ABSTRACT

Synthetic Aperture Radar (SAR) polarimetry is rapidly developing as a useful approach in radar remote sensing. Previous work has shown that polarimetric analysis is a superior approach to single channel imagery for feature analysis and terrain characterization applications. Multi-frequency returns aid in providing a more complete description of surface parameters. Radar reflection from a surface depends on the transmitted and received signal orientation, surface roughness, local geometry including volumetric structure, electrical properties of the target, and other parameters. The scattering signature is the combination of scattering contributions from various interactions within the SAR resolution cell. Independent scattering mechanisms may be the result of single, double, or multiple bounce effects. Polarization shifts inherent in the scattering characteristics of the radar signal may be used as an additional discriminant in feature analysis. From this perspective, we analyzed multi-frequency, polarimetric JPL-AIRSAR data over a region in central Maryland containing fields, forested land, open water, transportation features, and built-up areas. In our approach, we synthesized individual polarization data bands from original Stokes matrix files for the C, L, and P frequency bands, representing different combinations of polarization shifts in the scattering process. We then applied band ratioing, decomposition techniques, and image differencing techniques to these polarization bands in the separation and identification of terrain features. Results show that polarization shift information inherent in the scattering process provides added value to statistical and band analysis of multi-frequency, polarimetric SAR for terrain characterization.

Key Words: (1) SAR, (2) polarimetry, (3) feature analysis, (4) scattering, (5) band ratios.

BACKGROUND

Synthetic Aperture Radar’s all-weather operation, sensitivity to the terrain environment, and wide coverage has proven to be an exceptional sensor for terrain remote sensing. Most current operational radar sensors provide single polarization data. Image classification, feature extraction, and categorization is based on the received intensity. Excellent results have been obtained with these radars. However, uncertainties are often present that make reliable and accurate operations a difficult task if no additional data is available (Simental and Damron, 2001). The polarization of radar is an important property in remote sensing of the Earth's environment. So far, SAR polarimetry has been limited to a number of experimental airborne SAR systems and the SIR-C shuttle mission. Full polarimetry radar provides five (5) datasets from each polarization band, namely HH, HV, VH, VV, and total power (TP). However, only three of these sets are independent. The reciprocity theorem states that HV and VH are identical and total power (TP) is the sum of the polarization responses. The remaining three (3) sets provide information, not otherwise obtainable, about the Earth’s surface characteristics by controlling the polarization of the energy that is transmitted and received. Polarimetric radar data provides much more detailed information about the surface geometry, terrain cover, and subsurface discontinuities than image brightness alone (Elachi et al., 1990). It is known, for example, that the polarization of the incident radar waves and the physical structural characteristics of the illuminated features govern the polarization of the backscatter radar waves (Vander Sanden and Gross, 2001). Polarized radar signatures have been used to discriminate geologic deposits (Evans, et al., 1986; Abundo, et al.,
1998). They have also aided in vegetation discrimination as revealed by variation in density and structure (Evans, et al., 1986; Ranson and Sun, 1994). This type of information, only available in polarimetry data, is inestimable in remote sensing tasks.

Next generation radar airborne and spaceborne sensors will have increased capabilities such as full polarimetry and IFSAR modes combined. These next generation sensors will provide, in addition to a higher grade of remote sensing information, the opportunity to enhance and exploit SAR data for new applications. Polarimetric radar data will become more prevalent in remote sensing and although there are many well tested and proven techniques for the analysis of these data types, better, faster, and more efficient techniques for interpretation, analysis, processing, and exploitation will have to be developed.

In this study, we analyze a multi-frequency, polarimetric SAR dataset to conduct band ratioing, decomposition techniques and statistical analysis to aid in the separation and identification of terrain features. The dataset will be described and then the methods will be discussed. Finally, the results and conclusions will be presented.

OBJECTIVES

The basic objective of this study is a data mining effort to exploit a limited polarimetric dataset for segmentation, feature extraction, classification, and terrain analysis. Full SAR polarimetric data consists of 32-bit floating-point complex numbers. Our limited dataset is 8-bit real number data scaled from 0.0 to 1.0 that represents power or intensity values. Tools that are employed for the rigorous analysis of polarimetric data require the complex numbered data, but it is possible to extract some information that is not available in single polarization data from limited polarimetric datasets. Additional objectives are to determine the usefulness of decomposition techniques when trying to characterize terrain features.

METHODOLOGY

Several tools for the texture analysis of polarimetric radar data have been developed throughout the years. There are several basic parameters for terrain texture analysis; among them are smoothness, homogeneity, and correlation. There are a number of tools for analysis of components in each of these parameters, but usually these components are highly correlated and there is no need to use more than one (1) tool in each group (Ersahin et al., 2004). For this study, we elected to use band ratios, linear operations, and autocorrelation. The precise definitions of these parameters are not possible nor important since at times they have been used interchangeably with each other and with other terms. The interpretation of results after using these tools seems to be more important.

