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Spectrometry and Hyperspectral Remote Sensing of Urban Road Infrastructure

Martin Herold

Margaret E. Gardner

Val Noronha

Dar A. Roberts

SPECTROMETRY AND HYPERSPECTRAL REMOTE SENSING OF URBAN ROAD INFRASTRUCTURE

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Introduction

Detailed and accurate information about the road network is the foundation for comprehensive management and planning of transportation infrastructure and assets. Quality standards for the required data have evolved considerably over the last decades as traffic and applications have become more demanding, and include a wide range of variables such as road centerline and geometry, pavement type, and road surface conditions. Remote sensing has the potential to provide detailed road mapping and may offer more up-to-date and economical methods to improve common practice transportation network observations (Jensen and Cowen 1999, Usher 2000). However, remote sensing of road infrastructure faces several challenges. Given the three-dimensional land surface structure, roads are the “bottom layer” that can be covered or shadowed by surrounding surfaces such as trees, buildings, or cars (Figure 1). The road surface structure and geometry are mixed and result in a spectrally indistinct response with a high amount of spatial variability. Within urban areas, where the road network is particularly dense, these factors become even more complex. The abundance and three-dimensional structure of artificial materials such as roofs, transportation surfaces, vegetation, bare soil, and other cover types result in a spatial and spectral heterogeneity that far exceeds natural and quasi-natural environments (Figure 1), making urban remote sensing image analysis a challenging process. In fact, the discrimination and mapping of road surfaces has to consider the full complex spectral characteristics of urban materials and land cover types.

Figure 1: Illustrated examples of challenges in remote sensing of the road transportation network.

Recent developments in remote sensing technology have provided a variety of potential avenues for generic and systematic research on these problems. These investigations can help one determine capabilities and limitations in remote sensing of road infrastructure and hopefully overcome the known challenges.. One of the innovative concepts involves ground spectrometry (from ground measurements) and hyperspectral remote sensing (from airplane or satellite sensors). These sensors sample the earth surface in a large number of narrow spectral bands over a continuous range. Such detailed measurements allow for precise investigations and understanding of chemical and physical material properties as well as surface geometry that are reflected in distinct spectral characteristics (Goetz et al.1985). Imaging spectrometry has been increasingly explored to support the application of remote sensing for earth observation purposes, i.e. for detailed spectroscopic analysis of natural targets such as vegetation and minerals (Roberts et al. 1998, Clark 1999, van der Meer and de Jong 2001). Despite these advantages, the knowledge about spectral characteristics of man-made surface types is quite weak and little research has focused on the spectrometry of urban materials and road surfaces (e.g. Ben Dor et al. 2001). In fact, the lack of a general understanding of urban spectral properties is one of the major limiting factors in detailed remote sensing of these environments and of transportation infrastructure. There is inadequate understanding about the spectral characteristics of road surfaces (of varying type, age and condition) and how these targets differ spectrally from other urban materials and land cover types. The capabilities and limitations of common multispectral sensor systems are unclear, as are the most suitable sensor configurations for mapping the road network in urban areas. If these questions are answered then the role of remote sensing technology in road infrastructure mapping can be better understood.

A research program initiated by the US Department of Transportation focuses on these research questions and explores the potential of remote sensing in transportation. As a result, a “National Consortium on Remote Sensing in Transportation” (NCRST Infrastructure 2002) has been established at the Department of Geography, University of California Santa Barbara. One of the research objectives is to utilize imaging spectrometry and hyperspectral remote sensing in mapping urban road infrastructure. An important element in this research is the development of a comprehensive regional spectral library of urban materials and road surfaces. Urban spectral libraries were developed using a handheld spectrometer in the field and from high-resolution remotely sensed data (Airborne Visible/Infrared Imaging Spectrometer). The spectral libraries and field observations provide a comprehensive database for spectral studies using principles of imaging spectrometry on the scale of individual materials (ground spectrometry) and land cover types (hyperspectral remote sensing).

Data and Methods

This study focuses on the urban area of Santa Barbara and Goleta, California that is characterized by a versatile mix of urban land cover types and surface materials including various categories of roofs and different road types and conditions. The hyperspectral remote sensing data from NASA-JPL's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) were acquired on June 9th, 2000. The AVIRIS sensor records 224 spectral bands with a bandwidth of ~ 10 nm each, covering a spectral range from 350 to 2500 nm. The data set was acquired at a spatial resolution of approximately 4 meters, comparable to current high-resolution space-borne sensor systems like IKONOS. The data meet the generally proposed spatial resolution standard of less than 5 m for detailed urban area mapping (Welch 1982, Jensen and Cowen 1999), and the high spectral resolution lends itself well to comparative land cover mapping. The data were intensely processed by the Jet Propulsion Laboratory (JPL) in Pasadena and the University of California, Santa Barbara (UCSB) for motion compensation and reduction of geometric distortions. The AVIRIS data were processed to apparent surface reflectance using a modified Modtran radiative transfer model (Green et al. 1993; Roberts et al. 1997) and adjusted using a ground reflectance target (Clark et al. 1993). The development of the AVIRIS urban spectral library was based on a comprehensive training dataset from ground observations and mapping that was developed for land cover classification mapping purposes (see Herold et al. 2003). The spectral library includes 26 different cover types and contains 956 individual spectra.

