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Target Characterization in 3D Using Infrared Lidar

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ABSTRACT

We report examples of the use of a scanning tunable CO₂ laser lidar system in the 9-11 μm region to construct images of vegetation and rocks at ranges of up to 5 km from the instrument. Range information is combined with horizontal and vertical distances to yield an image with three spatial dimensions simultaneous with the classification of target type. Object classification is made possible by the distinct spectral signatures of both natural and man-made objects. Several multivariate statistical methods are used to illustrate the degree of discrimination possible among the natural variability of objects in both spectral shape and amplitude.

Keywords: lidar, multispectral imaging, matched-filter analysis, vegetation mapping, target detection

1. INTRODUCTION

Infrared remote sensing instruments have been developed and applied to many different applications involving imagery of the earth's surface.¹ In principle, both passive instruments (detecting reflected or emitted light) and active instruments (using reflected laser light) can provide such spatial and spectral information, but passive instruments are more widely used because of their greater simplicity. In this paper, we demonstrate an application of a multispectral lidar platform to mapping of vegetation and rock. Active lidar imagery provides three spatial dimensions rather than two, simultaneously with the identification of the physical target sampled by the laser. At longer wavelengths accessible by a CO₂ laser, terrestrial features can be identified by their distinct spectral signatures.

Lidar sensing of vegetation offers some complementary characteristics to passive remote sensing. In the thermal infrared (8-12 μm), lidar interrogation of natural targets is essentially a pure reflectance measurement, unaffected by topographical shading and spatial variations in temperature. Differential measurements using CO₂ lasers have been known for some time to be useful in discriminating between vegetation types,²⁻⁴ tree species, and rock types.⁵ We have investigated the utility of a scanning CO₂ DIAL system in constructing vegetation maps for broad areas. Although the scanning of a narrow lidar beam is a time-consuming process compared to imaging sensors, the detailed spectral characteristics in the reflectance information may be useful in many applications.

2. EXPERIMENTAL APPROACH

The lidar system for these measurements utilizes a CO₂ laser developed at Los Alamos that combines advantages of high repetition rate, rapid and broad tunability, moderate pulse energy, and good quality spatial profile. The acousto-optically (AO) tuned laser has been described in detail,⁶ so only major features will be repeated here. The pulsed laser operates at 5 kHz prf. The wavelength is changed on every shot to a different CO₂ laser line, sweeping through both the 9.6 and 10.6 μm bands of CO₂ and providing 44 wavelengths. The 44-wavelength pattern is repeated to give a net frequency of 113 spectra per second. The pulse energy ~ 0.8 mJ averaged over strong and weak lines. Fluctuations in the laser energy are measured on a shot-to-shot basis with a thermoelectrically cooled HgCdTe detector. The beam is expanded with reflective optics to an initial beam waist of ~ 5 cm and a beam divergence of ~ 300 -350 μrad ($2w_0$ parameter). Spatial profiles of the beam at different wavelengths were measured and are overlapped to within $\frac{1}{4}$ of a beam diameter. This is required so that the various wavelengths interrogate the same target or mixture of targets simultaneously.

The receiver system of the lidar bench consists of a 30 cm aperture telescope and a HgCdTe detector cooled to 35 K. An 8-12 μm bandpass filter cooled to 77 K is situated in front of the detector to reduce background photons. For target ranging, time traces of the return signal are collected with a digitizer. The peak of the return signal is located and used to position a boxcar gate for detection. The automated ranging system follows range changes as the lidar system is scanned across terrain with an

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accuracy of ~10 ns, equivalent to a range accuracy of ~1.5 m. The laser is vertically polarized when it exits the optical train, and no polarization filtering is used in the receiver.

A rotating gimbal mirror steers transmit and receive beams together with an accuracy of ~30 μ rad, or about 1/10 of the beam size. Lidar images were obtained by sweeping the lidar line of sight across scenes in a raster manner. The typical data accumulation time employed was one second at each mirror location, giving a total of 256 seconds for a 16X16 grid of points over a scene.

