MULTISCALE ADAPTIVE ESTIMATION FOR FUSING INTERFEROMETRIC RADAR AND LASER ALTIMETER DATA

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Abstract - Interferometric synthetic aperture radar (INSAR) data are fused with laser altimeter (LIDAR) data to produce improved estimates of bare-surface topography and vegetation heights. The data from both sensors are first transformed into estimates of surface elevations and vegetation heights to obtain linear measurement-state relations. A spatially-adaptive multiscale estimation framework is then used to combine the data, which were acquired at different resolutions. The estimation is performed in scale and space via a set of Kalman filters. It yields better error characteristics than the nonadaptive multiscale filter and accommodates non-stationarity in the image data.

1. INTRODUCTION

Interferometric synthetic aperture radar (INSAR) sensors have been used extensively to map topography. Accuracies are limited over vegetated regions, however, because the observations are not measurements of true surface topography. The measurements correspond to a height above the true surface that depends on both the sensor and the vegetation. Laser altimeter (LIDAR) systems, conversely, can map topography over smaller areas very accurately. In order to determine surface elevations and vegetation heights from dual-baseline INSAR data, we solve an inverse problem for INSAR scattering [1].

To keep the inverse problem well-posed, a simplified scattering model is used, which can lead to large uncertainties in the height estimates. LIDAR observations that are acquired over specific regions of interest are combined with the INSAR inversion results to improve the estimates of ground elevations and vegetation heights. We combine the two data types using a multiresolution Kalman filter approach, which provides the estimates and estimate uncertainties at each pixel. Combining data from the two sensors provides estimates that are more accurate than those obtained from INSAR alone, yet have coverage that is both dense and extensive, which is difficult to obtain with LIDAR.

For a 2-D process, the multiscale estimation is implemented on a quadtree. It is initiated with a fine-to-coarse sweep up the quadtree that is analogous to Kalman filtering with an added merge step. This is followed by a coarse-to-fine sweep down the quadtree that corresponds to Kalman smoothing. Using the scalar form for clarity, the linear coarse-to-fine model is given as

$$\begin{aligned} x(s) &= \Phi(s)x(Bs) + \Gamma(s)w(s) \quad \forall s \in \mathcal{S}, s \neq s_0 \\ y(s) &= H(s)x(s) + v(s) \qquad \forall s \in \mathcal{T} \subseteq \mathcal{S} \end{aligned} \tag{1}$$

where x is the state variable, and y represents the observations. The stochastic forcing function w is assumed to be a Gaussian white noise process with identity variance, and the measurement error v is a Gaussian white noise process with scale dependent variance $R(s)$. $\mathcal{S}$ represents the set of all nodes on the quadtree, and $\mathcal{T}$ denotes those nodes at which an observation is available. s is the node index on the tree, and s_0 denotes the root node. B is a backshift operator in scale, such that Bs is one scale coarser than s. Φ is the coarse-to-fine state transition operator, Γ^2 is the process noise variance, H is the measurement-state relation, and R represents the measurement variance of the observations.

The standard Kalman formulation provides optimal estimates (in the mean squared sense) when there is perfect *a priori* knowledge of the state and measurement models $\{\Phi(s), \Gamma(s), H(s), R(s)\}$. A statistically self-similar process, $1/f$ noise, is used to describe the evolution of the topography through scale. The $1/f$ behavior across scales is an idealization though and does not account for spatial variability at a given scale. If errors exist in the assumed process or measurement noise variances, the computed estimates and estimate uncertainty will be incorrect. We develop an adaptive multiscale estimation approach that admits spatial variability in the noise processes. As the filter operates in the spatial dimension, deviations from optimality are used to detect where the model is in error. The process noise variance for the spatial component of the filter is then updated.

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We apply this estimation framework to remotely sensed data acquired over the coast of Texas. The study area contains both forested and grassland areas. Dual-baseline INSAR imagery was acquired by the NASA/JPL TOPSAR sensor over the entire study area. High-resolution LIDAR data were also acquired over the study area by an Optech, Inc. ALTM sensor. The contributions of this work include (1) extending adaptive estimation techniques to spatially-varying multiscale processes and (2) improving estimates of ground elevations and vegetation heights for remote sensing applications.