Ground spectra were acquired with an Analytical Spectral Devices (ASD) Full Range spectrometer. The spectrometer samples a spectral range of 350-2500 nm at a sampling interval of about 2 nm. Spectra were measured between May 23 and June 5, 2001 from a height of about 1 meter with a field of view of 22° (0.39 m at a height of 1 m). Ground spectra were acquired in sets of five for each field target. Four to six sets of spectra were bracketed by measurements of a Spectralon (Labsphere, North Sutton, NH) reflectance standard. Spectra were inspected for quality, and suspect observations were discarded. Each urban surface spectrum was divided by its appropriate standard spectrum to create a reflectance spectrum. The entire Santa Barbara urban ASD spectral library consists of nearly 6000 individual reflectance spectra, representing 147 unique materials and surface types.

Table 1: Examples of different materials and land cover in the two urban spectral libraries. Each target is linked to a diagram that contains two example spectra and the spectral name/identification that is used in the spectral libraries.

Land cover type	ASD urban spectral library	AVIRIS urban spectral library
Roofs/Buildings	Wood shingle roof Tan composite shingle roof Tar roof Red tile roof Red gravel roof Grey tile roof	Wood shingle roof Dark-gray composite shingle roof Tar roof Red tile roof Grey gravel roof Light-gray asphalt roof Brown metal roof
Transportation surfaces	Asphalt road Concrete road Gravel road Parking lot	Asphalt road Concrete road Gravel road Parking lot Railroad tracks
Non-built up and other urban surfaces	Green vegetation Non-photosynthetic vegetation Bare soil	Green vegetation Non-photosynthetic vegetation Bare soil Swimming pool Green tennis court Red sport field tartan

Example spectra from both libraries are described and linked in Table 1. The spectra represent the complex characteristics and variability of urban surface types, including built-up materials (e.g. various roof types and road materials) and non-built up surface types (e.g. green vegetation, non-photosynthetic vegetation and bare soil). The different materials and land cover types are organized in a land cover classification system . Given the general research objectives, the ASD spectral library has a strong focus on road surfaces and specific roof types (e.g. composite shingle roofs). The AVIRIS library represents a larger range and variability of land cover classes but with less detailed descriptions of the specific surface characteristics. This fact is represented by the examples shown in Table 1. They indicate a larger variability within each class and a more “noisy” spectrum in AVIRIS spectra due to minor residuals of atmospheric distortions, especially for low reflectance targets. The spectral libraries are available for research purposes (please contact the authors).

Both spectral libraries were used to analyze the spectral properties of urban materials and road surfaces of different type, age and conditions. The spectral analysis included an evaluation of separability between these different surface types and an assessment of suitable spectral bands in separating them. Only a brief description of the methods is given here, for more detailed information of the spectral analysis methods, image classification, and accuracy assessment see Herold et al. (2003). The processing was performed using the public domain program “MultiSpec.” This program was designed for processing and analyzing high dimensional and hyperspectral remote sensing data sets (Landgrebe and Biehl 2001). The primary method used is the Bhattacharyya distance (B-distance). This measure calculates the statistical distance between two Gaussian distributions (Kailath 1967) and incorporates both first and second order statistics. The B-distance is widely used for spectral separability analysis and band prioritization to focus an application on a set of most suitable spectral bands (Chang et al. 1999). The AVIRIS data were classified using a Maximum Likelihood classification algorithm. The classification resulted in a land cover map that considered several types of roads, e.g. with asphalt, concrete, and gravel surfaces, and parking lots.

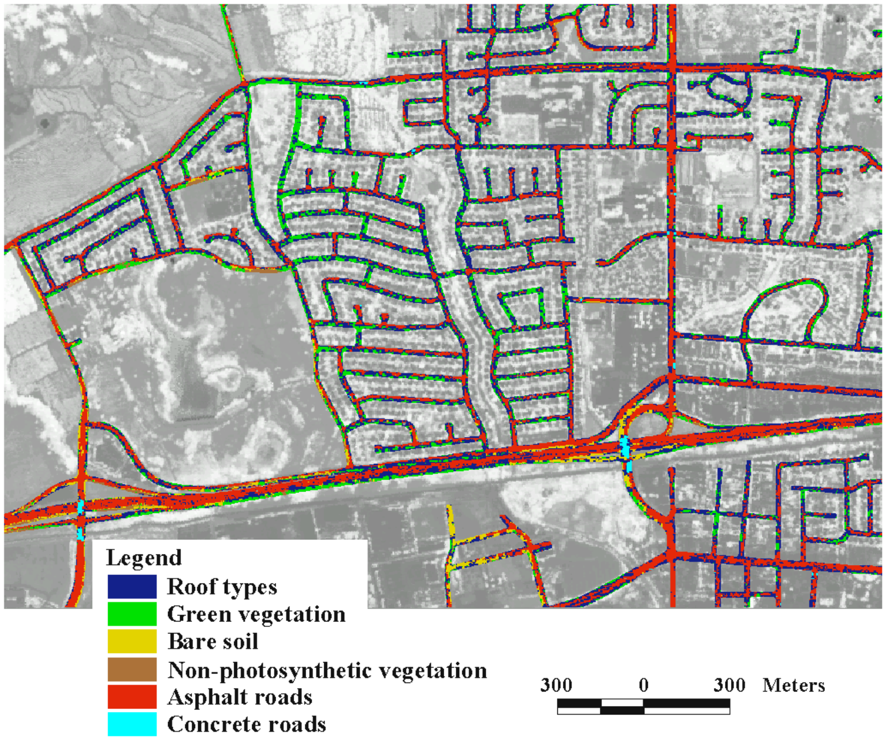


Figure 2: Subset of the road network from the land cover classification. The background image is the NDVI.

