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Hyperspectral imaging utility for transportation systems

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ABSTRACT

The global transportation system is massive, open, and dynamic. Existing performance and condition assessments of the complex interacting networks of roadways, bridges, railroads, pipelines, waterways, airways, and intermodal ports are expensive. Hyperspectral imaging is an emerging remote sensing technique for the non-destructive evaluation of multimodal transportation infrastructure. Unlike panchromatic, color, and infrared imaging, each layer of a hyperspectral image pixel records reflectance intensity from one of dozens or hundreds of relatively narrow wavelength bands that span a broad range of the electromagnetic spectrum. Hence, every pixel of a hyperspectral scene provides a unique spectral signature that offers new opportunities for informed decision-making in transportation systems development, operations, and maintenance. Spaceborne systems capture images of vast areas in a short period but provide lower spatial resolution than airborne systems. Practitioners use manned aircraft to achieve higher spatial and spectral resolution, but at the price of custom missions and narrow focus. The rapid size and cost reduction of unmanned aircraft systems promise a third alternative that offers hybrid benefits at affordable prices by conducting multiple parallel missions. This research formulates a theoretical framework for a pushbroom type of hyperspectral imaging system on each type of data acquisition platform. The study then applies the framework to assess the relative potential utility of hyperspectral imaging for previously proposed remote sensing applications in transportation. The authors also introduce and suggest new potential applications of hyperspectral imaging in transportation asset management, network performance evaluation, and risk assessments to enable effective and objective decision- and policy-making.

Keywords: Highway capacity, hyperspectral remote sensing, pushbrooming, spectroscopy, transportation, unmanned.

1. INTRODUCTION

The global transportation system is interdependent on the performance of large and complex multimodal and intermodal facilities that move people, goods, and waste. The U.S. transportation infrastructure consists of more than 4 million miles of roadways, 600,000 bridges, 1.5 million miles of above- and under-ground oil and gas pipelines, 100,000 miles of railroad tracks, 25,000 miles of navigable waterways, and 19,000 airports[1]. Trucks alone carry more than 8 billion tons of goods valued at more than $10 trillion each year[2]. All countries rely on a high-performance multi-modal transportation infrastructure for sustained economic growth and prosperity. Consequently, the need for regular performance measures of the entire network has become critical.

Climatic factors and heavy vehicle traffic accelerate deterioration. Figure 1 illustrates the interdependencies between economic growth and performance measures. Population growth and quality-of-life pursuits drive economic growth, which in turn fuels higher demand to transport more people and goods. To meet those demands while realizing economies of scale, organizations increase the size of the carriers such as trucks, rail cars, ships, pipelines, and aircrafts. Consequently, the infrastructure must bear a higher load density from the aggregate increase in the gross weight of carriers and their miles traveled. Together with climatic factors, an increase in load density accelerates the deterioration

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rate of surface transportation infrastructure such as roads, bridges, railroads, and runways. Maintaining a state-of-good repair requires regular performance measures to enable optimized maintenance cycles[3]. Such practices improve the efficiency and cost-effectiveness of asset management goals to maximize the amount of infrastructure in good condition and to support a sustainable cycle of economic growth.

U.S. highway agencies collectively spend billions of dollars annually to maintain highways[4]. Freight railroads incur similar expense levels[5]. The old adage that "you cannot fix what you don't know is broken" highlights the importance of regular performance measurements. Enhanced situational awareness of maintenance needs will optimize resource planning to curb adverse effects of escalating traffic load density. However, existing approaches to network-wide and continuous performance measures are expensive and time-intensive. Most jurisdictions still use manual labor to visually inspect and report on infrastructure condition. In most cases, network capacity diminishes when agencies must close portions of the network to accommodate the operations of non-destructive evaluation (NDE) and surface scanning equipment[6]. Hence, agencies everywhere are seeking faster and more affordable ways to collect and analyze data to assess the capacity, performance, safety, and security of the transportation infrastructure.

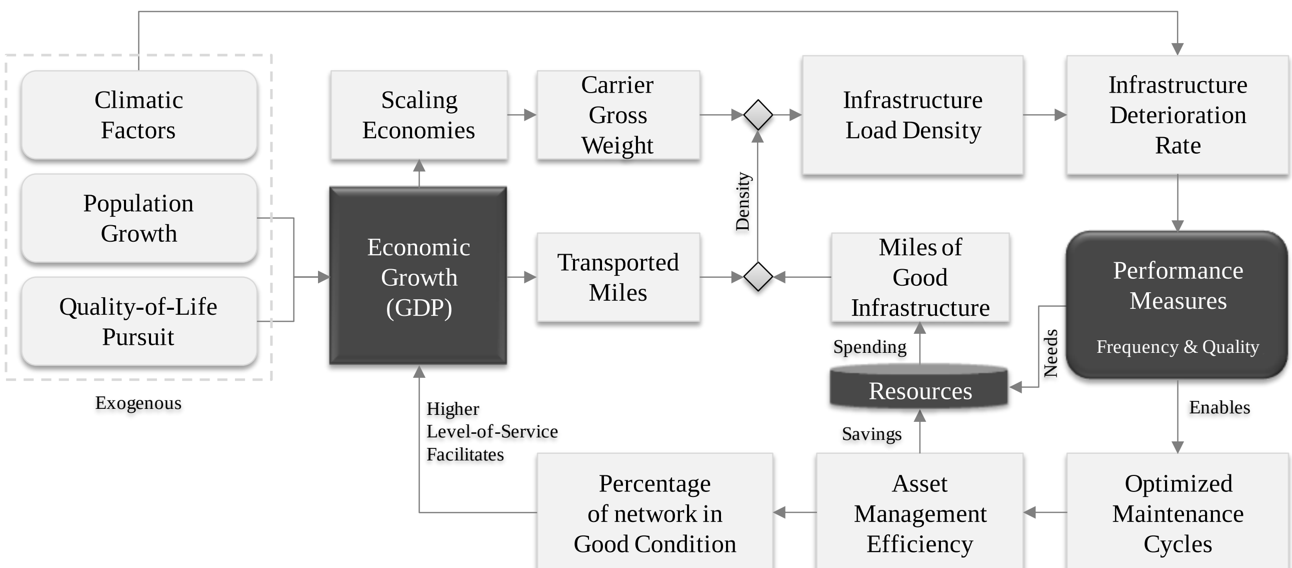

Figure 1. Infrastructure performance measures linked to economic growth.