The linear operations are the sums or differences of the three (3) polarimetry images in different combinations. For example,

\[
S_{hh} + S_{vv}, \quad S_{hh} - S_{vv}, \quad S_{hh} \cdot S_{hv}, \quad \frac{S_{hh} - S_{vv}}{S_{hh} + S_{vv}}
\]

where

- \( S_{hh} \) is the dataset horizontal transmitted, horizontal received
- \( S_{vv} \) is the dataset vertical transmitted, vertical received
- \( S_{hv} \) is the dataset horizontal transmitted, vertical received

The co-polarizations, Horizontal-Transmitted-Horizontal-Received and the Vertical-Transmitted-Vertical-Received datasets are shown here, but the cross-polarization, Horizontal-Transmitted-Vertical-Received, set can be substituted for the co-polarizations to provide additional information. The second and third expressions in the examples above are equivalent because the denominator in the third expression is just a scaling factor. This sum-difference is the form of the Normalized Difference Vegetation Index that has been used in spectral studies to quantify vegetation in image scenes. This form has been extended in a wavelet series to quantify other features besides vegetation and may have applications in radar imagery (Simental et al., August 2004). The sum and
difference in $S_{HH}$ and $S_{VV}$ is well known and well used in the Pauli decomposition (Karathanassi and Dabboor, 2004). The Pauli decomposition products can be displayed using an RGB composite in which the differences are assigned to the red, the sums to the blue and the cross-polarization to the green channel (See the results below).

The band ratios are simply the ratios of the three (3) polarimetry transmitted and received images with each other, namely,

$$
\begin{align*}
  r_1 &= \frac{S_{HH}}{S_{VV}}, \\
  r_2 &= \frac{S_{HV}}{S_{VV}}, \\
  r_3 &= \frac{S_{HV}}{S_{HH}}
\end{align*}
$$

The inverse of these ratios provide the complement image, but no additional information. The above polarimetry parameters are shown in the same frequency, but mixed frequency band ratios, sum/difference, provide significant information. For example, L frequency radar penetrates vegetation more than C, and P penetrates more than L. Therefore, vegetation is transparent in some frequencies and not in others and the differences between C, L, and P will yield vegetation information to varying degrees.

Autocorrelation has different definitions in different fields of study and not all are equivalent. Basically, autocorrelation is the correlation between two values of the same variable separated or shifted by time, distance, orientation, or some other parameter. In our case, the separation is the transmitted/received orientation. This function has the property of being in the range of $[0.0, 1.0]$. Perfect autocorrelation is designated by a value of 0.0 and perfect anti-correlation by a value of 1.0. For this effort, the definition adopted for autocorrelation is that it is a measure of the similarity of one pixel’s response in a particular frequency to a different frequency. The following is the mathematical expression for the autocorrelation, at lag $l$,

$$
\tau_l = \frac{\sum_{k=0}^{N-l-1} (x_k - \bar{x})(x_{k+l} - \bar{x})}{\sum_{k=0}^{N-1} (x_k - \bar{x})^2}
$$

where

- $x_k$ is the $k^{th}$ measurement
- $\bar{x}$ is the mean of the measurements
- $l$ is the lag, and
- $N$ is the number of measurements

The numerator in the above equation is known as the auto-covariance, but it is frequently used interchangeably with auto-correlation (Breiman, 1969). It can be seen that if all $x_k$ are identical (perfect correlation), then the mean is also identical and the numerator and denominator in the above equation are zero, producing a mathematical undefined quantity. To alleviate this condition, we have used only the covariance quantity in our analysis. The denominator is only a scaling factor and no information is lost.

DATASET

The data used in this study is from the airborne synthetic aperture radar (AIRSAR) managed by the Jet Propulsion Laboratory, National Aeronautics and Space Administration (JPL/NASA). The instrument is mounted on a modified NASA DC-8 aircraft. The AIRSAR is a side-looking radar instrument and collects fully polarimetric data (POLSAR) at three radar wavelengths: C-band (5.6 cm), L-band (24.5 cm), and P-band (68 cm) (JPL Website and Abundo et al., 1998).

The study area is in the Bowie, Maryland vicinity. This suburb in the Washington, D.C. metropolitan area is characterized by urban structures (residential, commercial buildings and roads), some open fields and rural parkland.
The imagery was flown in 1995. Road construction and other man-made features have added to the changes in the area since 1995. Figure 1 shows the study area as recorded in AIRSAR Band C and HH polarization. This area is 8.8 x 10.5 km in size. Various subsets of the study area were selected for detailed analysis based on selected features. Features include, but are not limited to, roads, fields, buildings, forest, bare ground, and powerlines. A previous study by the authors examined the same data set with an emphasis on terrain feature classification (Simental et al., 2004).