Mapping of road types and road centerlines

A subset of the road network from the land cover classification is presented in Figure 2. The map shows the roads and how they were classified from the AVIRIS data. Areas in red and light blue indicate road pixels that were classified correctly. Areas in other colors represent road pixels that were misclassified into non-road categories, indicating distinct inaccuracies in the classification. The road classification accuracies are presented in Table 2. The accuracy assessment was based on a random cluster sampling with 100 individual reference points for each class (Herold et al. 2003). The accuracy is lowest for asphalt roads (about 70 %), with improvements for concrete roads (about 80%) and highest for gravel roads (about 90 %).

Table 2: Classification accuracies for different road types (Note: The producer accuracy gives a general measure of classification performance. The user accuracy describes the “overmapping” of the class, e.g. the lower the user accuracy the more the class appears in areas of other land cover types).

Road type	Producer accuracy	User accuracy
Light asphalt (new)	89 %	64 %
Dark asphalt (old)	55 %	85 %
Concrete	71 %	95 %
Gravel	83 %	100 %

The different sources of error are clearly highlighted in Figure 2 and reflect the challenges that were discussed in the introduction. The road surfaces that are mapped as bare soil represent construction areas. The appearance of roof and vegetation pixels within the road areas shows the significant confusion between those classes, particularly for dark and shadowed road. Some of these errors are related to the spatial resolution. Major roads are mapped more accurately than minor residential roads and the edges of major roads seem to be more likely classified as roofs; a typical mixed pixel problem. However, some of the inaccuracies are of spectral nature and will be investigated in more detail with the ASD ground spectral library.

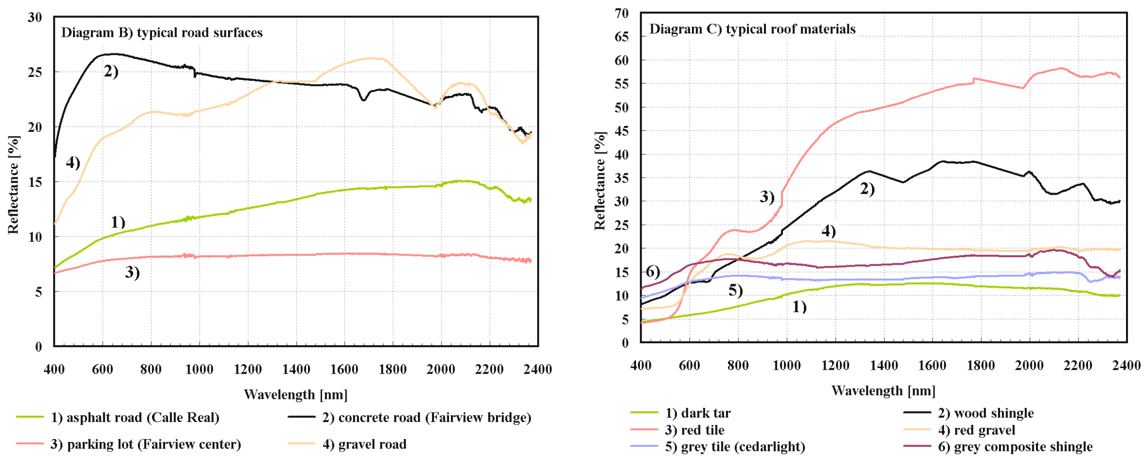


Figure 3: Spectra of typical road and roof materials from the Santa Barbara ASD urban spectral library, Note: The small-scale variations at ~950 nm are an artifact of the field spectrometer and represent the area of transition/overlap between the sensor materials. Other sensor induced spectral variations relate to the “noisy” signal in the SWIR II region above 2300 nm. These artifacts are present in all spectra and appear strongly in low reflectance targets. The major water vapor absorption bands are interpolated. Note the different scales in the y-axis.

Figure 3 presents the spectra of typical road and roof materials. They show a general spectral shape of increasing reflectance towards longer wavelengths with a reflectance peak in the SWIR. Concrete and gravel roads have the highest reflectance; parking lots have the lowest over the entire spectral range. The road material spectra contain absorption features in the SWIR that can be related to their mineral and hydrocarbon components. Red tile roofs and wood shingle roofs show distinct spectral signatures compared to the other materials. Both roof types show a significant reflectance increase in the NIR and SWIR region. Tar, gray tile and composite shingle materials show the lowest reflectance that is fairly constant over the whole spectral range with only minor absorption features in the

SWIR. They have a spectral signature similar to asphalt roads, partly due to the fact that they are composed of similar generic materials. The spectral similarity between these targets is emphasized by the spectral separability measurements (B-distance) derived from the ASD ground spectra. Figure 4 shows that the lowest separability values of nearly all investigated urban materials appear between specific types of roofs and roads. These spectral similarities are generic material properties and are responsible for the inaccuracies in the land cover classification (Figure 2). In fact, the spectral confusion between individual roofs and roads is higher than for different road surface types as confirmed by the classification results. As indicated in Figure 4, concrete roads and to some extent asphalt roads have fairly high average and low minimum separability. This indicates a large within class variability and emphasizes the spectral complexity of transportation surfaces compared to other urban land cover types. In rural areas where asphalt roads are surrounded by vegetation and natural surfaces, this problem is certainly less evident, where classification is impeded primarily by foliage and cloud cover.