2. MULTISCALE FILTER

In previous work [2] we implemented a data fusion framework based on a multiscale Kalman filter [3]. A quadtree data structure is created with the leaf nodes corresponding to the high resolution LIDAR data, while the INSAR data are used at the next coarser scale. The objective is to estimate ground surface topography z_g and vegetation heights Δz_v from INSAR and LIDAR data. Our approach has two components. First, the observations from each sensor are transformed to obtain estimates of the ground elevations and vegetation heights. This is done by numerically inverting an INSAR scattering model and applying an empirical algorithm to the LIDAR data that removes the vegetation component. Then the transformed INSAR and LIDAR data are combined in a multiresolution spatially-adaptive Kalman filter to obtain optimal estimates of z_g and Δz_v.

The state transition operator in scale $\Phi(m)$ is determined by matching the power spectrum of the INSAR observations to that of the stochastic data model. This provides a good estimate for the evolution of the state process in scale. However, $\Phi(m)$ is constant at each scale, hence it cannot accommodate non-stationarities in the imagery at a particular scale. An image that contains more than one landcover type, e.g. grassland and forest, represents a non-stationary 2-D process. Therefore, using a state transition operator that is variable in scale but uniform in space will lead to suboptimal estimates in general.

3. ADAPTIVE ESTIMATION

Several approaches to adaptive estimation have been reported in the literature. The *innovation - correlation* method is employed in this work. This method is theoretically based, and is computationally attractive because it is noniterative. It is also well suited to stochastic problems in which the precise dynamics of the process are not known. The measurement residuals (innovations) comprise a zero-mean, white, Gaussian sequence when the model parameters are correct. Therefore, testing the innovation sequence for non-white behavior by computing the autocorrelation function indicates whether the model contains errors or not.

Mehra showed that the process noise variance in a Kalman filter could be correctly estimated using the autocorrelation function of the innovation sequence to obtain the optimal filter [4] for the stationary case. Recently, this method has been extended to examine the innovation sequence locally, and thus update the estimate of the process noise locally for non-stationary processes [5]. We extend the method of [5] to the multiresolution case.

The innovation sequence is a function of the process noise variance Γ^2, which is estimated from the local autocorrelation function. This method produces asymptotically normal, unbiased, and consistent estimates of Γ^2. The method of [5] uses a batch of recently computed estimates to update the process noise variance. We generalize the linear system model in (1) to describe separable processes in scale and spatial dimensions. We adaptively estimate Γ^2 in the spatial component of the filter.

4. MULTI-DIMENSIONAL STATE MODEL

We make use of the Fornasini-Marchesini Form II (FM-II) multi-dimensional linear system model [6] to admit process dynamics in multiple dimensions. First, it is generalized to admit one dimension of non-uniform support (scale) and two spatial dimensions. The node index s is written in terms of these dimensions $s = \{m, i, j\}$, where m represents scale (level of the quadtree) and (i, j) are the image pixel coordinates. The coarse-to-fine state model is given by

$$\begin{aligned} x(m,i,j) = \Phi(m \mid m-1)x(m-1,\lceil i/2\rceil,\lceil j/2\rceil) + \\ \Phi(i \mid i-1)x(m,i-1,j) + \Phi(j \mid j-1)x(m,i,j-1) + \\ \Gamma(m \mid m-1)w(m-1,\lceil i/2\rceil,\lceil j/2\rceil) + \\ \Gamma(i \mid i-1)w(m,i-1,j) + \Gamma(j \mid j-1)w(m,i,j-1) \end{aligned} \tag{2}$$

where $\{(m+1,\lceil i/2\rceil,\lceil j/2\rceil),(m+1,\lceil i/2\rceil+1,\lceil j/2\rceil),(m+1,\lceil i/2\rceil,\lceil j/2\rceil+1),(m+1,\lceil i/2\rceil+1,\lceil j/2\rceil+1),(m,i-1,j),(m,i,j-1)\}$ is the set of nodes from which the priors in the upward filter are derived.

The filter initiates at the base of the quadtree in the standard multiscale manner [3]. Upon reaching a level that contains observations, two 1-D Kalman filters then operate along the rows and columns of the image. The *a priori* estimates of the spatial filters include the multiscale estimates from the level below. The location dependent estimates from the row-wise filter are incorporated into the *a priori* estimates of the column-wise filter. The process noise is updated by each filter in blocks of 16 pixels. The spatial portion of the Kalman filter is applied only at levels in the quadtree where dense observations are present so that the innovation sequences have uniform support. The estimates from the column-wise filter are then used as the observations in the multiscale component of the filter at the current level. The filter then proceeds in the standard multiscale way up the remainder of the quadtree.