Remote sensing using spaceborne and airborne imaging platforms offer the key advantage of broad spatial coverage without degrading the infrastructure performance or capacity. Nevertheless, there have been relatively few applications of remote sensing in transportation. Even fewer use techniques involving hyperspectral image acquisition. Table 1 summarizes the literature available on remote sensing in transportation. The table indicates which application used a mix of panchromatic (P), color (C), multispectral (M), and hyperspectral (H) types of image acquisition.

It is apparent from the literature review that the year 2000 marked the beginning of transportation related applications of hyperspectral remote sensing. Government investment in transportation research hastened most of those early activities in the U.S. The Transportation Equity Act (TEA-21) directed the United States Department of Transportation (USDOT) to collaborate with the National Air and Space Administration (NASA) to form the National Consortia for Remote Sensing in Transportation (NCRST). The act resulted in a grant award that initiated the NCRST in 2000.

The objective of this research is to characterize the barriers to hyperspectral remote sensing in transportation, assess the emerging opportunities, and to propose new utilities. The organization of the rest of this paper is as follows: the methodology of the next section will catalog the available platforms for hyperspectral remote sensing, assess the requirements from sensors and the data processing, and characterize some of the key non-technical barriers. The third section will then explore emerging opportunities that address some of the key barriers identified. The fourth section will introduce transportation application taxonomies that include new ideas to benefit from hyperspectral remote sensing. A scenario study will demonstrate how the models of highway capacity planning could leverage capabilities of remote sensing to update their parameters for improved performance. The final section summarizes and concludes the study.

Table 1. Applications of hyperspectral remote sensing in transportation.

Application	P	C	M	H
Asphalt road surface condition assessment, *Institute of Atmospheric Pollution Research & University of Rome*, Italy[7]	x	x	x	x
Oil spill detection and impact prediction in ice-affected marine environments, *LOOKNorth Center of Excellence for Commercialization and Research*, NL Canada[8]		x	x	x
Land use monitoring in response to urbanization, *Jawaharlal Nehru University*, New Delhi, India[9]			x	
Produce road condition indices from panchromatic images available at 46 cm from WorldView-2 (Digital Globe) satellite, the highest spatial resolution available in 2014, *University of Colorado at Boulder*, CO, USA[10]	x			
Road condition monitoring from hyperspectral imagery, *University of São Paulo, Brazil & the Brazilian Transportation Planning Society*, Brazil[11]				x
Three-dimensional image reconstruction of scenes to identify and characterize unpaved road defects, *Michigan Tech Research Institute*, MI, USA[12]		x		
Three-dimensional image reconstruction of scenes to identify and characterize unpaved road defects, *Geographic Information Science Center of Excellence*, South Dakota, USA[13]		x		
Road type classification by distinguishing between asphalt, cement, and unpaved roads and course classification (good, intermediate, bad) of road condition, the *University of Applied Sciences*, Stuttgart, Germany[14]				x
Information fusion, including hyperspectral and other remote sensing techniques, for transportation infrastructure surveillance by the Earth Observation and Natural Hazard Technologies Consortium of the *European Commission*, Italy[15]	x	x	x	x
Use of unmanned aircrafts to monitor construction progress and inventory roadway assets, *Utah State University*, UT, USA[16]		x		
Correlate the amount of of dead vegetation along pipeline right-of-ways to gas leaks, *International Institute for Geo-information Science and Earth Observation & Utrecht University*, the Netherlands[17]				x
Pipeline right-of-way monitoring for leak and encroachment detection, *Electricore, Inc*., CA, USA[18]		x	x	
Trained classification of transportation infrastructure from hyperspectral scenes, *Midwest Transportation Consortium, University of Iowa*, IA, USA[19]				x
Automated classification of urban surfaces to distinguish between roofs, roads, and other land features, the *German Remote Sensing Data Center*, Oberpfaffenhofen, Germany (Heiden et al., 2005)[20]				x
Pothole identification and road condition assessment, *Research Systems Inc.* VA, USA, and *SpecTIR Corp*., NV, USA[21]		x		x
Railroad track inventory and use assessment, *Humboldt-University, Berlin, Germany* & *Center for Remote Sensing of Land Surfaces*, Bonn, Germany[22]	x	x	x	
Traffic analysis and forecasting using unmanned aircrafts, University of South Florida, FL, USA (Puri, 2005)		x		
Pavement condition assessment, the *National Consortia for Remote Sensing in Transportation* (NCRST), CA, USA[23]				x
Survey of potential applications of remote sensing, the *Aviation Institute at the University of Nebraska and the Nebraska Airborne Remote Sensing Facility*, NE, USA[24]				x
Roadway network extraction from remotely sensed images, *Boeing-Autometric Corporation*, CO, USA[25]				x
Wetland classification for compliance of environmental assessments, *North Carolina DOT, EarthData Technologies, Mississippi State University*, MS, USA[26]				x
Submerged aquatic vegetation hazard identification for navigable waterways, *George Mason University*, funded by the EPA and the USGS, VA, USA[27]				x
Classification of features in urban scenes, the *University of New South Wales*, Australia[28]				x

2. ASSESSMENT OF APPLICATION BARRIERS

Hyperspectral remote sensing promises significant utility in helping to advance applications in transportation. Although sensors and techniques of hyperspectral remote sensing have existed for several decades, practitioners have deployed only a few applications[29]. The subsections that follow will further explore the barriers to adoption that include:

- Limited availability of hyperspectral remote sensing platforms
- Accessibility limitations of remote sensing
- Difficulty of sensor miniaturization
- Extensive latencies in the image processing chain
- Non-technical barriers

These are not necessarily exhaustive but they represent some of the most important barriers.