	1: Com_sh	2: Grav_rf	3: Tar_rf	4: Gr_tile	5: Rd_tile	6: Wd_sh	7: Asp_rd	8: Concr	9: Grav_rd	10: P_lot
1: Composite shingle		*56*	*19*	*14*	*75*	*61*	*8*	*18*	*106*	*13*
2: Gravel roof	**405**		*36*	*46*	*109*	*189*	*51*	*17*	*88*	*84*
3: Tar roof	**190**	**599**		*30*	*69*	*127*	*17*	*20*	*135*	*26*
4: Gray tile roof	**92**	**178**	**67**		*34*	*32*	*35*	*16*	*61*	*31*
5: Red tile roof	**549**	**581**	**559**	**375**		*84*	*90*	*52*	*147*	*130*
6: Wood shingle roof	**315**	**359**	**171**	**172**	**197**		*218*	*31*	*152*	*249*
7: Asphalt road	**244**	**693**	**119**	**99**	**1331**	**351**		*28*	*68*	*7*
8: Concrete road	**687**	**735**	**1325**	**423**	**1247**	**977**	**1151**		*29*	*11*
9: Gravel road	**2533**	**2514**	**1733**	**2460**	**927**	**4370**	**3047**	**1799**		*117*
10: Parking lot	**194**	**700**	**98**	**81**	**1499**	**436**	**194**	**897**	**3832**	
Coding of values:	**Bold**: Average separability (lower left part of matrix) *Italic*: Minimum separability (upper right part of matrix)									
Gray background:	Average value ≤ 150 / Minimum value ≤ 20									

Figure 4: Matrix of B-distance values for minimum and average separability between different man-made land cover types.

The previous examples have explained the classification errors between road surfaces and roof types. The other major source of error presented in Figure 2 involves vegetation. In general, vegetation surfaces and roads have a very different spectral signature and confusion is expected to be minor (Figure 5). Some of the misclassifications are related to vegetation that is covering the road surfaces, i.e. a large tree overhanging a road. This problem is not avoidable from a remote sensing perspective. However, some of the roads are completely mapped as vegetation (Figure 2) although they are not completely covered by vegetation. These areas are covered by vegetation shadow. The spectral characteristics of these surfaces are shown in Figure 5. The diagram presents a concrete surface completely shaded by a tree canopy. The canopy scatters and transmits light downward onto the shaded surface, obscuring the spectral signature of the urban surface. While demonstrating overall low reflectance, the shaded spectrum possesses subtle spectral features typical of vegetated land cover, including a red edge and water absorption bands, hence creating a signature that is more characteristic of dark vegetation. Therefore, the effect of shadow is a problem at all resolutions, and spectra containing shadowed land cover should be analyzed with specific attention. In terms of road type mapping this effect can result in severe misclassifications when shaded roads are mapped as “dark vegetation”.

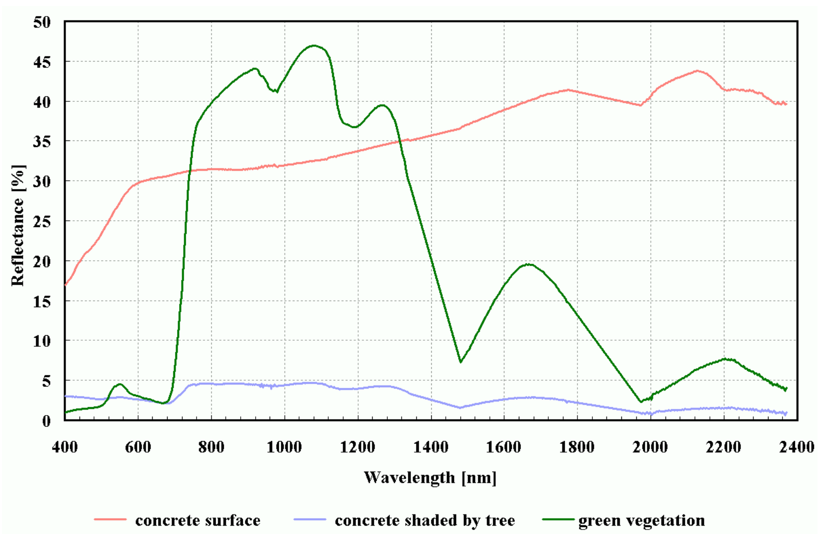
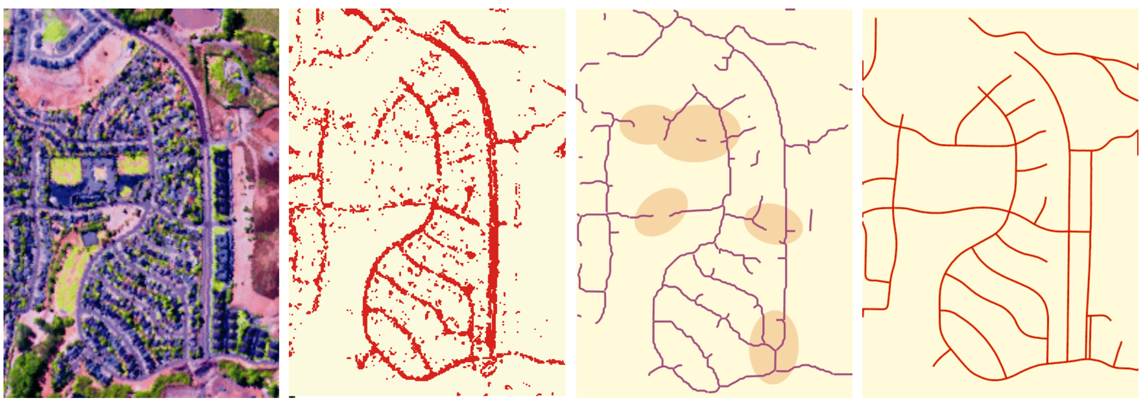


