Phase-Variance Thresholding and Uncertainty-based Weighted Averaging for Optimal Generation of InSAR-derived Mosaics of Permafrost Active Layer Thickness

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I. MOTIVATION

Large-scale thawing of arctic permafrost has a poorly-understood feedback effect on global climate through the release of CO2 and methane. Active Layer Thickness (ALT) is the maximum annual depth of thaw of surface soils and is designated by the World Meteorological Organization (WMO) as an essential climate variable for monitoring the status of permafrost. Interferometric Synthetic Aperture Radar (InSAR) is a widely-used geophysical technique for measuring surface deformation at high spatial resolution (Rosen et al. 2000). In recent years, InSAR has been successfully used to measure ground deformation due to seasonal permafrost freeze/thaw cycles and invert this deformation signature for a spatially extensive and finely-sampled map of ALT (Liu et al. 2012; Schaefer et al. 2015).

II. SCIENTIFIC BACKGROUND

The aim of this project was to extend various image processing techniques towards an area of active research in the geophysical climate community. Interferometric synthetic aperture radar (InSAR) is a well-established radar remote sensing technique (Rosen et al. 2000). The synthetic aperture radar (SAR) technique utilizes the principle of coherent radar pulse integration, and doppler processing to generate high-resolution (~5-10 m pixel resolution) radar images of the earth’s surface from earth-orbiting satellites (Rosen et a. 2000). Each pixel in a SAR image is a complex variable with an amplitude associated with the amount of returned scattered energy from the earth’s surface that is received by the radar, and a phase associated with the total distance from the radar unit to the earth’s surface. When multiple SAR images over a single region of interest are acquired, the (element-wise) product of one image with the complex conjugate of the other image yields the difference in phase between these two images. Because this phase is directly related to distance, this image of phase differential (hereafter referred to as an interferogram), encapsulates information related to the earth’s topography, and any surface deformation that occurred in-between the acquisition times of the two images (citation needed). If a priori information of the earth’s topography is available (conventionally a digital elevation model, or DEM), the topographic phase dependency can be removed from an interferogram, leaving behind the surface deformation signature and noise.

InSAR has a well-established heritage in studying the surface deformation associated with earthquakes, volcanoes, glacial ice flow, landslides, and ground subsidence (citation needed). In recent years, the InSAR technique has been used to study the ground deformation associated with freeze/thaw surface subsidence in arctic permafrost environments. Permafrost environments are regions that are cold enough such that the groundwater held in the pore space of soils is completely frozen for a significant portion of the year. During the spring thaw period, rising surface temperatures cause pore space water to gradually thaw from solid to liquid; because a given amount of water takes more volume in its solid state than its liquid state, this phase change of water causes the ground to subside (or ‘sink’ downwards) due to the effective decrease in volume in a column of soil during thaw. As the spring season progresses through summer, extended periods of above-zero surface temperature cause more and more of the subsurface pore water to thaw, thereby causing a greater amount of subsidence. Eventually, a given region of permafrost will experience its maximum thaw during the thaw season; the depth to which the subsurface has thawed is referred to as the active layer thickness (ALT). In autumn and winter, this liquid water freezes again, and the ground experiences uplift (or ‘rises’ upward) as the effective volume of the pore space in a soil column increases. Thus, over a seasonal cycle, permafrost environments experience freeze/thaw-associated cycles of ground deformation, which can be imaged and characterized by InSAR.

Permafrost regions contain large amounts of CO2 and methane within the shallow subsurface, and repeat thaw of permafrost can cause these greenhouse gases to be released into the atmosphere. Permafrost regions are thus a significant source of greenhouse gas emissions, and the process by which these gases are emitted is often a positive (unstable) feedback loop. Fully understanding the dynamics of permafrost freeze/thaw cycles is of high importance within the climate scientific community, and currently this is a poorly understand physical process. InSAR therefore is a promising technique that can shed light on this poorly understood, but very significant, earth system process. The ReSALT (Remotely-Sensed Active Layer Thickness) technique, developed by Liu et al. 2012, utilizes InSAR-derived surface deformation to invert for ALT across SAR scenes. This technique generates broad, regional...
distributions of ALT at a spatial scale of 10s of meters; a significant improvement on existing methods of regional ALT characterization.

III. METHODS

In this project, I have developed two image processing techniques that are directly applicable towards the ReSALT method, and can hopefully aid in 1) its applicability towards a larger range of permafrost environments, and 2) the ability to generate larger regional distribution maps of ALT. To address these aims, I have developed a phase-variance-based threshold masking routine, which successfully delineates surface features that are consistently wet (lakes, rivers, thaw ponds, etc.). These features bias the ReSALT technique with false, nonphysical estimates of active layer thickness (ultimately due to the scattering interaction between radar pulses and water surfaces), and thus must be masked out of ALT maps. The phase-variance masking routines takes advantage of the scattering interaction of radar pulses with water surfaces to directly identify regions within an interferogram that are water surfaces (without the use of secondary information such as optical imagery), and then mask out these regions. Secondly, I have developed a weighted arithmetic mean mosaicking algorithm that can be used to stitch together several scenes of estimated ALT, so that larger regions of ALT can be characterized. Instead of using a conventional mosaicking technique (such as feathering), I wanted to develop a method that took into account the uncertainties in measured ALT as a weighting method, so that ideally the mosaicking algorithm did not bias the measured values of ALT.