2.1 Limited availability of hyperspectral remote sensing platforms

Spaceborne platforms of hyperspectral remote sensing began in the year 2000 with the deployment of the experimental MightySatII.1[30]. As of 2014, only five satellites carry a hyperspectral imaging system. Table 2 provides their launch year and summarizes their key sensor operating parameters.

Table 2. Existing and planned airborne hyperspectral imaging platforms.

Satellites	Year	Operator	Type	BL	BU	N	GSD	Swath	Revisit
MightySatII.1	2000	USAF (inactive)	HSI	470	1050	145	30	15	5
EO-1 Hyperion	2000	NASA	HSI	400	2500	220	30	180	16
PROBA-CHRIS	2001	Europe	PAN			1	5	13	7
			HSI	400	1050	19	17	13	
			HSI	400	1050	63	34	13	
HJ-1A	2008	CAST (China)	MSI	430	900	4	30	700	4
			HSI	450	950	115	100	50	
ISS HICO	2009	NASA/ONRL	HSI	380	1000	102	92	42	14
YouthSat	2011	India/Russia	HSI	450	950	63	4000	70	5
HISUI ALOS-3	2015	Japan	HSI	400	2500	185	30	30	60
EnMAP	2017	Germany	HSI	420	2450	222	30	30	4
PRISMA	2017	Italy	HSI	400	2500	200	30	30	7
HyspIRI	2022	NASA/JPL	HSI	400	2500	200	60	145	19

HSI, MSI, and PAN indicate the type of imaging systems as hyperspectral, multispectral, and panchromatic respectively. BL and BU indicates the lower and upper wavelength bands respectively. *N* indicates the number of wavelength channels. The ground sensing distance (GSD) and swatch is in meters. The revisit period is in days. Spaceborne services have fixed orbits and they revisit a particular ground area at fixed intervals.

Table 3. Existing airborne hyperspectral imaging platforms.

Airborne	Owner	BU	BL	IFOV	N	FOV	F_r	Max Speed
AVIRIS	NASA/JPL	360	2500	1.0	224	677	100	730 km/h
HyMap	HyVista Corporation	450	2500	2.5	128	512	500	837 km/h
ProSpecTIR	SpecTIR	400	2500	1.3	244	320	100	210 km/h
CASI 1500H	Itres Research, Canada	380	1050	0.49	288	1500	85	223 km/h
HySpex	Norsk Elektro Optikk	400	2500	0.75	256	1600	100	263 km/h
APEX	European Space Agency	380	2500	0.48	508	1024	43.4	310 km/h

From the literature review, Table 3 summarizes some of the most extensively utilized airborne platforms. Operators can schedule flight paths and missions with greater flexibility than spaceborne platforms. However, their operation may require special permits and approvals to enter restricted airspace above the targeted ground area. Secondly, airborne missions are limited to a shorter window of the day when the sun angle is within the desired range for proper illumination whereas satellites maintain a sun synchronous orbit to achieve constant illumination. Table 3 includes the instantaneous field-of-view (IFOV) per pixel of the optical system in milliradians (*mr*) and the total detector field-of-view (FOV) in number of spatial pixels. For comparison with the spaceborne platforms, the GSD $\Delta\phi_x$ varies with flight altitude h_s as

$$\Delta\phi_x = 2h_s \tan\left(\frac{IFOV}{2}\right). \tag{1}$$

For small angles, tan(θ) ≈ θ, hence $\Delta\phi_x \approx h_s \times$ IFOV. The frame rate F_r of the optical system is in frames per second and the maximum speed of the aircraft is in km/h.

2.2 Accessibility limitations of remote sensing

Remote sensing is a type of non-destructive evaluation (NDE) method that complements surface scanning techniques. Hyperspectral systems provide signature recognition capability for many targets that other methods such as multispectral and infrared remote sensing cannot discriminate.

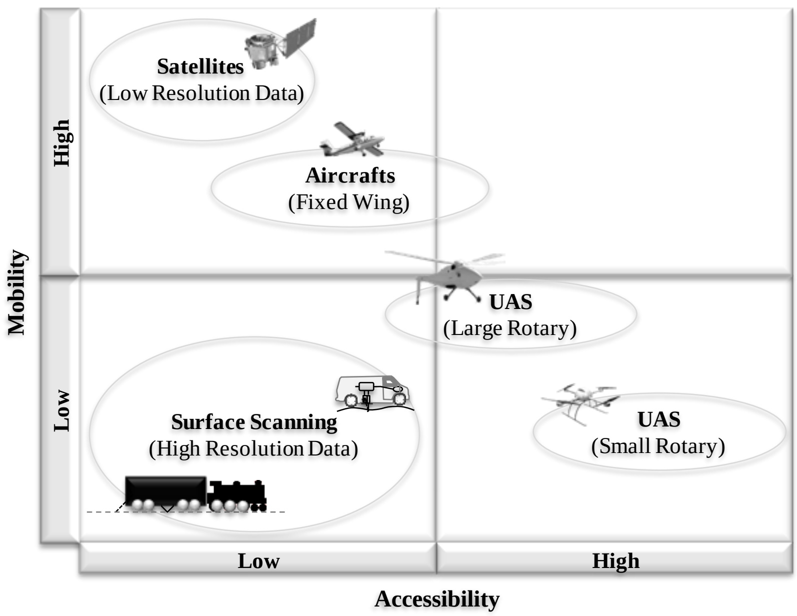

Figure 2. Remote sensing tradeoff in mobility and accessibility.

The technique relies on how light of different wavelengths interact with the unique composition and the variations in particle sizes at the molecular level. The diffraction, refraction, and reflection of incident light are unique at the different narrow band wavelength regions. Remotely sensed imagery from satellites provides a birds-eye view of the ground, therefore shadowing from trees and other large objects will occlude visibility. Although satellites can revisit areas in several days, cloud cover could hamper image acquisition. The atmosphere absorbs transmitted and reflected irradiance. This loss in energy reduces signal intensity and adds background noise. In addition, dust, dirt, or moisture on surfaces can reduce the image quality.