Figure 5: Spectra of concrete surface, green vegetation and concrete surface shaded by tree from the Santa Barbara ASD urban spectral library.

These errors, though understood, can have significant impacts on the derivation of road centerlines. Once roads or specific road types are classified from remote sensing data, the mapping product might be used to derive road centerlines. This process has to consider the inaccuracies in the mapping process (gaps in road network and overmapped road areas) and the spatial resolution of the remote sensing system. Based on the mapping result from the AVIRIS data, the process of centerline extraction is presented in Figure 6. Note that Figure 6(c) incorporates results of separate processes of linear filtering (to remove non-linear features such as roofs and other isolated pixels), gap removal, vectorization and smoothing. The final centerline map still shows areas of inaccuracies in particular from major gaps in the remote sensing mapping product.



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

Figure 6: The process of road centerline extraction from land cover classification: (a) AVIRIS image, (b) Classification of road surfaces (includes some driveways and roofs), (c) Linear filter applied, gaps removed, and centerlines vectorized and smoothed, (d) Reference centerline map for comparison. Principal areas of disagreement are highlighted in (c); some discrepancies arise because the imagery predates the map. Driveways are easily removed by analysis of connectivity and length.

Spectral sensor characteristics

One of the purposes of spectrometry is to identify the most important spectral bands for discriminating surface materials. This research aims to identify bands that best discriminate among urban materials, particularly pavement types. For such specific land cover classification purposes having 224 bands from a sensor like AVIRIS provides “too much” spectral information. Mapping accuracy can actually decrease if too many highly correlated spectral bands are applied for such purposes (Landgrebe 2000). The question of most suitable bands is additionally important in assessing spectral capabilities and limitations of common multispectral satellite remote sensing systems such us IKONOS or Landsat TM. The spectral sensor characteristics of these earth observation systems were designed for mapping a variety of surfaces, especially for acquisition of natural and quasi-natural environments. Considering the unique spectral characteristics and complexity of urban land cover types, it is assumed that there are specific limitations in detailed mapping of such an environment from these sensors. Therefore, it is important to consider the design of specific sensors, optimized for urban/transportation infrastructure mapping, that could achieve comparable results at a far lower cost than for a full hyperspectral system.

The derivation of the most suitable bands was based on the B-distance that provides a separability score between each land cover class. The B-distance can be used to identify the bands that contribute the most spectral contrast between the classes. Related investigations of the ASD spectral library and AVIRIS data have resulted in a set of 14 most suitable bands that allow the greatest spectral separability of urban land cover classes (these 14 bands were used to derive the AVIRIS classification result as presented in the previous section). The derivation of the most suitable bands was based on the B-distance as a quantitative score of separability to determine individual band combinations that are most useful in separating urban materials and land cover types. The analysis was performed for the urban spectral library and AVIRIS. The individual results were combined resulting in a set of 14 most suitable bands. For more information on the derivation of most suitable bands for this study see Herold et al. (2003).

