ENHANCEMENT OF THE MODIS SNOW AND ICE PRODUCT SUITE UTILIZING IMAGE SEGMENTATION

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ABSTRACT

A problem has been noticed with the current MODIS Snow and Ice Product in that fringes of certain snow fields are labeled as "cloud" whereas close inspection of the data indicates that the correct labeling is a non-cloud category such as snow or land. This occurs because the current MODIS Snow and Ice Product generation algorithm relies solely on the MODIS Cloud Mask Product for the labeling of image pixels as cloud. It is proposed here that information obtained from image segmentation can be used to determine when it is appropriate to override the cloud indication from the cloud mask product. Initial tests show that this approach can significantly reduce the cloud "fringing" in modified snow cover labeling. More comprehensive testing is required to determine whether or not this approach consistently improves the accuracy of the snow and ice product.

Index Terms— MODIS data products, Image segmentation, Remote sensing.

1. INTRODUCTION

The authors are members of a project team which is seeking to maintain, enhance, validate and perform error analysis on the MODIS Snow and Ice Product Suite under the NASA Science Mission Directorate's program for Earth System Science Research using Data and Products from the Terra, Aqua, and ACRIMSAT Satellites. The paper reports on the team's progress in fulfilling one of its project objectives: improving snow/cloud and sea ice/cloud discrimination in current algorithms. In particular, this paper focuses on approaches utilizing image segmentation.

One problem addressed by the team is the so-called "cloud fringe" problem. Here the fringes of certain snow fields are labeled as "cloud" whereas close inspection of the data indicates that the correct labeling is a non-cloud category such as snow or land. The reason this occurs is that the current MODIS Snow and Ice Product generation algorithm relies solely on the MODIS Cloud Mask Product (MOD35) for the labeling of image pixels as cloud, without any regard to spatial context. It is proposed here that image segmentation can provide a spatial context through which the MODIS Cloud Mask Product determination of cloud can be overridden whenever appropriate.

In the sections that follow an overview of the MODIS Snow and Ice Product generation is provided followed by a high level description of the image segmentation approach used in this study. Then a proposed approach to an appropriate overriding of the MODIS Cloud Mask Product determination of cloud utilizing image segmentation results is described. Results are provided for a MODIS data set and compared with the current MODIS Snow and Ice Product.

2. MODIS SNOW AND ICE PRODUCT

The MODIS instrument is a part of the instrument suite on both the Terra and Aqua satellites. The Terra satellite was launched by NASA on 18 December 1999 and the Aqua satellite was launched by NASA on 24 June 2002. The core of the MODIS Snow and Ice Product generation algorithm is the normalized snow difference index (NDSI) which is defined for MODIS as [1]:

$$\mathrm{NDSI} = \frac{\chi_4 - \chi_6}{\chi_4 + \chi_6} \qquad (1)$$

where χ_i is the value of an image pixel from MODIS band-*i*. Since 70% of the band-6 detectors are non-functional on the Aqua MODIS instrument, band-7 is substituted for band-6, with some subsequent loss in accuracy of the snow and ice product. We will assume we are working with data from the Terra MODIS instrument for the rest of this paper.

Following [1], the global criteria for snow is a NDSI value greater than 0.4 together with a MODIS band-2 reflectance greater than 0.11 and a MODIS band-4 reflectance greater than 0.10. To enable detection of snow in dense vegetation a criteria using NDSI together with the normalized difference vegetation index (NDVI) is applied to image pixels that have an NDSI value in the range of 0.1 to 0.4. In this test, image pixels with NDSI and NDVI values in a defined polygon of a scatter plot of the two indices and that has MODIS band-2 reflectance greater than 0.11 and MODIS band-1 reflectance greater than 0.1 are determined to be snow. NDVI is defined for MODIS as:

$$\mathrm{NDVI} = \frac{\chi_2 - \chi_1}{\chi_2 + \chi_1}. \qquad (2)$$

This test is applied without regard to ecosystem. An additional surface temperature screening test is applied to prevent bright warm surfaces from being erroneously detected as snow. If the surface temperature, calculated from MODIS bands 31 and 32, is more than 283K, an image pixel is assumed to not to be snow or ice.