Airborne sources provide significantly less area coverage because of their lower mobility. However, they do offer greater degrees of accessibility that addresses some of the visibility issues of spaceborne sources. Manned aircrafts still have limited accessibility to provide the resolution needed to monitor some aspects of the transportation infrastructure. For example, transverse pavement cracks become visible with one-meter resolution and manhole covers become visible at the centimeter resolution scale[24]. Unmanned aircraft systems (UAS) promise even higher accessibility and resolution but their substantial reduction in mobility increases the time needed per unit to monitor a vast transportation network. A fleet of UAS could remediate the mobility shortcoming but at the expense of additional training, maintenance, and operating costs. Even with higher resolution remote sensing, it remains infeasible to measure some physical parameters such as ride-quality, which is an important indicator of road condition[31].

2.3 Difficulty of sensor miniaturization

Techniques of wavelength separation involve high quality prisms, diffraction grating, or interferometers. Prisms use the principle of refraction that separate EM wavelengths based on their speed differences through transparent but denser than air media. Gratings use the principles of diffraction and interference; their mass production relies on an ability to create nanometer scale temperature-stabilized grooves. Interferometers use the principle of constructive interference from EM phase alignment. Their construction relies on the ability to machine temperature-stabilized and nanometer-scale precision optical blocks with integrated beam-splitters. These stringent precision requirements establish the need for minimum size and dimension requirements to maintain material strength and operating stability across a large temperature range. The focusing elements are lenses, curved mirrors, or combinations of those. Their design requirements such as long focal distance, shock resistance, and temperature stability set stringent design constraints that prevent scaling their construction below certain minimum dimensions.

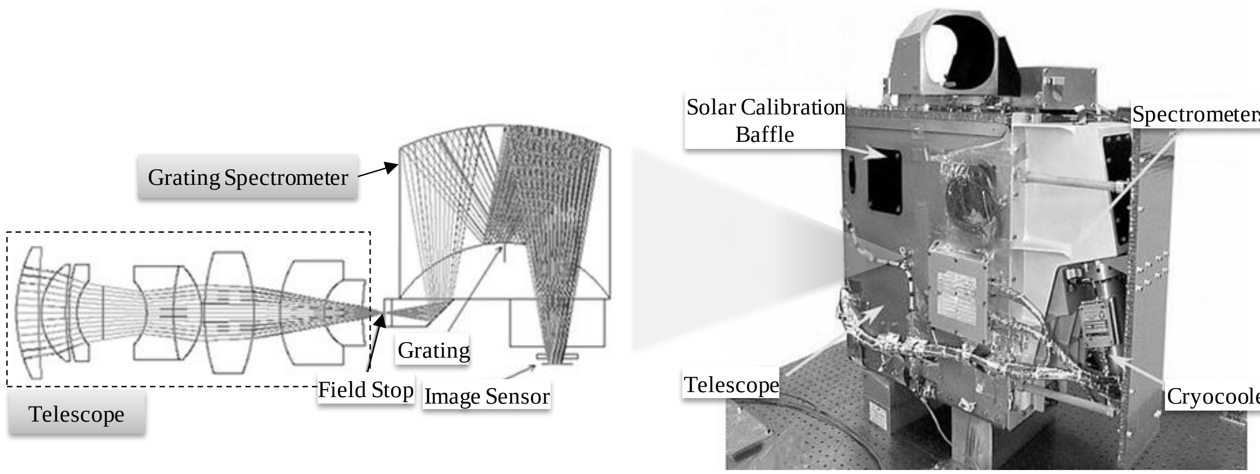

Figure 3. Optical configuration of the Hyperion hyperspectral remote sensing.

Figure 3 shows the optical configuration of the Hyperion imager that NASA deployed on the EO-1 satellite[32]. The unit weighs 49 kg (~ 108 lbs) and has a volume of approximately 0.2 cubic-meters, which is about 25-times the volume of a regulation size basketball.

2.4 Excessive latencies in the image process chain

Existing spaceborne and airborne services to acquire hyperspectral images require an application process that can take weeks or months and then a subsequent scheduling of the mission[33]. Once initiated, the flow of data from the image capture platform to the user is relatively slow. The EO-1 satellite revisits the same ground area every 16 days, but weather and cloud cover can prevent image acquisition. Once cleared, the satellite requires 10.5 minutes of lead-time before collecting the scene, and about 4 minutes of additional time to collect calibration data. The typical scene collection time is 30 seconds. After downlink, the ground station forwards the raw data to NASA for ‘Level 0’ processing to decode, parse, validate, aggregate, and format the data. NASA can take up to 5 days to complete the Level 0 processing. Subsequently, NASA sends the data on tape via surface mail to TRW Inc. for ‘Level 1’ processing to apply radiometric calibration and data interpolation. TRW then returns the processed data to NASA within 3 days for distribution. The user then performs image classification using a variety of supervised and unsupervised methods that are relatively computational complex. The process for existing airborne platforms is similarly extensive. For instance, the USGS suggest that researchers must allocate one to four months after AVIRIS data collection before receiving the processed image files.

2.5 Non-technical barriers

In addition to the technical and process impedances presented in the previous sections, there are numerous non-technical barriers. They include regulatory restrictions on flight missions, privacy concerns, liability, and the lack of standards.

FAA restrictions

The Federal Aviation Administration (FAA) banned commercial UAS operations until the agency can address their safe operations amongst non-cooperative aircrafts and other airborne operations[34]. As of 2014, the FAA requires certificates-of-authorizations (COAs) to conduct research at one of the six national test sites.

Privacy concerns

The public is generally concerned about the loss of privacy from the practice of capturing images remotely, particularly when using small UAS with integrated cameras. The national press regularly highlights cases that involve the use of drones by law enforcement agencies to conduct investigations. Such reports tend to awaken concerns about the legality of such surveillance and the potential violation of civil liberties[34].