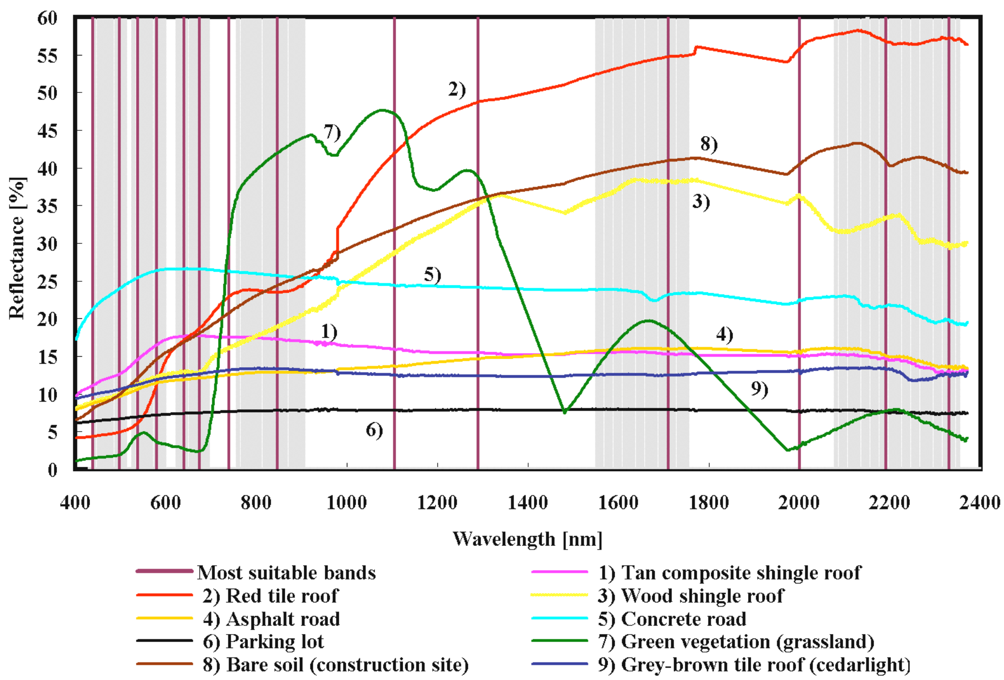


Figure 7: Most suitable spectral bands for urban mapping derived from the ASD spectral library and the AVIRIS data compared to spectral signatures of several urban land cover types and the spectral coverage of LANDSAT TM satellite sensor (gray in the background).

The most suitable bands for urban mapping appear in nearly all parts of the spectrum with a fair number in the visible region (Figure 7). This supports the previous observation that narrow spectral bands are important in resolving small-scale spectral contrast (e.g. color, iron absorption features) among materials and land cover types in this spectral region. Additional bands appear in the near and short-wave infrared that represent the larger dynamic range of reflectance values and specific absorption features in the short-wave infrared. Most of the bands are located outside or near the edges of the Landsat TM spectral configuration indicating possible spectral limitations of this and similar sensor systems.

To further investigate this issue, multispectral bands of IKONOS data were simulated from AVIRIS to allow detailed analysis of sensor limitations in terms of spectral resolution. This step used sensor specific spectral functions, available from the data vendor, to convolve AVIRIS data into IKONOS wavelengths. IKONOS has a similar spatial but significantly lower spectral resolution than the AVIRIS data. Using land cover classification accuracy as an indicator, the limitations of IKONOS in mapping the urban environment are shown in Figure 8. The graph shows the improvements in land cover classification considering different spectral sensor characteristics. The first, “Top 5 VIS,” assumes 5 narrow most suitable bands (10 nm bandwidth) in the visible (VIS) and near infrared

(NIR) region instead of the 4 broad bands of IKONOS. The second setting (IKONOS + 2 top SWIR bands) assumes the IKONOS bands with two additional most suitable bands in the short-wave infrared, a region not covered with IKONOS. Finally, we consider a spectral configuration that uses all 14 most suitable bands shown in Figure 7.

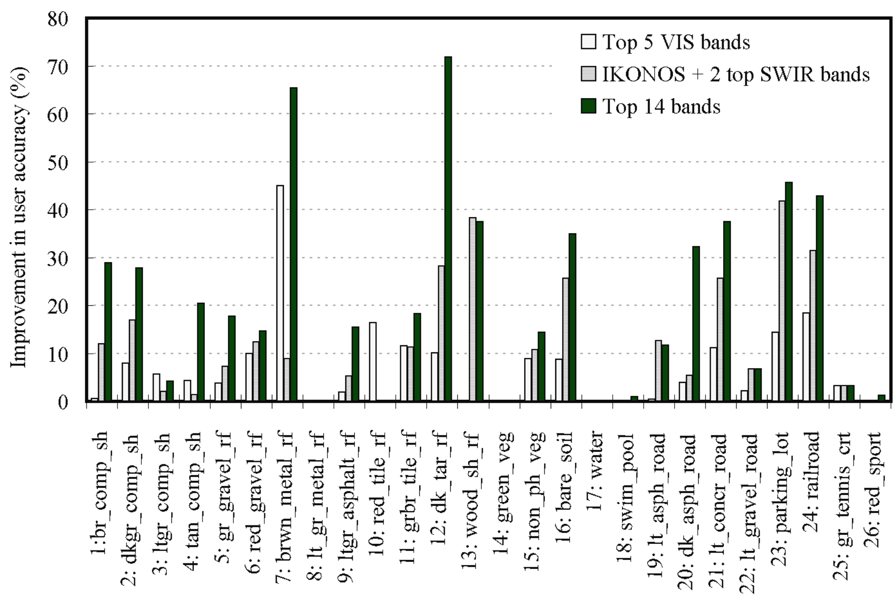


Figure 8: Improvement in classification accuracy for different spectral configurations compared to classification based on IKONOS.

The improvements shown in Figure 8 are obvious for nearly all classes, especially for individual roof and road types. No improvements are found for classes that were already mapped at very high accuracy with IKONOS, such as water, vegetation and swimming pools. The figure shows that IKONOS has limitations in detailed urban mapping due to the broadband character of the spectral bands and the fact that it does not cover the short-wave infrared region. The improvements are especially evident for different road types, particularly for asphalt and concrete roads and parking lots. For these targets, user accuracy increases between 10% and 40% when using the most suitable Top 14 bands, indicating the great limitation of IKONOS in mapping roads in an urban environment.

These results suggest that urban areas represent a spectral diversity that far exceeds that of natural systems, as indicated by previous studies (Green and Boardman 2000, Ben Dor et al. 2001, Small 2001). Common multispectral sensor systems have significant limitations for mapping the urban environment considering different roof materials, road surfaces of variable age and quality, parking lots, bare soil and urban vegetation. For example, the broad band channels do not resolve small-scale spectral absorption features in the visible and SWIR II region that have been described for several built up and some non-built up cover types. The design of new "optimized" multispectral remote sensors has to take these issues into consideration to meet the needs for detailed mapping of urban land cover, road types and road conditions. However, these findings are true of the Santa Barbara region, and might be different if other urban areas are considered.