5. RESULTS

MSE for vegetation height estimates from the INSAR inversion alone (no LIDAR data), multiscale fusion with the LIDAR, and multiscale spatially-adaptive fusion with the

Table 1. Mean squared error before filtering, after multiscale Kalman smoothing, and after adaptive filtering. $H = \{0,1\}$ represents all pixels at the finest scale, $H = \{1\}$ represents pixels where LIDAR was present, and $H = \{0\}$ represents pixels where LIDAR was not present.

Vegetation height MSE (m^2)			
	INSAR only (no fusion)	multiscale fusion	spatially adaptive multiscale fusion
H=$\{0,1\}$	22.7	5.24	4.42
H=$\{1\}$	24.7	0.424	0.940
H=$\{0\}$	21.1	9.16	7.25

LIDAR are summarized in Table 1 for a portion of the study area. The error is the difference between the estimates and the full set of LIDAR data. The algorithm estimates bare surface topography as well as vegetation height, and a similar reduction in MSE was observed for bare surface elevations. We use the mean squared error (MSE) for our performance measure since the Kalman filter is optimal with respect to this measure. There is a dramatic reduction in MSE when the LIDAR data are combined with the INSAR data. There is a significant additional reduction in global MSE when the spatially adaptive filter is used.

Figure 1 shows the estimated vegetation heights and the corresponding estimate uncertainty. The uncertainty is lowest where there is LIDAR data and where there is minimal vegetation. The uncertainty varies continuously between regions with and without LIDAR data; however, in this example, the transition appears sharp because the measurement uncertainties of the two sensors are the same order of magnitude and the two observation types reside on adjacent levels in the quadtree.

6. CONCLUSION

We have developed a multiscale spatially adaptive state-space filter for data fusion. It yields better error characteristics than the nonadaptive multiscale filter and accommodates non-stationarities in the image data. Continuing research will focus on extending the spatial filter to non-separable 2-D processes. Multiple-model (filter bank) approaches to the adaptive estimation will also be investigated.

7. REFERENCES

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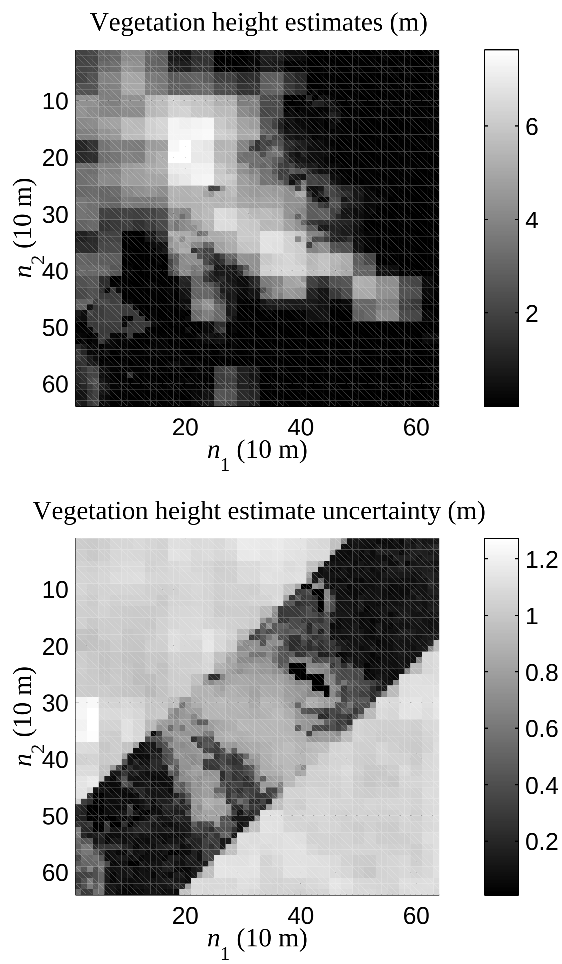

Fig. 1. Vegetation heights (top). The oval shaped bright region in the center of the image is a grove of trees. The surrounding dark area is grassland. Estimate uncertainty (bottom). The diagonal swath in the image results from including LIDAR data from a single representative pass.