A Study of Material Identification using SAR

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Abstract—We investigate the feasibility of using synthetic aperture radar (SAR) data to identify materials at each pixel in a SAR image. A fundamental concept underlying our approach is to extract the dispersion of the reflectivity at each pixel by dividing the data into several frequency sub-bands. We first compute synthetic radar data using parameters that are characteristic of a typical wide-band SAR system operating in a spotlight mode and illuminating several scattering regions that differ in their frequency response. Secondly, we process the data by subdividing the full data set into frequency sub-bands thereby extracting the dispersion at each pixel. Third and finally, we perform the material identification using a rudimentary classification analysis. The approach described herein offers a new method for planning experimental data collections for the purpose of material identification through SAR image formation.

I. INTRODUCTION

Imaging systems that are based on the detection of electromagnetic radiation exist over a wide range of frequencies. Sensors at radio (RF), infrared (IR), and optical (EO) frequencies continue to advance in capability. Designing imaging systems that provide finer spatial resolution in addition to finer spatial resolution are a key focus. Imaging systems for which useful spectral information is available and used to classify spatial regions have been well developed in the IR [1] and optical bands [2] and is an active field of research in the higher frequency RF bands, particularly near Terahertz frequencies [3]. In contrast, radar imaging systems, particularly SAR, typically focus exclusively on achieving high spatial resolution and disregard available spectral information for the purpose of identifying or classifying components. This may be due to system hardware limitations of many SAR systems, specifically being relatively narrow-band, as well as the limitation between spatial and spectral resolution. Increasing spectral resolution by using more frequency subbands decreases the bandwidth within each subband therefore lowering spatial resolution that is available to identify materials. However, wide-band SAR systems exist and this is sufficient motivation to investigate whether additional processing techniques can extract useful spectral information from wide-band SAR data for the purpose of material identification.

Air Force scientists and colleagues have been interested in measuring dielectric properties of materials for several reasons including remote environmental monitoring and safety [4]. Materials analyses were performed to discriminate materials in synthetic aperture radar scenes [5], and a computationally and statistically complex time-domain algorithm to estimate pixel reflectivity has been developed and tested on synthetic data [6] [7]. This paper is a frequency domain approach that appears, at this time, to provide more direct and physically appealing computing and inference than the time domain approach.

II. SAR DATA GENERATION

For the purposes of creating synthetic data, we model our data collection scenario as a ground-imaging spotlight SAR with characteristics similar to that of an L-band radar being flown on-board a helicopter. We use a flight path of radius 140 m at an altitude of 184 m. We assume the radar data to be a complex signal composed of the usual in-phase (real) and quadrature (imaginary) components such as that produced by low-pass filtering a demodulated return from an LFM chirped transmission. We assume a minimum frequency of \( f_{\text{min}} = 1.6 \) GHz, a maximum frequency of \( f_{\text{max}} = 2.8 \) GHz, and \( N_s = 320 \) samples per pulse. This results in a range resolution, \( \delta L_r = c/2B \approx 0.125 \) m, a bandwidth \( B = f_{\text{max}} - f_{\text{min}} = 1.2 \) GHz, a maximum alias-free range extent, \( L_r = c/2f_{\text{step}} \approx 39.9 \) m and a frequency step size of \( f_{\text{step}} = B/(N_s - 1) \approx 3.76 \) MHz. For a given subaperture, we set the angular step size \( \phi_{\text{step}} \) and the angular extent, \( \Phi \), such that the alias-free cross-range extent, \( \delta L_\phi \) and cross-range resolution, \( \Phi_{\text{step}} \), are similar to those of range. This yields \( \phi_{\text{step}} = c/(2f_{\text{max}}L_\phi) = 0.0750^\circ \) and an angular extent of \( \Phi = c/(2f_{\text{cen}}\delta L_\phi) = 30.0^\circ \) with \( f_{\text{cen}} = (f_{\text{max}} + f_{\text{min}})/2 \). The number of pulses per subaperture is the ratio \( \Phi/\phi_{\text{step}} = 400 \). We consider a circular flight path consisting of twelve of these subapertures as is shown to scale in Fig. 1a.

The generation of phase histories is performed separately for each region of scatterers corresponding to a given material and then summed to generate the total phase history as it would be measured, implicitly invoking an assumption of linearity. Each material region is given a unique dielectric response, i.e. a frequency dependent reflectivity. Phase history generation for each material is accomplished using reprojection, which computes the phase history using a combination of one-dimensional FFTs and interpolation operations that is essentially the reverse process of backprojection. See, e.g., [8] for a discussion of this approach along with techniques for numerical acceleration. Uniformly distributed random phases are added to each simulated point scatterer to avoid artifacts from the underlying simulation grid.
A major goal of our research activity is to develop a capability to better plan experimental data collections for the purpose of evaluating material identification through SAR image formation. This guides our choice of materials and scene composition. We choose material regions to be square so that we can easily truth the data. We choose the frequency responses to be linear due to practical considerations involving real world SAR systems and real world materials. This simply reflects that the frequency response of most natural environmental [9] and man-made building [10] materials are of low order over frequency bands of likely SAR systems under consideration for data collects in the near future.