In summary, the MODIS Snow and Ice Product generation algorithm uses criteria based on MODIS bands 1, 2, 4, 6, 31 and 32 to determine whether or not an image pixel is either snow or ice (a pixel is snow if on land and ice or snow on ice if on water).

Cloud masking is the final step of the MODIS Snow and Ice Product generation algorithm. Following [1], clouds are masked using data from the MODIS Cloud Mask Product (MOD35_L2). If the cloud mask algorithm was applied to an image pixel, it is considered to be "cloud obscured" if so indicated by the summary cloud result unobstructed field-of-view flag.

3. IMAGE SEGMENTATON

The image segmentation approaches utilized in this study are forms of best merge region growing: (i) the Hierarchical Stepwise Optimization (HSWO) approach of Beaulieu and Goldberg [2], and (ii) the Recursive Hierarchical Segmentation (RHSEG) approach of Tilton [3, 4].

Both HSWO and RHSEG produce a hierarchical set of image segmentations. This segmentation hierarchy is a set of several image segmentations of the same image at different levels of detail in which the segmentations at coarser levels of detail can be produced from simple merges of regions at finer levels of detail. A unique feature of a segmentation hierarchy that distinguishes it from most other multilevel representations is that the segment or region boundaries are maintained at the full image spatial resolution for all levels of the segmentation hierarchy.

3.1. Hierarchical Stepwise Optimization (HSWO)

HSWO is an iterative process, in which the iterations consist of finding the best segmentation with one region less than the current segmentation. The HSWO approach can be summarized as follows:

1. Initialize the segmentation by assigning each image pixel a region label. If a pre-segmentation is provided, label each image pixel according to the pre-segmentation. Otherwise, label each image pixel as a separate region.
2. Calculate a dissimilarity criterion value between all pairs of spatially adjacent regions, find the pair of spatially adjacent regions with the smallest dissimilarity criterion value, and merge that pair of regions.
3. Stop if no more merges are required. Otherwise, return to step 2.

HSWO naturally produces a segmentation hierarchy consisting of the entire sequence of segmentations from initialization down to the final trivial one region segmentation (if allowed to proceed that far). For the purposes of this study, the segmentation utilized is taken from the HSWO iteration at which the maximum mean normalized region standard deviation (maximum over spectral bands) first exceeds a preset threshold value, *chk_mn_std_dev*.

The MODIS granules are relatively large images, consisting of 2708 columns and 4060 rows of data. If HSWO is initialized by assigning each image pixel with a unique region label, HSWO would be initialized with 10,994,480 regions. For computers with no more than a couple GBytes of RAM, this can easily exceed the memory resources. The memory requirements of HSWO can be reduced by initializing HSWO with a pre-segmentation. In this study, HSWO was initialized with a first merge region growing approach based on Muerle and Allen [5] with random selection of seed pixels.

3.2. Recursive Hierarchical Segmentation (RHSEG)

RHSEG is a recursive approximation of Hierarchical Segmentation (HSEG). HSEG is similar to HSWO, but adds an option to interject between HSWO iterations merges of spatially non-adjacent region (i.e., spectrally based merging of clustering) constrained by a threshold derived from the previous HSWO iteration. The relative importance of region growing and spectral clustering merges is controlled by the parameter *spclust_wght*, which can vary from 0 to 1. When *spclust_wght* = 0.0, only merges between spatially adjacent regions are allowed (as with HSWO). With *spclust_wght* = 1.0, merges between spatially adjacent and spatially non-adjacent regions are given equal priority. For 0.0 < *spclust_wght* < 1.0, spatially adjacent merges are given priority over spatially non-adjacent merges by a factor of 1.0/*spclust_wght*. Thus for *spclust_wght* > 0.0, spatially connected region objects may be grouped or classified into spatially disjoint region classes.

While the addition of constrained spectral clustering significantly reduces the number of regions required to characterize an image, especially for larger highly varied images, it also significantly increases HSEG's computational requirements. This increase in computational requirements is counteracted by RHSEG, a computationally efficient recursive approximation of HSEG. RHSEG also has an effective parallel implementation for MIMD clusters.