Liability

As image acquisition devices reduce in size, researchers will likely install them on small UAS. The severity of a UAS failure depends on the type, size, and propulsion option of the UAS. Fuels can ignite in the event of a crash[34]. Some UAS crashes have involved injury and property damage. Pilot distraction is another area of concern that is similar to the notion of distracted driving.

Lack of standards

Contemporary systems for hyperspectral data acquisition consist of a broad range of sensors, platforms, resolutions, and image quality. The transportation industry currently lacks standards for image treatment within and across different acquisition platforms, spectral libraries, timeframes, and meteorological conditions. There are no standard recommendations for the systematic removal of sensor bias, geometric distortions, and radiometric non-uniformity. In addition, relatively few efforts incorporate atmospheric correction. Assembling full scenes from a mosaic of smaller swaths can introduce significant geometric and alignment errors. A first step in addressing the challenges posed by this situation is the systematic acquisition of spectral libraries using standard procedures, sensor settings, illumination, and meteorological conditions.

3. EMERGING OPPORTUNITIES

This section reviews the pushbrooming approach to hyperspectral image sensing and illustrates how the technique leverages sensor size reduction to enable use on small UAS platforms and small satellites. Advancements in computing that include more computationally capable microprocessors and cloud-computing techniques are also enablers of the pushbrooming approach when deployed on small UAS.

3.1 Pushbrooming approach to Hyperspectral imaging

The typical image sensor is a planar two-dimensional (2D) array of $x \times y$ photosites. The sensor has one electronic photosensor beneath each photosite to produce one pixel of the digital image.

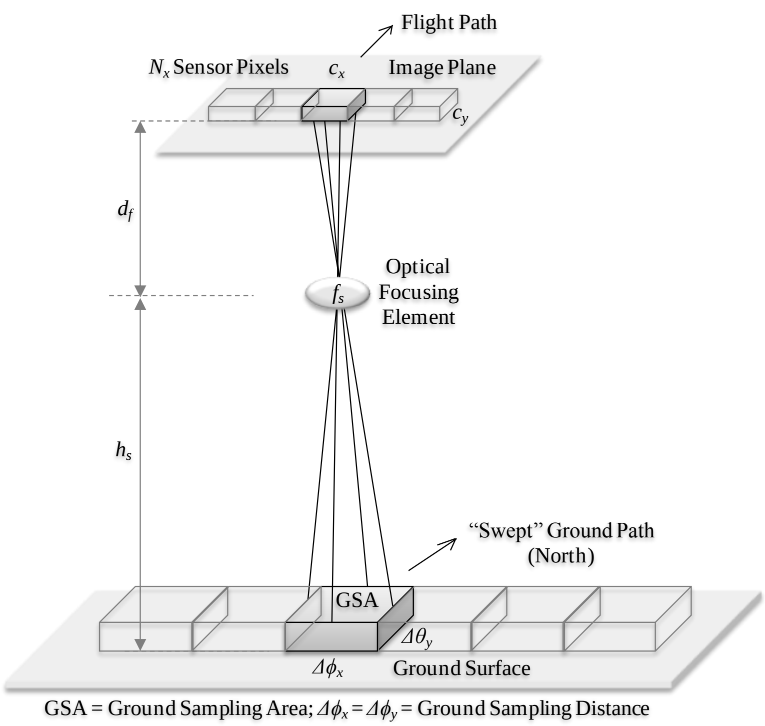

Figure 4. Pushbrooming approach of hyperspectral remote sensing.

Most single chip color imagers include a color filter array, such as a Bayer filter mosaic, to pass energy from red (R), green (G), and blue (B) wavelength bands onto the individual photosensors of each photosite. To render the image, de-mosaicing image processing algorithms must subsequently interpolate light intensity from neighboring pixels to produce intensity values for the other two wavelength bands such that the final color image data maps one R-G-B triplet to each pixel of the image sensor. Other approaches use beam splitters or wavelength selective optical filters with multiple sensor arrays[35]. A hyperspectral scene is a meta-data cube where each layer is a picture of the same scene sensed at a different wavelength band of the electromagnetic (EM) spectrum. Hence, the color imaging approaches do not scale much beyond the three R-G-B wavelength bands to accommodate the hundreds of wavelength bands of hyperspectral scenes.

A pushbrooming approach to image acquisition enables the use of standard 2D photosensor arrays with pixel size $c_x \times c_y$. This technique sweeps a narrow field-of-view (FOV) of dimensions

$(N_x \times \Delta\phi_x) \times \Delta\theta_y$ along the ground path of the flight trajectory. The aperture of a pushbrooming imaging system limits the FOV to one row of the image sensor that contains N_x pixels as illustrated in Figure 4. The optical magnification factor for square pixels is $M_\eta = (c_x/\Delta\phi_x)^2$. Wavelength separating optics focus the EM energy from different wavelength bands onto each row of the image sensor. Therefore, each captured frame of the 2D image sensor will contain the equivalent of one row of the image, but each row will register the same image from a different wavelength band. Hence, a relatively constant speed V_G will improve the quality of the hyperspectral scene assembled from the sequence of image frames. Some amount of FOV overlap γ will be necessary to aid the image assembly algorithm. Altogether, the constraints of the pushbrooming geometry dictate a minimum image capture frame rate F_{rm} of

$$F_{rm} = \frac{V_G}{c_y \sqrt{M_\eta}(1-\gamma)}. \quad (2)$$

The Hyperion imager aboard the EO-1 satellite uses this approach and likely requires less FOV overlap than an airborne platform because of its relatively constant speed above the atmosphere. Airborne platforms will dictate a FOV overlap requirement that depends on the expected ride-quality at the selected flight altitude and speed. The relative instability of small UAS platforms will also dictate more computationally complex approaches for image frame assembly, image noise reduction, geometric correction, and image classification.

3.2 Hyperspectral sensor miniaturization

Although the miniaturization of the focusing and wavelength separation elements continues to pose significant challenges, there has been some progress. Figure 5 illustrates the key components of a hyperspectral camera. Advancements in precision machining enable the mass production of transmissive holographic diffraction gratings that implement the wavelength separation method[36]. The ability to create micro-lenses and to integrate aberration-corrected optical elements directly on top of the image sensor enables significant size and cost reduction of the light focusing element[37].