A 10 meter Digital Elevation Model (DEM) obtained from the United States Geological Survey (USGS) was used to generate a shaded relief image of the area. This DEM was obtained more recently than the AIRSAR imagery and helped provide some ground truth for our data. All of the AIRSAR frequency and polarization data layers were geo-registered to the DEM using Quarter-quad Digital Orthophoto Quadrangles (DOQQs) available from USGS. These images are digitized color infrared aerial photographs in GeoTIFF format with embedded geo-referenced information. The DOQQs, the USGS DEM, National Land Cover Data (NLCD) from USGS, EarthSat imagery, and printed 7.5-minute topographic quadrangle maps were the sources of ground truth used for the AIRSAR radar data analysis. A mosaic of portions of six DOQQ color infrared images depicting the study area is shown in Figure 2.

Figure 1. AIRSAR (C\textsubscript{HH}) image of the study site in the Bowie, Maryland area
RESULTS

A 600 x 600 pixel sub-area of the site shown in Figure 1 was selected for analysis. An image of the sub-area is shown in Figure 3. The difference image between the $C_{HH}$ and the $P_{HH}$ polarization images of the sub-areas was computed and is shown in Figure 4. This difference can be considered a measurement of surface roughness. A fairly level area scene, one void of vegetation, buildings, severe elevation anomalies and depressions, is expected to respond to radar illumination in the same manner regardless of the polarimetry parameters involved (Carande, 2004), producing a difference image of low, uniform intensity. The ‘sameness’ decreases as the number of different features and anomalies increases, increasing the general brightness of the difference image as well as its spatial variability. Surfaces with small irregularities will show a small difference. Therefore, it can be assumed that corresponding pixels in the different frequencies and orientations that are close to each other in backscatter intensity represent single bounce, smooth, and fairly level terrain. Radar shadow pixels tend to present a false conclusion. Since radar shadow areas return no energy to the sensor regardless of the incident polarization, they would appear similar to areas of low surface roughness. Radar shadows, therefore, should be identified as such prior to image differencing. In our test area, however, what radar shadows exist are only a few pixels in content and should not cause any major misrepresentations.

Figure 5 is a histogram of this difference image ($C_{HH} - P_{HH}$). It can be seen in this figure that the distribution is centered on ‘0’ and then the differences drop off very fast in both directions. The pixels on or close to zero represent surface scattering unaffected by a difference in radar frequency. The pixels that have large differences, those pixels that are less than $-0.7$ and greater than $0.7$ are pixels that represent multiple scattering or features that are highly sensitive to radar frequency, mostly some kind of vegetation. Vertical objects affect the HH polarization weakly whereas for the VV the opposite is true (Thomas and Kober, 1991). Figure 6 is a maximum similarity image derived from a difference image of $P_{HH}$ and $P_{VV}$, same frequency, different polarization. The difference values have been normalized to $\pm 1$. The blue pixels are those that have a difference close to zero, between $\pm .03$, in the two polarizations and the white pixels are outside this range. One can conclude from analysis of Figure 6 that the area scene is fairly void of anomalies and that the solid blue areas represent open fields, parking lots, large building roofs, or very unlikely, smooth vegetation canopies.

Figure 7 is a representation of the pixels that have the greatest difference, $\pm .9$. Large differences in the two polarizations are evidence of vertical structures (Thomas and Kober, 1991). The series of yellow dots in Figure 7, from the lower left corner going to the top right-center edge of the image indicate evidence of vertical structures, like the presence of power line poles. These dots (poles) follow a railroad bed that contains three sets of tracks as confirmed by EarthSat digital imagery of the area. The poles are at periodic intervals and on each side of the railroad bed.
Figure 3. Image of sub-area.