2.1 Signal Averaging Considerations

Noise in the measurement of the hard-target lidar return energy can arise from a variety of factors, including detector “dark current,” thermal radiation from the scene, atmospheric turbulence, and laser instability. Laser speckle noise produced by the beam on the target can be a limiting factor for lidar measurements in the LWIR region. Goodman⁷ derived the following expression for the speckle signal-to-noise ratio in lidar measurements of this type.

$$S / N = \sqrt{M} \approx \left(\frac{S_m}{S_c} \right)^{1/2} = \sqrt{S_m} \frac{L}{z\lambda} \quad (1)$$

where M is approximately the number of detected speckles in the image of the beam spot (for $M \gg 1$), S_m is the telescope area, S_c is the speckle area on the target, λ is the wavelength, z is the range to target, and L is the width of the beam on target. L/z is the beam divergence, set to achieve speckle $S/N \sim 8$, or shot-to-shot speckle fluctuations of ~13%.

Ideally, speckle noise and the other noise sources are reduced by signal averaging as the square root of the number of shots.⁸ Consequently, high-repetition rate is an important characteristic in producing good-quality lidar spectra and lidar images. In a one-second measurement for a given target, the speckle noise would be reduced from 13% to 1.2% (assuming 113 shots/s at each wavelength). We observed, however, that ideal averaging was not obtained in all cases. Experiments on various natural targets such as trees, bushes, and grassy vegetation at short range (< 2 km) showed that shot-to-shot fluctuations could be reduced by averaging to 1-5%, but then reached a plateau. Similar behavior has been noted in early CO₂ lidar work by Menyuk and Killinger,⁹ who proposed that non-independent speckle patterns on consecutive laser shots impart a temporal correlation to the return signal which impedes signal averaging. While our measurements were performed at much higher repetition rate (5000 Hz vs. 10 Hz), similar considerations probably apply. We find that targets such as grass and trees, with reflecting elements that are small and mobile, exhibit better averaging (~1% standard deviation after several seconds) than targets such as dirt and insulation board (~3-5%), which are more fixed.

3. RESULTS AND DISCUSSION

We have examined lidar spectra of a number of different materials, including grassy vegetation (a mixture of species dominated by Blue Grama Grass, *Bouteloua gracilis*), One-seed Juniper (*Juniperus monosperma*), Ponderosa Pine (*Pinus ponderosa*), a synthetic foam insulation board, a dirt/gravel mixture, and a shrub called Chamisa (*Chrysothamnus nauseosus*). Pinyon Pine (*Pinus edulis*), in addition, appears spectrally similar to Ponderosa Pine. The spectra were corrected for instrument response by dividing them by the observed spectrum of a roughened (flame-sprayed) aluminum target board positioned at about the same range and oriented at near-normal incidence to the laser. Roughened aluminum has a reflectance of ~80% and a nearly flat spectral response in the 9-11 μ m range.^{10,11} There are distinct differences in the overall reflectance of these objects, and slight differences in the spectral shape. The trees, shrubs, and grass have a low reflectance of ~1-3%, while the synthetic insulation foam (~30%) and the dirt/gravel mixture (~5%) are considerably higher. We find that these differences are somewhat reproducible among individuals of the same species, and can be used as a criterion for identification, but further work is necessary to clarify the statistical properties of large numbers of objects. Some variation in reflectance is expected from the dependence on angle of incidence.¹² The dirt and insulation foam spectra exhibit larger wavelength-to-wavelength and shot-to-shot variations than the other objects, which is a result of speckle noise described above. Even apart from amplitude differences, many spectra can be distinguished by shape. Dried grass, for example, has a distinctly rising spectral feature at longer wavelengths.