![Fig. 1: Our first scenario is an ultrawide L-band spotlight SAR illuminating a ground patch composed of three materials. In (a) the flight path (gray) is shown relative to the ground patch. It is a full circle divided into twelve 30° subapertures, each bounded by the black plus marks. In (b) a close-up of the ground patch is shown. The units are in meters.](image)

Our first scenario consists of three materials arranged into two square patches (4 m by 4 m) and a background (20 m by 20 m). The material reflectivity in each square patch is given a linear frequency response, one increasing (positive slope) and the other decreasing (negative slope) with values ranging from 1 to 5 throughout the entire band. The background is given a flat frequency response; with a reflectivity equal to 1 throughout the entire band. A scale representation of the material regions are shown color-coded in Fig. 1b. A second scenario involving the same flight path, but illuminating a smaller 5 m by 5 m area will be discussed in Sec. V.

### III. MULTIBAND SAR PROCESSING

We use the backprojection algorithm to form images from the phase history data [11]. Our backprojection formulation is written in MATLAB and closely follows standard practice [12]. We coherently process each subaperture, and incoherently sum each subaperture contribution to form an image for the complete flightpath. A high resolution image formed using the full bandwidth is shown in Fig. 2a. We use a 200 by 200 pixel grid to discretize the 20 m by 20 m area so that each pixel is 0.1 m by 0.1 m. Recall that the nominal system resolution is approximately 0.125 meters in both range and cross-range. So this full-band high-resolution image is sampled slightly finer than the Nyquist limit. The other five images correspond to only using a portion of the full bandwidth (a subband), each using just one fifth the original bandwidth. As expected the spatial resolution of the subband images in Figs. 2b-2f is degraded; range resolution scales with the reciprocal of bandwidth. Also, and more to the point, the square patches in images in Figs. 2b-2f clearly show a variation in frequency response. The reflectivity of one patch appears to increase with frequency, the other appears to decrease. This directly supports the fundamental idea that it is possible to separately process the data from multiple subbands to extract spectral information from a fullband data set. We plot the reflectivity versus frequency (i.e. subband) in Fig. 3 to show the dispersion. Fig. 3 clearly shows that extracting dispersion from SAR data is possible using the proposed technique within a similar range.

![Fig. 2: SAR images formed corresponding to (a) a high resolution image using all the data 1.6 – 2.8 GHz (b) using 1.60 – 1.84 GHz (c) using 1.84 – 2.08 GHz (d) using 2.08–2.32 GHz (e) using 2.32–2.56 GHz (f) using 2.56–2.80 GHz. The images shown are normalized to the high resolution image shown in Fig. 2a and are logarithmic (40 dB).](image)
Fig. 3: The reflectivities per subband for the three regions. The units are relative to the SAR truth data used as input to create the phase history. For example a reflectivity of one with a flat response across the entire bandwidth was assumed for the region denoted by background. See the discussion at the end of Sec. II.

IV. MATERIAL IDENTIFICATION

We use a rudimentary classifier algorithm to facilitate material identification. After multiband SAR processing, a feature vector is formed for each pixel. The feature vector length is the number of sub-bands, and the entries are simply the pixel magnitudes from each sub-band image. The classifier is based on computing the inner-products of the feature vectors with the expected feature vectors for each class (i.e. the material response). The feature vectors are normalized using their Euclidean norm.

This rudimentary pattern matching classifier produces noisy results with frequent misclassifications as is shown in Fig. 4a. In an attempt to improve these results, the feature vectors are spatially averaged using a 5 by 5 pixel sliding window and the results are shown in Fig. 4b. There is some improvement, yet there are still some misclassification distributed throughout the image. In a second attempt to improve these results, the pixel sliding window size is increased to 7 by 7 and is shown in Fig. 4c. Notice the misclassifications are much less distributed throughout the image. In a third attempt, the pixel sliding window size was increased to 9 by 9 and the results are shown in Fig. 4d; the remaining misclassifications are located near the material interfaces.