RHSEG is a recursive, divide-and-conquer, approximation of HSEG. Following [3] and [4], it can be described for 2-spatial dimension image data as:

1. Given an input image X, specify the number of levels of recursion (*rnb_levels*) required and pad the input image, if necessary, so that for each spatial dimension the image can be evenly divided by $2^{(rnb\_levels-1)}$. (A good value for *rnb_levels* results in an image section at *level* = *rnb_levels* consisting of roughly 1000 to 4000 pixels.) Set *level* = 1.
2. Call rhseg(*level,X*).
3. Execute the HSEG algorithm on the image X using as a pre-segmentation the segmentation output by the call to rhseg( ) in step 2.

where rhseg(*level,X*) is as follows:

2.1. If *level* = *rnb_levels*, go to step 2.3. Otherwise, divide the image data into 2^2 equal subsections and call rhseg($level+1,X/2^2$) for each image section (represented as $X/$).

2.2. After all 2^2 calls to rhseg() from step 2.1 complete processing, reassemble the image segmentation results.

2.3. If *level* < *rnb_levels*, initialize the segmentation with the reassembled segmentation results from step 2.2. Otherwise, initialize the segmentation with one pixel per region. Execute the HSEG algorithm on the image X with the following modification: Terminate the algorithm when the number of regions reaches the preset value *min_nregions*.

Under a number of circumstances, the segmentations produced by the RHSEG algorithm exhibit processing window artifacts. These artifacts are region boundaries that are along the processing window seams, even though the image pixels across the seams are very similar. However, the processing window artifacts can be completely eliminated by adding a 4th step to the definition of rhseg(*level,X*) given above in which certain pixels are split out from their original region assignment and remerged into a more appropriate region (see [6]).

The region mean images of segmentations produced using HSEG or RHSEG very closely approximate the original image with very few region classes. Thus these algorithms can be iterated until a small number of regions remain (the program default is 64 regions) before results from the segmentation hierarchy need to be retained. And once the hierarchical segmentation results start being retained, HSEG and RHSEG utilize an approach for selecting the minimum number of hierarchical levels to guarantee that each region class is involved in no more than one merge from one hierarchical level to the next.

3.3. Dissimilarity Criteria for HSWO and RHSEG

A variety of dissimilarity criteria may be used with HSWO and RHSEG (see [4] for a complete list). In this study, the "square root of band sum mean squared error" criterion was utilized. This criterion is defined as:

$$d_{BSMSE}^{1/2}\left(X_i, X_j\right)=\left[\frac{n_i n_j}{\left(n_i+n_j\right)}\sum_{b=1}^{B}\left(\mu_{ib}-\mu_{jb}\right)^2\right]^{1/2}, \qquad (3)$$

where n_i (n_j) is the number of pixel in region X_i (X_j), and μ_{ib} (μ_{jb}) is the mean of region X_i (X_j) for spectral band b.

4. SCHEME FOR OVERRIDING OF THE MODIS CLOUD MASK PRODUCT

Since the MODIS Snow and Ice Product generation algorithm depends directly on MODIS bands 1, 2, 4, 6, 31 and 32, our first thought was to perform image segmentations on the combination of these six bands. However, results using these six bands turned out to be unsatisfactory. Inspection of the results revealed that the segmentations were adversely affected by the influence of MODIS bands 31 and 32. Therefore only four bands, (MODIS bands 1, 2, 4 and 6) are used as input to the image segmentation algorithms in the approach described here.

Using a segmentation result from either HSWO or RHSEG, in our proposed scheme the NDSI and NDVI values are calculated using the region mean values for each region object. The current MODIS Snow and Ice Product generation algorithm is executed, up to the cloud masking step, using these region mean values for NDSI and NDVI. However, the surface temperature is calculated based on the original (un-segmented) MODIS bands 31 and 32.

Instead simply applying the cloud mask directly from the MODIS Cloud Mask Product, the numbers of cloud obscured pixels are counted for each region object. Then if the majority of pixels in a region object are *not* cloud obscured, then *none* of the pixels in that region object are considered to be cloud obscured. However, if the majority of pixels in a region object *are* cloud obscured this characterization is *not* extended to all pixels in the region object.

5. RESULTS

Two test results are reported here for Terra MODIS granule A2007069.1750.005. This granule was collected on March 10, 2007 and covers an area over the north central USA and south central Canada. A large area of snow is observed in the central portion of this data set. Pronounced, inaccurate cloud fringing is observed in the MODIS Snow Product along the southwest edge of the snow field. A portion of band 4 of this data set is displayed in Fig. 1(a). The corresponding section of the MODIS Snow and Ice Product is displayed in Fig. 1(b).