Figure 1 shows typical results for an image constructed from the lidar return signal strength. Two disparate wavelengths are illustrated, and the sum over all wavelengths is also shown. Included in this scene are a rocky cliff, trees, and grassy vegetation, at a range of 4.1 km. A photograph of the scene is shown in Figure 2. The lidar data were obtained over a 16X16 grid of points, with the separation between points being close to the beam size ($\sim 350 \mu\text{rad}$). At each pixel location, 128 shots were collected at each wavelength, corresponding to a dwell time of 1.1 s. Because of additional mirror settling time, the full scan required 8.7 minutes to complete. The outline of the trees is apparent in the sum image, but less distinct at the laser line 10P20 ($\lambda = 10.59 \mu\text{m}$). The contrast between trees and grass and between grass and rock varies depending on wavelength. This would indicate that a multispectral analysis will yield more information than single-wavelength images, as expected.

Figure 1. Images of lidar return energy for two selected wavelengths ($9.27 \mu\text{m}$ and $10.59 \mu\text{m}$), and summed over all wavelengths. White refers to lower return strength, and black to higher return strength. The scene is the same as shown in Fig. 2. The range is 4.1 km, and the dimensions of the image are 21 m in both horizontal and vertical directions.

A useful type of analysis that incorporates the spectral information is “k-means clustering,” which has frequently been employed in the analysis of passive images.¹ This approach essentially groups together pixels that have similar spectra, organizing them into k different groups or “clusters.” Mathematically, the spectra obtained at each pixel (by averaging for one second) are denoted as pixel vectors $\mathbf{y}_i$, with i denoting the pixel number; each vector has $p \approx 40$ components corresponding to laser wavelengths. (In practice, a few noisy laser lines are discarded depending on laser performance.) The vectors $\mathbf{y}_i$ have both direction and magnitude in p -dimensional space. They are grouped in the space in k groups and the mean vectors $\bar{\mathbf{y}}_j$ are found. The points for each pixel are moved between groups in an iterative fashion until the overall squared distance

$$d_{tot}^2 = \sum_{j=1}^k \sum_{i=1}^{n_j} (\mathbf{y}_{ij} - \bar{\mathbf{y}}_j)^T (\mathbf{y}_{ij} - \bar{\mathbf{y}}_j) \quad (2)$$

is minimized. Here, $\mathbf{y}_{ij}$ is the i 'th pixel belonging to the cluster j , and n_j is the number of pixels in cluster j . The superscript T indicates the vector transpose. The Euclidean distance d is used here for simplicity and because no *a priori* information is used for objects in the scene. The application of this method yields the result shown in Figure 2. Four clusters are used in the analysis ($k=4$) because it corresponds to an intuitive breakdown of the scene elements into trees, grassy areas, and two types of rock, each indicated by a different symbol. In the rocky portion of the scene in the bottom of the image, detailed features are brought out by the analysis. An area of vegetation appears between the rock bands that is not obvious in the photograph. Field inspection confirmed that some sparse vegetation indeed occurs here. In the central upper portion of the photograph, an area of dead branches appears within the grouping of Juniper trees. That area is also revealed in the lidar data (circle symbol), the cluster most closely matching the spectrum of that pixel. In the region of rocks in the bottom half of the scene, the lidar data fall into two clusters. The crosses correspond to rock that is either uncovered by lichen or rock that is different in texture because it is partially broken into gravel.

The resultant spectra that correspond to the clusters in the image are shown in Figure 3. These are the mean spectra $\bar{\mathbf{y}}_j$ obtained for the set of pixels belonging to each cluster. Figure 3 displays spectra in two ways: as absolute return signal energies, and as differences from the mean spectrum of the entire image. When viewed in the first way, it is clear that all spectra share some common features, particularly evident in the $9 \mu\text{m}$ band. The attenuation in this region is well understood as absorption from atmospheric ozone (present at $\sim 50 \text{ ppb}$).¹³ Atmospheric CO_2 and water vapor also contribute to the

overall spectral shape. We have been able to synthesize these features, based on postulated concentrations, for similar spectra taken at ranges up to 7 km. In this way, the lidar system provides an accurate measure of atmospheric concentrations, averaged over the propagation length.