IV. PHASE VARIANCE MASK

For the phase variance mask, I first calculate the phase variance of each interferogram using an algorithm developed in my research group (note: I do not include this algorithm in my final project, just the output after running it). This algorithm calculates the phase variance associated with each pixel in an interferogram, and for each pixel, returns 1-(variance/threshold variance), where threshold variance is an input value for the expected maximal variance in a scene. For each SAR stack of N coregistered interferograms, I sum together the output of this phase variance algorithm, I.E.:

\[ V_{ij} = \sum_{k=1}^{N} \max[0, \left(1 - \frac{\sigma_{ij,k}}{\sigma_{\text{threshold}}}\right)] \]

This output, V(i,j) is therefore the sum total of phase variance per pixel in a stack of interferograms, rescaled such that a pixel value of 0 corresponds to a pixel whose variance is consistently greater than sigma_thresh in all N interferograms, and a pixel value of N corresponds to a pixel whose variance is 0 in all N interferograms. I then explore different threshold values of V(i,j) to use as a phase-variance mask to mask out unwanted regions (lakes, rivers, swamps, marshes) whose estimates of ALT are nonphysical. I find that a simple threshold of 0 successfully removes these regions, and sharply preserves the borders of these regions (up to the SAR resolution). I.E., the threshold is:

\[ M_{i,j} = 1, \text{if } V_{i,j} > 0 \]
\[ M_{i,j} = 0, \text{if } V_{i,j} = 0 \]

I include the output phase variance images for each interferogram in each stack ("...").phase.mask.nc), a list of these images (ncphaseslist) in a separate subdirectory for each SAR stack. These images are input for the phase-variance thresholding algorithm, which outputs the phase-variance mask ("...").mask.nc).

V. WEIGHTED ARITHMETIC MEAN MOSAICKING ALGORITHM

The algorithm used to invert deformation for ALT is similarly not included in my final report, as it is beyond the scope of this course. This algorithm inverts deformation for

\[ \text{Figure 2: (Top) ALT distribution unmasked (top) and masked using the phase variance threshold mask (bottom). Notice that the mask successfully removes anomalous, unphysical large estimates of ALT that occur at the surface of thaw ponds (bright yellow at top, masked out at bottom).} \]
using a functional relationship between deformation and active layer thickness that depends upon soil porosity, saturation, organic matter content, and density contrasts and distributions within the soil column. The output of the algorithm is an estimate of ALT, and associated uncertainties from the model (“..._alt.nc, and “..._err.nc, respectively). I include these images within each SAR stack subdirectory, and the associated latitude and longitude ranges of each geocoded stack (lat.nc and lon.nc, respectively).

The weighted arithmetic mean mosaicking algorithm I developed utilizes the ALT and ALT uncertainty images for each stack, as well as their associated latitude and longitude ranges as inputs. The algorithm first determines the spatial offsets between each image, and generates a global scene within which it places each image (in an analogous manner to the panorama stitching routine developed in the last homework set for this course). Then, the algorithm determines the regions of overlap between all of the images, and performs a weighted arithmetic mean of each overlapping image, using the ALT image’s associated uncertainties as its weighting term. I.E:

\[
E_{i,j} = \frac{\sum_{k=1}^{N_o} I_{k,i,j}}{\sum_{k=1}^{N_o} (\sigma_{k,i,j})^2}
\]

The output mosaic is compared to mosaics generated with a simple averaging technique. The weighted arithmetic mean is seen to produce ‘smoother’ distributions of ALT when compared to these simpler mosaicking routines. Furthermore, by incorporating actual uncertainty measurements into the estimate, this averaging routine does not introduce artificial biases into the physical ALT estimate in regions of image overlap.

**CONCLUSION**

The phase-variance threshold masking technique successfully pixels associated with poorly-correlated surface water regions. By using phase variance as a threshold, this mask sharply preserves the edges of water features, and drastically improves scene-wide estimates of active layer thickness by removing false values associated with these water features. The weighted arithmetic mean mosaicking algorithm successfully co-geolocates several different InSAR stack scenes within a single global scene. Additionally, the algorithm ‘blends’ regions of image overlap by using a weighting averaging scheme that utilizes model uncertainty as a weight. This improves active layer thickness estimates by reducing uncertainties in regions of image overlap, and allows for the generation of large, regional distributions of active layer thickness. These two techniques have improved the ReSALT technique performance in wetland arctic regions, and can help generate more complete distribution maps of active layer thickness for climate change studies.

**REFERENCES**