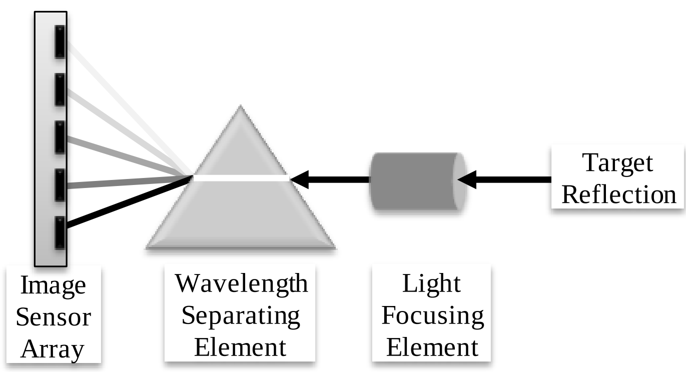

Figure 5. Key components targeted for sensor miniaturization.

The ubiquitous adoption of image sensors for mobile phones results in the continuous quest for their performance enhancement and cost reduction.

Numerous manufacturers currently leverage these trends to produce Hyperspectral imagers that weigh less than 2 kilograms (less than 5 pounds) and those are suitable for installation on small UAS platforms[38].

3.3 Proliferation of small UAS platforms

Lower building costs and a proliferation of commercial applications for UAS has led to their widespread use[34]. In 2014, the FAA issued exemptions to the commercial movie and television production industry that allow small UAS operations but with various restrictions[39]. Pending FAA regulations to integrate UAS into the airspace will likely spur growth for smaller and more affordable aircrafts. Large organizations such as Amazon, Google, and Facebook announced their intent to deploy small UAS for a variety of commercial purposes. Analysts expect that the UAS industry will spend \$89 billion by 2023 to develop more useful, safer, and easier to fly aircrafts[40]. These trends will continue to challenge sensor manufacturers in the size, power, and weight reduction of hyperspectral imaging systems.

3.4 Advancements in computing

The collection, processing, and interpretation of hyperspectral data involve significant computing resources. Image processing involves radiometric calibration, atmospheric correction, geometric alignment, and image stitching. Radiometric calibration involves the removal of temporal or spatial brightness variations in images that are associated with the image sensing system rather than the actual scene reflectance. Through wavelength selective absorption, scattering, and diffraction, the atmosphere modifies the target irradiance both spatially and spectrally, and those modification change with time. The amount of unwanted light depends on the atmospheric conditions at the time, the terrain of the scene, and the flight altitude. Atmospheric correction algorithms attempt to estimate and compensate for atmospherically induced variations in irradiance. Off-nadir viewing from pushbroom operations distorts three-dimensional (3D) image projections onto two-dimensional (2D) planes[41]. Geometric correction entails knowing the instantaneous position and attitude (orientation) of the platform at the time of image acquisition.

Image classification is a significant aspect of the interpretation and decision-making process. The classification methods and algorithms vary widely but they generally fall into two categories: supervised or unsupervised[42]. Supervised methods involve both statistical and machine learning approaches. The computation generally requires a complex calculation between every hyper-pixel and the endmember of a spectral class[43]. The algorithms of unsupervised methods are generally at least $O(PN^2+N^3)$ computationally complex[44]. P is the number of pixels, and N is the number of bands. The continuous advancement and proliferation of multi-core processors, digital signal processors (DSP), and cloud computing architectures could now accommodate these complexities with greater ease.

4. NEW APPLICATION UTILITIES

This section illustrates how the pushbroom framework of hyperspectral remote sensing could enhance the utility of existing transportation applications as well as create new utilities. To focus the illustration, this section selects road condition assessment for the scenario study. The taxonomies of transportation applications introduced reveal numerous applications that could benefit from hyperspectral remote sensing. The scenario analysis selects highway capacity planning to demonstrate the link between theory and practice using results of the hyperspectral image classification.

4.1 Utility enhancement of existing applications

About 94% of the 4 million miles of paved roads in the United States contains asphalt. The material also covers about 85% of the nation's airport runways and parking areas[45]. Hyperspectral remote sensing offers numerous utilities in the assessment of roadway surface condition. Asphalt is easily discernible from other road types because the hydrocarbon of the bitumen binder has maximum absorption bands around 1730 nm and 2300 nm[46]. New asphalt has generally low reflectance (albedo) because bitumen absorbs solar radiation throughout the 250 – 2500 nm range[47]. Deeper absorption bands also indicate newer roads[48]. The average reflectance across the EM spectrum increases as a pavement loses its bitumen surface from erosion and tire polishing[23]. With the loss of binder material, aggregate outcropping begins to reveal their mineral signatures[7]. Severe pavement cracking could decrease albedo by about 7% because of shadowing and scattering effects[49]. Hence, agencies could use hyperspectral remote sensing to catalog the age and relative condition of pavements.

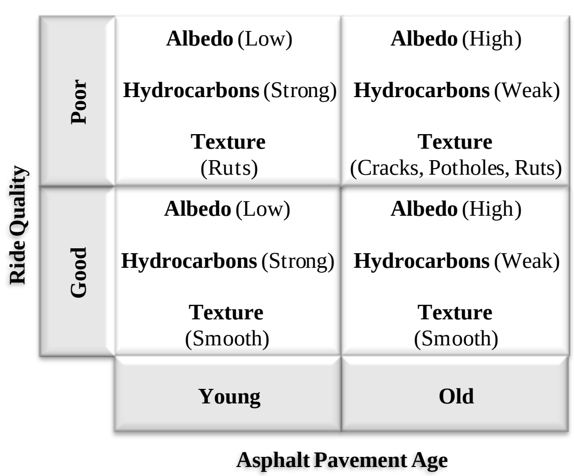

Figure 6. High resolution enhances applications.