Spectrometry of asphalt surface conditions

One obvious contribution of imaging spectrometry is the detailed study of surface properties and their impacts on spectral characteristics. Once distinct spectral characteristics are identified in the spectral library, they can be explored in remote sensing mapping applications. Figure 9 investigates the effects of asphalt surface conditions and age on the spectral signature. The spectra represent the ASD measurements and show the influence of different degrading processes on the asphalt surface material (SHRP 1993). Most apparent are the general increase in brightness, the development of specific absorption features that relate to the decreasing asphalt content in the aggregate, the oxidation of in place material (increase in iron absorption features at ~ 520 nm, 670 nm and 870 nm), and degradation from polished aggregates and raveling.

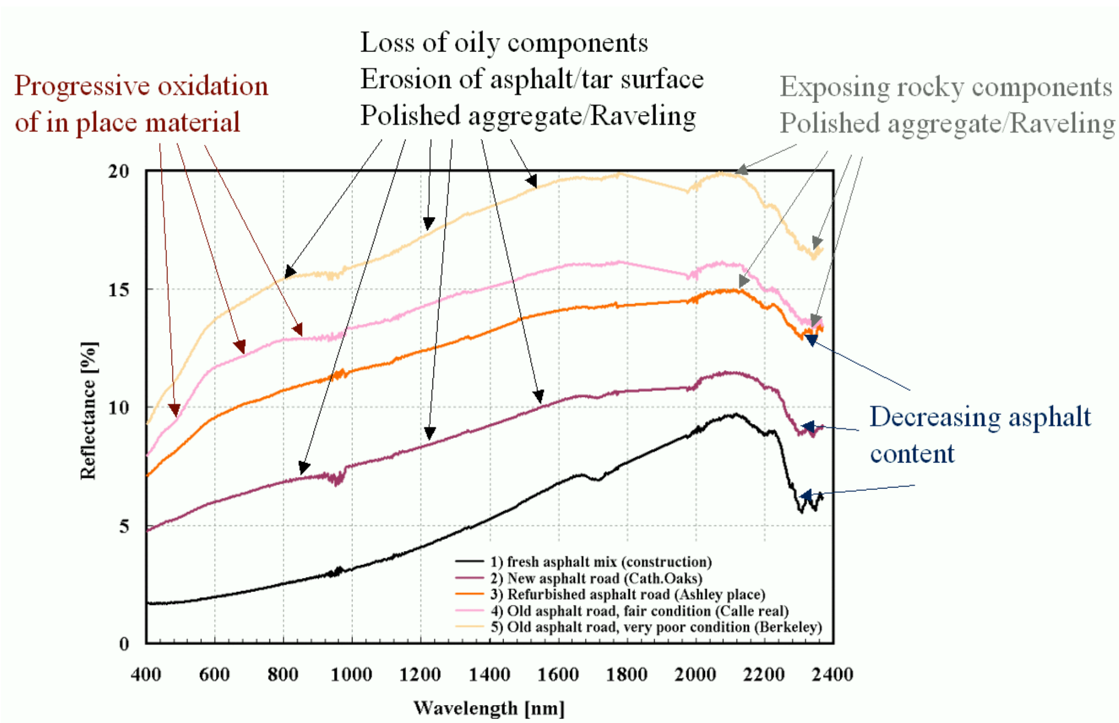


Figure 9: Spectral characteristics of asphalt road surface conditions and age from the ASD spectral library.

Despite the distinct spectral signals in Figure 9, the scaling from ground measurements to remote sensing data usually decreases the amount of spectral detail. This is shown in Figure 10. AVIRIS data are generally more noisy due to atmospheric interference and system noise, especially for low reflectance targets like asphalt surfaces. Furthermore, data in 4 m spatial resolution don't necessarily represent spectrally "pure" asphalt surfaces, e.g. other surface types that appear near roads can produce spectrally mixed pixels. However, the AVIRIS spectra shown in Figure 10 indicate distinct differences among roads with different age and conditions especially in the visible and short-wave infrared regions. These differences in reflectance can be represented in specific band ratios that can be used to map these surface characteristics with AVIRIS. Figure 10 shows the bands used in the ratios in this study. They were derived using a simple subtraction of the reflectance values; four bands in the visible/near-infrared region and two bands in the short-wave infrared region.