Figure 2. Photograph of scan area and cluster image representation, generated by the k-means cluster analysis of the lidar data. The dashed line in the left photograph indicates the scan area. On the right, symbols corresponding to the four clusters are overlaid on the same picture.

Figure 3. Spectra of the clusters indicated in Fig. 2. Each spectrum is the mean spectrum for all of the pixels belonging to that cluster. In the left panel, the absolute spectra are plotted (referenced to aluminum). In the right panel, the spectra are plotted as the difference from the mean spectrum of the entire image. The abrupt shift near the center is due to a large wavelength gap between the 9.6 and 10.6 micron bands of the laser.

The reflectance spectrum of the lidar target is superimposed on the atmospheric absorption spectrum. Thus, it is somewhat easier to recognize spectral differences in target types if the atmospheric contribution is first removed. This can be accomplished in an approximate fashion by subtraction of the mean spectrum of the entire image, with results shown in Fig. 3b. (The difference spectrum is subsequently divided by the mean, yielding a spectrum with fractional difference from the mean.) Here it can be seen that different objects in the scene have slowly varying spectra with distinct slopes and amplitudes, as expected from known spectra of natural materials.¹¹

Within one cluster, there is considerable spread in the observed spectra. In natural scenes of the type shown here, the spread may be larger than the distance between cluster centers. Despite the large spread, we find that the clustering results are quite

reproducible. When the same scene is scanned days and even weeks apart, only a few percent of the observed pixels change identity. The amplitude differences between clusters are also reproducible. If the spectra are normalized to remove the pixel-to-pixel variation in return signal strength, the grass and trees in the scene are not as clearly distinguishable. This suggests that overall return signal amplitude is an important criterion in distinguishing between target types.

Figure 4. Plot of first two discriminant values, D_2 vs. D_1 for each pixel, labeled by cluster assignment.

The degree of separation between groups derived from K-means clustering can be clarified by simultaneous treatment of the ~ 40 wavelengths in a multivariate analysis. As described by Rencher,¹⁴ we construct discriminant functions which when applied to the individual pixel vectors $\mathbf{y}_i$ yield a scalar result that indicates the degree of separation between the points. The discriminant functions are labeled $D_n = \mathbf{a}_n^T \mathbf{y}_i$, where T indicates transpose. The value of $D_n(i)$ is a scalar obtained as a dot product between the discriminant vector $\mathbf{a}_n$ and the data vector (or pixel spectrum) $\mathbf{y}_i$. The optimal discriminants are obtained as eigenvectors of the matrix $\mathbf{E}^{-1}\mathbf{H}$, where $\mathbf{E}$ and $\mathbf{H}$ are similar to covariance matrices for the data within and between clusters. Specifically, the matrices are defined by the following.

$$\mathbf{H} = \sum_{j=1}^k n_j (\bar{\mathbf{y}}_j - \bar{\mathbf{y}}_{tot})(\bar{\mathbf{y}}_j - \bar{\mathbf{y}}_{tot})^T$$

$$\mathbf{E} = \sum_{j=1}^k \sum_{i=1}^{n_j} (\mathbf{y}_{ij} - \bar{\mathbf{y}}_j)(\mathbf{y}_{ij} - \bar{\mathbf{y}}_j)^T$$
(3)

Here, k is the number of clusters, n_j is the number of pixels belong to cluster j , $\bar{\mathbf{y}}_j$ is the mean spectrum of cluster j , $\bar{\mathbf{y}}_{tot}$ is the mean spectrum of the whole image; $\mathbf{y}_{ij}$ is the spectrum of the i 'th pixel belonging to the cluster j . Thus, $\mathbf{H}$ is a weighted sum of matrices related to the differences between clusters, while $\mathbf{E}$ is related to the sums of squares between pixel vectors belonging to a given cluster. The largest eigenvalue of $\mathbf{E}^{-1}\mathbf{H}$ corresponds to the first eigenvector $\mathbf{a}_1$, and the second largest to $\mathbf{a}_2$, and so on. Application of these to each pixel i in the data produces discriminant function values $D_1(i)$ and $D_2(i)$. Other authors have also described this type of discriminant analysis.^{1,15} Values of the first two discriminant functions for the set of pixels is shown in Fig. 4. The zones between clusters are reasonably distinct. The discriminant plot also shows that the various pixels seem to be correctly assigned to clusters, with the possible exception of a few near the boundaries between clusters. Given the substantial beam size (1.4 m), mixed pixels are expected at these boundaries. Distinctions between clusters are less apparent when two-dimensional plots such as Fig. 4 are generated from selected wavelengths. The ability of the discriminant functions to improve class separability illustrates that multispectral analysis of the lidar data is necessary to distinguish between objects in the scene. K-means clustering, used to produce the map in Fig. 2 is also obviously a multispectral analysis.