Improved condition assessment accuracy is also possible by analyzing higher resolution images from UAS platforms. As cracks develop, higher resolution images reveal a sharpening of the hydrocarbon features from the exposed layers of the original asphalt mix beneath. Water inlets create absorption bands in the longer wavelength regions. As water interacts with material beneath, iron absorption peaks also appear at 520, 670, and 870 nm[50].

The age and surface condition of pavements are important asset management parameters but agencies are generally more concerned about characterizing their ride-quality. Although there is generally a strong correlation between the age of a road and the ride quality it provides, the former is not necessarily an indicator of the latter. For instance, agencies often characterize the ride-quality of new roads to assess the contractor's performance and to determine fee penalties based on overall roughness. Hence, estimating the age of the pavement from its albedo and the sharpness of its hydrocarbon spectral features alone is not necessarily sufficient information to characterize its ride-quality, which is a task that nearly all state highway agencies undertake annually[51].

The higher resolution and greater accessibility of UAS could yield 3D images that also enable texture analysis[12]. The combined information obtained from a pushbrooming approach using UAS platforms could result in an ability to classify ride-quality qualitatively as shown in Figure 6.

4.2 Taxonomy of transportation applications suitable for hyperspectral remote sensing

The transportation applications that can benefit from utilizing hyperspectral remote sensing fall into the two groups of a) planning and development and b) maintenance and operations. Figure 7 illustrates the taxonomy. The first group has two sub-categories, namely capacity planning and environmental assessment.

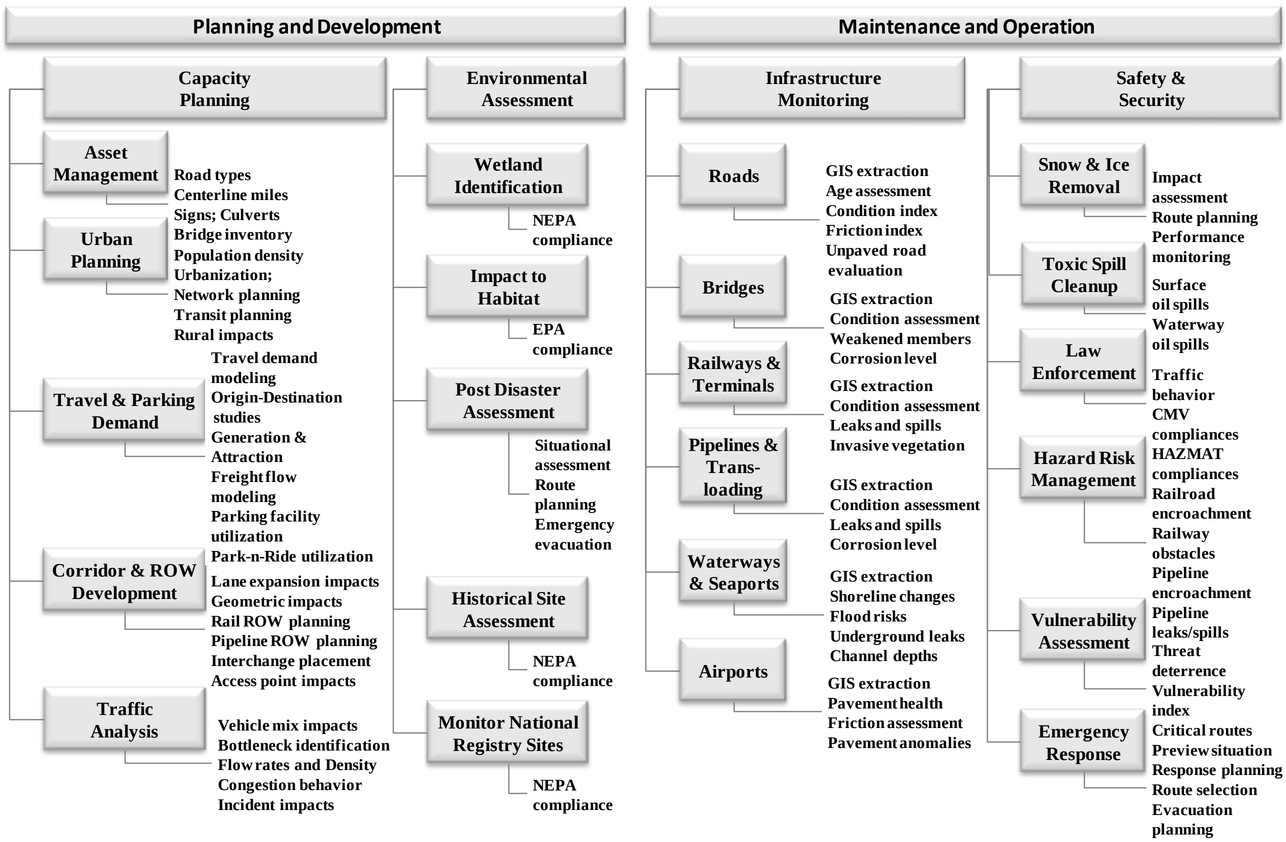

Figure 7. Application taxonomy for remote sensing utility in transportation applications.

Likewise, the second group has two sub-categories: infrastructure monitoring, and safety & security. Sustainable transportation development means that actions taken today must not adversely affect the ability of future generations to thrive. Hence, planning in transportation focuses on how to design and manage the system capacity and assets to accommodate the mobility and accessibility demands of travel, now and in the future. Developments must be sustainable as population, traffic, and production grows. Therefore, planners aim to minimize adverse impacts to the environment while accommodating the demands. Infrastructure monitoring involves multimodal performance measures as previously described. Safety and security aspects of transportation involve a variety of risk management and emergency response measures as the taxonomy indicates. Future research will expand on the details of how hyperspectral remote sensing provides utility and benefits for each of these areas. As an example, the next section provides a scenario study for one specific area.

4.3 Application scenario in highway asset management

The capacity of a transportation network depends on the density and speed at which traffic can safely flow through its corridors. To illustrate how data from hyperspectral remote sensing could be valuable in planning, this section first develops the capacity and operational models for freeways.