We use the confusion matrix as a simple quantitative method for evaluating classifier performance. Table I shows the confusion matrix for the four specific values of spatial averaging chosen in Figs. 4a-4d. Each entry gives the probability of declaring the row class is the true pixel material. Thus, each row sums to unity. One finding is that the most frequent errors come from mis-classifying background pixels to be material 2. This is explained as due to a slight bias in the computed reflectivity that acts to reduce the reflectivity with increasing frequency as shown in Fig. 3. This bias is most obvious for the background since the computed reflectivity has a slight negative slope, whereas it should be flat (zero slope). The second and more important finding is that spatial averaging improves performance up to a certain point and then progresses to hurt performance thereafter. Notice that the 7 by

|               | Background | Material 1 | Material 2 |
|---------------|------------|------------|------------|
| no spatial averaging |           |            |            |
| Background    | 0.8875     | 0.0053     | 0.1071     |
| Material 1    | 0.0506     | 0.9494     | 0.0000     |
| Material 2    | 0.0000     | 0.0000     | 1.0000     |
| 5 by 5 sliding window |           |            |            |
| Background    | 0.9539     | 0.0040     | 0.0421     |
| Material 1    | 0.0149     | 0.9851     | 0.0000     |
| Material 2    | 0.0000     | 0.0000     | 1.0000     |
| 7 by 7 sliding window |           |            |            |
| Background    | 0.9611     | 0.0033     | 0.0355     |
| Material 1    | 0.0137     | 0.9863     | 0.0000     |
| Material 2    | 0.0000     | 0.0000     | 1.0000     |
| 9 by 9 sliding window |           |            |            |
| Background    | 0.9618     | 0.0027     | 0.0355     |
| Material 1    | 0.0161     | 0.9839     | 0.0000     |
| Material 2    | 0.0000     | 0.0000     | 1.0000     |

TABLE I: Confusion matrix corresponding to four spatial averaging choices.
7 pixel and 9 by 9 pixel sliding windows seem to yield the best performance. The performance of spatial averaging beyond the 9 by 9 pixel sliding window (not shown) slowly degraded with increasing spatial extent.

V. ERROR ANALYSIS

Our results in Sec. IV show considerable promise assuming certain conditions are met. We assumed materials have linear frequency responses, that these responses significantly differ, and that the spatial regions are sufficiently large such that spatial averaging is appropriate. How does our technique perform under a broader range of conditions? We address this by performing a set of simulations where we vary the size of a patch and the frequency response of background.

We consider a second scenario for the purpose of this analysis. It utilizes the same flight path as the first, but the radar illuminates a smaller 5 m by 5 m area, subdivided into 50 by 50 pixels. This again results in 0.1 m by 0.1 m sized pixels; the same as the first scenario. The area is composed of only two material regions, one a central square patch and the other background. The patch size is varied from one pixel to 26 by 26 pixels (2.6 m by 2.6 m). The frequency response of the patch is fixed; its reflectivity is a linear response from one to five over the band. The frequency response of the background is varied; its linear response ranges from one to five (the same as the patch) to five to one (opposite in sign from each other); the background response is 5 to 1. The frequency response, that these responses significantly differ, C_{22} approaches its maximum value (for this scenario, no spatial smoothing is done, random spatial variations prevent C_{22} from reaching unity). Secondly, notice that for identical frequency response, C_{22} approaches zero. This makes sense; if there is no difference between two materials, the classifier cannot distinguish one from another. Thirdly, notice that for patch sizes below the system resolution, the probability of identification goes to zero.

VI. CONCLUSION

We demonstrate that SAR imaging offers the possibility of material identification at each pixel. The approach is based upon dividing the radar data into several frequency subbands and extracting the dispersion through the image formation process. We also demonstrate a rudimentary classifier algorithm that is capable of accurate material identification away from material borders.

VII. ACKNOWLEDGEMENTS

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This set of simulations therefore tests for how small a patch can be identified and how easily two linear materials can be distinguished using our method. For this analysis no spatial averaging is performed, since it would compromise the results at the smaller patch sizes. As in Sec. IV we compute the confusion matrix, only now it is a 2 × 2 matrix instead of 3 × 3, because there are only 2 materials (i.e. the patch and background). The results are shown in Fig. 5. The element of the confusion matrix, C_{22}, gives the probability that the patch material is correctly identified. First notice that for larger patch sizes and increasingly different frequency responses, C_{22} approaches its maximum value (for this scenario, no spatial smoothing is done, random spatial variations prevent C_{22} from reaching unity). Secondly, notice that for identical frequency response, C_{22} approaches zero. This makes sense; if there is no difference between two materials, the classifier cannot distinguish one from another. Thirdly, notice that for patch sizes below the system resolution, the probability of identification goes to zero.

Fig. 5: A contour plot of C_{22}. The frequency response units are normalized as the ratio of the two responses, the patch and background. A value of one indicates the two materials have identical frequency responses; the background response is 1 to 5. A value of negative one indicates the responses are opposite in sign from each other; the background response is 5 to 1. A value of zero indicates the background response is flat, 3 to 3. The normalized patch size is the physical edge length relative to the system resolution. So the maximum 2.6 m scales to 20.8 and the minimum 0.1 m scales to 0.8.