi[1]$ plus the square root operation. The wavelength ratios are pre-computed. The AVN requires $\Pi[2]$ operations. The WSC operates on each of the P hyper-pixels only once to determine their {AVN, WSI} coordinate. The WSC assigns each coordinate to the class having the minimum Euclidian distance. There are $P \times K$ Euclidian distance calculations that require $2\Pi[C] + \Pi[3]$ operations. Therefore, the one-time WSC computation per hyper-pixel and the assignment to a class requires $P \times \{\Pi[2N] + 2\Pi[C] + \Pi[3]\}$ and $P \times K \times \{2\Pi[C] + \Pi[3]\}$ operations, respectively. Therefore, the total MACC of the WSC classifier is

$$\Pi_{\text{WSC}} = P \times K \times \{2\Pi[C] + \Pi[3]\} + P \times \{\Pi[2N] + 2\Pi[C] + \Pi[3]\}. \qquad (11)$$

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Assigning WSC features to a rectangular quadrant of the feature space would reduce the complexity further by requiring only $P \times K$ subtraction operations. This would yield a WSC-Rectangular (WSC-R) classifier that has a complexity of

$$\Pi_{\text{WSC-R}} = P \times 1 \times \{\Pi[2N] + 2\Pi[C] + \Pi[3]\}. \tag{12}$$

6. Analytical Results and Discussions

This section will quantify the two key performance measures of endmember separability and the computational complexity.

6.1 Separability Analysis

Table 1 summarizes the normalized separation distances for materials in the denser cluster near the centre of the feature WSN space. This comparison excludes the outlier clusters such as hydrocarbons and snow to remove comparison bias. The selected combinations also simplify the table to a more meaningful set of materials for ease of visualization and clarity. Hence, these endmember samples from the large spectral library will serve as the standard for comparing the separability of candidate and prevailing classifiers for a specific application. The average separability for the selected materials is 23.7%. The average inter-class separability (emphasized in bold font) is 33.9% whereas the intra-class separability is 3.4%. Borrowing from the interpretation of chi-squared statistics goodness-of-fit testing that uses a 5% significance threshold, a candidate signature is not likely a member of the tested class if its separability is greater than 5%. Hence, these results indicate that the WSC will be effective in identifying specific contaminants such as oil spills or non-native materials that disrupts the homogeneity of a hyperspectral scene.

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[Table 1 near here]

6.1.1 Case study of relative separability

The SAM requires that the compared spectra have the same bands and bandwidths. Of the available material combinations in the endmember sample set, only six were comparable. It is possible to re-sample spectra to equalize their wavelength bands but resampling introduces errors that distort the results of the feature extraction methods. Table 2 compares the separability of the SAM combinations available from the sample set.

[Table 2 near here]

The SAM separability advantage over the WSC is 8.2%. The average inter-class and intra-class improvements are 8.9% and 7.9%, respectively. The relatively small improvement of the SAM over the WSC indicates that the latter has the potential to approach the performance levels of prevalent classifiers for a small improvement in image quality that would reduce the interval of uncertainty.

6.1.2 Case study of computational complexity

The case studies will use parameters for an existing airborne remote sensing platform and a state-of-the-art processor to benchmark the computational requirements. At the time of this publication, the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor is still the most popular platform for airborne hyperspectral image acquisition.[13] It provides $N = 224$ spectral channels that range from 360 to 2500 nanometres. When the host aircraft is a Twin-Otter flying at an altitude of 4 km, the AVIRIS provides a spatial resolution of 4 meters. Hence, there will be $P = 62{,}500$ hyper-pixels per square-kilometre of the scene. Although a typical application

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will tend to classify materials into dozens of classes, this case study will use the $K = 15$ material

types shown for the WSC as prototype endmembers for a class. The highest exponent of the

polynomial in the series expansion should be at least $C = 3$ when computing the arccosine,

logarithm, and square root functions with at least one significant digit of accuracy.[14] To

summarize, the parameters for the case study are $P = 62,500$, $N = 224$, $C = 3$, and $K = 15$.

Table 3 lists the processing requirements per square-kilometre of hyperspectral scenes

collected with the AVIRIS Twin Otter system. For this scenario, the number of classifications

per frame is $P \times K$, which totals 937,500. The third and fourth columns list the number of MAC

operations per classification ($\Pi s/PK$) and the total MACs per frame (Total Πs), respectively. It is

evident that the SAM requires 19 and 24 times more processing capacity than the WSC and the

WSC-R, respectively.

[Table 3 near here]

The last column of Table 3 lists the execution time for each method when using a

processor that can allocate 20 million multiply-accumulate cycles per second (MMACS) of

capacity. The latest generation of mobile computers has approximately 400 MMACS of total

processing capacity.[15] Hence, the WSC will consume 5% of that capacity whereas the SAM

would require 94% of it to classify scenes at the same rate. The WSC and the WSC-R processing

speeds shown will support image acquisition rates greater than 0.5 square-kilometres per second.