The models then provide insights for practitioners to incorporate remotely sensed data to update their various parameters for improved accuracy in analyzing different portions of the complex network. Roadway capacity depends on numerous factors that include their functional class, geometry, terrain, traffic mix, peak hour volume, and the driver familiarity with the route. The Highway Capacity Manual (HCM) of the Transportation Research Board (TRB) is the accepted standard for highway capacity and level of service determination[52].

Freeways are divided highway facilities with full control of access because regulations limit their access to certain types of vehicles, and their access points are limited to specific locations. They typically have two or more lanes for the exclusive use of through traffic in each direction and the HCM defines their capacity C_f as

$$C_f = 1700 + 10 \times S_{ff} \tag{3}$$

where S_{ff} is the free-flow speed. The base free-flow speed S_{bff} is a function of the speed limit whereas the free-flow speed is the speed at which drivers feel comfortable traveling the facility. Hence, adjustments to the base free-flow speed produce the free-flow speed as follows:

$$S_{ff} = S_{bff} - f_{LW} - f_{LC} - f_N - f_{ID} \tag{4}$$

where f_{LW}, f_{LC}, f_N, and f_{ID} are adjustment factors that account for non-ideal lane widths, lateral clearance, number of lanes, and interchange density, respectively. To calculate the level-of-service provided, the HCM converts the peak hour volume of vehicles V_T to passenger car equivalents (PCE) or V_{PCE} where

$$V_{PCE} = \frac{V_T}{f_{PH} \times N_L \times f_{HV} \times f_p} \tag{5}$$

in units of passenger cars per hour per lane (pcphpl). The number of lanes in one direction is N_L and the factor that accounts for driver familiarity with the facility is f_p. The default driver-population factors for urban and rural highways are 1.0 and 0.975, respectively. The peak-hour factor f_{PH} is an indicator of the cyclical variations in traffic distribution through the segment for any given day. It is the ratio of the *vehicle* volume in the peak hour period V_{60} to the vehicle volume in the peak 15-minute period V_{15} of that hour such that

$$f_{PH} = \frac{V_{60}}{4 \times V_{15}}. \tag{6}$$

The default peak-hour factors for urban and rural areas are 0.92 and 0.88, respectively. Heavy vehicles require more time-headway than passenger cars to accommodate their limited acceleration and maneuverability on different terrain. Hence, a heavy vehicle factor f_{HV} will normalize the traffic mix to passenger car equivalents. The f_{HV} factor is

$$f_{HV} = \frac{1}{1 + P_T(E_T - 1) + P_R(E_R - 1)} \tag{7}$$

where P_T and P_R are the proportions of trucks (and busses) and recreational vehicles, respectively. E_T and E_R are corresponding terrain-dependent model parameters provided in tables of the HCM. The ability to identify and classify vehicle types as well as traffic density using hyperspectral remote sensing provides a low-cost means to update the model parameters regularly, or for individual jurisdictions.

A popular model for the non-linear change in average speed S_{av} with volume is[53]:

$$S_{av} = \frac{D_s}{T_{AADT}} \left[1 + \gamma_s \left(\frac{V_{PCE}}{C_s} \right)^{\rho} \right] \tag{8}$$

where T_{AADT} is the annual average daily travel time for vehicles traveling a segment of length D_s and capacity C_s. Using hyperspectral remote sensing to update the average speed, travel time, and volume of a segment will update the model parameters γ_s and ρ. The average speed S_{av} relates to the traffic density D_{PCE} as follows:

$$D_{PCE} = \frac{V_{PCE}}{S_{av}} \tag{9}$$

in units of passenger cars per mile per lane (pcpmpl). Remotely sensed data can regularly identify the average speed and density of vehicles across any segment of the roadway. The high spectral contrast between manufactured and natural surfaces improves the classification accuracy to determine geometric factors such as lane widths, number of lanes, shoulder clearances, median type, terrain type, and access point or interchange densities, even from relatively low-resolution satellite images. The current version of the highway capacity model does not include a factor that accounts for the influence of surface condition on average speed. Hence, the ability to estimate a condition index using the method described in Figure 6 and calibrating for the average speed and density observed for different facilities will further improve the model. The emerging opportunities that would enable real-time hyperspectral remote sensing also introduce the possibility of adaptive modeling. Such capabilities would enable the adaptive models to account for short-term changes in traffic conditions, incidents, and weather events that affect corridor capacity. This general approach is applicable to multimodal capacity estimation that includes railways, pipelines, and waterways.

5. SUMMARY AND CONCLUSIONS

The increasing loads from heavy vehicles that support growth in commerce accelerate infrastructure deterioration. Agencies adopt asset preservation practices to prolong the service life of infrastructure. However, they lack the resources needed to monitor asset condition with the frequency necessary to identify their optimized maintenance cycles. The multimodal transportation infrastructure is vast and dynamic. Existing methods of condition and performance assessments are laborious and expensive. This research highlighted the emerging opportunities for hyperspectral remote sensing to address the resource gaps and to provide broad coverage and timely assessments. The barriers to deployment identified provided some insights to explain the lack of hyperspectral remote sensing utility in transportation applications. The analysis highlighted five barriers to deployment. Amongst them, the accessibility limitations of existing sensor platforms and their extensive process chain latencies burden transportation applications that require high-resolution images and rapid results. The other three barriers that include a lack of imaging platforms, bulky sensors, and regulatory constraints are common to most other applications such as precision agriculture. However, emerging opportunities that are countering those barriers include the popularization of UAS utility in consumer applications, sensor miniaturization, and advancements in computing. In particular, the pushbrooming method of hyperspectral image acquisition leverages the cost and size reduction trends of conventional image sensor systems that are now common in nearly all mobile phones. These emerging opportunities also enhance the benefits of applying hyperspectral remote sensing to existing applications in transportation such as pavement condition assessment. These opportunities create new utilities in nearly all categories of transportation applications. This research used the scenario of highway capacity planning to demonstrate a link between the models and the practice of updating them by extracting relevant data from the analysis of hyperspectral scenes. Future opportunities that enable real-time hyperspectral remote sensing will lead to adaptive multimodal models that account for short-term changes that affect corridor capacity.

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