Figure 4. $C_{HH} - P_{HH}$ Difference image

Figure 5. Histogram of ‘Difference Image’

Figure 6. $P_{HH} - P_{VV}$ max. similarity image

Figure 8 is the difference image of $P_{HH} - P_{HV}$ using the same thresholds as the $P_{HH} - P_{VV}$ dataset. It is very similar to Figure 6. The relatively flat areas facing the radar are going to respond the same regardless of the polarization, therefore the similarity in the two datasets. The $P_{HH} - P_{HV}$ image supports the conclusions of the $P_{HH} - P_{VV}$ image, but adds no more information.
Several band ratios were computed and analyzed. The different ratios seem to provide similar information so only one ratio is presented here, $P_{HH}$ over $P_{VV}$ ratio. Figure 9 is an image of the ratio. This black-white type of image does not provide much information because of scaling the range of ratio values less than one. However, major linear features and variations in vegetative cover are still evident. The railroad line described above is faded, but is still obvious. The white streaks about two-thirds down the image and close to the left edge are part of cleared right-of-way running east-west. Figure 10 is a color-coded image of the ratio. The yellow pixels are in the range of $1 \pm 0.01$. Patterns are still discernible, but tend to fade in the size compression and printing. This information is consistent with the one obtained with the linear operations; that is, yellow pixels should represent single bounce, relatively smooth areas.
The autocorrelation paradigm was implemented using the horizontal-transmitted-horizontal-received polarization with the three (3) C, L, and P band frequency datasets as the measurements of a single variable so that each pixel in the image has a corresponding correlation coefficient associated with the three frequencies. A lag of 1 was used in the computation since in detecting non-randomness only the first lag is of interest. The array of coefficients is displayed as an image and is shown in Figure 11 below. The image is scaled so that dark to white corresponds to lowest to highest correlation. Figure 12 is the autocorrelation of the L-band frequency and the three (3) polarizations. Figures 11 and 12 seem to verify the results of Figure 6, that the preponderant scene is one of terrain with low surface roughness. The figures are also consistent in showing the polarimetric backscatter decorrelation of certain features. Examples can be seen in Figure 11, such as the pattern of power line poles along the railroad line extending primarily north-south, and the treeline just north of the transmission line right-of-way running east-west below the center of the image and a dark region of lower correlation just to the right and below image center in Figure 12. A magnified image of this area is shown in Figure 12A. This area appears to be one of reduced canopy height and/or low woody vegetation, as depicted in DOQQ color infrared imagery (Figure 13). In the case of forested areas showing a wide variation in correlation, reduced correlation may be interpreted as increased volume scattering, due to lower vegetation structure density and/or smaller leaf surfaces in the upper canopy. In the case of built-up areas, greater randomness is expected in the radar return, resulting in decorrelation. Roads are more apt to be smooth level surfaces with few features and one would expect all radar returns to be much alike regardless of polarimetric orientation.

Figure 14 depicts the full study area and shows a Pauli decomposition RGB composite of the C-band in which the $C_{HH}$ and $C_{VV}$ subtraction is displayed in red, the $C_{HH}$ and $C_{VV}$ addition is displayed in blue and the cross-polarization ($C_{HV}$) is displayed in green. The flat fields and roads appear mostly dark. Built-up areas are mostly magenta in color, representing a composite of red and blue inputs. This would imply that man-made structures are dominated by single-bounce ($C_{HH}$ minus $C_{VV}$) and double-bounce ($C_{HH}$ plus $C_{VV}$) effects. The vegetative canopy appears mostly green in the Pauli decomposition image; we expect that this is mostly due to the depolarizing effect ($C_{HV}$) of canopy structure.

Elevation data are essential in terrain categorization. A scaled, relative elevation shaded relief model is shown in Figure 15. The dominant broad, flat feature represents the floodplain of the Little Patuxent River. The image shows exaggerated elevations differences, but it is very helpful in collaborating information derived from the above tools.
Figure 12A. Magnified image of reduced canopy height.

Figure 13. DOQQ image of decorrelation area

Figure 14. RGB composite (C-band) of Pauli decomposition
CONCLUSIONS

During the past few years, radar technology has consistently experienced dramatic development and rapid growth in an increasing number of fields. Radar has provided scientists with information otherwise inaccessible in other sensor platforms. In this technological evolution, we may witness an even faster growth in the coming years. One prerequisite for the continued progress is the exploitation of the fully polarimetric properties of radar. Many of the upcoming remote sensing radar platforms will have a system providing full polarimetry data. There is at least one known commercial satellite platform that is scheduled to launch in March 2006 that will provide high resolution, fully polarimetric, multi-frequency data. The trend towards full polarization radar is accompanied by the expectation that these measurements will provide a valid method for improving the quality of feature extraction, classification, change detection and other remote sensing tasks in more challenging fields. One of the challenging tasks will be in the field of detection of micro-terrain features. Micro-terrain features are an important element in national defense programs and DOD agencies have invested many resources for the detection of these (Blundell et al., 2004).

In this effort, it is clear that the tools used can effectively segment an image into surface and volume scatterers. Inference techniques can than be used for feature extraction and classification. It is not necessary to use all these tools in the same dataset since sometimes these methods are highly correlated. These tools will work even better with higher resolution, fully polarimetric, complex datasets. As polarimetry becomes more prevalent, it will afford the opportunity for greater image exploitation.

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