Examination of Fig. 4 shows that there is clearly significant variation within the four clusters of data. This is due primarily to physical variation in the scene. For example, the Juniper trees vary in foliage density. The grassy area in the scene is inhomogeneous due to a natural distribution of plants on the ground. One might ask whether this extent of variation can be

quantified by the lidar measurement. One way to do this is to examine the range of values of the discriminant functions within a given cluster. An alternative way is to construct matched filters corresponding to each individual cluster and apply the filters to the whole scene, looking for variations in the matched filter output.^{14,16} To accomplish this for a given cluster, we segregate the data into target (the cluster of interest: trees for example) and background pixels (all other pixels in the scene: rock, grass). If the target data has spectrum $\mathbf{y}_{\text{targ}}$ and sample covariance matrix $\mathbf{S}_{\text{targ}}$, the background data has mean $\mathbf{y}_{\text{bkg}}$ and sample covariance matrix $\mathbf{S}_{\text{bkg}}$, then an optimal matched filter for the target is

$$\mathbf{a}_n = \frac{\mathbf{S}_{tb}^{-1}(\mathbf{y}_{\text{targ}} - \mathbf{y}_{\text{bkg}})}{(\mathbf{y}_{\text{targ}} - \mathbf{y}_{\text{bkg}})^T \mathbf{S}_{tb}^{-1}(\mathbf{y}_{\text{targ}} - \mathbf{y}_{\text{bkg}})} \quad (4)$$

where the appropriate covariance matrix is the pooled, or weighted average covariance matrix between target and background:

$$\mathbf{S}_{tb} = \frac{1}{n_t + n_b - 2} [(n_t - 1)\mathbf{S}_{\text{targ}} + (n_b - 1)\mathbf{S}_{\text{bkg}}] \quad (5)$$

and n_t and n_b are the number of pixels belonging to target and background, respectively.¹⁴ For each of the four clusters in the current analysis, we choose target and background pixels and generate the four matched filter vectors $\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3, \mathbf{a}_4$. Performing a dot-product application of each of these to all of the image pixels yields a set of four images as shown in Fig. 5. This is a different scene than Fig. 2, and it contains significant “depth” because a ridge runs through the middle of the scene, separating the lower foreground from the more distant background. Within each cluster, there is a range of values of filter output, i.e. varying degrees of membership to that particular cluster.

Figure 5. Matched-filter images shown in 3D. The dimensions of each image are 39 m in horizontal and vertical extent, and 400 m in the axis in and out of the page (i.e., the lidar range axis). Black represents high output of the matched filter, and white represents low values.

The three dimensional display of the data illustrates the power of pulsed lidar in characterizing targets within the scene. Objects are located in three dimensional space and simultaneously classified using their spectral signatures. One of the four clusters, that corresponding to trees, is clearly distributed between both foreground and background. The others are situated mainly in either foreground or background.

Finally, we note that chemical plumes can be imaged in the same fashion as landscape features. If the plume is situated between the instrument and the lidar target, it can be detected as an absorption feature. By using clustering and other techniques such as Principal Component Analysis,^{1,14} the chemical signature can be optimally retrieved from a background with a varying spectral signature. This has been discussed recently in connection with passive infrared imaging.¹⁶

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