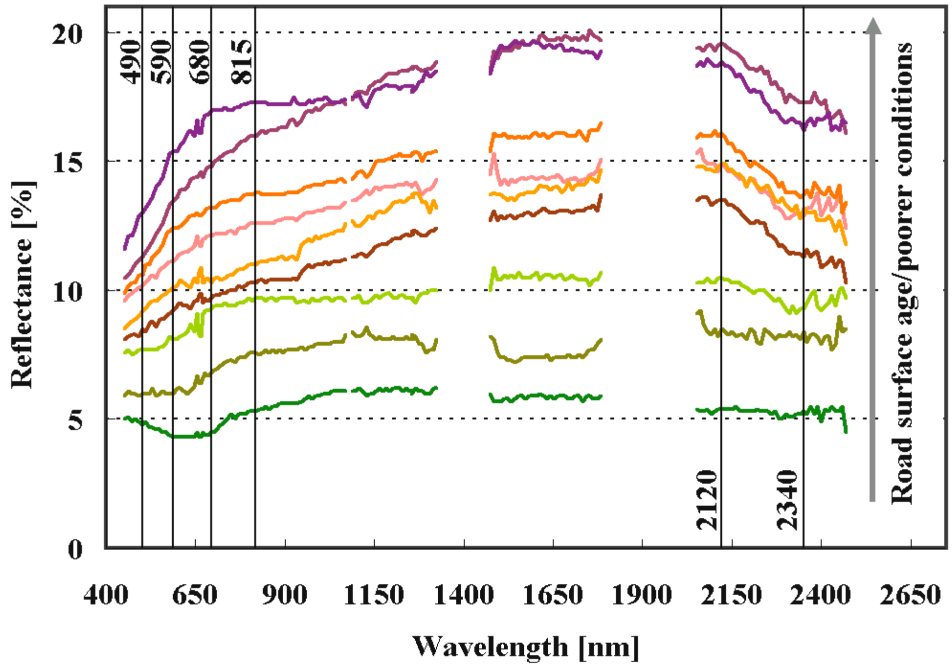


Figure 10: AVIRIS spectra of asphalt roads with varying age and conditions. Spectral wavelengths used for the band ratios are indicated.

Examples of two ratios are shown in Figure 11. The ratio using the short-wave infrared represents the age and the effect of raveling (dislodging of aggregate particles and loss of asphalt binder) of the asphalt surface (SHRP 1993). Recently paved roads appear with low change in reflectance (green and yellow colors) and the ratio increases with older and more worn asphalt. The ratio of the VIS/NIR bands represents a different spatial pattern, with newly paved roads not separating as well. Important low value areas appear at intersections due to the accumulation of tire material and oil. Most roads indicate intermediate age and decent surface conditions. In general, high ratio values characterize highly oxidized surfaces with polished surfaces and raveling effects, and therefore represent old roads in poor conditions.

Figure 11: Two band ratios from the AVIRIS showing the age/condition of road asphalt surfaces.

The results presented in Figure 11 are qualitative and somewhat experimental but show the potential of remote sensing in mapping specific types of asphalt surface conditions. There are, however, some general limitations. With these data, it is only possible to determine gross age and condition of pavement. Transportation professionals are usually more interested in pavement *quality* (e.g. rutting, cracking), but these are sub-meter phenomena and are not detectable in hyperspectral imagery of this resolution. Although cracking and patching tend to be spatially concentrated and therefore potentially detectable in

4 m imagery, the research shows that there is too much variability among pavement aggregates to be able to isolate cracked and patched areas with any certainty. Therefore, it is important to further investigate these issues with data in higher spatial resolution and appropriate quantitative ground observations of pavement conditions.

Conclusions

Imaging spectrometry provides interesting and innovative avenues for exploring the capabilities and limitations of remote sensing in surveying transportation infrastructure. This study focuses on mapping road infrastructure within urban areas that are known to be particularly complicated given the spatial and spectral characteristics of these environments. To explore the role of remote sensing in transportation the investigations focused on methods of imaging spectrometry for a sophisticated understanding of the spectral properties of road surfaces and urban land cover types, their separability and mapping accuracy. This study was based on principles of imaging spectrometry using an ASD ground spectral library and high-resolution hyperspectral AVIRIS data acquired in the Santa Barbara, CA urban area. The analyses provide comprehensive information about the spectral characteristics of urban materials and road surfaces of different type, age and condition. Findings show that problems in spectral classification of road surfaces are related to generic spectral similarities among specific roof and asphalt road materials. Further errors appear for vegetation covering the road surface and a vegetation shadowing effect imposing a dark vegetation spectrum onto the road surface. Accordingly, road detection and centerline extraction from AVIRIS data are only somewhat successful in urban areas. The success in road delineation might be improved by using additional contextual information from object-oriented image classification (Blaschke and Strobl 2001), especially since the spectral separability of different road surface materials is fairly high. The hyperspectral approach to road mapping in rural areas should be simpler and more successful, because pavement signatures are less prone to confusion with those of surrounding materials. Rural areas are not well suited to field-based mapping technologies and a remote sensing solution would be valuable in these areas. This research project was not designed to examine rural areas, but this area has great potential for future efforts.

This research has provided some interesting results on the effect of asphalt condition and age on the spectral characteristics of road surfaces. It is possible to describe general pavement age and specific surface defects, such as raveling, and estimate their spatial characteristics from AVIRIS. Other common pavement quality parameters (e.g. rutting, cracking), however, were found to be undetectable at spatial sensor resolutions of 4 m.

Ultimately, the success of remote sensing in transportation will depend largely on economics. The focus on imaging spectrometry, particularly using full hyperspectral systems like AVIRIS (currently an experimental sensor), can be criticized as being overly complex and too expensive for most agencies. In regard to this issue, this research aimed to generalize the problem to the multispectral level, while addressing the science of material discrimination at the more rigorous 224-band hyperspectral level. Currently, common multispectral satellite systems show significant spectral limitations in mapping road infrastructure within the urban environment. The location of their spectral bands and their broadband character are insufficient to resolve the distinct spectral characteristics of urban materials and land cover types. This research shows that there is a potential future for a multispectral sensor designed for use in urban and pavement mapping that would allow successful urban mapping at a large scale and an affordable price.

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