In the first test HSWO was used to produce the image segmentation. Hierarchical segmentation results were selected at *chk_mn_std_dev* = 0.10, 0.15, 0.20 and 0.25. These segmentation results contained 27,208, 10,848, 3,415 and 625 region objects, respectively.

The 625 region object result performed best in terms of reducing the cloud fringing errors, but introduced errors elsewhere in the data set by removing clouds inappropriately. The 3,415 region object result performed next best in terms of reducing the cloud fringing errors, and the cloud removal errors elsewhere in the data set are much reduced versus the 625 region object result. A portion of the Snow and Ice Product utilizing the 3,415 region object HSWO segmentation is shown in Fig. 1(c).

In these tests HSWO was performed on a 1.8 GHz Pentium 4 computer with 1 GByte of RAM. The processing time averaged about 9 minutes for each case. HSWO was initialized with the Muerle and Allen first merge region growing approach with a dissimilarity threshold of 0.40.

In the second test RHSEG was used to produce the image segmentation. Hierarchical segmentation results were obtained at 28, 17, 10, 8 and 4 region classes. These segmentation results contained 589,562, 334,277, 253,250, 209,525 and 106,310 region objects, respectively.

The 4 region class result performed best in terms of reducing the cloud fringing errors, but introduced errors elsewhere in the data set by removing clouds inappropriately. The 8 and 10 region class results performed nearly the same in reducing the cloud fringing errors, with noticeably fewer errors in removing clouds elsewhere inappropriately. The 17 and 28 region class results did not perform as well in reducing the cloud fringing errors. A portion of the Snow and Ice Product utilizing the 10 region class RHSEG segmentation is shown in Fig. 1(d).

In these tests RHSEG was performed using 16 CPUs of the "palm" SGI Altix 3000 computer at the NASA Goddard Space Flight Center. The individual CPUs are 1.5 GHz Itanium 2 processors. The RHSEG run took 18 minutes and 52 seconds to complete.

6. FUTURE WORK

We obviously need to test our approach on a wider range of MODIS data sets. In doing so, we also need to develop quantitative methods to evaluate our results.

We also intend to develop and test other variations on this scheme for reducing cloud fringing errors. For example, instead of performing the image segmentation directly on the MODIS spectral bands, we also plan to test segmenting on the NDSI and NDVI feature values. Another variation would be to add cloud sensitive MODIS spectral bands, such as MODIS bands 27, 31 and 35, as input to the segmentation algorithms. Alternatively, the brightness temperatures base on these cloud sensitive bands could be utilized as inputs.

7. REFERENCES

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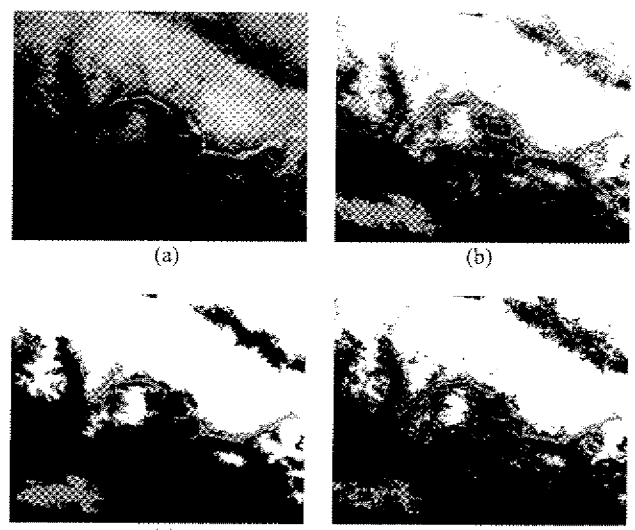

(a) (b) (c) (d)

Figure 1. (a) A 512x400 pixel section of band 4 of Terra MODIS granule A2007069.1750.005. (b) The corresponding section of the MODIS Snow and Ice Product. White is snow, grey is either clouds or water and black is land. (c) The corresponding section of the modified Snow and Ice product utilizing the HSWO 3,415 region object segmentation result. (d) The corresponding section of the modified Snow and Ice product utilizing the RHSEG 10 region class segmentation result.