The AVIRIS Twin-Otter can capture hyperspectral images at a maximum rate of approximately

0.4 square-kilometre per second.[13] This result indicates that a hypothetical unmanned aircraft

system (UAS) platform with a similar capture rate can classify hyperspectral scenes in real-time

by using the WSC and WSC-R.

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7.   Summary and Conclusions

The search for dynamic targets with remote sensing platforms demands a rapid detection ability so that the system can take action to enhance the spatial resolution of the target area for immediate verification. Small unmanned and autonomous vehicles are emerging, and so are tiny hyperspectral imagers that are suitable payloads. However, the missing capability is rapid hyperspectral image classification. The wavelength sensitivity classifier (WSC) is a low-complexity method of hyperspectral image classification that would enable small autonomous vehicles to perform rapid searches.

The new technique extracts simple statistical and shape features of the spectra for comparison with target endmembers. The features are the wavelength normalized average albedo (AVN) and the wavelength sensitivity index (WSI). Together, these features establish the simple two-dimensional (2D) feature space of the WSC. We further define two new measures of performance. They are the separability of the feature space and the multiply-accumulate complexity (MACC) of the classifier. The former is analogous to comparing their relative signal-to-noise ratio (SNR) requirements for a given level of classification accuracy desired.

The separability analysis demonstrates that the WSC provides approximately 24% separation among library endmembers that comprises a majority of typical ground cover materials. Prevailing algorithms such as the spectral angle mapper (SAM) provide a modest improvement in separability of 8.2% for those materials that form tighter clusters in the WSC feature space. The complexity benchmark revealed that the SAM requires at least 19 times more processing capacity than the WSC to perform image classifications at the same rate.

The case study used optical specifications for a system that has capabilities that are similar to the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) aboard a Twin-Otter

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aircraft. The results indicate that the WSC will require a processing capacity of 20 million

multiply-accumulate cycles per second (MMACS) to classify hyperspectral images at a rate that

exceeds the image capture capacity of the AVIRIS platform. This requirement represents only

5% of the processing capacity available from state-of-the-art mobile computing platforms,

including smartphones. Mobile sensing platforms utilize most of the available computing

capacity for navigational controls, communications, and sensor operations. The SAM will

require 94% of the available processing capacity to provide hyperspectral image classifications at

the same rate of the WSC. Hence, the reduced complexity of the WSC will enable longer flight

endurance by trading off excess computational capacity for lower power consumption. The

results of this research motivate the additional step of future research to evaluate more

completely the classification accuracy of the WSC with extensive field data collected using a

variety of small unmanned aircraft system platforms.

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Rapid hyperspectral image classification to enable autonomous search systems

Table 1. WSC separability matrix for typical ground cover.

	Soil (Dark)	Tree (Con)	Tree (Dec)	Concrete	Ice
Soil (Light)	6.4%	**47.6%**	**45.2%**	**57.3%**	**71.6%**
Grass (Green)		0.9%	3.0%	**14.1%**	**23.4%**
Tree (Conifer)			2.4%	**16.1%**	**26.4%**
Shingle (Asphalt)				4.0%	**16.8%**
Pavement (Concrete)					**20.3%**

Table 2. Separability comparison of the SAM and the WSC.

Class Separability	SAM	WSC	Δ
Soil (Light) – Soil (Dark)	17.2%	6.4%	10.7%
Grass (Green) – Tree (Deciduous)	8.0%	0.9%	7.1%
Tree (Evergreen) – Tree (Deciduous)	4.1%	2.4%	1.7%
Shingle (Asphalt) – Concrete	16.2%	4.0%	12.2%
Shingle (Asphalt) – Ice	25.8%	16.8%	9.0%
Concrete – Ice	29.1%	20.3%	8.8%
AVERAGE	16.7%	8.5%	8.2%

Table 3. Relative complexities of the classifiers.

Model	Computational Cost Model	Πs/PK	Total Πs	Time (s)
SAM	$P \times K \times \{\Pi[3N]+\Pi[8C]+\Pi[44]\}$	740	694M	34.7
B-Distance	$P \times K \times \{\Pi[2(N+1)]+\Pi[2(C+1)]+\Pi[172]\}$	630	591M	29.5
MLC	$P \times K \times \{\Pi[2N]\}+\Pi[P(N+1)]+\Pi[2(C+1)]$	463	434M	21.7
WSC	$P \times K \times \{\Pi[2C]+\Pi[3]\}+P \times \{\Pi[2N]+\Pi[2C]+\Pi[3]\}$	39	37M	1.9
WSC-R	$P \times 1 \times \{\Pi[2N]+\Pi[2C]+\Pi[3]\}$	30	29M	1.4